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Is Smart Beta Investing Profitable? Evidence from the Nordic Stock Market

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Abstract

This study examines the profitability of the mixing and integrating approach for constructing multi-factor smart beta portfolios. While most studies explore this issue in a U.S. market setting, this is the first study that exclusively focus on the Nordic equity market, which exhibits some unique and stylized features as recently highlighted in the literature. Our findings indicate first strong evidence for return variations for sorting stocks on value-, momentum-, and ex-ante beta-signals. Surprisingly, variations in payoffs are not only small stock phenomena in the Nordic equity markets. While the current literature does not yet agree on a consensus, our study supports the literature documenting the superiority of the integrating approach. Our results challenge the efficient market hypothesis in a market environment offering a high-level of information-flow-efficiency.

Keywords: Smart beta, multi-factor investing, value, momentum, low beta
JEL classification: G12, G14

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1. Introduction

In recent years, smart beta investing has increased in popularity among private and institutional investors. Due to its popularity, especially among institutional investors, the FTSE Russel started conducting annual smart beta surveys amongst the institutional client base in 2014. The most recent 2019 survey included 178 global institutional asset owners with approximated cumulative AUM of USD 5 trillion. It shows that 83% of asset owners globally have a smart beta investment allocation and either have evaluated or are planning to evaluate this issue in the next 18 months. Of all the asset managers in the survey, 58% had an existing smart beta allocation, compared to 32% in 2014. In line with the survey, Hou, Xue and Zhang (2018, p.6) also highlight that "with trillions of dollars invested in factors-based exchange-traded funds and quantitative hedge funds worldwide, the financial interest is overwhelming."

Academics and practitioners appear to agree that smart beta strategies are long-only strategies that aim at outperforming the capitalization-weighted (benchmark) index through alternative weighting methodologies that exploit investment styles such as size, value, momentum and low beta (Jacobs and Levy 2014; Malkiel 2014; Asness, Ilmanen, Israel and Moskowitz, 2015). One way to implement multi-factor smart beta strategies is the so-called 'mixing approach', where the portfolio combines two or more long-only strategies focusing on individual styles. For instance, one could allocate 50% to a long-only portfolio focused on value and 50% to long-only portfolio focused on momentum. An obvious benefit of the mixing approach is a high-level of transparency simply because it is easy to deconstruct returns of the portfolio to returns generated by each individual style. The mixing approach is also flexible, as the investor can easily control the allocations across styles (Fitzgibbons, Friedman, Pomorski, and Serban, 2017; Leippold and Rueegg, 2018).

Another way to implement multi-factor smart beta strategies is the so-called 'integrating approach', where stocks are selected that have simultaneous exposures to multiple desired risk factors while mitigating negative exposures to the undesired factors. For instance, this approach selects stocks with high exposure to value and momentum characteristics, whereas the same stocks might not be selected by the mixing approach. On the other hand, stocks with the strongest exposure to value or momentum might be left out of the integration approach, given that these stocks have negative exposure to momentum or value, respectively (Fitzgibbons et al., 2017; Leippold and Rueegg, 2018). Hence, the returns of the integration approach cannot be easily deconstructed in terms of returns to different styles, implying that the transparency of this approach is less than that of the mixing approach. On the other hand, the integration approach avoids unwanted risk exposures – which are obviously possible in the mixing approach because value stocks, for example, may carry negative exposure to the momentum factor (Fitzgibbons et al., 2017).

Clarke, De Silva, and Thorley (2016), Bender and Wang (2016), Fitzgibbons et al. (2017), Ghayur, Heaney, and Platt (2018) and Chow, Li, and Shim (2018) compared the profitability of the mixing and integrating approach in various settings and concluded that the integrating approach is superior because it first produces higher Sharpe ratios, and second generates higher risk adjusted returns. Furthermore, Leippold and Rueegg (2018) state that there is no statistically significant difference between the returns of mixing and integrating approaches. They argue that the integrated approach does not carry a clean exposure to any style and its returns are diluted, resembling rather the returns of a low risk anomaly. However, this reduction in risk does not translate into an improved risk adjusted performance. In this regard, Chow et al. (2018) argue that the integration approach involves higher implementation costs because the investment universe grows thin when investors rank stocks as having strong exposure to multiple factors. The authors argue that the mixing approach should be preferred when constructing multi-factor smart beta portfolios. In sum, the literature has not yet agreed on a consensus regarding which one of those two approaches is superior.[1]

Motivated by this strand of literature, we examine the profitability of the mixing and integrating approach when implementing multi-factor smart beta strategies in the Nordic equity market. Our study uses stocks listed on the OMX Helsinki, OMX

[1] Recent related studies investigating smart-beta factor investing are De Franco and Monnier (2019), Shimiziu and Shiohama (2020), Jiang, Du, An, and Zhang (2020), and Lester (2019). De Franco and Monnier (2019) explore a multifactor portfolio from a performance-agnostic point of view and argue that investing in a long–short static multifactor strategy implies that one invests into a new (synthetic) factor. They conclude that the equal-weighting of these factors (e.g., value, size, momentum and low volatility) results in a synthetic factor that has surprisingly no predictive power on stocks' return. Shimiziu and Shiohama (2020) explore risk-based asset allocation approaches for factor investing strategies and propose an inverse factor volatility strategy. Their findings indicate that factor portfolios using their proposed inverse factor volatility strategy significantly outperformed market capitalization weighted portfolios by successfully acquiring factor risk premiums. Jiang et al. (2020) and Lester (2019) confirm Shimiziu's and Shiohama's (2020) results in finding that factor tracking strategies outperform naïve diversification.

Stockholm, OMX Copenhagen and OMX Oslo and covers a sample from December 1991 to January 2019. After replicating portfolio sorts associated with the value, momentum and betting-against-the-beta strategies, we implement our long-only smart beta portfolios that account for value, momentum and low-beta signals. We compare the returns of the mixing and integrating approach using risk-adjusted portfolio returns and Sharpe ratios. Specifically, in our study we address the following research hypotheses:

> H1: *Investing systematically to stocks with high B/M, strong relative past performance and low (ex-ante) beta generate returns exceeding the returns of the Nordic market index.*
>
> H2: *Abnormal returns of smart-beta strategies are most pronounced within the small stock universe.*
>
> 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.*

Our study contributes to the existing literature in some important ways. First, we contribute to the ongoing discussion about which approach is superior in constructing multi-factor smart beta strategies. While the majority of the conducted research favors the integrating approach (Clarke et al., 2016; Bender and Wang, 2016; Fitzgibbons et al., 2017; Ghayur et al., 2018), some contradicting evidence is found in the studies of Leippold and Rueegg (2018) and Chow et al. (2018). This is an important issue due to the enormous sum of dollars invested in factor-investing mutual funds. Further, our study takes a novel perspective by employing Nordic stocks. In this regard, Grobys and Huhta-Halkola (2019) point out that Nordic stock markets exhibit some interesting features such as (*i*) relatively high-level of liquidity, (*ii*) a low-risk environment and–unlike emerging market economies–the Nordic countries (*iii*) have been offering stable political environments. Finally, Nordic countries (*iv*) offer a low credit risk environment.[2] Hence, our study contributes to the young but growing strand of literature investigating investment strategies in Nordic equity market settings (Grobys and Huhta-Halkola, 2019; Jokipii and Vähämaa, 2006; Leivo, and Pätäri, 2009; Leivo, 2012; Nikkinen, Sahlström, Takko, and Äijö, 2009; Rinne and Vähämaa, 2011). Finally, our

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[2] As pointed out in Grobys and Huhta-Halkola (2019), Nordic countries have held constantly a triple-A credit rating (with the exception of Finland which is currently rated at the same level as the US.)

study contributes to the wide strand of literature testing the efficient market hypothesis (Fama, 1970). Our study adds to this literature by using portfolio approaches involving multiple signals implemented in a market environment offering a high-level of information-flow-efficiency.

Our results indicate that, on average, smart-beta strategies based on value, low beta and momentum signals have outperformed the stock markets in the Nordics, which is in line with the vast body of earlier research. Surprisingly, our findings indicate that value, momentum and low beta premiums are–in general–not driven by the size effect. A novel finding of our study is that in the Nordic equity markets, multi-factor long-only strategies tilting towards momentum and low beta generate higher Sharpe ratios than any other strategy considered. Furthermore, the integrating approach appears to generate superior risk-adjusted returns compared to the mixing approach confirming the majority of earlier studies conducted (Clarke et al., 2016; Bender and Wang, 2016; Fitzgibbons et al., 2017; Ghayur et al., 2018). In line with Fitzgibbons et al. (2017) and Bender and Wang (2016), according to both our intuition and empirical evidence, the superior performance of the integrating approach appears to be explained by the pure exposure to the desired risk factors, whereas the mixing approach often suffers from undesired levels of exposures. Overall, our results provide useful information about the risk and return characteristics of different smart beta strategies implemented in the Nordic market setting.

This study is organized as follows: The second section presents the data, the methodology and the results. The third section outlines our results and the last section presents the conclusion.

2. Data

The sample consists of publicly listed companies from the Nordic countries, that is, Finland, Sweden, Denmark and Norway. Iceland is excluded from the sample because of the scarcity and small size of Icelandic public companies. The data were 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.[3] As per previous related 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 (Fama et al., 1992, 1993 and Asness, Moskowitz and Pedersen, 2013). In addition, all non-equity investment instruments such as ETFs are excluded from the data. It is important to note that in accordance with Tikkanen and Äijö (2018) and Gray and Vogel (2012), we excluded the smallest 10% of companies from the sample due to potential liquidity issues. By doing so, we control ex-ante, as any potential return variation resulting from portfolio sorts based on certain characteristics cannot be micro stock issue only (Fama and French, 2008). Furthermore, in line with Fama and French (1992), companies with negative book value of equity are also excluded from the sample. Since the data contain firms that have gone bankrupt, the analysis is free from any survivorship bias. As a final note, congruent with Tikkanen and Äijö (2018) and Piotroski (2000), the delisting return of a stock is assumed to zero.

Descriptive statistics are reported in Table 1. We observe from Table 1 that Swedish companies account for almost a half of all companies in the sample. Interestingly, the average size of a Swedish company is considerably smaller than in Finland or Denmark. Specifically, the average market capitalization of Finnish firms is inflated by Nokia, whereas the corresponding figure for Danish firms is inflated by Novo Nordisk.[4] In addition to firm specific parameters, macro level data of Nordic markets were obtained. Also, we retrieved the 6-month interbank offered rates for Finland, Sweden, Denmark and Norway. In this regard, 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 the previous academic literature, where the US T-bill rate is used as a proxy for risk free rate, we construct a Nordic risk free rate for our study. The representative risk free rate for the Nordic region is calculated as reported by Grobys

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[3] A similar period is considered in Grobys and Huhta-Halkola (2019) as it corresponds to a time frame, where the Nordic stock markets have been fairly liquid and open to the international investors.

[4] Note that the average market capitalization of Finnish companies excluding Nokia would is EUR 806 million and average size of Danish companies excluding Novo Nordisk is EUR 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 a disproportionally large effect on the population parameters.

and Huhta-Halkola (2019). Specifically, the Nordic risk free rate is a simple average of 6-month interbank offered rates of each country. Due to the low interest rate environment that the global markets have experienced in recent years, the 6-month rate is preferred to the 3-month rate.

Furthermore, we follow Grobys and Huhta-Halkola (2019) in constructing the Nordic stock market index using the total return indices of each country under study. Our market index is then the equal-weighted average of 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, returns of the simple return indices are used for Copenhagen and Stockholm.

3. Methodology

3.1 Univariate portfolio sorts

We start our empirical investigation by analyzing univariate sorts on value, momentum and ex-ante low-beta signals. That is, in the end of each month, all the stocks in the sample are sorted into quintiles based on their style measures (signals).[5] In line with Asness et al. (2013, 2014 & 2015), portfolios are constructed using these quintile ranks, and rebalanced at the beginning of each month. In addition, we replicate Grobys' and Huhta-Halkola's (2019) method in constructing equal-weighted portfolios because the Nordic stock universe exhibits an extraordinary variability in market capitalizations; hence, a few outliers with extremely high market capitalization would dominate some portfolios. As value-weighting would give misleading (biased) results, we follow earlier research in Nordic equity markets and implement equal-weighted strategies only.

3.1.1 Measuring value signals

The perhaps most commonly used measure–or signal–for value is the ratio of book value of equity divided by market value of equity, also known as book to market (B/M) ratio (e.g. Fama et al. 1992, 1993; Lakonishok, Shleifer and Vishny, 1994). Consequently, this measure is also used in our study. As per Asness et al. (2013, 2015)

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[5] It is important to bear in mind that our analyses presented in the following sections exclude 10% of the smallest stocks.

we use six months lagged book values when calculating B/M ratios for individual stocks to ensure data availability for investors. The six months lagged book values are then divided by the most recent market capitalization. The market capitalizations and book values of Swedish, Danish and Norwegian companies are converted into 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.

3.1.2 Measuring momentum signals

In the momentum literature, the most common measure for implementing the momentum strategy is based on the past 12-month cumulative (raw) stock return, skipping the most recent month's return (e.g., Asness et al. 2013, 2015). Note that the most recent month is skipped to avoid possible one-month return reversals caused by negative serial-correlation in monthly stock returns, as documented first by Jegadeesh (1990). If a company has less than 12 months of price data, the stock is excluded.

3.1.3 Measuring low ex-ante beta signals

In line with Frazzini and Pedersen (2014), the pre-ranking (ex-ante) beta $\hat{\beta}_i^t$ for stock *i*, given by,

$$\hat{\beta}_i^t = \hat{\rho}\,\frac{\hat{\sigma}_i}{\hat{\sigma}_m}$$

is estimated by using rolling regressions of excess returns of each stock on excess returns of the Nordic market index, where $\hat{\beta}_i^t$ denotes 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 stock *i* 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 the specific volatility estimate. Correlations are calculated using five-year rolling correlation of logarithmic excess returns between the market *m* and stock *i*. Unless at least three years of non-missing data are available to calculate correlations, the stock is excluded from the sample. According to Frazzini and Pedersen (2014), longer non-missing data series are required for correlations because correlations move more slowly than volatilities.

3.1.4 Risk-adjustment and performance measures

We measure the performance of our portfolios using the Sharpe ratio (Sharpe 1966 & 1994), which is common practice for evaluating portfolio performance given by

$$S_{p,i} = \frac{R_{p,i} - R_f}{\sigma_{p,i}},$$

where $S_{p,i}$ is the Sharpe ratio of portfolio i, $R_{p,i}$ is the return of portfolio i, R_f is the risk free rate and $\sigma_{p,i}$ denotes standard deviation of portfolio i's excess returns. In addition to the Sharpe ratio, we employ the CAPM to measure the abnormal returns of our portfolios relative to the market. To account for potential heteroscedasticity and autocorrelation, we use Newey West's (1987) standard errors for estimating robust *t*-statistics. The risk-adjusted returns are then estimated by using the following regression,

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

where R_{it} is the return of portfolio *i* at time *t*, R_{ft} is the risk free rate at time *t*, α_i is the intercept which is the equivalent of the risk-adjusted return in our context, β_i is the slope coefficient measuring the exposure of portfolio i to the market factor, and ε_{it} denotes the error term of portfolio i at time t. We employ the CAPM to measure risk adjusted returns, as Barber, Huang and Odean (2016) demonstrated that the CAPM-alphas are the best predictors of flows into mutual funds of multiple competing performance evaluation models. Similar findings were documented by Berk and Van Binsbergen (2016) when assessing which asset pricing model investors use to make capital allocation decisions. Moreover, the objective of this study is to explore the possible risk adjusted excess returns that our long-only strategies generate over the market in the Nordic stock market universe.[6]

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[6] Future studies are encouraged to explore risk-adjusted payoffs using other pricing models such as the Fama and French (2015) five-factor model. Due to the increasing number of asset pricing models proposed in the literature, this exercise is left for future research.

3.1.5 Returns to univariate portfolio sorts

From Table 2 we observe that there is a clear positive relation between B/M ratios and excess returns in the Nordic equity markets. Excess returns, alphas and Sharpe ratios increase monotonically with B/M ratio, which indicates the presence of the value premium. The average monthly excess return moves from 0.3% per month for the lowest B/M (growth) portfolio to 0.90 per cent per month for the highest B/M (value) portfolio. The portfolio spread corresponds to 7.20 per cent in annual terms. Interestingly, we note that the positive relation between B/M ratios and excess returns is not driven by market exposure, as the realized beta is lower for the value portfolio (0.78) than that for the growth portfolio (1.03). It is noteworthy that the average market capitalization of stocks in the value portfolio is significantly smaller than the market capitalization of stocks in growth portfolio indicating that the value premium could be subject to the size effect. We also observe from Table 2 that the value portfolio has the largest monthly drawdown of -22.90 per cent, whereas the growth portfolio has strikingly the largest maximum drawdown of -85.90 per cent occurring in March 2003 after the burst of tech bubble.

Table 3 outlines the performance for portfolios sorted by the momentum signal. The winner portfolio outperformed the loser portfolio by an impressive margin–the spread corresponds to 18.00 per cent per annum.[7] Furthermore, the monthly CAPM-alpha of the winner portfolio is 0.70 per cent with highly statistically significant robust *t*-statistic of 3.35. It appears that the outperformance of the winner portfolio is not driven by higher market risk because the winner portfolio exhibits a lower realized beta (0.84) than the loser portfolio (1.07). We also find that the winner portfolio is less risky than the loser portfolio when measured by both the annualized standard deviation and drawdowns. In addition, stocks in the winner portfolio are, on average, considerably larger than the stocks in loser portfolios; hence the momentum premium does not appear to be exposed to the size effect. However, it is important to note that the loser portfolio has periods of significant outperformance, making typical long-short momentum strategy prone to crashes.

[7] This figure is in line with Grobys (2016) who explored the profitability of momentum in the European Union.

Table 4 illustrates the results of portfolios sorted by the ex-ante beta signal. From Table 4 we observe that excess returns decrease as we move from the low-beta to the high-beta portfolio. The portfolio containing stocks with ex-ante beta between the 20th percentile and 40th percentile exhibits the highest returns measured by both the CAPM-alpha and Sharpe ratio. Specifically, the CAPM-alpha corresponds to 0.40 per cent per month, and is significant on even a 1% level. Moreover, the portfolio containing stocks with lowest ex-ante beta exhibits a positive alpha corresponding to 0.30 per cent per month, which is significant only at 10% level, whereas the alphas of higher ex-ante beta portfolios lose statistical significance or are significantly negative.[8] Estimated average ex-ante betas are not precisely the same as the realized betas (e.g., ex-post) because ex-ante betas are only estimates. Especially, we observe a high level of estimation uncertainty for betas in low and high portfolios. However, portfolios from group 2 to 4 have fairly similar ex-ante and ex-post betas. The drawdowns of the low beta portfolio portray the low risk of the strategy. The worst monthly drawdown of only -12.90 per cent and maximum drawdown of only -55.40 per cent are significantly lower than any other portfolio under investigation in this study. For comparison reasons, the worst monthly return of the market is -18.80 per cent and the maximum drawdown is -63.90 per cent over the sample period. As the average market capitalization monotonically increases as we move from low to high ex-ante beta, higher average returns of the low ex-ante beta portfolio could be associated with the size effect.

3.2 Portfolios using double sorts

We next turn our attention to investigating whether the style premiums are driven by small stocks (Fama and French, 2008). In Tables 5 to 7, we report the average monthly excess returns and CAPM-alphas of 15 portfolios that are intersections of sorts on size and the style signals. It is important to note that these results should be considered with caution because double sorting stocks into 15 portfolios leads to relatively thin portfolios. For example, the portfolio consisting of large low ex-ante beta stocks has only 20 stocks on average, whereas the average amount of stocks in the large loser portfolio is only 22.

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[8] This finding is in line with Frazzini and Pedersen (2014).

From Table 5 we observe that both excess returns and CAPM-alphas increase almost monotonically with B/M ratio regardless of size group. Nevertheless, the value premium is strongest within the small stock universe. However, the value premium is marginally present in the large cap universe too as implied by its CAPM-alpha corresponding to 0.50 per cent, which is significant on at least a 10% level. Surprisingly, there is no significant CAPM-alpha to be gained in the medium size group. As the average excess returns of the high B/M portfolios are the same for the small cap group and the large cap group, we find that the payoffs of portfolios sorted by B/M cannot be referred to as a small stock phenomenon only.[9]

From Table 6 we observe that portfolios sorted by momentum have generated positive and statistically significant CAPM-alpha, regardless of size group. Unsurprisingly, similarly to the value premium, the momentum premium is strongest within the small stock universe. In addition, all loser portfolios generate statistically significant and economically large negative CAPM-alphas in all size groups. As a result, we can conclude that the payoffs from portfolios sorted by momentum are not exclusively driven by the size effect either.

Finally, Table 7 outlines the performance of portfolios sorted by their ex-ante betas and market capitalization. Similarly to observations from Table 4, the CAPM-alphas decrease almost monotonically when moving from low ex-ante to high ex-ante beta portfolios, regardless of size group. It is especially interesting to note that there is only a small variation in the raw excess returns of the large stock universe with monthly payoffs ranging between 0.50 per cent and 0.90 per cent. However, when looking at alphas, there is a clear variation in risk-adjusted monthly payoffs ranging between 0.50 per cent and -0.20 per cent. This indicates that the security market line is flat, especially within the large stock universe. Another interesting finding is the statistically significant and economically large negative CAPM-alpha of the portfolio consisting of small stocks with high ex-ante beta corresponding to -1.00 per cent per month. Furthermore, the statistically significant positive alpha of 0.50 per cent per month of the portfolio consisting of large and low ex-ante beta stocks exceeds the corresponding figure for the small stock universe (i.e., 0.30 per cent per month), which indicates that the performance of the low beta strategy is not driven by the size effect. Indeed, the

[9] Our main conclusions remain unchanged when making inference based on the CAPM-alphas.

evidence provided here shows rather the opposite, namely this effect appears to be a large cap phenomenon.

Taken together, the results presented in section 3.2 indicate that the performance of these strategies is not a small stock phenomenon.

3.3 Returns to multi-factor portfolios

Finally, we explore whether superior risk-adjusted returns can be generated through mixing or integrating the long-only smart beta strategies to multi-factor strategies. This is an important issue to address from both practical and academic points of view. From a practical point of view, this is important because nowadays trillions of dollars are invested in factors-based exchange-traded funds, as pointed out by Hou, Xue and Zhang (2018). The societal impact of the performance of these new investment vehicles on future consumption, retirement funds etc. is overwhelming. From a more academic point of view, a vast literature has argued for the superiority of multi factor investing compared to single factor investing (e.g. Clarke et al. 2016; Bender and Wang 2016, Fitzgibbons et al. 2017; Ghayur et al. 2018; Li and Shim, 2019). This is the first study, however, that explores this issue in the Nordic equity market, which has some unique features as discussed in detail by Grobys and Huhta-Halkola (2019). We construct multifactor portfolios following the 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. By this, we implicitly control for size.[10] Moreover, this subset of stocks can be deemed to exhibit enough liquidity for implementation in real time. The average size of a stock company in this sample varies between EUR 879 million in December 1995 and EUR 4,255 million in March 2015.

3.3.1 Returns to multi-factor portfolio using the mixing approach

All portfolios constructed employing the mixing approach are equal-weighted and monthly rebalanced. For instance, the value-momentum portfolio has 50% allocation to value portfolio and 50% allocation to momentum portfolio in each month. Table 8 presents the results of portfolios constructed by using the mixing approach. The

[10] Note that we have at this stage already excluded ex-ante the smallest 10% of companies from the sample as detailed in section 2.

combination of momentum and low ex-ante beta generated the highest Sharpe ratio of 0.73, while the combination of value and momentum had the lowest Sharpe ratio of 0.68. Notably, the value-momentum portfolio generated the highest average excess return of 1.00 per cent per month, but at the same time, the strategy had the highest volatility and market beta, which has a negative effect on both Sharpe ratio and alpha.

The CAPM-alphas of all mixed portfolios are 0.50 per cent per month with statistical significance on any level. 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 are implementable in real time. When comparing the CAPM-alphas of Table 8 with the CAPM-alphas of large-capitalization portfolios of single factor strategies (see tables 5–7), we observe that the multi-factor portfolios using the mixing approach are superior to any single factor portfolio. For instance, the CAPM-alpha of the large-cap value portfolio of Table 5 is 0.50 per cent in monthly terms, but the alpha is not statistically significant at a 5% level, unlike the CAPM-alphas incorporating value-signals in Table 8. Thus, the mixing approach can be deemed to create superior risk-adjusted returns when compared to single factor strategies, which is in line with earlier literature (e.g. Clarke et al. 2016; Bender and Wang 2016, Li and Shim, 2019; Fitzgibbons et al. 2017; Ghayur et al. 2018).

3.3.2 Returns to multi-factor portfolio using the integrating approach

To construct a multi-factor portfolio using the integrating approach, stocks with the desired exposure to multiple factors are selected to form the multi-factor smart beta portfolio. Similar portfolio construction methodologies have been discussed and applied by Fitzgibbons et al. (2017) and Novy-Marx (2013; 2014). In Figure 1, the idea behind the integration approach is visualized, which could at the same time provide some insight into why this approach might offer better exposures to the desired styles than the mixing approach. In Figure 1, momentum signal intensifies from left to right and value signal strengthens when moving on the vertical axis upwards. For a stock to be included in the integrated value-momentum portfolio, it is required to have both high value and high momentum signal simultaneously.

To build an integrated portfolio, stocks are sorted by their factor signals into quintile portfolios at the beginning of each month. Then stocks that rank above the 60th percentile breakpoint in both value and momentum simultaneously are selected for the integrated multi-factor smart beta portfolio. By applying this methodology, the portfolios will exclude undesired exposures. For example, if a stock sorted on the momentum signal happens to be a growth stock, i.e. in Figure 1 the stock would be on the bottom right hand side (in box 5,1). This stock, which potentially exhibits a strong momentum signal, could at the same time exhibit a negative value signal, which is not optimal for an investor aiming at optimizing the exposure to value and momentum signals simultaneously. The same stock, however, would be included in the momentum portfolio of some mixed multi-factor (smart beta) portfolio. On the other hand, other stocks that have relatively strong value and momentum signal at the same time (stocks in box 4,4), are included in the integrated multi-factor (smart beta) portfolio, while the same stocks would not be accounted for in the mixed multi-factor portfolio, as they do not have strong enough signals to either of the single factors.

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, the median breakpoint is used instead of the 60th percentile breakpoint. At this stage, accounting for a lower breakpoint is necessary to construct the three-factor portfolio, as otherwise the number of stocks would be too low to generate well-diversified portfolios (when using the 60th percentile breakpoint). Table 9 illustrates the returns of various portfolios constructed using the integrating approach. When comparing the excess returns, CAPM-alphas and Sharpe ratios of the multi-factor strategies of Table 9 (e.g., integrating approach) with the multi-factor strategies of Table 8 (e.g., mixing approach), it is evident that the integrating approach is superior to the mixing approach, which is also in line with the vast majority of the literature (Clarke et al. 2016; Bender and Wang 2016; Fitzgibbons et al. 2017; Ghayur et al. 2018; Chow et al. 2018).

Notably, our results imply that investing into stocks that have momentum and low ex-ante beta is the best strategy in terms of both CAPM-alpha and Sharpe ratio. Specifically, the strategy exhibits a CAPM-alpha of 70 basis points per month with a robust *t*-statistic of 3.49 and an impressive Sharpe ratio of 0.86. The second best strategy is the “All” portfolio that also exhibits 70 basis points CAPM-alpha which is significant on a 1% level. However, the Sharpe ratio corresponding to 0.79 is slightly lower. Integrating value and momentum has the highest excess returns, which corresponds to 1.20 per cent in monthly terms, but both the high realized beta and volatility decrease the risk-adjusted return measures of this strategy. Creating a portfolio that includes stocks with value and low ex-ante beta signal seems to have the worst performance of those integrated multi-factor portfolios under investigation. Still, this portfolio generates a statistically significant CAPM-alpha of 0.50 per cent per month.

3.3.3 Robustness checks

Hou et al. (2018) who conducted an extensive replication of 452 asset pricing anomalies found that 65 per cent of those anomalies fail scientific replication. This is not surprising as Schwert's (2003) findings indicate that after anomalies are documented, the cross-sectional patterns often appear to disappear, reverse, or at least weaken. In this regard, McLean and Pontiff (2016) document that the average return spreads of 97 anomalies considerably decline post publication. Hence, one may wonder whether our results are sample-specific. To address this issue, we split the overall subsample into two subsamples of equal length. The first subsample is from December 1995 to July 2007 and the second subsample is from July 2007 to January 2019. Both samples comprise 139 monthly observations. We replicate Tables 8 and 9 and report in Tables 10 and 11 the key figures, that is, sample averages, CAPM-alphas and market sensitivities.

Table 10 shows that the sample averages of the mixing approach, as reported in Table 8, appear to be mainly driven by the first subsample because the plain sample averages in the second subsample are statistically not different from zero – irrespective of which strategy is implemented. Only the CAPM-alphas of the value and low-beta combination portfolio as well as the mixing portfolio combining all three strategies generate about 30 basis points per month CAPM-alphas that are statistically significant on a 5% level. However, these point estimates are considerably lower than for the earlier subsample.

Next, from Table 11 we observe that even though the payoffs for all strategies using the integrating approach appears to be higher in the earlier subsample, all strategies generate statistically significant average returns also in the later subsample ranging from 90 to120 basis points per month. In addition, the CAPM-alphas are statistically significant across all strategies in the later subsample. Overall, our results of the sample-split analysis substantiate our argument raised earlier that the integrating approach appears to be superior.

4. Conclusion

During the last ten years, asset managers around the world have allocated trillions of dollars to smart beta ETFs and funds. The global and rapid emergence of this investing approach and its performance is the main motivation to explore the returns of different smart beta strategies in the scarcely researched Nordic stock markets. Our results suggest that in the Nordic equity market, stock returns show significant variations with respect to certain characteristics such as B/M, past performance, or ex-ante beta. Moreover, single factor premiums related to value-, momentum-, or low-beta-investing are not small stock phenomena. This is an interesting finding, given that the vast majority of the literature advocates that cross-sectional asset pricing phenomena are stronger when implemented among small stocks. Finally, the integrating approach, which selects stocks based on multiple signals simultaneously, tends to generate superior returns.

It is, however, important to note that the integrating approach has some drawbacks compared to the mixing approach. For instance, the integrating approach requires more trading and is less transparent than the mixing approach. Another aspect that should be considered is that the integrating approach potentially narrows the available investment universe to a group of stocks that does not deliver portfolios exhibiting a high-level of diversification. Even though our findings suggest that multi-factor smart beta portfolios that condition the investment allocation on multiple signals do not necessarily perform better than those that account for less signals, our result strongly challenge the efficient market hypothesis. Long-only portfolios that allocate funds to stock exhibiting desired exposures, such as high B/M, high relative past performance or low ex-ante beta, generate impressive returns in excess of the market factor. This is an interesting result, given that the Nordic stock market covering large cap stocks (which we control for by conditioning most of our analysis on large caps) can be considered nearly free of market frictions.

Overall, the results of this study provide useful information about the risk and return characteristics of different smart beta strategies implemented in the Nordic equity market. This study also provides information about alternative smart beta multi-factor portfolio construction approaches for professional asset managers focused on the Nordic stock markets. While our study followed the mainstream of the literature in using the CAPM as benchmark model, future research could for instance investigate the different dimensions of risks of integrated and mixed multi-factor smart beta portfolios by using multi-factor regressions. Also, studying smart beta portfolios constructed by using Environmental, Social, and Corporate Governance (ESG) screens could be a valuable and novel area of future research.

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Figures and Tables

Figure 1. Value-momentum portfolio constructed with the integration approach

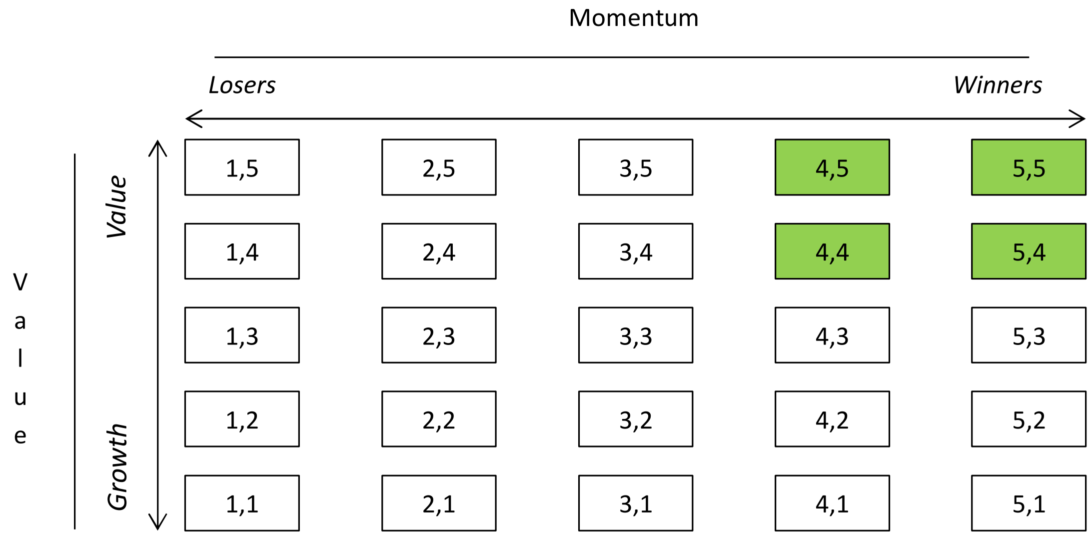

Table 1. Descriptive statistics

This table reports the minimum, maximum and average amount of companies and the average market capitalization by country. The sample period is from December 1995 to January 2019 covering 278 months.

	Finland	Sweden	Norway	Denmark	Total
Minimum number of stocks	70	144	112	89	429
Maximum number of stocks	133	464	1876	131	836
Average number of stocks	113	296	151	107	666
Average market value (in Million EUR)	1,252.3	871.9	803.3	1,291.4	4219

Table 2. Returns to value signals

This table shows portfolio returns sorted by the value signal. 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. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. Robust *t*-statistics are given in parentheses below regression estimates.

Portfolio	**Low**	**2**	**3**	**4**	**High**
Excess return	0.30	0.50	0.60	0.60	0.90**
	(0.53)	(1.19)	(1.58)	(1.63)	(2.12)
CAPM alpha	-0.30	0.00	0.20	0.20	0.50*
	(-1.40)	(0.08)	(0.99)	(1.05)	(1.81)
Beta (realized)	1.03	0.84	0.79	0.74	0.78
Std.Dev.[a]	21.50	17.10	16.40	15.40	17.60
Sharpe ratio	0.15	0.34	0.47	0.48	0.61
Worst monthly drawdown[b]	-19.70	-18.20	-18.70	-18.90	-22.90
Maximum drawdown[b]	-85.90	-67.50	-66.20	-63.70	-64.40
Portfolio characteristics					
B/M	0.17	0.37	0.56	0.83	1.70
ME	1718	1105	1005	809	329
n	128	127	127	127	128

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.
[a] In annualized figures.
[b] In monthly figures.

Table 3. Returns to momentum signals

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, the following 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 given portfolio. Point estimates of the average excess returns are rounded figures and CAPM alphas are rounded figures and given in per cent per month. Robust t-statistics are given in parentheses below the regression estimates.

Portfolio	Losers	2	3	4	Winners
Excess return	-0.30	0.40	0.70**	0.90**	1.20***
	(-0.58)	(0.92)	(2.00)	(2.39)	(2.85)
CAPM alpha	-0.90***	-0.10	0.30**	0.50***	0.70***
	(-3.67)	(-0.42)	(1.97)	(2.71)	(3.35)
Beta (realized)	1.07	0.79	0.77	0.76	0.84
Std.Dev.[a]	23.70	16.50	14.70	14.80	17.90
Sharpe ratio	-0.16	0.27	0.59	0.70	0.81
Worst monthly drawdown[b]	-24.80	-21.10	-18.10	-16.80	-18.60
Maximum drawdown[b]	-87.80	-66.10	-58.40	-59.00	-61.40
Portfolio characteristics					
Average cumulative 12-1 return	-53.70	-10.50	6.90	23.20	58.10
ME	469	1012	1202	1275	1135
n	124	123	123	123	124

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.
[a] In annualized figures.
[b] In monthly figures.

Table 4. Returns to ex-ante low beta signals

This table shows low ex-ante beta-sorted portfolio returns. At the beginning of each calendar month, stocks are ranked in ascending order on the basis of their estimated betas 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, the following time-series average portfolio characteristics are presented: Average estimated beta (ex-post), average company size (ME, in EUR millions) and average number of companies (*n*) in a portfolio. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. Robust *t*-statistics are given in parentheses below the regression estimates.

Portfolio	Low	2	3	4	High
Excess return	0.60**	0.80**	0.70*	0.60	0.20
	(1.97)	(2.27)	(1.87)	(1.58)	(0.39)
CAPM Alpha	0.30*	0.40**	0.30	0.10	-0.50**
	(1.74)	(2.21)	(1.45)	(0.72)	(-2.32)
Beta (realized)	0.45	0.59	0.73	0.91	1.26
Stdev	11.30	13.20	15.30	18.20	25.40
Sharpe	0.63	0.71	0.54	0.42	0.10
Worst monthly drawdown	-12.90	-16.70	-17.50	-19.60	-25.40
Maximum drawdown	-55.40	-61.10	-59.90	-63.40	-82.30
Portfolio characteristics					
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

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.
[a] In annualized figures.
[b] In monthly figures.

Table 5. Returns to double sorted portfolios on size and value signals

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. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. Robust *t*-statistics are given in parentheses below the regression estimates.

Portfolio	Low	2	3	4	High
Panel A: Excess returns of size-value portfolios					
Small	-0.20	0.40	0.70	0.30	1.00**
	(-0.02)	(0.84)	(1.51)	(0.88)	(2.54)
Mid	0.30	0.50	0.70	0.80*	0.70
	(0.49)	(1.12)	(1.54)	(1.91)	(1.31)
Large	0.50	0.60	0.60	0.80*	1.00**
	(1.15)	(1.45)	(1.46)	(1.91)	(2.33)
Panel B: Alphas of size- value portfolios					
Small	-0.60	-0.10	0.20	0.00	0.60**
	(-1.46)	(-0.19)	(0.97)	(-0.05)	(2.58)
Mid	-0.30	0.00	0.20	0.30	0.20
	(-1.22)	(0.12)	(0.88)	(1.43)	(0.51)
Large	-0.10	0.10	0.10	0.30	0.50*
	(-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

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.

Table 6. Returns to double sorted portfolios on size and momentum signals

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. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. Robust *t*-statistics are given in parentheses below the regression estimates.

Portfolio	Low	2	3	4	High
Panel A: Excess returns of size-momentum portfolios					
Small	-0.40	0.50	0.70**	1.00**	1.50***
	(-0.72)	(1.11)	(2.00)	(2.54)	(3.22)
Mid	-0.40	0.30	0.70*	0.80**	1.30***
	(-0.60)	(0.66)	(1.83)	(2.15)	(2.83)
Large	0.00	0.30	0.70*	0.90**	1.00**
	(-0.02)	(0.79)	(1.89)	(2.27)	(2.25)
Panel B: Alphas of size- momentum portfolios					
Small	-0.90***	0.10	0.40*	0.60***	1.10***
	(-3.27)	(0.37)	(1.76)	(2.72)	(3.56)
Mid	-1.10***	-0.20	0.30	0.40**	0.80***
	(-3.60)	(-0.76)	(1.53)	(1.98)	(3.01)
Large	-0.70**	-0.20	0.30	0.40**	0.40**
	(-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

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.

Table 7. Returns to double sorted portfolios on size and ex-ante beta signals

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. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. Robust *t*-statistics are given in parentheses below the regression estimates.

Portfolio	Low	2	3	4	High
Panel A: Excess returns of size-low beta portfolios					
Small	0.60	0.80**	0.60	0.50	-0.40
	(1.65)	(2.05)	(1.38)	(1.15)	(-0.82)
Mid	0.60*	0.70*	0.70*	0.70	0.40
	(1.88)	(1.91)	(1.69)	(1.50)	(0.64)
Large	0.70**	0.90**	0.80**	0.70*	0.50
	(2.37)	(2.64)	(2.13)	(1.81)	(0.99)
Panel B: Alphas of size- low beta portfolios					
Small	0.30	0.50*	0.20	0.10	-1.00***
	(1.32)	(1.86)	(0.79)	(0.22)	(-3.57)
Mid	0.30	0.30	0.20	0.10	-0.40
	(1.52)	(1.43)	(1.03)	(0.68)	(-1.30)
Large	0.50**	0.50***	0.30*	0.20	-0.20
	(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

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.

Table 8. Returns to multifactor portfolios employing the mixing approach

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. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. Robust t-statistics are given in parentheses below the regression estimates.

Portfolio	Value-Momentum	Value-Low beta	Momentum-Low beta	All
Excess return	1.00**	0.90**	0.90**	0.90**
	(2.49)	(2.45)	(2.56)	(2.55)
CAPM alpha	0.50***	0.50**	0.50***	0.50***
	(2.82)	(2.43)	(2.89)	(2.91)
Beta (realized)	0.91	0.71	0.72	0.78
Std.Dev.[a]	17.80	14.90	14.90	15.50
Sharpe ratio	0.68	0.69	0.73	0.71
Worst monthly drawdown[b]	-19.70	-17.60	-17.40	-17.80
Maximum drawdown[b]	-63.80	-58.80	-60.70	-61.10
Portfolio Characteristics				
n	87	83	82	126

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.
[a] In annualized figures.
[b] In monthly figures.

Table 9. Returns to multifactor portfolios employing the integrating approach

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 (in case of low beta strategy, the requirement is that the beta of a stock is below the 40th percentile point, i.e. that the stock has low beta relative to the cross section). The "All" portfolio that integrates the three factors requires that value and momentum factor signals are above median break point, while beta needs to be below 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. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. Robust *t*-statistics are given in parentheses below the regression estimates.

Portfolio	Value-Momentum	Value-Low beta	Momentum-Low beta	All
Excess return	1.20***	0.90***	1.10***	1.10***
	(2.85)	(2.69)	(3.06)	(2.76)
CAPM Alpha	0.70***	0.50***	0.70***	0.70***
	(2.75)	(2.75)	(3.46)	(2.79)
Beta (realized)	0.81	0.63	0.66	0.68
Std.Dev.[a]	18.10	14.30	14.80	16.10
Sharpe ratio	0.78	0.75	0.86	0.79
Worst monthly drawdown[b]	-19.20	-17.00	-19.30	-20.60
Maximum drawdown[b]	-64.80	-55.50	-60.80	-65.90
Portfolio Characteristics				
n	25	31	31	21

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.
[a] In annualized figures.
[b] In monthly figures.

Table 10. Sample-split tests for portfolios employing the mixing approach

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 are presented. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. The first subsample is from December 1995 – July 2007 and the second subsample is from July 2007 – January 2019. Both subsamples have 139 monthly observations. Robust *t*-statistics are given in parentheses below the regression estimates.

Portfolio	Value-Momentum	Value-Low beta	Momentum-Low beta	All
Panel A. Sample from December 1995 – July 2007				
Excess return	1.50***	1.20**	1.30***	1.30***
	(2.92)	(2.56)	(2.73)	(2.81)
CAPM alpha	0.90***	0.70**	0.70***	0.70***
	(2.97)	(2.09)	(2.68)	(2.72)
Beta (realized)	0.79	0.58	0.65	0.67
Panel B. Sample from July 2007 – January 2019				
Excess return	0.50	0.50	0.50	0.50
	(0.84)	(1.10)	(1.07)	(1.09)
CAPM alpha	0.20	0.30**	0.30*	0.30**
	(1.45)	(2.23)	(1.81)	(2.18)
Beta (realized)	1.03	0.88	0.82	0.91

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.

Table 11. Sample-split tests for portfolios employing the integrating approach

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 (in case of low beta strategy, the requirement is that the beta of a stock is below the 40th percentile point, i.e. that the stock has low beta relative to the cross section). The "All" portfolio that integrates the three factors requires that value and momentum factor signals are above median break point, while beta needs to be below median break point. Average excess returns, alphas and betas from regressions are presented. Point estimates of the average excess returns and CAPM alphas are rounded figures and given in per cent per month. The first subsample is from December 1995 – July 2007 and the second subsample is from July 2007 – January 2019. Both subsamples have 139 monthly observations. Robust *t*-statistics are given in parentheses below the regression estimates.

Portfolio	Value-Momentum	Value-Low beta	Momentum-Low beta	All
Panel A. Sample from December 1995 – July 2007				
Excess return	1.70**	1.20***	1.30***	1.50***
	(3.28)	(2.67)	(2.93)	(3.03)
CAPM alpha	1.20***	0.80**	0.80***	1.00***
	(2.85)	(2.29)	(2.61)	(2.71)
Beta (realized)	0.60	0.47	0.55	0.50
Panel B. Sample from July 2007 – January 2019				
Excess return	1.20***	0.90***	1.00***	1.00***
	(2.89)	(2.72)	(3.06)	(2.76)
CAPM alpha	0.70***	0.50***	0.70***	0.70***
	(2.75)	(2.75)	(3.40)	(2.75)
Beta (realized)	0.80	0.63	0.66	0.68

* Statistically significant on 10% level.
** Statistically significant on 5% level.
**** Statistically significant on 1% level.