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Playing it Safe

An inquiry into the beta anomaly in the Nordic markets

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Abstract

Extensive research indicates the existence of a beta anomaly across international markets and various asset classes. However, the mechanisms driving the anomaly and the feasibility of profitably exploiting it have been heavily debated. This thesis provides compelling evidence of the existence of a beta anomaly in the Nordic markets, with the results being robust to controlling for the size, value and momentum factors. Furthermore, our findings from implementing Frazzini and Pedersen's (2014) Betting against beta strategy among larger companies indicate that the anomaly can be profitably exploited.

By analyzing the relation between correlation and return, we investigate whether systematic risk can be identified as a driver of the anomaly. However, we do not find any conclusive evidence supporting this. While a strategy that bets against correlation yields positive Fama-French three-factor alpha, these results are not robust to controlling for momentum. This pattern persists across all versions of the strategies we implement in our study. In summary, despite indications of an exploitable beta anomaly, conclusive evidence of a systematic component behind it remains elusive.

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1 Introduction

The notion that investors should be compensated for taking on risk is one of the basic building blocks in the field of finance. Therefore, the existence of a low-risk effect where assets with lower risk achieve higher returns than assets with high risk presents a striking puzzle. The empirical evidence of the low-risk effect can be dated back to Black, Jensen and Scholes (1972), who found that the capital market line was "too flat" compared to the predictions of CAPM. This lack of relation between market beta and return has later been dubbed the "beta anomaly". Since this finding, the drivers of the anomaly and the low-risk effect in general have been heavily debated in the literature.

One explanation, offered by Black et al. (1972) is the theory of leverage constraints. This theory states that some investors are constrained in terms of the amount of leverage they can apply. Therefore, investors with higher risk tolerance are forced to buy high-beta assets instead of levering up low-beta assets to their desired level of risk. This theory was extended by Frazzini and Pedersen (2014) in their seminal "Betting against beta" (BAB) paper. In this paper, they present a trading strategy designed to exploit the beta anomaly. The strategy's spectacular performance has made "Betting against beta" one of the most downloaded papers in the Journal of Financial Economics.

Since the publication of BAB, several explanations have been made for the drivers of the strategy's performance. Novy-Marx and Velikov (2022) have argued that it can be explained by unconventional procedures applied when constructing the strategy. These procedures lead to an overweighting of the smallest stocks in the market on both the long- and short side. Hence, they claim the strategy is impossible to implement in practice.

Bali et al. (2011) argue that the anomaly can be explained by lottery demand, as investors prefer to invest in assets with lottery-like payoffs. In order to tie the performance of Betting Against Beta to the theory of leverage constraints, Asness et al. (2020) decompose BAB into a betting against correlation (BAC) component and a betting against volatility (BAV) component. The BAC strategy seeks to isolate the effect of systematic risk as proxied by correlation as a driver of the beta anomaly. The strategy generates significant and positive alpha across both US and international markets.

Motivated by the ongoing debate, this thesis sets out to investigate the beta anomaly in the Nordic markets from the perspective of a Norwegian investor. In doing so we wish to answer three questions: 1) Is there a beta anomaly in the Nordic markets? 2) Can the anomaly be attributed to systematic risk? 3) Are the answers to the previous questions robust across firm size?

By analyzing systematic risk as a driver of the beta anomaly, we seek to add a perspective on the underlying mechanisms behind it. Asness et al. (2020) argue that systematic risk is more closely related to the theory of leverage constraints compared to non-systematic risk. Hence, convincing evidence of systematic risk as a driver of the anomaly would point toward the theory of leverage constraints as an underlying mechanism.

In our quest to answer our questions, we replicate the BAB, BAC and BAV strategies as described by Frazzini and Pedersen (2014) and Asness et al. (2020). These strategies are tested in both the original rank-weighted and value-weighted versions. Furthermore, we comment on the holdings and turnover across quintiles sorted on firm size. We also test the robustness of the strategies when restricted to the top two and bottom three quintiles sorted on firm size. We conclude by running Fama-MacBeth regressions on our estimated beta and correlation. By doing so, we analyze the pricing ability of beta and correlation at the firm level in our sample.

BAB, BAC and BAV all generate positive and significant CAPM alphas of 1.1%, 0.7% and 0.93%, respectively, when replicated in the full sample. When regressed on the Carhart (1997) four-factor model, BAB and BAV are the only strategies still generating significantly positive alphas, with monthly estimates of 0.41% and 0.42%, respectively.

When we examine the holdings across size-sorted quintiles in our set, all strategies tend to overweight the smallest stocks in our sample on either the long- or short-side. In the case of BAB, we observe a meaningful dependence on smaller stocks in both the long- and short-leg. BAC and BAV exhibit a more skewed holding pattern. BAC tends to overweight the smallest stocks in the long leg while shorting larger stocks. Conversely, BAV typically overweights the smaller stocks in the short leg while going long the larger stocks. This pattern is reflected in the turnover of the strategies, raising questions regarding their implementation in a real-world setting.

When tested in value-weighted versions, BAB, BAC and BAV generate positive and significant CAPM alphas of 0.77%, 0.62% and 0.69%, respectively. However, when tested against the Carhart (1997) four-factor model, BAV is the only strategy generating significant alpha. The estimated alphas of both BAB and BAC are still positive, but marginally insignificant.

The relationship between BAB, BAC and BAV and size is further examined when we replicate the strategies across the two largest and three smallest quintiles sorted on market capitalization in our set. BAB generates positive and significant alphas in both the large and small brackets. The alpha of the large bracket is also robust to controlling for size, value and momentum. BAC generates positive CAPM alphas in both the large and small brackets. When including size, value and momentum as explanatory variables, however, the alpha estimates become insignificant.

In our Fama-MacBeth (1973) regressions, we find a statistically significant negative relation between estimated betas and excess returns. This holds when controlling for B/M, market capitalization and prior 12-month return. In the case of correlation, we find no relation when volatility is the only explanatory variable included. When adding the three control variables, we do see contours of a positive relationship, albeit with an insignificant coefficient.

Overall, our thesis provides convincing evidence of the existence of a beta anomaly in the Nordic markets. This anomaly cannot be explained by the Carhart (1997) four-factor model, and we argue that it should be possible to exploit in a real-world setting. Regarding systematic risk as a driver of the anomaly, the evidence is less clear. While the BAC strategy generates positive and significant CAPM and FF3 alphas across all tests, none of these results are robust to controlling for momentum. Furthermore, in Fama-MacBeth regressions, we do see signs of a positive relationship between correlation emerging when adding B/M, market capitalization and prior 12-month return as explanatory variables. Hence, we do not provide convincing evidence that systematic risk, and consequently the theory of leverage constraints, is a driver of the anomaly in the Nordic markets.

Our thesis proceeds in the following way. We start by presenting previous literature relevant to our thesis. We then proceed to walk through the data and methodology utilized for answering our research questions. In section 5, we present the results of our analysis, before we conclude based on our findings.

2 Literature Review

One of the more puzzling anomalies in finance is the low-risk effect. A basic premise in the field is that investors should be compensated for taking on risk. Empirical evidence, however, undermines this relationship, with riskier assets delivering lower returns than predicted by theory. In this section, we will walk through the most important findings from prior research on the low-risk effect. We split the research into two branches based on the preferred measure of risk, systematic or non-systematic.

2.1 Systematic Risk

A basic building block in most courses taught on finance is the capital asset pricing model (CAPM) as developed by Sharpe (1964), Lintner (1965) and Mossin (1966). CAPM states that investors should be compensated for carrying non-diversifiable systematic risk measured by an asset's market beta. Contrary to this, Black, Jensen and Scholes (1972) find empirically that the capital market line is "too flat", with high-beta assets delivering little to no excess return compared to low-beta assets.

The theory of leverage constraints is introduced as an explanation of this "beta anomaly" by Black (1972) and extended by Frazzini and Pedersen (2014). It is built on the premise that a meaningful share of investors are leverage-constrained. This prohibits them from obtaining their desired level of risk through the use of leverage. Instead they are forced to buy high-beta assets, causing excessive demand for these assets compared to low-beta assets. The excessive demand leads to an overpricing of these high-beta assets. Hence, these assets should have lower expected returns than low-beta assets. In fact, the theory predicts that an asset's CAPM alpha should be inversely related to its market beta.

Having presented their theoretical framework, Frazzini and Pedersen (2014) propose a trading strategy designed to exploit the resulting mispricing. The strategy is known as Betting Against Beta (BAB). It is constructed as a self-financing strategy going long (short) the stocks with a beta lower (higher) than the cross-sectional median each month. Both the long- and short side are leveraged to a beta of one, giving the long-short strategy an ex-ante beta of zero. The strategy delivers positive and significant alpha across US and international markets, as well as different asset classes. The results are robust when controlling for size, value, momentum and liquidity, and across time periods (Frazzini & Pedersen, 2014).

2.2 Non-Systematic Risk

The other branch of research on the low-risk effect is concerned with the relation between non-systematic measures of risk and return. Ang et al. (2006, 2009) mark the beginning of this branch as they find a negative relationship between an asset's idiosyncratic risk and return. Stambaugh et al. (2015) extend this finding by showing that the negative relation between idiosyncratic risk and return is related to mispricing, and driven disproportionately by overpriced stocks. Specifically, they find idiosyncratic risk to be positively related to return among underpriced stocks, but negatively related to return among overpriced stocks. They explain their findings by arbitrage risk, as high idiosyncratic volatility deters arbitrageurs from shorting stocks, and thereby correct mispricing.

Related to the research on idiosyncratic risk are the findings of Bali et al. (2011). They document a negative relation between lottery demand and return. Lottery demand is measured by the maximum daily return of a stock during the last month (MAX). They find MAX to be significantly negatively related to return at both the portfolio and firm level.

2.3 Explanations of the Low-Risk Effect

In addition to differing estimates of risk, the two branches of low-risk research also differ in their explanation of the underlying mechanisms behind the effect. While the theory of leverage constraints resides within the rational camp, behavioral explanations have been offered by Bali et al. (2011) for the low MAX effect, while Stambaugh et al. (2015) favors limits to arbitrage-based explanations for the idiosyncratic volatility effect.

Efforts have also been made to tie the different estimates of risk together. Bali et al. (2017) find that the beta anomaly disappears when controlling for MAX, and argues that this can explain the beta anomaly. Furthermore, Liu et al. (2018) connects idiosyncratic risk to the beta anomaly. As beta and idiosyncratic risk are positively correlated, they argue that the idiosyncratic risk effect is the main driver of the beta anomaly. As evidence to support their thesis, they find the beta anomaly to be significant only among overpriced stocks, and in periods where beta and idiosyncratic volatility are more strongly related.

A central problem when trying to uncover the mechanisms behind the low-risk effect in general, and the beta anomaly in particular, is that the different measures of risk are highly correlated. Furthermore, attempts at defining causes, such as that presented by Stambaugh et al. (2015) are plagued by a circularity problem. If over- or underpricing can explain the beta anomaly, this might just mean that leverage constraints are the cause of both mispricing and the beta anomaly.

Asness et al. (2020) seeks to address these issues in their betting against correlation paper. They argue that the best way to distinguish between different explanations of the beta anomaly is to create a new strategy that is closely related to one explanation, while unrelated to others. In pursuit of this goal they decompose BAB into two sub-components: Betting against correlation (BAC) and Betting against volatility (BAV). Both strategies are constructed in a way that isolates the effect of each variable by holding the other variable constant.

As BAC is unrelated to both general volatility, MAX, and idiosyncratic volatility, they argue that BAC effectively isolates the effect of betting against systematic risk. Both BAC and BAV deliver positive and significant alphas in both US and international markets. The alpha persists after controlling for the Fama and French (2015) five-factor model. Since the systematic component of risk in itself should be unrelated to behavioral explanations of the beta anomaly, Asness et al. (2020) argue that their results point towards the theory of leverage constraints as an underlying driver of the anomaly,

2.4 Critique of the Low-Risk Research

Betting against beta has been criticized for employing non-standard methods to achieve their extraordinary results. Among these methods are a non-standard beta estimation and rank-weighting[1] as opposed to the more standard value-weighting of portfolios. Beta estimation is not a central topic in our thesis, but we note that it has limited effect on

[1] See section 4.2.1 for more details.

returns generated by the strategy (Novy-Marx and Velikov, 2022). More meaningful for returns is the rank-weighting scheme. Novy-Marx and Velikov argue that this method is a backdoor to equal-weighting. They show that an equal-weighted long-short strategy going long the third of the market with the lowest beta and short the third with the highest beta performs almost identically to BAB.

The result of this weighting scheme is a large emphasis on the absolute smallest stocks in the market in both the long- and short leg of BAB. When replicating BAB with a more standard value-weighting methodology, Novy-Marx and Velikov (2022) find that while BAB's alpha is reduced, it remains positive and significant even after adjusting for the Fama and French (2015) five-factor model. When computing returns net of transaction costs, the value- and rank-weighted versions of the strategy generate similar positive but insignificant FF5 alphas.

The interaction with firm size is also present in the betting against correlation paper, albeit in a somehow different manner. While betting against beta loads heavily on small stocks in both the long- and short leg, betting against correlation tends to be long smaller stocks and short larger stocks on average. Asness et al. (2020) attribute this to smaller stocks being less diversified.

Han and Pan (2021) add an additional perspective on this. They run Fama-MacBeth (1973) regressions to estimate the relation between correlation and returns. While they find no relationship when correlation is the only explanatory variable, the relationship becomes significantly positive when controlling for size. When regressing returns on beta and the same controls, they find no relationship. Based on these findings, they argue that size acts as an omitted variable obscuring the positive relation between correlation and returns (Han and Pan, 2021).

As we have seen, the relation with firm size raises questions regarding the possibility of implementing BAB and BAC profitably. We seek to address these questions in our thesis. By examining the holdings and turnover of each strategy within quintiles sorted on market capitalization, we comment on transaction costs in addition to the feasibility of implementing the strategies in practice. Furthermore, we construct value-weighted versions of each strategy and test the strategies across size universes in our set. We round off by conducting Fama-MacBeth regressions on excess returns with beta and correlation as explanatory variables. Our findings support the existence of a beta anomaly in the Nordics, and we are optimistic regarding the feasible implementation of BAB in the real world. Regarding correlation, we are not able to conclude that systematic risk, and consequently the theory of leverage constraints is a driver of the beta anomaly in the Nordic markets.

3 Data

The sample used to conduct our analysis is retrieved from the Compustat Global database of Wharton Research Data Services (WRDS). We collect annual fundamental data and daily stock price data from Norway, Sweden, Denmark and Finland from January 1990 through July 2023. Data from before 1990 is excluded due to limited sample size and poor data quality.

The scope of the thesis is to analyze the performance of selected low-risk strategies in the Nordic market, from the perspective of a Norwegian investor. We therefore transform all values to Norwegian Kroner (NOK) using historical data from Norges Bank for the currency developments of USD, EUR, DKK and SEK. When handling Finnish stocks traded in FIM before 1999 we translate the values to NOK via USD, using USD/FIM rates obtained from the Federal Reserve. For stocks traded in FIM after the fixed FIM/EUR rate was set, we exchange to NOK via this EUR rate.

To remove all duplicate observations of the same firm, we filter out all observations where the value in the exchange column does not equal the issue's primary exchange, as identified by Compustat. Furthermore, we include only stocks traded on the major Nordic exchanges in Oslo, Stockholm, Copenhagen or Helsinki. We also include only ordinary common shares as defined by code 0 in the column tpci in Compustat. As an additional filter, we remove all observations with a market cap below 25 million NOK, as these very small stocks are more susceptible to data-quality issues.

Given the perspective of a Norwegian investor with NOK as the base currency, the relevant risk-free rate for computing excess returns is the risk-free rate in NOK. As a proxy for this risk-free rate, we obtain daily data on 1-month NIBOR rates from Macrobond. The rates obtained are in annual percentages. These are translated to daily and monthly rates using simple returns. To create the daily rate, we divide by 365, while we divide by 12 to get the monthly rate.

We calculate daily and monthly returns in NOK adjusted for dividends and stock splits for all stocks in our set. All returns are winsorized at the 0.1 and 99.9 percentiles to minimize the impact of outliers and faulty return observations. The daily returns are utilized when estimating betas, while monthly returns are used in regressions.

Compustat does not state any delisting returns for Nordic stocks, so we create these manually based on the stated delisting reason. Delisting returns are set to 0% in the case of mergers, acquisitions or leveraged buyouts and -100% in the case of bankruptcy or liquidation. For delistings that occur for other reasons than the ones stated above, we follow Asness et al. (2019) and assign a return of -30%.

For our market return, we create a value-weighted index comprising all stocks in our dataset at a given time. The return of each stock contributes to the market return at time t based on its share of the total market capitalization at time $t-1$. We compute the market return both on a daily (for beta estimation) and monthly basis.

A summary of the filtered daily sample is shown in Table 3.1.

Table 3.1: Descriptive statistics

This table provides descriptive statistics of our filtered daily dataset. Distinct companies is the number of companies observed in our set each day. Market capitalization and daily return figures are reported at both firm and market level. Returns are winsorized so that the maximum and minimum return correspond to the 0.1 percentile values. This is done to reduce the impact of outliers in our sample. Market capitalization numbers are in million NOK for both individual shares and the market. Returns are reported in daily percentages.

Statistic	Distinct companies	Market capitalization	Total market capitalization	Daily stock return	Daily market return
Mean	732	8 767	8 630 282	0.05	0.05
Median	769	754	6 380 521	0.00	0.07
Max	1 408	3 204 115	23 151 559	88.43	8.00
Min	108	25	375 188	-50.23	-8.87

4 Methodology

4.1 Beta Estimation

We adopt the methodology developed by Frazzini and Pedersen when estimating betas for our analysis. Rolling standard deviations and market correlation are computed separately, with horizons of one year (252 trading days) and five years (1260 trading days) respectively. We demand at least 120 days of non-missing trading data for the standard deviations, and 750 days of non-missing trading data in the case of correlation, for computation. Stocks that do not meet both of these filters at time t are not assigned a valid beta at time t. They will then be excluded from our set until a valid beta can be computed. To control for nonsynchronous trading, overlapping three-day log returns $r_{i,t}^{3d} = \sum_{k=0}^{2} \ln(1 + r_{t+k}^{i})$ are applied when estimating correlation (Frazzini & Pedersen, 2014).

A stock's time-series beta is estimated on a daily basis $\hat{\beta}_i^{TS} = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}$, where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ is the volatility of the stock and the market, respectively, and $\hat{\rho}$ is the correlation between the two.

In accordance with Frazzini and Pedersen (2014), we shrink the estimated time series beta towards its cross-sectional mean. This adjustment reduces the impact of outliers and has previously been done by Vasicek (1973) and Elton et al. (2014):

$$\hat{\beta}_i = w_i\hat{\beta}_i^{TS} + (1 - w_i)\hat{\beta}^{XS} \tag{4.1}$$

Just like Frazzini and Pedersen (2014) we apply $w = 0.6$ and $\beta^{XS} = 1$ throughout our data. As the shrinking is done uniformly across stocks, it does not affect the beta rankings that lay the grounds for our portfolio formation. However, the leverage employed to scale the portfolios to a beta of 1 will change as a consequence of the shrinking procedure. Distributions of our final ex-ante estimates are shown in Table 4.1.

Table 4.1: Distribution of key variable

This table displays the distribution of our ex-ante estimates of beta, correlation and standard deviation. Panel A presents the mean, standard deviation and selected percentiles of the respective variables for the full sample. Panel B reports the averages of the respective estimates within quintiles sorted on market capitalisation. At the beginning of each month, all stocks are assigned to a quintile depending on the relative size of the company, with the averages reflecting the distribution of observations within these over time. For comparison, the time-series mean value-weighted beta estimate is 1.05 for our sample.

Panel A: Key statistics			
Statistic	Beta	Correlation	Standard deviation
Mean	0.94	0.36	0.028
Standard deviation	0.26	0.17	0.014
25th percentile	0.75	0.23	0.018
50th percentile	0.91	0.35	0.024
75th percentile	1.09	0.47	0.033
Panel B: Key statistics across size quintiles			
Size quintile	Beta	Correlation	Standard deviation
1 (Highest Mcap)	1.04	0.55	0.020
2	0.97	0.43	0.023
3	0.90	0.33	0.026
4	0.87	0.28	0.029
5 (Lowest Mcap)	0.90	0.23	0.041

4.2 Betting Against Beta

The construction of the betting against beta (BAB) factor starts by ranking stocks based on their ex-ante betas at the beginning of each month. All securities are then assigned to either a low-beta long portfolio or a high-beta short portfolio. Consequently, the long (short) side includes all stocks with a beta below (above) the median at formation.

4.2.1 Rank-Weighting

The original methodology by Frazzini and Pedersen (2014) decides the weightings within each portfolio in a rank-based manner. Specifically, stocks with lower (higher) beta are assigned greater weights in the long (short) portfolio. Weightings are recalculated at the beginning of each month.

To calculate the weights we first determine the deviation of a stock's beta rank, $z_i = \text{rank}(\beta_{i,t})$, from the cross-sectional mean beta rank $\bar{z} = \frac{1}{n}\sum_{i=1}^{n} z_i$, where n is the number of securities in the given month. The portfolio weights for the high and low portfolios are then given by:

$$w_H = k \times (z_i - \bar{z})^+ \qquad\qquad w_L = k \times (z_i - \bar{z})^- \tag{4.2}$$

k in this instance is a normalization constant that is calculated at the beginning of each month, ensuring that the weights for both the high and low portfolio add up to one:

$$k = \frac{2}{\sum_{i=1}^{n} |z_i - \bar{z}|} \tag{4.3}$$

These weightings, when multiplied by an asset's return for the month, determine the asset's weighted return contribution to its respective portfolio that month.

The BAB factor is computed by combining the two portfolios, going long the low portfolio and shorting the high portfolio. We (de)leverage them so they both obtain a beta of one at portfolio formation. Thus, we end up with a self-financing zero-beta portfolio (Frazzini & Pedersen, 2014).

$$r_{t+1}^{BAB} = \frac{1}{\hat{\beta}_t^L}(r_{t+1}^L - r^f) - \frac{1}{\hat{\beta}_t^H}(r_{t+1}^H - r^f) \tag{4.4}$$

Where $\hat{\beta}_t^L$ ($\hat{\beta}_t^H$) represent the weighted beta of the unlevered low (high) portfolio at formation $\sum_{i=1}^{n} \hat{\beta}_{i,t} w_L$ ($\sum_{i=1}^{n} \hat{\beta}_{i,t} w_H$), serving as the respective portfolios' (de)leverage factor. While r_{t+1}^L (r_{t+1}^H) represents the unlevered return of the respective portfolios $\sum_{i=1}^{n} r_{i,t+1} w_L$ ($\sum_{i=1}^{n} r_{i,t+1} w_H$).

4.2.2 Value-Weighting

To analyze the impact of the choice of rank-weighting by Frazzini and Pedersen (2014), we also construct a value-weighted BAB factor. Stocks are still split into either the high or low beta portfolio based on each stock's beta ranking at the beginning of each month. The difference being that weightings in this case are decided by the relative market capitalization (MC in equation 4.5) of the stocks compared to the entire market capitalization of their respective portfolio at the time of formation. The weightings are applied at the beginning of each month.

$$w_L = \frac{MC_i^L}{\sum_{i=1}^{n(L)} MC_i^L} \qquad w_H = \frac{MC_i^H}{\sum_{i=1}^{n(H)} MC_i^H} \tag{4.5}$$

Where MC_i^L (MC_i^H) represents a stock i within the low (high) portfolio and $n(L)$ ($n(H)$) is the number of stocks within each of these for a given month. The unlevered return of the two portfolios can once again be found using $r_{t+1}^L = \sum_{i=1}^{n} r_{i,t+1} w_L$ ($r_{t+1}^H = \sum_{i=1}^{n} r_{i,t+1} w_H$). Both the long- and short portfolio are scaled to an ex-ante beta of 1 following the same approach as the rank-weighted version. See equation 4.4.

4.3 Betting Against Correlation and Betting Against Volatility

For the betting against correlation (BAC) and betting against volatility (BAV) portfolios the construction method resembles the one of BAB. We also utilize the same beta, correlation and volatility estimates as those obtained in section 4.1 throughout the process of constructing the BAV and BAC factors. Firstly, the stocks in the BAC (BAV) method are divided into terciles[2] based on their volatility (correlation) ranking. Thereafter stocks within each tercile are split into a long- or short portfolio depending on whether their correlation (volatility) is below or above the median within their respective tercile. Thus, we each month have six portfolios, one long and one short per tercile.

Similar to what we saw in equation 4.2 stocks are weighted at the beginning of each month. Rank-weightings are based on a stock's deviation from the cross-sectional mean correlation (volatility) rank and a normalization constant like the one in equation 4.3.

[2]The original paper by Asness et al. (2020) uses quintiles. Because of our sample size, we operate with terciles instead. Using quintiles, we would run the risk of each sub-portfolio containing too few stocks leading to a high standard deviation of returns. This problem is especially acute in the beginning of our sample. Despite this, we keep the q superscript to avoid any confusion with the time variable t.

Only in this case, these actions are done separately within each tercile.

$$w_H^q = k^q \times (z_i^q - \bar{z}^q)^+ \qquad w_L^q = k^q \times (z_i^q - \bar{z}^q)^- \tag{4.6}$$

$$k^q = \frac{2}{\sum_{i=1}^{n(q)} |z_i^q - \bar{z}^q|} \tag{4.7}$$

Where $n(q)$ is the number of stocks within each volatility tercile for a given month. For value-weighting the essence is the same. We perform the same operation as with BAB, only within each portfolio of each tercile.

$$w_H^q = \frac{MC_i^{L,q}}{\sum_{i=1}^{n(L,q)} MC_i^{L,q}} \qquad w_L^q = \frac{MC_i^{H,q}}{\sum_{i=1}^{n(H,q)} MC_i^{H,q}} \tag{4.8}$$

Where $MC_i^{L,q}$ ($MC_i^{H,q}$) represents the market capitalization of a stock i within a specific tercile low (high) portfolio. $n(L,q)$ ($n(H,q)$) is the number of stocks within the respective portfolios that month.

With the weightings of the respective low and high portfolios within each tercile done, each of these correlation (volatility) portfolios are (de)levered to a beta of 1 based on the weighted portfolio beta. In this way we create three self-financing zero-beta BAC (BAV) factors, one within each volatility (correlation) tercile. Thus, we end up with a return computation per tercile that is similar to the one in equation 4.4:

$$r_{t+1}^{BAC(q)} = \frac{1}{\hat{\beta}_t^{L,q}}(r_{t+1}^{L,q} - r^f) - \frac{1}{\hat{\beta}_t^{H,q}}(r_{t+1}^{H,q} - r^f). \tag{4.9}$$

Where $\hat{\beta}_t^{L,q}$ ($\hat{\beta}_t^{H,q}$) is the weighted unlevered beta of a tercile's low (high) portfolio and ($r_{t+1}^{L,q}$ (($r_{t+1}^{H,q}$) is the unlevered return of the respective portfolios.

The overall BAC factor return can be obtained by calculating the simple average of the individual BAC factors of the respective terciles, $r_{t+1}^{BAC} = \frac{1}{3}\sum_{q=1}^{3} r_{t+1}^{BAC(q)}$. The final BAV factor is calculated using the same method, averaging the BAV factors of the three correlation terciles.

4.4 Explanatory Variables in Factor Regressions

As explanatory variables in our regressions, we use the Fama-French three-factor model, augmented with the momentum (UMD) factor (Carhart, 1997). The three-factor model is constructed following the methodology of Fama and French (1993), with some adjustments to accommodate our dataset, as described below.

4.4.1 Size and Value

In June each year, all stocks in our sample are ranked based on size, as defined by market capitalization. Fama and French use the NYSE median to split stocks in a large and small bracket. As NYSE stocks tend to be larger than Nasdaq and Amex stocks, this results in a disproportionate number of shares in the small bracket. Still, the small bracket accounts for only 8% of the combined value of all stocks in their sample. We have no equivalent to the NYSE median in our set and therefore need to pick another breakpoint. Following Asness and Frazzini (2013), we choose the 80th percentile. As of June 2023, the stocks in our small group make up 6.24% of the total market capitalization in our set.

Independent of the size sort, we also sort stocks into three book-to-market (B/M) portfolios each June in year t. Book value is defined as the SEQ (Stockholders equity) variable in Compustat. B/M is then calculated as the last reported book value in year t-1 divided by the market capitalization at the end of year t-1. The book value utilized in the calculation will therefore be at least 6 months old at the time of portfolio formation, minimizing the risk of look-ahead bias. Both book value and market capitalization are converted to NOK before calculation based on prevailing exchange rates at the time. Shares with missing or negative book values are excluded.

We then form six portfolios based on the intersection between the size and B/M sorts. Shares that are in both the small bracket based on size and the high B/M bracket are sorted into the small-value portfolio. In the same way, shares in the large size bracket and low B/M bracket are sorted into the large growth portfolio. The sorts are illustrated in Table 4.2.

Each portfolio is value-weighted, and rebalanced monthly. Furthermore, they are reformed in June of year t+1 based on updated B/M values. After forming the portfolios, the size (SMB) and value (HML) factors are constructed in the following way: SMB is the average return of the three small portfolios minus the average return of the three large portfolios, using simple averages. Similarly, HML is the average return of the two portfolios with high B/M value minus the average return of the two portfolios with high book-to-market value.

Table 4.2: Construction of the SMB and HML factors

When constructing the SMB and HML factors, companies are split into six different portfolios depending on their book-to-market ratio and market capitalization. The SMB factor is created by taking the simple average return of the three small portfolios minus that of the three big portfolios. Similarly, the HML is the simple average of the returns from the two value portfolios minus those from the two growth portfolios.

B/M / Size	Small	Big
Low	Small Growth	Large Growth
Medium	Small Neutral	Large Neutral
High	Small Value	Large Value

4.4.2 Momentum

The momentum (UMD) factor is constructed in a similar way to HML, using six portfolios sorted on size and past return. We split our sample into two size brackets based on the 80th percentile of market capitalization. Shares are then sorted into three brackets based on the return over the past year, with breakpoints being the 30th and 70th percentile. The return sorts are independent of the sorts on size. Specifically, return is calculated as the total return from t-12 to t-1, skipping the most recent month. All returns are in NOK, and size and return brackets are refreshed and rebalanced monthly. Six portfolios are then formed based on the intersection of the size and return brackets. Portfolios are value-weighted following the same methodology as for HML. The UMD factor is constructed as the average return of the two high-return portfolios minus the average return of the two low-return portfolios.

4.5 Size Brackets

Looking into the drivers of our estimated factors, one can observe in Table 5.5 that both BAB and BAC load quite heavily on stocks within the smaller market capitalization quintiles. A smaller market capitalization normally indicates a larger degree of illiquidity. Should this be the case, the strategies might be prone to implementation issues due to availability, especially with respect to shorting.

We therefore apply size brackets to test the feasibility of the strategies when movement across size is constrained. This is done by ranking all stocks by market capitalization at the beginning of each month and then segregating them into the bottom 60% and top 40%. Subsequently, we construct the factors within each size bracket following the same methodology described earlier in this section.

4.6 Fama-MacBeth Regressions

In order to study the properties of the low-risk effect in the cross-section, we conduct Fama-MacBeth (1973) regressions. Each month, we regress each asset's excess return on our estimated ex-ante beta and correlation, controlled for volatility. We gradually enhance the models by adding different company characteristics as control variables. Specifically, the natural logarithm of market capitalization and book-to-market and prior 12-month return. The coefficients reported are the time-series average of those obtained from each cross-sectional regression. We compute Newey-West (1987) standard errors to account for heteroskedasticity and autocorrelation.

More formally: Let ER_{it} be the excess return of asset i at time t, $\hat{\beta}_{it}$ the estimated FP beta for asset i at time t, and $\hat{\psi}_{it}$ be the estimated exposure towards each control variable for asset i at time t. Each cross-sectional regression can then be described as:

$$ER_{it} = \alpha_t + \lambda_t \hat{\beta}_{it} + \phi_t \hat{\psi}_{it} + \epsilon_{it} \tag{4.10}$$

Where λ_t is the risk premium associated with the FP beta at time t, and ϕ_t is the risk premium associated with factor ψ at time t. The estimated coefficients are then averaged over time:

$$\frac{1}{n}\sum_{t=1}^{n}\hat{\lambda}_t \qquad\qquad \frac{1}{n}\sum_{t=1}^{n}\hat{\phi}_t \tag{4.11}$$

Where n represents the number of months in our set. The time-series average of the coefficients represents the estimated risk premia associated with the factors across our study. When running Fama MacBeth regressions on correlation, our estimated correlation $\hat{\rho}_{it}$ takes the place of $\hat{\beta}_{it}$ in equation 4.10. We also add estimated volatility as a control. Otherwise, the methodology is the same.

The explanatory variables in each cross-sectional regression are the ex-ante estimates of beta and correlation, respectively, obtained earlier in the thesis (See section 4.1). Similarly, volatilities are computed following the methodology described in the same section. Book-to-market ratios and prior 12-month return are the same as those used in the construction of our control variables. We apply the natural logarithm to both market capitalization and book-to-market in the regressions for improved linearity.

5 Analysis

In this section we present the results of our empirical analysis. The main scope of this thesis is threefold: 1) Can we document a beta anomaly in the Nordic markets? 2) Can the anomaly be explained by systematic risk as proxied by correlation 3) Are the answers to the questions above robust across firm size? To answer these questions, we run several tests. Firstly, Betting against beta (BAB), Betting against correlation (BAC) and Betting against volatility (BAV) are replicated following the methodologies of Frazzini and Pedersen (2014) and Asness et al. (2020). Our main focus will be on BAB and BAC. BAB because it seeks to document a beta anomaly in our sample. BAC because it isolates the part of this anomaly that is driven by systematic risk.

After replicating the factors in our set, we turn our attention to the relationship between BAB, BAC, BAV and size. This is approached from multiple angles. We start by commenting on the strategies' holdings and turnover across size-sorted quintiles in our set. Thereafter, we construct value-weighted versions of each strategy. We also construct versions of each strategy across size-sorted universes in our set. Rounding off, we run Fama-MacBeth regressions to check whether or not beta and correlation are priced at the firm level.

5.1 Replication

5.1.1 Betting Against Beta

We commence our analysis by replicating Betting against Beta as described by Frazzini and Pedersen (2014). We run univariate and multivariate regressions on both the long-short strategy and five equal-weighted quintiles sorted on ex-ante beta. The explanatory variable in the univariate regressions is the excess return of the market. In the multivariate regressions, we add the Fama and French (1993) size and value factors, in addition to momentum (Carhart, 1997). Our regressions can be expressed in the following way:

$$R_{pt} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \epsilon_{pt} \tag{5.1}$$

$$R_{pt} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \lambda_p R_{SMB} + \rho_p R_{HML} + \epsilon_{pt} \tag{5.2}$$

$$R_{pt} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \lambda_p R_{SMB} + \rho_p R_{HML} + \delta_p R_{UMD} + \epsilon_{pt} \tag{5.3}$$

Where $(R_{mt} - R_{ft})$ is the return of the market factor, SMB is the size factor, HML is the value factor and UMD is the momentum factor.

The results are summarized in Table 5.1. The estimated betas succeed in capturing differences in realized beta, which increases monotonically across the quintiles sorted on ex-ante beta. There is however a clear tendency for our ex-ante betas to be overestimated compared to the realized betas. We have seen the same tendency in Novy-Marx and Velikov (2022), although to a lesser extent[3]. Turning to estimated CAPM alphas, these tend to decrease as betas increase across the quintiles. The effect is particularly pronounced for the highest-beta quintile which exhibits a negative alpha estimate albeit insignificant.

The long-short BAB strategy echoes the results of the beta-sorted quintiles. The strategy generates an excess return of 0.93% together with a statistically significant monthly CAPM alpha of 1.1% When adding FF3 and UMD as explanatory variables, the estimated alpha decreases to 0.41% while still statistically significant at the 5% confidence level. For comparison, Frazzini and Pedersen (2014) obtain CAPM and Carhart (1997) four-factor alphas of 0.73% and 0.55%, respectively, in their US sample.

In their original study, Frazzini and Pedersen (2014) report separate estimates of excess return and FF3 + UMD alpha on long-short BAB portfolios for each of the countries in our study. Those figures are not directly comparable to our results as 1) Frazzini and Pedersen calculate returns in USD while we use NOK. 2) There are differences in the period and horizon of the samples. 3) Our betas are estimated against a value-weighted Nordic index while Frazzini and Pedersen use separate country indexes. Nevertheless, we conclude that our findings are similar to what was found in the original study in direction and magnitude. The decreasing alpha estimates across beta-sorted quintiles, together

[3] An interesting observation is that our ex-ante betas seem to be overestimated across all beta quintiles. We believe some of this effect is driven by a particular quirk in our sample. During the late 1990s to early 2000s, Nokia and Ericsson become a dominant force in our value-weighted market index. At most, the two companies combined constitute around 60% of our market. If we exclude Nokia and Ericsson from our set, the overestimation is much less severe. Our main findings are robust to excluding these companies. More details are provided in Appendix A.

Table 5.1: BAB and beta-sorted portfolios

This table shows alphas, betas and excess return of beta-sorted portfolios as well as the BAB factor. The five beta portfolios are quintiles sorted on ascending ex-ante betas. At the beginning of each month, stocks are assigned to their designated portfolio. Once all stocks are placed within a given portfolio, returns are equal-weighted, with monthly rebalancing. The BAB factor is constructed by assigning all stocks into one of two portfolios, low and high, depending on whether the stocks' beta is below or above the cross-sectional median beta. Weightings are performed in a rank-based manner, meaning that securities with a lower (higher) beta have larger weights in the low (high) portfolio. Both portfolios are (de)levered to have a beta of 1 at portfolio formation. Portfolios are rebalanced and rescaled at the beginning of each month. The BAB factor is a self-financing portfolio that is long the low portfolio and short the high portfolio. The excess returns of the portfolios are regressed on the market excess return, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. Alphas are reported in monthly percentages with corresponding t-stats in parenthesis beneath them. Ex-ante beta is the time-series average beta estimate of the portfolios, while Realized Beta is the market beta obtained from monthly CAPM regressions of portfolio excess return on market excess return.

	1 (Low β)	2	3	4	5 (High β)	BAB
Excess Return	0.82	0.99	0.87	0.96	0.72	0.93
	(4.28)	(3.68)	(3.35)	(3.13)	(1.69)	(4.42)
CAPM Alpha	0.47	0.48	0.27	0.23	−0.35	1.10
	(2.51)	(2.10)	(1.25)	(0.98)	(−1.47)	(5.44)
FF3 Alpha	0.22	0.21	0.02	−0.03	−0.56	0.84
	(2.02)	(1.50)	(0.19)	(−0.26)	(−3.09)	(4.69)
FF3 + MOM Alpha	0.25	0.25	0.19	0.23	0.03	0.41
	(2.16)	(1.68)	(1.43)	(1.85)	(0.15)	(2.32)
Ex-ante Beta	0.64	0.80	0.91	1.04	1.29	0
Realized Beta	0.40	0.59	0.70	0.85	1.25	−0.21

with a significant CAPM alpha of 1.1% for the long-short strategy underpins the existence of a beta anomaly in our sample.

5.1.2 Betting Against Correlation and Betting Against Volatility

In our analysis of correlation and volatility, we start by creating nine equal-weighted portfolios sorted on volatility and then conditionally on correlation. The results from CAPM regressions on these portfolios are reported in Table 5.2. We find a clear relationship with CAPM alpha for both correlation and volatility, as alphas tend to decrease as we increase both volatility and correlation. The relation is most pronounced on the downside, where the high correlation and volatility portfolio exhibits a significant and economically meaningful monthly alpha of minus 0.84%.

Table 5.2: Portfolios sorted on volatility and correlation

This table displays the properties of nine portfolios formed by sorting stocks on volatility and correlation. At the beginning of each month, stocks are first divided into terciles based on their ex-ante volatility estimates. Within each tercile, stocks are then sorted conditionally into terciles based on ex-ante correlation estimates. The returns of stocks in each portfolio are equal-weighted, with monthly rebalancing. Panel A, reports the alphas from time-series CAPM regressions on each portfolio, presented in monthly percentages with corresponding t-stats in parenthesis beneath them. Panel B presents the market beta obtained from the same CAPM regressions.

Panel A: CAPM Alphas

	Conditional sort on correlation		
	P1 (low)	P2	P3 (high)
Volatility Ranks:			
P1 (low)	0.58	0.63	0.29
	(3.82)	(3.90)	(1.97)
P2	0.37	0.60	0.08
	(2.13)	(3.33)	(0.44)
P3 (high)	0.20	0.03	−0.84
	(0.74)	(0.10)	(−3.44)

Panel B: CAPM Betas

	Conditional sort on correlation		
	P1 (low)	P2	P3 (high)
Volatility Ranks:			
P1 (low)	0.45	0.56	0.74
P2	0.54	0.75	0.98
P3 (high)	0.69	0.91	1.24

We further construct the long-short strategies known as Betting Against Correlation (BAC) and Betting Against Volatility (BAV), as outlined in Asness et al. (2020). For BAC (BAV), stocks are first sorted into three brackets based on volatility (correlation). Within each of these brackets, we construct a rank-weighted long-short strategy based on stocks' correlation (volatility) rank within its respective bracket. Each strategy is levered to achieve an ex-ante beta of 1. The overall BAC (BAV) factor is computed as the equal-weighted average of the returns from each sub-strategy. Regression results for these are presented in Table 5.3.

Table 5.3: BAC and BAV portfolios

This table shows alphas, betas and excess return of the BAC and BAV factors. For BAC (BAV), stocks are divided into terciles based on the ranking of their volatility (correlation). Thereafter stocks within these terciles are similarly split into a low and high portfolio determined by whether their estimated correlation (volatility) is below or above the median within their tercile. These portfolios are then rank-weighted meaning that securities with a lower (higher) correlation (volatility) have larger weights in the low (high) portfolio. The tercile assignment and weightings are done at the beginning of every calendar month. These six (three low and three high) portfolios are all (de)levered to a beta of one at formation. Within each volatility (correlation) tercile, the BAC (BAV) factor is formed by calculating the return of the self-financing BAC (BAV) portfolio, which is long the low-correlation (volatility) portfolio and short the high-correlation (volatility) portfolio. The overall BAC (BAV) factor represents the simple average of the returns from the BAC (BAV) factors within each tercile. Rescaling of the portfolios is done monthly. The table displays alphas from regressions on the market, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. Alphas are reported in monthly percentages with corresponding t-stats in parenthesis beneath them. Ex-ante beta is the time-series average beta estimate of the portfolios, while Realized Beta is the market beta obtained in time-series CAPM regressions.

	BAC	BAV
Excess Return	0.59	0.77
	(3.09)	(3.75)
CAPM Alpha	0.71	0.93
	(3.72)	(4.64)
FF3 Alpha	0.49	0.81
	(3.07)	(4.48)
FF3 + MOM Alpha	0.30	0.42
	(1.77)	(2.31)
Ex ante Beta	0	0
Realized Beta	−0.13	−0.19

BAC and BAV yield positive and significant alphas of 0.71% and 0.93%, respectively, in univariate regressions. When adding FF3 and UMD as explanatory variables, the estimated alphas are still positive for both strategies, but in the case of BAC it becomes marginally insignificant. The interpretation of the multivariate alphas will be addressed in the factor loadings section of our thesis. For now, we conclude that CAPM fails to explain BAC and BAV, while the Carhart (1997) four-factor model might be able to explain BAC.

In Table 5.4, we report the results of regressing BAB on BAC and BAV. In doing so, we check whether we have succeeded in decomposing BAB into its sub-components BAC and BAV. As we can see, BAB loads heavily on both BAC and BAV with BAC being the most important driver. Furthermore, the intercept is insignificant from zero. The adjusted R^2 suggests that we are able to explain the majority of variation in BAB with our BAC and

BAV factors. We therefore conclude that we have succeeded in decomposing BAB into its two subcomponents.

Table 5.4: Decomposition of BAB

This table displays the decomposition of BAB into its sub-components, BAC and BAV. The excess return of BAB is regressed on the excess returns of BAC and BAV. Coefficients are reported with corresponding t-stats in parenthesis beneath them. Intercept is the monthly percentage of unexplained return.

	Dependent variable:
	BAB
BAC	0.84
	(41.15)
BAV	0.53
	(27.72)
Intercept	0.02
	(0.28)
Adjusted R^2	0.88

Our replication documents a beta anomaly in the Nordic markets. The theory of leverage constraints states that CAPM alphas should decrease as a function of estimated beta. This further implies that CAPM alphas should decrease as a function of correlation (volatility) when holding volatility (correlation) constant (Asness et al., 2020). Our findings provide evidence in support of this view. When examining portfolios sorted on beta, CAPM alphas exhibit a clear decreasing tendency as beta increases. The same holds for the portfolios sorted on volatility and correlation. As correlation (volatility) increases, estimated CAPM alphas decrease. Furthermore, both the BAB, BAC and BAV strategies deliver highly significant CAPM alphas in our sample. When adding SMB, HML and UMD as explanatory variables, BAB and BAV still generate significant alphas, while the estimate on BAC becomes marginally insignificant. Hence, while CAPM and the Fama and French (1993) three-factor model are not able to explain the returns of any of the strategies, the Carhart (1997) may be able to explain the returns associated with BAC.

5.2 Holdings Across Size Quintiles

Having observed the results of our replicated BAB, BAC and BAV strategies, a natural question to consider next is whether or not the strategies can be implemented in a real-world setting. Novy-Marx and Velikov (2022) have pointed out that BAB tends to concentrate among small stocks in both the long- and short leg. In this section, we investigate whether this is true in our sample, and if BAC and BAV suffer from similar issues.

Starting with BAB, we observe a similar pattern as Novy-Marx and Velikov (2022) in Table 5.5. The long leg in particular puts a disproportionate share of its total investment in the absolute smallest stocks. In fact, about half of the total stocks acquired are located within the two smallest quintiles of our sample. To give the reader a perspective on how small these stocks are, we show the market capitalization for the smallest stock in each quintile as of July 2023. As we can see, the two smallest categories consist of stocks with a market capitalization below 900m krone.

Table 5.5: Holdings across quintiles sorted on market capitalization

This table displays the time-series average holdings for the market and the long-short portfolios of BAB, BAC and BAV across quintiles sorted on market capitalization. The figures reported are after (de)leveraging. At the beginning of each month, stocks are allocated to one of five quintiles based on their market capitalization. Within each quintile, portfolio weightings are aggregated monthly. The table reports the time-series mean of these aggregated values. The rightmost column shows the market capitalization of the smallest company in each quintile as of July 2023 in MNOK.

		BAB		BAC		BAV		
Quintile	Market	Long	Short	Long	Short	Long	Short	Smallest Company
1 (Highest Mcap)	83.6	14.2	27.9	6.8	40.5	33.7	10.7	15 437
2	10.4	25.9	18.4	18.2	22.1	31.0	13.8	3 357
3	3.8	34.6	12.6	30.7	13.7	31.6	14.5	924
4	1.6	40.7	10.8	41.5	8.9	26.0	19.2	266
5 (Lowest Mcap)	0.6	33.2	16.0	42.8	6.2	11.1	36.3	26
Total	100	148.6	85.7	140.1	91.3	133.4	94.4	

While not as extreme, the short leg also takes advantage of the smallest part of our sample. On average, for every krone invested the strategy is short 26.8 øre of stocks from the two smallest quintiles. While this might not sound excessive, remember that the short leg is short only 85.7 øre in total. In other words, 31.4% of the total short exposure resides in these two quintiles. In comparison, our market index's exposure to these segments is only 2.2%.

Table 5.5 also reports the weightings of BAC and BAV across the size quintiles. We observe a clear pattern where the BAC strategy goes long the smallest stocks and short the largest stocks in our sample. The relationship is resounding, as weightings decline monotonically with increasing company size. In the long leg, 60.2% of the gross exposure is towards stocks in the two smallest quintiles. The short leg, in comparison, allocates only 16.5% of its gross investment in the same quintiles. BAV, on the other hand, exhibits the opposite pattern. This strategy tends to be short the smallest stocks, with 38.5% of its gross short exposure residing in the absolute smallest quintile.

The difference in weightings across the strategies is not surprising. We have observed that correlation tends to increase with size, while volatility exhibits the opposite tendency. This is consistent with the findings of Asness et al. (2020), where their BAC factor loads heavily on the SMB factor. They note that smaller stocks tend to be less diversified and, consequently, less correlated to the market.

The observed concentration in smaller stocks raises two primary questions: 1) Is it possible to implement the strategies profitably in a real-world setting? 2) Can the observed CAPM alphas of the strategies be attributed to a risk premium for holding smaller stocks? In the next section, we will address the first question by examining the strategies' turnover across size deciles. The second question will be commented on in the subsection about factor loadings.

5.3 Turnover and Transaction Costs

Table 5.6 illustrates the annual turnover associated with trading BAB, BAC and BAV. Our replicated BAB strategy has a total annual turnover of 200.1%. Considering our estimated annual Carhart (1997) four-factor alpha of 4.92% for the long-short strategy, the turnover implies break-even transaction costs of 246bps. This is way above any reasonable estimate of transaction costs for larger stocks. However, it is well known that smaller stocks tend to have meaningfully higher transaction costs (See for example Novy-Marx and Velikov (2022) or Frazzini et al (2018)). Given our estimated 94.5% turnover within the two smallest size quintiles, transaction costs may be a cause for concern after all.

Based on BABs turnover in their US sample, Novy Marx and Velikov estimate annual transaction costs of 696bps (Novy-Marx & Velikov, 2022). Given that our turnover is similar to what they obtain, this estimate may provide a ballpark estimate for our sample. If their estimate of 696 bps is applied to our estimated annual Carhart (1997) four-factor alpha of 4.92%, the estimated alpha would disappear entirely. The same is the case if we apply a similar estimate of transaction costs to the BAC strategy.

Table 5.6: Annual turnover across quintiles sorted on market capitalization

This table reports the annual turnover of the BAB, BAC and BAV factors, split into long- and short-side contributions, across market capitalization sorted quintiles after (de)leveraging. At the beginning of each month, all stocks are assigned to a quintile based on their market capitalization. Monthly turnover is the average of purchases and sales each month. We then compute the time-series average of the monthly turnover within each quintile. Finally, average monthly turnovers are multiplied by twelve for annualization.

	BAB		BAC		BAV	
Quintile	Long	Short	Long	Short	Long	Short
1 (Highest Mcap)	10.9	19.3	7.6	25.1	26.4	13.5
2	19.8	15.7	19.5	21.3	29.8	18.3
3	26.1	13.7	30.3	16.7	32.9	20.5
4	31.9	12.5	39.0	11.7	28.8	27.0
5 (Lowest Mcap)	31.1	19.0	43.2	8.9	15.3	41.8
Total	119.9	80.2	139.6	83.7	133.2	121.1

Novy-Marx and Velikov (2022) use an estimate of effective bid/ask spread to calculate transaction costs. However, this method has been subject to criticism. Frazzini et al. (2018) argue that the contribution to total transaction costs from bid/ask spreads in reality is orders of magnitude lower than those typically estimated in the literature. Based on their study, market impact plays a much larger role in total transaction costs. As market-impact costs are dependent on the investor trading the strategy, it is impossible to say anything general about this in our case. However, the perspective of Frazzini et al. (2018) suggests that the transaction costs faced by the marginal investor trading BAB, BAC and BAV in our sample might be lower than the estimates provided by Novy-Marx and Velikov (2022).

Further complicating the feasibility of the BAB strategy is the short leg's 31.6% turnover in the two smallest quintiles. We doubt that there is a functioning lending market for all these stocks at all, let alone at a reasonable cost. This problem is even more acute for BAV, as the short leg here turns over 68.9% annually among the two smallest quintiles. In the case of BAC, this problem is less pronounced. While BAC also has a healthy turnover of 102.7% within the two smallest quintiles, a vast majority of this turnover, 82.1%, occurs in the long leg.

Based on the discussion above, we are sceptical as to whether any of the strategies we study can be implemented profitably in their current form by any sizable investor. However, this conclusion presupposes that the strategies are traded exactly as implemented in our study. In reality, an investor could mitigate these transaction costs through a number of measures. For example, one could reduce the rebalancing frequency, employ a different weighting regime or restrict trading to the largest universe of stocks. Our thesis will proceed by studying value-weighted implementations of BAB, BAC and BAV. We will then move on to restricting the original rank-weighted strategies to specific size quintiles.

5.4 Value-Weighted Portfolios

The rank-weighting procedure employed by Frazzini and Pedersen (2014) has been identified as an important driver of BAB's extraordinary performance in the US (Novy-Marx and Velikov, 2022). By constructing a value-weighted version of the strategy, we test if this is the case in our sample as well. Furthermore, we create value-weighted BAC and BAV portfolios to test the impact of rank-weighting on these strategies.

5.4.1 Regression results

The value-weighted portfolios are constructed in the same way as the rank-weighted ones, except for the weightings within each long-short strategy. Instead of weighting based on deviation from the mean rank, we now weight each stock based on the lagged share of total market capitalization in the portfolio. The results of time series regressions on these factors are reported in Table 5.7.

The value-weighted BAB strategy exhibits a positive monthly CAPM alpha of 0.77% in our sample. While somewhat lower than the rank-weighted version, this still represents a significant effect from both a statistical and economic point of view. However, the

Table 5.7: Value-weighted portfolios

This table shows the alphas of value-weighted versions of BAB, BAC and BAV. The BAB factor is constructed using the method of Frazzini and Pedersen (2014) for creating a low- and high-beta portfolio. Instead of employing their rank-based weighting system, portfolios are now value-weighted. After splitting into the low and high portfolios, stocks are weighted based on their share of total market capitalization within their respective portfolio. Each portfolio is then (de)levered to a beta of one at formation, where the BAB factor is a self-financing zero-beta short the low and long the high portfolio. BAC (BAV) are first split into terciles based on estimated volatility (correlation) before they are sorted into low- and high-correlation (volatility) portfolios within each tercile. Similarly to BAB, stocks are then weighted each month based on their share of the total market capitalization within their respective portfolio. Each portfolio is then (de)leveraged to a beta of one at formation, to create self-financing BAC (BAV) factors within each tercile. The overall BAC (BAV) factor is constructed by taking the simple average of these tercile BAC (BAV) factors. The table displays alphas from time-series CAPM, Fama and French (1993) three-factor and Carhart (1997) four-factor regressions. Alphas are reported as monthly percentages with corresponding t-stats in parenthesis beneath them. Ex-ante beta is the estimated beta of the different strategies, while realized beta is the market beta estimated from CAPM regressions.

	BAB	BAC	BAV
Excess Return	0.51	0.54	0.49
	(2.18)	(2.71)	(2.42)
CAPM Alpha	0.77	0.62	0.69
	(3.48)	(3.12)	(3.56)
FF3 Alpha	0.56	0.44	0.63
	(2.66)	(2.49)	(3.37)
FF3 + MOM Alpha	0.34	0.34	0.51
	(1.54)	(1.85)	(2.55)
Ex-ante Beta	0	0	0
Realized Beta	−0.30	−0.10	−0.23

CAPM alpha is notably strengthened by the negative realized beta of 0.3. Examining excess returns, the reduction in performance is more pronounced, falling from 0.93% in the rank-weighted version to 0.51% in the value-weighted one. When including HML and SMB as explanatory variables, the estimated alpha is reduced to 0.56% but still statistically significant. Further adding UMD renders the alpha insignificant, although the estimate remains positive.

Our findings point in the same direction as those of Novy-Marx and Velikov (2022), who report excess returns of 0.56% for value-weighted BAB in the US.[4] Hence, we find that

[4]Note that our results are not directly comparable to those of Novy-Marx and Velikov (2022). While our value-weighted strategy goes long (short) the bottom (top) half of stocks sorted by ex-ante beta, Novy-Marx and Velikov (2022) split their set in three when value-weighting. Specifically, the long (short) portfolio goes long (short) the third of stocks with the lowest (highest) beta rank each month.

value-weighting the strategy does reduce performance compared to rank-weighting in our sample as well.

Turning to BAC, the rank-weighting procedure seems to be a less important driver of overall performance than for BAB. While the estimated monthly CAPM alpha of 0.62% is lower than the 0.7% estimate from the rank weighted portfolio, the difference is much less pronounced. The same goes for excess returns which fall only marginally from 0.59% in the rank-weighted version to 0.54% in the value-weighted version. When adding HML and SMB to the regression, the alpha falls to 0.44% while still statistically significant. As for BAB, adding UMD renders our results insignificant, but only marginally.

Finally, the value-weighted BAV strategy also delivers a statistically significant CAPM alpha. We observe the same pattern as for BAC, with the reduction in alpha being smaller than for the overall BAB strategy. Controlling for HML, SMB and UMD, BAV is the only factor still generating statistically significant alpha at the 5% level.

The difference in performance between BAB and its components BAC and BAV is smaller with value-weighted portfolios than what we observed with rank-weighted portfolios. This is not surprising due to the way the factors are constructed. As we have seen in table 4.1, there is a close relation between volatility (correlation) and firm size. When we first split stocks in terciles based on volatility (correlation) when constructing BAC (BAV), we also sort indirectly on firm size. As a result, the overall BAC (BAV) strategy will be composed of three long-short portfolios, each created within terciles of differing average firm sizes. Consequently, the ability to take advantage of smaller stocks is less limited by value-weighting in the case of BAC and BAV compared to BAB.

5.4.2 Factor loadings

Turning our attention to the factor loadings, these are reported in Table 5.8 for both the rank- and value-weighted versions of the strategies. Before we discuss the impact of the different factor loadings, we provide some context on the performance of the factors in our sample. SMB and HML generate insignificant excess returns, with monthly estimates of 0.01% and 0.1% respectively. UMD on the other hand generates significant excess returns of 1.22% monthly across our sample. Hence, exposure towards the UMD factor is punished more heavily than SMB and HML.

Table 5.8: Factor loadings in FF3+UMD regressions

This table reports the estimated coefficients obtained from time-series regressions on the Carhart (1997) four-factor model, for the rank- and value-weighted portfolios. The rank-weighted BAB factor is constructed following the methodology of Frazzini and Pedersen (2014). At the beginning of each month, stocks are ranked in ascending order based on their estimated beta. Stocks with a beta above the cross-sectional median are sorted to the high-beta portfolio while stocks with a beta below the cross-sectional median are sorted to the low-beta portfolio. Stocks are then weighted based on their deviation from the mean beta rank in the sample, ensuring that stocks with lower (higher) betas receive larger weightings in the low-beta (high-beta) portfolios. Both the high- and the low-beta portfolio are then (de)leveraged to a beta of one at formation. The BAB factor is the return of the low-beta portfolio minus the return of the high-beta portfolio. The rank-weighted BAC and BAV factors are created following Asness et al. (2020), except we sort stocks into terciles instead of quintiles based on correlation and volatility. At the beginning of each month, all stocks are sorted into terciles based on their estimated volatility in the case of BAC and correlation in the case of BAV. Within each tercile, we create the BAC (BAV) factors in the exact same way as for BAB, except we now rank on correlation (volatility) instead of beta. The overall BAC (BAV) factor is then created by taking the simple average of the tercile BAC (BAV). The value-weighted portfolios are created in the same way as the rank-weighted ones, except stocks are weighted based on their share of total market capitalization within their respective portfolios. Both the rank-weighted and value-weighted portfolios are (de)leveraged to a beta of one at formation. All coefficients are reported with their corresponding t-stats in parenthesis beneath them. Alphas are reported in monthly percentages.

	BAB		BAC		BAV	
Weight type:	Rank	Value	Rank	Value	Rank	Value
MKT	0.09	−0.08	0.11	0.11	−0.06	−0.18
	(2.31)	(−1.75)	(3.04)	(2.69)	(−1.52)	(−4.37)
SMB	0.48	0.31	0.79	0.77	−0.46	−0.33
	(6.50)	(3.37)	(11.33)	(9.96)	(−6.02)	(−4.03)
HML	0.37	0.31	0.19	0.13	0.36	0.20
	(9.18)	(6.23)	(5.06)	(3.22)	(8.74)	(4.41)
MOM	0.30	0.15	0.14	0.06	0.27	0.09
	(7.16)	(2.96)	(3.47)	(1.47)	(6.37)	(1.88)
Alpha	0.41	0.34	0.30	0.34	0.42	0.51
	(2.32)	(1.54)	(1.77)	(1.85)	(2.31)	(2.55)

The BAB strategy loads positively on all factors in both rank- and value-weighted versions. It is in fact the only factor that exhibits a statistically significant loading on UMD in the value-weighted version. This helps illuminate why BAB is punished more severely than the other strategies in the four-factor regressions.

BAC loads heavily on SMB in both the rank- and value-weighted versions. This is no surprise as we have already seen that this strategy tends to go long the smallest stocks and short the largest stocks in our sample. Interestingly, the FF3 alpha for both the rank- and value-weighted versions of BAC is statistically significant. Hence, we refer to the discussion presented in section 5.2. If SMB represents exposure towards a risk factor as argued by Fama and French (1993), the excess returns obtained by the BAC strategy can not be explained by this exposure. When viewed in conjunction with UMD, exposure towards the factors is however able to explain the returns of both the value- and rank-weighted versions of BAC.

The difference between results obtained in three-factor and four-factor regressions presents a question regarding which model is the "correct model" to use when testing the low-risk effect. If the control variables in the model used are interpreted as risk factors, the four-factor alpha is the relevant result. Asness et al. (2020), however, argue that the theory of leverage constraints may be the underlying cause of some of the factors identified in the previous literature.[5] Hence, they argue that one might risk "throwing the baby out with the bathwater" by controlling for factors whose underlying cause is leverage constraints. Our thesis offers no useful results for determining the correct interpretation of factors included in asset-pricing models. Hence, we follow the more conventional interpretation of the factors as risk exposure. Accordingly, we put the most weight on the four-factor results obtained.

Overall, value-weighting the strategies reduces performance across the board. Despite this, neither the CAPM nor the FF3 model alone can explain the returns generated by any of the strategies. However, when tested against Carhart's four-factor model, BAV is the only strategy that generates a significant alpha. Hence, in our value-weighted tests, we have not obtained support for an exploitable beta anomaly in our sample. The same applies to correlation as a driver of this anomaly.

While value-weighting the strategies makes them more feasible to implement, we also run the risk of removing some of the signal. The way the factors are constructed, both the value-and rank-weighted versions are forced to go long one half of our sample and short the other half. While rank-weighting the strategies weight the more extreme beta observations

[5]The argument of Asness et al. (2020) is specifically directed at the Fama and French (2015) five-factor model. The general point, however, extends to all factors correlated with excess returns that could be caused by leverage constraints.

on either side more heavily, this is not the case in the value-weighted versions. Hence, the difference in beta between the largest positions on the long side and the largest position on the short side might be quite minimal. Therefore, the estimated alphas may be deemed insignificant due to a lack of signal rather than because of the increased implementability.

We seek to address this in the next section. Instead of value-weighting the strategies, we split our stocks into a large and a small bracket based on firm size and implement the rank-weighted strategies within these size brackets. Thereby, the large bracket will contain more implementable versions of the strategies without the loss of signal that value-weighting runs the risk of.

5.5 Size Split

We have seen that both the BAB, BAC and BAV strategies tend to concentrate among the smallest stocks in the long (BAB and BAC) or short (BAB and BAV) leg. These small stocks are typically more costly to trade than larger stocks. In light of this, we set out to test how sensitive the strategies are to the inclusion of these small stocks in our set. We once again turn to our size quintiles, assigning companies into these based on their market capitalization at the beginning of each month. The rank-weighted versions of BAB, BAC and BAV are then replicated within different combinations of these quintiles. We split our sample in two, with the large pool containing the two largest quintiles and the small pool containing the three smallest quintiles.

Table 5.9 reports the results from this exercise. Our estimated CAPM alpha for the BAB strategy holds up well, with 1.17% within the small category and 1.11% within the large category. This is similar to the results obtained in the overall sample. Interestingly, the large bracket tends to be somewhat more robust when controlling for the FF3+UMD factors than the small bracket, with a positive and significant alpha estimate of 0.47%.

Turning to BAC, the estimated CAPM alphas of 0.64% and 0.61% for the small and large groups respectively are somewhat lower than the estimate of 0.71% obtained in the full sample. Nevertheless, the effect is still significant from both a statistical and economic point of view. When controlling for FF3 and UMD, the estimated alpha is still positive, but insignificant. The strategy's momentum tilt tends to be larger in both the

Table 5.9: Rank-weighted strategies across size quintiles

This table reports the results of BAB, BAC and BAV when limited to the bottom three (small) and top two (big) size quintiles respectively. At the beginning of each month, stocks are ranked into quintiles based on market capitalization. Subsequently, each factor is constructed separately within both the small and big size brackets. The BAB factor is constructed following the methodology of Frazzini and Pedersen (2014). In the beginning of each month, stocks are ranked in ascending order based on their estimated beta. Stocks with a beta above the cross-sectional median are sorted to the high-beta portfolio while stocks with a beta below the cross-sectional median are sorted to the low-beta portfolio. Stocks are then weighted based on their deviation from the mean beta rank in the sample, ensuring that stocks with lower (higher) betas receive larger weightings in the low-beta (high-beta) portfolios. Both the high- and low-beta portfolio are then (de)leveraged to a beta of one at formation. The BAB factor is the return of the low-beta portfolio minus the return of the high-beta portfolio. The BAC and BAV factors are created following Asness et al. (2020), except we sort stocks into terciles instead of quintiles based on correlation and volatility. At the beginning of each month, all stocks are sorted into terciles based on their estimated volatility in the case of BAC and correlation in the case of BAV. Within each tercile, we create the BAC (BAV) factors in the exact same way as for BAB, except we now rank on correlation (volatility) instead of beta. The overall BAC (BAV) factor is then created by taking the simple average of the tercile BAC (BAV). Panel A displays excess returns and alphas obtained from CAPM, Fama and French (1993) three-factor and Carhart (1997) four-factor regressions. Both alphas and excess returns are reported in monthly percentages with corresponding t-stats in parenthesis beneath them. Realized Beta is the MKT coefficient from CAPM regressions. In panel B loadings of the Fama French three-factor model with the momentum are reported, with corresponding t-stats in parenthesis beneath them.

Panel A: Regression Alphas and CAPM Beta

	BAB		BAC		BAV	
	Small	Big	Small	Big	Small	Big
Excess Return	1.06	0.83	0.57	0.48	1.00	0.37
	(4.43)	(3.58)	(2.83)	(2.65)	(4.16)	(1.98)
CAPM Alpha	1.17	1.11	0.64	0.61	1.11	0.57
	(4.91)	(5.17)	(3.13)	(3.49)	(4.57)	(3.20)
FF3 Alpha	0.96	0.88	0.50	0.48	0.98	0.44
	(4.22)	(4.40)	(2.51)	(2.89)	(4.24)	(2.68)
FF3 + MOM Alpha	0.37	0.47	0.14	0.16	0.54	0.34
	(1.64)	(2.32)	(0.70)	(0.93)	(2.28)	(1.92)
CAPM Realized Beta	−0.13	−0.32	−0.08	−0.16	−0.12	−0.23

Panel B: Factor Loadings in FF3 + Momentum

	BAB		BAC		BAV	
	Small	Big	Small	Big	Small	Big
MKT	0.13	−0.06	0.10	0.02	0.03	−0.13
	(2.69)	(−1.51)	(2.32)	(0.54)	(0.61)	(−3.39)
SMB	0.13	0.29	0.33	0.50	−0.35	−0.25
	(1.38)	(3.48)	(3.86)	(7.18)	(−3.63)	(−3.38)
HML	0.39	0.36	0.19	0.14	0.36	0.28
	(7.81)	(8.07)	(4.11)	(3.63)	(6.84)	(7.23)
UMD	0.42	0.29	0.25	0.22	0.31	0.08
	(7.95)	(6.04)	(5.21)	(5.67)	(5.58)	(1.82)

large and small sample than what we observed in the full sample. As the UMD factor generates strong excess returns in our sample, the estimated alpha takes a large hit from this loading.

For the betting against volatility strategy, we observe a pronounced difference between the small and large sample. The strategy performs meaningfully better among the smaller stocks compared to the larger ones. Within the smallest three quintiles, the estimated monthly CAPM alpha of 1.11% is larger than the 0.93% obtained in the full sample. On the other hand, the estimated CAPM alpha within the large sample is considerably lower at 0.57%. Based on these results, we can infer that BAV seems to be more reliant on the smaller stocks to achieve its results, at least in our sample. Controlling for FF3 and UMD reduces the alpha within the small sample to 0.54%. Turning to the factor loadings, we observe a marked difference between the large and small BAV portfolios. While the loading of the large portfolio is insignificant, the UMD loading of the small portfolio is highly significant at 0.31.

In the case of BAB, both CAPM and Carhart four-factor alphas tend to be robust to the size of the stocks studied. Despite showing a concentration among the smallest stocks in the full sample, the availability of these stocks does not seem decisive for the strategy's overall viability. The two largest quintiles in our set consist of stocks with a market capitalization of above 3.3 billion NOK as of July 2023. Focusing only on this part of the universe should make the strategies more feasible to implement in the real world. Hence, the results obtained in this section indicate that BAB generates alpha, also in versions that could be implemented by sizable investors. BAV on the other hand seem to be driven more by the smallest stocks in our set.

Turning to BAC, the evidence is less conclusive. While the strategy generates significant CAPM alphas in both the large and small bracket, the four-factor model is able to explain the returns of the strategy in both the large and small bracket. When viewed in conjunction with the value-weighted version of the strategy, we are not able to conclude on correlation as a driver of the beta anomaly as of yet.

5.6 Cross-Sectional Regressions

The time-series tests conducted so far point towards the existence of a beta anomaly at the portfolio level in the Nordic markets. The evidence of systematic risk as a driver of this effect is less conclusive. In this section, we test the pricing ability of beta and correlation the firm level through Fama-MacBeth regressions.

According to CAPM, there should be a positive relation between an asset's market beta and return. This can be seen clearly in the following equation:

$$E_R = R_F + \beta(E_{RM} - R_F) \tag{5.4}$$

The presence of a beta anomaly would therefore imply either a non-positive or negative relationship between beta and return. When testing the CAPM in our sample we start with the following null hypothesis:

1) Beta is not positively related to return

Turning to correlation as a driver of the beta anomaly, we can test the relationship between correlation and excess returns when holding volatility constant. If we replace beta with its components:

$$E_{Rp} = R_F + \rho_{pm} \times \frac{\sigma_p}{\sigma_m}(E_{RM} - R_F) \tag{5.5}$$

As market volatility is the same for all assets at time t, we can remove this from the equation. Further holding volatility constant results in the following relation:

$$E_{Rp} = R_F + \rho_{pm} \times (E_{RM} - R_F) \tag{5.6}$$

Consequently, correlation as a driver of the beta anomaly would imply a non-positive relation between correlation and return when controlling for volatility. Hence, we can test the following hypothesis:

2) Correlation is not positively related to return when controlling for standard deviation

We follow Han and Pan (2021) in utilizing Fama-MacBeth (1973) regressions to test these hypotheses. Specifically, we run cross-sectional regressions on monthly return for each asset each month in our sample. As explanatory variables, we use beta and correlation as estimated using the method of Frazzini and Pedersen (2014). For regressions on correlation, volatility (also as per Frazzini and Pedersen) is included as a control variable. We also control for firm size, book-to-market and momentum (prior twelve-month return). The results reported are the time series average of the coefficients obtained.

Our results are reported in Table 5.10. Consistent with the presence of a beta anomaly, we fail to reject the null hypothesis that beta is not positively related to return. In fact, we obtain a significant negative estimate for the relation between beta and excess return. These results hold when controlling for size, book-to-market and momentum. This is in line with the findings of Han and Pan (2021), and support the existence of a beta anomaly in the Nordic markets.

Turning to correlation, the picture is more nuanced. When including only correlation and volatility as explanatory variables, we find no significant relationship between correlation and excess return. Interestingly, controlling for firm size does not change the missing relationship. In line with our findings in the time series, size does not seem to be a priced factor in our cross-sectional study either. This is contrary to the findings of Han and Pan (2021), who find a positive and significant relationship between correlation and return when controlling for size. Conversely, our volatility estimate exhibits a clear negative relationship with return across both univariate and multivariate regressions. Viewed in isolation, this finding is more in line with overall volatility as a driver of the low-risk effect than correlation.

When adding book-to-market and momentum as explanatory variables, the relationship is still insignificant at the 5% confidence level. Nevertheless, there is a clear tendency that a positive relationship between correlation and return is appearing when controlling for additional variables. Therefore, while we fail to reject the null hypothesis of no relation, we are hesitant to conclude regarding correlation as a driver of the low-risk effect.

Table 5.10: Fama-MacBeth regressions

This table displays the results of a range of Fama-MacBeth regressions on the Nordic stock market. Panel A shows results of Fama and MacBeth (1973) regressions on excess returns with beta as the explanatory variable. We use the rolling beta estimates obtained following the methodology of Frazzini and Pedersen (2014). Each month, we run cross-sectional regressions on excess returns, with beta and a range of controls as explanatory variables. Panel B reports results of Fama and MacBeth (1973) regressions on excess returns with correlation and a range of controls as explanatory variables. We apply the same methodology as in Panel A. Correlation and volatility are rolling estimates computed following the methodology of Frazzini and Pedersen (2014). In the case of both A and B, the reported results are the time-series average of the coefficients obtained in cross-sectional regressions. All coefficients are shown with their Newey-West robust standard errors beneath them.

Panel A: Beta

	1	2	3	4
Constant	1.37	1.14	1.26	1.64
	(6.70)	(1.53)	(1.66)	(2.52)
Beta	−0.67	−0.74	−0.48	−0.45
	(−3.20)	(−3.45)	(−2.11)	(−2.03)
ln Market Capitalization		0.01	0.00	−0.03
		(0.41)	(0.05)	(−0.94)
ln Book to Market			−0.00	0.03
			(−0.07)	(0.44)
Momentum				0.94
				(5.26)

Panel B: Correlation and Standard Deviation

	1	2	3	4
Constant	1.27	2.30	2.10	3.35
	(5.57)	(3.06)	(2.82)	(4.96)
Correlation	−0.30	0.25	0.28	0.69
	(−0.80)	(0.74)	(0.75)	(1.56)
Standard Deviation	−12.23	−12.82	−8.74	−14.22
	(−2.35)	(−2.36)	(−1.42)	(−2.36)
ln Market Capitalization		−0.05	−0.05	−0.12
		(−1.75)	(−1.59)	(−3.93)
ln Book to Market			−0.02	−0.01
			(−0.29)	(−0.14)
Momentum				1.03
				(5.31)

Our cross-sectional results echo those obtained in time series analysis. Our results when examining the relationship between beta and excess returns offer support for the existence of a beta anomaly in our sample. Regarding correlation, our results are more sensitive to the model used to explain the results. When studying correlation with volatility as the only control, we find no evidence of a positive relation between correlation and return. This is in line with the notion of correlation as a driver of the beta anomaly. When controlling for size, B/M and momentum, we do see contours of such a relationship, albeit with a marginally insignificant estimate. Hence, the cross-sectional evidence for correlation as a driver of the beta anomaly is inconclusive.

6 Conclusion

In this thesis we investigate the beta anomaly in the Nordic markets by answering three questions: 1) Is there a beta anomaly in the Nordic markets? 2) Can the anomaly be explained by systematic risk as proxied by correlation? 3) Are the answers to the questions above robust across firm size? To answer these questions, we replicate the Betting against beta (BAB), Betting against correlation (BAC) and Betting against volatility (BAV), as presented by Frazzini and Pedersen (2014) and Asness et al. (2020). We test these strategies in both their original rank-weighted and value-weighted versions and within size brackets. Furthermore, we conduct Fama-MacBeth regressions to test the pricing ability of beta and correlation at the firm level.

We find strong evidence of the existence of a beta anomaly in the markets studied. The betting against beta strategy generates positive and significant alpha in both univariate and multivariate regressions when replicated in the full sample. When tested in a value-weighted version, BAB generates positive and significant CAPM and FF3 alpha. When adding UMD as an explanatory variable, the estimated alpha is still positive, although marginally insignificant at the 5% level.

Interestingly, when testing BAB within the two largest size quintiles of our sample, we obtain significantly positive alpha estimates across both univariate and multivariate regressions. Hence, we argue that BAB should be possible to implement profitably in a more scalable version than the original replication. The existence of a beta anomaly is further supported by our Fama-MacBeth (1973) regressions. Our estimated betas exhibit a significantly negative relation with excess returns in the cross-section. This result holds when including size, B/M and momentum as explanatory variables.

The evidence of correlation as a driver of the beta anomaly is less conclusive. While CAPM alone is unable to explain the returns of the BAC strategy, the Carhart (1997) four-factor model is. This result holds in both rank- and value-weighted versions, as well as in both the small and large size brackets in our sample. BAC's CAPM alpha is also more sensitive to being restricted to the two largest (or three smallest) size-sorted quintiles in our set than what we observed for BAB and BAV.

A similar pattern emerges when we test the cross-sectional pricing ability of correlation in Fama-MacBeth regressions. When correlation and volatility are the only explanatory variables, correlation shows no ability to predict return. When adding size, B/M and UMD, a positive relationship emerges. When viewed in conjunction with our time-series tests, we are not able to conclude that correlation is a driver of the beta anomaly in our sample.

Our findings support the idea that the beta anomaly can be exploited within the Nordic markets. We find it encouraging to observe that the Betting Against Beta strategy can generate returns that are robust to controlling for the Carhart (1997) also when restricted from exploiting small-cap stocks. This indicates a potential for feasible implementation of the strategy. When it comes to drivers of the BAB factor's apparent success in the Nordics, more research is needed. We were not able to find compelling evidence of systematic risk, and hence the theory of leverage constraints, as a driver of the anomaly in our thesis.

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Appendices

A Nokia and Ericsson

Figure A.1 illustrates market capitalization of Nokia and Ericsson as a proportion of total market capitalization over time. As we can see, the companies represented a meaningful share of our market during the late 1990s to early 2000s. At most, the two companies combined constituted above 60% of our market index.

Figure A.1: Nokia and Ericsson's share of total market capitalization

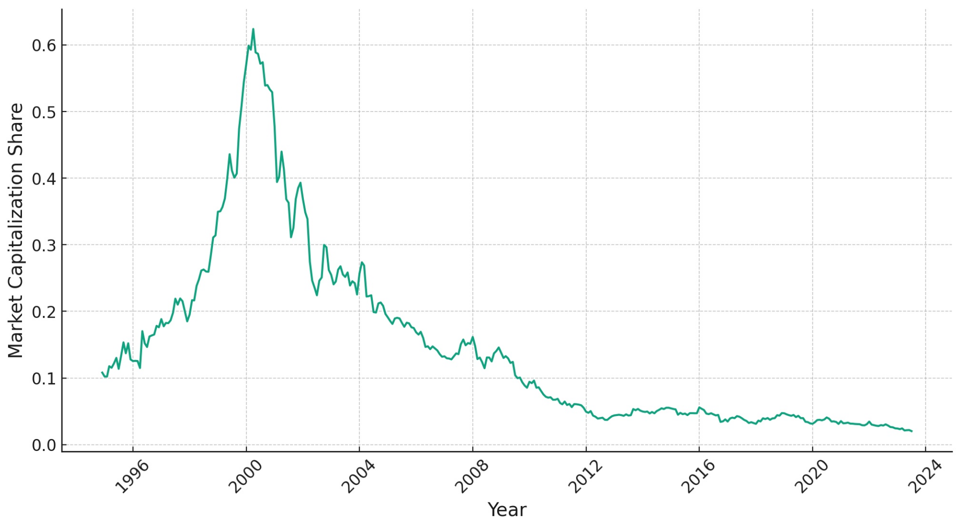

Fig A.1: This figure illustrates the combined share of total market capitalization over time for Nokia and Ericsson combined. Market capitalization for all companies is calculated in NOK on a monthly basis.

We use a value-weighted market index for both beta estimation and regressions on monthly returns. One could worry that the observed dominance of only two companies in our market could lead to skewed results. We therefore report results of beta-sorted portfolios and the BAB factor when we exclude Nokia and Ericsson from our set. The companies are excluded from both the daily data used to estimate ex-ante betas and the monthly set used in regressions. The companies are also excluded when constructing SMB, HML and UMD. As we can see in Table A.1, our main findings are robust to excluding these companies from our sample. The CAPM alpha of the BAB factor is reduced slightly from 1.1% to 0.89%. However, the strategy still generates positive and significant alphas both in CAPM, Fama and French (1993) three-factor, and Carhart (1997) four-factor regressions. Furthermore, the overestimation of betas is less severe when excluding these companies. This can be seen both across the beta-sorted quintiles, and the BAB factor where realized beta falls from -0.21 to -0.08.

Table A.1: BAB and beta-sorted portfolios, without Ericsson and Nokia

This table offers an analysis analogous to Table 5.1, but with Ericsson and Nokia omitted from the sample. The five beta portfolios are quintiles sorted on ascending ex-ante betas. In the beginning of each month, stocks are assigned to its designated portfolio. Once all stocks are placed within a given portfolio, returns are equal-weighted, with monthly rebalancing. The BAB factor is constructed by assigning all stocks into one of two portfolios, low and high, depending on whether the stocks' beta is below or above the cross-sectional median beta. Weightings are performed in a rank-based manner, meaning that securities with a lower (higher) beta have larger weights in the low (high) portfolio. Both portfolios are (de)levered to have a beta of 1 at portfolio formation. Portfolios are rebalanced and rescaled at the beginning of each month. The BAB factor is a self-financing portfolio that is long the low portfolio and short the high portfolio. The excess returns of the portfolios are regressed on the market excess return, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. Alphas are reported in monthly percentages with corresponding t-stats in parenthesis beneath them. Ex-ante beta is the time-series average beta estimate of the portfolios, while Realized Beta is the market beta obtained from monthly CAPM regressions of portfolio excess return on market excess return.

	1 (Low β)	2	3	4	5 (High β)	BAB
Excess Return	0.81	1.00	0.87	0.88	0.76	0.83
	(4.31)	(3.75)	(3.32)	(2.85)	(1.79)	(4.66)
CAPM Alpha	0.34	0.34	0.09	−0.05	−0.49	0.89
	(2.40)	(1.98)	(0.68)	(−0.40)	(−2.37)	(4.98)
FF3 Alpha	0.19	0.21	−0.01	−0.15	−0.55	0.74
	(2.18)	(1.62)	(−0.16)	(−1.39)	(−3.00)	(4.48)
FF3 + MOM Alpha	0.17	0.18	0.09	0.05	−0.03	0.35
	(1.78)	(1.36)	(0.82)	(0.40)	(−0.14)	(2.16)
Ex-ante Beta	0.66	0.82	0.94	1.07	1.34	0
Realized Beta	0.56	0.78	0.92	1.10	1.48	−0.08