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SMART BETA INVESTING IN THE NORDIC STOCK MARKET

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ABSTRACT:

This study explores the risk and return characteristics of different smart beta strategies in the Nordic stock markets. The aim is to investigate the risk adjusted returns of smart beta portfolios constructed to mimic value, momentum and low beta strategies. Additionally, two alternative multi-factor smart beta portfolio construction methodologies are studied to understand the benefits of factor exposure diversification.

Earlier research on smart beta strategies using data from the Nordic stock markets is fairly scarce. Particularly novel aspect is the study on the returns of two alternative multi-factor smart beta portfolio construction methodologies. Thus, this thesis complements the existing literature on smart beta by investigating the returns of different smart beta strategies and alternative portfolio construction methodologies in a novel geography.

Results indicate that value, low beta and momentum smart beta strategies have generated abnormal returns in the Nordics during the period under study. Value premium shows cyclicality, while momentum and low beta are more consistent trough time. Diversifying factor exposure from single factor to multi-factor portfolios improves the risk adjusted returns. Integrating multi-factor portfolio construction methodology is found to generate superior returns compared to mixing approach. The results are useful for investors that are considering smart beta investments in the Nordic stock market.

1. INTRODUCTION

1.1. Background

Smart beta investing has increased in popularity among private and institutional investors during the recent past. Smart beta investing has grown so prominent among institutional investors that FTSE Russel started conducting annual smart beta surveys amongst the institutional client base in 2014. The 2019 survey includes 178 global institutional asset owners with approximated cumulative AUM of $5 trillion. According to the survey, 83% of asset owners globally have a smart beta investment allocation, have evaluated or are planning to evaluate this topic during the next 18 months. Of all the asset managers in the survey, 58% have an existing smart beta allocation, a significant increase from 32% in 2014. The trend towards smart beta investing is also visible in flows into smart beta funds and indices. According to multiple research houses, the inflows into smart beta ETFs and funds remain at a healthy level. The increasing popularity of smart beta investing is one of the main motivators to study this subject. Furthermore, empirical research regarding smart beta investing within the Nordic equity market universe is fairly scarce, making this topic particularly interesting.

There is no universally accepted definition for smart beta in the academic literature. However, academics and practitioners seem to agree that smart beta strategies are long-only strategies that aim to outperform the capitalization-weighted market index through alternative weighting methodologies that emphasize investment styles such as size, value, momentum and low beta (Jacobs & Levy 2014; Malkiel 2014). For example, Assness, Ilmanen, Israel and Moskowitz (2015) classify smart beta investing as tilting towards certain investment styles, but instead of constructing zero cost long-short portfolios, smart beta portfolios are long-only. Thus, smart beta portfolios have significant market exposure, i.e. high correlation with the equity market. The significant market exposure is one of the main weaknesses of smart beta strategies when compared to its market neutral long-short counterparts. Long-only smart beta strategies, however, have multiple advantages when compared with long-short strategies. The advantages

include lower management fees, generally lower transaction volumes, increased transparency, and maybe most importantly, accessibility for investors with shorting constraints (Stambaugh, Yu & Yuan 2012; Jacobs & Levy 2014).

Existence of style premium has been widely studied by the academics during the past 30 or so years. Eugene Fama and Kenneth French are among the most influential researchers in the area. In their early studies in the beginning of 1990s, they describe the cross-section of equity market returns through two additional factors (styles): value and size with their famous three-factor model (1992, 1993). By applying the three-factor model, Fama and French find negative correlation between firm size and expected returns and positive correlation between book-to-market (B/M) ratio and expected returns. This implies that investors could earn higher returns by investing in small value stocks than predicted by the traditional capital asset pricing model (CAPM).

Since the discovery and proper documentation of value and size premiums, the academics have been in frantic search for additional persistent and systematic sources of excess returns that cannot be explained by the CAPM or other asset pricing models. Many attempts to identify additional return premiums from the stock markets have lacked proper robustness, which is most likely a result of data mining. However, according to Asness et al. (2015), few equity investment styles with robust academic research and economic rationale backing them have been identified and widely accepted by the academics and practitioners. The styles are value, momentum and low beta. Value was originally documented by Graham and Dodd already in 1934, momentum was initially documented by Jegadeesh & Titman in 1993 and low beta was initially discussed by Jensen, Black and Scholes in 1972, but more recently researched by Frazzini & Petersen (2014).

1.2. Purpose of the study

As mentioned, smart beta strategies aim to generate higher risk adjusted returns than traditional capitalization-weighted market index by using alternative weighting

schemes. This is in conflict with the traditional equilibrium model of the pricing of capital assets introduced by Sharpe (1964) and Lintner (1965). According to the traditional financial theory, the relation between expected returns on individual assets and their systematic risk can be measured with market beta. Consequently, the linear relation between expected return and systematic risk of an asset can be described with CAPM. In this thesis, smart beta portfolios are constructed based on styles listed by Asness et al. (2015). Value, momentum and low beta portfolios are constructed and their respective returns are regressed against returns of Nordic market index to test whether the long-only smart beta strategies have generated above market risk adjusted returns over long time period.

Furthermore, each portfolio will be sorted by size to check if the style premium is driven by the size effect (Banz, 1981). Additionally, the over 20 year sample period is divided into two equally long subsamples to ensure that smart beta returns are consistent through time. Frazzini et al. (2014) use similar methodology to confirm the persistency of style returns. Finally, multi-factor portfolios are constructed using mixing and integrating approaches following Chow, Li and Shim (2018). Empirical research is conducted whether the multi-factor portfolios can enhance the risk adjusted returns when compared with single-factor portfolios. When studying the returns of multi-factor strategies, only the top 30% of largest stocks are used to make sure that the multi-factor strategies are actually implementable and scalable, at least to some extent.

In short, this paper contributes to finance literature by providing evidence of performance of different long-only smart beta strategies in the scarcely researched Nordic stock market universe. In addition, possibility to earn superior returns by mixing and integrating the long-only style tilts to multifactor portfolios is examined.

1.3.   Hypotheses

In this section research questions are introduced and hypotheses constructed based on the questions. The portfolio holding period in this study starts in December 1996 and ends in January 2019. This period includes 278 monthly observations and subsumes multiple economic cycles. Thus, the sample period can be deemed well representative of the Nordic stock market's fairly short history.

The first and obvious research question is whether different long-only smart beta strategies tilting towards value, momentum and low beta styles have generated economically and statistically significant excess returns over CAPM during the research period in the Nordic stock market universe. The results of this study are expected to be in line with previous literature showing that the strategies of interest do generate excess returns in the international equity markets (see e.g., Rouwenhorst 1998; Fama and French 1998; Griffin, Ji and Martin 2003; Asness, Moskowitz and Pedersen 2008; Walkshäusl 2014; Frazzini et al. 2014; Asness et al. 2015).

> H0: Investing systematically to stocks with high B/M, strong recent relative performance and low beta are expected to generate abnormal returns over the Nordic market index.

Given that abnormal returns are found, the natural question is whether the excess returns are driven by small companies (Banz 1981). Previous literature has shown that different style premiums are stronger within small stock universe (see e.g., Fama and French 2011 and 2015; Asness, Frazzini, Israel and Moskowitz 2018), and similar results are expected to be found from the Nordic equity market data.

> H1: Abnormal returns of strategies are strongest within the small stock universe, but exist in all size groups.

Previous literature has shown that value premium can be cyclical and might experience prolonged periods of poor performance (see e.g., Asness, Friedman, Krail and Liew

2000; Cohen, Polk and Vuolteenaho 2001; Zhang 2005). However, earlier research concerning momentum and low beta have shown persistency in returns of the styles through time (see e.g., Frazzini et al. 2014; Asness, Frazzini, Israel and Moskowitz 2014). Motivated by the findings of earlier research, the consistency of style premium through time is studied in the Nordic stock market, with expectation that the results are in line with previous literature.

> H2: Smart beta strategy tilting towards value has cyclical nature, while momentum and low beta are more consistent through time.

Lastly, the risk adjusted returns of different multi-factor long-only portfolios created by mixing and integrating the smart beta strategies is explored. According to Fitzgibbons, Friedman, Pomorski and Serban (2016) and Chow, Li and Shim (2018), multifactor strategies generate superior returns when compared to any single factor portfolio. Furthermore, when comparing the two multi-factor portfolio construction strategies, integrating approach is found to be superior to mixing approach.

> H3: Multi-factor portfolios constructed by mixing and integrating the long-only smart beta strategies generate superior risk adjusted returns compared to single-factor portfolios

The hypothesis testing and results will be discussed in detail in chapters 6 and 7.

1.4.   Structure of the study

The thesis is organized as follows: next chapter will introduce efficient market theory, the cornerstone of modern finance and base of many hypotheses that are tested. The third chapter gets familiar with stock pricing models which are used to estimate the expected returns of stocks. The CAPM and multifactor models will be discussed in detail in this chapter. Thereafter previous academic literature on different styles is discussed and economic rationale and possible sources of risk premiums are presented.

In addition, studies regarding multi-factor smart beta investing are discussed. Fifth chapter will introduce data and portfolio construction methodology, and results of the study are presented in chapter six. Finally, chapter seven will conclude the thesis.

2. EFFICIENT MARKETS

In his Nobel Prize lecture called "Two Pillars of Asset Pricing" (2013), Eugene Fama states that two branches of research are the pillars of modern asset pricing literature. The first pillar is research regarding efficient capital markets, and the second pillar is research on asset pricing models. This chapter will focus on efficient capital markets, while the following chapter delves into the asset pricing models.

2.1. The concept of efficient capital markets

The concept of efficient markets is one of the most essential, and yet most disputed concepts in finance. As a term, market efficiency subsumes multiple different meanings. First of all, efficient markets allocate capital efficiently. This means that projects with best profitability will receive funding. Secondly, transactions done in the markets are carried out as efficiently as possible. This is called operational efficiency of the markets. Thirdly, notion of efficient markets include information efficiency, which implies that market prices of assets always fully reflect all available information. (Fama 1970.)

Research regarding efficient capital markets has a long history, initiating from random walk theory suggested by Bacheliere already in the beginning of the 1900s. However, the current widely accepted theory of efficient capital markets was formulated by Eugene Fama (1965, 1970). In order for the markets to be efficient to adjust asset prices to new information, few market conditions have to be made. The sufficient, but not necessary conditions for capital market efficiency are:

1. No transaction costs in trading
2. All available information is available to all market participants for free
3. All market participants agree to the implications of new information for the current price of an asset and distribution of future prices of each security

If the conditions 1-3 are met, asset prices would fully reflect all available information at all times. However, it is obvious that the frictionless markets described by the above criteria do not reflect the markets observed in practice. Fortunately, the listed conditions for market efficiency are not necessary for the markets to be efficient. For example, the fact that all investors do not consider a piece of new information to have the same implication for the price of an asset does not imply that the markets are inefficient. Markets can be considered efficient as long as investors cannot consistently make correct evaluations of new information's effect to the prices of assets, and this way generate consistent excess returns. (Fama 1970.)

2.2. Levels of efficiency

Stating that markets are efficient, i.e. that asset prices reflect all the available information at any given point of time is an extreme null hypothesis to put forth. As any extreme null hypothesis, the hypothesis of total efficiency cannot be expected to be literally true. Thus, Fama (1970) decided to divide market efficiency into three testable levels: Weak form, semi-strong form and strong form of efficiency. By categorizing efficient markets to different levels, scholars are able to pinpoint the level at which the hypothesis breaks down.

2.2.1. Weak form

When all information of past stock price performance is reflected in the stock price, markets can be considered to be weakly efficient. Consequently, technical analysis in weakly efficient markets is waste of time. Tests of weak form of efficiency are focused on finding serial correlation in returns of assets. One of the most common methods is to see if returns of assets follow random walk, i.e. if future returns are completely random and cannot be predicted by merely looking at past returns. Tests of weak form go a long way to prove the efficient market hypothesis to be valid, i.e. that returns follow random walk. (Fama 1970).

2.2.2. Semi-strong form

Semi-strong form of efficiency is achieved, when in addition to information of past returns of assets, all obviously available information (i.e. annual reports, interim reports, announcements of new security issues etc.) regarding the assets are reflected in the market prices. Testing of semi-strong form efficiency of markets is traditionally done through event studies. Events like stock splits and annual earnings announcements are often studied. Fama, Fisher, Jensen and Roll (1969) were among the first to study whether semi-strong form of efficiency is fulfilled. They study whether the information of stock splits is incorporated in the stock prices efficiently, and find supporting evidence for efficient market hypothesis. After Fama et al. (1969), multiple events have been studied and evidence of the studies have generally been in favor of the efficient market hypothesis. (Fama 1970).

2.2.3. Strong form

Lastly, the strong form of market efficiency is present when there are no investors who have monopolistic access to any information that can have an effect on the price of an asset. In the world of strong efficiency, there are no abnormal returns to be gained through insider investing. Tests regarding strong market efficiency have focused on the returns earned by certain groups of people with monopolistic access to information such as management teams of publicly listed companies. The tests have found that the efficient market hypothesis breaks down at this level, as investors with monopolistic access to information have been able to generate abnormal returns (Niederhoffer and Osbourne 1966, Fama 1970.)

2.3. Critique of efficient market hypothesis

As mentioned, the concept of efficient markets is one of the most essential, and yet most disputed concepts in finance. In this paragraph some of the most well-known research that goes against the efficient market hypothesis is presented.

In their research, Lo, Mamaysky and Wang (2000) find that the traditional charting techniques commonly used by traders, such as double-bottoms and head-and-shoulders, do provide some incremental information and might be of practical value. In fact, there is a vast pool of studies that find non-randomness and serial correlations in stock prices, i.e. that past performance of a stock have information about the future performance (see e.g., Lo and MacKinlay 1988; Jegadeesh et al. 1993; Chan, Jegadeesh and Lakonishok 1995). However, Allen and Karjalainen (1999) and Ready (2002) fail to find significant excess returns of technical trading strategies after taking into account for the trading costs.

Whereas research of Jegadeesh (1993) and Chan et al. (1996) show positive autocorrelation in medium time periods (i.e. momentum), research of De Bondt and Thaler (1985) find negative autocorrelation in long time periods. De Bondt et al. argue that the long term price reversal is caused by behavioral factors, as most people overreact to unexpected and impactful news. The idea that investors are not rational utility maximizers, which leads to under- and overreaction was introduced by Kahneman and Tversky in 1979 when they published their famous research regarding prospect theory. Thus, the results of De Bondt et al. point to substantial weak form inefficiencies of markets. However, Fama (1998) states that overreaction to new information is just as common as under reaction. In addition, Fama (1998) argues that research regarding long-term return anomalies is not robust, as the results are sensitive to methodology.

In addition to medium and long term autocorrelation in stock returns, a number of seasonal and day-of-the-week patterns have been found. The most common example is the January effect (Thaler 1987), which states that the average monthly return of January is significantly larger than the average returns of other months. This phenomenon was found to be especially strong within small stock universe. However, Malkiel (2003) argues that the January effect lacks consistency and is not dependable from period to period. In addition, Malkiel states that the nonrandom and seasonal events are small in economic size, thus they would not enable investors to generate excess returns after trading costs.

All in all, the theory of efficient markets is widely criticized and supported at the same time, which has led to an academic debate that has resulted to vast amount of studies with differing results. One interesting study was conducted by Schwert in 2002. He finds that some anomalies have weakened, or even vanished, after academic papers have been released regarding the anomalies. Schwert finds that anomalies such as value, small-firm, turn-of-the-year effect and the weekend effect are weaker than documented in the original academic publications. This implies that practitioners who implement the investing styles from the academic research may exploit the anomaly out of the market, i.e. cause the market to become more efficient. Thus, it can be concluded that markets are efficient, at least to the extent that finding persistent and scalable excess returns is exceedingly difficult. Short anomalies and periodical mispricing happen, but consistent and pervasive anomalies are extremely hard to come by.

3. ASSET PRICING MODELS

In this chapter, the most well-known asset pricing models are introduced in chronological order from CAPM of Sharpe (1964) and Lintner (1965) to six factor model of Fama and French (2018).

3.1. Capital asset pricing model (CAPM)

CAPM is based on a market equilibrium theory of asset prices under conditions of risk. The theory was derived simultaneously, but independently by Sharpe (1964) and Lintner (1965). The theoretical work of Sharpe and Lintner is built on modern portfolio theory which was introduced by Markowitz in 1952. CAPM is a single factor model that is used to derive the required rate of return of an asset. The formula of CAPM is commonly denoted as follows:

$$(1) \qquad E(R_i) = R_f + \beta_i [E(R_m) - R_f]$$

Where $E(R_i)$ denotes expected return of portfolio i, R_f denotes the risk free rate of return, β_i is the beta coefficient of portfolio i and $E(R_m)$ is the expected return on market portfolio.

In short, CAPM states that the expected return of an asset can be determined by its exposure to changes in economic activity, which is often called the systematic risk. The systematic risk of each asset is measured with β_i, which is the slope parameter of assets' return regressed on return of the market returns, denoted with $[E(R_m) - R_f]$. This implies that assets that are more correlated with economic activity, i.e. high beta stocks, are expected to have higher returns. Consequently, assets that are not affected by economic activity, i.e. low beta stocks, are expected to have lower returns. (Sharpe 1964.)

3.2.   Three factor model

CAPM was widely accepted among academics and practitioners for a long time after Sharpe and Lintner published their papers in 1964 and 1965 respectively. However, multiple empirical contradictions of the CAPM were found in 1980s. The most well-known being the size effect documented by Banz (1981). He finds that in addition to market β, the size of a company has explanatory power regarding average expected returns. Banz (1981) finds that average returns of companies with low market capitalization (calculated as shares outstanding times share price) are higher than companies with high market capitalization.

In addition, numerous empirical researches show that the ratio of a firm's book value of common equity to its market value, B/M, has explanatory power in the cross-section of average stock returns (see e.g. Stattman 1980, Rosenberg, Reid and Lanstein 1985 and Chan, Hamao and Lakonishok 1991).

Based on the empirical contradictions, Fama and French (1992) deduced that if assets are priced rationally; the risks of stocks are multidimensional, which could be the reason behind CAPM's inability to explain the expected returns of stocks. Fama and French (1993) reasoned that size and B/M must proxy for sensitivity for common and undiversifiable risk factors in returns. Motivated by this idea, Fama and French constructed their famous three factor model in 1993, which has two additional risk factors to the market β from CAPM: Size and B/M (value) factors. The factors for size and value are returns or excess returns of zero cost portfolios that are constructed by taking a long position in small and short position in large companies and long companies with high B/M and short companies with low B/M. Thus, the factors are often called small minus big (SMB) and high minus low (HML) factors. According to the three factor model, expected excess return of portfolio i is:

$$(2) \qquad E(R_i) - R_f = \beta_i \big[E(R_m) - R_f \big] + s_i E(SMB) + h_i E(HML)$$

The model states that the expected excess return of portfolio i is explained by the sensitivity of the portfolio to three factors:

1. The excess return of the broad market, denoted by $E(R_m) - R_f$
2. The expected difference between returns of portfolios of small and big companies denoted by E(SMB)
3. The expected difference between returns of portfolios of companies with high and low B/M ratio, denoted by E(HML)

In equation 2, β_i, s_i and h_i measure the factor sensitivities of the portfolio to the market factor, size factor and value factor respectively.

Fama and French argue that B/M ratio and the sensitivity to HML factor proxy for relative distress, while the SMB factor captures covariation in returns on small stocks that is not captured by the market β (Fama and French 1996).

In 1996, Fama and French used their three factor model to explain some of the most prominent anomalies in the stock markets at the time. They found that stocks with high earnings to price ratio (EP) or high cash flow to price ratio (CP) loaded positively on HML factor, which explained their higher future returns. In addition, long term reversal in stock prices was captured by both SMB and HML factors, as long term losers in the stock market tend to have positive loading on SMB and HML. According to Fama and French (1996), this was caused by the fact that long-term losers often are relatively distressed and small in market value, thus have higher future returns.

3.3. Five factor model

In 2013 Novy Marx found that firm profitability measured with gross profit scaled with total assets has explanatory power in expected stock returns. In addition, stocks with high profitability seemed to correlate negatively with value stocks, thus giving a good hedge to value strategies. Furthermore, it is shown that companies that invest less have

higher average returns compared to similar companies that invest aggressively (Aharoni, Grundy and Zeng 2013).

Motivated by these findings, Fama and French (2014) constructed a five factor asset pricing model that includes profitability and investment factors in addition to the market, size and value factors of the three factor model. The five factor model performs better at capturing the variation of stock returns than the three factor model. The model is presented below:

$$(3) \quad E(R_i) - R_f = \beta_i\big[E(R_m) - R_f\big] + s_i E(SMB) + h_i E(HML) +$$
$$r_i E(RMW) + c_i E(CMA)$$

The model says that the expected excess returns on a portfolio i is explained by the sensitivity of its returns to five factors: market, size, value, profitability and investment. Profitability factor is measured as difference in returns of portfolio of stocks with high profitability minus returns of portfolio of stocks with low profitability (RMW, robust minus weak) and the difference between returns of portfolio of stocks that invest less minus returns of portfolio of stocks that invest a lot (CMA, conservative minus aggressive) is the measure of investment factor.

3.4. Six factor model

In 2018 Fama and French published a paper, with a purpose to rank asset pricing models. In addition to the CAPM, the three factor model and the five factor model, Fama and French introduce a six factor model. The six factor model adds momentum factor to the five factor model (Fama and French 2014). The six factor model is presented below:

$$(4) \quad E(R_i) - R_f = \beta_i\big[E(R_m) - R_f\big] + s_i E(SMB) + h_i E(HML) +$$
$$r_i E(RMW) + c_i E(CMA) + m_i E(UMD)$$

The six factor model is identical to the five factor model, but it is augmented by adding the momentum factor (UMD, up minus down). The UMD factor is measured as a difference of returns of portfolio of stocks that have strong recent performance minus portfolio of stocks that have recently performed poorly.

The result of testing the ability of different models to explain the excess returns of portfolios shows that the six factor model seem to be superior to models with fewer factors. As momentum is a well-documented and empirically robust factor, the fact that the six factor model outperforms other models is unsurprising. However, Fama and French add the momentum factor to their previous five factor model somewhat reluctantly, because they see that the momentum factor does not have a similar theoretical motivation backing it as value, profitability, investment and size do.

4. PREVIOUS LITERATURE

This chapter is dedicated to present some previous literature on the equity investing styles that are studied in the thesis, namely value, momentum and low beta. Due to the plethora of academic research on each style, especially value and momentum, only few most influential and well known papers are presented. Additionally, a more recent area of academic interest is introduced: Multi-factor smart beta investing, and two alternative approaches of implementing a multifactor investing strategy.

4.1. Value

Within the equity universe, value investing is the best-known style. The idea behind value investing is fairly simple, to buy undervalued, or cheap stocks, and sell overvalued, or expensive stocks. Academia has researched value investing extensively. One could argue that the most profound publications have been done by Fama and French (see e.g. 1992, 1993, 1998, 2012). In 1992 and 1993 Fama and French document that there is a positive relation between book-to-market equity (B/M) ratio and average stock returns in the US stock markets. Similar findings have been documented by other scholars, who have used different signals to measure value, such as earnings to price (E/P) ratio, cash flow to price (C/P) ratio, enterprise value to EBITDA ratio etc. (see e.g. De Bondt and Thaler, 1985, Lakonishok, Shleifer and Vishny 1994, Grey and Vogel 2012).

Majority of the early research on value investing was done using the US equity market data. In their 1998 paper, however, Fama and French find that the value premium is present in the international markets too, which proves that value premium is not a US-specific market anomaly. Similar findings have been documented by Chan, Hamao and Lakanishok already in 1991, as they find value premium from Japanese stock markets. In addition, Asness, Moskowitz and Pedersen (2013) find that value generates excess returns in main international markets, and not only within the equity universe, but across different asset classes. More recently, Tikkanen and Äijö (2018) studied the performance of different long-only value investing strategies, and whether the strategies

can be improved using Piotoski's (2000) F-score screening within the European equity universe. The scholars use the F-score to screening to find value stocks with solid financial health to construct portfolios. The result show superior performance of the high F-score portfolios across the investment strategies studied.

Existence of the value premium is also documented in the Nordic stock markets. In 2009, Leivo and Pätäri study the returns of different value investing strategies using Finnish equity market data from 1993-2008. They construct portfolios based on multiple valuation ratios and evaluate the performance of the portfolios with several performance metrics. The results show existence of the value premium in the Finnish stock markets. Davydov, Tikkanen and Äijö report similar findings (2016). Cakici and Tan (2014) studied the value premium in various developed economies. They found positive returns for value strategies from Finland, Denmark and Norway, while value premium was not found to have significant over-performance in Sweden. Grobys and Huhta-Halkola (2019) found positive value premium by using data from Nordic stock universe.

Regardless of the thorough research that the academia has done considering the value premium, there is still dispute about the reasons and rationale behind it. There are two alternative views why the value premium exists in the global stock markets. The first view is that the value premium is a proxy for an undiversifiable risk. This view argues that the value stocks are fundamentally riskier than growth stocks, thus value investors, on average, deserve a higher rate of expected return on the increased risk they are carrying (see e.g. Fama and French, 1992, 1993; Griffin and Lemmon, 2002; Vassalou and Xiang, 2004, Cakici and Tan, 2014).

The opposing view argues that market participants are not rational, and their behavior is the root cause for the value premium. The behavioral view states that value companies tend to generate excess returns compared to growth stocks because markets tend to overestimate the future potential of expensive "glamour" companies and underestimate the prospects of value companies (see e.g. Lakanishok et al., 1994; La Porta, 1996; Chan and Lakanishok, 2004). Furthermore, it has been shown that companies with high

distress risk generate exceptionally low returns, but have high standard deviation, market beta and value factor loading. These patterns are inconsistent with the conjecture that value premium is compensation for higher risk (Campell, Hilscher and Szilagyi, 2008).

4.2. Momentum

Momentum investing is almost as well-known a strategy as value investing. Similarly to value, momentum is supported by vast amount of robust evidence by the academia, and the style is widely utilized by practitioners. Momentum investors exploit the tendency of securities to exhibit persistence in their strong (weak) relative performance to other securities within their asset class. The typical way of implementing momentum is to look at the past 12 months of returns for a universe of assets (a country's stock index, for example), and taking a long position in the securities that outperformed their peers, while shorting the underperformers. By implementing momentum as long-short strategy, the correlation with market returns is low. The described momentum is the most well-known form of momentum investing, where the momentum ranking is done by looking at assets' past returns. Momentum can also be implemented by utilizing momentum in securities' fundamentals. For example, one could rank stocks on basis of earnings momentum, changes in profit margins and analyst estimates. (Asness et al. 2015).

The first studies regarding momentum in security prices were conducted by Narasimhan Jegadeesh. In his 1990 paper, Jegadeesh reports negative first-order serial correlation in monthly stock returns, but finds positive autocorrelation when using longer lags. Especially 12 month positive serial correlation was found to be particularly strong. This means that stock prices tend to decline after a month of strong returns, but if a stock has performed well during the past 12 months, it is likely to have positive returns in the next month too. In 1993 Jegadeesh and Titman dig deeper into the topic of positive autocorrelation in stock returns. They study trading strategies that buy past winners and sell past losers (i.e. momentum), and find statistically and economically significant

abnormal returns that cannot be explained by higher systematic risk. Since then, similar results have been documented by multiple scholars in many different markets and asset classes (see e.g., Chan, Jegadeesh and Lakonishok (1996) and Grinplatt and Moskowitz (2004), Asness, Moskowitz and Pedersen (2008), Fama and French (2012), Asness, Frazzini, Israel and Moskowitz (2014) and Asness et.al. (2015)).

There is also a sizeable body of research on momentum factor returns using international stock market data, as scholars have strived to extend the findings from the US stock market to the international universe. Rouwenhorst (1998) examines the returns of his momentum strategy in 12 European countries, including Sweden, Norway and Denmark from the Nordics. Rouwenhorst uses six-month past returns as momentum signal and has six-month portfolio holding period in his research with data ranging from 1980-1995. He documents statistically significant returns of his momentum strategy in most of the countries under study. When looking at the Nordic countries more specifically, Denmark and Norway had significant momentum returns, while Sweden did not. Fama and French (2011) study size, value and momentum in international stock markets, and find significant momentum returns everywhere except Japan. Especially Europe showed strong returns for the momentum factor. Fama and French also document that momentum returns tend to be higher for small stocks than for large capitalization stocks. Similar findings were recorded by Cakici and Tan in their 2014 paper, where they investigate the returns of size, value and momentum in developed country equity returns. They use stock market data from 23 developed countries during sample period of 1990-2012 and find significant momentum returns from most of the markets under study. From the Nordics, Finland, Norway and Denmark had positive momentum returns, while in Sweden, significant momentum returns were found only from the small capitalization stocks.

Asness et al. (2013) study the correlations and performance of value and momentum strategies in eight different asset classes and markets. They document consistent value and momentum return premium across the studied asset classes and market. Furthermore, negative correlations between value and momentum within and across

asset classes are found. The results give strong evidence of presence of momentum and value premiums.

Similarly with the value premium, academics have not come to a clear consensus about the drivers behind the excess returns generated by the momentum strategy. With the momentum anomaly, the competing explanations are risk based and behavioral based explanations.

It has been shown that momentum is at least partly explained by the deteriorating returns of high credit risk companies. The deteriorating returns of high credit risk companies support momentum's returns, as the strategy actively takes short positions on past losers, which often consist of high credit risk companies (Avramov, Chordia, Jostova and Philipov 2012).

Another risk based explanation for the momentum anomaly is liquidity risk. According to Pastor and Stambaugh (2003), liquidity risk factor explains half of the profits of the momentum strategy over a long time period. They find that the returns of stocks with high sensitivity for liquidity factor exceed the returns of stocks with low sensitivity to liquidity factor by 7,5% annually. Similarly to Pastor and Stambaugh (2003), Sadka (2006) concludes that a substantial amount of momentum returns can be viewed as compensation for the exposure on unexpected variations in liquidity.

In addition, regardless of the strong positive average returns across multiple geographies and asset classes, momentum can experience infrequent but significant crashes in returns (Barosso, Perdo & Santa-Clara, 2015). Momentum crashes occur when the markets are in panic and volatility is high, and crashes are contemporaneous with market rebounds, as past losers notably over perform past winners (Daniel & Mozkowitz, 2016). This implies that the long-run reward of momentum investing could be compensation for investing in a style with negative skewness and fat left tail.

Already in the first published paper about the momentum anomaly, Jegadeesh and Titman (1993) claim that the performance of the momentum strategy cannot be entirely

explained by higher systematic risk. The scholars conclude that the driver behind momentum anomaly could be behavioral based, as investors over- and underreact to news. Subsequently, research on behavioral finance has grown considerably and multiple different models that try to explain the momentum anomaly by investor's over- and under reaction have been created.

One model was introduced by Grinblatt and Han (2002), where they aim to utilize the disposition effect to explain momentum returns. It has been documented that many investors have a lower propensity to sell loser stocks, while selling recent winner stocks is more common. This behavioral phenomenon is known as 'the disposition effect'. According to Grinblatt and Han (2002), the existence of the disposition effect creates momentum in stock prices. This happens as the irrational investors sell the stocks with strong recent performance, and hold on to their loser stocks, even though the fundamental value of the winner stocks has increased and vice versa for the loser stocks. This opens a "valuation spread" for the rational investors to exploit, but also makes the price discovery a slower process, thus creating momentum in share prices.

All in all, the existence of the momentum premium is well documented, but the reasons behind it, whether risk based or behavioral based, are still open for academic discussion.

4.3.   Low beta

Low beta investing is an old strategy, but it is not as extensively studied as value and momentum strategies. In low beta strategy, the investor aims to generate excess returns by going long stocks with low beta and shorting stocks with high beta (Asness et al., 2015). This is in direct contradiction with the traditional financial theory and the CAPM, which assume that the expected returns on individual assets are a linear function of the asset's systematic risk, or beta.

Already in 1972 Black, Jensen and Scholes show that the expected returns of stocks are not strictly proportional to their betas. In their paper, they use data from 1931 to 1965 to

examine returns of portfolios of stocks ranked on the basis of their systematic risk (beta). They find that portfolios with high beta, on average, earned less than the CAPM predicted, and vice versa with low beta stocks. This inverse risk-return relation has been studied by using volatility and beta as proxy for riskiness, and similar finding have been documented in the Us and international stock markets (Walkshäusl, 2014; Ang, Hodrick, Xing & Zhang, 2006; Blitz & Van Vliet, 2007; Asness et al., 2015; Frazzini & Pedersen, 2014).

Similarly to value and momentum premiums, there are competing theories why low beta stocks earn higher returns than high beta stocks. According to Asness et al. (2015), the most compelling reason for the outperformance of low risk stocks is the fact that many investors are leverage averse or constrained of using leverage. Leverage constraints drive investors with return objectives to invest in high beta stocks to reach targeted returns, whereas they could reach similar or better risk adjusted returns by investing in low risk stocks with leverage. Thus, market participants with leverage constraints lower the prospective returns of high beta stocks, while investors who are willing to take the other side and hold low beta stocks may be compensated in the long run.

4.4. Multi-factor smart beta investing

As smart beta strategies have swiftly gained market share and attracted trillions of dollars in assets (Jacobs & Levy, 2014), there is a rising interest in studying how to implement smart beta strategies in the most efficient way. By definition, smart beta strategies carry concentrated risk exposure to the chosen strategy, e.g. momentum, value or low beta. It is also well documented that while the mentioned strategies generate excess returns on average, the styles are prone to periods of poor returns. Momentum, for example is notorious of its crashes (Barroso & Santa-Clara, 2015). Thus, diversifying from single risk factor exposure to multi-factor exposure can improve risk adjusted returns. Furthermore, correlations between the returns of the smart beta strategies are low, or even negative, which indicates that by careful implementation of multi-factor strategies investors can improve their risk adjusted returns when compared to single factor investing (Clarke & De Silva, 2016; Bender & Wang, 2016; Brightman,

Kalesnik, Li & Shim, 2017; Fitzgibbons, Friedman, Pomorski & Serban, 2017; Ghayur, Heaney & Platt 2018; Li & Shim, 2019).

There are alternative ways to implement multi-factor smart beta investing strategies, but two distinctive approaches have been identified as practical and efficient. The most studied approaches to implement multi-factor smart beta strategies are called mixing and integrating (see e.g. Fitzgibbons et al., 2017; Leippold & Rueegg, 2018).

4.4.1. Multifactor portfolio construction: Mixing vs integrating

Mixing is the more obvious way of building a multi-factor smart beta portfolio. The portfolio is simply built by combining two or more long-only portfolios focused on individual styles. For example, one could allocate 50% to a long-only portfolio focused on value and 50% to long-only portfolio focused on momentum. This way the investor would capture the risk premiums of both strategies and enjoy diversification benefits that are created by the low correlation of the two strategies' returns. The benefit of mixing approach is that it is very transparent, meaning that it is easy to deconstruct returns of the portfolio to returns generated by each individual style. Mixing approach is also flexible, as the investor can easily control the allocations across styles. (Fitzgibbons et al., 2017; Leippold & Rueegg, 2018).

Integrating approach is implemented by selecting stocks that have simultaneously exposures to multiple wanted risk factors. Thus, the integrating approach does not offer clean risk exposure to any single style, but an integrated exposure to multiple factors at once. For example, stocks with reasonably strong value and momentum characteristics get picked by this approach, while the same stocks would not be picked by single style portfolios of the mixing approach. In addition, stocks with the strongest value or momentum exposures might be left out of the integration approach, if these stocks have negative exposure to momentum or value respectively (Fitzgibbons et al., 2017; Leippold & Rueegg, 2018). The returns of the integration approach are not easily deconstructed to returns of different styles, meaning that the transparency of the approach is not as good as in the mixing approach. However, the integration approach

avoids unwanted risk exposures which are possible in the mixing approach, as value stocks, for example, may carry negative exposure to momentum factor (Fitzgibbons et al., 2017).

Clarke et al. (2016) study the returns of the two different long-only multi-factor portfolio construction approaches during 1968-2014, analyzing the combinations of four different styles: low beta, value, momentum and size. They find that the mixing approach captures less than half of the potential improvement over the market portfolio's Sharpe ratio, while the integrating approach performs significantly better. They conclude that when securities are viewed as groups of styles instead of styles being viewed as groups of securities, more of the potential risk adjusted returns can be captured.

Bender and Wang (2016) find similar results. They analyze returns of different multi-factor portfolios of value, momentum, low volatility and quality with data from 1993 to 2015 and find that integrating approach provides superior returns. The integration approach yields especially strong over performance compared to mixing approach when the correlations between the returns of the two styles are low. Thus, they report starkest differences between the two multi-factor portfolio construction methodologies when mixing and integrating value with quality or momentum. Bender and Wang conclude that the better performance of the integrated approach is backed by both intuition and empirical evidence.

Supporting results are also documented by Fitzgibbons et al. (2016) as they study the combination of long-only value and momentum styles using data between 1993 and 2015. They find that the integrated portfolio outperforms the simple mix across every performance metric. The outperformance of integrated portfolio is driven by the fact that both of the portfolios in the simple 50/50 mix approach include stocks with negative loading against the other style i.e. some stocks in the value portfolio have poor momentum, and a portion of stocks in the momentum portfolio are growth stocks.

Furthermore, Ghayur et al. (2018) find that the integrating approach delivers higher risk adjusted returns compared to mixing approach when the portfolios are constructed to target high levels of factor exposures. However, if the portfolios are allowed to have only small tracking error, which leads to lower levels of exposure to each style, the mixing approach performs better. Ghayur et al. study long-only multi-factor portfolios constructed from exposures to value, momentum, quality and low volatility using data from 1979 to 2016. Chow et al. (2018) report similar findings and add that integrated portfolios targeting high factor exposures carry higher implementation costs. This is because the investment universe grows thin when investors rank stocks to have strong exposure to multiple different factors. Chow et al. end up recommending the mixing approach for multi-factor smart beta portfolio construction because of its simplicity, transparency and lower trading costs.

Contradicting the findings of other scholars, Leippold and Rueegg (2018) state that there is no statistically significant difference between the returns of mixing and integrating approaches. They state that as the integrated approach does not carry clean exposure to any style; its returns are diluted and resemble more the returns of the low risk anomaly. However, this reduction in risk does not translate to improved risk adjusted performance. In their research, Leippold and Rueegg use data from 1963 to 2016 and study various long-only multi-factor portfolios constructed using single factor portfolios with exposure to value, momentum, profitability, size, investment and low volatility. Differing from previous research, Leippold and Rueegg use new approaches for hypothesis testing. In the previous literature, scholars have used single hypothesis testing and found economically and statistically sound excess returns. Leippold and Rueegg, however, use multiple hypothesis framework and fail to find statistically significant over performance for the integrated approach.

Majority of the research regarding different approaches to construct long-only multi-factor portfolios support the integrating approach (Clarke et al., 2016; Bender & Wang, 2016; Fitzgibbons et al., 2016; Ghayur et al., 2018). Main explanation for the superior risk-adjusted returns of the integrated multi-factor portfolio is that the simple mixed portfolios often include stocks that have unwanted negative exposure to other targeted

factors. However, few contradicting views have already been published (Leippold & Rueegg, 2018, Chow et al., 2018). To conclude, one should note that smart beta multi-factor implementation is still fairly novel field of research (all the publications introduced here are published within the last 5 years), and there could still be new multi-factor smart beta portfolio construction methodologies and preferences introduced.

5. DATA AND METHODOLOGY

The purpose of this chapter is to introduce the data, portfolio construction and return measurement methodologies.

5.1. Data

The sample consists of public companies from the Nordic countries. The countries chosen in the sample are Finland, Sweden, Denmark and Norway. Iceland is excluded from the sample because of scarcity and small size of Icelandic public companies.

The data is obtained from Thompson Reuters Data Stream database. The data set is compiled with OMX Helsinki, OMX Stockholm, OMX Copenhagen and OMX Oslo listed companies' monthly historical total return indices, monthly price to book ratios, quarterly book values and monthly market values from December 1991 to January 2019. The time period from December 1991 until January 2019 contains vast majority of the time that the Nordic stock markets have been fairly liquid and open to the international investors.

As usual to the literature, financial companies are excluded from the sample because the high leverage that is normal for financial companies does not have the same interpretation with nonfinancial companies. (see e.g. Fama et al., 1992, 1993 and Asness et al. 2013). In addition, all non-equity investment instruments such as ETFs are excluded from the data. Following Tikkanen et al. (2018) and Gray and Vogel (2012), the smallest 10% of companies are excluded from the sample due to possible liquidity issues. Furthermore, companies with negative book value of equity are excluded from the sample following Fama et al. (1992). The data contains firms that have gone bankrupt, so the results should be free of survivor bias. As a final note, following Tikkanen et al. (2018) and Piotroski (2000), the delisting return of a stock is assumed to be zero.

Descriptive statistics can be seen from the Table 1. Swedish companies account for almost a half of all the companies in the sample. However, the average size of a Swedish company is significantly smaller than an average company's size from Finland or Denmark. Finland's average market capitalization is inflated by Nokia and Denmark's by Novo Nordisk. Average market capitalization of Finnish companies excluding Nokia would is €806 million and average size of Danish companies excluding Novo Nordisk is €958 million. The large effect of excluding a single observation from the sample depicts the nature of the Nordic stock markets well, as one or two stocks can have disproportionally large effect on the population parameters.

Table 1. Descriptive statistics

Descriptive statistics of the data set; December 1995-January 2019, 278 months.
Minimum, maximum and average amount of companies by country. In addition, average market capitalization of a company in the sample is presented.

	Finland	Sweden	Norway	Denmark	Total
Min number of stocks	70	144	112	89	429
Max number of stocks	133	464	186	131	836
Average number of stocks	113	296	151	107	666
Average market value, € million	1 252,3	871,9	803,3	1 291,4	4219,0

In addition to firm specific parameters, macro level data of Nordic markets is also obtained. Following Grobys and Huhta-Halkola (2019) a representative risk-free rate and market index for the Nordic countries are constructed. To construct the Nordic indices, total return indices of OMX Helsinki, Stockholm, Copenhagen and Oslo are obtained. In addition, 6-month interbank offered rates of each country under study are attained.

5.1.1. Risk-free rate

Sweden, Norway and Denmark have central banks that are committed to perform their own monetary policy. Unlike the other Nordic countries, Finland is in the Euro area,

thus the European Central Bank decides the appropriate level of interbank interest rate for Finland.

Unlike in previous academic literature, where US T-bill rate is used as a proxy for risk free rate, a Nordic risk free rate is constructed in this thesis. The Nordic rate gives better proxy of risk free investment for investors that are focused on the Nordic stock markets, such as national pension and insurance funds of the Nordic region. The representative risk free rate for the Nordic region is calculated following Grobys et al. (2018). The Nordic risk free rate is a simple average of 6-month interbank offered rates of each country. Because of the low interest rate environment the global markets have experienced in recent years, 6-month rate is preferred to 3-month rate.

Figure 1 shows the development of monthly risk-free rates calculated from 6-month interbank offered rates of each country during the period of 1995-2018. On average, Norway's interbank offered rate is the highest, rooting from the strong economy supported by the oil and gas industry. In addition, it is worth mentioning that the 6 month interest rates of Finland, Sweden and Denmark have negative values for prolonged periods from 2015 onwards. However, the average Nordic interest rate is mostly above zero, supported by the higher interest rate of Norway.
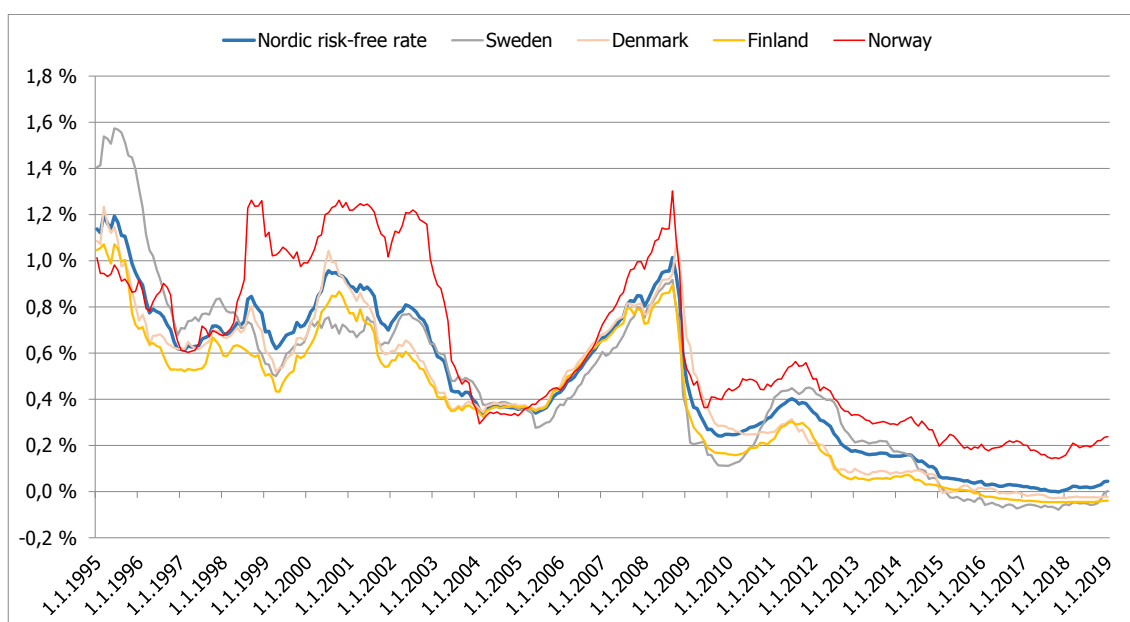
Figure 1. Monthly interbank offered rates

5.1.2.   Market index

Following Grobys et al. (2019), Nordic stock market index is constructed using value weighted total return indices of each country under study. The market index is simply average of linear returns of each index. However, total shareholder return indices for OMX Copenhagen and Stockholm are not available prior January 2001 and December 2002 respectively. For the period before availability of total shareholder return indices, price return indices are used for Copenhagen and Stockholm. This leads to slight underestimation of the market returns for the period.

It is important to notice that value weighted indices are used to construct the Nordic market index, while all the portfolios constructed in this thesis are equally weighted. This may lead to over estimating alphas of portfolios that have equal weighting for small and large sized stocks. This problem is taken into account by studying all strategies with double sort to different size groups, i.e. small, mid and large-capitalization companies. When creating the double sorts, 33.3th percentile break points for market capitalization are used. Furthermore, all the multi factor portfolios are constructed using only the top 30% of the largest shares. The portfolios that include only large cap companies can be considered to have a higher hurdle to exceed, as the value weighted portfolios have small cap stocks included.

Figure 2 shows the development of each individual index and the constructed equally weighted Nordic index. The returns are calculated as linear returns and indexed to 1 in December 1995. The largest discrepancy between indices can be seen during the tech bubble of 1995-2001, when the Finnish index peaks relative to other Nordic stock indices.
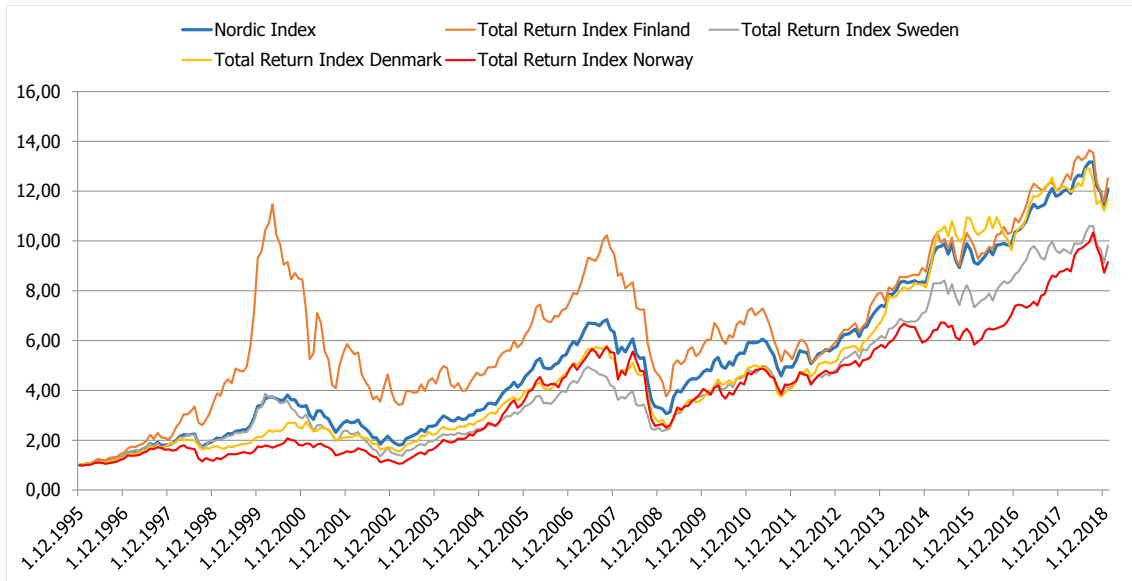
Figure 2. Historical performance of Nordic stock indices (linear returns)

There is significant correlation between different country indices. As indicated by the table 2, the total return indices of Sweden, Norway and Denmark are highly correlated during the sample period, while Finland is notably less correlated with the other Nordic countries caused by the tech bubble.

Table 2. Correlations between country indices

Correlation matrix of linear returns of Nordic total return indices indexed to 1 in December 1995

	Total Return Index Finland	Total Return Index Sweden	Total Return Index Denmark	Total Return Index Norway
Total Return Index Finland	1,00			
Total Return Index Sweden	0,89	1,00		
Total Return Index Denmark	0,86	0,99	1,00	
Total Return Index Norway	0,85	0,96	0,96	1,00

5.2. Portfolio construction and style measures

In the end of each month, all the stocks in the sample are sorted into quintiles based on their style measures (signals). Portfolios are constructed using these quintile ranks, and rebalanced monthly, following Asness et al. (2013, 2014, 2015). The style signals are discussed in more detail below.

Following Tikkanen et al. (2018) and Davydov et al. (2016), the portfolios are constructed as equally weighted. This is especially intuitive in the Nordic stock universe because the variability in size of the companies is significant. There are few outliers with very high market capitalization compared to rest of the stocks in the sample. Consequently, if one would use value weighted portfolios, the performance of a portfolio would largely be driven by the few stocks with high market capitalization.

5.2.1. Value signal

Commonly used measure or signal of value is the ratio of book value of equity divided by market value of equity, also known as book to market (B/M) ratio (see e.g. Fama et al. 1992, 1993 and Lakonishok, Shleifer and Vishny, 1994). The same measure of value is used in this thesis. When calculating B/M ratios for individual stocks, book values are lagged six months to ensure data availability to investors following Asness et al. (2013, 2015). The six months lagged book values are then divided by most recent market capitalization. The market capitalizations and book values of Swedish, Danish and Norwegian companies are converted to Euros in the end of each month using the exchange rate of the day of conversion. Companies with missing or negative book value of equity are excluded from the sample.

5.2.2. Momentum signal

In academic literature relating to the momentum strategy, the common measure of momentum is the past 12- month cumulative raw return, skipping the most recent month's return. Similar methodology has been used by Jegedeesh et al. (1993), Fama

and French (1996) and Asness et al. (2013, 2015). The most recent month is skipped to avoid possible one-month reversal caused by negative serial-correlation in monthly stock returns, documented by Jegadeesh in 1990. The widely accepted 12-1 momentum measure is also used in this thesis. If a company has less than 12 months of price data, the stock is excluded.

5.2.3. Low beta signal, *ex ante beta*

The low beta signal has been calculated following Frazzini and Pedersen (2014). The estimation of pre ranking ex ante betas is done by using rolling regressions of excess returns of each stock on excess returns of the Nordic market index. The betas are given by equation 5.

$$(5.) \qquad \hat{\beta}_i^t = \hat{\rho}\,\frac{\hat{\sigma}_i}{\hat{\sigma}_m}$$

where $\hat{\beta}_i^t$ is the estimated beta of the stock i at time t, $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the stock and the Nordic stock market respectively and $\hat{\rho}$ is correlation between the stock and the market. The volatilities are one-year rolling standard deviations of logarithmic excess returns. At least 12 months of non-missing data is required to calculate volatility. Correlations are calculated using five-year rolling correlation of logarithmic excess returns between the market and the stock. At least three years of non-missing data is required to calculate correlation, otherwise the stock is excluded from the sample. Longer non-missing data series is required for correlations because correlations move more slowly than volatilities. (Frazzini & Pedersen, 2014.)

5.3. Risk-adjusted performance measures

The risk-adjusted performance of portfolios is measured with the Sharpe ratio (1967, 1994), which is a standard measure of portfolio performance. The Sharpe ratio divides the excess returns of a portfolio with the standard deviation of excess returns to adjust for risk. Sharpe ratio is calculated as follows:

$$(6.) \qquad S_p = \frac{R_p - R_f}{\sigma_p}$$

Where S_p is the Sharpe ratio of the portfolio, R_p is the return of portfolio, R_f is the risk free rate and σ_p denotes standard deviation of the excess returns of the portfolio.

In addition to Sharpe ratio, CAPM is used to measure the abnormal returns of portfolios relative to the market. In order to account for heteroscedasticity and autocorrelation, Newey West's (1986) standard errors are used in the regressions. The abnormal returns are estimated with the following equation:

$$(7.) \qquad R_{it} - R_{ft} = \alpha_i + \beta_i(R_m - R_f) + \varepsilon_{it}$$

Where R_i is the return of portfolio i, R_f is the risk free rate, α_i is the intercept, i.e. the abnormal return unexplained by the excess return of the market, β_i is the slope coefficient and ε_{it} denotes the error term.

CAPM is deemed to be an appropriate model to measure risk adjusted returns, as it is shown by Barber, Huang and Odean (2016) that CAPM alphas are the best predictor of flows into mutual funds of multiple competing performance evaluation models. Similar findings were documented by Berk and Van Binsbergen (2016) as they assessed which asset pricing model investors use to make capital allocation decisions.

Furthermore, the goal of this thesis is to study the possible risk adjusted excess returns that the chosen long-only strategies generate over the market in the Nordic stock universe. The CAPM is suitable for this particular task. However, using multi-factor models, such as the Fama-French 5 factor model, to assess the returns of the integrated and mixed multi-factor portfolios could be an interesting topic of further research.

6. RESULTS

This section aims to answer the research questions presented in chapter 1.3. All regressions are done by using Newey West's correction, thus t-statistics are robust for heteroscedasticity and autocorrelation.

The first research question is whether the different long-only smart beta strategies have generated excess returns in the Nordic markets during the portfolio holding period from December 1995 until January 2019. Tables from 3 to 5 present the empirical findings concerning excess returns and risk adjusted returns of each smart beta strategy. In addition, some descriptive portfolio characteristics and common measures of risk, such as maximum drawdown and annualized standard deviation are shown.

6.1. Smart beta portfolios tilting towards value

The evidence in table 3 indicates that there is positive relation between B/M ratios and excess returns. Excess returns, alphas and Sharpe ratios increase monotonically with B/M ratio, which indicates that value premium is present in the Nordic stock markets. The average monthly excess return rise from 0,3% for the lowest B/M (growth) portfolio to 0,9% for the highest B/M (value) portfolio. The spread between to the portfolios is 0,6% per month, representing ~7,2% spread per annum. Furthermore, it is noteworthy that the positive relation between B/M ratios and excess returns is not driven by market exposure, as the realized beta is lower for value portfolio (0,78) than the growth portfolio (1,03).

However, regardless of the impressive monthly alpha of 0,5% of the value portfolio, the t-stat of 1,81 is significant only at 10% level, so no strong statistical significance can be found for the value premium. It should also be noted that the average market capitalization of stocks in the value portfolio is significantly smaller than the market capitalization of stocks in growth portfolio. This indicates that the value premium could be driven by the size effect.

Table 3 also shows that the value portfolio has the largest monthly drawdown of -22,9%. However, growth portfolio has strikingly large maximum drawdown of -85,9%. This occurred in March 2003 after the burst of tech bubble.

Table 3. Returns of long-only value portfolios

Value tilt in the Nordic stock market, Dec 1995-Jan 2019. 90% of largest companies included.

This table shows value-sorted portfolio returns. At the beginning of each calendar month, stocks are ranked in ascending order on the basis of their value signal (i.e book-to-market ratio) at the end of the previous month. The ranked stocks are assigned to one of five quintile portfolios. All stocks are equally weighted within a portfolio, and portfolios are rebalanced every month to maintain equal weights. Average monthly excess returns, alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Worst monthly drawdowns and maximum drawdowns are also shown. In addition, time-series average portfolio characteristics are presented: Average book-to-market (B/M), average company size (ME, in EUR millions) and average number of companies (n) in a portfolio. T-stats are found in brackets below regression estimates.

Portfolio	Low	2	3	4	High
Excess return	0,3 %	0,5 %	0,6 %	0,6 %	0,9 %
	(0,53)	(1,19)	(1,58)	(1,63)	(2,12)
CAPM Alpha	-0,3 %	0,0 %	0,2 %	0,2 %	0,5 %
	(-1,40)	(0,08)	(0,99)	(1,05)	(1,81)
Beta (realized)	1,03	0,84	0,79	0,74	0,78
Stdev	21,5 %	17,1 %	16,4 %	15,4 %	17,6 %
Sharpe	0,15	0,34	0,47	0,48	0,61
Worst monthly drawdown	-19,7 %	-18,2 %	-18,7 %	-18,9 %	-22,9 %
Maximum drawdown	-85,9 %	-67,5 %	-66,2 %	-63,7 %	-64,4 %
Portfolio Charactereistics					
B/M	0,17	0,37	0,56	0,83	1,70
ME	1718	1105	1005	809	329
n	128	127	127	127	128

6.2. Smart beta portfolios tilting towards momentum

Table 4 presents the performance of different long-only momentum portfolios. The winners portfolio outperformed the losers portfolio by a considerable margin. The spread between monthly excess returns is 1,5% indicating annual spread of 18%. Alpha

of the winners portfolio is 0,7% with highly statistically significant t-stat of 3,35. It also seems that the outperformance of the winners portfolio is not driven by higher market risk, as the winners portfolio has lower realized beta (0,84) than losers portfolio (1,07).

The winners portfolio is less risky than the losers portfolio when measured with annualized standard deviation and drawdowns. In addition, stocks in the winners portfolio are on average considerably larger than the stocks in losers portfolios, so the momentum premium is seemingly not driven by the size effect. However, it is important to note that the losers portfolio has periods of significant outperformance, which makes long-short momentum strategy prone to crashes.

Table 4. Returns of long-only momentum portfolios

Momentum tilt in the Nordic stock market, Dec 1995-Jan 2019. 90% of largest companies included.

This table shows momentum-sorted portfolio returns. At the beginning of each calendar month, stocks are ranked in ascending order on the basis of their momentum signal (i.e. 12-month cumulative raw return, skipping the most recent month) at the end of the previous month. The ranked stocks are assigned to one of five quintile portfolios. All stocks are equally weighted within a portfolio, and portfolios are rebalanced every month to maintain equal weights. Average excess returns, alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Worst monthly drawdowns and maximum drawdowns are also shown. In addition, time-series average portfolio characteristics are presented: Average 12-1 return, average company size (ME, in EUR millions) and average number of companies (n) in a portfolio. T-stats are found in brackets below regression estimates.

Portfolio	Losers	2	3	4	Winners
Excess return	-0,3%	0,4%	0,7%	0,9%	1,2%
	(-0,58)	(0,92)	(2,00)	(2,39)	(2,85)
CAPM Alpha	-0,9%	-0,1%	0,3%	0,5%	0,7%
	(-3,67)	(-0,42)	(1,97)	(2,71)	(3,35)
Beta (realized)	1,07	0,79	0,77	0,76	0,84
Stdev	23,7%	16,5%	14,7%	14,8%	17,9%
Sharpe	-0,16	0,27	0,59	0,70	0,81
Worst monthly drawdown	-24,8%	-21,1%	-18,1%	-16,8%	-18,6%
Maximum drawdown	-87,8%	-66,1%	-58,4%	-59,0%	-61,4%
Portfolio Charactereistics					
Average 12-1 return	-53,7%	-10,5%	6,9%	23,2%	58,1%
ME	469	1012	1202	1275	1135
n	124	123	123	123	124

6.3. Smart beta portfolios tilting towards low beta

Table 5 reports the results of five beta sorted portfolios. The average excess returns of portfolios from Low to 4 are fairly similar, varying between 0,6%-0,8%. The low variation in excess returns of different beta sorted portfolios is in line with the well-known relatively flat security market line found by Black in 1972 in the US stock market. Also, similarly to Black et al. (1972) and Frazzini et al. (2014), the high beta portfolio has lowest excess returns and significantly negative alpha.

Altogether, excess returns, Sharpe ratios and alphas decrease almost monotonically from the low-beta to high-beta portfolios. The portfolio containing stocks with beta between the 20th percentile and 40th percentile has highest returns measured with alpha and Sharpe ratio. The positive alpha of 0,4% is significant at 1% level. The portfolio containing stocks with lowest beta has positive alpha of 0,3%, which is significant only at 10% level, while the alphas of higher beta portfolios lose statistical significance or are significantly negative. This finding is in line with Frazzini et al. (2014) findings of international stock markets.

Estimated average ex ante betas of the portfolios are not precisely same as the realized betas of portfolios representing the fact that the ex ante betas are estimates. Especially high noise is in the estimation of betas in low and high portfolios. However, portfolios from 2 to 4 have fairly similar estimated and realized betas.

The drawdowns of the low beta portfolio portray the low risk of the strategy. The worst monthly drawdown of only -12,9% and maximum drawdown of only -55,4% are significantly lower than any other portfolio studied in this thesis. To compare, the worst monthly return of the market is -18,8% and maximum drawdown is -63,9%. Also, annualized standard deviation of low beta portfolio is very low, only 11,3%.

The market capitalization of average stock in a portfolio increases monotonically with beta. This means that the excess returns of low beta portfolios might be driven by the size effect.

Table 5. Returns of long-only low beta portfolios

Low beta tilt in the Nordic stock market, Dec 1995-Jan 2019. 90% of largest companies included.

This table shows beta-sorted portfolio returns. At the beginning of each calendar month, stocks are ranked in ascending order on the basis of their estimated beta at the end of the previous month. The ranked stocks are assigned to one of five quintile portfolios. All stocks are equally weighted within a portfolio, and portfolios are rebalanced every month to maintain equal weights. Average excess returns, alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Worst monthly drawdowns and maximum drawdowns are also shown. In addition, time-series average portfolio characteristics are presented: Average estimated beta, average company size (ME, in EUR millions) and average number of companies (n) in a portfolio. T-stats are found in brackets below regression estimates.

Portfolio	Low	2	3	4	High
Excess return	0,6 %	0,8 %	0,7 %	0,6 %	0,2 %
	(1,97)	(2,27)	(1,87)	(1,58)	(0,39)
CAPM Alpha	0,3 %	0,4 %	0,3 %	0,1 %	-0,5 %
	(1,74)	(2,21)	(1,45)	(0,72)	(-2,32)
Beta (realized)	0,44	0,59	0,73	0,91	1,26
Stdev	11,3 %	13,2 %	15,3 %	18,2 %	25,4 %
Sharpe	0,63	0,71	0,54	0,42	0,10
Worst monthly drawdown	-12,9 %	-16,7 %	-17,5 %	-19,6 %	-25,4 %
Maximum drawdown	-55,4 %	-61,1 %	-59,9 %	-63,4 %	-82,3 %
Portfolio Charactereistics					
Beta (ex ante)	0,16	0,55	0,81	1,14	1,89
ME	506	902	1217	1367	1590
n	108	107	107	107	108

Tables 3, 4 and 5 give reasonably strong evidence of the existence of value, momentum and low beta premium in Nordic stocks markets. When measured with excess returns, all strategies have statistically significant positive returns. In addition, value and low beta strategies have positive alpha at 10% significance level, while momentum has highly positive monthly alpha of 0.7% at 1% significance. Furthermore, growth, losers

and high beta portfolios have negative alphas. It is important to note that out of the three strategies studied, momentum has the highest turnover, meaning that if transaction costs would be taken into account, the momentum portfolio would not yield such impressive returns. Value and low beta strategies require less trading, thus there would be lower transaction costs.

6.4. Testing for the size effect

The second research question is whether the style premiums are driven by small stocks, i.e. the size effect (Banz, 1981). Tables 6, 7 and 8 represent the average monthly excess returns and alphas of 15 portfolios that are intersections of sorts on size and the style signals. It is important to note that the results in tables 6, 7 and 8 should be considered with caution, because double sorting the stocks into 15 portfolios leads to set of thin portfolios. For example, the portfolio consisting of large low beta stocks has only 20 stocks on average, while the average amount of stocks in large loser portfolio is only 22.

6.4.1. Size-value double-sort

Albeit the average market capitalization of a stock in value portfolio is significantly smaller than the average size of a stock in growth portfolio in table 3, the value premium is not solely driven by the size effect. As can be seen from table 6, both excess return and alpha increase almost monotonically with B/M ratio regardless of the size group. Nevertheless, the value premium is strongest within the small stock universe, as the alpha of 0.6% with highly significant t-stat of the small value portfolio shows. However, value premium is strongly present in the large cap universe too with alpha of 0.5% and t-stat of 1.92. Surprisingly, no significant alpha or significantly positive excess returns can be found from the mid-capitalization universe.

Because alphas of growth portfolios are negative in every size group and statistically significant positive alpha can be found from small and large stock universe, it can be concluded that the value premium is not driven solely by the size effect. However, it is

clear that value premium lacks consistency, as the mid-capitalization portfolios do not generate positive alpha. In addition, value seems to be strongest within the small stock universe.

Table 6. Returns of size-value sorted portfolios

Average returns of size-B/M portfolios, Dec 1995-Jan 2019. 90% of largest companies included.

This table shows average monthly excess returns and alphas for portfolios formed on size and B/M. At the end of each month, stocks are allocated to three size groups using 33,3th and 66,6th percentiles as breakpoints for market capitalization. Stocks are also allocated independently to five B/M groups by using quintile breakpoints. At the beginning of each month, 15 equally weighted size-B/M portfolios are formed using the grouping of the end of previous month. The t-stats are found in brackets below the regression estimates.

Portfolio	Low	2	3	4	High
Panel A: Excess returns of size-value portfolios					
Small	-0,2 %	0,4 %	0,7 %	0,3 %	1,0 %
	(-0,02)	(0,84)	(1,51)	(0,88)	(2,54)
Mid	0,3 %	0,5 %	0,7 %	0,8 %	0,7 %
	(0,49)	(1,12)	(1,54)	(1,91)	(1,31)
Large	0,5 %	0,6 %	0,6 %	0,8 %	1,0 %
	(1,15)	(1,45)	(1,46)	(1,91)	(2,33)
Panel B: Alphas of size- value portfolios					
Small	-0,6 %	-0,1 %	0,2 %	0,0 %	0,6 %
	(-1,46)	(-0,19)	(0,97)	(-0,05)	(2,58)
Mid	-0,3 %	0,0 %	0,2 %	0,3 %	0,2 %
	(-1,22)	(0,12)	(0,88)	(1,43)	(0,51)
Large	-0,1 %	0,1 %	0,1 %	0,3 %	0,5 %
	(-0,32)	(0,43)	(0,62)	(1,30)	(1,92)
Panel C: Average number of stocks					
Small	36	33	37	44	58
Mid	43	42	43	40	44
Large	49	51	47	43	26

6.4.2. Size-momentum double-sort

As table 7 presents, long-only portfolios tilting towards momentum style have generated positive and statistically significant alpha regardless of the size groups. Similarly to value premium, the momentum premium is strongest within the small stock universe. In addition, all loser portfolios generate statistically and economically significant negative

alphas in all size groups. Thus, we can conclude that the momentum premium is not driven by the size effect.

Table 7. Returns of size-momentum sorted portfolios

Average returns of size-momentum portfolios, Dec 1995-Jan 2019. 90% of largest companies included.

This table shows average monthly excess returns and alphas for portfolios formed on size and momentum signal. At the end of each month, stocks are allocated to three size groups using 33,3th and 66,6th percentiles as breakpoints for market capitalization. Stocks are also allocated independently to five momentum groups by using quintile breakpoints. At the beginning of each month, 15 equally weighted size-momentum portfolios are formed using the grouping of the end of previous month. The t-stats are found in brackets below the regression estimates.

Portfolio	Low	2	3	4	High
Panel A: Excess returns of size-momentum portfolios					
Small	-0,4 %	0,5 %	0,7 %	1,0 %	1,5 %
	(-0,72)	(1,11)	(2,00)	(2,54)	(3,22)
Mid	-0,4 %	0,3 %	0,7 %	0,8 %	1,3 %
	(-0,60)	(0,66)	(1,83)	(2,15)	(2,83)
Large	0,0 %	0,3 %	0,7 %	0,9 %	1,0 %
	(-0,02)	(0,79)	(1,89)	(2,27)	(2,25)
Panel B: Alphas of size- momentum portfolios					
Small	-0,9 %	0,1 %	0,4 %	0,6 %	1,1 %
	(-3,27)	(0,37)	(1,76)	(2,72)	(3,56)
Mid	-1,1 %	-0,2 %	0,3 %	0,4 %	0,8 %
	(-3,60)	(-0,76)	(1,53)	(1,98)	(3,01)
Large	-0,7 %	-0,2 %	0,3 %	0,4 %	0,4 %
	(-2,33)	(-1,02)	(1,54)	(2,39)	(2,11)
Panel C: Average number of stocks					
Small	63	41	33	30	34
Mid	39	41	40	40	44
Large	22	42	50	54	46

6.4.3. Size-low beta double-sort

Table 8 presents the performance of portfolios sorted by their ex ante betas and market capitalization. Similarly to table 5, alphas decrease almost monotonically when moving from low-beta to high-beta portfolio regardless of the size group. It is especially interesting to notice that there is only small variation in the returns of the large stock universe, between 0,5% and 0,9%. However, when looking at alphas, there is clear

variation in abnormal returns between 0,5% and -0,2%. This indicates that the security market line is flat, especially within the large stock universe.

In addition, statistically and economically significant negative alpha of the portfolio consisting of small stocks with high beta is an interesting observation. Furthermore, the statistically significant positive alpha of 0,5% of the portfolio consisting of large low beta stocks indicates that the abnormal returns of long-only low beta strategy are not driven by the size effect.

Table 8. Returns of size-low beta sorted portfolios

Average returns of size-beta portfolios, Dec 1995-Jan 2019. 90% of largest companies included.

This table shows average monthly excess returns and alphas for portfolios formed on size and beta. At the end of each month, stocks are allocated to three size groups using 33,3th and 66,6th percentiles as breakpoints for market capitalization. Stocks are also allocated independently to five beta groups by using quintile breakpoints. At the beginning of each month, 15 equally weighted size-beta portfolios are formed using the grouping of the end of previous month. The t-stats are found in brackets below the regression estimates.

Portfolio	Low	2	3	4	High
Panel A: Excess returns of size-low beta portfolios					
Small	0,6 %	0,8 %	0,6 %	0,5 %	-0,4 %
	(1,65)	(2,05)	(1,38)	(1,15)	(-0,82)
Mid	0,6 %	0,7 %	0,7 %	0,7 %	0,4 %
	(1,88)	(1,91)	(1,69)	(1,5)	(0,64)
Large	0,7 %	0,9 %	0,8 %	0,7 %	0,5 %
	(2,37)	(2,64)	(2,13)	(1,81)	(0,99)
Panel B: Alphas of size- low beta portfolios					
Small	0,3 %	0,5 %	0,2 %	0,1 %	-1,0 %
	(1,32)	(1,86)	(0,79)	(0,22)	(-3,57)
Mid	0,3 %	0,3 %	0,2 %	0,1 %	-0,4 %
	(1,52)	(1,43)	(1,03)	(0,68)	(-1,30)
Large	0,5 %	0,5 %	0,3 %	0,2 %	-0,2 %
	(2,08)	(2,92)	(1,79)	(1,02)	-(1,15)
Panel C: Average number of stocks					
Small	52	35	28	25	28
Mid	36	37	34	32	35
Large	20	35	45	50	44

Altogether, the results of tables 6 to 8 show that the value, momentum and low beta premiums are not driven by the size effect. Momentum is strong in all size groups, while value seems to have some inconsistency because mid-capitalization stocks lacked value premium. Low beta strategy shows clear trend in all size groups, but statistical significance can only be found in alphas of few portfolios.

6.5. Testing for persistency in smart beta premiums

The third research question is whether the style premiums are robust through time. This research question is motivated by the findings of earlier research that states that value premium has cyclical nature and can experience prolonged periods of poor performance (Asness et al. 2000; Cohen et al. 2001 and Zhang 2005). Furthermore, momentum and low beta have been shown to be more persistent trough time (Frazzini et al. 2014, Asness et al. 2014). Thus, studying persistency of style premiums in the Nordic stock market is deemed important for understanding the risks of different styles and to complement the existing literature.

Panels A and B of tables 9 to 11 show the alphas of size-style double-sorted portfolios for December 1995 − June 2007 and July 2007 − January 2019 respectively. Both subperiods include 139 monthly observations.

6.5.1. Testing for consistency of value

Results of table 9 show that the value premium is present only in the first subperiod with significant strength. The high B/M portfolios generate high alphas with robust statistical significance in all size groups. However, the value premium vanishes in the second subperiod. The high B/M portfolios do not generate any significant alpha during the second subperiod, not even in the small-capitalization universe. These findings confirm the cyclicality of the value premium also in the Nordic stock markets, which is in line with previous literature.

Findings of tables 6 and 9 depict the inconsistency of value premium well. The first finding is that there is no value premium in the mid-capitalization stock universe when studying the whole sample period. The finding, supported by results of table 9, is that mid-capitalization stocks have negative alpha in the latter subperiod. It is well known that value strategy experiences times of prolonger weak returns, but the exceptionally weak performance of mid-sized Nordic stocks during the past 10 years is an interesting observation.

In short, the findings imply that value investing is not consistent through time.

Table 9. Subperiod returns of value

Subperiod alphas for size-B/M portfolios. 90% of largest companies included.

This table shows monhtly alphas for portfolios formed on size and B/M for two equal lenght subperiods. At the end of each month, stocks are allocated to three size groups using 33,3th and 66,6th percentiles as breakpoints for market capitalization. Stocks are also allocated independently to five B/M groups by using quintile breakpoints. At the beginning of each month, 15 equally weighted size-B/M portfolios are formed using the grouping of the end of previous month. The t-stats are found in brackets below the estimates.

Portfolio	Low	2	3	4	High
Panel A: Alphas Dec 1995 - Jun 2007, 139 months					
Small	-0,6 %	-0,2 %	0,7 %	0,2 %	1,1 %
	(-0,96)	(-0,46)	(1,78)	(0,56)	(3,19)
Mid	-0,6 %	-0,2 %	0,4 %	0,7 %	0,9 %
	(-1,48)	(-0,56)	(1,42)	(2,11)	(2,01)
Large	-0,2 %	-0,1 %	0,3 %	0,5 %	1,1 %
	(-0,72)	(-0,41)	(0,90)	(1,31)	(2,76)
Panel B: Alphas Jul 2007 - Jan 2019, 139 months					
Small	-0,6 %	0,1 %	-0,2 %	-0,1 %	0,2 %
	(-1,65)	(0,18)	(-0,65)	(-0,49)	(0,73)
Mid	-0,2 %	0,3 %	0,0 %	0,0 %	-0,5 %
	(-0,47)	(1,03)	(0,02)	(0,08)	(-1,32)
Large	0,0 %	0,3 %	0,0 %	0,2 %	0,1 %
	(0,24)	(1,91)	(0,27)	(1,27)	(0,24)

6.5.2. Testing for consistency of momentum

Unlike the value premium, momentum premium has generated robust premiums in both subperiods as table 10 presents. The size and statistical significance of alphas was larger

in the first subperiod, but the momentum premium is clearly present in the second subperiod also. However, the large-capitalization momentum portfolios in panel B show some inconsistency, as portfolios 3 and 4 show significant positive alphas while the high momentum portfolio has alpha of only 0,1% per month with t-stat of 0,64.

All in all, regardless of its crashes, momentum premium seems to be fairly robust tough time.

Table 10. Subperiod returns of momentum

Subperiod alphas for size-momentum portfolios. 90% of largest companies included.

This table shows monthly alphas for portfolios formed on size and momentum signal for two equal lenght subperiods. At the end of each month, stocks are allocated to three size groups using 33,3th and 66,6th percentiles as breakpoints for market capitalization. Stocks are also allocated independently to five momentum groups by using quintile breakpoints. At the beginning of each month, 15 equally weighted size-momentum portfolios are formed using the grouping of the end of previous month. The t-stats are found in brackets below the estimates.

Portfolio	Low	2	3	4	High
Panel A: Alphas Dec 1995 - Jun 2007, 139 months					
Small	-0,7%	0,3%	0,5%	0,9%	1,3%
	(-1,54)	(0,91)	(1,44)	(2,45)	(2,68)
Mid	-0,7%	0,0%	0,4%	0,6%	0,9%
	(-1,42)	(0,07)	(1,49)	(2,32)	(2,01)
Large	-0,7%	-0,3%	0,3%	0,4%	0,8%
	(-1,42)	(-0,90)	(0,95)	(1,29)	(2,36)
Panel B: Alphas Jul 2007 - Jan 2019, 139 months					
Small	-1,1%	-0,1%	0,3%	0,5%	0,8%
	(-3,61)	(-0,40)	(1,21)	(1,68)	(2,47)
Mid	-1,4%	-0,3%	0,2%	0,2%	0,7%
	(-4,00)	(-1,27)	(0,98)	(0,95)	(2,26)
Large	-0,7%	0,0%	0,3%	0,5%	0,1%
	(-1,99)	(-0,20)	(1,97)	(3,55)	(0,64)

6.5.3. Testing for consistency of low beta

Table 11 presents the alphas of size-beta sorted portfolios for the two subperiods. The results show consistency with the results of table 8. The portfolio 2 yields positive and both economically and statistically significant monthly alpha in all size groups in the

first subperiod. In addition, all high beta portfolios consistently generate negative alpha, but almost all negative alphas are lacking statistical significance. However, the portfolio containing small-capitalization high beta stocks yields exceedingly negative monthly alpha of -1,5% with t-stat of -4,49 in the second subperiod. In addition, large-capitalization low beta portfolios generated a statistically significant monthly alpha of 0,7% during the latter subperiod. Altogether, the alphas seem to have clear negative relation with beta regardless of size group and time period, which is in line with the findings reported by Frazzini et al. (2014).

Table 11. Subperiod returns of low beta

Subperiod alphas for size-low beta portfolios. 90% of largest companies included.

This table shows monthly alphas for portfolios formed on size and beta for two equal lenght subperiods. At the end of each month, stocks are allocated to three size groups using 33,3th and 66,6th percentiles as breakpoints for market capitalization. Stocks are also allocated independently to five beta groups by using quintile breakpoints. At the beginning of each month, 15 equally weighted size-beta portfolios are formed using the grouping of the end of previous month. The t-stats are found in brackets below the estimates.

Portfolio	Low	2	3	4	High
Panel A: Alphas Dec 1995 - Jun 2007, 139 months					
Small	0,6 %	1,0 %	0,3 %	0,2 %	-0,6 %
	(1,62)	(2,41)	(0,73)	(0,45)	(-1,26)
Mid	0,7 %	0,7 %	0,4 %	0,2 %	0,0 %
	(2,00)	(2,03)	(0,59)	(0,72)	(-0,54)
Large	0,3 %	0,9 %	0,5 %	0,4 %	-0,4 %
	(0,77)	(3,05)	(1,61)	(1,05)	(-1,35)
Panel B: Alphas Jul 2007 - Jan 2019, 139 months					
Small	0,1 %	0,1 %	0,1 %	-0,1 %	-1,5 %
	(0,54)	(0,41)	(0,49)	(-0,16)	(-4,49)
Mid	0,0 %	0,0 %	0,2 %	0,1 %	-0,5 %
	(0,18)	(0,09)	(0,85)	(0,37)	(-1,34)
Large	0,7 %	0,4 %	0,3 %	0,1 %	-0,1 %
	(2,69)	(2,00)	(1,67)	(0,61)	(-0,28)

6.6. Returns of multi-factor portfolios

The final research question of this thesis is whether superior risk adjusted returns can be generated through mixing or integrating the long-only smart beta strategies to multi-factor strategies. This topic has attracted some attention from the academics recently, as the popularity of smart beta ETFs and funds has increased. All the published research on multi-factor smart beta investing is supporting the superiority of multi factor investing compared to single factor investing (see e.g. Clarke & De Silva, 2016; Bender et al. 2016, Li & Shim, 2017; Fitzgibbons, Friedman, Pomorski & Serban, 2017; Ghayur, Heaney & Platt 2018; Li & Shim, 2019).

Multifactor portfolios are constructed following methodology of Fitzgibbons et al. (2017). In addition, all the portfolios constructed in this section consist only of the top 30% of the largest stocks measured by market capitalization. This subset of stocks is deemed to be liquid enough for actual implementation. Average size of a stock in this sample varies between EUR 879 million in December 1995 and EUR 4 255 million in March 2015.

6.6.1.   Multi-factor portfolios constructed using mixing approach

All of the portfolios created with mixing approach are equally weighted and rebalanced monthly. This means that the value-momentum portfolio has 50% allocation to value portfolio and 50% allocation to momentum portfolio in each month.

Table 12 presents the results of portfolios constructed by using the mixing approach. The combination of momentum and low beta generated the highest Sharpe ratio of 0.73, while the combination of value and momentum had the lowest Sharpe of 0.68. However, value-momentum portfolio generated the highest average excess return of 1.0% per month, but at the same time the strategy had the highest volatility and market beta, which have negative effect on Sharpe ratio and alpha.

The alphas of all the mixed portfolios are 0.5% per month with high statistical significance. The alpha of each portfolio is impressive, as all the stocks in portfolios are large capitalization stocks, meaning that there is no small stock effect and the strategies

should actually be implementable, at least to some extent. When comparing the alphas of table 12 with alphas of large-capitalization portfolios of single factor strategies from tables 6, 7 and 8, we can observe that the multi-factor portfolios created by mixing are superior to any single factor portfolio. The alpha of large-cap value portfolio of table 6 is 0.5% per month, but the alpha is not statistically significant at 5% level, unlike the alphas of table 12. Thus, mixing approach can be deemed to create superior risk adjusted returns when compared to single factor smart beta portfolios. This conclusion is in line with large body of earlier research.

Table 12. Returns of multi-factor portfolios, mixing approach

Multifactor portfolios, mixing, Dec 1995-Jan 2019. 30% of largest companies inclided

This table shows returns for different smart beta portfolios constructed by mixing value, momentum and low beta strategies. The portfolios with two strategies are weighted 50/50 and the right hand portfolio has 1/3 allocation to each strategy. Average excess returns, alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Worst monthly drawdowns and maximum drawdowns are also shown. In addition, average number of companies (n) in a portfolio is presented. T-stats are found in brackets below regression estimates.

Portfolio	Value-Momentum	Value-Low beta	Momentum-Low beta	All
Excess return	1,0 %	0,9 %	0,9 %	0,9 %
	(2,49)	(2,45)	(2,56)	(2,55)
CAPM Alpha	0,5 %	0,5 %	0,5 %	0,5 %
	(2,82)	(2,43)	(2,89)	(2,91)
Beta (realized)	0,91	0,71	0,72	0,78
Stdev	17,8 %	14,9 %	14,9 %	15,5 %
Sharpe	0,68	0,69	0,73	0,71
Worst monthly drawdown	-19,7 %	-17,6 %	-17,4 %	-17,8 %
Maximum drawdown	-63,8 %	-58,8 %	-60,7 %	-61,1 %
Portfolio Charactereistics				
n	87	83	82	126

6.6.2.   Multi-factor portfolios constructed using integrating approach

To construct a multi-factor portfolio using the integrating approach, stocks with the best fit across multiple factors are chosen to each portfolio. Similar portfolio construction methodology has been applied by Fitzgibbons et al. (2017) and Novy-Marx (2013 & 2014) to name a few. Figure 3 is used as visualization of the idea behind integration,

and why the integrating approach offers better exposure to the wanted styles than the mixed approach. In figure 3, momentum signal intensifies from left to right and value signal strengthens when moving upwards.

In order for a stock to be included into the integrated value-momentum portfolio, it has to have high value and momentum signal simultaneously. To build an integrated portfolio, stocks are sorted by their factor signals to quintile portfolios in each point of time. After sorting, stocks that rank above the 60th percentile breakpoint in both value and momentum simultaneously are picked to the integrated portfolio. By applying this methodology, the portfolios will exclude unwanted negative exposure to other targeted styles. For example, a momentum stock is often also a growth stock, i.e. in figure 3 the stock would be on bottom right hand side (in box 5,1). This stock has strong momentum signal, but negative value signal, which is not ideal for an investor who is aiming to optimize her exposure to both value and momentum. The same stock, however, would be included in the momentum portfolio of mixed multi-factor portfolio. Furthermore, stocks that have relatedly strong value and momentum signal at the same time (stocks in box 4,4), are included in the integrated portfolio, while these same stocks would be ranked out of the mixed multi-factor portfolio, as they do not have strong enough signal to either single factor portfolio.
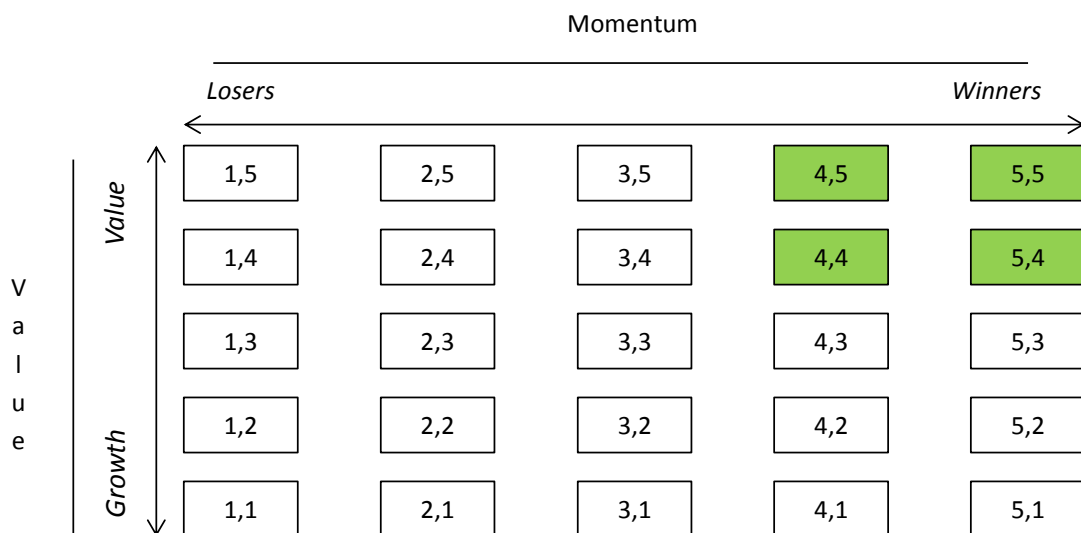

Figure 3. Value-momentum portfolio constructed with integration approach

Novy-Marx (2014) concludes that the integrating approach, which selects stocks on the basis of combined style signals, achieves significantly higher factor loadings than the mixed multi-factor portfolio.

To construct the multi-factor portfolio that integrates value, momentum and low beta, median breakpoint is used instead of 60th percentile breakpoint. Lower breakpoint needs to be accepted to construct the 3 factor portfolio because the portfolio would be unbearably thin if all factor signals are required to be above the 60th percentile simultaneously.

Table 13 presents the returns of different portfolios constructed using the integrating approach. When comparing excess returns, alphas and Sharpe ratios of the multi-factor strategies of table 13 (integrating approach) with the multi-factor strategies of table 12 (mixing approach), it seems that the integrating approach is superior to mixing approach. This finding is in line with earlier research.

Results of table 13 imply that investing into stocks that have momentum and low beta is the best strategy when measured with alpha and Sharpe ratio. The strategy has alpha of 0.7% per month with t-stat of 3.49 and impressive Sharpe ratio of 0.86. The second best strategy is the "All" portfolio that also has 0.7% alpha with 1% significance, but slightly lower Sharpe ratio of 0.79. Integrating value and momentum has the highest excess returns, 1.2% per month, but high realized beta and volatility decrease the risk adjusted return measures of the portfolio. Creating a portfolio that includes stocks with value and low beta signal seems to have the worst performance of the studied integrated multi-factor portfolios. The portfolio, however, still generates statistically significant alpha of 0.5% per month.

Table 13. Returns of multi-factor portfolios, integrating approach

Multifactor portfolios, integrating approach, Dec 1995-Jan 2019. 30% of largest companies inclided

This table shows returns for different smart beta portfolios constructed by integrating value, momentum and low beta strategies. The portfolios with two strategies require that both factor signals are above the 60th percentile breakpoint. The "All" portfolio that integrates the three factors require that all factor signals are above median break point. Average excess returns, alphas and betas from regressions, annualized standard deviations and Sharpe ratios are presented. Worst monthly drawdowns and maximum drawdowns are also shown. In addition, average number of companies (n) in a portfolio is presented. T-stats are found in brackets below regression estimates.

Portfolio	Value-Momentum	Value-Low beta	Momentum-Low beta	All
Excess return	1,2 %	0,9 %	1,1 %	1,1 %
	(2,85)	(2,69)	(3,06)	(2,76)
CAPM Alpha	0,7 %	0,5 %	0,7 %	0,7 %
	(2,75)	(2,75)	(3,46)	(2,79)
Beta (realized)	0,81	0,63	0,66	0,68
Stdev	18,1 %	14,3 %	14,8 %	16,1 %
Sharpe	0,78	0,75	0,86	0,79
Worst monthly drawdown	-19,2 %	-17,0 %	-19,3 %	-20,6 %
Maximum drawdown	-64,8 %	-55,5 %	-60,8 %	-65,9 %
Portfolio Charactereistics				
n	25	31	31	21

Altogether, results of tables 12 and 13 exhibit that multi-factor portfolios, whether mixed or integrated, generate superior returns compared to any single style portfolio. Furthermore, integrating approach seems to yield superior returns when compared to mixing approach. These findings are broadly in line with the findings of previous research from other equity markets.

It should be kept in mind, however, that the integrating approach has multiple weaknesses when compared to mixing approach. According to Chow et al. (2018), the integrating approach requires more trading and is less transparent than the mixing approach. Thus, when accounting for trading costs and loss of transparency, mixing might be a better approach for constructing multi-factor portfolios.

7. CONCLUSIONS

Asset managers around the world have allocated trillions of dollars into smart beta ETFs and funds during the past 10 years. The global and rapid emergence of this investing methodology is the main motivation to research the returns of different smart beta strategies in the scarcely researched Nordic stock markets. Along with the increased interest in smart beta investing, multi-factor portfolio implementation has surfaced as a timely topic of academic discussion, which is also studied in this thesis.

The results show that, on average, value, low beta and momentum smart beta strategies have outperformed the stock markets in the Nordics. The findings are in line with vast body of earlier research. Value premium, however, is shown to be cyclical by nature and partly driven by the size effect in the Nordic stock universe. Similar results of value premium's cyclicality have been documented earlier in the other stock markets. In the Nordics, long-only strategies tilting towards momentum and low beta are shown to generate more consistent excess returns over time, and the returns are not as dependent on the size effect as the returns of the value strategy.

By combining single-factor smart beta portfolios to multi-factor portfolios, investors can enhance the risk-adjusted returns of their smart beta strategies. The improvement in returns is driven by diversification benefits, as value and momentum, for example, have relatively low correlation with each other. From the two multi-factor portfolio construction methodologies studied, integrating approach is shown to generate superior risk adjusted returns compared to the mixing approach. A large body of earlier research has found similar results. The better performance of the integrating approach is explained by the pure exposure to the wanted risk factors, whereas mixing approach often includes some unwanted negative exposures.

However, when assessing the alternative methodologies of smart beta investing, investors should not only consider the expected returns of different approaches. For example, transparency, turnover, transaction costs and possible management fees of the alternative smart beta investing methodologies should also be considered.

When comparing the integrating and mixing approaches, it is clear that the mixing approach has some advantages over the integrating approach, regardless of its slightly lower expected returns. By mixing simple single-factor smart beta portfolios into a multi-factor portfolio, investors can easily decompose their returns and risk exposures to the different factors. Mixing also allows easy reweighting between the factor exposures, if one's investment strategy is based on factor timing. One aspect that should also be considered is that the integrating approach potentially narrows down the available investment universe to a fairly thin group of stocks, which could increase the trading costs of the integrating approach if AUM is large. Finally, as the integrating approach requires more active management, the fees of funds applying the integrating approach are most likely higher compared to the fees of the mixing approach. Thus, albeit the integrating approach seem to generate higher returns, mixing approach could be more suitable for investors that appreciate transparency, lower fees as well as lower transaction costs.

Overall, the results of this study provide useful information about the risk and return characteristics of different smart beta strategies. The thesis also provides information about alternative smart beta multi-factor portfolio construction approaches for professional asset managers focused on the Nordic stock markets. Future research could, for example, investigate the different dimensions of risks of integrated and mixed multi-factor smart beta portfolios by using the traditional multi-factor regressions. Also, studying smart beta portfolios constructed by using ESG screens could be a valuable and novel area of future research.

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