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Beta Anomalies in Scandinavian Financial Markets

Master Thesis

by

Jinoorthan Sellathurai & Simen Henmo Rognsvåg

MSc. in Business, Major in Finance

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Supervisor: Alessandro Graniero

Abstract

In our master thesis, we build upon the works of Pedersen and Frazzini to study the beta anomaly. We first replicate their method for constructing the BAB factors in Norway, Sweden, and Denmark. Then we adjust our assumptions to account for criticism the original paper has gotten over the years. We find results that indicate the existence of the proposed beta anomaly, however primarily for stocks above a certain level of market capitalisation. We conclude that the difference between low-beta alpha and high-beta alpha is generally insignificant, but investors can profit from the betting against beta strategy in Norway and Sweden, but not Denmark.

Acknowledgements

First, we would like to thank our thesis supervisor, Alessandro Graniero, for steering us in the right direction and answering any question we have had. Second, we would also like to acknowledge our classmate Ådne Refseth for providing invaluable assistance in retrieving market capitalisation data for our thesis when we were unable to access the database.

Thank you,

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Contents

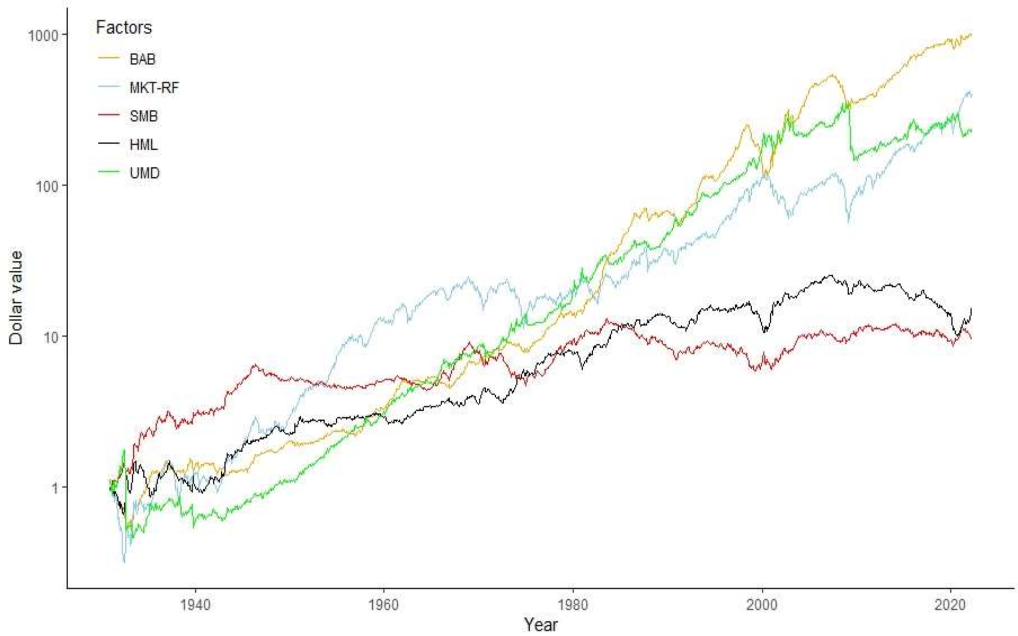
1. Introduction

One of the fundamental assumptions in finance is that investors will not assume any risk unless they can be compensated adequately for it. The correlation between risk and the expected return has been a topic of great significance for the last sixty years, originating with (Sharpe, 1964) and (Lintner, 1965). Before their breakthrough, there had been no asset pricing models built from first principles about the nature of risk preferences, investment opportunities and precise, testable predictions about risk and return.

Decades later, the capital asset pricing model is still the most widely used application for estimating the cost of equity capital and evaluating the performance of managed portfolios. The capital asset pricing model hereafter referred to as CAPM implies that a security's beta directly impacts its expected return. A security's beta is the computed regressor coefficient in a univariate regression of that security's returns on the market. The higher a stock's beta, the more amplified its returns are compared to the market. Hence, both expected returns and risk are increasing in beta.

Figure 1: Cumulative returns of BAB vs Factors

This figure plots the cumulative returns for the BAB-factor vs the cumulative returns of the excess market return (MKT-RF), the size factor (SMB), the value factor (HML), and the momentum factor (UMD) in the US from 1930 to 2022. This figure is based on the original paper by Frazzini and Pedersen using their comprehensive data. Y-axis is logarithmic.



However, empirical studies do not support this proposition, as low-beta stocks have continuously and consistently outperformed high-beta stocks (Black, 1972; Friend & Blume, 1970). Researchers have explored these findings and shown that a strategy betting against beta, holding a long position of low-beta assets and a short position of high-beta assets in a self-financing, market-neutral portfolio generates a robustly positive return in the US stock market (Frazzini & Pedersen, 2014). Hence they find that alpha is decreasing in beta.

Frazzini and Pedersen explain that the empirical reasoning for this anomaly is that, as opposed to achieving satisfactory expected returns and risk exposure on their investments by levering, or delivering, the tangency portfolio (Markowitz, 1991), they overweight high-beta assets. Consequently, the approach makes high-beta assets require lower risk-adjusted returns (alpha) than low-beta assets that require leverage. Hence, investors such as hedge funds encountering fewer leverage constraints than other institutional investors in the market can exploit this anomaly by employing a market-neutral strategy like betting against beta (Frazzini & Pedersen, 2014).

Though, not without criticism. Novy-Marx and Velikov (Novy-Marx & Velikov, 2022) argue that BAB's outstanding performance is driven by two unconventional procedures in the construction of the portfolios. Firstly, the rank-weighting in both arms of the self-financing portfolio, and secondly, their hedging to achieve market neutrality is done by leveraging (deleveraging) the portfolio's long (short) arm. The latter is usually achieved by buying the market in proportion to the short tilt.

In this paper, we replicate propositions 1 and 2 from (Frazzini & Pedersen, 2014) on data from the Nordic countries. That is, (1) alpha is decreasing in beta (high beta returns low alpha), and (2) that a self-financing portfolio that is long low-beta assets and short high-beta assets expects positive excess returns. We will analyse the validity of these propositions in the Norwegian, Swedish, and Danish stock markets. We have chosen these markets because they are our native and neighbouring countries and because their markets are similar[1]. Nevertheless, only Sweden produced statistically significant returns and alpha in Frazzini & Pedersen's original paper. To contextualise the success of the BAB factor, we will compare its

[1] Our assumption. Based on geography, similar political climates, sizes, somewhat shared cultures, etc.

performance to other known equity factors such as Eugene Fama and Kenneth French's three-factor model (Fama & French, 2021) and Carhart's four-factor model (Carhart, 1997). We would also like to control its performance for some of its criticisms. One such criticism is the points mentioned above by Novy-Marx and Velikov, and another is that investor demand for lottery-like stocks is an essential driver of the beta anomaly and is no longer detected when beta-sorted portfolios are neutralised to this demand (Bali et al., 2017).

2. Literature Review

In this section, we explore relevant literature to establish a foundation for our analysis of the beta anomaly in the Scandinavian markets. Firstly, we discuss how current research and frameworks within asset pricing have affected our risk outlook and expected returns in capital markets. Secondly, we investigate the CAPM's features and explore variations of it. Lastly, we review the current research surrounding the beta anomaly, which has led to the "Betting against Beta" strategy.

2.1. Risk and Return in Capital Markets

The stock market's core function is allocating ownership of the economy’s capital stock. The ideal is a market in which prices provide an accurate signal for resource allocation allowing investors to choose among the securities under the assumption that the price at any time “fully reflects” all available information. A market with prices which always “fully reflect” available information is called “efficient” (Fama, 1970). If all available information is reflected in security prices, investors can only attain higher than average returns by assuming higher than average risk. This is done in two ways: investing a more significant proportion of their capital in riskier securities or leveraging their portfolio of less risky securities. In reality, our financial markets are not fully efficient as prices reflect the information of informed individuals (arbitrageurs) but only partially, so those who expend resources to obtain information receive compensation (Grossman & Stiglitz, 1980).

2.2. The CAPM

The Capital Asset Pricing Model (CAPM), derived by (Sharpe, 1964), (Lintner, 1965) and (Black, 1972), is a widely used model describing the relationship between systematic risk and the expected return of assets, particularly stocks. It is based on Harry Markowitz's modern portfolio theory, which states that investors select a portfolio at time $t-1$, to achieve a specific return in time t (Markowitz, 1991). The underlying assumption of the model is that investors are risk averse, meaning that investors are willing to sacrifice a portion of their returns to reduce their total risk. Therefore, it follows that additional risk is expected to carry a greater return. Investors are also interested in the mean and variance of their one-period returns, and as a result, investors choose among mean variance-efficient portfolios.

(Sharpe, 1965) and (Lintner, 1965) add two more assumptions for the CAPM to hold. (1) They assume a standard pure interest rate, with all investors able to borrow or lend funds on equal terms. In other words, all investors have access to leverage at the risk-free rate, independent of the amount leveraged. (2) The other assumption is the homogeneity of investor expectations – that all investors agree on the prospects of all assets, such as the expected return, standard deviations, and correlation coefficients. In short, investors agree on the joint distribution of the investments. Fischer Black believed that the (1) assumption was not a good approximation for many investors and implied that the model described above would be substantially changed if this assumption was dropped (Black, 1972).

2.3 Betting against beta

The premise of our paper lies in the fact that there has not been found empirically reliable and robust linkage between the beta and expected stock returns (Frazzini & Pedersen, 2014). Low beta stocks have been shown to produce greater than average expected returns, and high beta stocks generate less than average expected returns. This beta anomaly has been branded as "betting against beta" and has also been dubbed "the greatest anomaly in finance" (Baker et al., 2011). To be more precise, contrary to basic finance principles, high-beta and high-volatility stocks have long underperformed low-beta and low-volatility stocks. The volatility anomaly refers to the empirical finding that low volatility stocks provide greater returns than high-volatility stocks (Blitz & Vliet, 2007); this has been shown to hold worldwide (Ang et al., 2009).

The CAPM has stringent restrictions, and the one (Frazzini & Pedersen, 2014) and (Black, 1972) critique is that all investors can borrow and lend freely at the risk-free rate. Many considerably large institutions in the capital markets like mutual funds and pension funds are restricted in how much leverage they hold. If all investors were able to freely access leverage at the same rates, all of them would invest in the same tangency portfolio, and leverage/deleverage it to fit their risk-return preferences since it carries the highest excess return per unit of risk (Sharpe

Ratio) (Sharpe, 1994). Hence, to achieve higher expected returns, constrained investors overweight high-beta assets – lowering those assets' overall risk-adjusted returns.

Frazzini and Pedersen introduce a dynamic model that accounts for leverage constraints. Specifically for agents restricted from using leverage altogether and agents that can take on leverage but are subject to margin requirements. Some agents might also be required to keep a portion of their wealth in cash for liquidity reasons – like an insurance company needs cash to pay claims. The implication of this model is a flatter Security Market Line, i.e., alpha is decreasing in beta – low-beta assets outperforming high-beta assets compared to the CAPM's prediction. More specifically, the model predicted that the expected return is given by:

$$E_t\left[r_{t+1}^i\right] = r^f + \psi_t + \beta_t^i \lambda_t$$

Where $\lambda_t = E_t[r_{t+1}^m] - r^f - \psi_t$ and ψ_t is a measure of the funding constraints. This implies a flatter Security Market Line ($\psi_t \geq 0$) since assets with a beta below 1 will earn a premium ($\psi_t - \beta_t \psi_t \geq 0, when\ \beta_t < 1$) and assets with a beta above 1 are "discounted" ($\psi_t - \beta_t \psi_t \leq 0, when\ \beta_t > 1$). Rearranging the terms gives the expression:

$$\alpha_t^i = \psi_t\left(1 - \beta_t^i\right)$$

Where it is straightforward that higher beta gives lower alpha. This is Proposition 1 in Frazzini and Pedersen's paper.

Unconstrained investors can exploit this beta anomaly by going long the generally overperforming low-beta assets and shorting the generally underperforming high-beta stocks. This strategy is what the authors call "betting against beta". Hence, the expected return of a market-neutral, self-financing betting against beta strategy is positive. Mathematically:

$$E_t[r_{t+1}^{BAB}] = \frac{\beta_t^H - \beta_t^L}{\beta_t^H \beta_t^L} \psi_t \geq 0$$

The expected return is increasing in the ex-ante beta spread and the tightness of funding – proposition 2 in Frazzini and Pedersen's "Betting against beta".

3. Testable hypotheses

Proposition 1 predicts that high-beta assets have lower alpha than low-beta. To test this, we will run regressions of the following factor models:

$$r_t^{PTF} - r^f = \alpha^{PTF} + \beta^{MKT}(r_m - r^f)$$
$$r_t^{PTF} - r^f = \alpha^{PTF} + \beta^{MKT}(r_m - r^f) + \beta^{SMB}SMB_t + \beta^{HML}HML_t$$
$$r_t^{PTF} - r^f = \alpha^{PTF} + \beta^{MKT}(r_m - r^f) + \beta^{SMB}SMB_t + \beta^{HML}HML_t + \beta^{MOM}MOM_t$$

Which are the CAPM, Fama-French 3-factor model, and the Carhart 4-factor model, respectively. Where "PTF" refers to the beta-sorted portfolios, running the regressions for both low-beta and high-beta portfolios to test for significant differences between estimated alpha#s (risk-adjusted returns) of the two portfolios:

$$H_0: \alpha^L = \alpha^H$$
$$H_A: \alpha^L > \alpha^H$$

Also, the factors included are the market factor (market portfolio return over the risk-free rate), the size factor ("Small Minus Big", SMB), the value factor ("High Minus Low", HML), and the momentum factor (MOM, also referred to as UMD "Up Minus Down").

Proposition 2 predicts that the "Betting Against Beta" (BAB) portfolio will have positive expected excess returns. We will, by rebalancing the portfolio every month, check if it does indeed produce, on average, positive and significant returns. We will also run these computed returns against the factor models mentioned above to estimate the BAB-alpha(s):

$$r_t^{BAB} - r^f = \alpha^{BAB} + \beta^{MKT}(r_m - r^f)$$
$$r_t^{BAB} - r^f = \alpha^{BAB} + \beta^{MKT}(r_m - r^f) + \beta^{SMB}SMB_t + \beta^{HML}HML_t$$
$$r_t^{BAB} - r^f = \alpha^{BAB} + \beta^{MKT}(r_m - r^f) + \beta^{SMB}SMB_t + \beta^{HML}HML_t + \beta^{MOM}MOM_t$$

4. Methodology

4.1 Estimating Betas

As mentioned in the literature review, our time-series betas are estimated as the covariance of an asset and the market portfolio divided by the market portfolio's variance, which simplifies:

$$\hat{\beta_\iota}^{TS} = \frac{\hat{\sigma}_{i,m}}{\hat{\sigma}_m^2} = \frac{\hat{\rho}(\hat{\sigma}_i \hat{\sigma}_m)}{\hat{\sigma}_m^2}$$

$$\rightarrow \hat{\beta_\iota}^{TS} = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m}$$

Where $\hat{\sigma}_i$ is our estimated volatility (standard deviation) of asset i, $\hat{\sigma}_m$ is the estimated standard deviation of the market and $\hat{\rho}$ Volatilities are estimated from one-day log returns, but correlations are estimated from three-day overlapping log returns to control for nonsynchronous trading: is the estimated correlation between the individual asset and the market. As Frazzini and Pedersen did, correlations will be estimated separately from volatilities as correlations tend to move slower than volatilities(de Santis & Gerard, 1997). Thus, we require a longer rolling window for correlations. We will be using daily equity returns with rolling windows of one year (250 trading days) and five years (1250 trading days) for volatilities and correlations, respectively.

$$r_{i,t}^{3d} = \Sigma_{k=0}^{2} \ln\left(1 + r_{t+k}^{i}\right).$$

To reduce the effect of outliers, we shrink the time-series beta $\hat{\beta_\iota}^{TS}$ towards its cross-sectional mean $\hat{\beta}^{XS}$:

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

To avoid complications by having asset-specific and time-varying shrinkage factors as in (Vasicek, 1973), we set $w = 0{,}6$ and $\hat{\beta}^{XS} = 1$ for all periods and states – like Pedersen and Frazzini did. Since the shrinkage factor is the same across all periods and states, it will not impact the ranking of betas. However, it will affect the construction of the BAB portfolios since the estimated betas are used to scale (leverage/deleverage) the long and short sides of the portfolios.

4.2 BAB Portfolio Construction

Our methodology for constructing the Betting Against Beta portfolio follows Frazzini and Pedersen's method in their paper. We construct two portfolios: a long portfolio consisting of low beta assets and one short portfolio consisting of high beta assets. All stocks are sorted in ascending order based on their estimated beta. The ranked stocks are then assigned to the corresponding portfolio. To replicate a realistic ex-ante construction of our portfolios, we compute daily betas and choose the last day of the month's beta as a signal for the following month's composition.

The weighting of the constituents of each portfolio is based on an ascending beta rank. Let z be the $n \times 1$ vector of beta ranks $z_i = rank(\hat{\beta}_{it})$ at portfolio formation and $\bar{z}$ be the average rank ($\bar{z} = 1_n' \cdot \frac{z}{n}$). The weight of security i within the high or low portfolio is given by:

$$w_{H,i} = k(z_i - \bar{z})^+, \qquad if z_i > \bar{z}$$
$$w_{L,i} = k(z_i - \bar{z})^-, \qquad if z_i < \bar{z}$$

Where k is a normalising constant $k = 2/1_n'|z - \bar{z}|$. Both portfolios are rebalanced monthly and rescaled to have an ex-ante beta of one. We do this by leveraging the long low-beta portfolio and deleveraging the short high-beta portfolio such that the self-financing portfolio is market neutral. The return of the BAB portfolio is given by:

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}\left(r_{t+1}^L - r_{lev}^f\right) - \frac{1}{\beta_t^H}\left(r_{t+1}^H - r_{delev}^f\right)$$

Where,

$$r_{t+1}^L = r_{t+1}' w_L \, , r_{t+1}^H = r_{t+1}' w_H \, , \beta_t^L = \beta_t' w_L \, , and \ \beta_t^H = \beta_t' w_H .$$

5. Data

For summary statistics on all data we use, see Table 1 below. The table reports all data we had access to, though we did not end up using data from all time periods listed for every data set.

We use Refintiv's Eikon platform to collect daily market prices for all primary and currently active stocks listed on the Oslo, Stockholm, and Copenhagen exchanges. Because (Frazzini & Pedersen, 2014) has a unique approach to calculating a stock's beta, we had to drop all stocks with less than 1250 trading days from our sample. Consequently, five years of data also become worthless for performance testing.

This limitation considered, we felt that 20 years of historical daily stock prices would be adequate for our purposes. The acquired period, May 2002 until March 2022, brings several periods of economic distress. Most notably, the subprime mortgage crisis of 2008-2009, the Eurozone crisis of 2010-2011, the oil price collapse of 2014-2016 and lastly, the one we are all too familiar with, the COVID-19 global pandemic.

Ideally, we would have liked to keep delisted stocks in our sample, but due to limited programming experience, we could not clean that data into its desired form for the analysis[2]. We understand that this limits the cross-section of our sample, but we believe it is large enough for our portfolios to have sufficient diversification.

Our betas are computed using the corresponding MSCI local market index as a proxy for the market return and excess return above the US Treasury bill rate[3]. As the MSCI country indices seek to approximate 85% of each country's free float-adjusted market capitalisation, its constituents vary over time. To cover our basis, we tested different proxies in the form of all share indices for each country and observed a similar spread and distribution of betas as with the MSCI as a proxy. The original authors' results are robust to the choice of benchmark; thus, for the purpose of replication, we will be employing the same.

The original paper's authors have collected this data from Compustat and XpressFeed Global, and both the source and handling of data are considered reliable enough for the purpose of this paper.

Our alphas are computed with respect to each country's market and factor returns based on size (SMB), book-to-market (HML) and momentum (UMD) from (Asness & Frazzini, 2013)[4]. This dataset is available on AQR's website and is regularly updated, and the last edition is from March 2022.

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[2] Delisted stocks reported their last closing price for the rest of our sample period, and our attempt to remove consecutive duplicates did not have the desired outcome.

[3] Original data for international markets was collected from Compustat and XpressFeed Global for the period between January 1989 and March 2012, updated data from the same sources until present date is readily available at AQR’s homepage.

[4] SMB, HML and UMD originates from Ken French’s data library, and is collected second hand from AQR’s website.

5.1 Adjusted Data

A significant criticism of (Frazzini & Pedersen, 2014) is that its construction significantly contributes to the strategy's performance. Specifically, the weighting by beta ranking drastically overweights small market capitalisation stocks compared to the more conventional value weighting of stocks (Novy-Marx & Velikov, 2022). Hence, we introduce data on the stocks' market capitalisation to analyse this. This led to some stocks in the original price dataset being filtered out since they did not appear in our market capitalisation data. Ideally, we would not want that to be the case, but it was necessary (see Appendix A for discussion on available data).

When computing daily returns for each market, we observe certain outliers which drastically impact our analysis. Some of these stocks have daily returns above 4000%. The common belief is that high and abnormal returns are, on average, overrepresented in small capitalisation, illiquid stocks, also referred to as penny stocks or lottery-like stocks (Bali et al., 2017). One suggested approach to alleviate this problem is to filter out stocks based on their stock price (10 NOK) and market capitalisation (below 1 MNOK) (Ødegaard, 2021). However, we observe that for our sample, that would result in also removing highly liquid, large market capitalisation stocks. Thus, our preferred and executed solution is to winsorise the sample at its top and bottom 1% level, similarly to (Laeven & Tong, 2012) approach.

Table 1: Summary Statistics

This table shows summary statistics for the data sets we have used in our study. The data we retrieved for stocks were originally daily closing prices, but in this table, they have been converted to daily returns as that is more contextual. For the data on stocks and related market capitalisation data, N describes the number of stocks in the sample, while for the rest, N describes the number of observations. Market capitalisation is measured in US Dollars for comparison. Market capitalisation in a foreign currency is not problematic as we are only interested in ratios at the same points in time. Hence, exchange rates would always be the same for interacting numbers. Mean, Max, and Min are in per cent unless otherwise indicated.

Variable	Frequency	Start	End	N	Mean	Max	Min
Stocks (UF-N)	Daily	2002	2022	333	0.06	4 054.55	-97.59
Stocks (F-N)	Daily	2002	2022	321	0.04	39.44	-29.93
Stocks (UF-S)	Daily	2002	2022	760	0.09	907.69	-94.85
Stocks (F-S)	Daily	2002	2022	750	0.05	170.67	-37.18
Stocks (UF-D)	Daily	2002	2022	177	0.06	4 171.43	-90.00
Stocks (F-D)	Daily	2002	2022	171	0.04	31.64	-24.02
RF	Daily	1926	2022	26 114	0.01	0.06	0.00
MKT-RF (N)	Daily	1986	2022	9 457	0.04	12.79	-21.61
MKT-RF (S)	Daily	1986	2022	9 457	0.06	13.72	-14.07
MKT-RF (D)	Daily	1986	2022	9 457	0.04	10.08	-11.66
Market Cap (N)	Monthly	2007	2022	321	1.63bn	123.73bn	296.65K
Market Cap (S)	Monthly	2007	2022	750	1.59bn	81.28bn	116.54K
Market Cap (D)	Monthly	2007	2022	171	2.69bn	198.41bn	58.33K
RF	Monthly	1926	2022	1 149	0.27	1.31	-0.06
MKT-RF (N)	Monthly	1986	2022	435	0.89	22.98	-30.93
MKT-RF (S)	Monthly	1986	2022	435	0.95	25.31	-26.65
MKT-RF (D)	Monthly	1986	2022	435	0.88	21.62	-25.44
SMB (N)	Monthly	1990	2022	381	-0.09	10.56	-12.09
SMB (S)	Monthly	1990	2022	381	-0.18	11.65	-21.37
SMB (D)	Monthly	1990	2022	381	-0.10	10.49	-11.29
HML (N)	Monthly	1990	2022	381	0.24	20.49	-15.50
HML (S)	Monthly	1990	2022	381	0.31	23.39	-23.63
HML (D)	Monthly	1990	2022	381	-0.07	12.09	-11.59
UMD (N)	Monthly	1987	2022	423	1.15	20.12	-22.44
UMD (S)	Monthly	1987	2022	423	0.84	20.72	-29.30
UMD (D)	Monthly	1987	2022	423	1.17	13.10	-22.62

6. Results

For the entire thesis, we have chosen that we will determine statistical significance by a critical t-value of 2.5 (results in a p-value of approximately 1%). This is strict, higher than Frazzini & Pedersen used in their original paper. However, as we discussed in section 5 since the exclusion of delisted stocks made our samples narrower than desired, we would like to avoid faulty conclusions based on likely biased data.

6.1 Raw data sets

6.1.1 – Alpha is decreasing in beta

As section 3 of the paper discussed, we first set out to replicate and illustrate (Frazzini & Pedersen, 2014) proposition 1. Their model predicts that BAB factors have a positive average return and that the return increases in the ex-ante tightness of constraints. In other words, average returns decrease in beta.

We replicate this by constructing three long portfolios for each country, such that the constituents are distributed equally and in ascending beta order. We will have three portfolios where the first tertile comprises the constituents with the lowest betas and the last, the highest. We then consider alphas with respect to the market factor, size and momentum described in table 2 for each of the three portfolios. We were initially surprised by our hypothesis testing, as the results did not align with the original paper. However, they are consistent with the performance of our BAB factors, which will be discussed further in section 6.1.2.

Table 2: Statistical differences in alpha

This table shows the t-stats of the differences between estimated alphas for low-beta and high-beta portfolios (see Tables 3-5 for estimated alphas). T-stats are estimated by taking the alpha of the low-beta portfolio (portfolio 1) minus the corresponding alpha of the high-beta portfolio (portfolio 3) and dividing the result by the standard error of the low-beta alpha. A t-value above 2.5 implies that picking stocks with high beta diminishes alpha.

Factor Model	**Norway**	**Sweden**	**Denmark**
CAPM Alpha	2.28	0.70	0.88
FF3 Alpha	**2.59**	0.86	0.83
FFC4 Alpha	1.28	0.47	0.47

6.1.2 – Market neutral BAB portfolio earns positive expected excess return

In this section, we have replicated the betting against beta portfolios (BAB factors) based on Norwegian, Swedish, and Danish stock market data – following the same procedure, estimation techniques, and construction criteria as (Frazzini & Pedersen, 2014) in their original paper.

6.1.2.1 - Norway

Table 3 shows the results of three beta-sorted long portfolios and the long-short BAB factor for Norway. We observe that both the low-beta portfolio and the BAB-factor generate significant excess returns. Additionally, all alphas in the BAB factor are significant, producing monthly risk-adjusted returns of 1.56% (CAPM), 1.91% (FF3), and 1.37% (FFC4). Hence, the strategy works well at determining stock selection and market timing in Norway. We can reject the null hypothesis that the alphas are zero for all factor models.

Table 3: Beta sorted portfolios and BAB in Norway

This table shows key characteristics and regression outputs for three equal-weighted portfolios sorted by their estimated betas and the BAB factor from 2007 to 2022 in Norway. Betas are estimated as explained in section 4.1, and the BAB factor is constructed and rescaled as explained in section 4.2. The explanatory variable in CAPM is excess market return. The explanatory variables in FF3 are excess market return, SMB, and HML. The explanatory variables in FF4 are excess market return, SMB, HML, and UMD (MOM). Reported excess returns and alphas are in monthly per cent. T-values are reported below their respective estimates in brackets. Estimates in bold imply statistical significance; we use 2.5 as the critical value, though we are aware this is strict. Volatilities are reported in per cent and are along with Sharpe Ratios annualised.

	Low Beta	**Mid Beta**	**High Beta**	**BAB**
Excess return	**0.85**	0.72	0.21	**1.35**
	(2.96)	(1.56)	(0.35)	(2.67)
CAPM Alpha	**0.69**	0.38	-0.28	**1.56**
	(2.88)	(1.18)	(-0.81)	(3.39)
FF3 Alpha	**1.05**	**0.79**	0.07	**1.91**
	(5.24)	(2.69)	(0.22)	(4.30)
FFC4 alpha	**1.02**	**0.96**	0.49	**1.37**
	(4.78)	(3.12)	(1.50)	(3.03)
Realised beta	0.28	0.57	0.84	-0.36
Volatility	13.41	21.37	27.70	23.38
Sharpe Ratio	0.77	0.40	0.09	0.69

Figure 2: Beta-sorted long portfolios in Norway (Unfiltered data)

This figure shows the cumulative returns of investing NOK 1 in either of three portfolios comprised of the stocks in the lowest tertile (green), middle tertile (blue), and highest tertile (red) from 2007 to 2022. Portfolios are rebalanced monthly.

We add the three long portfolios to our analysis to "deconstruct" the BAB factor to observe the characteristics of the stocks that drive its performance. We sort it into three portfolios rather than two (which would be precisely the long and short legs of the BAB) to observe the difference between the extremes. To truly see the extremes, we would divide it into ten portfolios as (Frazzini & Pedersen, 2014) did. However, we stop at three as our sample is relatively small compared to their US-based sample, and we would like to maintain good diversification.

In Norway's case, the alphas are primarily generated from the relative overperformance of the factor's low-beta (long) side, where the alphas are significant for all factor models. Despite not all results being statistically significantly different, we still observe the expected trends. More specifically, we observe that low-beta outperforms high-beta in terms of expected and risk-adjusted returns, in line with the (Frazzini & Pedersen, 2014) proposal. Also, we see that both realised beta (0.28, 0.57, 0.84) and volatility (13.41, 31.37, 27.70) are monotonically increasing in beta, as is expected due to the definition of beta.

While all are not statistically significant, expected excess returns are monotonically decreasing from low to high (0.85%, 0.72%, 0.21%) with an extra sharp drop-off between mid-beta and high beta. This implies that the Security Market Line (SML) is not just flatter than the CAPM predicts but also inverted.

We also observe that the betas we have estimated in the same way as (Frazzini & Pedersen, 2014) severely miss the mark at proxying the actual beta since we get a realised beta of -0.36 on the estimated BAB-factor in Norway. This implies that our betas are underestimated as we end up with a significant net market short on the BAB factor.

Figure 2 shows the performance of the three Norwegian beta-sorted portfolios over time. We can see that stocks with low betas have outperformed the rest significantly, approximately quadrupling initial investment over the sample period. Contemporarily, the portfolio of high-beta stocks never recovered from the downturn at the start of the sample period (the 08-09 financial crisis). Additionally, we see that most of the differences between the portfolios were created by the rally of low-beta stocks after the initial Covid-19 shock. As a response to the Covid-19 shock, Norwegian interest rates, along with the rest of the world's rates (Settlements, 2022), fell (Bank, 2022). This could explain the rally among low-beta stocks and the lack of one among the high-beta stocks since (Driessen et al., 2019) found that low-volatility stocks are negatively exposed to interest rates and that high-volatility stocks have positive exposure.

6.1.2.2 – Sweden

Table 4 shows the results of three beta-sorted long portfolios and the long-short BAB factor for Sweden. Similarly to Norway, the low-beta portfolio generates statistically significant excess returns (0.99%), and the alphas are significant for all factor models (0.77%, 1.09%, and 1.09%, respectively). However, in contrast to Norway, we do not find any statistical significance in expected excess return or risk-adjusted returns from the BAB factor, except for FF3. Hence, we can only reject the null hypothesis that alphas are significantly different from zero for the FF3 model. The alpha disappears when controlling for momentum – indicating that the strategy relies too much on investing in previous winners (shorting losers).

By looking at the three beta sorted portfolios, we observe the reason for the BAB-factors insignificance. While excess returns from the mid-beta portfolio and high-beta portfolio are statistically insignificant, we can see the trend that those excess returns from each portfolio (low: 0.99%, mid: 0.90%, and high: 0.75%) are all higher than the corresponding numbers from Norway. However, the expected excess return from the low portfolio is only up by 0.14% (0.85% & 0.99%), whereas expected excess return from the high portfolio is up 0.54% (0.21% & 0.75%).

Regarding the implied Security Market Line, we observe the same trend in Sweden as in Norway. The expected excess returns are still monotonically decreasing in beta, implying an inverted SML, though significantly flatter than the one implied in Norway. The same trend applies to realised beta and volatility, as they increase in beta. However, we observe that both the realised betas (0.40, 0.43, 0.55) and the volatilities (17.37, 18.32, 21.64) are more clustered in Sweden than in Norway. This could be due to Sweden's sample being more than twice as large as Norway's (760 & 333), thus being more diversified and less prone to outliers.

Table 4: Beta sorted portfolios and BAB in Sweden

Reported excess returns and alphas are in monthly per cent. T-values are reported below their respective estimates in brackets. Estimates in bold imply statistical significance. We use 2,5 as a critical value, though we know this is strict. Volatilities are reported in per cent and are along with Sharpe Ratios annualised.

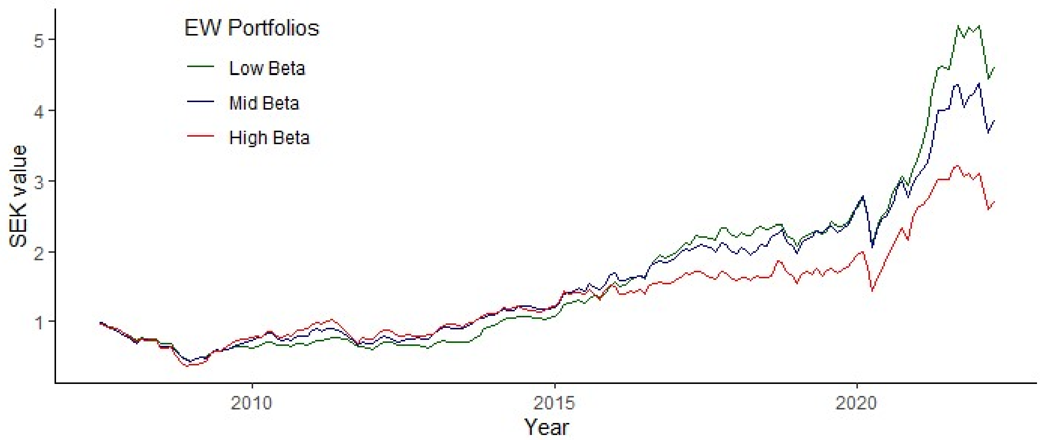
	Low Beta	**Mid Beta**	**High Beta**	**BAB**
Excess return	**0.99**	0.90	0.75	0.90
	(2.62)	(2.27)	(1.61)	(2.47)
CAPM Alpha	**0.77**	0.66	0.45	0.90
	(2.58)	(2.14)	(1.31)	(2.45)
FF3 Alpha	**1.09**	**0.98**	0.72	**0.94**
	(3.97)	(3.37)	(2.19)	(2.93)
FFC4 Alpha	**1.09**	**1.02**	**0.88**	0.62
	(3.78)	(3.32)	(2.55)	(1.93)
Realised beta	0.40	0.43	0.55	-0.02
Volatility	17.37	18.32	21.64	16.80
Sharpe Ratio	0.68	0.59	0.42	0.64

While the expected excess return and most risk-adjusted returns of Sweden's BAB-factor are statistically insignificant, its realised beta is interesting. Its realised beta is -0.02 and statistically insignificant. This indicates that (Frazzini & Pedersen, 2014)'s proposed method of estimating true betas is accurate on Swedish stocks – a sharp contrast from the corresponding result in Norway.

Figure 3 shows the performance of the three Swedish beta-sorted portfolios over time. We can observe the same trends as Table 4 indicates – performances are decreasing in beta, but not to the same extent as in Norway, the spread is much tighter. All classes of stocks (classed by beta) were impacted equally by the 08-09 financial crisis and tracked each other accurately until approximately 2016, when we observed the start of some divergence, primarily due to high-beta stocks stagnating. Norway's large spread came as a result of low-beta rallies post-covid; the same happened in Sweden, though the spread did not widen as much since high-beta stocks also rallied. This points to, as mentioned earlier, that Norway and Sweden shares beta-trends, but Sweden's results are less drastic as portfolios, and the BAB factor are more diversified.

Figure 3: Beta-sorted long portfolios in Sweden (Unfiltered data)

This figure shows the cumulative returns of investing SEK 1 in either of three portfolios comprised of the stocks in the lower-third beta-tier (green), middle-third beta-tier (blue), and higher-third beta-tier (red) from 2007 to 2022. Portfolios are rebalanced monthly.



6.1.2.3 – Denmark

Table 5 shows the results of three beta-sorted long portfolios and the long-short BAB factor for Denmark. Here we observe no values of statistical significance, and nothing is even close. However, the estimated values for excess returns and alphas for low-beta stocks and the BAB factor do, at first glance, look high enough to be statistically significant. They are all over 1% monthly, which was enough to gain statistical significance in Norway and Sweden. However, we observe that those two have extreme volatilities compared to previously discussed portfolios (38.79 and 59.18), which increase the standard errors of all estimates and lower their t-stats.

By looking at Figure 4, we can see why that is. In November 2019, there was a significant spike in low-beta cumulative returns (consequently also in the BAB-factor) that created the vast difference in performance between low-beta and high-beta stocks, but also the volatility of the sample. As a result, we cannot draw any conclusions from these results[5]. This motivated us to run further analysis on winsorised return data to avoid such spurious outliers. Denmark has the smallest sample of the three (177 stocks) and therefore does not have the same level of "protection" from diversification from such extremes as Norway and Sweden do.

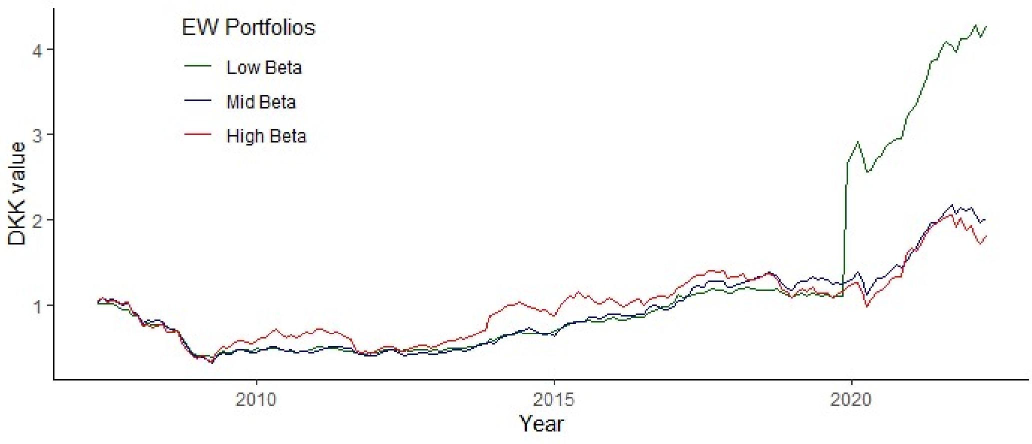
Table 5: Beta sorted portfolios and BAB in Denmark

Reported excess returns and alphas are in monthly per cent. T-values are reported below their respective estimates in brackets. Estimates in bold imply statistical significance. We use 2.5 as the critical value, though we know this is strict. Volatilities are reported in per cent and are along with Sharpe Ratios annualised.

	Low Beta	**Mid Beta**	**High Beta**	**BAB**
Excess return	1.18	0.53	0.54	1.54
	(1.41)	(1.37)	(1.11)	(1.21)
CAPM Alpha	1.00	0.30	0.21	1.60
	(1.22)	(0.95)	(0.57)	(1.24)
FF3 Alpha	1.26	0.60	0.51	1.68
	(1.52)	(2.03)	(1.46)	(1.30)
FFC4 Alpha	1.06	0.55	0.62	1.08
	(1.21)	(1.77)	(1.67)	(0.80)
Realised beta	0.30	0.39	0.57	-0.07
Volatility	38.79	17.82	22.67	59.18
Sharpe Ratio	0.36	0.35	0.29	0.31

Figure 4: Beta-sorted long portfolios in Denmark (Unfiltered data)

This figure shows the cumulative returns of investing DKK 1 in either of three portfolios comprised of the stocks in the lower-third beta-tier (green), middle-third beta-tier (blue), and higher-third beta-tier (red) from 2007 to 2022. Portfolios are rebalanced monthly.



[5] Note that, like Sweden and unlike Norway, Denmark's BAB-factor ends up with a small and insignificant realised beta. Hence, (Frazzini & Pedersen, 2014)'s beta estimation seems to be inaccurate only for Norway.

6.1.3 – BAB criticisms and further analysis

A significant criticism of Frazzini & Pedersen's betting against beta strategy is its unconventional portfolio construction. Specifically, (Novy-Marx & Velikov, 2022) claim that weighting stocks in the portfolios by their ranked betas results in overweighting small-cap stocks. Smaller stocks do not have the market and liquidity that larger stocks do. Hence, large unproportionate holdings of these stocks will carry large transaction costs that make paper returns unfeasible to realise. Therefore, the more conventional technique when constructing portfolios is to weigh the stocks proportionally according to their market capitalisation. Previous research has shown that stocks with low institutional ownership and small market capitalisation represent the stocks with the strongest beta anomaly (Bali et al., 2017).

Therefore, we are interested to see the decomposition of the BAB-factor, specifically to check if the proportions of different size segments are different between the low- and high-beta counterparts. In Table 6, we label each stock at each point in time with a number indicating its size on a scale from 1 to 4 and a number indicating its beta on a scale of 1 to 2. Then we see the proportional holdings of each segment in either of the low-beta long legs or high-beta short legs.

Table 6: Proportions of company sizes in the BAB factor

This table shows the proportion of four different company sizes within the BAB's long (low-beta) and short (high-beta) legs in the three studied countries. The companies are sorted in ascending order, s.t. 1 represents small-cap stocks, and 4 represents high-cap stocks. All numbers are in per cent.

	Norway		**Sweden**		**Denmark**	
	Low Beta	**High Beta**	**Low Beta**	**High Beta**	**Low Beta**	**High Beta**
1	28.87	21.69	36.90	13.45	36.24	14.33
2	32.56	17.42	30.83	19.28	34.66	15.67
3	24.67	25.23	23.62	26.26	22.55	27.36
4	13.89	35.66	8.65	41.01	6.54	42.64

In Table 6, we observe that the three countries share a trend consistent with (Bali et al., 2017)'s criticism that the beta anomalies were much more prevalent among the small-cap stock segments. We observed statistically significant alphas in Norway and Sweden for the bottom-third beta segments. While statistically insignificant (due to the extreme volatility), the Danish results also showed the same trend of low-beta producing higher alpha. However, as we observe in Table 6, the low-beta long legs of all three countries are overweighted in stocks from the lowest quartile of market capitalisation (Norway 28.87%, Sweden 36.90%, Denmark 36.24%) and significantly underweighted in the highest quartile (Norway 13.89%, Sweden 8.65%, Denmark 6.54%). On the other hand, the high-beta short legs are significantly overweight in the top quartile of market capitalisation while underweight in the lower segments.

Hence, we are interested in observing how the alphas are distributed among market capitalisation levels for each beta-ranked segment.

6.2 – Winsorised data sets

As mentioned, when presenting the initial results from Denmark, we will continue our analysis with winsorised return data to mitigate unrepresentative volatilities that ruin estimated t-stats, which are caused by spurious outliers. Specifically, after computing daily returns, we winsorise them by replacing every value outside the 1%-99% interval with their tail values. Also, when matching the new market capitalisation data sets with our price data, we see that some stocks are missing. Thus, the data sets used from this point on are slightly smaller than above (see discussion in Appendix A for details).

6.2.1 – Double sorted portfolios

To see which market capitalisation segment (or segments) drives the performance of the beta-sorted portfolios, we have sorted all stocks into three portfolios based on their ranked betas. Then, within each beta portfolio, we have sorted all stocks into three portfolios based on their ranked market capitalisations. Stocks within each portfolio are equal-weighted. That results in nine different portfolios. However, in the tables that display the results, we have excluded the three portfolios consisting of stocks from the middle segment of betas. We do this since we are more interested in observing where the return of the more extreme betas originates.

6.2.1.1 - Norway

Table 6 shows the results from Norway's double-sorted equal-weighted portfolios. The results surprise us. On the low-beta side, we observe that the high-cap stocks drive the returns on the long side of the BAB factor, having extremely statistically significant values for excess return and all three alphas (1.19%, 1.05%, 1.32%, and

1.30%, respectively), as well as for the mid-cap stocks (though smaller). This initially contrasts sharply with (Novy-Marx & Velikov, 2022)'s findings that the BAB-factor's returns are generated by the unconventional rank weighting of stocks, which drastically overweighs small-cap stocks. It also contrasts with (Bali et al., 2017), who find that the beta anomaly is more prevalent among small-cap stocks since we find that (among low-beta stocks) the beta anomaly is more present among the larger stocks.

Table 6: Double sorted equal-weighted portfolios (Norway)

Stocks are for each month ranked in ascending order according to estimated beta and, based on said rank, are sorted into three equally sized portfolios. Then, within each portfolio, the stocks are ranked in ascending order according to their market capitalisation and sorted into three equally sized portfolios. In total, stocks are sorted into nine portfolios for every month. The mid-level beta portfolios are excluded here as our main focus is the difference between especially low and especially high betas. Within each portfolio, stocks are equally weighted. T-stats are in brackets below their respective estimates. The explanatory variables are market excess return, small minus big, high minus low, and momentum. Excess returns, alphas and volatilities are all in per cent. Sharpe Ratios and volatilities are annualised. Significant values are highlighted in bold (critical value = 2.5).

	Low Beta			**High Beta**		
	Low Cap	**Mid Cap**	**High Cap**	**Low Cap**	**Mid Cap**	**High Cap**
Excess return	-0.30	**0.91**	**1.19**	**-2.22**	0.49	0.95
	(-1.11)	(2.79)	(4.33)	(-3.22)	(0.80)	(2.11)
CAPM Alpha	-0.41	**0.76**	**1.05**	**-2.71**	0.01	0.55
	(-1.63)	(2.60)	(4.42)	(-5.23)	(0.03)	(2.44)
FF3 Alpha	-0.13	**1.15**	**1.32**	**-2.22**	0.32	0.51
	(-0.56)	(4.42)	(5.99)	(-4.60)	(0.85)	(2.23)
FFC4 Alpha	-0.16	**1.11**	**1.30**	**-1.18**	0.67	**0.67**
	(-0.64)	(4.04)	(5.57)	(-3.63)	(1.72)	(2.78)
Realised beta	0.19	0.25	0.24	0.81	0.80	0.68
Volatility	12.75	14.82	12.48	31.94	28.31	19.84
Sharpe Ratio	-0.29	0.72	1.12	-0.83	0.21	0.55
Average MktCap ($)	26.56 mil	115.46 mil	652.79 mil	104.82 mil	832.43 mil	13.25 bn
Median MktCap ($)	21.81 mil	93.13 mil	383.03 mil	51.72 mil	571.54 mil	6.10 bn

However, we also observe that the only statistically significant results among high-beta stocks are the significantly negative return (-2.22%) and factor model alphas (-2.71%, -2.22%, -1.18%) from small-cap stocks. Since the BAB-factor overweighs small-cap stocks in the portfolios, these stocks are critical drivers of the BAB-factor's return as it is short these stocks. That is more in line with (Bali et al., 2017) as the relative underperformance of high-beta stocks is much more apparent among low-cap stocks. Though that implies that the risk-adjusted returns of low-beta, low-cap stocks should be significantly positive – but they are not. In fact, they are tilting negative as well[6]. We observe that the high-beta, low-cap portfolio's alpha improves substantially when controlling for momentum (UMD), further indicating that this characteristic of stocks is a consistent loser.

We note that the market capitalisation sizes are not to scale for low-beta and high-beta. Low-beta stocks are generally much smaller than high-beta stocks. E.g., we observe that the mean market capitalisation of high-beta, low-cap stocks is approximately four times the size of their low-beta counterparts – a trend that holds for all tertiles. Even when controlling for outliers by computing medians, we observe the same tendency. Hence, evidence from our analysis suggests that smaller stocks tend to have lower betas.

Intuitively, one expects that smaller stocks have high betas because they are generally perceived to be more volatile. However, their volatilities are not necessarily based on correlation with the market but rather with a different factor (such as SMB) or simply idiosyncratic. In fact, since larger stocks have a much more significant impact on how the market moves (market portfolios are value-weighted), it follows that they covary closer with the market. That would imply a beta close to 1, which classifies high betas in our sample.

6.2.1.2 - Sweden

Table 7 shows the results from the double-sorted equal-weighted portfolios for Sweden. Similarly to Norway, it is apparent that the best performing segment is the low-beta, high market capitalisation portfolio since, like in Norway, both excess return and all factor alphas are significantly positive (1.43%, 1.09%, 1.10%, and 0.85%, respectively). Though, unlike Norway, the mid-cap portfolio has no statistically significant values. We also observe that both low-cap portfolios (both for low- and high-beta segments) trend negative for excess returns and alphas, though only some of the alphas are statistically significant (CAPM- and FF3-alpha for low, only FF3-alphas for high).

[6] However, they are statistically insignificant.

Table 7: Double sorted equal-weighted portfolios (Sweden)

	Low Beta			High Beta		
	Low Cap	**Mid Cap**	**High Cap**	**Low Cap**	**Mid Cap**	**High Cap**
Excess return	-0.73	0.75	**1.43**	-0.29	0.82	0.79
	(-1.87)	(2.11)	(4.16)	(-0.58)	(1.70)	(2.08)
CAPM Alpha	**-1.03**	0.42	**1.09**	-0.78	0.27	0.35
	(-3.23)	(1.62)	(4.66)	(-2.31)	(1.07)	(1.86)
FF3 Alpha	**-1.01**	0.47	**1.10**	**-0.73**	0.29	0.34
	(-3.48)	(2.14)	(5.07)	(-2.69)	(1.17)	(1.90)
FFC4 Alpha	-0.87	0.34	**0.85**	-0.60	0.35	0.36
	(-2.91)	(1.51)	(3.97)	(-2.17)	(1.36)	(1.88)
Realised beta	0.45	0.48	0.50	0.72	0.81	0.65
Volatility	18.00	16.39	15.84	22.99	22.18	17.58
Sharpe Ratio	-0.49	0.55	1.08	-0.15	0.44	0.54
Avg. MktCap ($)	13.15 mil	63.12 mil	1.07 bn	114.61 mil	1.74 bn	15.65 bn
Med. MktCap ($)	10.61 mil	53.58 mil	446.35 mil	78.00 mil	1.38 bn	9.94 bn

Interestingly, the high-beta, low-cap portfolio outperforms its low-beta counterpart (excess return and all three alphas are higher). This is the opposite of the case in Norway. This is interesting because it implies that Sweden's BAB-factor will perform better if weighted based on relative market capitalisation since the better performing low-beta, high-cap stocks will be weighted heavier – and the value-destroying low-caps will be weighted lighter[7].

Similarly to how the sorted portfolios ended up in Norway, we observe that all three low-beta portfolios consist of much smaller stocks than their high-beta counterparts. E.g., the median market capitalisation of the low-beta, high-cap (446.35 million) is less than one-twentieth of the high-beta, high-cap portfolio (9.94 billion) – providing further evidence that smaller stocks have a low beta.

[7] The mid-beta stocks are excluded from Table 7, though they are of course included in the BAB-factor, hence the statement might be slightly inaccurate. So this statement is not made a complete analysis of the resulting BAB-factor but rather based on its contrast to (Novy-Marx & Velikov, 2022), who find that performance falls when changing to value weighting instead of rank-based weighting, thus rendering the numbers interesting at first glance. The actual performance of a value weighted BAB-factor will be presented later in the thesis.

6.2.1.3 – Denmark

Table 8 shows the results for the double-sorted portfolios consisting of Danish stocks. Similarly to Denmark's results in section 6.1.2, there is little statistical significance. However, the winsorisation of returns has fixed the flawed volatility. Our findings in the analysis of this set are consistent with previously stated findings for its neighbouring countries. The low-beta portfolio has increasing excess return and alphas from the lowest market capitalisation tertile to the highest, where the highest is the only one with significant values (excess return, FF3 alpha, and FFC4 alpha). For our high-beta portfolio, we observe similar performance (increasing in market capitalisation) and, unsurprisingly[8], significantly negative alphas for low market capitalisation stocks (CAPM, FF3).

Table 8: Double sorted equal-weighted portfolios (Denmark)

	Low Beta			**High Beta**		
	Low Cap	**Mid Cap**	**High Cap**	**Low Cap**	**Mid Cap**	**High Cap**
Excess return	-0.36	0.37	**0.81**	-1.11	0.61	**1.13**
	(-1.07)	(1.26)	(2.89)	(-2.26)	(1.37)	(2.83)
CAPM Alpha	-0.67	0.04	0.47	**-1.74**	-0.05	0.50
	(-2.25)	(0.16)	(2.10)	(-4.57)	(-0.19)	(2.06)
FF3 Alpha	-0.50	0.19	**0.61**	**-1.41**	0.17	**0.61**
	(-1.72)	(0.80)	(2.80)	(-4.05)	(0.63)	(2.56)
FFC4 Alpha	-0.36	0.41	**0.65**	-0.98	0.58	**0.84**
	(-1.17)	(1.69)	(2.77)	(-2.72)	(2.04)	(3.37)
Realised beta	0.37	0.38	0.39	0.74	0.79	0.74
Volatility	15.48	13.43	12.98	22.88	20.77	18.57
Sharpe Ratio	-0.28	0.32	0.75	-0.58	0.35	0.73
Avg. MktCap ($)	13.23 mil	61.21 mil	719.05 mil	156.18 mil	1.67 bn	17.56 bn
Med. MktCap ($)	11.71 mil	55.04 mil	227.72 mil	58.68 mil	1.35 bn	10.84 bn

Additionally, like the other two countries, Denmark's results also indicate that larger stocks have higher betas since high-beta portfolios have much larger market capitalisations than the low-beta ones. However, unlike the other two countries, Denmark has significant returns in the high-beta, high-cap portfolio. This portfolio has the highest excess return (1.13%) of the six presented portfolios and significant

[8] Based on prior results from Norway and Sweden.

alphas for the FF3 and FFC4 models. Hence, the results indicate that the largest stocks overperform (referring to the high-beta, high-cap portfolio as its average size is significantly larger than the other five) and that the smallest stocks drastically underperform.

6.2.2 – Rank Weighted vs Value Weighted BAB Factor

Table 9: Filtered and winsorised BAB factors, Rank Weighted & Value Weighted

This table compares key characteristics and regression outputs for beta-rank weighted and value-weighted BAB factors for Norway, Sweden, and Denmark. The rank-weighted BAB factors are constructed the same way described in sections 4.1 and 4.2, but now on filtered and winsorised data to be comparable to the value-weighted alternate. The value-weighted BAB factors are constructed by ranking the stocks based on the beta, sorting the lower half into the long side and the higher half into the short side. Then, within the long and short legs of the factor, the stocks are weighted based on their market capitalisation and rescaled to achieve market neutrality, as described in section 4.2. Reported excess returns and alphas are in monthly per cent. T-values are reported below their respective estimates in brackets. Estimates in bold imply statistical significance. We use 2.5 as a critical value, though we know this is strict. Volatilities are reported in per cent and are along with Sharpe Ratios annualised.

	Norway		**Sweden**		**Denmark**	
	RW	**VW**	**RW**	**VW**	**RW**	**VW**
Excess return	**1.48**	**1.03**	0.42	**1.48**	0.33	0.44
	(3.16)	(2.66)	(1.48)	(4.62)	(1.02)	(1.17)
CAPM Alpha	**1.72**	**1.10**	0.48	**1.47**	0.48	0.55
	(4.23)	(2.85)	(1.67)	(4.53)	(1.52)	(1.46)
FF3 Alpha	**2.05**	**1.55**	0.49	**1.47**	0.49	0.74
	(5.27)	(4.53)	(1.96)	(4.89)	(1.53)	(1.99)
FFC4 Alpha	**1.60**	**1.51**	0.27	**1.19**	0.37	0.61
	(4.02)	(4.16)	(1.07)	(3.93)	(1.09)	(1.55)
Realised beta	-0.41	-0.11	-0.08	0.03	-0.18	-0.13
Volatility	21.79	18.05	13.23	14.84	14.88	17.66
Sharpe Ratio	0.81	0.69	0.38	1.20	0.26	0.30

In this section, we analyse the effects of alternative weighting to address some of the criticism the BAB factor has received – specifically from (Novy-Marx & Velikov, 2022). Thus, the stocks are sorted in two portfolios, sorted ascendingly by beta, exactly as (Frazzini & Pedersen, 2014), but now we weigh the stocks by their relative market capitalisation inside the two portfolios (i.e., value weighting). (Novy-Marx & Velikov, 2022) argues that weighting the stocks based on their ranked betas is essentially the same as equal weighting, which results in overweighting stocks in small companies. This is problematic as stocks with low market capitalisations have much more limited markets, making liquidating their positions costly – thus diminishing a large part of the estimated paper return.

Table 9 presents a side-by-side comparison of the original beta-ranked BAB factor and the value-weighted BAB factor. The rank-weighted BAB factors are created in the same manner as we have outlined previously in this thesis, but to compare "apples to apples", we have reconstructed it using the same adjusted and winsorised data we have been using from section 6.2 and onward.

For Norway, we observe that the BAB factor still performs statistically well even after changing to value-weighting as both excess return and all factor alphas are statistically significant. Interestingly, the value-weighted BAB factor's realised beta becomes much closer to zero than the rank-weighted one (-0.11 and -0.41, respectively). This indicates that the small-cap stocks' volatilities are less based on correlation with the market than what the high-cap stocks' volatilities are, implying that low-cap is low beta[9].

In Sweden, as noted in section 6.2.1.2, performs better when changing value weighting. There are no statistically significant results in the rank-weighted BAB factor, but when value weighting, both excess return and BAB factor become significant (1.48%, 1.47%, 1.47%, and 1.19%, respectively). While initially surprising, the trend that caused this is common for all three counties. The trend is that among the low-beta stocks, it is the high-cap stocks that perform, hence value weighting will enhance their effect.

Denmark, however, has no significant results in either of the BAB factors. Contrary to expectations about the beta anomaly, Denmark's best-performing segment is the high-beta, high-cap. However, we are not surprised by this result since Denmark did not have any significant results in (Frazzini & Pedersen, 2014)'s original paper either.

[9] In Norway. While Sweden and Denmark also show the trend that VW BAB factors have realised betas closer to zero, their realised betas were already close to zero in the RW BAB factors. Hence, this is not evidence for a common trend.

7. Conclusion

The remarkable performance of (Frazzini & Pedersen, 2014) strategy has garnered global attention, but not all their peers were convinced that other equity factors could not explain the above-average yields. This thesis seeks to replicate the original author's BAB factor, using the same methodology on Norwegian, Swedish and Danish market data. The strategy builds on several preceding findings from the likes of (Black, 1972; Friend & Blume, 1970. Their extensive research on the beta anomaly and the construction of the CAPM has opened the door for further research.

We begin our research by analysing proposition 1 in (Frazzini & Pedersen, 2014). The general idea is that some agents cannot use leverage, and thus overweight high-beta assets, causing said assets to offer lower returns. This would allow unconstrained agents to exploit the anomaly by creating a market-neutral long-short strategy shorting high-beta assets and buying low-beta assets. Our findings from the Scandinavian markets suggest that although all our low-beta alphas exceed their high-beta counterparts, their differences are generally statistically insignificant (the lone exception being Norway FF3).

We sought to address the points made by (Bali et al., 2017) regarding the demand for lottery-like stocks being a significant contributor to the BAB factor's performance. Their research found that the beta anomaly was strongest among low market capitalisation stocks, suggesting that the factors overweighting these stocks caused the highly significant alpha. A related criticism was made by (Novy-Marx & Velikov, 2022), in which they argued that (Frazzini & Pedersen, 2014)'s proposed BAB-factor construction overweights small-cap stocks whose lack of liquidity causes significant transaction costs that diminish realised returns. Hence, they proposed more conventional construction – value weighting.

Our replication effort left us perplexed, as many of our findings were not aligned with our expectations and were dissimilar to both (Bali et al., 2017; Frazzini & Pedersen, 2014). First, we found that only Norway's BAB factor produced results of any significance, though Sweden showed the "right" tendency. Then we saw that the returns in all three countries originated predominantly in the high market capitalisation portfolios, which contrasts with the criticisms mentioned above, as they both indicated that it "should" be the low-cap portfolios. Lastly, culminating in Table 9, which, in essence, gave us three different results, one from each country[10]. This makes it hard to draw concise conclusions, as results are either insignificant or ambivalent. We suspect this is due to the nature of our data, mainly the involuntary exclusion of delisted stocks (see appendix A for details). Though perhaps also because our time frame is too short[11]. We also suspect that Denmark, with only 177 stocks at most, was too small for a strategy like this to perform properly. Hence we see a lot of insignificant results in that sample.

That said, based on our results, we can conclude that a self-financing BAB portfolio is profitable in Norway and Sweden as it yields statistically significant risk-adjusted returns – even after changing the portfolio construction to the more conventional value weighting, which will also make paper returns closer to feasible realised returns as a value-weighted portfolio will carry less transactions costs. We also find indications that smaller stocks (measured by market capitalisation) tend to have lower betas, while larger stocks have betas closer to 1.

[10] In Norway RW outperformed VW. In Sweden VW outperformed RW. In Denmark there were no significant results.
[11] Frazzini and Pedersen had a US BAB factor that spun from 1926 to 2012, and BABs for other developed markets that spun from 1989 (84 for Canada) to 2012.

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Appendix

Appendix A: Data availability and potential sample bias

Most data we have used in our thesis was retrieved from Eikon's Refinitiv platform, which we gained access to through BI's library. This was the only proper way, we found, to access the large and complex data sets we required for this thesis.

Our order of working with the thesis consisted of first fully completing the replication process of Frazzini & Pedersen's "Betting against Beta"-paper before making any adjustments based on critiques and own ideas. Refinitiv had a weird quirk when reporting the values of stocks that have been delisted from the exchange during the selected time period. Specifically, once delisted, the data set would contain the last known stock closing price for every day until the end of the time series. This would show up as numbers in the data frame and hence be sorted into portfolios, even though the stock did not exist anymore. Therefore, we removed those stocks completely and planned to fix them after replication.

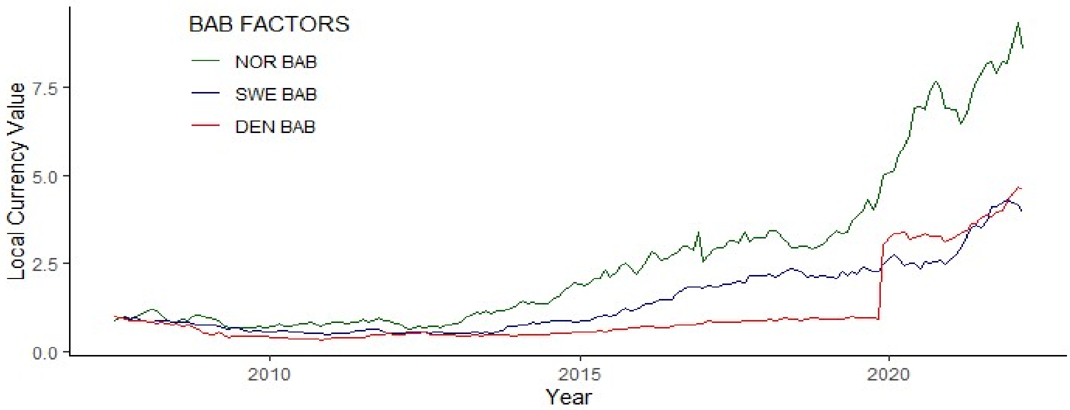
June arrived, and we were ready to retrieve a new set with delisted stocks we found ourselves struggling to access the Refinitiv database. After weeks of trying to access it, we were told by library staff that BI's "data retrieval quota" for June from Refinitiv was used up, thus, we could not access more data – unable to adjust our sample ahead of the July 1 deadline. This has most likely caused bias in our sample as some stocks are missing from the "menus". Sweden's sample is wide enough that it may not be that impactful. However, especially Denmark has a sample that is less than a fourth of Sweden's width, and its listed companies are, on average, much larger than Sweden's and Norway's, thus potentially more exposed to the aforementioned bias.

Additionally, we were unable to access market capitalisation data ourselves for the same reason. However, a classmate of ours was still able to access the database, despite both ourselves and BI’s librarians being unable to access it. Hence, he accessed the market capitalisation data we needed and passed it on to us. Due to some miscommunication, the datasets he provided us did not overlap with our existing price data, so we had to cut approximately ten stocks per country when using this data (Table 1 shows exact amounts per country).

Appendix B: Non-winsorised, raw-data, rank-weighted BAB plots

Figure Appendix-B: BAB-factors in studied countries (Unfiltered data)

This figure shows the cumulative returns of investing 1 unit of local currency in either of three national BAB factors.



Appendix C: RW vs. VW BAB factors for each country

Figure Appendix-C1: RW vs VW BAB factors Norway

This figure shows the cumulative returns of investing 1 NOK in the rank weighted or the value-weighted BAB factors in Norway

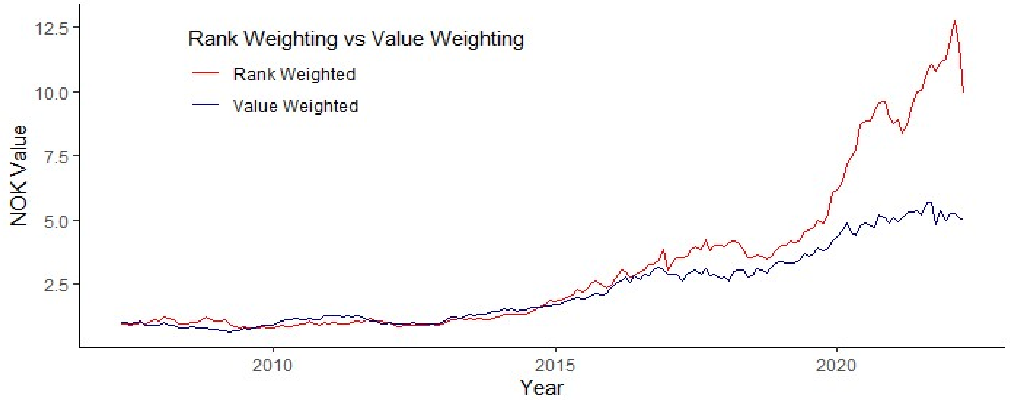


Figure Appendix-C1: RW vs VW BAB factors Sweden

This figure shows the cumulative returns of investing 1 SEK in the rank weighted or the value-weighted BAB factors in Sweden

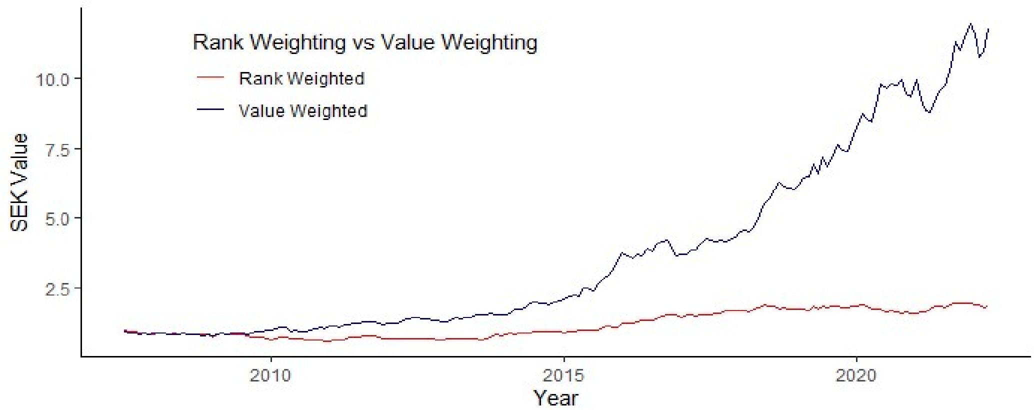


Figure Appendix-C1: RW vs VW BAB factors Denmark

This figure shows the cumulative returns of investing 1 DKK in the rank weighted or the value-weighted BAB factors in Denmark