BI Norwegian Business School - campus Oslo

GRA 19703

Master Thesis

Thesis Master of Science

Pitfalls of the Betting-Against-Beta Strategy in Norway

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Start: 15.01.2021 09.00

Finish: 01.07.2021 12.00

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by

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MSc in Business, Major in Finance

Oslo, July 1, 2021

Abstract

In this master thesis, we study the Betting Against Beta strategy in the Norwegian market between 1983 and 2019. We study the drivers of return and evaluate whether investors can profit from the strategy. We find that the main driver of return is overweighting of small stocks in the low-beta portfolio, which in turn is utilized by an unconventional hedging method. We conclude that, in practice, investors are not able to profit from the strategy in Norway.

Acknowledgements

We would like to thank our supervisor, Patrick Konermann, for all support and guidance through this process. His extensive knowledge and expertise has been of great value.

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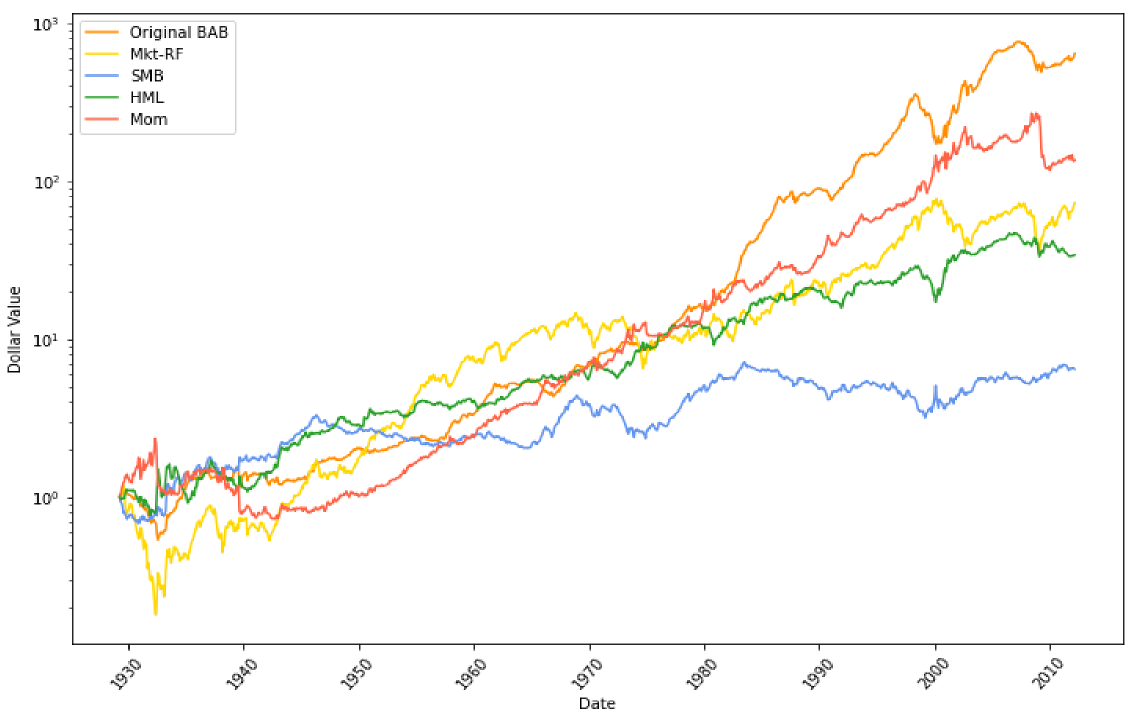
1 Introduction

The relationship between risk and expected return has had a considerable focus in finance. One of the most well-known theories regarding this relationship is the Capital Asset Pricing Model (CAPM), stating that a stock's expected return can be described as a linear function of the stock's beta. However, Friend and Blume's (1970) and Black et al.'s (1972) research shows that stocks with low betas tend to outperform higher beta stocks, a phenomenon called the low beta anomaly.

Frazzini and Pedersen (2014) proposed a new strategy to exploit the mispricing between low- and high-beta stocks, namely the Betting Against Beta (BAB) strategy. They created a BAB factor by investing in low-beta stocks and shorting high-beta stocks, leveraged and de-leveraged to have a beta of 1. By this factor, they managed to exploit the mispricing without being exposed to market risk. The BAB factor is the new addition to other well-known factors used to explain the cross-section of returns. To understand its significant impact, we plot the cumulative return of the BAB factor in addition to the market (MKT), small minus big (SMB), high minus low (HML), and momentum (MOM) factors in Figure 1.

Figure 1: Cumulative returns of BAB vs. established factors

This table plots the cumulative return for the BAB factor constructed by Frazzini and Pedersen (2014), the market excess return (Mkt-RF), the Fama and French (1992) factors SMB and HML, and the Carhart (1997) momentum factor (MOM) in the US from 1930 until 2012.



The SMB and HML factors are from the Fama-French three-factor model (1993), and the momentum factor is from Carhart (1997). We see that its excess return over the risk-free rate outperforms all well-known factors. Even more impressive, Frazzini and Pedersen (2014) report a Sharpe Ratio of 0.78, which is well above the then maintained threshold of 0.46 obtained by the momentum factor[1].

The article has received much attention due to its outstanding results based on a relatively simple idea. With over 450 citations, it is ranked among the top 1% in its academic field of economics and business. This may be somewhat surprising, as the strategy is based on the empirically well-established beta anomaly. Frazzini and Pedersen (2014) claim that abnormal BAB returns stem from funding liquidity risk but have received criticism from several economists. Bali et.al (2014) argue that the factor is driven by lottery-like stocks, while Novy-Marx and Velikov (2021) and Han (2019) highlight the use of unconventional procedures in the methodology. Procedures used to create factor-returns should be based on what an investor reasonably can obtain, not on what drives the performance. This motivates us to isolate the effect of these unconventional procedures to understand better what drives the performance in the Norwegian market. In addition, we explore whether the BAB alpha persists if a more standardized methodology is adopted. Our research question is

"Can investors achieve a positive alpha by implementing the Betting Against Beta strategy in the Norwegian market?"

First, we will test our hypothesis by implementing the methodology of Frazzini and Pedersen (2014) on stocks on the Oslo Stock Exchange. Then, we will look into the drivers of the BAB factor by a comparison of unfiltered- and filtered data set using beta-sorted and double-sorted analysis. Further, we will change the assumptions in the methodology made by Frazzini and Pedersen (2014) based on the criticism it has received, using more conventional procedures to construct the factor. The topic is most relevant to hedge funds as they are less restricted than many private investors, pension funds, and mutual funds regarding short-selling and leveraging investments.

[1] See Table 11 in Appendix A

2 Literature Review

Literature which is relevant for the thesis has been reviewed. Firstly, we explore the most relevant frameworks within asset pricing, which has affected how we look at the expected return. Secondly, we look into contradictions of the conditional CAPM, as it is an alternative to the CAPM. Then we assess liquidity restrictions and idiosyncratic risk, which affect the price of a security. Lastly, we evaluate the origin of the beta anomaly and articles that claim to have found a solution to the low beta anomaly. We find these topics essential to review as they explain the underlying theories upon which the strategy is built.

2.1 Contradictions of the unconditional CAPM

The relationship between risk and return has had a great focus in finance. The first framework regarding the relationship is the Capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and Lintner (1965). The CAPM is defined as:

$$E(R_i) = R_f + \beta_i(E(R_M) - R_f)$$

where $E(R_i)$ is the expected return of stock i, R_f is the risk-free rate, β_i is the stock's volatility in relation to the overall market, and $(E(R_M) - R_f)$ is the expected market risk premium. The CAPM builds on Markowitz's (1952) mean-variance efficiency model, stating that investors care only about expected return and risk. Black (1972) came up with another version of the model, called the Black-CAPM or zero-beta CAPM. The model does not assume the existence of a riskless asset and allows for unlimited short selling. The work of Sharpe (1964), Lintner (1965), and Black (1972) resulted in the Sharpe-Lintner-Black (SLB) model. Even though the impact of CAPM has been significant on asset pricing, it has also faced criticism for not being able to measure returns well enough.

The findings of Fama and French (1992) concluded that systematic risk is not the only risk factor determining the return of an asset. They came up with the Fama-French three-factor model, suggesting that exposure to value and size factors affect expected returns. Carhart (1997) further expanded the model by including the momentum factor. The momentum factor explains that investors tend to have delayed over- and underreactions, leading to short-term persistence in expected returns. Fama and French (2015) later added two new factors to the three-factor model, profitability and investment.

2.2 Contradictions of the conditional CAPM

The CAPM, also referred to as the static or unconditional CAPM, lacks empirical support and fails to predict cross-sectional stock returns. CAPM is a static model because it considers time as one period, where a stock's market beta is constant. However, the systematic risk of a stock varies depending on the economic state. A model that captures these changes is the conditional CAPM which is an extension of the unconditional CAPM. The expected returns can change over time, depending on movements in the market's risk premium, the market's conditional variance, and the covariance between the asset's and the market's return. According to Cederburg and O'Doherty (2016) the conditional CAPM implies that:

$$\alpha_{i,t} \equiv E(R_{i,t}|I_{t-1}) - \beta_{i,t}E(R_{m,t}|I_{t-1}) = 0,$$

where $R_{i,t}$ is portfolio i's expected return during period t, $R_{m,t}$ is the excess market return, I_{t-1} is the investors information set at the end of period $t-1$, and $\beta_{i,t} = Cov(R_{i,t}, R_{m,t}|I_{t-1})/Var(R_{m,t}|I_{t-1})$ is the conditional beta of portfolio i. Since the market beta can be different in a recession and a boom, the static CAPM might over-or underestimate the stock's expected return.

Bodurtha and Mark (1991) tested the conditional CAPM by modeling the beta components as autoregressive conditionally heteroskedasticity processes (ARCH) and the market premium as an autoregression. Their findings were more supportive of the conditional CAPM than earlier research (Ng, 1991), where they used different models such as generalized autoregressive conditional heteroskedasticity (GARCH). Jagannathan and Wang (1996) added human capital to the model. They tested the conditional CAPM using the value-weighted index from CRSP as their market portfolio. They used stock returns from the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and Nasdaq. Jagannathan and Wang (1996) found that the conditional CAPM is a better model to explain cross-sectional return.

While some studies (Jagannathan & Wang, 1996; Lettau & Ludvigson, 2001; Petkova & Zhang, 2003) suggest that the conditional CAPM holds period-by-period, Lewellen and Nagel (2006) conclude that the conditional CAPM does not explain asset pricing anomalies. They found that to explain anomalies like momentum and value premium, the variation in betas and the equity premium would have to be much larger. Further, their findings show that the conditional CAPM performs almost as poorly as the unconditional CAPM. Hence neither the unconditional nor the conditional CAMP can explain the asset pricing anomalies.

2.3 Liquidity restrictions

One of the restrictions of the CAPM is that all investors can take a long or short position of any size in any asset, including the risk-free rate. However, the restriction is quite unlikely, and Black (1972) tested the validity of the CAPM when investors are not allowed to borrow in the riskless asset. Black's (1972) findings suggest that the security market line (SML) is less steep in cases of restricted borrowing than predicted by the CAPM. These findings were supported by Fama and Macbeth (1973).

Acharia and Pedersen (2005) came up with liquidity-adjusted CAPM, proving that the expected return of a security is increasing in its illiquidity. They state that the required return of a security depends on expected liquidity and the covariance of its return, and the market returns and liquidity. They find that a persistent negative shock to the liquidity of a security results in low returns in the given period and high predicted future returns.

Asness et al. (2012) discuss how leverage aversion changes the predictions of modern portfolio theory. Leverage aversion pushes down prices for low-beta stocks, thus increasing the risk-adjusted return compared to riskier assets. They state that a risk parity portfolio exploits the high risk-adjusted returns of safer assets by putting more weight on safer assets and less weight on riskier assets relative to their weights in the market portfolio. The portfolio will have a lower risk than the market portfolio but can achieve the same risk by using leverage, hence receiving a higher expected return.

Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) state that funding liquidity risk is linked to market liquidity risk. It also affects the required return (Acharya & Pedersen, 2005).

2.4 Idiosyncratic risk

The CAPM states that since idiosyncratic risk can be diversified away, it should not affect the price or return. However, research has shown that it does not hold. According to Falkenstein (1994), the return of a stock is negatively correlated with its variance, resulting in lower returns for stocks with higher volatility holding everything else equal. When controlling for size, Falkenstein (1994) was able to show that idiosyncratic risk is negatively correlated with expected returns regarding securities on NYSE&AMEX. Ang et al. (2006, 2009) support these findings and found that stocks with recent high idiosyncratic volatility tend to have lower returns than stocks with low idiosyncratic volatility. Frazzini and Pedersen (2014) find that the BAB-factors are significant even after controlling for idiosyncratic risk.

2.5 Beta anomaly

Findings have shown that stocks with high beta tend to have lower returns than predicted by the CAPM, while stocks with low beta tend to have higher returns (Black et al., 1972). Hence, high-beta stocks tend to generate negative alphas, while low-beta stocks generate positive alphas. Findings by Baker et al. (2011) support that stocks with high beta offer low risk-adjusted returns. They suggest that part of the low-volatility anomaly is due to investor mandate to beat a fixed benchmark, which discourages arbitrage activity in high-alpha low-beta stocks, and low-alpha high-beta stocks.

The findings of Frazzini and Pedersen (2014) regarding the betting-against-beta (BAB) strategy have proven meaningful insight in further explaining the relationship between expected return and risk. After the article was published, multiple articles have tried to disprove their hypothesis. Bali et al. (2014) argue that price pressure driven by demand for lottery-like stocks plays a significant role in generating the betting against beta phenomenon. They find evidence that after controlling for lottery demand, the betting against beta phenomenon disappears.

Novy-Marx and Velikov (2021) state that the strong performance of Frazzini and Pedersen (2014) is due to being heavily overweight in the smallest and least liquid stocks while ignoring transaction costs and implementation issues. They argue that by accounting for transaction costs, the profitability of the strategy will be reduced significantly. They further state that significantly positive average net returns are earned by tilting towards profitability and investment. These are exposures for which they are fairly compensated, and the strategy does not have a significant net alpha when regressed on the Fama-French five-factor model.

According to Cederburg and O'Doherty (2016), the conditional beta for the high-minus-low beta portfolio covaries negatively with the equity premium and positively with market volatility. They claim that the unconditional alpha is a downward-biased estimate of the true alpha and find that the conditional CAPM resolves the beta anomaly.

3 Testable hypothesis

We replicate[2] the methodology from Frazzini and Pedersen (2014) when testing the strategy. We will regress the returns on the same risk factors, namely the Fama-French three-factor model (Fama & French, 1993), momentum (Carhart, 1997), and liquidity risk (Naes et al., 2009). Hence, the regression equations for the CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha becomes:

$$r^{BAB} = \alpha + \beta_1(r^m - r^f) \tag{1}$$

$$r^{BAB} = \alpha + \beta_1(r^m - r^f) + \beta_2 r^{SMB} + \beta_3 r^{HML} \tag{2}$$

$$r^{BAB} = \alpha + \beta_1(r^m - r^f) + \beta_2 r^{SMB} + \beta_3 r^{HML} + \beta_4 r^{MOM} \tag{3}$$

$$r^{BAB} = \alpha + \beta_1(r^m - r^f) + \beta_2 r^{SMB} + \beta_3 r^{HML} + \beta_4 r^{MOM} + \beta_5 r^{LIQ} \tag{4}$$

where r^{BAB} is the excess return of the BAB factor over the risk-free rate r^f, $(r^m - r^f)$ is the market premium, r^{SMB} is the size premium, r^{HML} is the value premium, r^{MOM} is the momentum premium, and r^{LIQ} is liquidity premium. $\beta_{1,2,3,4,5}$ is factor coefficients and α is the excess return after accounting for risk factor premiums.

We hypothesize that the betting against beta strategy does not generate returns that these risk factors can not explain. Thus, equation (4) represent our final testable hypothesis, while the equation (1), (2) and (3) are used for analysis and interpretation. First, we test the strategy under the original methodology, both with unfiltered and filtered data. We perform an extended analysis to understand the impact of their current methodology. Thereafter, we change parts of the assumptions that Frazzini and Pedersen (2014) have made to construct their methodology and test if our hypothesis still holds. Hence, we have the following null- and alternative hypothesis:

$H_0 : \alpha = 0$

$H_a : \alpha > 0$

[2] For replication and further analysis we use Python 3.9

Campell et al. (2016) claim that a t-statistic of two is too low to determine whether a factor is significant. They argue that it is a mistake to use the usual statistical cutoffs in asset pricing tests considering that many factors are tested, making it too big of a chance for factors deemed to be significant by chance. Further, they state that a minimum threshold of three should be used when evaluating new factors when determining statistical significance. However, a factor using first principles should have a lower threshold t-statistic than a factor that is discovered as a purely empirical exercise. Based on these statements, we will use a critical value of three to determine if our results are statistically significant.

4 Methodology

Frazzini and Pedersen (2014) have based their methodology on three assumptions. In this section, we elaborate on how we replicate the BAB factor using the same assumptions.

4.1 Assumption 1A: Estimation of betas

To estimate betas, we use rolling regressions of excess returns on market excess returns. The betas are computed with respect to the market portfolio. For each security, i, the beta is estimated in the following way for each period, t:

$$\hat{\beta}_{it}^{TS} = \hat{\rho}_t \frac{\hat{\sigma}_{it}}{\hat{\sigma}_{mt}} \tag{5}$$

where $\hat{\rho}_t$ is the correlation between security i and the market, and $\hat{\sigma}_{it}$ and $\hat{\sigma}_{mt}$ are the estimated volatilities for security i and the market respectively. Volatilities and correlations are estimated separately, as volatilities are based on one-year rolling standard deviations, while correlations use five-year rolling windows. This enables us to control for the fact that correlations often move slower than volatilities (De Santis & Gerard, 1997). Further, to control for non-synchronous trading which only affects correlations, we use overlapping three-day log returns, $r_{i,t}^{3d} = \Sigma_{k=0}^{2} ln(1 + r_{t+k}^{i})$ for correlations $\hat{\rho}_t$, and one-day log returns to estimate volatilities $\hat{\sigma}_{it}$ and $\hat{\sigma}_{mt}$.

Lastly, we shrink the time series estimate of beta β_{it}^{TS} from equation (5) towards the cross-sectional mean β_{it}^{XS}. This contributes to reducing the influence of outliers and is achieved by decreasing the weight put on β_{it}^{TS}.

The following expression describes the approach:

$$\hat{\beta}_{it} = w_i \hat{\beta}_{it}^{TS} + (1 - w_i)\hat{\beta}^{XS} \tag{6}$$

For simplicity, we set $\beta^{XS} = 1$ and $w_i = 0.6$ for all periods, consistent with mean shrinkage factor found by Vasicek (1973). Since the shrinkage factor w_i does not change the ranking of the betas, the sorting of securities into portfolios is unaffected. However, when constructing BAB portfolios, the betas will be used to scale the long and short sides of high- and low beta portfolios. Thus, the returns of the BAB portfolios are affected by the shrinkage factor. To fully understand how it impacts the returns, we need to look into the construction of the BAB factors.

4.2 Assumption 2A: Portfolio weights

The objective is to construct portfolios that are long low-beta stocks and short high-beta stocks. First, we rank the stocks in each market in ascending order based on their estimated beta. After that, we assign the stocks into high- and low-beta portfolios separated by the median beta. The stocks in each portfolio are weighted by their ranking. In the high-beta portfolio, the stocks with higher betas are given higher weights, while the low-beta portfolio gives higher weight to low-beta stocks. We rebalance the two portfolios each month.

We set $z_i = rank(\beta_{it})$ at portfolio formulation to create a $nx1$ vector z that consists of the ranked betas $\hat{\beta}_{it}$ from equation (6). To calculate the weights in the portfolio, we need to set an average rank $\bar{z} = 1_n' z/n$, where n is the number of stocks and 1_n is an nx1 vector of ones. Further, we can calculate the portfolio weights in the low- and high beta portfolios as

$$w_H = k(z - \bar{z})^+ \tag{7}$$

$$w_L = k(z - \bar{z})^- \tag{8}$$

Since we have two independent long and short portfolios, we include a normalizing constant $k = 2/1_n'|z - \bar{z}|$ to get the sum of weights to not deviate from 100%. The x^+ and x^- are an indication of positive and negative elements in the vector $z - \bar{z}$. We will refer to the portfolios constructed this way as Rank-Weighted (RW) portfolios.

4.3 Assumption 3A: Hedging procedure

We will construct the BAB factor the following way:

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}(r_{t+1}^L - r^f) - \frac{1}{\beta_t^H}(r_{t+1}^H - r^f) \tag{9}$$

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

The strategy has a market beta of zero, making it a market-neutral strategy. To achieve it, we leverage the long low-beta side to have a beta of 1 and de-leverage the short high-beta side to have a beta of 1. More specifically, we use the betas $\hat{\beta}_{it}$ from equation (6) and weights from equation (7) and (8) to scale the long and short side by the weighted average betas. We refer to this as hedging by leverage. By using offsetting positions in the risk-free rate, the BAB factor becomes a self-financing portfolio. Hence, similar to the HML- and SMB- and Momentum factor, the BAB factor gives the excess return of a self-financing portfolio.

5 Data

5.1 Data Unfiltered

We have collected daily stock returns for Norway from the Oslo Børs Information (OBI) database from January 1980 to December 2019. The Oslo Stock Exchange All Share Index (OSEAX), the value-weighted index (VW), the risk-free rate (RF), the value factor (HML), the size factor (SMB), and the Carhart factor (PR1YR), in addition to the liquidity factor (LIQ), are obtained from Bernt A. Ødegaard's webpage[3]. We will use the value-weighted index to estimate betas, and the OSEAX, which is an index containing all stocks on Oslo Børs, as the market return for the Norwegian market in our regressions.

The Fama French factors, HML and SMB, are calculated as by Fama and French (1998) using Norwegian data, while the Momentum factor, PR1YR, is calculated by Carhart (1997) using Norwegian data. The liquidity factor for OSE, LIQ, is calculated using the methodology of Naes et al. (2009). Finally, the risk-free rate is estimated as the forward-looking interest rate for overnight borrowing. In Table 1 we report the summary statistics for the unfiltered stocks and the variables used in our analysis.

[3] https://ba-odegaard.no/

5.2 Data Filtered

Some of the criticism of Frazzini and Pedersen (2014) is that a part of the high performance of the strategy is due to overweight in small and illiquid stocks (Novy-Marx & Velikov, 2021). Such stocks are referred to as penny stocks and are known for having very high volatility. Ødegaard (2021) argues that such stocks should not be included as they tend to have exaggerated returns. We use the same filter as Ødegaard (2021) in our analysis to exclude penny stocks on OSE, excluding stocks with a price below NOK 10 or a market capitalization (market cap) below NOK 1 million.

After the initial filtration, we still observe some stocks with returns above 10.000%. Therefore, we will winsorize our data set in line with Laeven & Tong (2012). That is, we replace all returns above the 99.9th percentile and below the 0.1st percentile with their tail values. We do this to reduce the effect of possible spurious outliers, which might bias the estimation of the betas (Theodossiou & Theodossiou, 2014). Spurious outliers can cause a false impression of the strategy's performance, both under portfolio construction and by leveraging (de-leveraging) when calculating BAB factor returns. The summary statistics for the filtered stocks can be found in Table 1.

Table 1: Summary Statistics

The table reports the summary statistics for the variables used in in our analysis. For all of the factors, N is the number of observations, while N for stocks counts the total number of stocks in our data set. We report summary statistics for both our unfiltered data (UN) and our filtered data (F). Numbers are in percentage.

Variable	Frequency	Start	End	N	Mean	Max	Min
Stocks (UN)	Daily	1980	2019	941	0.21	78 025	-99.91
Stocks (F)	Daily	1980	2019	833	0.11	101	-50.4
RF	Daily	1980	2019	9911	0.03	0.26	0.002
VW	Daily	1980	2019	10033	0.10	11.37	-17.81
RF	Monthly	1983	2019	442	0.51	2.07	0.05
Mkt	Monthly	1983	2019	442	1.18	17.45	-27.42
SMB	Monthly	1983	2019	442	0.68	21.08	-16.63
HML	Monthly	1983	2019	442	0.29	22.17	-19.64
PR1YR	Monthly	1983	2019	442	0.84	15.43	-16.78
LIQ	Monthly	1983	2019	442	0.13	16.42	-17.66

6 Results

To ensure that we have implemented the methodology correctly, we have replicated the results of Frazzini and Pedersen (2014) for the US market. Table 12 in Appendix A reports the original article's results and our replication, showing that we have slightly higher alphas than the article. The discrepancy in results may be due to changes in the CRSP data as they make corrections to their historical data as errors are identified. In addition, we notice that our data set contains fewer stocks than Frazzini and Pedersen (2014), and we are overall missing 58 stocks. Nevertheless, we can draw the same conclusions as the article based on the results, namely that the strategy yields abnormal returns statistically significant for all of the regressions. Further, we find that the BAB returns in our replication are 97% correlated with the original BAB returns.

6.1 Results with unfiltered data set

Table 2 reports the results for the BAB factor in Norway. We observe that the realized beta is negative, namely -0.07. The negative realized beta indicates that we have over-estimated our beta, hence leveraging the low beta portfolio too little and de-leveraging the high beta portfolio too much. The BAB factor yields a high monthly average excess return of 1.46% and an even higher CAPM alpha of 1.51%. When adjusting the returns for the Fama-French factors, SMB and HML, the strategy delivers an alpha of 1.15%. The decrease in alpha indicates that while the excess return of the strategy is high, a lot of the return is earned by tilting towards size- and value risk. Lastly, when expanding the regression to including Carhart's (1997) momentum factor, PR1YR, and Næs et al. (2008) liquidity factor, the BAB factor yield monthly abnormal returns of 1.02% and 0.98%, respectively. All of the alphas are statistically significant, with three as our critical value. Hence, we reject our null hypothesis that the five-factor alpha is zero. Our findings indicate that based on an unfiltered data set, we can conclude that investors can achieve a positive five-factor alpha from the betting against beta strategy in the Norwegian market.

Table 2 also reports the results from beta-sorted portfolios. We do this analysis to explore whether it exists a beta anomaly in Norway. In addition, it will contribute to identifying the drivers of the alphas obtained by the BAB factor. We sort the stocks into three portfolios based on their estimated beta, where 1 is the low-beta portfolio, and 3 is the high-beta portfolio. The stocks within each portfolio are equal-weighted. We use three portfolios as the data sample is relatively small,

Table 2: Beta-sorted portfolios and the BAB factor in Norway

This table reports the characteristics and regression results for the EW beta-sorted portfolios and the BAB factor from 1983 to 2019 in Norway. The betas are estimated using one-year rolling standard deviations and five-year correlations, as explained in Section 4.1. For the beta-sorted portfolios, the betas are sorted in ascending order and assigned to one of the three portfolios based on their rank. Portfolio 1 contains the stocks with the lowest betas, and Portfolio 3 contains the stocks with the highest betas. All stocks within each portfolio are equal-weighted. To construct the BAB factor, we rank the stocks, assign them to the low beta portfolio or the high beta portfolio, and weight them according to the methodology described in Section 4.2. We rescale the two portfolios to have a beta of 1 at portfolio formation each month and go long the low beta portfolio and short the high beta portfolio. The explanatory variables are the monthly excess return (OSEAX), the SMB and HML factors calculated as by Fama and French (1998), momentum factor PR1YR calculated as by Carhart (1997), and the liquidity factor LIQ calculated using the methodology of Naes, Skjeltorp, and Odegaard. The CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha are regressed as in equation 1, 2, 3 and 4. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and statistical significance with a critical value of three is in bold. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	1 (Low)	**2**	**3 (High)**	**BAB**
Excess return	**1.2**	0.81	0.62	**1.46**
	(5.47)	(2.84)	(1.59)	(5.36)
CAPM alpha	**0.87**	0.30	-0.09	**1.51**
	(5.41)	(1.79)	(-0.43)	(5.50)
Three-factor alpha	**0.49**	-0.12	-0.42	**1.15**
	(3.40)	(-0.78)	(-2.00)	(4.23)
Four-factor alpha	**0.55**	-0.10	-0.16	**1.02**
	(3.73)	(-0.68)	(0.80)	(3.71)
Five-factor alpha	**0.54**	-0.10	-0.15	**0.98**
	(3.73)	(-0.67)	(-0.73)	(3.75)
Beta (realzed)	0.53	0.82	1.14	-0.07
Volatility	15.91	20.76	28.22	19.87
Sharpe ratio	0.9	0.47	0.26	0.88

and by using fewer portfolios, we obtain more stocks in each portfolio. However, we require more than two portfolios to capture the effect of overweighting more extreme betas. Using three portfolios makes each portfolio[4] in our analysis diversified in accordance with research conducted by Ødegaard (2021). He finds that ten stocks are regarded as sufficient for being diversified.

The results show that it is mainly the long leg that drives the return of the BAB strategy in the Norwegian market. The regressions on the beta-sorted portfolios show that the alphas decrease monotonically from the low- to the high-beta

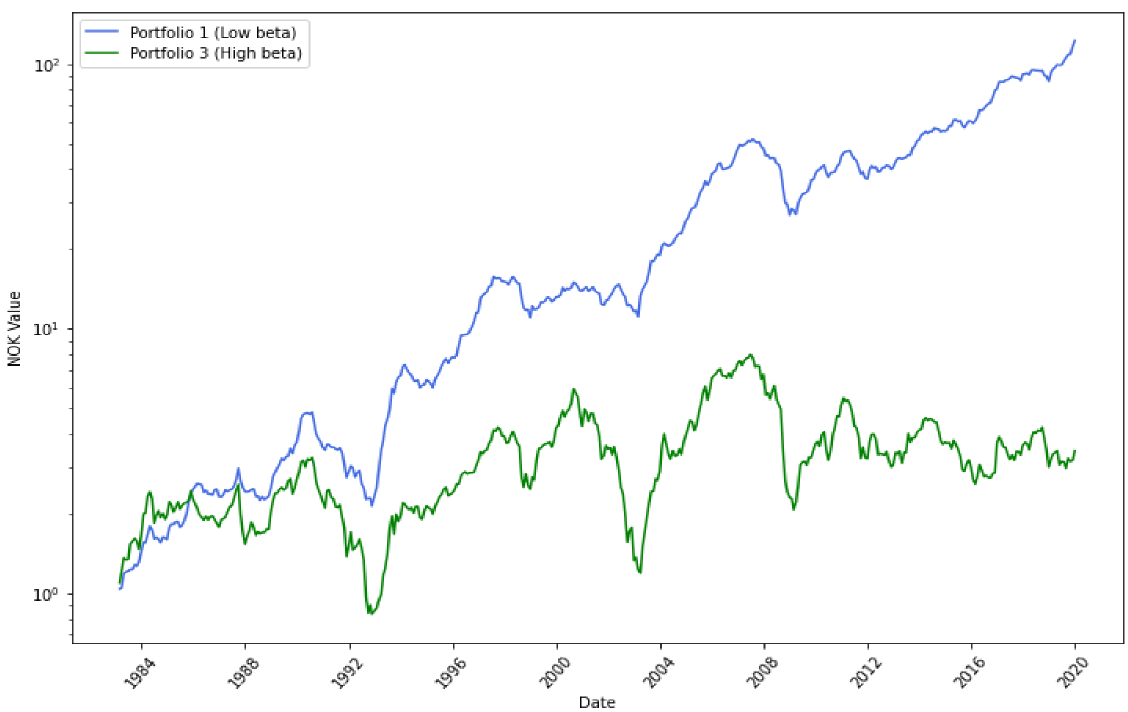
[4]See Appendix B for an overview of the number of stocks which meet the requirements to be included in one of the portfolios each year.

portfolio. Table 2 shows that the CAPM alpha decreases from 0.87% per month for the lowest quantile (1) to -0.09% for the highest quantile (3). However, the low-beta portfolio is the only one with statistically significant alphas with three as critical value. The excess returns are monotonically decreasing, indicating an inverted SML in Norway. The volatility increases for each portfolio with higher betas, resulting in Sharpe ratios decreasing from the low- to the high-beta portfolio. These results are in line with the findings of Frazzini and Pedersen (2014), namely that low-beta portfolios tend to have higher alphas and Sharpe ratios than high-beta portfolios.

Figure 2 plots the cumulative returns for the low- and high beta-sorted portfolios from 1983 to 2019. We do this to obtain a better overview of the performance of the low- and high-beta stocks in the Norwegian market in different periods. We see that the portfolio with the low-beta stocks clearly outperforms the portfolio with high-beta stocks. For example, if we had invested NOK 1 in the low-beta portfolio in 1983, we would have NOK 122 by the end of 2019, while the high-beta portfolio would only have increased to NOK 3.5. We observe an increasing gap after the

Figure 2: Cumulative returns of high- and low beta-sorted portfolios

This figure plots the cumulative return for the low beta portfolio, Portfolio 1, and the high beta portfolio, Portfolio 3, in Norway between 1983 and 2019. The portfolios are constructed by splitting the stocks into three portfolios based on their estimated beta by the beginning of each month and equal-weighting them.



financial crisis in 2008. Some of the rationales behind the good performance of the low-beta portfolio may be attributed to the gradually declining interest rates and lower econimic growth after 2008 (Mølsæter, 2021). This alignes with Driessen et al. (2019) findings that negative exposure to interest rates explains part of the outperformance of low-volatility stocks. Furthermore, the high-beta portfolio might be stagnating due to low profitability in industries like raw materials and banking after the financial crisis (Mølsæter, 2021). These are highly influential industries on the Oslo Stock Exchange (Næs et al., 2008). This can explain parts of the economic drivers behind the positive alphas obtained by the BAB factor in the Norwegian market.

All of the beta-sorted portfolios in Table 2 have positive exposure to the size factor, SMB. Usually, we expect the high-beta stocks to have this relation, as more volatile stocks tend to have a lower market cap. However, it turns out that the low-beta stocks are also exposed to size risk. These findings are interesting when we relate them to assumption 2A in the methodology of Frazzini and Pedersen (2014), as it has faced criticism for overweighting small stocks (Novy-Marx & Velikov, 2021). The effect of their unconventional methodology might falsely convince us to interpret the alphas of the BAB factor in Table 2 as obtainable for investors, even though this might not be realistic.

To better understand how assumption 2A might drive the alphas of the BAB factor, we evaluate the holdings in market cap quantiles for the low- and high beta portfolios. We see in Table 3 that the BAB factor overweights low market cap stocks in the low-beta portfolio. For example, the 1. quantile, which consists of the stocks with the lowest market cap, makes up 30.9% of the low beta portfolio, compared to the highest quantile, which only makes up 6% of the portfolio. These findings further support our claims that the performance in the low-beta portfolio is due to being heavily invested in low market cap stocks. On the other hand, we observe an opposite pattern for the high-beta portfolio, where the high market cap stocks are overweighted compared to the low market cap stocks.

The results partly corresponds with findings by Novy-Marx and Velikov (2021). They find that low market cap stocks are overweighted in both low- and high beta portfolios for the US market. However, for the Norwegian market, it is only the low-beta portfolio that has the same relation. Considering the rank-weighting scheme implemented by Frazzini and Pedersen (2014) in assumption 2A, it seems like the most extensive weighted stocks in the high-beta portfolio are stocks with the highest market cap. This may be because many large market cap stocks on

Table 3: Weighting of low and high market cap stocks in the BAB factor

This table reports the time-series average holdings in low- and high market cap quantiles within the rank-weighted low- and high beta portfolios used to construct the BAB factor in Norway from 1983 until 2019. 0 is the low beta portfolio on the horizontal line, and 1 is the high beta portfolio. On the vertical line, 1 is the quantile for the stocks with the lowest market cap, and 5 is the quantile for the stocks with the highest market cap.

	0	**1**
1	0.309	0.153
2	0.269	0.147
3	0.228	0.154
4	0.134	0.227
5	0.060	0.319

Oslo Stock Exchange are in industries like raw materials and banking, which are often high-beta stocks (Mølsæter, 2021).

Our findings motivate us to investigate whether the opposite overweighting of stocks in the beta-sorted portfolios will have implications for the alphas of the BAB factor in the Norwegian market. We analyze by using double sorted portfolios in Table 4, where we use the previous beta-sorted portfolios and perform an independent second sort on the mean market cap. The amount of stocks in each portfolio is in line with Ødegaard's (2021) studies on diversification in the Norwegian market[5].

We observe that the low-beta portfolio with low market cap yields higher alphas than the high market cap portfolio. For the low-beta and low market cap portfolio, all of the alphas are statistically significant, with three as our critical value. However, only the excess return and CAPM alpha are statistically significant for the low-beta portfolio with high market cap. The higher excess returns and CAPM alpha for low market cap portfolios are similar for the other beta-sorted portfolios, but neither are statistically significant. Summarized, the weight loadings in Table 3 and the results for low- and high-beta portfolios show overweighting of low market cap stocks with higher excess return in the long leg and high market cap stocks with lower excess return in the short leg. Both findings have a positive impact on the alphas obtained by the BAB factor. Considering the statistical significance of the results, we can conclude that overweighting of smaller stocks in the low beta portfolio drives the BAB factor.

[5] See Appendix B

Table 4: Double sorted portfolios

This table reports the characteristics and regression results for the double sorted portfolios from 1983 to 2019 in Norway. The betas are estimated using one-year rolling standard deviations and five-year rolling correlations, as explained in Section 4.1. The betas are sorted in ascending order for the beta-sorted portfolios and assigned to one of the three portfolios based on their rank. Portfolio 1 contains the stocks with the lowest betas, and Portfolio 3 contains the stocks with the highest betas. We have first sorted into three portfolios based on each stock's estimated beta and after that sorted each portfolio into two based on each stock's market cap. All stocks within each portfolio are equal-weighted. To construct the BAB factor, we rank the stocks, assign them to the low beta portfolio or the high beta portfolio, and weight them according to the methodology described in Section 4.2. We rescale the two portfolios to have a beta of 1 at portfolio formation each month and go long the low beta portfolio and short the high beta portfolio. The explanatory variables are the monthly excess return (OSEAX), the SMB and HML factors calculated as by Fama and French (1998), momentum factor PR1YR calculated as by Carhart (1997), and the liquidity factor LIQ calculated using the methodology of Naes, Skjeltorp, and Odegaard. The CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha are regressed as in equation 1, 2, 3 and 4. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and statistical significance with a critical value of three is in bold. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	1 Low	**1 High**	**2 Low**	**2 High**	**3 Low**	**3 High**
Excess return	**1.59**	**0.80**	0.82	0.79	0.73	0.50
	(5.66)	(3.76)	(2.43)	(2.71)	(1.58)	(1.33)
CAPM alpha	**1.28**	**0.45**	0.34	0.24	0.06	-0.26
	(5.24)	(3.16)	(1.31)	(1.58)	(0.18)	(-1.72)
Three-factor alpha	**0.83**	0.15	-0.25	0.01	-0.58	-0.26
	(3.56)	(1.15)	(-1.04)	(0.09)	(-1.74)	(-1.72)
Four-factor alpha	**0.94**	0.16	-0.17	-0.04	-0.23	-0.09
	(3.98)	(1.18)	(-0.70)	(-0.27)	(-0.71)	(-0.63)
Five-factor alpha	**0.92**	0.15	-0.17	-0.03	-0.22	-0.07
	(3.98)	(1.14)	(-0.72)	(-0.22)	(-0.68)	(-0.53)
Beta (realized)	0.5	0.55	0.77	0.87	1.06	1.22
Volatility	20.45	15.40	24.61	21.07	33.43	27.42
Sharpe ratio	0.93	0.62	0.40	0.45	0.26	0.22

6.2 Results with filtered data set

We have observed how some of the BAB returns are due to overweight in stocks with low market cap. As some of these stocks can be difficult to trade and can give an unrealistic view of the returns investors can achieve in practice, we will use a filtered data set in the rest of our analysis.

Table 5 reports the BAB factor results from the regressions after filtering our data[6]. The alphas and the significance are reduced, indicating that the strategy

[6]We report filtered results without winsorization in Table 14 in Appendix C. The results confirm that the negative impact on the BAB factor is only due to the exclusion of penny

performs worse when excluding penny stocks. The excess return and CAPM alpha in the Norwegian market has been reduced to 0.89% and 0.99%, with t-statistic of 3.47 and 3.89. These results are significant with a critical value of three, compared to the three-factor alpha, which is only significant at a 5% significance level, while the four- and five-factor alphas are insignificant. We notice that the volatility is somewhat lower when excluding penny stocks. The heavily reduced excess return and barely lower volatility results in a remarkably lower Sharpe ratio that has been reduced to 0.57. These results show that a lot of the previous performance of the BAB strategy was due to the inclusion of penny stocks. The findings

stocks.

Table 5: Beta-sorted portfolios and the BAB factor in Norway

This table reports the characteristics and regression results for the EW beta-sorted portfolios and the BAB factor from 1983 to 2019 in Norway when using a filtered data set. The betas are estimated using one-year rolling standard deviations and five-year rolling correlations, as explained in Section 4.1. The betas are sorted in ascending order for the beta-sorted portfolios and assigned to one of the three portfolios based on their rank. Portfolio 1 contains the stocks with the lowest betas, and Portfolio 3 contains the stocks with the highest betas. All stocks within each portfolio are equal-weighted. To construct the BAB factor, we rank the stocks, assign them to the low beta portfolio or the high beta portfolio, and weight them according to the methodology described in Section 4.2. We rescale the two portfolios to have a beta of 1 at portfolio formation each month and go long the low beta portfolio and short the high beta portfolio. The explanatory variables are the monthly excess return (OSEAX), the SMB and HML factors calculated as by Fama and French (1998), momentum factor PR1YR calculated as by Carhart (1997), and the liquidity factor LIQ calculated using the methodology of Naes, Skjeltorp, and Odegaard. The CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha are regressed as in equation 1, 2, 3 and 4. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and statistical significance with a critical value of three is in bold. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	1 (Low)	**2**	**3 (High)**	**BAB**
Excess return	**1.0**	**0.82**	0.86	**0.89**
	(4.91)	(3.22)	(2.54)	(3.47)
CAPM alpha	**0.71**	0.36	0.19	**0.99**
	(4.55)	(2.46)	(1.26)	(3.89)
Three-factor alpha	0.34	-0.05	-0.01	0.52
	(2.41)	(-0.41)	(-0.07)	(2.13)
Four-factor alpha	0.38	-0.04	0.13	0.44
	(2.71)	(-0.73)	(0.91)	(1.79)
Five-factor alpha	0.36	-0.04	0.15	0.40
	(2.72)	(-0.34)	(1.02)	(1.76)
Beta (realized)	0.47	0.74	1.07	-0.16
Volatility	14.83	18.66	24.75	18.59
Sharpe ratio	0.81	0.53	0.41	0.57

align with Novy-Marx and Velikov's (2021) findings, namely that the strategy performs worse when excluding small and illiquid stocks. As Novy-Marx and Velikov's (2021) findings are for the US market during 1968-2019, our discovery shows that these results hold in different markets during different periods. As the five-factor alpha is insignificant, we can not discard our null hypothesis. Hence, after filtration, investors will not be able to achieve a positive alpha from the strategy.

Furthermore, we investigate the beta-sorted portfolios to understand how the small and illiquid stocks impact the BAB factor. Table 5 reports our findings when using a filtered data set. In accordance with Frazzini and Pedersen (2014) and our initial findings, the CAPM alpha of the three portfolios is still monotonically decreasing. However, only the low-beta portfolio is statistically significant, with three as our critical value. The three-, four-, and five-factor alpha do not have the same pattern but are all insignificant. While the low beta portfolio still has the highest excess return, the excess return is not monotonically decreasing. Thus, our findings do not imply an inverted SML as we experienced with the unfiltered data set but rather indicate a flatter SML. These findings are more in line with the findings of Frazzini and Pedersen (2014), who found that the SML is flat in the US market.

The impact of excluding penny stocks[7] is different on the low- and high beta portfolio. The excess return and CAPM alphas of the low beta decrease, while both increase for the high-beta portfolio. The effect on the low-beta portfolio substantiates the findings of Novy-Marx and Velikov (2021) that small and illiquid stocks drive the BAB return. The increase in the high-beta portfolio can be explained by two phenomenons already highlighted in previous literature. First, Bali et al. (2014) find evidence that demand for lottery-like stocks, which are often volatile penny stocks, drives a high-beta portfolio's returns down. By filtering out stocks lower than NOK 10, we exclude many of the lottery-like penny stocks, causing the high-beta portfolio to perform better. Second, Diether et al. (2009) find evidence for difficulties in shorting penny stocks. This will contribute to overpricing, which often is penalized at a later point in time. Our results provide indications that the same effects might be present in the Norwegian market, even though the results are not statistically significant. Besides, looking at the two portfolios' impact on the BAB factor alpha make it evident that the low-beta portfolio is the main driver.

[7] Filtered results without winsorization in Table 14 in Appendix C show even stronger indications of the effects of penny stocks on the beta-sorted portfolios.

Table 6 reports the results for the double sorted portfolios after filtration. When comparing it to the unfiltered results obtained in table 4, we notice that the higher alphas for low market cap stocks in the low-beta portfolio persist. The CAPM-, three-, four- and five-factor alphas are significant, with three as our critical value. At the same time, the excess return is the only statistically significant result in the low beta with a high market cap portfolio. This shows that even though we have excluded penny stocks, which have reduced the overall performance of the BAB factor, stocks with low market cap are still the main driver of returns for the low-beta portfolio. Furthermore, we see that the same relation holds for the alphas

Table 6: Double sorted portfolios

This table reports the characteristics and regression results for the double sorted portfolios from 1983 to 2019 in Norway when using a filtered data set. The betas are estimated by using one-year rolling standard deviations and five-year rolling correlations, as explained in Section 4.1. The betas are sorted in ascending order for the beta-sorted portfolios and assigned to one of the three portfolios based on their rank. Portfolio 1 contains the stocks with the lowest betas, and Portfolio 3 contains the stocks with the highest betas. We have first sorted into three portfolios based on each stock's estimated beta and after that sorted each portfolio into two based on each stock's market cap. All stocks within each portfolio are equal-weighted. To construct the BAB factor, we rank the stocks, assign them to the low beta portfolio or the high beta portfolio, and weight them according to the methodology described in Section 4.2. We rescale the two portfolios to have a beta of 1 at portfolio formation each month and go long the low beta portfolio and short the high beta portfolio. The explanatory variables are the monthly excess return (OSEAX), the SMB and HML factors calculated as by Fama and French (1998), momentum factor PR1YR calculated as by Carhart (1997), and the liquidity factor LIQ calculated using the methodology of Naes, Skjeltorp, and Odegaard. The CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha are regressed as in equation 1, 2, 3 and 4. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and statistical significance with a critical value of three is in bold. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

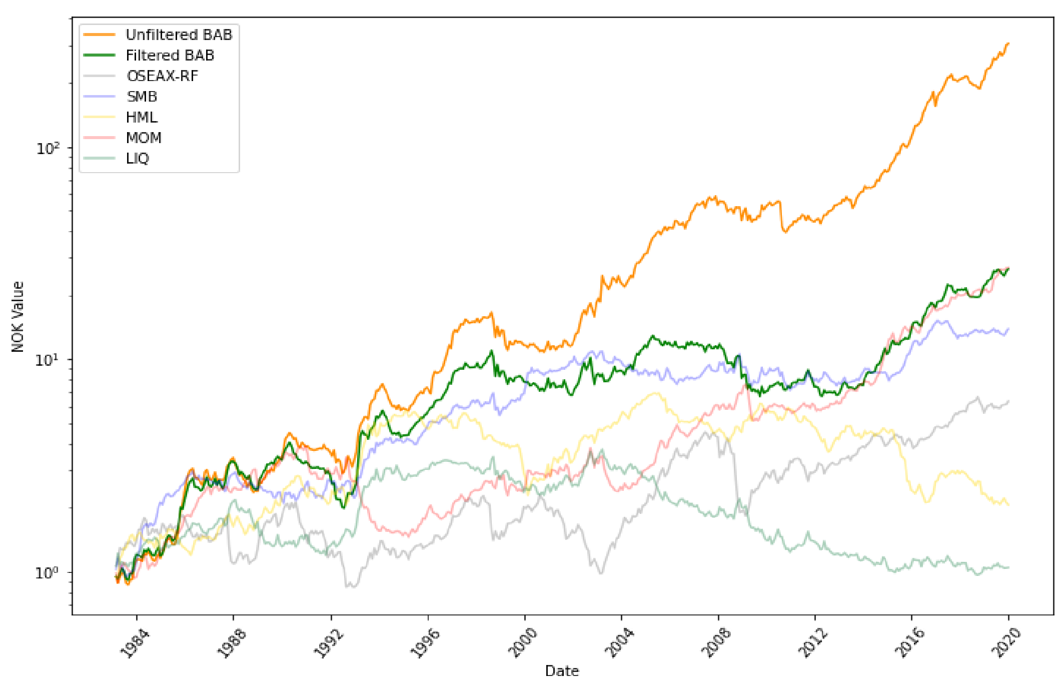
	1 Low	**1 High**	**2 Low**	**2 High**	**3 Low**	**3 High**
Excess return	**1.17**	**0.82**	0.78	**0.88**	1.05	0.66
	(5.47)	(3.32)	(2.73)	(3.18)	(2.88)	(1.85)
CAPM alpha	**0.92**	0.48	0.35	0.37	0.45	-0.08
	(5.04)	(2.48)	(1.68)	(2.44)	(1.84)	(-0.59)
Three-factor alpha	**0.53**	0.14	-0.21	0.12	0.00	0.00
	(3.13)	(0.74)	(-1.17)	(0.83)	(-0.04)	(-0.07)
Four-factor alpha	**0.58**	0.18	-0.16	0.08	0.16	0.12
	(3.40)	(0.95)	(-0.85)	(-0.54)	(0.68)	(0.90)
Five-factor alpha	**0.56**	0.17	-0.17	0.09	0.16	0.13
	(3.47)	(0.89)	(-0.89)	(0.61)	(0.71)	(1.10)
Beta (realized)	0.40	0.54	0.68	0.82	0.97	1.18
Volatility	15.55	18.02	20.70	20.05	26.58	26.06
Sharpe ratio	0.90	0.55	0.45	0.52	0.48	0.30

of the high-beta portfolio, even though the results are not statistically significant. This clarifies that parts of the abnormal return the BAB factor achieves stems from the overweighting reported in Table 3, which is caused by the rank-weighting in assumption 2A.

To summarize how the strategy performs with a filtered data set relative to the unfiltered BAB and other risk factors, we plot the cumulative returns in Figure 3. We see that the unfiltered BAB outperforms the other factors by far, but the previous discussion shows that it is not representative of what investors can achieve in practice. The final amount in 2020 if NOK 1 was invested in 1983 is NOK 305.9, NOK 26.5, NOK 6.3, NOK 13.9, NOK 2.1, NOK 27, NOK 1.1 for unfiltered BAB, filtered BAB, OSEAX-RF, SMB, HML, MOM, and LIQ respectively. Hence, the filtered BAB is outperformed by the momentum factor in the given investment horizon. The established factors are constructed such that investors are able to profit from the strategy themselves. The BAB factor has received criticism for having unconventional methodology, which can be difficult to implement in practice. Therefore, we want to evaluate how the strategy performs when implementing a more standard approach, creating a BAB factor that is more comparable to the other factors.

Figure 3: The cumulative return for unfiltered and filtered BAB in addition to the market and established factors in Norway in excess of the RF-rate

This table plots the cumulative excess return for the unfiltered and filtered BAB, the market, and the factors SMB, HML, MOM and LIQ in Norway between 1983 and 2019.



6.3 Alternative methodology

In this section, we will change the methodology assumptions 1A, 2A and 3A by Frazzini and Pedersen (2014) outlined in section 4. We do this to elaborate on whether these assumptions will have implications from conclusions drawn from asset pricing tests. We will also clarify whether their methodology makes it infeasible for investors to obtain abnormal returns and propose a more realistic BAB factor.

6.3.1 Alternative weighting

We change assumption 2A used by Frazzini and Pedersen (2014) regarding how the stocks are weighted within each portfolio. We do this to understand better how the rank-weighting (RW) of stocks affects the performance of the strategy. We refer to our first alternative assumption as 2B, where we will use equal-weighted (EW) portfolios. We will split the stocks into three portfolios based on the ranking of their betas and invest in the portfolio with the lowest betas and short the portfolio with the highest betas. In the EW portfolios, we will give all of the stocks in each portfolio an equal weight. Novy-Marx and Velikov (2021) find that the difference in holdings in a RW portfolio compared to an EW portfolio that holds the top and bottom thirds of stocks is 17.4%. Thus, these procedures should yield very similar results.

In our second alternative assumption titled 2C, we will use Value-Weighted (VW) portfolios. The VW portfolio is based on the same portfolios as assumption 2B but instead weighted by each stock's market cap relative to the portfolio's market cap. We change the assumption as VW portfolios represent a more realistic approach to what investors can achieve in practice. Moreover, it is the standard way of weighting stocks within asset pricing. The extensive research on the weighting procedures in assumption 2B and 2C will enable a further explanation of the impact of RW in assumption 2A.

Table 7 reports the BAB strategy results when we change assumption 2A to 2B and 2C. Using assumption 2B with EW portfolios, we can see that the results are pretty similar to using RW in assumption 2A. The EW BAB strategy is yielding monthly excess returns and CAPM alpha of 0.93% and 1.03%. There is a close resemblance to 0.89% and 0.99% obtained by RW BAB. For both RW BAB and EW BAB, the excess return and CAPM alpha are significant at a critical value of three, while the three-factor alpha is significant at a 5% significance level. The four- and five-factor alpha yield insignificant results. For assumption 2C with VW portfolios, the strategy performs worse than RW BAB using assumption 2A. With a monthly excess return of 0.68% and a t-statistic of 2.62, it yields both lower and less significant results. None of the alphas are statistically significant at a critical value of three, but the excess return and CAPM alpha are statistically significant at a 5% significance level.

Table 7: EW, VW and RW BAB

This table reports the characteristics and regression results for the BAB factor. We use value-weighting and equal-weighting to weight the stocks within the low beta and high beta portfolios. The betas are estimated using one-year rolling standard deviations and five-year rolling correlations, as explained in Section 4.1. To construct the BAB factor, we rank the stocks, assign them to the low beta portfolio or the high beta portfolio according to the methodology in Section 4.2, and weight them according to the methodology described in Section 4.3.1. We rescale the two portfolios to have a beta of 1 at portfolio formation each month and go long the low beta portfolio and short the high beta portfolio. The explanatory variables are the monthly excess return (OSEAX), the SMB and HML factors calculated as by Fama and French (1998), momentum factor PR1YR calculated as by Carhart (1997), and the liquidity factor LIQ calculated using the methodology of Naes, Skjeltorp, and Odegaard. The CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha are regressed as in equation 1, 2, 3 and 4. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and statistical significance with a critical value of 3 is in bold. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	EW	**VW**	**RW**
Excess return	**0.93**	0.68	**0.89**
	(3.36)	(2.62)	(3.47)
CAPM alpha	**1.03**	0.77	**0.99**
	(3.73)	(2.99)	(3.89)
Three-factor alpha	0.57	0.37	0.52
	(2.14)	(1.47)	(2.13)
Four-factor alpha	0.51	0.30	0.44
	(1.89)	(1.16)	(1.79)
Five-factor alpha	0.47	0.28	0.40
	(1.87)	(1.11)	(1.76)
Beta (realized)	-0.15	-0.15	-0.16
Volatility	20.13	18.92	18.59
Sharpe ratio	0.55	0.43	0.57

We plot the cumulative return for the strategy with the different assumptions in Figure 4 to see how they perform over time compared to each other. The returns with assumption 2A and 2B are very similar, and we find that they correlate 96%. Thus, the portfolios constructed using the methodology of Frazzini and Pedersen (2014) are almost indistinguishable from EW portfolios, which is a more straightforward type of weighting. These findings are in line with the ones of Novy-Marx and Velikov (2021). Moreover, it shows that the relation between rank- and equal weighting holds for the Norwegian market.

Figure 4: The cumulative return for BAB with RW, EW and VW

This table plots the cumulative excess return for the RW, EW, and VW BAB in Norway between 1983 and 2019.

The similarity between RW and EW is interesting when comparing the attributes of EW and VW portfolios. EW portfolios achieve in general higher alphas and Sharpe ratios than VW portfolios. Plyakha et al. (2012) demonstrate how the higher excess returns in EW portfolios than VW portfolios are partly due to larger exposure to systematic risk factors. Our findings support their statements, as we find that the EW BAB has higher exposure to the SMB and HML factors than the VW BAB. Consequently, conclusions drawn from tests of asset-pricing models differ when using EW and VW portfolios, reasoning that the alphas that are statistically significant for EW BAB are insignificant for VW BAB. This is not surprising, considering our findings in section 6.1 and 6.2. It aligns with the better performance of low market cap stocks in the low beta portfolio and less statistical significance in the high market cap portfolios in Table 6.

Another reason for the gap in portfolio performance is the monthly rebalancing in the RW and EW strategies. Plyakha et al. (2015) find a positive relationship between rebalancing frequency and the alphas of EW portfolios. Increasing to a yearly rebalancing frequency makes the alphas of EW- and VW portfolios almost identical. The rebalancing can be viewed as a form of mean-reversion, as stocks that have performed well and hence have a higher weight at the end of the month will be scaled down when rebalancing. The resulting turnover of EW and RW portfolios in assumption 2A and 2B causes higher trading costs than the VW portfolio in assumption 2C. Hence, rebalancing is necessary for the BAB factor to maintain its performance, and it is reasonable to assume it to be considerably lower when applying trading costs.

A strategy using VW portfolios is more manageable for investors in practice. It does not require buying a large number of stocks with low market cap, which can be illiquid and expensive to trade. In addition, a VW portfolio has a close resemblance to a buy-and-hold strategy where rebalancing is not necessary. This indicates that the returns that investors can achieve in practice are lower than the initial BAB returns. Our findings show that it is reasonable to assume that the VW in assumption 2C constructs a more representative BAB factor for investors. We can not discard our null hypothesis using this weighting procedure, meaning that investors will not obtain a positive alpha by utilizing the BAB strategy in the Norwegian market.

6.3.2 Alternative beta

In this section, we will change assumption 1A regarding the estimation of betas. Frazzini and Pedersen (2014) use one-year rolling standard deviations and five years rolling correlation to estimate betas. They state that they follow this procedure as correlations tend to move more slowly than volatilities, yet it has been argued that this procedure does not yield actual CAPM betas (Novy-Marx & Velikov, 2021). Therefore, as a robustness test, we will estimate betas as a slope coefficient from CAPM regressions.

Whether to use daily or monthly data and regarding what period to use when estimating betas, researchers disagree. Daves et al. (2000) state that standard errors are reduced using daily returns. However, Scholes and Williams (1977) argue that when using daily returns, problems regarding non-synchronism increase. Based on this, we will continue to use daily returns to reduce standard errors and use overlapping three-day log returns for estimating standard deviations and correlations to reduce the impact of non-synchronism. There are also disagreements concerning the time-horizon of the historical period for the beta estimation. Using lengthier periods improves the estimation confidence but reduces the ability to capture the time-variation of the beta (Patton & Timmermann, 2010). Therefore, we will use five years of data to estimate betas. We believe that this will enable us to capture both the effect of reduced standard errors compared to when using shorter periods and higher explanatory power than when using longer periods. Hence, in addition to assumptions 2B and 2C, we will include a new assumption, 1B. We use five years of daily data to calculate volatilities and correlations used for our beta estimations.

Table 8 shows that the effect of the new beta estimation is different on EW and VW BAB. All of the alphas on the EW BAB with assumption 1B, except for the three-factor alpha, perform better than the EW BAB with assumption 1A. However, the increased alphas do not affect the conclusion as all of the alphas that were significant (insignificant) before still are significant (insignificant). With VW,

Table 8: EW and VW BAB with new beta estimation

This table reports the characteristics and regression results for the EW and VW BAB with alternative beta estimation. The betas are estimated by using five-years rolling standard deviations and correlations as described in Section 4.3.2. To construct the BAB factor, we rank the stocks, assign them to the low beta portfolio or the high beta portfolio according to the methodology in Section 4.2, and weight them according to the methodology described in Section 4.3.1. We rescale the two portfolios to have a beta of 1 at portfolio formation each month and go long the low beta portfolio and short the high beta portfolio. The explanatory variables are the monthly excess return (OSEAX), the SMB and HML factors calculated as by Fama and French (1998), momentum factor PR1YR calculated as by Carhart (1997), and the liquidity factor LIQ calculated using the methodology of Naes, Skjeltorp, and Odegaard. The CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha are regressed as in equation 1, 2, 3 and 4. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and statistical significance with a critical value of three is in bold. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	EW	**VW**
Excess return	**0.95**	0.57
	(3.53)	(2.22)
CAPM alpha	**1.07**	0.64
	(4.04)	(2.50)
Three-factor alpha	0.54	0.17
	(2.15)	(0.68)
Four-factor alpha	0.53	0.12
	(2.08)	(0.49)
Five-factor alpha	0.48	0.11
	(2.12)	(0.43)
Beta (realized)	-0.19	-0.11
Volatility	19.62	18.65
Sharpe ratio	0.58	0.37

however, the strategy performs worse with the new beta estimation. The alphas are lower, and the significance has been reduced. These findings are in line with the ones of Novy-Marx and Velikov (2021), namely that the EW BAB performs better when using both five years standard deviations and correlation to estimate betas.

6.3.3 Alternative hedging

In assumption 3A, we see how Frazzini and Pedersen (2014) achieve market neutrality by leveraging and de-leveraging the portfolios such that they each have a beta of 1. This procedure will construct a hedge based on buying portfolios with similar weighting as the original strategy (Novy-Marx & Velikov, 2021). As our alternative portfolio weights suggest, the rank-weighted portfolios yield very similar results to equal-weighted portfolios. This indicates that Frazzini and Pedersen's hedging procedure reflects a direct hedging method that buys the equal-weighted market portfolio rather than using the more common value-weighted market portfolio.

According to Novy-Marx and Velikov (2021), hedging by leveraging is a non-standard procedure. They state that it is more common to hedge the strategy's market risk by buying the market according to the underlying strategy's observed short market tilt. We will therefore change the construction of the BAB factor in equation (9) under assumption 3A and introduce assumption 3B on how we hedge against market risk. In assumption 3B, we will go long in the low-beta portfolio, short the high-beta portfolio, and invest a proportion in the market to achieve market neutrality. To estimate the beta of the long-short strategy, we will run one-year rolling regressions of the returns of a long low-beta and short high-beta strategy on the market returns. The resulting betas will be used to buying an adequate proportion in the value-weighted market portfolio. More precisely, we will calculate the BAB returns in the following way:

$$r_{t+1}^{BAB} = (r_{t+1}^{L} - r^f) - (r_{t+1}^{H} - r^f) - \beta^{LH}(r^m - r^f)$$

Where β^{LH} is the market exposure when going long in the low-beta portfolio and short in the high-beta portfolio.

Table 9 shows that the EW BAB performs worse with the new hedging. The monthly excess return is 0.56%, clearly lower than the previous monthly excess return of 0.95%. In addition, the alphas are less significant, where none of them are statistically significant. Further, the volatility is reduced with the new hedging methodology, resulting in only a slightly smaller Sharpe ratio. The lower performance indicates that some of the performance of the BAB strategy is due to how the market exposure is hedged. These findings are interesting because it confirms that hedging by leverage, as done by Frazzini and Pedersen (2014), drives the performance of the BAB factor. As the rank-weighting is almost identical to equal-weighting, it proves that hedging by leverage is a back-door to buying the equal-weighted market portfolio.

The results of the VW BAB in Table 9 are relatively similar to before the new hedging method was applied. The monthly excess return is almost identical, namely 0.56%. However, even though the excess return is quite similar, the t-

Table 9: EW and VW BAB with new beta estimation and new hedging method

This table report the characteristics and regression results for the EW and VW BAB with alternative beta estimation and alternative hedging. The betas are estimated by using five years rolling standard deviations and correlations as described in Section 4.3.2. To construct the BAB factor we rank the stocks, assign them to the low beta portfolio or the high beta portfolio according to the methodology in Section 4.2, and weight them according to the methodlogy described in Section 4.3.1. We go long the low beta portfolio and short the high beta portfiolio, and buy a proportion in the market such that the strategy has a beta of zero, such as described in Section 4.3.3. The explanatory variables are the monthly excess return (OSEAX), the SMB and HML factors calculated as by Fama and French (1998), momentum factor PR1YR calculated as by Carhart (1997) and the liquidity factor LIQ calculated using the methodology of Naes, Skjeltorp, and Odegaard. The CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha are regressed as in equation 1, 2, 3 and 4. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and statistical significance with a critical value of 3 is in bold. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	EW	**VW**
Excess return	**0.56**	0.56
	(3.02)	(2.92)
CAPM alpha	0.51	0.47
	(2.76)	(2.52)
Three-factor alpha	0.27	0.16
	(1.48)	(0.88)
Four-factor alpha	0.23	0.14
	(1.26)	(0.75)
Five-factor alpha	0.22	0.13
	(1.38)	(0.74)
Beta (realized)	0.10	0.17
Volatility	13.30	13.72
Sharpe ratio	0.51	0.49

statistic has increased to 2.92. We see the most significant difference for the CAPM alpha, where it has been reduced from 0.64% to 0.47%. The results for the three-, four- and five-factor alphas are pretty similar to before, but with slightly higher t-statistics, even though they are still insignificant. The similarity in the results is in line with our expectations, as findings of Novy-Marx and Velikov (2021) show that hedging by leverage like assumption 3A is almost identical to buying portfolios with the same weighting as the underlying strategy. Our results support their statement, as the VW BAB hedged by leverage in Table 8 will have a close resemblance to a strategy hedged by buying the VW market portfolio.

The close relation between assumption 2A and assumption 3A contribute to the BAB factor's performance. Due to the high correlation between EW BAB and the BAB factor, EW BAB with alternative hedging can be interpreteted as the BAB factor hedged with a value weigted market portfolio. The similar results of EW BAB and VW BAB with alternative hedging indicate that hedging by leverage in assumption 3A is another driver of the BAB factor. By its direct impact on the return of the low- and high-beta portfolio it utilizes the effect of rank-weighting in assumption 2A.

The results show that VW BAB avoids the problems caused in RW BAB and EW BAB. However, the good performance is reduced drastically, indicating that investors are unlikely to obtain an alpha by investing in the strategy. Furthermore, we have not accounted for transaction costs when performing our analysis. Accounting for transaction costs would reduce the strategy's performance even further, substantiating our claims that investors will not be able to profit from the strategy. Based on our results, we can not reject our null hypothesis that the strategy does not yield an alpha in the Norwegian market.

7 Conclusion

The betting against beta strategy is based on findings of the low beta anomaly from almost 50 years ago (Friend & Blume, 1970; Black et al., 1972). While the strategy has received much attention due to its remarkable results, not all researchers agree that the strategy yields any return that other risk factors can not explain. Considering the critique, we have explored whether investors can obtain a positive alpha in the Norwegian stock market.

Bali et al. (2014) were early on criticizing the strategy. Their findings suggest that the high return is due to price pressure driven by demand for lottery-like stocks. Our findings indicate that the lottery-like stocks increase the strategy's performance, as our high-beta portfolio performed better when excluding penny stocks. The newest criticism comes from Novy-Marx and Velikov (2021). They state that the betting against beta strategy overweights stocks with a low market capitalization in both the low- and high-beta portfolio. Our findings partly aligned with their findings. We found that the strategy overweight small stocks in the low-beta portfolio and big stocks in the high-beta portfolio. When excluding the smallest stocks, the strategy's performance decreased drastically, substantiating the results of Novy-Marx and Velikov (2021). As the smallest stocks tend to be illiquid and expensive to trade, our findings indicate that the high performance of the BAB factor is not possible to obtain in practice.

Novy-Marx and Velikov (2021) also criticized the unconventional methodology used for constructing the BAB factor, which has also been highlighted by Han (2019). The similarity between equal-weighting and rank-weighting indicate that the hedging by leverage utilizes the weighting procedure by having a close resemblance to buying an equal-weighted market portfolio. We tested the strategy by using a more conventional methodology and isolated the effects. Our findings show that the combination of rank-weighting and the hedging method applied by Frazzini and Pedersen (2014) drives the BAB factor.

The high relation between rank-weighting and equal-weighting enables a comparison with VW portfolios. Research by Plyakha et al. (2012) raises the question of whether we can consider a test of the betting against beta strategy to be a clean asset pricing test. We saw that when using VW portfolios, which is the standard way of weighting stocks within asset pricing, the problems caused by non-standard weighting and hedging disappear. However, the strategy's performance was drastically reduced, and none of the alphas were statistically significant.

Overall, we do not observe that the BAB factor presented by Frazzini and Pedersen (2014) shows substantial evidence of outperforming other well-known risk factors. Instead, it highlights the impact non-standard procedures can have on conclusions drawn for asset pricing tests. While the Betting Against Beta strategy yields high and significant alphas in Norway, its performance is driven by an unconventional methodology. Considering our research question, we find that investors are unable to profit from the strategy in the Norwegian market.

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A Appendix - Results for the US market

We downloaded stock returns in the US and the CRSP Value-Weighted Index from CRSP through WRDS. The data contains daily returns on all common stocks from 1926 until 2012, where we use the holding period return as our return estimate. We obtain the daily and monthly risk-free (RF) rate and monthly data on the market (MKT), the value factor (HML), the size factor (SML), and the momentum factor (UMD) from Kenneth French's website. Further, we obtain Pastor and Stambaugh's (2003) monthly liquidity factor (LIQ) from CRSP through WRDS.

Table 10: Summary Statistics for the US market

The table reports the summary statistics for the variables used in our replication of Frazzini and Pedersen (2014). For all of the factors, N is the number of observations, while N for stocks counts the total number of stocks in our data set.

Variable	Frequeny	Start	End	N	Mean	Max	Min
Stocks	Daily	1926	2012	23 480	0.086	1900	-97.17
RF	Daily	1926	2012	22693	0.013	0.061	0.003
VW	Daily	1926	2012	22693	0.041	15.68	-17.16
RF	Monthly	1926	2012	1029	0.29	1.35	-0.06
Mkt	Monthly	1926	2012	1029	0.63	38.85	-29.13
SMB	Monthly	1926	2012	1029	0.22	36.70	-16.82
HML	Monthly	1926	2012	1029	0.40	35.46	-13.28
MOM	Monthly	1926	2012	1029	0.64	22.59	-29.82
LIQ	Monthly	1968	2012	531	0.475	11.675	-12.777

Table 11: Factor statistics for the US market

This table reports the excess return, volatility and sharpe ratio for the original BAB factor by Frazzini and Pedersen (2014),the market, the SMB and HML factors from Fama and French (1993) and the MOM factor by Carhart (1997) in the US market.

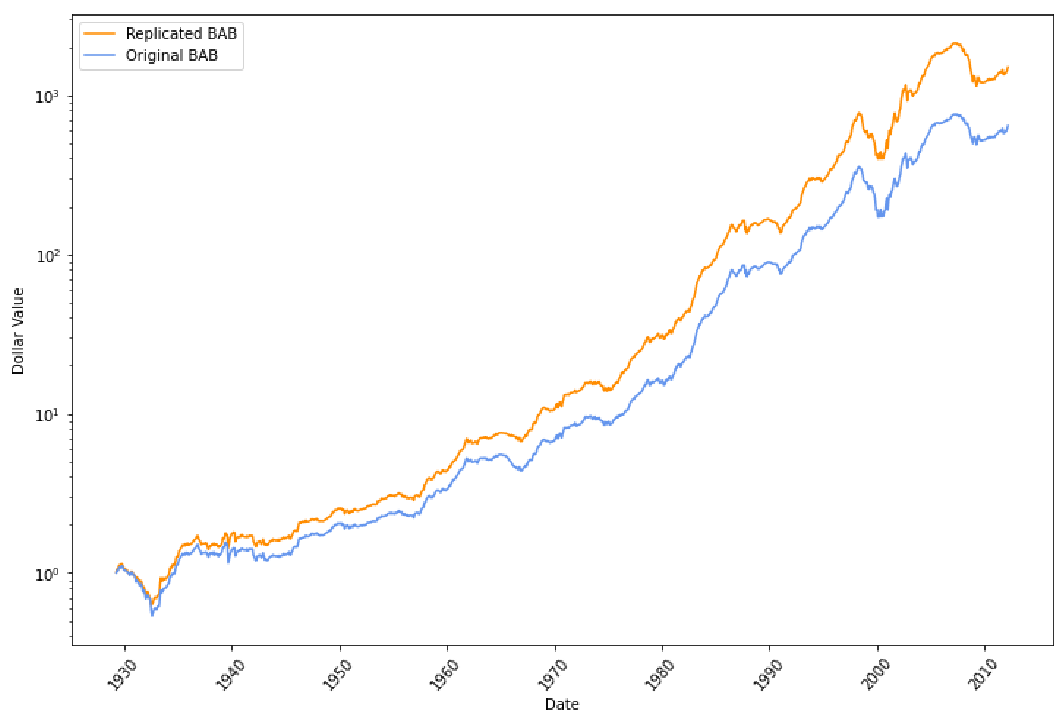
	BAB	**MKT**	**SMB**	**HML**	**MOM**
Excess return	0.70	0.58	0.24	0.42	0.60
Volatility	10.75	19.08	11.34	12.43	15.62
Sharpe ratio	0.78	0.37	0.25	0.40	0.46

Table 12: Results US

This table reports the characteristics and regression results for the US from 1926 to 2012. The middle column is our replication of the BAB factor in the US, while the right column is the original results from the article (Frazzini and Pedersen (2014)). The alpha is the intercept in a regression of monthly excess return. The explanatory variables are monthly returns from Fama and French (1993) mimicking portfolios, Carhart (1997) momentum factor and Pastor and Stambaugh's (2003) liquidity factor. The liquidity factor is only available between 1968 and 2012. All alphas are monthly and in percent.

	Replication	**Original**
Excess return	**0.75**	**0.70**
	(7.82)	(7.12)
CAPM alpha	**0.79**	**0.73**
	(7.91)	(7.44)
Three-factor alpha	**0.77**	**0.73**
	(7.68)	(7.39)
Four-factor alpha	**0.63**	**0.55**
	(6.265)	(5.59)
Five-factor alpha	**0.60**	**0.55**
	(4.23)	(4.09)
Beta (realized)	-0.02	-0.06
Volatility	10.91	10.75
Sharpe ratio	0.82	0.78

Figure 5: The cumulative return for US BAB, replicated and original



B Appendix - Number of stocks

Table 13: Number of stocks in the BAB factor each year

Year	Unfiltered	Filtered
1983	42	38
1984	50	48
1985	83	79
1986	100	95
1987	105	98
1988	102	95
1989	105	96
1990	99	90
1991	88	79
1992	84	69
1993	103	74
1994	98	91
1995	98	86
1996	102	91
1997	115	107
1998	127	117
1999	137	122
2000	143	120
2001	157	120
2002	161	116
2003	158	102
2004	159	110
2005	157	108
2006	148	103
2007	145	102
2008	158	111
2009	169	106
2010	188	108
2011	201	112
2012	193	104
2013	191	102
2014	186	100
2015	177	101
2016	174	97
2017	178	104
2018	181	107
2019	183	108

C Appendix - Additional results

Table 14: Filtered Beta-sorted portfolios and BAB in Norway pre-winsorization

This table reports the characteristics and regression results for the EW beta-sorted portfolios and the BAB factor from 1983 to 2019 in Norway when using a data set without penny stocks. The betas are estimated using one-year rolling standard deviations and five-year rolling correlations, as explained in Section 4.1. The betas are sorted in ascending order for the beta-sorted portfolios and assigned to one of the three portfolios based on their rank. Portfolio 1 contains the stocks with the lowest betas, and Portfolio 3 contains the stocks with the highest betas. All stocks within each portfolio are equal-weighted. To construct the BAB factor, we rank the stocks, assign them to the low beta portfolio or the high beta portfolio, and weight them according to the methodology described in Section 4.2. We rescale the two portfolios to have a beta of 1 at portfolio formation each month and go long the low beta portfolio and short the high beta portfolio. The explanatory variables are the monthly excess return (OSEAX), the SMB and HML factors calculated as by Fama and French (1998), momentum factor PR1YR calculated as by Carhart (1997), and the liquidity factor LIQ calculated using the methodology of Naes, Skjeltorp, and Odegaard. The CAPM alpha, three-factor alpha, four-factor alpha, and five-factor alpha are regressed as in equation 1, 2, 3 and 4. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and statistical significance with a critical value of three is in bold. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	1 (Low)	**2**	**3 (High)**	**BAB**
Excess return	**0.91**	**0.85**	0.91	**0.83**
	(5.14)	(3.28)	(2.63)	(3.33)
CAPM alpha	**0.70**	0.39	0.23	**0.95**
	(4.91)	(2.53)	(1.45)	(3.86)
Three-factor alpha	0.33	-0.02	0.02	0.49
	(2.65)	(-0.19)	(0.111)	(2.09)
Four-factor alpha	0.36	-0.03	0.18	0.38
	(2.87)	(-0.20)	(1.18)	(1.61)
Five-factor alpha	0.34	-0.02	0.19	0.35
	(2.89)	(-0.18)	(1.27)	(1.57)
Beta (realized)	0.45	0.74	1.08	-0.19
Volatility	13.87	18.96	25.08	18.20
Sharpe ratio	0.84	0.54	0.43	0.55