Beyond Rational

– A study on the drivers of the beta anomaly in Sweden*

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Abstract

Inspired by previous findings that low (high) beta stocks earn abnormally high (low) returns we set out to explore this relation, often called the beta anomaly. We prove that the beta anomaly is present in our sample of Swedish stocks. The alpha generated by a *betting against beta* portfolio that exploits the beta anomaly is 1.71% per month. Both rational reasons such as leverage constrained investors and behavioural reasons such as lottery-seeking investors have been presented as explanations for the beta anomaly. Since lottery demand is mainly attributed to individual investors, Sweden is an interesting subject of study due to its high proportion of individual investor market participation. We examine the merit of the two explanations and conclude that the strange relation between beta and return can be attributed to both idiosyncratic and systematic factors. Finally, we construct a novel strategy that overcomes some of the problems of implementing a betting against beta portfolio. Invested in only 20% of our stock universe, the portfolio yields a monthly alpha of 2.17% and a Sharpe ratio of 1.14.

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1 Introduction

Beta, a stock's sensitivity to the market return, is one of the cornerstones in asset pricing. It has been so since the pioneering work of Sharpe (1964) and Lintner (1965) and continues to be the subject of extensive research to this day. In the classic Capital Asset Pricing Model (CAPM), beta is the sole determinant of excess return of assets. Another key property of the CAPM is that the most efficient portfolio is the market portfolio. This implies that all investors, regardless of return preferences, will hold the market portfolio. Investors can simply use leverage to reach their desired level of return and the corresponding risk level. While this truth holds in theory, it is not supported by empirical findings. Black, Jensen, and Scholes (1972) find that SML is too flat, i.e beta does poorly at predicting future returns. This empirical phenomenon is often referred to as the beta anomaly.

While the beta anomaly itself is widely accepted, there is still much debate to what is driving the anomalous relation between beta and excess returns. The two most prominent explanations for the beta anomaly are leverage constraint put forth by Frazzini and Pedersen (2014) and novel findings by Bali et al. (2016) where lottery demand is presented as an explanation. We are intrigued by nature of the opposing explanations, one rational (Frazzini and Pedersen 2014) and the other behavioural (Bali et al. 2016). Both explanations are very recent and it is important to verify the findings in different markets. We examine both explanations using a Swedish data set. Sweden is of special interest as the proportion of individual investor stock market participation is among the highest in the world (Guiso and Sodini 2013). Individual investors are often seen as the drivers of lottery demand (Kumar 2009).

In an effort to investigate this anomalous relationship between risk and reward, Frazzini and Pedersen (2014) present a model featuring both leverage constrained investors and arbitrageurs trying to exploit the beta anomaly. Their model predicts that the SML slope is to flat due to the leverage constraint of the average investor and therefore persistent. To verify their theoretical predictions they construct a portfolio to exploit the beta anomaly. This portfolio, named BAB (Betting Against Beta) is a long-short portfolio that is long low-beta stocks and short high-beta stocks. A portfolio of US stocks constructed using this method generates a Fama-French-Carhart 4-Factor

(FFC4) alpha of 0.55% per month and is statistically significant. The beta anomaly is also present in other geographical regions and also in other asset classes than stocks.

We start our research by doing a portfolio level analysis, constructing ten equal- and value-weighted portfolios based on ascending sorts on beta. Where the high beta decile contains stocks with the highest beta in the cross section and the low beta decile contains stocks with the lowest beta in the cross section. We evaluate the excess return and the FFC4 alphas in the subsequent month. The excess return difference between the low and high beta deciles in the equal-weighted portfolio is 1.22% and significant at the 10% level. The FFC4 alphas are not significant for either the equal- or the value-weighted portfolios and the excess return difference of the value-weighted portfolios is also not significant. These results are in contrast to the findings of Bali et al. (2016) who find a significant FFC4 alpha of 0.51% in a US sample. Using this simple methodology we find inconclusive evidence of the beta anomaly in Sweden.

While portfolio level analysis is intuitive it has drawbacks, for example a large amount of information is lost in the process of aggregation. Therefore we investigate if the effect is detected on the firm level in the cross section using Fama and MacBeth (1973) regressions and find that beta has a significant negative coefficient thus confirming the beta anomaly in the Swedish sample. We test the robustness of our cross sectional findings by controlling for a number of measures designed to capture the effect of firm characteristics, return distribution and sensitivity to funding liquidity. We find that the two latter have a negative relation to the beta anomaly. Furthermore we test the beta anomaly following Frazzini and Pedersen (2014) and construct a factor mimicking BAB portfolio, this yields an FFC4 alpha of 1.03% per month and it is highly significant both statistically and economically.

We continue to examine the behavioural explanation for the beta anomaly. Of special interest is the inclination amongst some investors to seek assets that exhibit lottery-like returns. Kumar (2009) presents evidence of this occurring. Barberis and Huang (2008) use he cumulative prospect theory developed Tversky and Kahneman (1992) to explain this phenomenon and Bali, Cakici, and Whitelaw (2011) use the maximum daily return (MAX) of a stock as a proxy for lottery demand. Bali et al. (2016) argue that large positive jumps in stock prices, sought after by lottery-seeking investors, are partly due to a stocks correlation with the market, i.e. its beta.

Therefore, lottery demand will indirectly result in the relatively high prices and low returns of high beta stocks.

To examine the effect of lottery demand on the beta anomaly, we conduct a bivariate sort on the maximum daily return on beta and find that the beta anomaly is strongest in the high MAX portfolios and also that the MAX effect is strongest in the high beta portfolios. This would mean that there is a clear relation between a stocks lottery-like return distributions and its beta. When we continue our analysis of the relation between the beta anomaly and lottery demand, using firm level cross sectional regression controlling for MAX we find that lottery-demand has a negative impact on beta anomaly. This finding is much weaker compared to Bali et al. (2016) who find that the beta anomaly is reversed. We use different definitions of beta and MAX, perhaps this is the reason our results are not as clear. To conclude we find that the beta anomaly and lottery-demand are related but not that the beta anomaly can be explained by lottery-demand alone.

Due to the conflicting results regarding the explanations of the beta anomaly. we continue our analysis by using the methods proposed by Asness et al. (2016). By splitting beta into its two components, volatility and correlation, they show that a Betting against Correlation (BAC) portfolio is robust to MAX while a Betting against Volatility (BAV) portfolio is not. Their rationale for disentangling BAB is that correlation is more related to leverage constraints while volatility is more related to lottery-seeking behaviour. We use the same methodology and find that BAC is the largest driver of BAB in Sweden. BAC generates high FFC4 alpha of 0.71% per month after controlling for lottery demand and does not load on our MAX factor. BAV on the other hand yield a somewhat higher FFC4 alpha of 1.00% per month after controlling for lottery preferences, but it is not without a significant loading on the MAX factor. This differs from findings by previous researchers. However, MAX and volatility are not analogous. Volatility has been shown to be priced in the cross-section (Ang et al. 2009) and MAX is designed to capture lottery preferences and not volatility per se. Perhaps this is only a confirmation that MAX captures what it is supposed to.

We conclude that the BAB strategy is profitable and robust to an number of controls. An investor that is not leverage constrained could generate significant profits from the strategy. To implement the formal BAB strategy does however pose problems for a potential arbitrageur. Mainly, as constructed by Frazzini and Pedersen (2014), the BAB portfolio is rank-weighted and invested (either long or short) in all stocks in a specific sample. To maintain a portfolio of hundreds or thousands of long and short positions, with monthly rebalancing, it is likely to render much of the profit lost by trading costs. To address this, we finish our analysis by constructing a modified BAB portfolio that is considerably smaller and easy to maintain. We show that it is enough to only include the bottom- and top 10% beta stocks in the long-short portfolio. This generates a monthly alpha of 2.17% with a corresponding Sharpe ratio of 1.14, close to that of the original BAB portfolio. This portfolio return is robust to the same controls as the original BAB portfolio.

The remainder of this thesis is structured as follows. In section two we present our dataset and calculation of factors and variables. In section three, the beta anomaly is presented and investigated in greater detail. This is followed by section four in which we explore the relation between the beta anomaly and lottery demand. In section five, we continue to examine the relationship between correlation, volatility and lottery preferences using the BAC and BAV portfolio. In section six we construct a trading strategy to exploit the beta anomaly. In section seven we conclude.

2 Data and Variables

The focal point of our analysis is market beta and lottery demand for a stock. Following Frazzini and Pedersen (2014) our estimate of market beta is given by:

$$\widehat{\beta_i^{ts}} = \widehat{\rho_{i,m}} \frac{\hat{\sigma_i}}{\hat{\sigma_m}} \tag{1}$$

Where $\widehat{\beta_i^{ts}}$ is the time series beta estimate of stock i. The correlation, $\widehat{\rho_{i,m}}$ is estimated using logarithmic overlapping three day returns of the stock in relation to the market to account for non-synchronous trading. We estimate the correlation using a rolling window of five years of daily data. However we require at least three years of data (750 observations) for a stock to be included. Volatility of the stock, $\hat{\sigma_i}$ is the standard deviation of the daily logarithmic return of the stock. We estimate volatility using the past one year of daily data and require at least 120 valid daily observations.

For comparability reasons we follow Frazzini and Pedersen (2014) and scale beta towards the cross sectional average of one. This is to reduce the effect of outliers in the data. We follow the method suggested by Vasicek (1973) and Elton et al. (2009). We use the same shrinkage factor $w = 0.6$ and $\beta^{cs} = 1$ as Frazzini and Pedersen (2014) for the entire time series. The estimate for beta is then:

$$\widehat{\beta_i} = w\widehat{\beta_i^{ts}} + (1 - w)\beta^{cs} \tag{2}$$

We estimate lottery demand following Bali, Cakici, and Whitelaw (2011) and Hellgren and Helmy (2015) as the maximum daily return of a stock in the previous month. Here after referred to as MAX. The reason we choose the one day maximum return rather than the average of the five or three day maximum returns as Bali et al. (2016) is that we see this as a better proxy for lottery characteristic. Extreme one-day returns are more likely to attract attention of lottery-seeking investors than a series of smaller albeit large returns. We then construct a MAX factor replicating portfolio, FMAX, using Fama and Kenneth R. French (1993) methodology. To construct FMAX we sort stocks unconditionally on MAX and size (market capitalization) at the end of month t. Two groups are formed based on size and three groups are formed based on MAX, all portfolios have roughly an equal amount of stocks. The intersection of these groups form six different portfolios. The FMAX portfolio is then:

$$FMAX_{t+1} = \frac{R_{t+1}^{HMB} + R_{t+1}^{HMS}}{2} - \frac{R_{t+1}^{LMB} + R_{t+1}^{LMS}}{2} \tag{3}$$

Where R_{t+1}^{HMB} is the return in month $t+1$ of the portfolio of large stocks that are high MAX, and R_{t+1}^{HMS} is the return in month $t+1$ of the portfolio of small stocks that are high MAX, and R_{t+1}^{LMB} is the return in month $t+1$ of the portfolio of large stocks that are low MAX, and R_{t+1}^{LMS} is the return in month $t+1$ of the portfolio of small stocks that are low MAX. All returns are value weighted within their respective portfolio. FMAX is thus a size neutral portfolio that mimics the return of a lottery-seeking investor.

We apply a battery of other known risk factors as controls. Theses variables are grouped into three main categories. The first one is firm specific characteristics including size, book-to-market and momentum. The second category consists of measures of risk including skewness, co-skewness and downside beta. The third category is comprised of measures to estimate funding liquidity constraints. Including sensitivity to TED spread, sensitivity to the volatility of TED spread and sensitivity to the treasury bill rate. Frazzini and Pedersen (2014) put forth the hypothesis that it is funding liquidity constraints that causes the beta anomaly. In the following three sections we describe the calculation of thees variables.

2.1 Firm Characteristics

To control for firm characteristics in our regressions we source Swedish Fama and Kenneth R. French (1993) factors for Book to Market (HML) and size factor (SMB) from Gruodis (2015). We construct momentum factor (MOM) following Carhart (1997). At the end of each month we construct six value weighted portfolios based on size and prior year return excluding the most recent month. The portfolios are the intersect of the two portfolios formed on size and the three portfolios formed on prior return. The monthly breakpoint for size is the median market capitalization in that month and the breakpoints used for prior return are the 30th and 70th percentile. MOM is then:

$$MOM = \left(\frac{SmallHigh + BigHigh}{2}\right) - \left(\frac{SmallLow + BigLow}{2}\right) \tag{4}$$

2.2 Risk Measures

The relation between skewness of stock returns and future return has engaged the field of finance for quite some time. Kraus and Litzenberger (1976) and Harvey and Siddique (2000) find that investors have an aversion to variance and a preference for positive skewness. We calculate Co-skewness (COSKEW) following Harvey and Siddique (2000) as the slope coefficient of the squared term of a regression of the excess stock return on the excess market return and the squared excess market return. Using past one year of daily observations. COSKEW is then the estimate b_2 in the regression specification:

$$r_{i,d} - r_d^{rf} = a + b_1(r_{m,d} - r_d^{rf}) + b_2(r_{m,d} - r_d^{rf})^2 + \epsilon_{i,d} \tag{5}$$

Where $r_{i,d}$ is the return of stock i in day d, $r_{m,d}$ is the market return on day d and r_d^{rf} is the risk-free rate in day d. We define total skewness (TSKEW) for stock i in month t as the skewness in the preceding 250 trading days:

$$TSKEW = \frac{1}{250}\sum_{d=1}^{250}\left(\frac{R_{i,d} - \mu_i}{\sigma_i}\right) \tag{6}$$

Furthermore we estimate a downside beta (DRISK) following Bawa and Lindenberg (1977) as the slope coefficient in the regression of daily excess stock return on the daily excess market return using only days where the market return is below the median daily market return in the preceding 250 trading days. DRISK is then the estimated b_1 coefficient in the following regression specification:

$$r_{i,d} - r_d^{rf} = a + b_1(r_{m,d} - r_d^{rf}) + \epsilon_{i,d} \tag{7}$$

Where $r_{i,d}$ is the return of stock i in day d, $r_{m,d}$ is the market return on day d and r_d^{rf} is the risk-free rate in day d.

2.3 Funding liquidity measures

Frazzini and Pedersen (2014) argue that the beta anomaly can be explained by means of funding liquidity. The logic is that investors are not able to borrow and lend at the same rates and must therefore invest in high beta stocks to achieve a greater return than the market portfolio rather than just buying the market portfolio and applying leverage. This abnormal demand for high beta stocks causes them to be overvalued and therefore underperform. Therefore we measure the stock sensitivity to TED spread (TED), volatility of TED spread (VOLTED) and to the treasury bill rate (TBILL). TED is defined as the three month Stockholm interbank offered rate (STIBOR) less the three month treasury bill rate. VOLTED is the volatility of daily

TED spread in the given month. To measure sensitivity to the estimates we run a regression of excess return of a stock on TED VOLTED and TBILL separately. The sensitivities are then the beta of the respective regressions.

2.4 Data sources

In our analysis of beta and lottery characteristics we have used stock data on all Swedish common stocks listed on the main exchange between January 1997 and November 2016 the total number of stocks in our sample is 677 and we have an average of 290 stocks in each month. Preference shares have been excluded for comparability reasons with previous studies. We have used Thomson Reuters Datastream as the main data provider. To reduce the risk of survivorship bias we have manually added all de-listed stocks from the date of their first appearance on one of the main lists by using press releases from NASDAQ Stockholm web page[1]. This is also the reason why our data sample starts in January 1997, as there are no older, readily accessible press releases.

For our calculations of returns we have used total return index (TRI) which adjusts for all corporate actions including splits and dividends. Market value (MV) has been used to construct value weighted portfolio return. Book Value (BV) is the book value of common equity and is used to calculate the Book-to-Market metric. As a proxy for market return we use SIX Portfolio Return Index (SIXPRX). The index is adjusted for the same corporate actions as the TRI used on the stock level.

Datastream has some reported issues, such as decimal jumps. We have made sanity checks of the data following Ince and Porter (2006) and Schmidt et al. (2011) by confirming returns in excess of 100% using media archives.

[1]NASDAQ Stockholm is the main exchange in Sweden and a complete list of corporate action announcements can be found using the following link: (accessed 2017-05-01) http://www.nasdaqomx.com/transactions/markets/nordic/corporate-actions/stockholm/changes-to-the-list

Table I: Descriptive statistics
The table below presents descriptive statistics of ten beta sorted portfolios. All values are equal-weighted averages. BM is the book-to-market ratio. MV is reported in million Swedish krona. MAX is the maximum daily return in month t, MOM is the momentum return at the end of month t and Return is the $t+1$ monthly return, all reported in percentages. The risk measures COSKEW, TSKEW and DRISK are calculated at the end of month t. the funding liquidity measure β_{ted}, β_{tbill}, β_{volted} are also estimated at the end of month t.

Decile	BM	MV	MAX	MOM	Return	COSKEW	TSKEW	DRISK	β_{ted}	β_{tbill}	β_{volted}	β
1	0.28	7,917	5.43	14.11	1.53	-2.69	0.96	0.25	-4.01	-1.38	-2.51	0.51
2	0.40	4,070	4.90	17.09	1.45	-3.66	0.60	0.46	-6.17	-1.53	-10.23	0.64
3	0.32	8,224	5.17	17.94	1.53	-3.38	0.58	0.55	-6.09	-1.70	-10.83	0.71
4	0.30	14,387	5.26	17.10	1.24	-3.55	0.56	0.63	-4.48	-1.93	-10.08	0.76
5	0.40	15,430	5.25	17.04	1.37	-3.34	0.57	0.70	-3.39	-2.00	-1.36	0.82
6	0.40	24,443	5.56	14.01	1.23	-3.27	0.58	0.78	-2.45	-2.22	11.91	0.88
7	0.49	30,584	5.77	13.03	0.88	-3.03	0.51	0.86	0.77	-2.44	21.30	0.95
8	0.59	31,218	6.13	13.25	0.90	-2.29	0.51	0.99	1.81	-2.96	28.21	1.03
9	0.50	36,228	6.62	14.31	0.73	-2.32	0.56	1.14	4.03	-3.70	41.07	1.14
10	0.40	55,593	7.86	15.41	0.35	-2.48	0.50	1.35	8.96	-4.43	67.29	1.36

Table I presents descriptive statistics of decile portfolios formed on β. We can see that MV, and MAX increase almost monotonically in relation to beta, except for the decile 1 portfolio. DRISK and and the sensitivity to funding liquidity measures β_{ted} and β_{volted} follow a similar pattern. While β_{tbill} is inversely related to β. MOM, BM, TSKEW and COSKEW do not appear to have a clear relation to β. Most interestingly we find that Return is negatively related to β. The patterns in the data are similar to the findings of Bali et al. (2016) However they find a negative relation between BM and beta, a positive relation between MOM and beta also the relation between size and beta is not as prominent, their beta decile 2 through 8 have roughly the same market value, while the market value in decile 1 is low and the market value in decile 9 and 10 are high.

3 The Beta Anomaly

The starting point of our analysis is to examine the beta anomaly in a Swedish sample. To our knowledge this has not been done before. The beta anomaly is the tendency of high beta stocks to earn abnormally low returns, while low beta stocks earns abnormally high returns. In essence, this means that the SML is too flat and that beta does poorly at predicting the excess return of stocks. Black, Jensen, and Scholes (1972) show that this is the case and the beta anomaly has been the subject of extensive research ever since. In this section we set out to establish if the beta anomaly is present in our sample. We use standard portfolio analysis, cross-sectional regressions and also employ the novel BAB factor first proposed by Frazzini and Pedersen (2014).

3.1 Univariate portfolio sorts

The starting point of our investigation of the beta anomaly is a univariate portfolio level analysis. This method is intuitive and simple and should give us a first indication of the existence of the beta anomaly. At the end of each month we sort stocks into decile portfolios based on the stocks individual beta. Each portfolio has roughly an equal number of stocks. Table II presents the time series average equal and value weighted one month ahead excess returns. The FFC4 alphas are intercepts from a regression of one month ahead excess stock return on the market risk premium, SMB, HML and MOM. The column labeled Average β increases monotonically, by construction from 0.51 to 1.36. The row labeled 1-10 Hedge is the return of the long/short portfolio that is long the low beta decile portfolio and short the high beta decile portfolio. Newey and West (1987) t-statistics using 1 lag are presented in parenthesis.

The result of this analysis show that there is no relation between excess return of a beta sorted portfolio and returns. This indicates that beta does not predict future returns. This result is much weaker than e.g Bali et al. (2016) who find that there is a negative relation between beta sorted decile portfolios and future excess return in essence the SML has a negative slope. We fail to see a significant relation between beta and return in the univariate portfolio level analysis.

Table II: Univariate sort on Beta
At the end of each month stocks are sorted into decile portfolio based on beta. We calculate value-weighted (VW) and equal-weighted (EW) excess returns and alphas. Where the EW return is the arithmetic average of the individual constituents and the VW return is calculated using the market values of the constituents at formation. Excess return is the time series average of the one month ahead simple return less the risk free rate. FFC4 alphas are the intercept of a regression of excess one month ahead portfolio return on the market risk premium SMB HML and MOM factors. Average β is self explained. The row named 1-10 Hedge is the long/short portfolio that is long the low beta portfolio and short the high beta portfolio, corresponding Newey and West (1987) t-statistics, using a lag of 1, are presented in parenthesis.

	VW Portfolios		EW Portfolios		
Decile	Excess Return	FFC4 Alpha	Excess Return	FFC4 Alpha	Average β
Low Beta	0.28	0.43	1.35	1.16	0.51
2	0.41	0.37	1.27	0.98	0.64
3	0.30	0.26	1.40	1.02	0.71
4	0.53	0.59	1.05	0.75	0.76
5	0.65	0.81	1.16	1.05	0.82
6	0.93	1.05	0.99	0.91	0.88
7	0.78	0.77	0.66	0.51	0.94
8	1.24	1.50	0.57	0.54	1.02
9	0.41	0.05	0.41	0.41	1.14
High Beta	0.48	0.39	0.13	0.06	1.36
1-10 Hedge	-0.20	0.04	1.22	1.10	
t-stat	(-0.13)	(0.02)	(1.78)	(1.29)	

As a robustness check we do the same analysis using an alternative measure of beta. To make sure that the results are not simply driven by our beta estimates. The alternative measure of beta is the slope coefficient of a regression of five years of monthly excess returns of the stock on the monthly excess return of the market. We require at least two years of valid monthly stock returns for this estimate. The result of this robustness check are similar and are presented in the appendix.

3.2 Cross-sectional Fama-MacBeth regressions

We continue our research by conducting cross-sectional regressions at the firm level. Portfolio level analysis is intuitive and model free in the sense that it does not apply any kind of functional form . It does however aggregate firm-level data in the process of forming portfolios and thereby discards a large amount of information.

At the end of each month t we run cross sectional regression following Fama and MacBeth (1973) of one month ahead $(t+1)$ excess stock return on beta and on a series of control variables designed to capture firm characteristics, return distribution and sensitivity to funding liquidity. Note that the control variables in these regressions are not factor mimicking but firm specific observations. In the first regression presented in Table III we pick up a negative price of beta of -1.36 that is significant at the 5% level. This result is similar to the result of Table II that showed an FFC4 alpha of 1.10% per month for the low minus high beta portfolio. However the alpha in Table II is not significant while it is significant in the cross sectional Fama and MacBeth (1973) regression.

At a glance beta seams to have a negative price. However in regression 2 and 3 when we control for measures of return distribution of the stocks and sensitivity to funding liquidity we cannot at the 5% level say that the price of beta is negatively priced in our sample. This would mean that the beta anomaly is not detected and instead that beta is simply not priced in the cross section in the Swedish market.

Frazzini and Pedersen (2014) argue that funding liquidity can explain the beta anomaly. Regression 3 includes sensitivity to funding liquidity and beta is not priced in our sample when we take these measures in combination with the risk measure into account. We also regress one month ahead excess stock return on the control variables in category 1 and 3 combined, excluding the return distribution measure and find that beta has a coefficient of -1.47 with a corresponding Newey and West (1987) t-statistic of -2.30 and that beta ted has a significant and negative coefficient. We do not report these regressions for brevity. These results imply that funding liquidity alone cannot explain the beta anomaly in our sample. However, we continue to analyze the relation between beta and funding liquidity using factor construction in the next section.

Table III: Cross-sectional regressions
At the end of each month t we run Fama and MacBeth (1973) cross sectional regression of one month ahead stock excess return on beta and a battery of control variables. The control variables can be groups into the following three categories: (1) firm characteristics: including SIZE, which is the natural logarithm of market cap; BM, is the natural logarithm of Book-to-Market; MOM that is the one year prior return leaving out the most recent month. (2) Measures of risk; including COSKEW, TSKEW and DRISK. (3) Stock sensitivity to funding liquidity including β_{TED}, β_{VOLTED} and β_{TBILL}. The coefficients presented are the time series average coefficients of the regressions. Corresponding Newey and West (1987) t-statistics are presented in parenthesis. Bold indicates significancy at the 5% level. The row labeled R^2 is the average adjusted R-squared and n is the average number of stocks per month included in the regressions.

	BETA	SIZE	BM	MOM	COSKEW	TSKEW	DRISK	BETA TED	BETA VOLTED	BETA TBILL	INTERCEPT	R^2	n
(1)	**-1.36**	0.02	0.17	**0.01**							**1.95**	8.6%	244
	(-1.97)	(0.37)	(1.54)	(2.81)							(3.49)		
(2)	-1.45	0.01	0.17	**0.01**	-0.01	**-0.11**	0.12				**2.12**	11.1%	244
	(-1.83)	(0.17)	(1.54)	(2.84)	(-0.61)	(-2.29)	(0.35)				(3.83)		
(3)	-1.56	0.02	0.18	**0.01**	-0.00	-0.10	0.16	**-0.05**	0.00	0.10	**2.12**	13.5%	244
	(-1.90)	(0.26)	(1.76)	(4.28)	(-0.23)	(-0.76)	(0.47)	(-2.14)	(0.39)	(1.75)	(3.83)		

We perform the same regression using our alternative measure of beta. The result of this regression can be found in the appendix in Table A4. The results of thees regressions are similar, except we do not find a significant coefficient of beta in any of the specifications. This leads us to conclude that our results is sensitive to the estimation of beta.

3.3 Betting against Beta

Another way to examine the presence of the beta anomaly is to construct a portfolio that exploits the apparent mispricing of beta.In Frazzini and Pedersen (2014), the authors present the Betting Against Beta (BAB) factor. The BAB factors stems from a theoretical model in which leverage constrained investors choose high beta stocks. BAB is hence an instrument to prove that systematic factors drive the beta anomaly.

Using several samples of both stocks and other assets, their empirical results show a positive and statistically significant alpha generated by the BAB portfolio. We follow the same construction method for the BAB portfolio. At the end of month t portfolio with a long (short) position in low (high) beta stocks is formed. Within the two legs of the portfolio, stocks are rank-weighted. In the long (low beta) leg, stocks with relatively lower beta have larger weights than stocks with a relatively higher beta. The resulting portfolio is self-financing and constructed to have a total beta of zero. The return of the portfolios are evaluated at month $t + 1$. A more comprehensive description of the BAB factor construction can be found in the appendix.

In order to evaluate the performance of the BAB portfolio we conduct regression analysis of the total portfolio, and the long and short leg. The results can be found in Table IV. The low beta leg and the BAB portfolio both yield high and statistically significant excess returns, while the high beta portfolio does not. This is in line with the theoretical and empirical results of Frazzini and Pedersen (2014). When regressing the three portfolios on the market excess return in a standard CAPM fashion we again find that only the BAB and low beta portfolios generate a statistically significant alpha. The realized beta of the portfolios are 1.44 for the high beta portfolio and 0.56 for the low beta portfolio, this is expected due to the construction of the two portfolios. In theory BAB should have a realized beta of zero. However, ex-ante estimated betas are noisy predictors of realized betas in the next month. Therefore, the reported coefficient of -0.34 is not odd. The BAB portfolio loading on SMB is positive, indicating that low beta stocks are small on average. It is also interesting to note that the BAB portfolio is positively loaded on HML - the value factor. One explanation is that safe value stocks are avoided by leverage constrained investors that seek high returns. Momentum is usually considered to have little relation with the beta anomaly (Fama and Kenneth R French 2016), but we include it for reasons of completeness.

We also regress the BAB portfolio on three measure designed to capture funding liquidity. TED is the spread between the three month STIBOR and the three month treasury bill rate. A high TED spread can be interpreted as an indication that funding constraints are worsening. Thus the negative loading on TED is logical as the returns of the BAB portfolio are suppressed in times when funding constraints are high. Furthermore we can see that VOLTED and TBILL are not related to the BAB returns indicating that these measure do poorly at predicting funding liquidity constraints.

Table IV: The BAB portfolio
At the end of each month t we rank stocks in ascending order based on their beta. Based on this ranking, stocks are placed in the high or low beta portfolios. The stocks in the high (low) beta portfolio are the ones over (under) the average rank, which is also the beta median. In the high and low beta portfolios, stocks are rank-weighted based on how much the stock's rank differ from the average rank. I.e. the stock with the highest beta gets the largest weight in the high beta portfolio, and the stock with the lowest beta gets the largest weight in the low beta portfolio. The combined BAB portfolio is then the self-financing portfolio that is long the low beta portfolio and short the high beta portfolio. The two legs are (de)levered to make the BAB portfolio beta-neutral at formation. The table shows the average monthly percentage excess returns in month $t + 1$. Also presented are results from the regressions of the High Beta, Low Beta and BAB on MKT (presented in the rows labeled CAPM) and on MKT, SMB, HML and MOM (presented in the rows labeled FFC 4-factor). The rows labeled Funding Liquidity presents the results of a regression of BAB on TED, VOLTED and TBILL. Alphas are in percent per month. Corresponding Newey and West (1987) t-statistics are presented in parenthesis, bold indicates significancy at the 5% level. Annualized Sharpe ratios are presented in the row Sharpe ratio.

		High Beta		Low Beta		BAB	
	Excess return	0.39	(0.58)	**1.31**	(3.77)	**1.71**	(4.50)
CAPM	Alpha	0.21	(0.74)	**1.15**	(4.97)	**1.62**	(3.94)
	MKT	**1.44**	(16.90)	**0.56**	(8.85)	**-0.34**	(-2.88)
FFC 4-factor	Alpha	0.36	(1.35)	**0.85**	(4.17)	**1.03**	(2.69)
	MKT	**1.36**	(23.34)	**0.69**	(13.22)	-0.06	(-0.55)
	SMB	**0.43**	(5.37)	**0.39**	(5.96)	**0.29**	(1.98)
	HML	**-0.23**	(-3.96)	**0.14**	(2.31)	**0.36**	(3.56)
	MOM	**-0.18**	(-2.86)	0.05	(1.09)	**0.22**	(2.92)
Funding Liquidity	TED					**-0.06**	(-4.43)
	VOLTED					-0.06	(-1.17)
	TBILL					0.00	(0.57)
	SEK long	1.00		1.00		1.61	
	SEK short					0.87	
	Sharpe Ratio	0.15		1.07		1.12	

To conclude this section, we have found evidence that beta is not priced according to the CAPM. A high beta does not generate as much return as predicted by the SML. The high alphas of the BAB portfolio is the most apparent evidence of that. Although this is interesting by itself, it raises the question what causes this anomaly. Is it leverage constraints as proposed by some scholars or a tendency amongst certain investors to seek lottery-like returns. We seek the answer to this question in the following sections.

4 The relation between the Beta anomaly and lottery demand

In a recent paper by Bali et al. (2016) the beta anomaly is viewed in light of lottery demand. Using MAX as a proxy for lottery demand, they show that lottery demand can help explain the beta anomaly. Using several techniques to measure the beta anomaly, they find that it is not robust when MAX is included as a control variable. Hellgren and Helmy (2015) show that the MAX effect is more present in Sweden, as compared to the US and other European countries, using a similar sample as we do. Their findings are presented in Table A3 in the appendix. Having concluded that both the beta anomaly and lottery demand price effects are present in Sweden, we now set out to investigate their relationship in our universe of stocks.

Large positive jumps in stock prices, sought after by lottery-seeking investors, is partly due to a stocks correlation with the market, i.e. its beta. Therefore, lottery demand will indirectly result in the relatively high prices and low returns of high beta stocks. Bali et al. (2016) find that after controlling for MAX the beta anomaly is no longer detected. Using Swedish data Hellgren and Helmy (2015) find that beta is positively priced in the cross-section when controlling for size, book-to-market, reversal, momentum, liquidity and MAX. Although this is not the focal point of their paper. Thus, we have some preliminary evidence that the beta anomaly and lottery returns are related in the Swedish sample. The rest of this section examines this in great detail.

4.1 Bivariate portfolio level analysis

We begin our analysis of the relation between lottery demand and beta by conducting a bivariate portfolio analysis. We do two related yet different bivariate sorts, the first one examines the robustness of MAX (as a proxy for lottery demand) to beta while the second one examines the robustness of beta when controlling for MAX.

Panel A of Table V represents MAX controlling for beta. At the end of each month we create nine equal weighted portfolios. We first sort stocks into three portfolios based on beta. The breakpoints are the 30th and 70th beta percentiles. Within each of the beta portfolios we conditionally assign stocks into three MAX portfolios based on their maximum daily return in that month. The breakpoints are the 30th and 70th MAX percentiles. We use a similar approach as Bali et al. (2016) however since the Swedish stock universe is much smaller than its American counterpart we use different breakpoints. Panel B of Table V represents Beta controlling for MAX and is done using the same method as Panel A, however we first sort on MAX and then conditionally on beta, the breakpoints are the same.

Table V: Bivariate portfolio sort
We do two related yet different bivariate analysis, In Panel A (B) we sort stocks into three groups based on beta (MAX) the 30th and 70th beta (MAX) percentiles are the breakpoints. Within each group we then conditionally sort stock based on the maximum daily return (beta) in month t. The average one month ahead excess return is presented in the table. The column $\beta Avg.$ (MAX avg.) is the Max effect (beta anomaly) independent of beta (MAX). The Row Return and FFC4 α are the return and FFC4 alpha of the portfolio that is long MAX 3 (β3) and short MAX 1 (β1). Corresponding Newey and West (1987) t-statistics are presented in parenthesis. Bold indicates significance at the 5% level. We use a similar approach as Bali et al. (2016) however since the Swedish stock universe is much smaller than its American counterpart we use different breakpoints.

Panel A	$\beta 1$	$\beta 2$	$\beta 3$	β Avg.	Panel B	MAX 1	MAX 2	MAX 3	MAX Avg.
MAX 1	1.57	1.46	0.88	1.47	$\beta 1$	1.73	1.48	1.30	1.54
MAX 2	1.70	1.06	0.99	1.16	$\beta 2$	1.50	1.18	0.55	1.14
MAX 3	1.31	0.91	-0.37	0.61	$\beta 3$	1.14	0.79	-0.03	0.56
Return	-0.26	-0.55	**-1.25**	**-0.86**	Return	-0.59	-0.69	**-1.33**	**-0.99**
	(-0.72)	(-1.88)	(-3.15)	(-2.49)		(-1.60)	(-1.53)	(-2.15)	(-2.04)
FFC4 α	-0.53	**-0.84**	**-1.47**	**-1.09**	FFC4 α	-0.42	-0.44	-0.99	-0.74
	(-1.66)	(-2.67)	(-3.64)	(-2.86)		(-0.93)	(-0.81)	(-1.19)	(-1.21)

Panel A above shows that there is a relation between MAX and beta. The MAX effect is not robust to controls for beta and only seams to appear in the $\beta 2$ and $\beta 3$ columns with corresponding FFC4 alphas of -0.84 and -1.47, both highly significant. Also note that the high-low MAX portfolio return and alphas are significantly larger in the $\beta 3$ portfolio compared to the $\beta 2$ portfolio and that the return of the latter is not statistically significant. Neither the return nor the FFC4 alpha is significant in the $\beta 1$ column of Panel A.

Panel B above shows the beta anomaly controlling for MAX. Interestingly we only detect the beta anomaly in the high MAX stocks. The return of the high-low beta portfolio is -0.99% per month and significant. However when we control for Fama and Kenneth R. French (1993) and Carhart (1997) factors the beta anomaly is not detected. The column labeled MAX Avg. is the high-low beta portfolio not considering MAX i.e the beta anomaly.

The Bivariate Portfolio analysis clearly indicated that there is a relation between MAX and beta. As we see that the MAX effect is only present in the high beta portfolio and that the beta anomaly is only detected in the high MAX portfolio. However we cannot conclude that the beta anomaly is explained by MAX unlike Bali et al. (2016) since we detect the beta anomaly in the MAX 3 portfolio.

4.2 Firm level cross sectional regression

We continue our analysis of the relation between the beta anomaly and lottery demand phenomenon by conducting cross sectional Fama and MacBeth (1973) regressions. In each month t we run a cross-sectional regression of one month ahead excess stock return on beta and MAX and a series of other control variables known to influence stock return. The control variables are grouped into three categories: (1) Firm characteristics including: size, defined as the natural logarithm of the market value at the end of the month t; Book-to-Market (BM) defined as the natural logarithm of the most resent book value know at month in the end of month t [2] divided by the market value at the end of month t; Momentum (MOM) that is the return in month $t-1$ through $t-11$. (2) Measures of risk include: COSKEW, TSKEW and DRISK all designed to capture return distribution and are defined in section 2. (3) Sensitivity to funding liquidity including: β_{TED}, β_{VOLTED} and β_{TBILL} designed to capture a stocks return sensitivity to interest rates and differences in borrowing and lending rates.

[2] We allow six months too pass before we presume to know the book value for the most recent fiscal year. e.g a company in fiscal year Jan-Dec are assumed to file their annual report in the end of June in the subsequent year.

Table VI: Cross sectional regression with MAX
At the end of each month t we run Fama and MacBeth (1973) cross sectional regression of one month ahead stock excess return on beta and a battery of control variables. The control variables can be groups into the following three categories: (1) firm characteristics: including SIZE, which is the natural logarithm of market cap; BM, is the natural logarithm of Book-to-Market; MOM that is the one year prior return leaving out the most recent month; and MAX, the maximum daily return within month t. (2) Measures of risk; including COSKEW, TSKEW and DRISK. (3) Stock sensitivity to funding liquidity including β_{TED}, β_{VOLTED} and β_{TBILL}. The coefficients presented are the time series average coefficients of the regressions. Corresponding Newey and West (1987) t-statistics are presented in parenthesis. Bold indicates significancy at the 5% level. The row labeled R^2 is the average adjusted R-squarred and n is the average number of stocks per month.

	β	MAX	SIZE	BM	MOM	COSKEW	TSKEW	DRISK	β_{TED}	β_{VOLTED}	β_{TBILL}	INTERCEPT	R^2	n
(1)	-1.00	**-0.06**	-0.00	0.15	**0.01**							**2.38**	10.1%	244
	(-1.38)	(-3.03)	(-0.40)	(1.33)	(2.30)							(4.44)		
(2)	-1.04	**-0.05**	-0.00	0.15	**0.01**	-0.01	-0.06	0.03				**2.34**	12.4%	244
	(-1.25)	(-2.45)	(-0.30)	(1.47)	(2.18)	(-0.87)	(-1.12)	(0.01)				(4.40)		
(3)	-1.19	**-0.05**	-0.00	-0.17	**0.01**	-0.01	**-0.05**	0.07	**-0.04**	0	0.01	**2.33**	14.7%	244
	(-1.41)	(-2.24)	(-0.20)	(1.74)	(3.62)	(-0.47)	(-0.84)	(0.20)	(-2.10)	(0.23)	(1.81)	(4.38)		

Table VI presents the results of the cross-sectional Fama and MacBeth (1973) regressions. The coefficient of beta is negative in all three regression specifications, however not significant. Therefore we say that beta is not priced in the cross-section when we control for MAX. Instead it seems that beta does not play an important roll in the pricing of stocks. When we compare the results of regression (1) to the same regression in Table III we see that beta is no longer significant and we can conclude that MAX renders beta insignificant in the cross section. These results are much weaker then the results of Bali et al. (2016) who finds that the coefficient of beta is positive when controlling for MAX. Although beta is also insignificant in all other regressions presented in Table III and VI indicating that the beta anomaly to is weak if at all existing in the Swedish sample. However the BAB factor has a high monthly alpha indicating that the beta anomaly is in fact strong in Sweden. How robust then is this factor to controls for lottery demand?

4.3 BAB and FMAX

In the previous sections, we find conflicting evidence as to if the beta anomaly can be explained by lottery demand. Having constructed factor portfolios that mimic both the beta anomaly and lottery demand, we can now test the robustness of the beta anomaly to lottery demand using regression analysis. Table VII present the results. First, we note that the BAB portfolio is market neutral as it is supposed to be. What is most interesting is that BAB is robust to the inclusion of the FMAX factor. Although the coefficient of FMAX is negative (remember that FMAX is long lottery-like stocks) and highly statistically significant, the BAB alphas remain positive but are smaller when we include FMAX in the regression as compared to the alphas of Table IV. We continue by looking at the individual legs of the BAB portfolio. The high beta portfolio is significantly loaded on the FMAX factor in all model specifications. If lottery demand is driving the beta anomaly it is not surprising that the high beta portfolio is heavily loaded on the FMAX factor. The high beta portfolio does not yield any alpha in the FFC-4 factor specification when FMAX is included. The low beta portfolio does not have a insignificant and negative loading on FMAX in the CAPM or FFC-4 factor regression specifications. Again, the lottery-demand explanation does predict the negative loading, although we find it insignificant. It appears that the beta anomaly is not in its entirety driven by lottery demand as indicated by Bali et al. (2016). We find the resilience of the BAB factor interesting since we know that lottery demand is present and stronger in Sweden as compared to US and global samples. An explanation could simply be that the beta anomaly more systematic in nature in the Swedish sample.

Table VII: BAB and FMAX

The table shows the average excess return and the results of the regressions of all of the three dependent variables High beta, Low beta and BAB on FMAX (presented in the column labeled FMAX), MKT and FMAX (presented in the rows labeled CAPM+FMAX) and on MKT, SMB, HML, MOM and FMAX (presented in the rows labeled FFC 4-factor+ FMAX). Corresponding Newey and West (1987) t-statistics are presented in parenthesis, bold indicates significancy at the 5% level. Annualized Sharpe ratios are presented in the column labeled Sharpe ratio.

	FMAX		CAPM + FMAX			FFC 4-factor + FMAX					
	Alpha	FMAX	Alpha	MKT	FMAX	Alpha	MKT	SMB	HML	MOM	FMAX
High Beta	**1.02**	**1.24**	**0.54**	**1.10**	**0.52**	0.05	**1.19**	**0.40**	-0.08	**-0.12**	**0.36**
	(2.27)	(11.55)	(2.24)	(20.71)	(6.42)	(1.92)	(23.14)	(6.02)	(-1.19)	(-2.13)	(4.45)
Low Beta	**1.38**	**0.34**	**1.12**	**0.59**	-0.05	**0.84**	**0.72**	**0.40**	0.11	0.04	-0.05
	(4.23)	(5.66)	(4.63)	(8.00)	(-0.65)	(4.03)	(14.42)	(6.12)	(1.93)	(0.84)	(-0.89)
BAB	**1.31**	**-0.49**	**1.32**	-0.02	**-0.47**	**0.94**	0.12	**0.33**	0.20	**0.16**	**-0.38**
	(3.4)	(-4.37)	(3.31)	(-0.17)	(-3.57)	(2.15)	(1.36)	(2.11)	(1.20)	(2.08)	(-3.44)

In this section, employing several different techniques, we have found that demand for lottery-like stocks is not the sole driver of the beta anomaly. Instead, our results suggest that idiosyncratic lottery demand and systematic leverage constraints *together* causes the beta anomaly. It is by no means strange or unusual that several factors, very different in nature, cause a result. However, the beta measure itself is a combination of both volatility and correlation. This fact enable us to further dissect the relationship between the anomalous pricing of beta and the two explanations that have been proposed for it. Using a similar portfolio forming technique as that used to construct BAB, the beta anomaly can be decomposed into its volatility and correlation components. This decomposition is the main topic of the next section.

5 The BAC and BAV factors

The beta measure is by construction comprised of two components: correlation and volatility. Rational explanations of the beta anomaly has traditionally focused on the correlation term, while behavioral explanations focus on volatility. Asness et al. (2016) propose a decomposition of BAB into two factors: Betting Against Correlation (BAC) and Betting Against Volatility (BAV). BAC is constructed to go long in low correlation stocks and short high correlation stocks and at the same time match the volatility of the two legs. BAV is the opposite, long low volatility and short high volatility, at the same time being correlation neutral. We provide a technical description of how to construct the two factors in the appendix. The BAC factor should be less related to behavioural factors such as MAX, while BAV is. The rational leverage constraints theory should be captured by the BAC factor about as good as it is captured by BAB. This is since low correlation with the market equals a low beta. In essence, this allows us, using control variables, to further examine the underlying drivers of the beta anomaly in our dataset.

We start our analysis of the BAB decomposition by regressing BAB on BAC and BAV. First, this enables us to conclude if the decomposition is correct. Secondly, we can see if the BAB excess return is mostly due to correlation or volatility. The results are presented in Table VIII. We note that the regression of BAB on BAC and BAV yields an intercept that is that is statistically indifferent form zero. Furthermore, the

R^2 of the multiple regression is high at 92%. This leads us to the conclusion that the decomposition is correct. Moreover, regressing BAC on BAV and vice versa shows that BAC is not an explanator of BAV or the other way around.

Moving on to the matter of BAB's loadings on the two factors we can see that, in both the univariate and bivariate regressions, BAB is more heavily loaded on BAC than on BAV. In the univariate regressions, only BAC renders the intercept of BAB insignificantly different from zero. In the bivariate regression, the loading on the BAC factor is significantly higher. We see this as evidence that the excess return of the BAB portfolio in Sweden is more due to market correlation than volatility. In the next section we examine the performance of the BAC and BAV portfolios.

Table VIII: BAC and BAV as explanators for BAB
The following table shows the regression coefficients when regressing monthly Betting Against Beta (BAB) returns on Betting Against Correlation (BAC) and Betting Against Volatility (BAV). The two bottom rows show the regression coefficients when regressing BAC on BAV, and vice versa. t-statistics are shown in parentheses and coefficients in bold font indicates significance at the 5% level.

	alpha	BAC	BAV	R^2
BAB	0.05	**0.96**		65.4%
	(1.90)	(15.21)		
BAB	**1.03**		**0.60**	32.5%
	(2.63)		(4.93)	
BAB	-0.16	**0.91**	**0.54**	92.0%
	(-1.29)	(23.00)	(11.28)	
BAC	**1.30**		0.07	0.5%
	(3.56)		(0.68)	
BAV	**1.12**	0.08		0.5%
	(3.04)	(0.68)		

5.1 Performance of BAC and BAV

Having decomposed the BAB factor into BAC and BAV, we now turn to examining the performance of the two new factors. The results are presented in Table IX. Both BAC and BAV generate positive and statistically significant alphas, both in a CAPM setting and using the Fama-French 4-factor model. We note that for BAC, the ex-ante market hedge, i.e. beta neutrality, works as intended as the market beta is statistically indifferent from zero in both regression specifications. BAV is not market neutral. But given the high volatility of the short leg of BAV it is perhaps not that strange that the ex-ante beta estimates are a noisy prediction of ex-post beta for these stocks.

The Fama-French-Carhart factor loadings of the two portfolios are worth some thought. BAC has a highly significant loading on small minus big, while the opposite is true for BAV. This indicate that stocks with low market correlation, given a constant volatility are on average small. Low volatility stocks, given a constant market correlation, are on average large. A possible explanation why large stocks have higher correlation with the market compared to smaller stocks is simply that they are so large, sometimes accounting for 5% of the total index market value. Given their size they are large enough so that their return can itself move the index return, making the stock and index return correlated. An explanation to why large stocks tend to be less volatile is that trading is more informed, due to more analyst coverage and a larger degree of institutional ownership. BAV has a statistically significant positive loading on HML, but not BAC. We would have expected that both factors should have a positive loading on HML. This is since both correlation and volatility are associated with safe stocks. Safe stocks are avoided by leverage constrained investors as they seek to reach higher returns without leverage, leading to them becoming cheaper. This gives rise to a positive HML (value) factor. As discussed by Fama and Kenneth R French (2016), MOM is not an explanation for the low-beta anomaly, but we include it for reasons of completeness.

We conclude that BAC and BAV is robust using a standard CAPM specification and using several control variables. The leverage constraint theory of Frazzini and Pedersen (2014) suggest that they should be robust to a CAPM specification. What is more interesting is that it is robust to Fama-French factors, something that is not predicted by the aforementioned paper. Having found BAC and BAV robust to systematic factors, we now turn to the idiosyncratic lottery factor FMAX.

Table IX: BAC, BAV and lottery demand

At the beginning of month t, we form two portfolios: BAC and (BAV). Stocks are ranked in ascending order based on their volatility (correlation). Based on this ranking they are assigned into five quintiles. Within the quintiles, we place the stocks into either a low or high correlation (volatility) portfolio. In the high or low portfolio stocks are rank-weighted, i.e. stocks that are the most correlated (volatile) have the largest weights in the high correlation (volatility) portfolio and vice versa for low correlation (volatility) stocks. The two portfolios are constructed to be self-financing and are weighted to have a beta of one. Within each quantile, a final portfolio is formed that is long the low correlation (volatility) portfolio and short the high correlation (volatility) portfolio. The final BAC (BAV) portfolio is then the equal wheighted portfolio of the five quintile portfolios. The excess return of the BAC and BAV portfolio is then calculated and regressed both on the market alone (CAPM) and on Fama French 4 factors (MKT SMB HML and MOM). In the bottom part of the table represents regressions of excess stock return on FMAX; MKT and FMAX; MKT, SMB, HML, MOM and FMAX. SEK long/short is the SEK amount in the long and short leg of the portfolio and are presented in the table note. SR is the annualized Sharpe ratio of the portfolio and is presented in the table note. Alphas and excess returns are in percent per month. t-statistics are shown in parentheses and coefficients in bold font indicates significance at the 5% level.

	Excess return	CAPM		FFC 4-factor				
		Alpha	MKT	Alpha	MKT	SMB	HML	MOM
BAC	1.38	**1.26**	-0.19	**1.08**	0.04	**0.60**	0.10	**0.15**
	(4.46)	(3.66)	(-1.87)	(2.52)	(0.46)	(5.76)	(1.14)	(2.70)
BAV	1.23	**1.33**	**-0.35**	**1.10**	**-0.23**	**-0.39**	**0.50**	0.12
	(3.41)	(3.64)	(-3.77)	(3.84)	(-2.93)	(-4.21)	(5.74)	(1.64)

	FMAX		CAPM + FMAX			FFC 4-factor + FMAX					
	Alpha	FMAX	Alpha	MKT	FMAX	Alpha	MKT	SMB	HML	MOM	FMAX
BAC	**1.15**	-0.17	**1.21**	-0.13	-0.08	**0.71**	0.11	**0.61**	0.04	**0.13**	-0.15
	(3.42)	(-1.59)	(3.22)	(-1.13)	(-0.66)	(2.37)	(1.30)	(6.15)	(0.39)	(2.18)	(-1.87)
BAV	**0.93**	**-0.60**	**0.90**	0.06	**-0.64**	**1.00**	-0.04	**-0.35**	**0.33**	0.06	**-0.39**
	(3.30)	(-8.31)	(3.21)	(0.99)	(-8.59)	(3.93)	(-0.61)	(-4.42)	(4.25)	(1.11)	(-5.39)

The Sharpe ratios of the BAC and BAV portfolios are 1.11 and 0.88 respectively. The BAC portfolio is invested 1.56 SEK long and 0.93 SEK short, while the BAV portfolio is invested 1.42 SEK long and 1.00 SEK short.

5.2 BAC, BAV and lottery demand

So far our analysis has indicated that BAB, both as itself and decomposed into BAC and BAV yields positive excess returns in the Swedish stock market. We see evidence of both systematic and and idiosyncratic factors as explanatory of the beta anomaly. After finding BAB to be robust to lottery demand, we now turn our attention to lottery demand in the context of BAC and BAV. As BAC is designed to capture the systematic part of the beta anomaly, we expect it to be robust to lottery demand. BAV however is idiosyncratic in nature. As BAB was robust to lottery-seeking demand, it is worth testing if that is the effect of BAC "washing out" the idiosyncratic component (BAV) or if BAV itself is robust to out specification of lottery demand.

The results the regression analysis of BAC and BAV can be found in the lower part of Table IX. As expected, FMAX is not significant in any regression specification when BAC is the dependent variable. The opposite is true when it comes to BAV. Also worth noting is that when FMAX is included, the negative market loading in the BAV portfolio (see Table IX) disappears.

The BAC alpha is significant using all three regression specifications. This is not surprising since the lottery demand factor is not affecting BAC. The BAV regressions are more puzzling however. Even though FMAX is highly significant and negative (remember that FMAX is long stocks with high lottery demand), it does not render the alpha of the BAV portfolio insignificant. Asness et al. (2016) report statistically insignificant alphas for the BAV portfolios when FMAX is included in the regressions. We have a plausible explanations for the results differing. First, we use another definition of FMAX as compared Asness et al. (2016). While they use the average of the five daily highest one-day returns to construct FMAX, we use only the *one* day maximum return. As discussed earlier we see this as a better proxy for lottery demand. When using the five day return definition, FMAX is more a measure of volatility (or perhaps positive semi-variance) than our measure. If our measure is less correlated with volatility, it is not strange that BAV is robust to the FMAX control.

To conclude this section, we have found that both BAC and BAV is robust to a battery of control variables, both systematic and idiosyncratic in nature. The performance BAC, the systematic part of the BAB decomposition, appears to be the result of leverage constrained investors seeking high returns. BAV, the idiosyncratic part, is at least in part driven by lottery demand. It is safe to say that an arbitrageur that is not leverage constrained can reap profits from the beta anomaly in our sample. If so, why does not such arbitrageurs correct the beta anomaly? In the following section we shed light on that and propose a more implementable trading strategy.

6 TailBAB

The BAB factor has a positive alpha of 1.03 % as can be seen in Table IV. However the BAB factor is almost impossible to trade on. It requires a position in every single stock in the universe of stocks. Half of the positions are long and the other half short. Furthermore the turnover of the monthly rebalanced portfolio may be a concern when trying to construct a factor mimicking trading strategy. A likely scenario is that the investor who trades on BAB will see most of the strategies positive pre-cost alpha be engulfed by trading costs.

We propose a novel strategy that is based on BAB and uses the same methodology but does not hold positions in every single stock. We name this strategy TailBAB. The strategy produces a very impressing FFC4 alpha of 2.17% per month. With a Sharpe ratio of 1.14.

6.1 Constructing TailBAB

We construct TailBAB in a similar fashion as the regular BAB, except we only hold positions in the 10th and 90th beta percentiles.

At the end of each month t we calculate the 10th and 90th percentile breakpoints of stock betas. Stocks that fall within the 10th or 90th percentile breakpoints are then ranked so that the stocks with the highest and lowest beta have the highest rank and stocks that are closer to the breakpoints have lower ranks. We call this rank z_i. We base the weights in the individual stocks based on the rank z_i. The weights in the individual stocks is given by:

$$w_i = \frac{z_i - z_{max} + 1}{\sum\limits_{z=1}^{z_{max}} z} \tag{8}$$

Where z_i is the rank of stock i within the 10th or 90th percentile and z_{max} is the maximum rank within the 10th or 90th percentile and $\sum\limits_{z=1}^{z_{max}} z$ is the sum of the ranks within the given percentile.

The beta of the two portfolios is given by:

$$\beta_p = \sum_{i=1}^{N} (\beta_i w_i) \tag{9}$$

Where β_p is the beta of the portfolio and β_i and w_i are the beta and the weight of the individual stocks.

The one month ahead return of the portfolio is simply the weighted average of that portfolio such that:

$$r_{t+1}^{p} = \sum_{i=1}^{N} w_i r_i \tag{10}$$

We construct the TailBAB to be beta neutral ex-ante by scaling the invested amount in each portfolio. TailBAB is then:

$$TailBAB_{t+1} = \frac{1}{\beta^l}(r_{t+1}^{l} - r_t^{rf}) - \frac{1}{\beta^h}(r_{t+1}^{h} - r_t^{rf}) \tag{11}$$

Where β^l and β^h are the beta of the low and high portfolio respectively, r_{t+1}^{l} and r_{t+1}^{h} are the subsequent monthly returns of the low and high beta portfolio respectively.

6.2 Performance of TailBAB

Table X summarizes the performance of our TailBAB strategy and also the performance of the long and short leg (low and high beta). From the regression results we can see that TailBAB produces a highly significant excess return and highly significant monthly alphas of 2.83% when only controlling for the excess market return and 2.17% when controlling for FFC4 factors. The results are of large economic significance. Furthermore TailBAB does not load on systematic risk i.e. is independent of the market in the full model specification and negatively related to the market in the CAPM specification. Also, the Sharpe ratio of 1.14 is impressive.

What is also interesting is that the long and short side of the tailBAB strategy has a strong loading on SMB factor as well as the TailBAB strategy. This is because the TailBAB strategy is not constructed to be size neutral but only to be market neutral. Many factor mimicking strategies such as MOM and FMAX are constructed to be size neutral. The rational for constructing the portfolio to be market neutral as opposed to size neutral is that it is designed to capture the beta anomaly and not the size anomaly.

Table X: TailBAB

The table below shows the excess return, the coefficients of a regression of each of the dependent variables high beta, low beta and TailBAB on MKT (presented in the columns headed CAPM) and on MKT, SMB HML and MOM factors (presented in the columns headed FFC4-factor. The below part of the table include FMAX in the regressions as an independent variable. Newey and West (1987) t-statistics are reported in parenthesis below and 5% significancy is indicated in bold. Sharpe ratios and SEK amount long/short are presented in the table note.

	Excess return	CAPM		FFC 4-factor				
		Alpha	MKT	Alpha	MKT	SMB	HML	MOM
High Beta	0.05	0.00	**1.64**	0.12	**1.57**	**0.46**	**-0.30**	**-0.14**
	(0.06)	(0.01)	(15.55)	(0.31)	(17.49)	(3.88)	(-3.10)	(-1.49)
Low Beta	**1.36**	**1.35**	**0.37**	**1.07**	**0.5**	**0.38**	0.10	0.05
	(3.74)	(4.62)	(5.77)	(3.72)	(7.76)	(4.95)	(1.60)	(0.95)
TailBAB	**2.81**	**2.83**	**-0.48**	**2.17**	-0.18	**0.49**	**0.36**	**0.20**
	(4.01)	(4.02)	(-3.01)	(3.17)	(-1.02)	(2.19)	(2.44)	(1.83)

	FMAX		CAPM + FMAX			FFC 4-factor + FMAX					
	Alpha	FMAX	Alpha	MKT	FMAX	Alpha	MKT	SMB	HML	MOM	FMAX
High Beta	**0.94**	**1.44**	**0.42**	**1.21**	**0.65**	0.25	**1.33**	**0.41**	-0.09	**-0.05**	**0.5**
	(1.74)	(13.38)	(1.23)	(14.56)	(6.96)	(0.70)	(16.04)	(4.20)	(-0.84)	(-0.61)	(4.66)
Low Beta	**1.49**	**0.20**	**1.31**	**0.41**	-0.07	**1.04**	**0.54**	**0.39**	0.06	0.03	-0.10
	(4.31)	(3.81)	(4.42)	(5.30)	(-1.13)	(3.61)	(8.21)	(5.18)	(0.85)	(0.63)	(-1.66)
TailBAB	**2.42**	**-0.64**	**2.46**	-0.1	**-0.57**	**2.02**	0.1	**0.55**	0.12	**0.10**	**-0.58**
	(3.64)	(-5.46)	(3.70)	(-0.53)	(-4.17)	(2.15)	(0.60)	(2.67)	(0.69)	(0.98)	(-4.15)

The annualized Sharpe ratios of the High- and Low Beta portfolios are 0.06 and 1.20 respectively and the annualized Sharpe ratio of the TailBAB strategy is 1.14 and it is invested SEK 2.11 long and SEK 0.77 short.

MAX is related to extreme events and we have already seen in Table V that the MAX effect is predominantly present in high beta stocks. Therefore we control for the influence of lottery demand by including FMAX into our regression found in the bottom part of Table X.

As expected, when we include FMAX in the regressions TailBAB produces a lower alpha in all specifications. We can see that FMAX has a significant and negative price pressure on our TailBAB portfolio. Still we see a large significant alpha of 2.02% in the full model specification. We are intrigued by our findings of TailBAB. The strategy seams to perform well controlling for known market risk factors. A logical question that follows is - *Is it possible to implement the strategy and what might be the cost of doing so.*

6.3 Implementation of TailBAB

TailBAB has a large in sample pre-trading cost alpha. However to fully understand the profits of this strategy one must consider trading costs. Furthermore the strategy relies on short selling, this may not always be possible for any Swedish stock at any given time. We lack the data to fully evaluate the cost of pursuing this strategy but instead calculate the turnover of the portfolio. Turnover is directly related to trading costs and even though we do not attempt to estimate the net of cost performance, it serves as an indicator of the relative trading costs when compared to turnover in other mutual funds. We calculate the turnover for the long and short portfolios separately and find that the average turnover in the long portfolio is 7.05% per month. The turnover measure is calculated as the minimum of sales or purchases divided by the total assets. This can be compared to the average monthly turnover 7.96% found by Ferreira et al. (2013) in an international sample of active mutual funds. The short side of the strategy has a considerably higher turnover of 21.10%. This turnover must be considered very high on a monthly basis. The TailBAB strategy also has higher turnover then the BAB strategy that has a turnover of 4.82% and 4.96% for the long and short side respectively.

Another important measure of fund performance is maximum drawdown which represents the worst possible timing in fund purchase and selling. The maximum drawdown of the long- and short portfolios are 45.46% and 93.38% respectively and 54.5% for the total TailBAB strategy. Maximum drawdown is important as large drawdowns can cause investors to liquidate their position out of fear of further losses in turn causing the fund to liquidate position prematurely at the cost of the investors that are loyal.

TailBAB relies on the possibility of selling short stocks. Meanwhile all stocks are not possible to sell short in large enough quantities or at a reasonable price. We argue that the probability of finding shares to sell short is highly related the amount of floating stocks. We are not able to observe the floating stocks but instead calculate the median market size of the constituents in the two portfolios and use this as a proxy for the possibility of short selling. The median market value for the stocks that are in the short portfolio is 19.73 billion SEK. Many times more than the median of 2.02 billion in the complete sample and slightly lower than the average market value of 22.46 billion SEK. Therefore we can conclude that on average it is possible to implement the short portfolio. The average market value of the long side of the strategy is 9.24 billion SEK. However the market value of the constituents is highly skewed as the median market value is only 625 million SEK. The fact that so many of the stocks are small can pose problems when implementing the strategy as size and liquidity are often related, this is likely to reduce the return of the strategy. To conclude, we find that there are some problems with implementing our simplified version of the BAB strategy and this limit to arbitrage may be the reason why the beta anomaly is persistent.

7 Conclusion

We are able to conclude that the beta anomaly is present in Sweden. In univariate portfolio sorts, beta is not priced according to the CAPM. There is no statistically significant difference in return between low and high beta portfolios. In cross-sectional Fama and MacBeth (1973) regressions we see find the same result, beta is in fact negatively priced controlling for standard Fama-French-Carhart factors. The rank-weighted BAB portfolio generates significant alphas, even after a battery of control variables. This further leads us to conclude that the beta anomaly is present in our sample of Swedish stocks. Next we examine the underlying drivers of the beta anomaly, if they are systematic and a result of leverage constraints as proposed by Frazzini and Pedersen (2014) or an idiosyncratic phenomenon driven by lottery demand as argeud by Bali et al. (2016). In bivariate portfolio sorts on beta and MAX, we find that the MAX effect is only present in medium and high beta portfolios and that beta is only negatively priced in the high MAX portfolio. This is evidence that lottery plays some part in the beta anomaly. On the other hand, factors designed to measure the funding liquidity constraints removes the negatively priced beta in the cross-section, suggesting that leverage constraints also plays a part. Moreover, the return of the BAB portfolio is negatively loaded on the liquidity measure *Beta TED*. To further disentangle the systematic and idiosyncratic components of beta, we decompose the BAB portfolio into a BAC and a BAV portfolio, designed to split up the effects of correlation and volatility, i.e. the systematic and idiosyncratic components. Both portfolios generate significant alphas after FFC-4 factor control variables. We also control for lottery using the lottery demand factor FMAX. BAC is unsurprisingly found to be robust to the FMAX facrtor. More of a surprise is that the BAV factor is also robust to lottery demand. We argue that this is since MAX is designed to capture lottery demand and not volatility per se. To conclude, the beta anomaly is a result of both idiosyncratic and systematic factors. One limitation of the apparently profitable BAB strategy is that it requires a potential investor to hold a position in all stocks in a specific sample, with half of the positions being short. Those short positions are hard or even impossible to maintain and likely to consume much of the profit. To overcome this we propose a novel portfolio, TailBAB, that is only invested in 20% of the specific stock universe. This strategy is easier to maintain and generates a FFC4 alpha of 2.17% per month. Even a strategy that is long only yeids a FFC4 alpha of 1.07% per month with a Sharpe ratio of 1.2. However, even in our simple strategy present some challenges for a potential arbitrageur, such as short positions in small stocks. This highlights that limits to arbitrage could be one reason why the beta anomaly is not "traded away" by arbitrageurs.

One potentially fruitful topic for further research could be to investigate how BAB is best implemented in practise. The turnover of the BAB portfolio could be reduced if some slippage is allowed. Restricting the short side of the BAB portfolio to only include stocks that are indeed shortable at reasonable cost would yield important information on the viability of implementing BAB in practise.

We have shown that both lottery demand and leverage constraints do relate to the beta anomaly. Both explanations hold merit, however they use proxies to estimate their respective explanatory factors. Perhaps one way to address this is a more qualitative approach, simply interviewing fund managers to establish if leverage constraints make them more prone to buy high beta stocks. Also a dataset containing transactions of individual investors could help disentangle the effect of lottery-seeking behaviour in relation to the beta anomaly.

References

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. 2009. “High idiosyncratic volatility and low returns: International and further U.S. evidence.” *Journal of Financial Economics* 91 (1): 1–23.

Asness, Clifford S, Andrea Frazzini, Niels Joachim Gormsen, and Lasse Heje Pedersen. 2016. “Betting Against Correlation: Testing Theories of the Low-Risk Effect.” *Working paper, AQR Capital Management.*

Bali, Turan G., Stephen Brown, Scott Murray, and Yi Tang. 2016. “A Lottery Demand-Based Explanation of the Beta Anomaly.” *Georgetown McDonough School of Business Research Paper No. 2408146.*

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw. 2011. “Maxing out: Stocks as lotteries and the cross-section of expected returns.” *Journal of Financial Economics* 99 (2): 427–446.

Barberis, Nicholas, and Ming Huang. 2008. “Stocks as Lotteries: The Implications of Probability Weighting for Security Prices.” *The American Economic Review* 98 (5): 2066–2100.

Bawa, Vijay S., and Eric B. Lindenberg. 1977. “Capital market equilibrium in a mean-lower partial moment framework.” *Journal of Financial Economics* 5 (2): 189–200.

Black, Fischer, Michael C Jensen, and Myron S Scholes. 1972. “The capital asset pricing model: Some empirical tests.” *In Michael C. Jensen (ed.), Studies in the Theory of Capital Markets, New York:* 79–121.

Carhart, Mark M. 1997. “On persistence in mutual fund performance.” *The Journal of Finance* 52 (1): 57–82.

Elton, Edwin J, Martin J Gruber, Stephen J Brown, and William N Goetzmann. 2009. *Modern portfolio theory and investment analysis.* Hoboken, NJ: John Wiley & Sons.

Fama, Eugene F., and Kenneth R. French. 1993. “Common risk factors in the returns on stocks and bonds.” *Journal of Financial Economics* 33 (1): 3–56.

Fama, Eugene F., and Kenneth R French. 2016. “Dissecting anomalies with a five-factor model.” *Review of Financial Studies* 29 (1): 69–103.

Fama, Eugene F., and James D. MacBeth. 1973. “Risk, return, and equilibrium: Empirical tests.” *Journal of Political Economy* 81 (3): 607–636.

Ferreira, Miguel A., Aneel Keswani, António F. Miguel, and Sofia B. Ramos. 2013. "The Determinants of Mutual Fund Performance: A Cross-Country Study." *Review of Finance* 17 (2): 483.

Frazzini, Andrea, and Lasse H. Pedersen. 2014. "Betting against beta." *Journal of Financial Economics* 111 (1): 1–25.

Gruodis, Dominykas. 2015. "The Fama French Five Factor Asset Pricing Model for the Swedish Stock Market." *Working paper, Stockholm School of Economics.*

Guiso, Luigi, and Paolo Sodini. 2013. "Household finance: An emerging field." Chap. 21 in *Handbook of the Economics of Finance,* 1397–1532. Elsevier.

Harvey, Campbell R., and Akhtar Siddique. 2000. "Conditional skewness in asset pricing tests." *The Journal of Finance* 55 (3): 1263–1295.

Hellgren, Karl, and Alexander Helmy. 2015. "The MAX effect and what drives it - Evidence from the Swedish Stock Market." *Working paper, Stockholm School of Economics.*

Ince, Ozgur S., and R. B. Porter. 2006. "Individual equity return data from Thomson Datastream: Handle with care!" *Journal of Financial Research* 29 (4): 463–479.

Kraus, Alan, and Robert H. Litzenberger. 1976. "Skewness preference and the valuation of risk assets." *The Journal of Finance* 31 (4): 1085–1100.

Kumar, Alok. 2009. "Who gambles in the stock market?" *The Journal of Finance* 64 (4): 1889–1933.

Lintner, John. 1965. "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets." *The Review of Economics and Statistics:* 13–37.

Newey, Whitney K., and Kenneth D. West. 1987. "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix." *Econometrica* 55 (3): 703–708.

Schmidt, Peter S., Andreas Schrimpf, Urs von Arx, Alexander Wagner, and Andreas Ziegler. 2011. "On the Construction of Common Size, Value and Momentum Factors in International Stock Markets: A Guide with Applications." *CER-ETH Economics working paper series.*

Sharpe, William F. 1964. "Capital asset prices: A theory of market equilibrium under conditions of risk." *The Journal of Finance* 19 (3): 425–442.

Tversky, Amos, and Daniel Kahneman. 1992. "Advances in prospect theory: Cumulative representation of uncertainty." *Journal of Risk and Uncertainty* 5 (4): 297–323.

Vasicek, Oldrich A. 1973. "A Note on Using Cross-sectional Information in Bayesian Estimation of Security Betas." *The Journal of Finance* 28 (5): 1233–1239.

8 Appendix

Tables

Table A1: Univariate Portfolio level Analysis
At the end of each month stocks are sorted into decile portfolio based on beta. Excess return is the time series average of the one month ahead simple return less the risk free rate. FFC4 alphas are the intercept of a regression of excess one month ahead returns on the market risk premium SMB HML and MOM factors. Average β is self explained. The row named 1-10 Hedge is the long/short portfolio that is long the low beta portfolio and short the high beta portfolio, corresponding Newey and West (1987) t-stat using 1 lag is presented in parenthesis. 5% significancy is indicated in bold.

	VW Portfolios		EW Portfolios		
Decile	Excess Return	FFC4 Alpha	Excess Return	FFC4 Alpha	Average β
Low Beta	0.59	0.49	1.16	0.71	0.21
2	0.61	0.50	1.39	0.93	0.46
3	1.21	1.18	1.21	0.74	0.59
4	0.78	0.45	1.14	0.69	0.71
5	0.14	-0.37	1.11	0.77	0.81
6	0.86	0.50	1.30	0.91	0.94
7	1.10	0.99	1.07	0.70	1.08
8	0.54	0.28	0.71	0.40	1.26
9	0.52	0.59	0.58	0.15	1.51
High Beta	0.81	1.07	0.37	0.34	2.01
1-10 Hedge	-0.21	-0.59	0.79	0.38	
t-stat	(-0.23)	(-0.73)	(1.30)	(0.82)	

Table A2: Beta and MAX portfolio relations
At the end of each month stocks are sorted into decile portfolios based on beta and MAX. The table represents the cross section of this sort. The numbers represent the percentage probability of a stock that is in beta decile j to be in MAX decile i.

		MAX decile									
		1	2	3	4	5	6	7	8	9	10
Beta decile	1	26.35	8.95	7.50	7.67	6.32	7.37	6.09	7.35	9.35	13.04
	2	13.33	13.15	10.57	10.47	10.41	9.53	9.15	8.13	8.56	6.69
	3	11.44	11.72	11.13	10.41	10.53	10.03	9.35	8.60	9.27	7.53
	4	9.93	11.43	11.47	10.26	10.42	10.63	10.12	9.33	8.66	7.74
	5	10.38	11.94	11.14	10.79	10.92	9.83	9.19	9.31	8.76	7.74
	6	8.81	10.45	11.72	11.12	9.66	10.00	10.00	9.93	10.10	8.21
	7	8.41	10.16	11.11	10.35	10.88	9.83	10.55	9.79	9.56	9.36
	8	6.24	9.54	10.05	11.25	10.92	10.34	10.61	10.57	10.17	10.30
	9	4.43	7.77	9.84	9.28	10.00	11.74	12.09	12.98	10.75	11.12
	10	2.15	4.52	5.88	7.84	9.46	11.41	13.03	13.94	15.22	16.54

Table A3: Univariate sort on MAX

At the end of each month stocks are sorted into decile portfolio based on maximum one day return. Average return is the time series average value weighted (VW) and equal weighted(EW) one month ahead simple return. FFC4 alphas are the intercept of a regression of VW and EW excess one month ahead returns on the market risk premium SMB HML and MOM factors, respectively. Average β is self explained. The row named 10-1 Hedge is the long/short portfolio that is long the High MAX portfolio and short the Low MAX portfolio, corresponding Newey and West (1987) t-statistics using 1 lag are presented in parenthesis. 5% significancy is indicated in bold.

	VW Portfolios		EW Portfolios		
Decile	Average Return	FFC4 Alpha	Average Return	FFC4 Alpha	MAX
Low MAX	1.27	0.49	1.56	0.82	1.36
2	1.13	0.10	1.49	0.65	2.75
3	0.94	-0.02	1.53	0.68	3.38
4	0.78	-0.35	1.36	0.46	3.97
5	0.98	-0.17	1.10	0.19	4.61
6	0.76	-0.60	1.01	0.19	5.36
7	0.80	-0.21	0.78	0.01	6.29
8	1.26	0.42	0.93	0.26	7.61
9	1.00	-0.17	0.51	-0.36	9.85
High MAX	0.80	-0.19	0.16	-0.36	19.49
10-1 Hedge	-0.47	-0.68	**-1.40**	**-1.19**	
t-stat	(-0.68)	(-1.06)	(-2.31)	(-2.91)	

Table A4: Cross sectional regression with MAX, alternative measure of beta
At the end of each month t we run Fama and MacBeth (1973) cross sectional regression of one month ahead stock excess return on beta (a regression of monthly stock returns on monthly market returns, using a five year rolling window) and a battery of control variables. The control variables can be groups into the following three categories: (1) firm characteristics: including SIZE, which is the natural logarithm of market cap; BM, is the natural logarithm of Book-to-Market; MOM that is the one year prior return leaving out the most recent month; and MAX, the maximum daily return within month t. (2) Measures of risk; including COSKEW, TSKEW and DRISK. (3) Stock sensitivity to funding liquidity including β_{TED}, β_{VOLTED} and β_{TBILL}. The coefficients presented are the time series average coefficients of the regressions. Corresponding Newey and West (1987) t-statistics are presented in parenthesis. Bold indicates significancy at the 5% level. The row labeled R^2 is the average adjusted R-squared and n is the average number of stocks per month.

	Without MAX			With MAX		
	1	2	3	4	5	6
BETA	0.29	-1.45	-1.56	-1.00	-1.04	-1.19
	(-1.08)	(-1.83)	(-1.90)	(-1.38)	(-1.25)	(-1.41)
MAX				**-0.06**	**-0.05**	**-0.05**
				(-3.03)	(-2.45)	(-2.24)
SIZE	-0.01	0.01	0.02	-0.02	-0.02	-0.01
	(-0.23)	(0.17)	(0.26)	(-0.35)	(-0.26)	(-0.16)
BM	0.20	0.17	0.18	0.15	0.15	-0.17
	(1.66)	(1.54)	(1.76)	(1.33)	(1.47)	(1.74)
MOM	**1.10**	**0.01**	**0.01**	**0.01**	**0.01**	**0.01**
	(2.64)	(2.84)	(4.28)	(2.30)	(2.18)	(3.62)
COSKEW		-0.01	-0.00		-0.01	-0.01
		(-0.61)	(-0.23)		(-0.87)	(-0.47)
TSKEW		**-0.11**	-0.10		-0.06	-0.05
		(-2.29)	(-0.76)		(-1.12)	(-0.84)
DRISK		0.12	0.16		0.03	0.07
		(0.35)	(0.47)		(0.01)	(0.20)
BETA TED			**-0.05**			**-0.04**
			(-2.14)			(-2.10)
BETA VOLTED			0.00			0.00
			(0.39)			(0.23)
BETA TBILL			0.10			0.01
			(1.75)			(1.81)
INTERCEPT	1.28	2.12	2.12	2.38	2.34	2.33
	(2.28)	(3.83)	(3.83)	(4.44)	(4.40)	(4.38)
R^2	8.63%	11.10%	13.46%	10.12%	12.42%	14.72%
n	244	244	244	244	244	244

Factor Construction

BAB

In each month t, let the $(n \times 1)$ vector z_t be the ascending ranks of all (n) stocks with respect to beta.

$$z_i = rank(\beta_{it}) \tag{12}$$

The average rank $\bar{z} = 1_n' z/n$ where z_n' is a $(1 \times n)$ all-ones vector. To rank-weight the stocks in the respective portfolio; form two vectors of weights. One for the stocks with a beta under, and one for the stocks over $\bar{z}$. The rank-weight the stocks depend on their deviation from $\bar{z}$:

$$\begin{aligned} w_{High} &= \kappa(z - \bar{z})^+ \\ w_{Low} &= \kappa(z - \bar{z})^- \end{aligned} \tag{13}$$

The superscripts + and − indicate the positive or negative elements of the vector. For example, positive values are replaced by a zero weight in the vector w_{Low}. The normalizing constant $\kappa = 2/1_n'|z - \bar{z}|$ makes the weights sum to one in both portfolios. A zero-cost portfolio is then constructed, rescaling the two legs by their own beta in order to render the total portfolio beta neutral:

$$R_{t+1}^{BAB} = \frac{1}{\beta_t^{Low}}\left(R_{t+1}^{Low} - r_t^{rf}\right) - \frac{1}{\beta_t^{High}}\left(R_{t+1}^{High} - r_t^{rf}\right) \tag{14}$$

Where: $\quad R_{t+1}^{Low} = R_{t+1}' w_t^{Low} \qquad R_{t+1}^{High} = R_{t+1}' w_t^{High}$

$\quad \beta_t^{Low} = \beta_t' w_t^{Low} \qquad \beta_t^{High} = \beta_t' w_t^{High}$

The resulting portfolio R^{BAB} is long low-beta stocks financed by borrowing at the risk free rate. The short-sale proceeds from the high-beta stocks earns the risk-free rate.

BAC and BAV

The construction process of BAC and BAV is similar to that of BAB, with some additional steps. The following description is for BAC: In each month t, assign each stock into a quintile $q = 1, 2...5$ based on their ascending rank w.r.t. volatility. z_t^q is a $(n(q) \times 1)$ vector of ascending ranks w.r.t. correlation. $n(q)$ is the number of stocks in each quintile in each month and $\bar{z^q} = 1'_{n(q)} z^q / n(q)$ is the average correlation rank. $1_{n(q)}$ is an $(n(q) \times 1)$ all-ones vector. To rank-weight the stocks in the respective quintile; form two vectors of weights. One for the stocks with a correlation under, and one for the stocks over $\bar{z}$. The rank-weight the stocks depend on their deviation from $\bar{z}$:

$$\begin{aligned} w_{High} &= \kappa^q (z^q - \bar{z^q})^+ \\ w_{Low} &= \kappa^q (z^q - \bar{z^q})^- \end{aligned} \tag{15}$$

The superscripts + and − indicate the positive or negative elements of the vector. For example, positive values are replaced by a zero weight in the vector w_{Low}. The normalizing constant $\kappa^q = 2/1'_n |z^q - \bar{z^q}|$ makes the weights sum to one in both portfolios. A zero-cost portfolio is then constructed, rescaling the two legs by their own beta in order to render the total quintile portfolio beta neutral:

$$R_{t+1}^{BAC(q)} = \frac{1}{\beta_t^{Low,q}} \left(R_{t+1}^{Low,q} - R_t^{rf} \right) - \frac{1}{\beta_t^{High,q}} \left(R_{t+1}^{High,q} - R_t^{rf} \right) \tag{16}$$

Where:
$$R_{t+1}^{Low,q} = R_{t+1}^{q'} w_t^{Low,q} \qquad R_{t+1}^{High,q} = R_{t+1}^{q'} w_t^{High}$$
$$\beta_t^{Low,q} = \beta_t^{q'} w_t^{Low,q} \qquad \beta_t^{High,q} = \beta_t^{q'} w_t^{High,q}$$

The resulting five BAC quintile portfolios are zero cost and beta neutral. To make the final BAC portfolio volatility neutral, it is the equal weighted return of the five volatility quintile portfolio:

$$R_{t+1}^{BAC} = \frac{1}{5} \sum_{q=1}^{5} R_{t+1}^{BAC(q)} \tag{17}$$

The procedure for constructing BAV is similar, the only difference being that the quintiles are formed based on correlation and the intra-quintile ranking is done based on volatility.