LEVERAGE CONSTRAINTS AND THE BETA ANOMALY

BETTING AGAINST BETA IN THE SWEDISH STOCK MARKET

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Bachelor Thesis

Stockholm School of Economics

2024

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Abstract:

We expand on prior research around the beta anomaly by examining whether the superior performance of low-beta stocks compared to high-beta stocks persists in the Swedish market from 2011 to 2023. Building on the work in "Betting Against Beta" by Frazzini and Pedersen (2014), we construct a market neutral Betting Against Beta (BAB) factor and evaluate its performance. We contribute to the literature by updating their research with the most recent data from Sweden, focusing on stocks listed on Nasdaq Stockholm, and examining the underlying economics of the beta anomaly. The findings reveal how portfolios of low-beta stocks yield higher and statistically significant alphas compared to high-beta stock portfolios over the sample period, highlighting a superior performance of low-beta assets. Consistent with Frazzini and Pedersen's results, we observe a significant positive alpha for a self-financing BAB portfolio during the tested period, suggesting a breach of the assumptions underlying traditional asset pricing models such as the CAPM. Furthermore, we analyze ownership data on stocks listed on Nasdaq Stockholm and identify that leverage-constrained investors are a key factor driving the overpricing of high-beta assets in Sweden. Additionally, we find that periods of tighter leverage constraints, as measured by a Swedish equivalent of the TED-Spread, negatively impact the short-term returns of a BAB portfolio while having no significant effect on long-term performance.

Keywords:

Betting Against Beta, BAB, Leverage Constraints, Beta Anomaly, Sweden

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Bachelor Thesis
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I. Introduction

One of the most fundamental assumptions of contemporary finance is the Efficient Markets Hypothesis, imposing that all available information is incorporated in the pricing of assets. Under this belief, consistently gaining superior returns cannot be achieved without assuming additional risk (Fama, 1970). If this were the case, it would not be possible to get a higher Sharpe ratio - excess return in relation to risk - in any other way than levering or de-levering the market portfolio (Sharpe, 1964). However, prior research such as “Betting against beta” by Frazzini and Pedersen (2014) has shown how low beta stocks have been undervalued compared to high beta stocks in the US using a dataset from 1926-2012. Additionally, Jensen, Black and Scholes (1972) examine the US market between 1926-1966 and find that low beta assets outperform while high beta assets underperform in reference to their benchmark. This phenomenon is referred to as a beta anomaly. Even though this is a well-researched area with numerous studies exploring the topic, there has not been a study adapted for a full Swedish setting with the Nasdaq Stockholm Exchange. Frazzini and Pedersen (2014) include international benchmarks for Sweden rather than Sweden-specific measures, making it challenging to determine whether Swedish investors could attempt to exploit this anomaly. In our study, we use a more recent time-period, 2011-2023, intended to see whether trading on a beta anomaly is still relevant today. This leads to research question 1, which is whether low beta portfolios yield a positive and higher alpha compared to high beta portfolios in the Swedish market. To conduct our analysis, we categorized stocks from the Nasdaq Stockholm exchange into three equally weighted beta portfolios: low, medium, and high. We then perform monthly regressions on the returns of each portfolio using common asset pricing models throughout the sample period. We employ both rolling and constant beta methods and utilize Monte Carlo simulations to validate our findings. Our results indicate that low beta stocks produce a significantly higher alpha compared to high beta stocks over the examined period, supporting the existence of a beta anomaly.

To highlight how an arbitrageur could exploit a potential anomaly we construct a self-financing market-neutral betting against beta (BAB) portfolio, which goes long low beta assets and short high beta assets. We construct the factor by analyzing listed stocks on the Nasdaq Stockholm exchange and divide stocks into low versus high beta portfolios. This follows a similar methodology to the one outlined by Frazzini and Pedersen (2014), including a monthly reweighting and leveraging/de-leveraging of the portfolio for each month over the sample period. Consequently, our second research question examines whether a market-neutral BAB (Betting Against Beta) portfolio yields a positive alpha in the Swedish market. To investigate this, we construct the BAB portfolio using two different methods: calculating both rolling and constant betas. Our analysis reveals a statistically significant positive alpha for both methods. Additionally, Monte Carlo simulations confirm the robustness of these findings, indicating that there are opportunities to earn abnormal returns with a BAB portfolio in Sweden.

Moving on, we explore the underlying economics of the beta anomaly to see whether Frazzini and Pedersen’s (2014) explanation focused on leverage constrained institutional investors also applies to Sweden. The relevance of examining the investment behavior of institutional investors in Sweden is highlighted by their significant influence on the market (roughly 61% of the market in 2015 (Ehne, 2018)) as well as numerous EU laws that impose strict regulations on their legal compliance, financing, and risk management. Another significant benefit for conducting this analysis in Sweden is the large focus on transparency regarding stock ownership as regulated under The Swedish Companies Act (*Regeringskansliet,* 2005), which enables us to get unique insight into the types of owners and their investment behavior on the Nasdaq Stockholm Exchange. This leads to research question 3, which investigates whether investor groups in Sweden that are more constrained in terms of leverage tend to overinvest in high beta assets. We test this by looking at trends in ownership over time for those stocks with highest beta in our high portfolio as well as those stocks with lowest beta in our low portfolio. The findings indicate that pensions funds, asset management firms and mutual funds tilt their portfolios more towards high beta, potentially due to EU regulations restricting their ability to take on leverage. This highlights how explanations for the beta anomaly, such as the one by Frazzini and Pedersen’s (2014), are still relevant and contributes to a better understanding of the underlying economics of BAB factors.

Our final exploration examines how leverage constraints contribute to the beta anomaly on a macro level. We investigate whether changing funding restrictions effect the BAB portfolio's performance using the Swedish equivalent TED (STED) spread as a proxy. This leads to research question 4, which is whether more restrictive funding constraints initially reduce the BAB factor performance due to increased investment in high beta, and whether the BAB portfolio consequently receives a higher expected return as low beta becomes more undervalued. This understanding could help investors optimize their timing for investments in BAB portfolios, adjusting their strategies based on the prevailing financial conditions. We test this by regressing the monthly STED-Spread against our monthly BAB returns from research question 2 and identify that there is a contemporaneous significant decrease to BAB performance when funding constraints increase, but an insignificant relationship to future BAB returns. This indicates an opportunity for arbitrageurs to invest more/less or go long/short in the BAB portfolio from predictions on future financial conditions. However, our results do not indicate an opportunity to gain higher future returns on the BAB portfolio by trading on current financial conditions, as there is no significance to the lagged STED-Spread and BAB returns.

II. Related Literature

Our paper builds upon research related to the beta anomaly and the findings by Frazzini and Pedersen (2014). To properly understand this anomaly, it is crucial to relate it to the fundamental assumptions of risk and return in finance, including the premises of the Capital Asset Pricing Model (CAPM). It is also important to consider alternative asset pricing models such as the Fama-French three-factor (FF3) and the Fama-French-Carhart four-factor (FFC4) model, as these have shown to capture alpha from security prices more effectively than the CAPM. Thus, if significant alphas are present after accounting for these factors, we believe this strongly supports the existence of a beta anomaly that is not attributable to the omission of other relevant variables. The following sections discuss additional literature relevant for the beta anomaly, and we also conduct an in-depth review of the findings by Frazzini and Pedersen (2014).

A. Risk and Return

Modern Portfolio Theory (MPT), originally developed by Harry Markowitz (1952), provides a theoretical framework for understanding the trade-off between risk and return. Markowitz (1952) describes how well-diversified portfolios along the efficient frontier, referred to as tangency portfolios, maximize this relationship (see Graph A in Appendix C) and that, on the efficient frontier, it is not possible to increase returns without taking on more risk (Fabozzi, Gupta and Markowitz, 2002). This indicates the importance for our study to compare returns of different beta sorted portfolios while considering the risk that they assume.

B. CAPM

The CAPM, one of the foundational frameworks in asset pricing, builds on Markowitz's (1952) findings regarding risk and return. It adds to Markowitz (1952) by incorporating the concepts of the market portfolio and the risk-free rate of return, culminating in the creation of the Capital Market Line (CML) (see Graph B in Appendix C). The CML represents portfolios that optimally combine the market portfolio - all investable assets weighted by market value, serving as the tangency portfolio in this context - with a risk-free asset. To gain a higher/lower return while maximizing the Sharpe ratio (Sharpe, 1964) investors are assumed able to lever/de-lever the market portfolio, in accordance with one of the fundamental assumptions of the CAPM (Elbannan, 2015). See Appendix D for a comprehensive list of the CAPM assumptions.

C. FF3 and FFC4 Model

Fama and French (1993) found that market risk alone does not account for a significant portion of a stock's average return, highlighting how the CAPM does not explain enough of asset returns. In their analysis of a large historical dataset from the US CRSP (Center for Research in Security Prices) database, they identified two additional factors necessary for more accurate security return predictions. The first factor, Small Minus Big (SMB), is related to size, where historical data has shown a significant outperformance of small market capitalization stocks in comparison to large market capitalization stocks. Further, their second finding, High Minus Low (HML), is related to the outperformance of value stocks (high book-to-market ratio) compared to growth stocks (low book-to-market ratio)(Fama and French, 1993).

Adding to the findings of Fama and French (1993), Mark Carhart (1997) introduces a fourth factor, momentum or Up minus down (UMD), for the FFC4 model. Carhart (1997) analyzed mutual fund data from the CRSP and found that assets performing well in the recent past tend to continue performing well in the near future, and vice versa for assets performing poorly.

It is therefore apparent that the findings of Fama and French (1993) and Mark Carhart (1997) should help explain some of the alphas generated for security returns related to CAPM. However, even when controlling for these factors Frazzini and Pedersen (2014) find that there is a beta anomaly present in the market. Consequently, these findings appear insufficient to fully explain the higher alphas observed in low beta stocks compared to high beta stocks, indicating that additional reasoning must be considered to account for deviations from the CAPM.

E. Betting Against Beta (BAB)

Despite accounting for the CAPM, FF3 model, and FFC4 model, empirical evidence reveals that low-beta stocks have outperformed high-beta stocks. This suggests that the assumptions of the CAPM do not hold in the real world, and that one can observe an overvaluation of high beta stocks and undervaluation of low beta stocks. This is what Frazzini and Pedersen's article "Betting Against Beta" highlights, through data from the CRSP database for US equities, spanning 1926 to 2012. Additionally, they use the Xpressfeed Global database for 20 other international equity markets, including Sweden, from 1984 to 2012. The paper also demonstrates how a portfolio that goes long low beta stocks and short high beta stocks can generate significant positive alphas (Frazzini and Pedersen, 2014). Additionally, the paper "The Volatility Effect: Lower Risk without Lower Return" by Blitz and Van Vliet (2007) finds that the alpha spread between low and high volatility decile portfolios was at 12% per year globally from 1986-2006. Thus, this anomaly has been found over a large range of time periods and across numerous global geographies, contrary to what the efficient markets hypothesis would predict.

As discussed by Jensen, Black and Scholes (1972), one main rational explanation for the beta anomaly is due to the breach of the CAPM assumption that all investors can borrow at the risk-free rate. Research shows that investor groups like pension funds and mutual funds are restricted in the amount of borrowing they can take on and consequently, to get a higher expected return, put an overweight in more volatile assets instead of using leverage (Frazzini and Pedersen, 2014). Thus, investors are not able to maximize their Sharpe ratio, as they lack the ability to leverage the market portfolio to gain a higher expected return (Kourtis, 2016). For example, Boguth and Simutin (2018) find that time variations to leverage constraints impact asset prices through changes to the pricing kernel, where high-risk assets appreciate disproportionately to their true worth. This leads investors of such stocks to gain lower risk-adjusted returns than if they were to lever up and invest in lower risk stocks. In addition, a similar study by Jylhä (2018) showed that changes in US laws on margin requirements, which is used as a proxy for leverage constraints, lead investors to excessively tilt their portfolios towards more volatile stocks. For our Swedish setting, a large aspect to borrowing restrictions on investors are those put in place by the European parliament and the Swedish Financial Supervisory Authority (Finansinspektionen, 2018).

Building on the findings regarding leverage constraints, Frazzini and Pedersen (2014) show how this leads to a flatter Security Market Line (SML) than predicated by the CAPM. To account for this, Frazzini and Pedersen (2014) introduce a model that incorporates funding constraints, where the slope of the SML is influenced by the degree of tightness, i.e. the Lagrange multiplier (ψt), of these constraints on the average investor in the market. The equilibrium required return for a security i, is highlighted in Eq. (1) below (see Appendix A for a definition of variables).

$$E_t\left(r_{t+1}^i\right) = r^f + \psi_t + \beta_t^i \lambda_t \tag{1}$$

Additionally, the market risk premium (λ_t) in Eq. (1), is defined by Frazzini and Pedersen (2014) as in Eq. (2) below.

$$\lambda_t = E_t(r_{t+1}^M) - r^f - \psi_t \tag{2}$$

This demonstrates that when a funding constraint is prevalent ($\psi_t > 0$), the SML is flatter as securities with a beta below one will have a premium, as shown in Eq. (3), and securities with a beta above one will be discounted, as shown in Eq. (4).

$$\psi_t - \beta_t^i \psi_t > 0\,, \beta_t^i > 1 \tag{3}$$

$$\psi_t - \beta_t^i \psi_t < 0\,, \beta_t^i < 1 \tag{4}$$

Further, the relationship between a security's alpha (α) with respect to the market is demonstrated in Eq. (5). This equation highlights how a lower beta leads to a higher alpha, Frazzini and Pedersen's (2014) first prediction.

$$\alpha_t^i = \psi_t(1 - \beta_t^s) \tag{5}$$

Additionally, Frazzini and Pedersen (2014) move on to discuss how those investors who are unconstrained can take advantage of this anomaly, by building a self-financing portfolio that goes long low beta and short high beta. To construct this BAB factor, Frazzini and Pedersen (2014) use the formula represented in Eq. (6). The exact methodology for calculating weighted betas and returns is described in our methodology section.

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}(r_{t+1}^L - r^f) - \frac{1}{\beta_t^H}(r_{t+1}^H - r^f) \tag{6}$$

This leads into their second proposition, represented in Eq. (7), which portrays positive expected returns for BAB that increase with a larger spread in beta, shown in Eq. (8), and with a greater funding constraint (ψ_t) (Frazzini and Pedersen, 2014).

$$E_t(r_{t+1}^{BAB}) = \frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H}\psi_t > 0 \tag{7}$$

$$(\beta_t^H - \beta_t^L)/(\beta_t^L \beta_t^H) \tag{8}$$

Lastly, Frazzini and Pedersen (2014) predict that shocks to the portfolio constraints, or margin requirements, create short term losses for the BAB portfolio as its required return increases but then leads to long-term gains. They represent this through Eq. (9) and Eq. (10), showing that an increase in leverage constraints leads to a contemporaneous loss of the BAB factor;

$$\frac{\partial r_t^{BAB}}{\partial m_t^k} < 0 \tag{9}$$

and an increased future required return;

$$\frac{\partial E_t(r_{t+1}^{BAB})}{\partial m_t^k} > 0 \tag{10}$$

F. Our Contribution

In our study, we extended the research by Frazzini and Pedersen (2014) to a Swedish setting by examining the beta anomaly in the Swedish market between 2011 and 2023. We use a similar logic as the one outlined above, where the Lagrange multiplier accounts for the flatness of the SML, and alphas are assumed to decrease in beta (Eq. (5)). To construct our BAB factor, we use Eq. (6) but adapted with new datasets to account for a comprehensive Swedish analysis compared to Frazzini and Pedersen's (2014) more general international proxies to analyze the BAB factor in Sweden. More specifically, we use the Nasdaq Stockholm exchange, the Swedish 10-year government bond instead of the US Treasury bill as the risk-free rate and the Swedish FF3 and FFC4 model instead of general international versions. In addition, research question 4 builds on Eq. (9) and (10), but we adapt the method by Frazzini and Pedersen (2014) by using the STED-Spread instead of the US TED-Spread. Additionally, we extend Frazzini and Pedersen's (2014) analysis on underlying economics driving the beta anomaly in Sweden, by using data on the ownership structure for assets in the Swedish market. This enhances our understanding of how the investment behavior of different groups contributes to the beta anomaly, thereby expanding the general knowledge on the subject.

III. Methodology

We create beta sorted portfolios, a betting against beta (BAB) factor that goes long low beta securities and short high beta securities, analyze ownership characteristics that can help explain the beta anomaly as well as analyzing how changing funding constraints affect a potential anomaly.

A. Beta Calculation

To calculate betas, we utilize the method described by the Swedish House of Finance (Aytug, Fu and Sodini, 2020), where the beta coefficient is the sensitivity of stock "i" to the excess market return. Betas are calculated using the covariance between the excess asset return and the excess market return, divided by the variance of the excess market return (Eq. (11)).

$$\beta = Cov(r^M - r^f, r^i - r^f)/Var(r^M - r^f) \tag{11}$$

Frazzini and Pedersen (2014) analyzed the BAB factor for Sweden until 2012, and since we intend to update their findings, we collect observations from 2009 to 2023. In our methodology, we face constraints on utilizing multiple years for training data, as expanding the training period decreases the testing period. However, a too short training period could pose challenges due to a potential impact of period specific factors, such as macroeconomic conditions in specific years. To account for this, we construct betas utilizing two different methods. In the first method, referred to as "Method 1", we use a two-year training period (2009-2010) for calculating betas and then keep them constant for the remainder of the period (2011-2023). In the second method, referred to as "Method 2", we use a similar method to that of Frazzini and Pedersen (2014), regarding rolling betas over the calculation period. Using Method 1 offers a straightforward approach that is easier to implement, reduces computational complexity and facilitates our ownership and STED-Spread analysis. By keeping betas constant, it is assumed that the fundamental characteristics of assets do not change over longer periods of time, despite short-term fluctuations. However, by calculating betas only once, there is a risk that they do not accurately reflect the market dynamics during the entire period. This could cause our estimates to be biased and affect the validity of conclusions drawn about the portfolio performance. For example, most betas in our sample are calculated starting in 2009 following a period where the fall in the Swedish GDP growth was the largest since the great depression of 1929-1933 (Lindvall, 2012). However, the Swedish economy recovered quickly, bouncing back towards the third quarter of 2009, and showing a GDP growth of 6.1% in 2010 (Sveriges Riksbank, 2020). To account for any unusual results, we incorporate Method 2, mirroring Frazzini and Pedersen's (2014) beta calculations, as a robustness check to validate our approach for calculating betas. In Method 2, we calculate time-series betas over time, allowing us to adapt the betas to changes in market conditions. We acknowledge potential limitations in this method as well, such as the difficulty in determining our model's most appropriate calculation window and being unable to evaluate BAB returns for the entire first calculation window. Recognizing potential limitations inherent in both methods, we utilize both sets of betas to calculate our BAB factor and compare the resulting outcomes as a robustness check.

For Method 1, covariances between the market and the asset return are estimated on monthly data over a two-year training period between 2009 and 2010, for each individual asset in our sample. With stocks entering the market after 2009, a two-year calculation period from the moment the stock enters the market is applied. For example, if a stock enters the market in January 2015, the covariance between the market and the stock return will be calculated between January 2015 and December 2016. Due to our two-year training period for betas, stocks listed after 2021 are excluded from our analysis, as they cannot contribute to our portfolios. We also exclude delisted stocks, as we will elaborate upon in the data description. Variances for the market portfolio are estimated on monthly returns over a two-year period, using OMXS30 as a market index. Market variance used in beta calculations for stocks that entered the market after 2009 are adapted so that the market variance is calculated over a two-year period after the moment the stock was introduced to the market. Having calculated betas over a two-year training period, we keep them constant after the end of the training period. In accordance with Frazzini and Pedersen (2014), we account for outliers by shrinking our time-series beta estimates towards its cross-sectional mean, as seen in Eq. (12).

$$\hat{\beta}_i = w_i \hat{\beta}_i^{TS} + (1 - w_i)\hat{\beta}_i^{XS} \tag{12}$$

Our final betas are the weighted time series beta plus the weighted cross-sectional mean. To keep it simple and ensure comparability with Frazzini and Pedersen (2014), we follow their method of setting the weight to 0.6 and the cross-sectional mean to 1 for all periods across all assets. As the shrinking factor is the same across all periods it does not change the ranking of the betas and does not affect how securities are sorted into portfolios. On the contrary, it will impact the later calculated BAB factor, as it is calculated by using the beta to scale the long and short sides of the portfolio. Thus, noise from the ex-ante betas might affect the construction of the BAB factors. However, like

Frazzini and Pedersen (2014), we focus our inference on realized abnormal returns, which means that mismatches between ex ante and realized betas will be picked up by the realized loading in the regression. Hence, when we regress our portfolios on risk factors such as SMB, HML and UMD, the realized betas will not be shrunk as the ex-ante betas above. This means only the ex-ante betas are subject to selection bias.

For Method 2, betas are estimated using rolling regressions of excess security returns on the excess market return. Instead of monthly data, we look at daily market and asset returns, which strengthens the accuracy of covariance estimates as they improve with a greater sample frequency (Merton, 1980). The betas are estimated using Eq. (11) as in the previous method. Volatilities and correlations are estimated separately since correlations tend to move slower than volatilities (de Santis and Gerard, 1997). In accordance with Frazzini and Pedersen (2014), a five-year rolling correlation and one-year window for the standard deviations are used to estimate volatilities. Also, three-day log returns are used for correlations while one-day log returns are used for volatilities. We use the three-day log returns to account for non-synchronous trading in our correlation estimates, which should increase the credibility of our results and ensure that the BAB performance is not driven by any distortions from such an effect. Lastly, as with Method 1, a shrinking process is made to account for outliers. The same rationale regarding the shrinking factor, as applied in Method 1, also pertains to Method 2, where the shrinking process does not influence how betas are sorted into portfolios, but it does impact the ex-ante betas used for the construction of portfolios and the subsequently calculated BAB factor.

B. BAB Portfolio Construction

To construct the BAB portfolio, we follow the method described by Frazzini and Pedersen (2014). We divide the sample of assets into two portfolios: one long portfolio containing assets with low betas and one short portfolio containing assets with high betas. We sort assets by beta in ascending order, rank them, and assign them to a portfolio based on their ranking. The low beta portfolio includes all stocks with a beta below the median of their asset class, while the high beta portfolio includes all stocks with a beta above their median. These beta rankings are updated monthly. To ensure the portfolio is self-financing, we weight securities according to their beta rankings, assigning higher weights to lower beta assets in the low beta portfolio and higher weights to higher beta assets in the high beta portfolio. To formalize, let z be the $n \times 1$ vector of beta ranks $z_i = \frac{1}{4} rank(\beta_{it})$ at portfolio formation and $\bar{z} = 1_n' z/n$ be the average rank where 1_n is an n x 1 vector of ones and n the number of securities. Further, k is a normalizing constant where $k = 2/1_n'|z - \bar{z}|$. Also, our model ensures that $1_n' w_H = 1$ and $1_n' w_L = 1$. The weight of security i within the high and low portfolio is then given from the methodology shown in Eq. (13) and (14).

$$w_{H,i} = k(z_i - \bar{z})^+, \text{ if } z_i > \bar{z} \tag{13}$$

$$w_{L,i} = k(z_i - \bar{z})^-, \text{ if } z_i < \bar{z} \tag{14}$$

Both portfolios are rebalanced monthly and adjusted by leveraging the low beta portfolio and de-leveraging the high beta portfolio to maintain an ex-ante beta of one at portfolio formation. This ensures that the self-financing portfolio achieves market neutrality, and that the BAB-factor is self-financing with a beta of zero. This setup allows the overall investment to remain balanced in terms of market exposure, irrespective of individual security volatilities. The return of the BAB portfolio is highlighted in Eq. (15) and Eq. (16) defines the variables from Eq. (15).

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}(r_{t+1}^L - r_{lev}^f) - \frac{1}{\beta_t^H}(r_{t+1}^H - r_{delev}^f)\,, \tag{15}$$

where

$$r_{t+1}^L = r_{t+1}' w_L\,, r_{t+1}^H = r_{t+1}' w_H\,, \beta_t^L = \beta_t' w_L, \tag{16}$$
$$\text{and } \beta_t^H = \beta_t' w_H\,.$$

BAB portfolios are constructed, and regressions are run using both sets of betas in accordance with method Method 1 and 2.

C. Construction of Beta Portfolios

In addition to a BAB factor, we test our first research question by creating three different portfolios based on the beta characteristics of the securities in our sample. One low, one medium and one high beta portfolio. The portfolios are created through ranking the beta observations in ascending order and splitting into three equally large portfolios. We calculate monthly return and rebalance the portfolios on a monthly frequency, for both sets of betas.

D. Testing the Performance of our Portfolios

To measure the performance of the high, medium, and low portfolios, as well as the BAB portfolio, we make several OLS regressions with different risk factors. We look at the CAPM (Eq. (17)), FF3 model (Eq. (18)) and the FFC4 model (Eq. (19)). Equations (17), (18) and (19) show the methodology for the regressions, where r^{PTF} is the return of each specific portfolio (high, medium, low and BAB). The market risk premium is calculated using the market return minus the risk-free rate, while the FFC4 factors are taken from AQR's website.

$$r_t^{PTF} - r^f = \alpha^{PTF} + \beta^{MKT}(r^m - r^f) \tag{17}$$

$$r_t^{PTF} - r^f = \alpha^{PTF} + \beta^{MKT}(r^m - r^f) + \beta^{SMB} SMB_t + \beta^{HML} HML_t \tag{18}$$

$$r_t^{PTF} - r^f = \alpha^{PTF} + \beta^{MKT}(r^m - r^f) + \beta^{SMB}SMB_t + \beta^{HML}HML_t + \beta^{MOM}MOM_t \quad (19)$$

E. Ownership Structure

We test our third research question by looking at the ownership structure of the stocks within our sample. We refine our dataset to isolate the top 15 entities with the highest and lowest betas according to the betas computed in Method 1. This is to avoid the recategorization of low, medium, and high on a monthly basis, which we would have done using method 2. Subsequently, we extract information on the 15 principal investors in each of these 30 companies from the database. We categorize the owners into investor types and investigate the aggregate value invested in low and high beta stocks, segmented by investor class. Recognizing the potential disparity in the scale of low versus high beta firms, we apply a market capitalization-weighted approach to their investments throughout the period under review. The analysis is limited to the period between 2011 and 2019 to isolate negative COVID-19 externalities, such as the effects of a short-term increased government ownership in equities during COVID-19 (OECD*,* 2020). We compute the total value invested by each category of investor annually from 2011 to 2019, as well as the average investment into high versus low betas per year. These yearly figures are averaged to yield an overarching view of the investment held by the distinct groups over the specified timeframe. Additionally, we examine variances within investor groups to assess the homogeneity of our samples. This analysis helps determine whether we can infer any consistent behaviors or if the observed variances suggest random behavior.

F. Implications from Tightening Funding Conditions

The concluding segment of our methodology examines research question 4, by regressing the BAB-factor against a STED-Spread to assess how periods of tightening funding conditions impact the return of the BAB-factor. This approach aligns with Frazzini and Pedersen's (2014) methodology, but we adapt it to a Swedish context by using the Swedish 3-month government bond and the 3-month STIBOR rate for calculating the STED-Spread. Similar to the ownership analysis, we use a test period of 2011-2019, which intends to limit the effects of unusual macroeconomic policies observed during COVID-19. For example, the Swedish Central Bank introduced policies like reducing the overnight lending rate to banks and increased access to liquidity to stimulate the economy during this period (Sveriges Riksbank*,* 2023), which can significantly impact the STED-Spread. Therefore, we want to exclude these temporary irregular market conditions from our funding conditions analysis.

IV. Data Description

Table 1 shows summary statistics for the data we use throughout the thesis. When calculating asset returns, covariances and correlations we use Refinitiv Eikon's database to get closing prices on all primary and active stocks listed on the Nasdaq Stockholm main market from 2009 - 2023. This enables us to include a training period to calculate betas as well as a sufficiently large span of years to conduct an analysis. After cleaning the data (as described in the methodology section), our total dataset consists of 319 equities, which is 42 stocks less compared to the 362 listed stocks on Nasdaq Stockholm as of December 2023 (*NASDAQ NORDIC,* 2023). Additionally, stock data from Refinitiv Eikon does not include delisted stocks. Thus, stocks that were present in the data from 2009 but delisted before 2024 were not part of our sample. We recognize that this approach may limit our portfolio diversification, as not all equities are included. To explore whether this impacts the returns of our portfolios, we conduct Monte Carlo simulations to observe the effect of stocks dropping out of the market (see Appendix B). The main benefit of using only the primary market is that our data is not subject to highly volatile stocks such as penny stocks. However, a drawback of this exclusion is that abnormal returns tend to be overrepresented in penny stocks or lottery-like stocks. (Bali, Brown, Murray and Tang, 2017).

For the risk-free rate, we use the monthly Swedish government 10-year bond yield from 2009 - 2023, which is available in the Swedish Central Bank's (Riksbanken) database. The 10-year bond yield is used to get the most accurate term sheet, as our regressions will be over a 13 and a 9-year period. To capture a proxy for the Swedish market, we look at the monthly return of OMX Stockholm 30, consisting of the 30 most traded stocks on the Stockholm Exchange.

In estimating alphas for the three portfolios and our BAB factor, we collect data on excess market return, size (SML), value (HML) and momentum (UMD) factors for Sweden. Monthly excess market return between 2009 and 2023 are computed taking the market return (OMXS30) minus the risk-free rate (10-year Swedish Government Bond). SML, HML and UMD can be found on AQR's website, where they regularly post updated monthly factors for a list of countries, including Sweden. It is important to note that Table 1 shows an unusual trend over the tested period where both HML and SMB show negative returns in Sweden.

For the STED-Spread, we look at the difference between the interest rate banks can lend to each other over a three-month time frame and the interest rate at which the government is able to borrow money for a three-month period. To construct the STED-Spread, we use the 3-month government bond and the 3-month STIBOR-rate, which can be found in Riksbanken's and the Swedish Financial Benchmark Facilities databases.

Finally, we use the Holdings database to access ownership details of the companies within our research scope. We apply the Holdings filter specifically targeting Small-, Medium-, and High-cap stocks listed on the Swedish exchange, comprising approximately 370 stocks. These are matched with our existing dataset used to calculate betas. We refine our dataset to include only those stocks that have been active in the market since 2009, aligning with our intent to train betas over a two-year span, subsequently facilitating analysis from 2011 to 2019. The refined dataset is divided into seven distinct classifications: Mutual Funds, Asset Management Firms, Pension Funds, Insurance Funds, Holding Companies, Strategic Acquirers, Individual Investors and Other Investors. See Appendix E for the classification of the different investor types.

Table 1: Summary of Variables

Variable	Frequency	Date Start	Date End	N	Min	Max	Mean
Stocks (NASDAQ)	Daily	2009	2024	1431920	-0.9820	6.1313	0.0005
Stocks (NASDAQ)	Monthly	2009	2024	46241	-0.9852	5.5697	0.0135
RF 10-year	Monthly	2009	2024	183	-0.0036	0.0362	0.0142
RF 3-month	Monthly	2009	2024	180	-0.0079	0.0410	0.0043
STIBOR 10-year	Monthly	2009	2024	180	-0.0046	0.0439	0.0091
STIBOR 3-month	Monthly	2009	2024	180	-0.0062	0.0411	0.0075
MKT (OMXS30)	Daily	2009	2024	3826	-0.1057	0.0709	0.0004
SMB	Monthly	2009	2024	156	-0.0792	0.0799	-0.0016
HML	Monthly	2009	2024	156	-0.0895	0.0976	0.0003
UMD	Monthly	2009	2024	156	-0.1063	0.1288	0.0119
Holdings	Yearly	2011	2019	664	-	-	-

Table 1 shows summary statistics for the data used in our research. The summary statistics include the dataset, frequency, start date, end date, number of observations, minimum value, maximum value, and mean value. Number of observations corresponds to the number of dates multiplied by observations per date, in the data for all datasets.

V. The Beta Anomaly in the Swedish Market

The following section presents the results of research questions 1 and 2, followed by a section analyzing our findings. We display results in both scenarios of using Method 1 and 2 when calculating betas. To determine significance, we use a confidence level of 95%, resulting in a p-value of less than 0.05. The p-values from our regressions are incorporating t-values and degrees of freedom, and thus we can consider them to determine significance.

A. BAB Factor Shows a Positive Alpha that Decreases in Beta

To test research questions 1 and 2, we regress the excess return of our three beta sorted portfolios and the BAB portfolio on the different factor models. This enables us to consider alphas with respect to the market (MKT), size (SMB), value (HML), and momentum (UMD) factors.

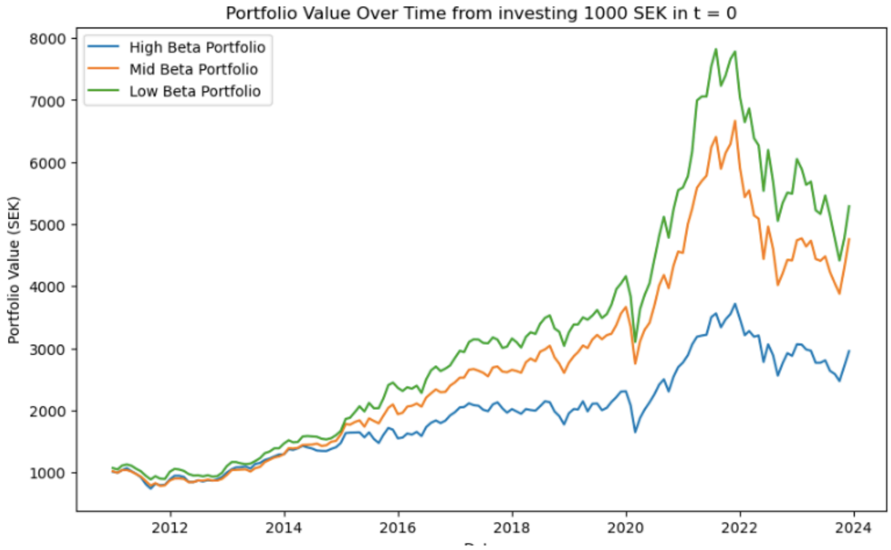
Table 2 demonstrates the result from our regressions using Method 1 betas. From the output, it is visible that the BAB portfolio shows positive and significant alphas under all controls. Looking at the high, medium, and low beta portfolios, we find statistical significance for a positive alpha in the low and mid beta portfolios for all the factor models. For the high beta portfolios, we find a significant alpha for the FFC4 model but not under the other models. From Table 2, it is also evident that alpha increases as beta decreases under all controls. Looking at Sharpe ratios, they are higher for low betas compared to high betas, implying a higher return for the same level of risk. Graph 1 shows the cumulative return from investing 1 000 SEK at time t = 0 in each beta sorted portfolio, rebalanced each month. The graph shows how low beta portfolios outperform mid and high beta portfolios, and our regressions suggest that this outperformance is still present when considering risk.

Table 2: BAB and Beta Portfolios Using Method 1 Betas

	BAB	**High Beta**	**Mid Beta**	**Low Beta**
CAPM Alpha	0.0559	0.0081	0.0111	0.0114
	0.019	0.063	0.008	0.009
FF3 Alpha	0.0633	0.0085	0.0118	0.0126
	0.005	0.053	0.004	0.003
FFC4 Alpha	0.0855	0.0123	0.0147	0.0165
	0.001	0.008	0.001	0.000
Volatility	0.295	0.054	0.051	0.054
Sharpe Ratio	0.206	0.158	0.224	0.226

Table 2 displays regressions results, volatility and Sharpe ratio using Method 1 betas. We sort betas into three equally weighted portfolios consisting of high, medium, and low betas. Alphas are calculated through OLS regressions where the monthly excess return of the portfolio is the dependent variable, and the factors in the factor models the independent variables. The factor in CAPM is market excess return, the factors in FF3 are market excess market return, SMB and HML, and the factors in FFC4 are excess market return, SMB, HML and UMD. P-values are shown under each alpha value. Sharpe ratios is annualized over the calculation period. See Tables 8-10 in Appendix F for exact correlations between each portfolio and specific factors.

Graph 1: Investing 1 000 SEK in Method 1 Beta Portfolios at Time t = 0



The graph displays the cumulative return from investing 1 000 SEK in each beta sorted portfolio at time 0 (2011). We divide our stocks into three equally large portfolios, where the Low Beta Portfolio consists of stocks with lowest betas, Mid Beta Portfolio consists of the second lowest stocks and High Beta Portfolio consists of all stocks with the highest betas.

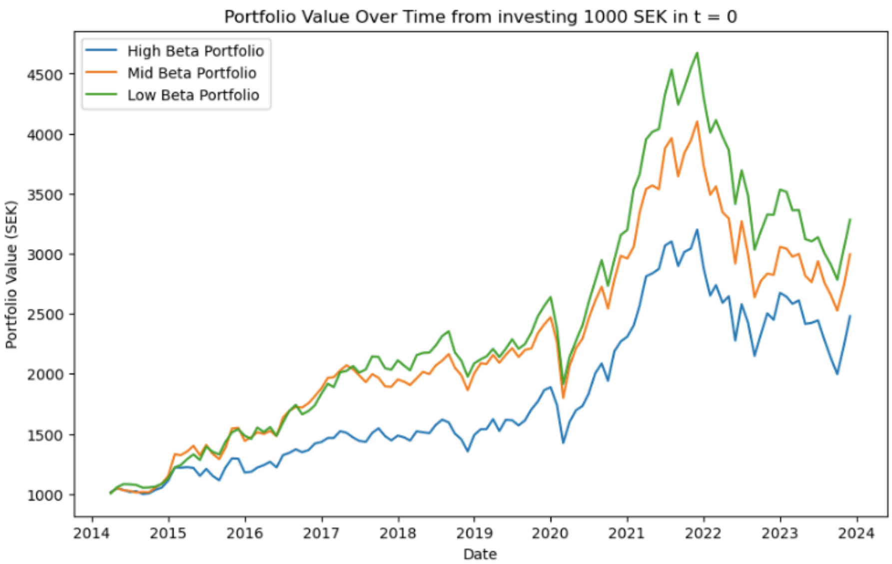
To strengthen the robustness of our method, we test research question 1 and 2 with betas from Method 2. Using this method, we find statistical significance for positive alphas generated by the BAB factor across all models (as shown in Table 3). Additionally, the alphas for the low and medium beta portfolios are positive and statistically significant in all models. We do not find significance for the high beta portfolio with the CAPM and FF3 models. However, we observe a significant alpha with the FFC4 model, consistent with the results from Method 1. With all models except FFC4, we see an increase in alpha as beta decreases. Importantly, across all models, the significance of the alpha is greater the lower the beta. Additionally, the Sharpe ratio declines as beta increases, further suggesting outperformance by the low betas over high. Lastly, Graph 2 plotting the cumulative return of high, medium, and low beta portfolios over time shows how the low beta portfolio seems to offer a higher return relative to the high beta portfolio. However, compared to Graph 1 with constant betas, Graph 2 shows a closer relationship between the low and mid beta portfolios. Despite this, the low beta portfolio still clearly outperforms the mid beta portfolio.

Table 3: BAB and Beta Portfolios Using Method 2 Betas

	BAB	**High Beta**	**Mid Beta**	**Low Beta**
CAPM Alpha	0.0155	0.0092	0.0108	0.0113
	0.004	0.083	0.040	0.022
FF3 Alpha	0.0166	0.0096	0.0115	0.0121
	0.001	0.069	0.028	0.012
FFC4 Alpha	0.0149	0.0144	0.0149	0.0144
	0.005	0.010	0.008	0.005
Volatility	0.057	0.056	0.056	0.052
Sharpe Ratio	0.281	0.167	0.200	0.223

The Table displays regressions results, volatility and Sharpe ratio using Method 2 betas. We sort betas into three equally weighted portfolios corresponding to high, medium, and low betas. Alphas are calculated through OLS regressions where the monthly excess return of the portfolio is the dependent variable, and the factors in the factor models the independent variables. The factor in CAPM is market excess return, the factors in FF3 are market excess market return, SMB and HML, and the factors in FFC4 are excess market return, SMB, HML and UMD. P-values are shown under each alpha value. Sharpe ratios are annualized over the calculation period. See Tables 11-13 in Appendix F for exact correlations between each portfolio and specific factors.

Graph 2: Investing 1 000 SEK in Method 2 Beta Portfolio at Time t = 0



The graph displays the cumulative return from investing 1 000 SEK in each beta sorted portfolio at time 0, being 2011. We divide our stocks into three equally large portfolios, where the Low Beta Portfolio consist of the stocks with lowest betas, the Mid Beta Portfolio of the stocks with the second lowest betas and the High Beta Portfolio consist of all stocks with the highest betas.

B. Analyzing the Performance of Low vs High Beta and the BAB Factor

It is evident that our results show strong support for a beta anomaly in Sweden using both Method 1 and 2, similarly to what Frazzini and Pedersen (2014) found in the US. To test the robustness of these findings, we isolate the years from 2020 to 2023 and find similar results, suggesting credible results even when accounting for potential COVID-19 effects. Interestingly, we discover this anomaly even when excluding low-quality stocks, as all securities analyzed are on the Nasdaq Stockholm exchange. Bradrania, Veron and Wu (2023) investigate the impact of high-quality versus junk (low-quality) stocks on the beta anomaly and find that the beta anomaly is significantly larger for junk stocks. Their results hold for several country portfolios, including Sweden which highlights that an even larger effect may be found if we were to consider the entire stock population in Sweden.

To further motivate our findings, we conduct Monte Carlo simulations (100 simulations) where we randomly exclude 20% of stocks for each month. This is to simulate delisting from the dataset, and we can observe how it impacts our results. Using a 20% threshold represents a more extreme case of delisting, ensuring that the performance of the BAB strategy remains consistent for a narrow sample and during periods with a high rate of securities leaving the exchange. The exact findings can be seen in Appendix B and show that the mean and median alphas of BAB returns remain positive and significant under all controls for both method 1 and 2 betas. This support increases the validity of our findings as it reduces the potential effect of having too little diversification due to delisted stocks. However, it is worth mentioning that for some simulations the alphas did not remain significant, which can be observed through the max p-values not remaining under the 5% threshold for all controls.

VI. Who owns high/low beta stocks?

Our research further investigates trends in holding characteristics across different investor groups. Building on the finding of a beta anomaly in the Swedish market, we employ holdings data to offer insights into why the BAB factor works in the Swedish market. We begin by presenting the outcomes of research question 3, followed by a detailed analysis of our findings. We analyze the owners of the highest and lowest beta stocks with regards to the betas calculated during the initial period from 2009 - 2020 with Method 1 betas. We deem this sufficient considering our similar results for a beta anomaly using both Method 1 and 2 betas.

A. Holdings Data

Table 4 summarizes our findings from analyzing the yearly average market cap weighted investment, into high versus low beta stocks over the period between 2011 - 2019. The ownership structure for the different investor types in our sample indicates that strategic acquirers, mutual funds, individual investors, and asset management firms exhibit the greatest absolute difference in ownership between low and high beta stocks. Specifically, mutual funds and asset management firms prefer high beta stocks whereas individual investors and strategic acquirers show a preference for low beta investments over the examined period. Further, pension funds, insurance funds and other investors show a smaller difference between their preferences for beta, but for all these three groups we see more of a tilt towards high securities.

Table 4: Ownership Percentages for Low and High Betas

Investor Type	Low Betas	High Betas	Abs. Diff	Ownership %
Other investors	36%	64%	29%	3.4%
Strategic acquirers	77%	23%	54%	5.8%
Holding companies	73%	27%	45%	1.1%
Individual investors	78%	22%	55%	27.8%
Insurance funds	45%	55%	10%	7.7%
Asset management firms	24%	76%	53%	16.9%
Mutual funds	22%	78%	56%	15.5%
Pension funds	41%	59%	17%	21.7%

Table 4 presents the market-cap weighted average ownership across different investor types, segmented into low and high beta categories. The percentages show how much of the group's capital is invested in high versus low betas. It displays both the absolute differences in investment between the low and high beta groups and the corresponding percentages of ownership.

B. Analyzing Ownership Percentage

The following section examines the trends observed in the data from our ownership analysis. When analyzing ownership percentages, we impose specific limitations on our analysis. First, the category labeled "other investors" consists of a diverse array of entities, ranging from labor unions to universities, each serving different functions. Given the varied nature of this group, we choose to exclude them from our ownership analysis. Second, the relatively low ownership percentages of the strategic acquirers and holding companies at 5.8% and 1.1%, respectively, along with their large heterogeneity in investment preferences, we choose to also exclude these two groups from our analysis. Instead, we concentrate our analysis on the other five investor types, being asset management firms, insurance funds, individual investors, pension funds, and mutual funds. It is worth highlighting that our analysis did not include data on retail investors. Instead, the individual investors in our study are predominantly wealthy individuals or corporate personnel with "skin in the game". This means that a portion of these investors probably have not actively purchased the stocks but instead received them as part of stock compensation for their involvement with the companies. Consequently, drawing conclusions about the effects of leverage constraints on these investors is challenging. Therefore, our focus will primarily be on institutional forces rather than individuals. However, given the significant presence of individual investors in the Holdings data, we will still analyze their behavior to see if any meaningful insights can be found.

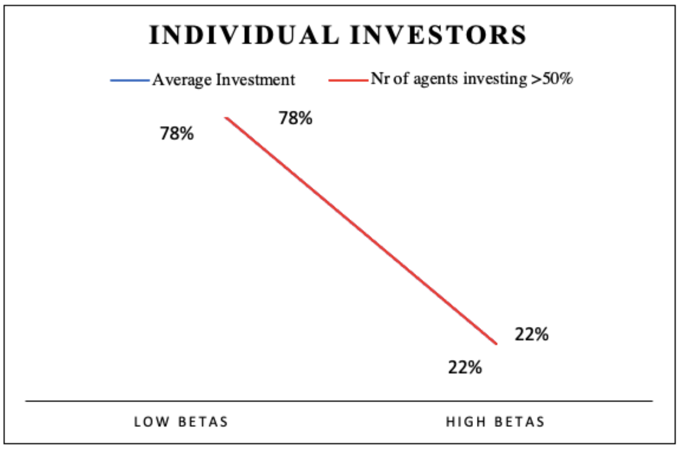
C. Individual Investors

Graph 3 illustrates that individual investors allocate 78% of their portfolios to low beta stocks and 22% to high beta stocks. The sample displays some degree of variability in portfolio tilting, evident in the 22% who allocate more to high beta stocks compared to the majority, who favor low beta stocks.

These findings would go against Frazzini and Pedersen's (2014) predictions, as individuals are leverage constrained due to margin requirements from banks. Nevertheless, it's important to consider that our findings may be attributed to our sample being comprised of only high-net-worth individuals, as all participants are among the 15 largest Swedish investors in the companies under analysis. Such high-net-worth individuals typically own large amounts of equity and therefore cannot be classified as leverage constrained in the same way as the typical retail investor. This is a limitation of the data available on Holdings, as we cannot see the behaviors of typical, more small-scale retail investors.

Additionally, it is important to consider that large shareholders in a company typically have a great deal of involvement in the company. For example, there might be board members or people from senior management present in our data, who choose to invest from their private information (Aboody and Lev, 2002). Research also shows that many heavily invested individuals are so from receiving stock options at the company they work for (Cremers, Driessen, Maenhout and Weinbaum, 2009). Thus, the nature of these high-net-worth individuals' large stake in a company could be driven by private information or "skin in the game" rather than a decision based on an asset's volatility. This would explain why we do not see a larger tilt towards high beta for this group. For example, from our data we can see that in the high beta group, the largest shareholder of individuals at New Wave Group in 2016 is Torsten Jansson, who is the founder and CEO of the company since 1990. Additionally, in the low beta group, we for instance see that the largest individual shareholder at the company Abliva in 2017 was Eskil Elmér who has been the Chief Scientific Officer at the company from 2008-2024. Alternatively, other explanations may be influencing these outcomes. For instance, it is possible that low beta companies are offering more equity as part of their compensation packages. This presents a promising direction for future research within the scope of this topic.

Graph 3: High vs Low betas for Individual Investors



The graph shows the average invested fraction in high versus low betas between 2011 and 2019 by individual investors, as well as the fraction of investors investing more than 50% into high or low betas.

D. Asset Management Firms

As portrayed in Graph 4, there is a 52% difference in the average ownership in high beta compared to low beta entities for the asset management firms over the sample period. On average, the group invests 76% in high beta firms and 24% in low beta firms. Of all the capital invested, asset management firms account for 16.9% (Table 4), implying that they are one of the biggest investors. Upon examining the sample of asset management firms, their investment behavior appears relatively homogenous. When analyzed the in-sample variance in holding characteristics by calculating the yearly market cap adjusted average ownership percentage, our findings indicate that 65% of the firms allocate more than 50% of their capital invested to high-beta companies, suggesting a preference for high beta stocks. Also, the 35% investing more than 50% into low beta entities only account for about 18% of the overall invested capital by the group, explaining the steeper average investment curve. Graph 5 displays the portion of average investment per year into high versus low beta stocks for asset management firms, where we can observe a relatively consistent pattern where high beta stocks are favored over time.

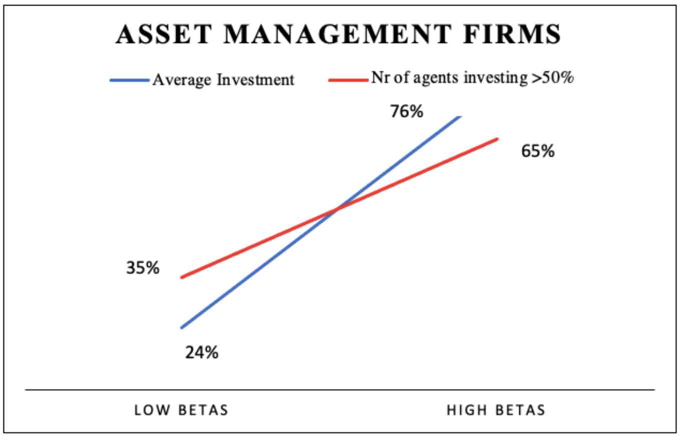
When investigating the market forces influencing the observed behavior, a potential driver for the investment patterns in favoring high beta firms could stem from European regulations such as the Capital Requirements Regulation (CRR). The law applies to a wide range of financial institutions, including credit institutions and asset management firms. It sets out prudential requirements these entities must meet, focusing particularly on the quality and quantity of capital to ensure financial stability and protect investors. The CRR includes a leverage ratio as a supplementary measure to the risk-based capital requirements, which according to the European parliament and the council of the European union is intended to become a binding requirement, ensuring that all institutions must maintain a minimum standard of non-risk-based capital against their total exposures

(Official Journal of the European Union, 2013). The regulatory capital constraints, including a maximum leverage ratio, impose limits on asset management firms' capacity for excessive leverage. Consequently, they may move towards riskier assets in pursuit of potentially higher returns on equity. This risk-return tradeoff, managed under the constraints of the Capital Requirements Regulation (CRR), is grounded in the fact that higher beta stocks inherently entail greater returns alongside increased risk, as outlined by Lundblad (2007). Thus, it could be a strategic choice for asset management firms to invest in stocks where their return on equity should be increased, especially when their leverage is restricted.

Also, since CRR is ensuring that firms hold sufficient capital against their investments, the regulations might encourage more calculated risk-taking, being another possible explanation for the skewness towards high beta investments. For example, due to the CRR regulations, a firm might aim to maximize the return per unit of exposure. Since the leverage ratio limits total exposure but not the risk or return of that exposure directly, choosing assets with higher expected returns (like high beta stocks) can be a move to optimize returns on limited allowable leverage. Such behavior by significant market participants could influence the BAB factor. If many asset management firms adopt a similar strategy, the trend could help explain the beta anomaly observed in the Swedish market. When investors systematically overinvest in high beta stocks, it drives up the value of securities, often higher compared to the underlying fundamentals (Becker and Ivashina, 2015). Such consistent favor for high-beta assets, could signal a departure from market efficiency as outlined by conventional financial theories. Looking at the yearly average return from our BAB factor, we observe an increase from 3.24% in 2012 to 11.11% in 2013, when CRR was introduced. Additionally, on a more detailed level, when CRR was introduced in June of 2013 (Official Journal of the European Union, 2013), the average BAB return went from 2% before June to 7% after June in 2013[1].

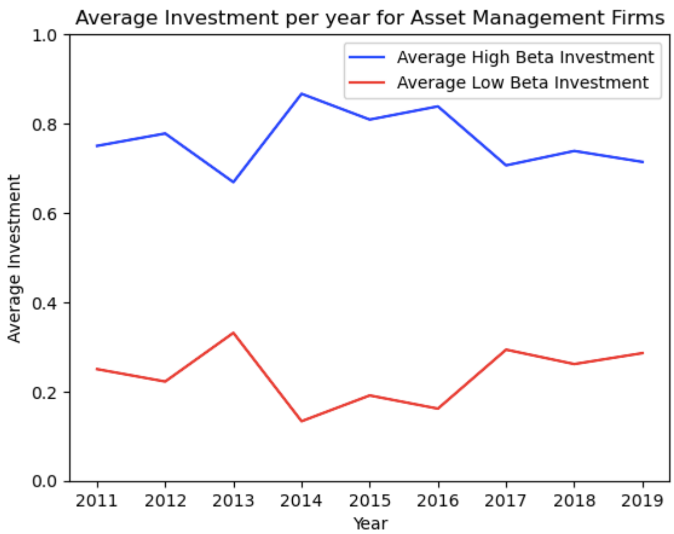
[1] Numbers are calculated by looking at the average monthly BAB return with Method 1 betas before June 2013 and after June 2013. That is, the average BAB return between Jan 2011 and Jun 2013 was 2% while the average BAB return between Jul 2013 and Dec 2023 was 7%.

Graph 4: High vs Low Betas for Asset Management Firms



The graph shows the average invested in high versus low betas between 2011 and 2019 by asset management firms. That is, of all the average invested capital between 2011 and 2019, how much is invested in high versus low betas. In addition, the graph shows the fraction of asset management firms investing more than 50% of their capital invested into our firms in high versus low beta entities.

Graph 5: Yearly Average Investment from Asset Management Firms



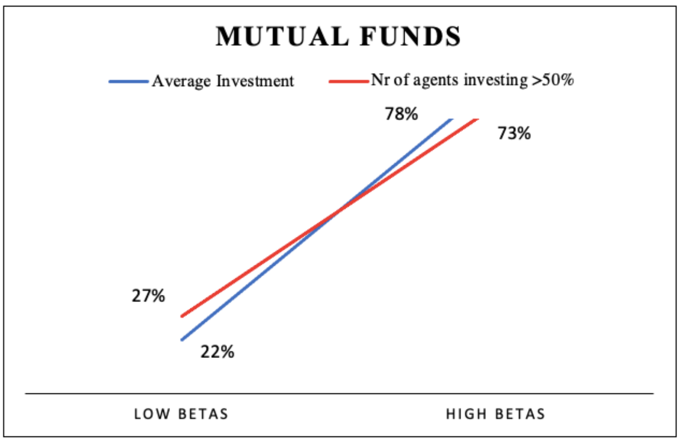
Graph 5 displays the fraction of average investment into high versus low beta firms per year, of all the capital invested by asset management firms in our sample.

E. Mutual Funds

Graph 6, highlights how mutual funds invest on average 78% in high beta entities and 22% in low beta entities, resulting in an absolute difference of 56%. Examining the inter-sample variance, we observe that 27% of the companies in our sample allocated more than 50% of their investments to low-beta firms. In contrast, the remaining companies directed at least half of their investments to high-beta firms. Like the asset management firms, the capital directed toward low-beta investments by these companies is a minor portion of the group's total invested capital. Specifically, within mutual funds, such investments represent about 4% of the total, indicating that these seven firms are in the minority and deviate from the group's predominant investment behavior.

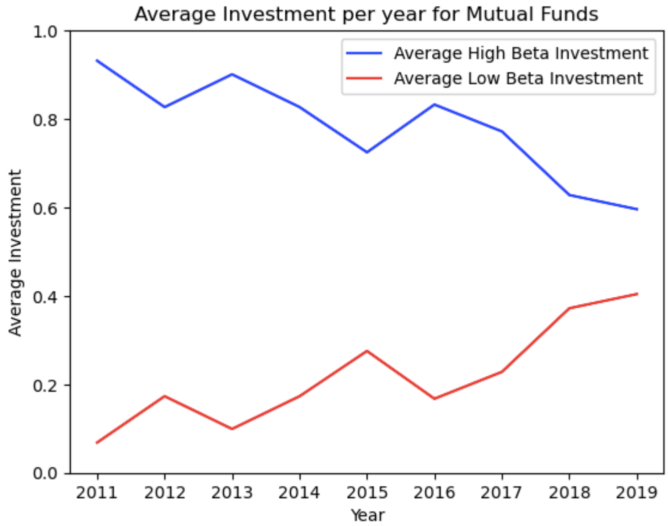
Like asset management firms, European regulations restrict mutual funds from assuming excessive leverage, which likely influences their investments. The Undertakings for Collective Investment in Transferable Securities (UCITS) regulation limits the ability of mutual funds to take on leverage. Specifically, UCITS restricts mutual funds to only borrowing up to 10% of their assets and to use borrowing only for temporary and limited purposes (Official Journal of the European Union, 2009, Directive 2009/65/EC). This might imply that mutual funds are seeking to adopt a strategy where they are choosing assets with higher expected returns (like high beta stocks) to optimize returns on limited allowable leverage. Boguth and Simutin (2018) propose a measure for the tightness of leverage constraints and show that mutual funds switch to riskier assets when leverage constraints tighten. When they are prohibited from using explicit leverage, they take on leverage implicitly by investing in high beta stocks. The same phenomena seem to apply for our Swedish setting, where we observe mutual funds being restricted in their leverage and investing a higher portion in high beta stocks. Also, Graph 7 reveals an interesting trend where the gap between the average investment in high and low beta stocks seems to decrease over time. This trend could hint at a possible shift in the group's investment approach in the future, offering ground for further research.

Graph 6: High vs Low Betas for Mutual Funds



The graph shows the average invested fraction in high versus low betas between 2011 and 2019 by mutual funds, as well as the fraction of mutual funds investing more than 50% of their capital invested into our firms in high versus low beta entities.

Graph 7: Yearly Average Investment for Mutual Funds



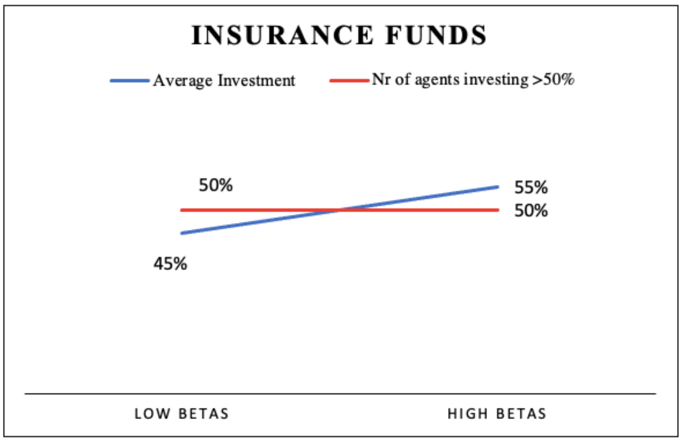
The graph displays the fraction of average investment into high versus low beta firms per year, of all the capital invested by mutual funds.

F. Insurance Funds

Graph 8 shows that on an average group level, insurance funds invest more in high beta (55%) compared to low beta (45%). This group exhibits much variation within its ranks. Analyzing the market cap weighted average investment from each fund in our sample, half of the funds allocated more than 50% of their total capital invested in our sample companies to low beta firms, while the other half direct more than 50% into high beta firms. This indicates a diverse group without a clear bias towards holding either high or low beta firms. Moreover, our data shows that the greater investment in high beta stocks across the group appears to be influenced by a few members. Additionally, Graph 9 indicates that the average investment in high and low beta stocks has remained relatively stable throughout the analyzed period.

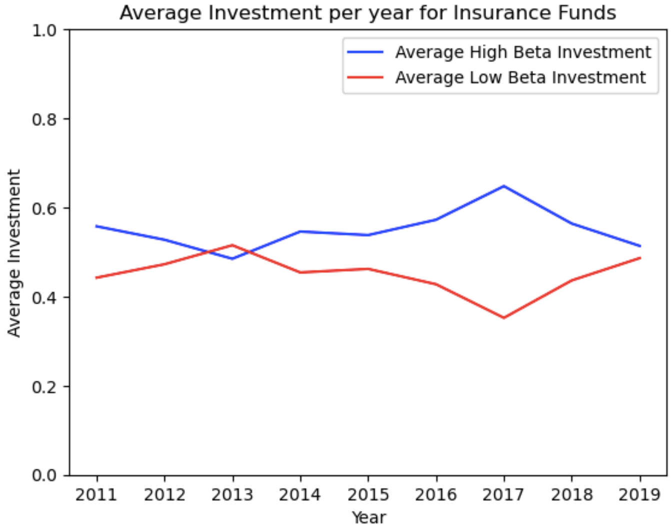
When analyzing the behavior from insurance funds, we focus on the Solvency 2 Directive in EU laws. The Directive was introduced in 2009 and imposes that insurance companies face several quantitative requirements. For instance, they must abide by Minimum Capital Requirements (MCR), which entails holding a minimum amount of cash to avoid regulatory intervention. Further, they must abide by Solvency Capital Requirements (SCR), which is a level of capital that an insurance company must hold to cover expected losses over a one-year period with a confidence level of 99.5%. In addition to these cash requirements, these companies must closely align their assets and liabilities due to requirements for Asset Liability Management. This alignment ensures that cash flows from assets can adequately meet the payment obligations from liabilities at any given time (Official Journal of the European Union, 2009, Solvency II Directive). Thus, we see that EIOPA, part of the European System of Financial Supervision, requires insurers to always maintain a significant amount of cash at hand as well as a restrictive liability to assets ratio. These constraints would lead us to predict more of a tilt towards high beta for insurance funds, which is partly what we find in the total amount invested. However, we see that many insurance funds are still invested in low beta firms, which could be explained by other requirements related to the second pillar of the Solvency 2 Directive. The second pillar requires insurers to continuously conduct an "Own Risk and Solvency Assessment (ORSA)", where systematic risks need to be evaluated and limited (Official Journal of the European Union, 2009, Solvency II Directive). These limits would encourage a movement away from riskier high beta investments into less risky low beta securities. Thus, despite constraining insurers on leverage, they are also constrained by limits to the allowed systematic risk. This would make it challenging for insurers to tilt their portfolio towards higher beta to gain higher returns. However, the difficulty in assessing the exact impact is highlighted through the heterogeneity of the funds in our sample, making it difficult to draw any conclusion regarding the group's investment behavior.

Graph 8: High vs Low Betas for Insurance Funds



The graph shows the average invested fraction in high versus low betas between 2011 and 2019 by insurance funds, as well as the fraction of insurance funds investing more than 50% of their capital invested into our firms in high versus low beta entities.

Graph 9: Yearly Average Investment by Insurance Funds



The graph displays the fraction of average investment into high versus low beta firms per year, of all the capital invested by insurance funds.

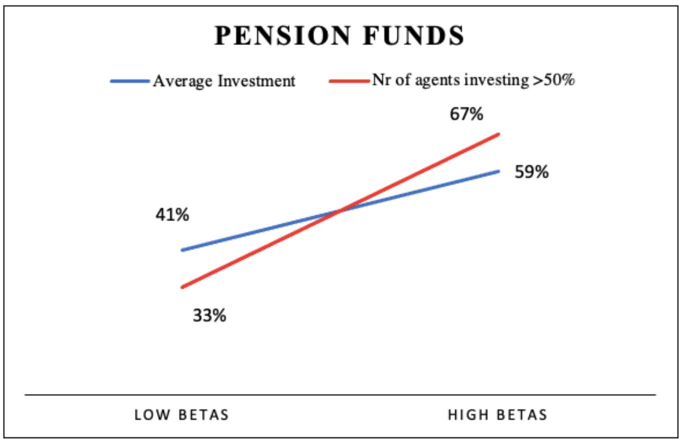
G. Pension Funds

Graph 10 demonstrates that pension funds on average invest 59% into high beta stocks compared to 41% for low beta stocks. Examining the variance within the sample, we find that 67% of the firms allocate more than 50% of their capital to high beta firms, whereas 33% invest more than 50% of their capital in low beta firms. Notably, the average investment of 41% in low beta firms is significantly influenced by a single large outlier, which allocates 68% of its capital to low beta firms and, when adjusted for market capitalization, represents 40% of the total capital invested by the companies in our sample. Therefore, despite some intra-sample variance there is a general trend of larger high beta investments, which is highlighted by such outliers driving up the share invested in low beta.

The nature of these investment decisions can be analyzed through the Institutions for Occupational Retirement Provision (IORP) Directive II, which aims to improve the risk management, transparency, and governance of pension funds. Within the directive there is a "Prudent Person Rule", which describes how pension funds are required to invest with prudence, diligence and avoid excessive risk-taking. This rule strictly limits the use of derivatives for investment practices, which thus imposes constraints on leverage. Further, the directive mandates that pension funds have proper risk-management processes in place. This incorporates the need to continuously evaluate the risks of their investment portfolios, including those associated with the use of leverage. The directive also enforces pension fund managers to hold a highly diverse portfolio, without exposing it too much to one type of risk (Official Journal of the European Union*,* 2016). Therefore, laws imposed on pension funds that are limiting the amount of leverage they can use, leads us to expect a higher investment in high beta stocks. These predictions are supported in research from Christoffersen and Simutin (2017), who find that pension fund managers are often evaluated in reference to a benchmark, and to beat these benchmarks the fund managers tilt their portfolios more towards high-beta stocks and away from low-beta stocks, even if that means a higher level of risk.

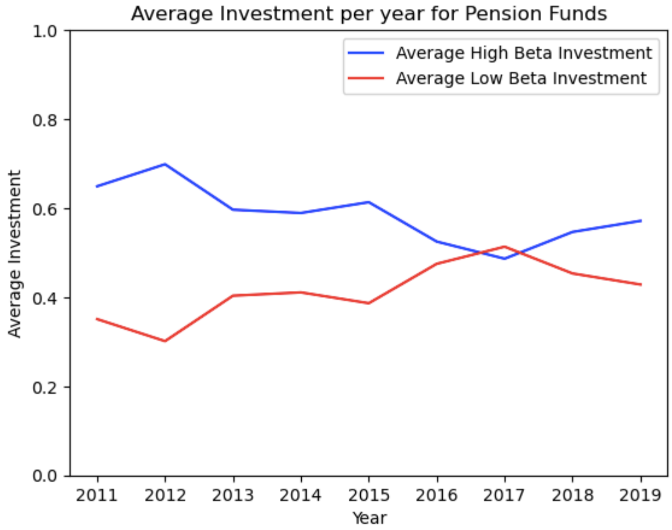
However, our data indicates that even though there is a clear shift towards high beta stocks, this trend is only moderate. One possible explanation for this is the nature of the IORP II Directive, imposing risk management regulations. For example, the regulation to limit the overall risk in their portfolios would indicate moving away from more risky securities (high beta stocks) and could explain why we observe that 33% of pension funds invest more in low beta companies, despite being constrained regarding leverage. Graph 11 shows how the average investment into high beta stocks for pension funds decreased until the end of 2016 but then increased for the rest of the period, which might be a consequence of the introduction of the IORP II Directive in December 2016 (Official Journal of the European Union*,* 2016). Thus, the investment behavior of pension funds somewhat mirrors that of insurance funds, largely due to both being governed by regulatory frameworks that have many similarities. However, the IORP II directive is less stringent with systematic risk-taking compared to the Solvency II directive, which may explain why pension funds lean more towards high beta firms compared to insurers. In general, the high ownership percentage of 22% (Table 5) and the preference for high beta assets shown in our data, could imply that pension funds are one institutional force behind the creation of a beta anomaly, due to an overinvestment in high beta assets.

Graph 10: High vs Low Betas for Pension Funds



Graph 10 shows the average invested fraction in high versus low betas between 2011 and 2019 by pension funds, as well as the fraction of pension funds investing more than 50% of their capital invested into our firms in high versus low beta entities.

Graph 11: Yearly Average Investment by Pension Funds



Graph 11 shows the fraction of average investment into high versus low beta firms per year, of all the capital invested by pension funds.

H. Hedge Funds & Leveraged Buy Out Firms

Two groups of investors that we have not touched upon and operate under different regulatory environments compared to those discussed above are Hedge Funds and LBO firms. Hedge Funds are subject to regulatory oversight, but this is mainly related to fraud and the application of systemic risk. Thus, they are not as tightly controlled regarding the use of leverage, which is typically applied through derivatives like futures, options, forwards, and swaps (Ang, Gorovyy and van Inwegen, 2011). Additionally, Leveraged Buy Out (LBO) firms, which are a type of private equity firm that apply a significant amount of leverage to raise their rate of return, have significantly less stringent restrictions for how much leverage they can take on. One of the main reasons for this is that they can use the acquired company's assets as collateral when taking on debt (Shivdasani & Wang, 2011). These two types of investors could be viewed as arbitrageurs and candidates that exploit the beta anomaly. Namely, they could apply leverage to less risky low beta securities, to gain higher risk-adjusted returns. Numerous researchers have found this to be the case, and for instance the paper "On the Performance of Hedge Funds" finds that unlike mutual funds, hedge funds generally have very low systemic risk in their portfolios (Liang, 1999). Additionally, LBO firms have been shown to invest in less cyclical and more stable companies as discussed in the paper "Consequences of leveraged buyouts" which describes how LBO firms invest in companies with lower business risk and increase their financial risk through debt instead (Palepu, 1990). This is supported by Frazzini and Pedersen (2014) who find that LBO firms have on aggregate invested in companies with a beta below 1 in the United States from 1963 to 2012. Thus, an interesting avenue for further research would be to see if the same behavior of Hedge Funds and LBO firms holds for a Swedish setting.

VII. How Changes in Funding Conditions Affect the BAB Factor

After analyzing how investor's degree of leverage constraints impacts the beta anomaly in the Swedish market, we investigate our fourth research question concerning the influence of changing funding conditions on the performance of the BAB factor. We display results using betas from Method 1, as this enables us to analyze the correlation already from 2011. Only using one of the methods is deemed sufficient as our previous results suggest a similar trend for both Method 1 and 2. To determine significance, we use a confidence level of 95%, resulting in a p-value of less than 0.05.

A. How Periods of Tight Funding Conditions Impact the Beta Anomaly

We examine research question 4 through regression analysis, using the BAB factor performance as the dependent variable and the STED-Spread as the independent variable. Table 5 demonstrates regression results for the impact of a STED-Spread and the BAB factor. The table shows that the constant is statistically significant, suggesting that when the STED-Spread and its changes are zero, the BAB portfolio will still generate positive returns. Further, the contemporaneous change to the STED-Spread has a negative and significant coefficient, of –49.741, with regards to the BAB portfolio. Lastly, the coefficient for the lagged STED-Spread is -11.492 which would indicate that an increase in the lagged STED-Spread leads to a decrease in the returns of the BAB portfolio. However, this finding is not statistically significant as can be seen through the p-value being larger than 0.05, which means that we cannot draw any certain conclusions from this value.

Table 5: Correlation Between STED Spread and BAB Returns

Variable	**Coefficient**
Constant	0.104
	0.001
Contemporaneous STED Spread	-49.741
	0.039
Lagged STED Spread	-11.492
	0.105

The table displays regression results for the impact of the STED-Spread, calculated as the 3-month STIBOR rate minus the 3-month Swedish government bond yield, on the returns from the BAB portfolio. The lagged STED-Spread is defined as the STED-Spread at the end of month t-1. The sample period is 2011-2019 since we omit data from 2020-2023 due to the anomalies in the movements of the financial market from

COVID-19. To have a sufficient sample period of 9 years, we have used BAB returns calculated from constant betas (training period 2009-2010). The p-values are shown under each coefficient value.

B. Analyzing the Impact of Tightening Leverage Conditions on the BAB Factor

Using the STED-Spread as a proxy for leverage constraint we gain interesting insights from Table 5. Our results demonstrate a statistically significant negative relationship between the change in STED-Spread and BAB returns. If we see the STED-Spread as a proxy for the tightness of leverage constraints (ψ), the negative relationship between the change in STED-Spread and contemporaneous returns of the BAB portfolio would agree with the model established by Frazzini and Pedersen (2014) (Equation 9). Frazzini and Pedersen (2014) reason that higher funding constraints lead investors to de-lever their portfolios away from low beta, as borrowing is more expensive. Investors may then also choose to invest in higher beta assets to attain a higher expected return, when leveraging low beta to do so is no longer feasible (Frazzini and Pedersen, 2014). Thus, on a short-term basis, more leverage constraints lead to a higher demand for more risky assets (higher beta), subsequently leading those assets to increase in price and have a higher return in that period. For low beta securities, the opposite is the case as the net selling of low-risk assets leads the prices to go down and we will see negative returns during that period.

On the contrary, we see from Table 5 that future returns are not higher from an increased funding constraint. The results show a negative, but insignificant, relationship between funding constraints and future returns on the BAB portfolio. This goes against the reasoning that the contemporaneous low demand for low beta stocks from higher funding constraints leads to a greater undervaluation of these securities and thus a higher future return. In Frazzini and Pedersen's research (2014), they also found results that went against their hypothesis. They found a statistically negative relationship between the lagged TED-Spread and returns of the BAB portfolio. They explained this unusual result by questioning what the TED-Spread demonstrates as a proxy. Instead of seeing the TED-Spread as the constraints that lenders are experiencing right now, they suggest that it may be an indication that agents' funding constraints are worsening. In this view, a higher TED-Spread would mean that banks and other creditors are credit-constrained and therefore raise the constraints for lenders over time. This would explain why an increase in the TED-Spread leads to lower future BAB returns. However, even though we find results that may indicate a negative relationship between the lagged STED-Spread and BAB returns, they are not significant, and therefore we cannot draw any certain conclusions from it.

VIII. Discussion

A. How Our Results Impact Financial Markets

If a market-neutral portfolio can consistently generate abnormal returns by exploiting the mispricing of high beta and low beta assets, it suggests that the market is not efficiently pricing assets according to their systematic risk, as indicated by the SML. Thus, our findings regarding a beta anomaly in the Swedish market suggests that the SML is flatter than what models like CAPM would predict. This might imply necessary re-evaluation of the assumptions behind these models, and including a BAB-factor in future asset pricing models can be useful to better predict the returns of a security.

Our findings further suggest that leverage constraints imposed on investors through legal requirements have an impact on the type of assets they choose to invest in. Such a tilting towards high beta is most homogenous for mutual funds, asset management firms and pension funds which combined make up roughly 54% of the market in our sample (Table 4). This shows support for the idea that superior returns of the BAB portfolio are due to a breach of the CAPM assumptions, leading to a flatter SML than predicted. However, it is also important to note that, as discussed, other legal requirements may impact decision making by investor groups. For instance, insurance funds are not only limited in the amount of leverage they can take on but are also heavily restricted in their appetite for systematic risk.

The above constraints highlight an opportunity for less leverage constrained investor groups, like hedge funds and LBO firms, to invest more heavily in low beta assets. Thus, capitalizing on the arbitrage opportunity created by the market dynamics and making abnormal returns. We would argue that this is a phenomenon that retail investors can take advantage of as well, but possibly not to the same extent. Even though it may be unfeasible for them to invest in a BAB portfolio due to its high complexity and need for leverage, they could still enhance their strategy by investing more of their savings in less volatile assets and thereby ensuring better risk-adjusted returns, even though this may appear less exciting.

Furthermore, knowledge of the BAB anomaly can make it necessary for portfolio managers to revise their strategies and models for risk management to capture the complexities of asset pricing and investor behavior more accurately. Given that the regulatory environment limits opportunities for investment approaches, we may see an even greater adoption of alternative methods in the future to achieve higher returns in an increasingly competitive market. This could affect international capital flows and posits an additional risk that must be accounted for (Guichard, 2016).

B. Possible Other Explanations for the Beta Anomaly

Our analysis mainly revolves around leverage constraints but other explanations for the beta anomaly are important to consider. One such explanation is investors' demand for lottery-like stocks which relates to how investors preferences for stocks closely resembles demand for lottery tickets. This implies that investors overinvest in stocks that offer a small chance of a huge payoff, which on a large scale can have a significant impact on stock prices and their returns. A few of the key factors that drive lottery demand include psychological attraction which relates to the appeal from potentially high payoffs of low probability events, behavioral biases related to the overconfidence, and overestimation of low probability outcomes and economic conditions as during recessions investors are more likely to take a chance on high risk, high reward investments in an attempt to recuperate losses. These behaviors are mainly driven by individual investors rather than institutional investors, who have constraints and mandates that limit them from taking highly speculative bets. This theory predicts that actions from individual investors drive up the prices of high-beta stocks to levels that are not justified by their fundamentals (Bali et al., 2017). In the study "Betting Against Beta or Demand for Lottery", it is found that the price pressure from a high demand for lottery-like stocks is a major explanation for the BAB anomaly. In their portfolio and regression analysis they observe that when controlling for lottery demand, the betting against beta abnormal returns disappear. They have determined this by looking at stocks listed in the US on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and the NASDAQ from 1963 to 2012 (Bali, Brown, Murray and Tang, 2014). This, in turn, provides an alternative explanation for the BAB anomaly other than leverage constrained investors.

The demand for lottery like stocks could be a driver for BAB's abnormal returns in Sweden, highlighted by it being a driver of the beta anomaly in the UK (Kambouroudis, McMillan and Khasawneh, 2024), India (Sharma and Chakraborty, 2019) and Australia (Bradrania and Veron, 2023). However, our data indicates that investors, who are typically not expected to hold high beta stocks according to the lottery-demand theory - such as pension funds, mutual funds, and asset management firms - do so in our sample of the Swedish market. These types of investors are on aggregate seen as informed and it would therefore appear unlikely that behavioral biases drive their investment strategy. Thus, even though the demand for lottery-like stocks may impact the beta anomaly in Sweden it appears unreasonable for it to be the sole explanation.

XI. Conclusions

We reason that the beta anomaly persists in the Swedish market as highlighted by our analysis demonstrating that low beta stocks outperform high beta stocks on a risk-adjusted basis (research question 1) as well as the BAB portfolio showing abnormal returns (research question 2). Consequently, we find a breach to the assumptions of CAPM, presenting opportunities for unconstrained arbitrageurs, like Hedge Funds and LBO firms, to achieve abnormal returns.

To explore why this anomaly occurs, we deep dive into the impact of leverage constraints on investor behavior (research question 3). These results portray how constraints lead to an excessive weighting in high beta, likely due to an attempt to outperform benchmarks, as they lack the ability to lever up a less volatile portfolio. We predict that this behavior from groups like mutual funds, asset management firms and pension funds is a key driver for why the beta anomaly persists in Sweden.

Our final area of research (research question 4), shows that increasing funding constraints, proxied with the STED-Spread, leads to a contemporaneous decrease in the returns of a BAB portfolio. This emphasizes the correlation between financial conditions and the beta anomaly. However, we find no significance to the relationship with future BAB returns. To potentially take advantage of these findings, an investor could make predictions on the future STED-Spread and time long/short trades on a BAB portfolio accordingly. As we do not see significance regarding a lagged relationship it would be interesting in future research to see if another proxy for leverage constraints could give better insight into the long-term impact on BAB, making it easier to take advantage of a potential correlation.

Future research could also explore the ownership characteristics of retail investors, investigating their behavior and how it influences and is influenced by the beta anomaly. Lastly, increased awareness on the beta anomaly could not only provide a shift to a profitable trading strategy for institutional investors but also educate a broader audience to make better-informed decisions in the future, ultimately benefiting individuals across all levels of society.

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Appendix

Appendix A: Defining Variables

Variable	Definition
r_{t+1}^{i}	Return of security i at period t+1
r^{f}	Risk-free rate of return
β_t^i	Beta of security *s* at period t
r_{t+1}^{M}	Return of market at period t+1
α_t^i	Alpha of security *s* at period t
r_{t+1}^{BAB}	Return of *BAB* at period *t+1*
β_t^L	Beta of low beta portfolio at period *t*
r_{t+1}^{L}	Return of low beta portfolio at period t+1
β_t^H	Beta of high beta portfolio at period *t*
r_{t+1}^{H}	Return of high beta portfolio at period t+1
∂	Partial derivative (rate of change)
m_t^k	Margin requirements at time t
$\widehat{\beta_\iota}$	Shrunk beta of security i
w_i	Weight of security i
$\hat{\beta}_i^{TS}$	Shrunk time series beta of security i
$\hat{\beta}_i^{XS}$	Shrunk cross-sectional mean beta of security i
$w_{H,i}$	Weight of security i in high beta portfolio
$w_{L,i}$	Weight of security i in low beta portfolio
r_{delev}^{f}	De-levered risk-free rate of return
r_{lev}^{f}	Levered risk-free rate of return
r_{t+1}'	Security returns before portfolio weighting at period t+1
α^{PTF}	Portfolio alpha
β^{MKT}	Market beta
β^{SMB}	Small Minus Big beta
β^{HML}	High Minus Low beta
β^{MOM}	Momentum beta
SMB_t	Small Minus Big returns at period t
HML_t	High Minus Low returns at period t
MOM_t	Momentum returns at period t

Appendix B: BAB Portfolio Returns With Monte Carlo Simulations

Table 6: Regression Results for Monte Carlo Simulations Using Method 1 Betas

	FFC4		FF3		CAPM	
	Constant	**P-value**	**Constant**	**P-value**	**Constant**	**P-value**
Min	0.060	0.000	0.019	0.000	0.018	0.000
Max	0.125	0.001	0.044	0.009	0.041	0.020
Mean	0.087	0.000	0.031	0.002	0.029	0.004
Median	0.086	0.000	0.031	0.001	0.028	0.003
Std.dev	0.014	0.000	0.006	0.002	0.005	0.004

The table displays summary statistics from running 100 different simulations with our Method 1 betas where we each time randomly exclude 20% of the stocks from our sample, which is intended to capture the effect of not accounting for delisted stocks. The constant refers to the alpha estimate of our BAB portfolio under the different asset pricing models, and P-values shows the significance of our alpha estimates. We report min, max, mean, median and standard deviation for both the constant and the p-value over all three models.

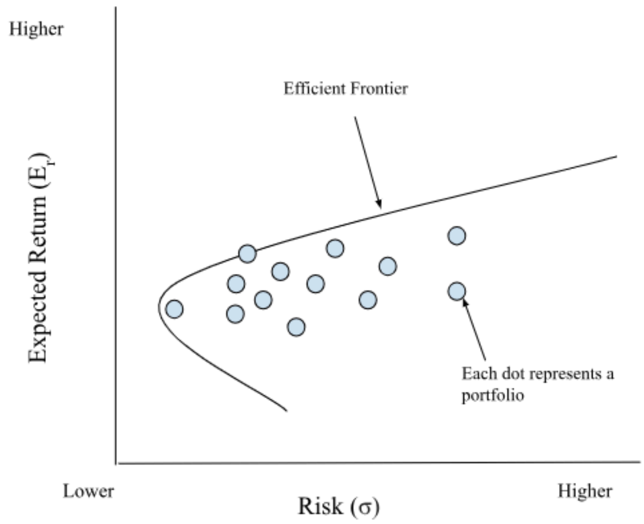
Table 7: Regression Results for Monte Carlo Simulations Using Method 2 Betas

	FFC4		FF3		CAPM	
	Constant	**P-value**	**Constant**	**P-value**	**Constant**	**P-value**
Min	0.007	0.000	0.008	0.000	0.008	0.000
Max	0.020	0.189	0.021	0.094	0.020	0.150
Mean	0.013	0.023	0.015	0.008	0.014	0.019
Median	0.014	0.013	0.015	0.003	0.014	0.009
Std.dev	0.002	0.032	0.002	0.015	0.002	0.028

The table displays summary statistics from running 100 different simulations with our Method 2 betas where we each time randomly exclude 20% of the stocks from our sample, which is intended to capture the effect of not accounting for delisted stocks. The constant refers to the alpha estimate of our BAB portfolio under the different asset pricing models, and P-values shows the significance of our alpha estimates. We report min, max, mean, median and standard deviation for both the constant and the p-value over all three models.

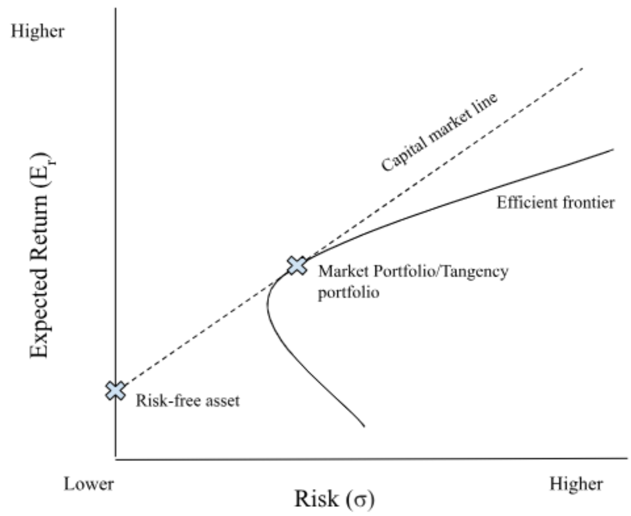
Appendix C: Graphs Related to CAPM and Modern Portfolio Theory

Graph A: Modern Portfolio Theory and the Efficient Frontier



The Graph shows the relationship between risk and expected return and how the tangency portfolio is represented on the efficient frontier. Each circle represents a portfolio.

Graph (B) - CAPM and the CML



The Graph shows the relationship between risk and expected return and how the tangency portfolio is represented on the efficient frontier, as well as how the capital market line relates to the efficient frontier. Each circle represents a portfolio.

Appendix D: CAPM Assumptions (Reilly and Brown, 2002)

- Investors, being risk-averse, aim to maximize their utility and returns relative to asset volatility (maximize Sharpe ratio) by selecting portfolios along the efficient frontier.
- Investors can borrow an unlimited amount at the risk-free rate.

- Investors have homogeneous expectations for future asset price movements.
- Investors hold investments for the exact same one-period of time.
- Investors can sell or buy portions of shares from any of the securities or portfolios that they hold.
- No taxes and transaction costs for buying or selling shares.
- Inflation and interest rates remain constant.
- All securities are fairly priced, meaning that investors cannot influence prices.

Appendix E: Classification of Investor Groups

- Mutual Funds consist of all conventional fund companies and funds within our dataset, except for pension and insurance funds which we consider separately.
- Asset Management Firms comprise entities engaged in investment activities, asset management, or similar ventures.
- Pension Funds incorporate pension entities, state-operated pension schemes, and standard pension funds.
- Insurance Funds represent those specializing in insurance.
- Holding Companies are characterized by passive investment stakeholders.
- Strategic Acquirers denote a range of companies holding ownership yet not categorized as investment firms, funds, or under any other label.
- Individuals Investors refer to natural persons with ownership stakes in our sampled companies, a mix of retail investors and company employees with equity interests.
- Other Investors includes a small number of banks, scholarship funds, endowment funds, and union investors.

Appendix F: Regression Output (Coefficients and p-values in brackets)

Table 8: FFC4 Regressions Using Method 1 Betas

Variable	BAB Portfolio	High Beta Portfolio	Mid Beta Portfolio	Low Beta Portfolio
BAB (constant)	0.086	0.012	0.015	0.017
	(0.000)	(0.008)	(0.001)	(0.000)
Excess Market Return	0.614	0.042	0.024	0.108
	(0.223)	(0.671)	(0.792)	(0.248)
SMB	3.193	0.138	0.311	0.542
	(0.000)	(0.352)	(0.026)	(0.000)
HML	-1.887	-0.177	-0.283	-0.284
	(0.030)	(0.296)	(0.076)	(0.079)
UMD	-1.852	-0.320	-0.246	-0.325
	(0.007)	(0.017)	(0.049)	(0.011)
No. Observations	156	156	156	156
R-squared	0.188	0.051	0.076	0.163

The table shows regression results for our FFC4 regression using Method 1 betas. P-values are represented by brackets and coefficient estimates in normal numbers.

Table 9: FF3 Regressions Using Method 1 Betas

Variable	BAB Portfolio	High Beta Portfolio	Mid Beta Portfolio	Low Beta Portfolio
BAB (constant)	0.063	0.085	0.012	0.0126
	(0.005)	(0.053)	(0.004)	(0.003)
Excess Market Return	0.684	0.054	0.034	0.1204
	(0.183)	(0.590)	(0.718)	(0.206)
SMB	3.353	0.1658	0.3319	0.5704
	(0.000)	(0.270)	(0.019)	(0.000)
HML	-1.5210	-0.114	-0.2345	-0.2195
	(0.082)	(0.503)	(0.140)	(0.175)
No. Observations	156	156	156	156
R-squared	0.148	0.014	0.052	0.125

The table shows regression results for our FF3 regression using Method 1 betas. P-values are represented by brackets and coefficient estimates in normal numbers.

Table 10: CAPM Regressions Using Method 1 Betas

Variable	BAB Portfolio	High Beta Portfolio	Mid Beta Portfolio	Low Beta Portfolio
BAB (constant)	0.046	0.008	0.011	0.011
	(0.019)	(0.063)	(0.008)	(0.009)
Excess Market Return	1.058	0.070	0.066	0.1863
	(0.047)	(0.471)	(0.477)	(0.057)
No. Observations	156	156	156	156
R-squared	0.025	0.003	0.003	0.023

The table shows regression results for our CAPM regression using Method 1 betas. P-values are represented by brackets and coefficient estimates in normal numbers.

Table 11: FFC4 Regressions Using Method 2 Betas

Variable	BAB Portfolio	High Beta Portfolio	Mid Beta Portfolio	Low Beta Portfolio
BAB (constant)	0.0149	0.014	0.0149	0.014
	(0.005)	(0.010)	(0.008)	(0.005)
Excess Market Return	0.026	0.070	0.035	0.057
	(0.822)	(0.562)	(0.769)	(0.610)
SMB	0.7809	0.072	0.342	0.415
	(0.000)	(0.690)	(0.059)	(0.014)
HML	0.133	-0.488	-0.2562	-0.254
	(0.502)	(0.020)	(0.216)	(0.186)
UMD	0.139	-0.393	-0.2806	-0.190
	(0.369)	(0.016)	(0.084)	(0.205)
No. Observations	117	117	117	117
R-squared	0.168	0.083	0.064	0.078

The table shows regression results for our FFC4 regression using Method 2 betas. P-values are represented by brackets and coefficient estimates in normal numbers.

Table 12: FF3 Regressions Using Method 2 Betas

Variable	BAB Portfolio	High Beta Portfolio	Mid Beta Portfolio	Low Beta Portfolio
BAB (constant)	0.017	0.010	0.012	0.012
	(0.001)	(0.069)	(0.028)	(0.012)
Excess Market Return	0.025	0.072	0.037	0.058
	(0.828)	(0.556)	(0.759)	(0.603)
SMB	0.7847	0.061	0.334	0.410
	(0.000)	(0.741)	(0.067)	(0.015)
HML	0.102	-0.400	-0.194	-0.212
	(0.601)	(0.056)	(0.346)	(0.264)
No. Observations	117	117	117	117
R-squared	0.162	0.034	0.038	0.065

The table shows regression results for our FF3 regression using Method 2 betas. P-values are represented by brackets and coefficient estimates in normal numbers.

Table 13: CAPM Regressions Using Method 2 Betas

Variable	BAB Portfolio	High Beta Portfolio	Mid Beta Portfolio	Low Beta Portfolio
BAB (constant)	0.016	0.009	0.011	0.011
	(0.004)	(0.083)	(0.040)	(0.022)
Excess Market Return	0.100	0.053	0.054	0.081
	(0.413)	(0.666)	(0.652)	(0.472)
No. Observations	117	117	117	117
R-squared	0.006	0.002	0.002	0.005

The table shows regression results for our CAPM regression using Method 2 betas. P-values are represented by brackets and coefficient estimates in normal numbers.

AI Appendix

LEVERAGE CONSTRAINTS AND THE BETA ANOMALY; BETTING AGAINST BETA IN THE SWEDSH MARKET

Degree Project in Finance – Spring 2024

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Recognition:
We have used the AI tool ChatGPT with help regarding specific coding methods.