Betting Against Beta

Andrea Frazzini and Lasse H. Pedersen*

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Abstract.

We present a model with leverage and margin constraints that vary across investors and time. We find evidence consistent with each of the model's five central predictions: (1) Since constrained investors bid up high-beta assets, high beta is associated with low alpha, as we find empirically for U.S. equities, 20 international equity markets, Treasury bonds, corporate bonds, and futures; (2) A betting-against-beta (BAB) factor, which is long leveraged low-beta assets and short high-beta assets, produces significant positive risk-adjusted returns; (3) When funding constraints tighten, the return of the BAB factor is low; (4) Increased funding liquidity risk compresses betas toward one; (5) More constrained investors hold riskier assets.

* Andrea Frazzini is at AQR Capital Management, Two Greenwich Plaza, Greenwich, CT 06830, e-mail: andrea.frazzini@aqr.com; web: http://www.econ.yale.edu/~af227/ . Lasse H. Pedersen is at New York University, AQR, NBER, and CEPR, 44 West Fourth Street, NY 10012-1126; e-mail: lpederse@stern.nyu.edu; web: http://www.stern.nyu.edu/~lpederse/. We thank Cliff Asness, Aaron Brown, John Campbell, Kent Daniel, Gene Fama, Nicolae Garleanu, John Heaton (discussant), Michael Katz, Owen Lamont, Michael Mendelson, Mark Mitchell, Matt Richardson, Tuomo Vuolteenaho and Robert Whitelaw for helpful comments and discussions as well as seminar participants at Columbia University, New York University, Yale University, Emory University, University of Chicago Booth, Kellogg School of Management, Harvard University, NBER Behavioral Economics 2010, the 2010 Annual Management Conference at University of Chicago Booth School of Business, the 2011 Bank of America/Merrill Lynch Quant Conference and the 2011 Nomura Global Quantitative Investment Strategies Conference.

A basic premise of the capital asset pricing model (CAPM) is that all agents invest in the portfolio with the highest expected excess return per unit of risk (Sharpe ratio), and lever or de-lever this portfolio to suit their risk preferences. However, many investors—such as individuals, pension funds, and mutual funds—are constrained in the leverage that they can take, and they therefore overweight risky securities instead of using leverage. For instance, many mutual fund families offer balanced funds where the "normal" fund may invest 40% in long-term bonds and 60% in stocks, whereas as the "aggressive" fund invests 10% in bonds and 90% in stocks. If the "normal" fund is efficient, then an investor could leverage it and achieve the same expected return at a lower volatility rather than tilting to a large 90% allocation to stocks. The demand for exchange-traded funds (ETFs) with built-in leverage provides further evidence that many investors cannot use leverage directly.

This behavior of tilting toward high-beta assets suggests that risky high-beta assets require lower risk-adjusted returns than low-beta assets, which require leverage. Indeed, the security market line for U.S. stocks is too flat relative to the CAPM (Black, Jensen, and Scholes (1972)) and is better explained by the CAPM with restricted borrowing than the standard CAPM (Black (1972, 1993), Brennan (1971), see Mehrling (2005) for an excellent historical perspective).

Several questions arise: How can an unconstrained arbitrageur exploit this effect, i.e., how do you bet against beta? What is the magnitude of this anomaly relative to the size, value, and momentum effects? Is betting against beta rewarded in other countries and asset classes? How does the return premium vary over time and in the cross section? Who bets against beta?

We address these questions by considering a dynamic model of leverage constraints and by presenting consistent empirical evidence from 20 international stock markets, Treasury bond markets, credit markets, and futures markets.

Our model features several types of agents. Some agents cannot use leverage and therefore overweight high-beta assets, causing those assets to offer lower returns. Other agents can use leverage but face margin constraints. They underweight (or short-sell) high-beta assets and buy low-beta assets that they lever up. The model implies a flatter security market line (as in Black (1972)), where the slope depends on the tightness (i.e., Lagrange multiplier) of the funding constraints on average across agents (Proposition 1).

One way to illustrate the asset pricing effect of the funding friction is to consider the returns on market-neutral betting against beta (BAB) factors. A BAB factor is a portfolio that holds low-beta assets, leveraged to a beta of 1, and that shorts high-beta assets, de-leveraged to a beta of 1. For instance, the BAB factor for U.S. stocks achieves a zero beta by holding $1.5 of low-beta stocks and short-selling $0.7 of high-beta stocks, with offsetting positions in the risk-free asset to make it zero-cost.[1] Our model predicts that BAB factors have a positive average return and that the return is increasing in the ex-ante tightness of constraints and in the spread in betas between high- and low-beta securities (Proposition 2).

When the leveraged agents hit their margin constraint, they must de-lever. Therefore, the model predicts that, during times of tightening funding liquidity constraints, the BAB factor realized negative returns as its expected future return rises (Proposition 3). Furthermore, the model predicts that the betas of securities in the cross section are compressed toward 1 when funding liquidity risk is high (Proposition 4). Finally, the model implies that more constrained investors overweight high-beta assets in their portfolios while less constrained investors overweight low-beta assets and possibly apply leverage (Proposition 5).

Our model thus extends Black's (1972) central insight by considering a broader set of constraints and deriving the dynamic time-series and cross-sectional properties arising from the equilibrium interaction between agents with different constraints.

We find consistent evidence for each of the model's central predictions. To test Proposition 1, we first consider portfolios sorted by beta within each asset class. We find that alphas and Sharpe ratios are almost monotonically declining in beta in each asset class. This finding provides broad evidence that the relative flatness of the

[1] While we consider a variety of BAB factors within a number of markets, one notable example is the zero-covariance portfolio introduced by Black (1972) and studied for U.S. stocks by Black, Jensen, and Scholes (1972), Kandel (1984), Shanken (1985), Polk, Thompson, and Vuolteenaho (2006), and others.

security market line is not isolated to the U.S. stock market but that it is a pervasive global phenomenon. Hence, this pattern of required returns is likely driven by a common economic cause, and our funding constraint model provides one such unified explanation.

To test Proposition 2, we construct BAB factors within the U.S. stock market, and within each of the 19 other developed MSCI stock markets. The U.S. BAB factor realizes a Sharpe ratio of 0.75 between 1926 and 2009. To put this BAB factor return in perspective, note that its Sharpe ratio is about twice that of the value effect and 40% higher than that of momentum over the same time period. The BAB factor has highly significant risk-adjusted returns, accounting for its realized exposure to market, value, size, momentum, and liquidity factors (i.e., significant 1, 3, 4, and 5-factor alphas), and realizes a significant positive return in each of the four 20-year sub-periods between 1926 and 2009.

We find similar results in our sample of international equities; Indeed, combining stocks in each of the non-US countries produces a BAB factor with returns about as strong as the U.S. BAB factor.

We show that BAB returns are consistent across countries, time, within deciles sorted by size, within deciles sorted by idiosyncratic risk, and robust to a number of specifications. These consistent results suggest that coincidence or data-mining are unlikely explanations. However, if leverage aversion is the underlying driver and is a general phenomenon, as in our model, then the effect should also exist in other markets.

Hence, we examine BAB factors in other major asset classes. For U.S. Treasuries, the BAB factor is a portfolio that holds leveraged low-beta, i.e., short-maturity, bonds and that short-sells de-leveraged high-beta long-term bonds. This portfolio produces highly significant risk-adjusted returns with a Sharpe ratio of 0.85. This profitability of short-selling long-term bonds may seem to contradict the well-known “term premium” in fixed income markets. There is no paradox, however. The term premium means that investors are compensated on average for holding long-term bonds rather than T-bills because of the need for maturity transformation. The term premium exists at all horizons, however: Just like investors are compensated for holding 10-year bonds over T-bills, they are also compensated for holding 1-year bonds. Our finding is that the compensation *per unit of risk* is in fact larger for the 1-year bond than for the 10-year bond. Hence, a portfolio that has a leveraged long position in 1-year (and other short-term) bonds and a short position in long-term bonds produces positive returns. This result is consistent with our model in which some investors are leverage constrained in their bond exposure and, therefore, require lower risk-adjusted returns for long-term bonds that give more "bang for the buck". Indeed, short-term bonds require tremendous leverage to achieve similar risk or return as long-term bonds. These results complement those of Fama (1986) and Duffee (2010), who also consider Sharpe ratios across maturities implied by standard term structure models.

We find similar evidence in credit markets: A leveraged portfolio of high-rated corporate bonds outperforms a de-leveraged portfolio of low-rated bonds. Similarly, using a BAB factor based on corporate bond indices by maturity produces high risk-adjusted returns.

We test the time-series predictions of Proposition 3 using the TED spread as a measure of funding conditions. Consistent with the model, an increase in the TED spread is associated with low contemporaneous BAB returns. Furthermore, the ex-ante beta spread predicts the BAB return positively, consistent with the model. The lagged TED spread predicts returns negatively, which is inconsistent with the model if a high TED spread means a high tightness of investors' funding constraints. This result could be explained if higher TED spreads meant that investors' funding constraints would be tightening as their banks diminish credit availability over time, though this is speculation.

To test the prediction of Proposition 4, we use the volatility of the TED spread as an empirical proxy for funding liquidity risk. Consistent with the model's beta-compression prediction, we find that the dispersion of betas is significantly lower when funding liquidity risk is high, and this result holds across a number of specifications. Furthermore, we find evidence consistent with the model's prediction that the BAB factors realize a positive conditional market beta when funding liquidity risk is high.

Lastly, we find evidence consistent with the model's portfolio prediction that more constrained investors should hold higher-beta securities than less constrained investors (Proposition 5). As more constrained investors, we study the equity portfolios of mutual funds and individual investors. Consistent with the model, we find that these investors hold portfolios with average betas above 1. On the other side of the market, we find that leveraged buyout (LBO) funds, which can apply leverage, acquire firms with betas below 1. Similarly, looking at the holdings of Berkshire Hathaway, we see that Warren Buffett bets against beta by buying low-beta stocks and applying leverage.

Our results shed new light on the relationship between risk and expected returns. This central issue in financial economics has naturally received much attention. The standard CAPM beta cannot explain the cross-section of unconditional stock returns (Fama and French (1992)) or conditional stock returns (Lewellen and Nagel (2006)). Stocks with high beta have been found to deliver low risk-adjusted returns (Black, Jensen, and Scholes (1972), Baker, Bradley, and Wurgler (2010)); thus, the constrained-borrowing CAPM has a better fit (Gibbons (1982), Kandel (1984), Shanken (1985)). Stocks with high idiosyncratic volatility have realized low returns (Falkenstein (1994), Ang, Hodrick, Xing, Zhang (2006, 2009)),[2] but we find that the beta effect holds even when controlling for idiosyncratic risk. Theoretically, asset pricing models with benchmarked managers (Brennan (1993)) or constraints imply more general CAPM-like relations (Hindy (1995), Cuoco (1997)), in particular the margin-CAPM implies that high-margin assets have higher required returns, especially during times of funding illiquidity (Garleanu and Pedersen (2009), Ashcraft, Garleanu, and Pedersen (2010)). Garleanu and Pedersen (2009) show empirically that deviations of the Law of One Price arises when high-margin assets become cheaper than low-margin assets, and Ashcraft, Garleanu, and Pedersen (2010) find that prices increase when central bank lending facilities lower margins. Furthermore, funding liquidity risk is linked to market liquidity risk (Gromb and Vayanos (2002), Brunnermeier and Pedersen (2010)), which also affects

[2] This effect disappears when controlling for the maximum daily return over the past month (Bali, Cakici, and Whitelaw (2010)) and when using other measures of idiosyncratic volatility (Fu (2009)).

required returns (Acharya and Pedersen (2005)). We complement the literature by deriving new cross-sectional and time-series predictions in a simple dynamic model that captures leverage and margin constraints and by testing its implications across a broad cross-section of securities across all the major asset classes. Finally, in a follow up paper, Asness, Frazzini and Pedersen (2011) report evidence of a low-beta effect across asset classes consistent with our theory and evidence within asset classes.

The rest of the paper is organized as follows. Section I lays out the theory, Section II describes our data and empirical methodology, Sections III-VI test Propositions 1-5, and Section VII concludes. Appendix A contains all proofs, and Appendix B provides a number of additional empirical results and robustness tests.

I. Theory

We consider an overlapping-generations (OLG) economy in which agents $i=1,...,I$ are born each time period t with wealth W_t^i and live for two periods. Agents trade securities $s=1,...,S$, where security s pays dividends δ_t^s and has x^{*s} shares outstanding. Each time period t, young agents choose a portfolio of shares $x=(x^1,...,x^S)'$, investing the rest of their wealth at the risk-free return r^f, to maximize their utility:

$$\max x'(E_t\left(P_{t+1}+\delta_{t+1}\right)-(1+r^f)P_t)-\frac{\gamma^i}{2}x'\Omega_t x \qquad (1)$$

where P_t is the vector of prices at time t, Ω_t is the variance-covariance matrix of $P_{t+1}+\delta_{t+1}$, and γ^i is agent i's risk aversion. Agent i is subject to the following portfolio constraint:

$$m_t^i\sum_s x^s P_t^s \le W_t^i \qquad (2)$$

This constraint requires that some multiple m_t^i of the total dollars invested—the sum of the number of shares x^s times their prices P^s—must be less than the agent's wealth.

The investment constraint depends on the agent *i*. For instance, some agents simply cannot use leverage, which is captured by $m^i=1$ (as Black (1972) assumes). Other agents not only may be precluded from using leverage but also must have some of their wealth in cash, which is captured by m^i greater than 1. For instance, $m^i = 1/(1\text{-}0.20)$=1.25 represents an agent who must hold 20% of her wealth in cash. For instance, a mutual fund may need some ready cash to be able to meet daily redemptions, an insurance company needs to pay claims, and individual investors may need cash for unforeseen expenses.

Other agents yet may be able to use leverage but may face margin constraints. For instance, if an agent faces a margin requirement of 50%, then his m^i is 0.50. With this margin requirement, the agent can invest in assets worth twice his wealth at most. A smaller margin requirement m^i naturally means that the agent can take greater positions. We note that our formulation assumes for simplicity that all securities have the same margin requirement, which may be true when comparing securities within the same asset class (e.g., stocks) as we do empirically. Garleanu and Pedersen (2009) and Ashcraft, Garleanu, and Pedersen (2010) consider assets with different margin requirements and show theoretically and empirically that higher margin requirements are associated with higher required returns (Margin CAPM).

We are interested in the properties of the competitive equilibrium in which the total demand equals the supply:

$$\sum_i x^i = x^* \tag{3}$$

To derive equilibrium, consider the first order condition for agent *i*:

$$0 = E_t\left(P_{t+1} + \delta_{t+1}\right) - (1 + r^f)P_t - \gamma^i \Omega x^i - \psi_t^i P_t \tag{4}$$

where ψ^i is the Lagrange multiplier of the portfolio constraint. Solving for x^i gives the optimal position:

$$x^i = \frac{1}{\gamma^i}\Omega^{-1}\left(E_t\left(P_{t+1}+\delta_{t+1}\right)-\left(1+r^f+\psi_t^i\right)P_t\right) \tag{5}$$

The equilibrium condition now follows from summing over these positions:

$$x^* = \frac{1}{\gamma}\Omega^{-1}\left(E_t\left(P_{t+1}+\delta_{t+1}\right)-\left(1+r^f+\psi_t\right)P_t\right) \tag{6}$$

where the aggregate risk aversion γ is defined by $1/\gamma = \Sigma_i 1/\gamma^i$, and $\psi_t = \sum_i \frac{\gamma}{\gamma^i}\psi_t^i$ is the weighted average Lagrange multiplier. (The coefficients $\frac{\gamma}{\gamma^i}$ sum to 1 by definition of the aggregate risk aversion γ.) The equilibrium price can then be computed:

$$P_t = \frac{E_t\left(P_{t+1}+\delta_{t+1}\right)-\gamma\Omega x^*}{1+r^f+\psi_t} \tag{7}$$

Translating this into the return of any security $r_{t+1}^i = \left(P_{t+1}^i+\delta_{t+1}^i\right)/P_t^i - 1$, the return on the market r_{t+1}^M, and using the usual expression for beta, $\beta_t^s = \text{cov}_t\left(r_{t+1}^s, r_{t+1}^M\right)/\text{var}_t\left(r_{t+1}^M\right)$, we obtain the following results. (All proofs are in Appendix A.)

Proposition 1.

(i) *The equilibrium required return for any security s is:*

$$E_t\left(r_{t+1}^s\right) = r^f + \psi_t + \beta_t^s\lambda_t \tag{7}$$

where the risk premium is $\lambda_t = E_t\left(r_{t+1}^M\right) - r^f - \psi_t$ *and* ψ_t *is the average Lagrange multiplier, measuring the tightness of funding constraints.*

(ii) *A security's alpha with respect to the market is* $\alpha_t^s = \psi_t\,(1-\beta_t^s)$. *The alpha decreases in the beta,* β_t^s.

(iii) *For an efficient portfolio, the Sharpe ratio is highest for an efficient portfolio with a beta less than 1 and decreases in* β_t^s *for higher betas and increases for lower betas.*

As in Black's CAPM with restricted borrowing (in which $m^i = 1$ for all agents), the required return is a constant plus beta times a risk premium. Our expression shows explicitly how risk premia are affected by the tightness of agents' portfolio constraints, as measured by the average Lagrange multiplier ψ_t. Indeed, tighter portfolio constraints (i.e., a larger ψ_t) flatten the security market line by increasing the intercept and decreasing the slope λ_t.

Whereas the standard CAPM implies that the intercept of the security market line is r^f, the intercept here is increased by the weighted average of the agents' Lagrange multipliers. One may wonder why zero-beta assets require returns in excess of the risk-free rate? The reason is that tying up capital in such assets prevents a constrained investor from making other profitable trades. Furthermore, if unconstrained agents buy a considerable amount of these securities, then, from their perspective, this risk is no longer idiosyncratic since additional exposure to such assets would increase the risk of their portfolio. Hence, in equilibrium, even zero-beta risky assets must offer higher returns than the risk-free rate.

Assets that have zero covariance to Tobin's (1958) "tangency portfolio" held by an unconstrained agent do earn the risk-free rate, but the tangency portfolio is not the market portfolio in this equilibrium. Indeed, the market portfolio is the weighted average of all investors' portfolios, that is, an average of the tangency portfolio held by unconstrained investors and riskier portfolios held by constrained investors. Hence, the market portfolio has higher risk and expected return than the tangency portfolio, but a lower Sharpe ratio.

The portfolio constraints further imply a lower slope λ_t of the security market line, that is, a lower compensation for a marginal increase in systematic risk. The slope is lower because constrained agents need this access to high un-leveraged returns and are therefore willing to accept less high returns for high-beta assets.

We next consider the properties of a factor that goes long low-beta assets and short-sells high-beta assets. To construct such a factor, let w_L be the relative portfolio weights for a portfolio of low-beta assets with return $r_{t+1}^L = w_L' r_{t+1}$ and consider similarly a portfolio of high-beta assets with return r_{t+1}^H. The betas of these portfolios are denoted β_t^L and β_t^H, where $\beta_t^L < \beta_t^H$. We then construct a betting-against-beta (BAB) factor as:

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}\left(r_{t+1}^L - r^f\right) - \frac{1}{\beta_t^H}\left(r_{t+1}^H - r^f\right) \qquad (8)$$

This portfolio is market neutral, that is, it has a beta of zero: the long side has been leveraged to a beta of 1, and the short side has been de-leveraged to a beta of 1. Furthermore, the BAB factor provides the excess return on a zero-cost portfolio, such as HML and SMB, since it is a difference between excess returns. The difference is that BAB is not dollar neutral in terms of only the risky securities since this would not produce a beta of zero.[3] The model has several predictions regarding the BAB factor:

Proposition 2.

The expected excess return of the zero-cost BAB factor is positive

$$E_t\left(r_{t+1}^{BAB}\right) = \frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H} \psi_t \ \geq 0 \qquad (9)$$

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[3] A natural BAB factor is the zero-covariance portfolio of Black (1972) and Black, Jensen, and Scholes (1972). We consider a broader class of BAB portfolios since we empirically consider a variety of BAB portfolios within various asset classes that are subsets of all securities (e.g., stocks in a particular size group). Therefore, our construction achieves market neutrality by leveraging (and de-leveraging) the long and short sides rather than adding the market itself as Black, Jensen, and Scholes (1972) do.

and increasing in the ex ante beta spread $\frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H}$ *and funding tightness* ψ_t *.*

This proposition shows that a market-neutral BAB portfolio that is long leveraged low-beta securities and short higher-beta securities earns a positive expected return on average. The size of the expected return depends on the spread in the betas and how binding the portfolio constraints are in the market, as captured by the average of the Lagrange multipliers ψ_t.

The next proposition considers the effect of a shock to the portfolio constraints (or margin requirements), m^k, which can be interpreted as a worsening of funding liquidity, a credit crisis in the extreme. Such a funding liquidity shock results in losses for the BAB factor as its required return increases. This happens because agents may need to de-lever their bets against beta or stretch even further to buy the high-beta assets. Thus, the BAB factor is exposed to funding liquidity risk, as it loses when portfolio constraints become more binding.

Proposition 3.

A tighter portfolio constraint, that is, an increase in m_t^k *for some of k, leads to a contemporaneous loss for the BAB factor*

$$\frac{\partial r_t^{BAB}}{\partial m_t^k} \le 0 \qquad (10)$$

and an increase in its future required return:

$$\frac{\partial E_t\left(r_{t+1}^{BAB}\right)}{\partial m_t^k} \ge 0 \qquad (11)$$

The market return tends to be low during funding liquidity crises since a higher m^k increases the required return of the market and reduces the contemporaneous market return. Hence, while the BAB factor is market neutral on average, funding liquidity shocks can lead to a correlation between BAB and the market. In other words, low-beta securities fare poorly during times of increased funding illiquidity relative to their betas while high-beta securities fare less poorly than their betas would suggest ("beta compression"). Intuitively, this result is because the percentage price sensitivity with respect to funding shocks, $\frac{\partial P_t^s}{P_t^s} / \partial \psi_t$, is the same for all securities s.[4]

Proposition 4.

Suppose that dividends are i.i.d. over time and wealth and margin requirements are independent over time. Then, a higher variance of funding liquidity ψ_t at time t generated by a higher variance of margin requirements m_t^i or wealth W_t^i compresses return betas β_{t-1}^i of all securities toward 1. The beta of the BAB factor increases if increase in funding liquidity risk is unanticipated in the construction of the BAB factor.

In addition to the asset-pricing predictions that we have derived, funding constraints naturally affect agents' portfolio choices. In particular, the more constrained investors tilt toward riskier securities in equilibrium whereas less constrained agents tilt toward safer securities with higher reward per unit of risk. To state this result, we write next period's security payoffs as

$$P_{t+1} + \delta_{t+1} = E_t\left(P_{t+1} + \delta_{t+1}\right) + b\left(P_{t+1}^M + \delta_{t+1}^M - E_t\left(P_{t+1}^M + \delta_{t+1}^M\right)\right) + e \qquad (12)$$

[4] Garleanu and Pedersen (2009) find a complementary result, studying securities with identical fundamental risk, but different margin requirements. They find theoretically and empirically that such assets have similar betas when liquidity is good, but when funding liquidity risk rises, the high-margin securities have larger betas as their high margins make them more funding sensitive. Here, we study securities with different fundamental risk, but the same margin requirements. In this case, higher funding liquidity risk means that betas are compressed toward one.

where b is a vector of market exposures, and e is a vector of noise that is uncorrelated with the market. We have the following natural result for the agents' positions:

Proposition 5.

Unconstrained agents hold risk-free securities and a portfolio of risky securities that has a beta less than 1; constrained agents hold portfolios of securities with higher betas. If securities s and k are identical except that s has a larger market exposure than k, $b^s > b^k$*, then any constrained agent j with greater than average Lagrange multiplier,* $\psi_t^j > \psi_t$*, holds more shares of s than k; conversely, the reverse is true for any agent with* $\psi_t^j < \psi_t$.

We next turn to the empirical evidence for Propositions 1-5.

II. Data and Methodology

The data in this study are collected from several sources. The sample of U.S. and international stocks includes 50,826 stocks covering 20 countries, and the summary statistics for stocks are reported in Table I. Stock return data are from the union of the CRSP tape and the Xpressfeed Global database. Our U.S. equity data include all available common stocks on CRSP between January 1926 and December 2009. Betas are computed with respect to the CRSP value-weighted market index. Excess returns are above the US Treasury bill rate. We consider alphas with respect to the market factor and factor returns based on size (SMB), book-to-market (HML), momentum (UMD), and (when available) liquidity risk.[5]

The international equity data include all available common stocks on the Xpressfeed Global daily security file for 19 markets belonging to the MSCI developed universe between January 1984 and December 2009. We assign individual issues to their corresponding markets based on the location of the primary exchange. Betas

[5] SMB, HML, and UMD are from Ken French's data library, and the liquidity risk factor is from WRDS.

are computed with respect to the corresponding MSCI local market index.[6]

All returns are in USD, and excess returns are above the US Treasury bill rate. To calculate the alphas, we compute international risk factors that mimic their US-based counterparts by applying the same methodology of Fama and French (1996) over our international universe.

We also consider a variety of other assets, and Table II contains the list instruments and the corresponding data availability ranges. We obtain U.S. Treasury bond data from the CRSP US Treasury Database. Our analysis focuses on monthly returns (in excess of the 1-month Treasury bill) on the Fama Bond portfolios for maturities ranging from 1 to 10 years between January 1952 and December 2009. Returns are an equal-weighted average of the unadjusted holding period return for each bond in the portfolios. Only non-callable, non-flower notes and bonds are included in the portfolios. Betas are computed with respect to an equally weighted portfolio of all bonds in the database.

We collect aggregate corporate bond index returns from Barclays Capital's Bond.Hub database.[7] Our analysis focuses on the monthly returns (in excess of the 1-month Treasury bill) of four aggregate US credit indices with maturity ranging from one to ten years and nine investment grade and high yield corporate bond portfolios with credit risk ranging from AAA to Ca-D and "Distressed."[8] The data cover the period between January 1973 and December 2009 although the data availability varies depending on the individual bond series. Betas are computed with respect to an equally weighted portfolio of all bonds in the database.

We also study futures and forwards on country equity indexes, country bond indexes, foreign exchange, and commodities. Return data are drawn from the internal pricing data maintained by AQR Capital Management LLC. The data are collected from a variety of sources and contains daily return on futures, forwards, or swap contracts in excess of the relevant financing rate. The type of contract for each asset depends on availability or the relative liquidity of different instruments. Prior

[6] Our results are robust to the choice of benchmark (local vs. global). We report these tests in the Appendix.
[7] The data can be downloaded at https://live.barcap.com
[8] The distress index was provided to us by Credit Suisse.

to expiration, positions are rolled over into the next most liquid contract. The rolling date's convention differs across contracts and depends on the relative liquidity of different maturities. The data cover the period between 1963 and 2009, although the data availability varies depending on the asset class. For more details on the computation of returns and data sources, see Moskowitz, Ooi, and Pedersen (2010), Appendix A. For equity indexes, country bonds, and currencies, the betas are computed with respect to a GDP-weighted portfolio, and for commodities, the betas are computed with respect to a diversified portfolio that gives equal risk weight across commodities.

Finally, we use the TED spread as a proxy for time periods where credit constraint are more likely to be binding (as in Garleanu and Pedersen (2009) and others). The TED spread is defined as the difference between the three-month EuroDollar LIBOR rate and the three-month U.S. Treasuries rate. Our TED data run from December 1984 to December 2009.

Estimating Ex-ante Betas

We estimate pre-ranking betas from rolling regressions of excess returns on excess market returns. Whenever possible, we use daily data rather than monthly data, as the accuracy of covariance estimation improves with the sample frequency (see Merton (1980)). If daily data are available, we use 1-year rolling windows and require at least 200 observations. If we only have access to monthly data, we use rolling 3-year windows and require at least 12 observations.[9] Following Dimson (1979) and Fama and French (1992), we estimate betas as the sum of the slopes in a regression of the asset's excess return of the current and prior market excess returns:

$$\begin{aligned} r_t - r_t^f &= \hat{\alpha} + \sum_{k=0}^{K} \hat{\beta}_k \left(r_{t-k}^M - r_{t-k}^f \right) + \hat{\varepsilon} \\ \hat{\beta}^{TS} &= \sum_{k=0}^{K} \hat{\beta}_k \end{aligned} \qquad (13)$$

[9] Daily returns are not available for our sample of US Treasury bonds, US corporate bonds, and US credit indices.

The additional lagged terms capture the effects of nonsynchronous trading. We include lags up to $K = 5$ trading days. When the sample frequency is monthly, we include a single lag. Finally, to reduce the influence of outliers, we follow Vasicek (1973) and Elton, Gruber, Brown, and Goetzmann (2003) and shrink the beta estimated using the time-series (β_i^{TS}) toward the cross-sectional mean (β^{XS}):

$$\hat{\beta}_i = w_i \hat{\beta}_i^{TS} + (1 - w_i)\hat{\beta}^{XS} \tag{14}$$

For simplicity, rather than having asset-specific and time-varying shrinkage factors as in Vasicek (1973), we set $w = 0.5$ and $\beta^{XS} = 1$ for all periods and across all assets, but our results are very similar either way.[10]

We note that our choice of the shrinkage factor does not affect how securities are sorted into portfolios since the common shrinkage does not change the ranks of security betas.[11] However, the amount of shrinkage affects the construction of the BAB portfolios since the estimated betas are used to the size the long and the short sides to make the portfolio market neutral at formation.

To account for the fact that noise in the ex-ante betas affects the construction of the BAB factors, our inference is focused on realized abnormal returns so that any mismatch between ex-ante and realized betas is picked up by the realized loadings in the factor regression. Of course, when we regress our portfolios on standard risk factors, the realized factor loadings are not shrunk as above since only the ex-ante betas are subject to selection bias. Our results are robust to alternative beta estimation procedures as we report in the Appendix.

We compute betas with respect to a market portfolio, which is either specific

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[10] The Vasicek (1973) Bayesian shrinkage factor is given by $w_i = 1 - \sigma_{i,TS}^2 / (\sigma_{i,TS}^2 + \sigma_{XS}^2)$ where $\sigma_{i,TS}^2$ is the variance of the estimated beta for security i, and σ_{XS}^2 is the cross-sectional variance of betas. This estimator places more weight on the historical times series estimate when the estimate has a lower variance or when there is large dispersion of betas in the cross section. Pooling across all stocks in our US equity data, the shrinkage factor w has a mean (median) of 0.51 (0.49).

[11] Using alternative rolling window, lag length, different shrinkage factors or using Scholes and Williams (1977) trade-only betas does not alter our main results. We report these robustness checks in the Appendix.

to an asset class or the overall world market portfolio of all assets. While our results hold both ways, we focus on betas with respect to asset-class-specific market portfolios since these betas are less noisy for several reasons. This approach allows us to use daily data over a long time period for most asset classes, as opposed to using the most diversified market portfolio for which we only have monthly data over a limited time period. Moreover, this approach is independent of assumptions about what the overall "market portfolio" is, and it is applicable even if markets are segmented.

As a robustness test, Table B9 in the Appendix reports the results when we compute betas with respect to a proxy for a world market portfolio. We use the world market portfolio from Asness, Frazzini, and Pedersen (2011).[12] The results are consistent with our main tests as the BAB factors earn large and significant abnormal returns in each of asset classes in our sample.

Constructing Betting-Against-Beta Factors

We construct simple portfolios that are long low-beta securities and that short-sell high-beta securities, hereafter "BAB" factors. To construct each BAB factor, all securities in an asset class (or within a country for international equities) are ranked in ascending order on the basis of their estimated beta. The ranked securities are assigned to one of two portfolios: low-beta and high-beta. In each portfolio, securities are weighted by the ranked betas (lower-beta security have larger weight in the low-beta portfolio and higher-beta securities have larger weights in the high-beta portfolio). The portfolios are rebalanced every calendar month. More formally, let z be the $n\times1$ vector of beta ranks $z_i = rank(\beta_{it})$ at portfolio formation, and let $\bar{z} = 1_n' z / n$ be the average rank, where n is the number of securities and 1_n is an $n\times1$ vector of ones. The portfolio weights of the low-beta and high-beta portfolios are given by

[12] See Asness, Frazzini, and Pedersen (2011) for a detailed description of this market portfolio. The market series is monthly and ranges from 1973 to 2009.

$$w_h = \quad k\,(z-\bar{z})^{+}$$
$$w_L = \quad k\,(z-\bar{z})^{-}$$

where k is a normalizing constant $k = 1_n^{'}\left|z-\bar{z}\right|/2$ and x^{+} and x^{-} indicate the positive and negative elements of a vector x. Note that by construction we have $1_n^{'} w_H = 1$ and $1_n^{'} w_L = 1$. To construct the BAB factor, both portfolios are rescaled to have a beta of one at portfolio formation. The BAB is the self-financing zero-beta portfolio (9) that is long the low-beta portfolio and that short-sells the high-beta portfolio.

$$r_{t+1}^{BAB} = \frac{1}{\beta_t^L}\left(r_{t+1}^L - r^f\right) - \frac{1}{\beta_t^H}\left(r_{t+1}^H - r^f\right) \qquad (14)$$

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

For example, on average, the U.S. stock BAB factor is long \$1.5 of low-beta stocks (financed by short-selling \$1.5 of risk-free securities) and short-sells \$0.7 of high-beta stocks (with \$0.7 earning the risk-free rate).

Data Used to Test the Theory's Portfolio Predictions

We collect mutual fund holdings from the union of the CRSP Mutual Fund Database and Thompson Financial CDA/Spectrum holdings database, which includes all registered domestic mutual funds filing with the SEC. The holdings data run from 1980 to 2009. We focus our analysis on open-end actively managed domestic equity mutual funds. Our sample selection procedure follows that of Kacperzczyk, Sialm, and Zheng (2008), and we refer to their Appendix for details about the screens that were used and summary statistics of the data.

Our individual investors' holdings data was collected from a nationwide discount brokerage house and contains trade made by about 78,000 households in the period from January of 1991 to November of 1996. This dataset has been used extensively in the existing literature on individual investors. For a detailed description of the brokerage data set, see Barber and Odean (2000).

Our sample of buyouts is drawn from the M&A and corporate events database maintained by AQR/CNH Partners.[13] The data contain various data items including initial, subsequent announcement dates, and (if applicable) completion or termination date for all takeover deals where the target is a U.S. publicly traded firm and where the acquirer is a private company. For some (but not all) deals, the acquirer descriptor also contains information on whether the deal is a Leveraged or Management Buyout (LBO, MBO). The data run from 1963 to 2009.

Finally, we download holdings data for Berkshire Hathaway from Thomson Financial Institutional (13f) Holding Database. The data run from 1980 to 2009.

III. Betting Against Beta in Each Asset Class

We now test how the required premium varies in the cross-section of beta-sorted securities (Proposition 1) and the hypothesis that long/short BAB factors have positive average returns (Proposition 2). As an overview of these results, the alphas of all the beta-sorted portfolios considered in this paper are plotted in Figure 1, and the Sharpe ratios are plotted in Figure B1 in the Appendix. We see that declining alphas and Sharpe ratios across beta-sorted portfolios are general phenomena across asset classes as we discuss in detail below.

Stocks

Table III reports our tests for U.S. stocks. We consider 10 beta-sorted portfolios and report their average returns, alphas, market betas, volatilities, and Sharpe ratios. The average returns of the different beta portfolios are similar, which is the well-known relatively flat security market line. Hence, consistent with Proposition 1 and with Black (1972), the alphas decline almost monotonically from the low-beta to high-beta portfolios. Indeed, the alphas decline when estimated relative to a 1-, 3-, 4-, and 5-factor model. Moreover, Sharpe ratios decline monotonically from low-beta to high-beta portfolios.

[13] We would like to thank Mark Mitchell for providing us with this data.

The rightmost column of Table III reports returns of the betting-against-beta (BAB) factor of Equation (9), that is, a portfolio that is long leveraged low-beta stocks and that short-sells de-leveraged high-beta stocks, thus maintaining a beta-neutral portfolio. Consistent with Proposition 2, the BAB factor delivers a high average return and a high alpha. Specifically, the BAB factor has Fama and French (1993) abnormal returns of 0.69% per month (t-statistic = 6.55). Further adjusting returns for Carhart's (1997) momentum-factor, the BAB portfolio earns abnormal returns of 0.55% per month (t-statistic = 5.12). Last, we adjust returns using a 5-factor model by adding the traded liquidity factor by Pastor and Stambaugh (2003), yielding an abnormal BAB return of 0.46% per month (t-statistic = 2.93). [14] We note that while the alpha of the long-short portfolio is consistent across regressions, the choice of risk adjustment influences the relative alpha contribution of the long and short sides of the portfolio. Figure 2 plots the annual abnormal returns of the stock BAB portfolio and the BAB portfolios in the other asset classes.

Our results for U.S. stocks show how the security market line has continued to be too flat for another four decades after Black, Jensen, and Scholes (1972). More interestingly, we next consider beta-sorted portfolios for international stocks and later turn to altogether different asset classes. We use all 19 MSCI developed countries except the U.S. (to keep the results separate from the U.S. results above), and we do this in two ways: We consider international portfolios where all international stocks are pooled together (Table IV), and we consider results separately for each country (Table V). The international portfolio is country neutral, that is, the stocks are assigned to a low (high) beta basket within each country.[15]

The results for our pooled sample of international equities in Table IV mimic the U.S. results: the alpha and Sharpe ratios of the beta-sorted portfolios decline (although not perfectly monotonically) with the betas, and the BAB factor earns risk-adjusted returns between 0.41% and 0.74% per month depending on the choice of risk adjustment, with t-statistics ranging from 2.48 to 4.15.

[14] Note that Pastor and Stambaugh (2003) liquidity factor is available on WRDS only between 1968 and 2008, thus cutting about 50% of our observations.

[15] We keep the international portfolio country neutral because we report the result of betting against beta across equity indices BAB separately in Table IX.

Table V shows the performance of the BAB factor within each individual country. The BAB delivers positive Sharpe ratios in 18 of the 19 MSCI developed countries and positive 4-factor alphas in 13 out of 19, displaying a strikingly consistent pattern across equity markets. The BAB returns are statistically significantly positive in 7 countries, while none of the negative alphas is significant. Of course, the small number of stocks in our sample in many of the countries (with some countries having only a few dozen securities traded) makes it difficult to reject the null hypothesis of zero return in each individual factor. Figure B3 in the Appendix plots the annual abnormal returns of the BAB international portfolio.

Tables B1 and B2 in the Appendix report factor loadings. On average, the U.S. BAB factor goes long $1.52 ($1.51 for International BAB) and short-sells $0.71 ($0.86 for International BAB). The larger long investment is meant to make the BAB factor market-neutral because the stocks that are held long have lower betas. The U.S. BAB factor realizes a small positive market loading, reflecting the fact that our betas are measured with noise. The other factor loadings indicates that, relative to high-beta stocks, low-beta stocks are likely to be larger, have higher book-to-market ratios, and have higher return over the prior 12 months, although none of the loadings can explain the large and significant abnormal returns.

The Appendix reports further tests and additional robustness checks. We report results using different window lengths (1, 3, 5 years) to estimate betas, different benchmarks (local, global), different estimation methods (OLS, Scholes and Williams (1977)), and different risk adjustment (U.S. risk factors, international risk factors). We split the sample by size and time periods, we control for idiosyncratic volatility (both level and changes) and report results for alternative definition of the risk-free rate. All of the results are consistent: equity beta-neutral portfolios that bet against betas earn significant risk-adjusted returns.

Treasury Bonds

Table VI reports results for US Treasury bonds. As before, we report average excess returns of bond portfolios formed by sorting on beta in the previous month. In the cross section of Treasury bonds, ranking on betas with respect to an aggregate

Treasury bond index is empirically equivalent to ranking on duration or maturity. Therefore, in Table VI, one can think of the term "beta", "duration", or "maturity" in an interchangeable fashion. The rightmost column reports returns of the BAB factor. Abnormal returns are computed with respect to a one-factor model where alpha is the intercept in a regression of monthly excess return on an equally weighted Treasury bond excess market return.

The results show that the phenomenon of a flatter security market line than predicted by the standard CAPM is not limited to the cross section of stock returns. Indeed, consistent with Proposition 1, the alphas decline monotonically with beta. Likewise, Sharpe ratios decline monotonically from 0.73 for low-beta (short maturity) bonds to 0.27 for high-beta (long maturity) bonds. Furthermore, the bond BAB portfolio delivers abnormal returns of 0.16% per month (t-statistic = 6.37) with a large annual Sharpe ratio of 0.85. Figure B4 in the Appendix plots the annual time series of returns.

Since the idea that funding constraints have a significant effect on the term structure of interest may be surprising, let us illustrate the economic mechanism that may be at work. Suppose an agent, e.g., a pension fund, has $1 to allocate to Treasuries with a target excess return of 2.5% per year. One way to achieve this return target is to invest $1 in a portfolio of Treasuries with maturity above 10 years as seen in Table VI, P7. If the agent invests in 1-year Treasuries (P1) instead, then he would need to invest $11 if all maturities had the same Sharpe ratio. This higher leverage is needed because the long-term Treasures are 11 times more volatile than the short-term Treasuries. Hence, the agent would need to borrow an additional $10 to lever his investment in 1-year bonds. If the agent has leverage limits (or prefers lower leverage), then he would strictly prefer the 10-year Treasuries in this case.

According to our theory, the 1-year Treasuries therefore must offer higher returns and higher Sharpe ratios, flattening the security market line for bonds. Empirically, short-term Treasuries do in fact offer higher risk-adjusted returns so the return target can be achieved by investing about $4 in 1-year bonds. While a constrained investor may still prefer an un-leveraged investment in 10-year bonds, unconstrained investors now prefer the leveraged low-beta bonds, and the market can clear.

While the severity of leverage constraints varies across market participants, it appears plausible that a 4-to-1 leverage (on this part of the portfolio) makes a difference for some large investors such as pension funds.

Credit

We next test our model using several credit portfolios. In Table VII, the test assets are monthly excess returns of corporate bond indexes with maturity ranging from 1 to 10 years. Table VII Panel A shows that the credit BAB portfolio delivers abnormal returns of 0.13% per month (t-statistic = 4.91) with a large annual Sharpe ratio of 0.88. Furthermore, alphas and Sharpe ratios decline monotonically.

Panel B of Table VII reports results for the portfolio of US credit indices where we try to isolate the credit component by hedging away the interest rate risk. Given the results on Treasuries in Table VI, we are interested in testing a pure credit version of the BAB portfolio. Each calendar month, we run 1-year rolling regressions of excess bond returns on excess return on Barclay's US government bond index. We construct test assets by going long the corporate bond index and hedging this position by short-selling the appropriate amount of the government bond index: $r_t^{CDS} - r_t^f = (r_t - r_t^f) - \hat{\theta}_{t-1}(r_t^{USGOV} - r_t^f)$, where $\hat{\theta}_{t-1}$ is the slope coefficient estimated in an expanding regression using data from the beginning of the sample and up to month *t-1*. One interpretation of this returns series is that it approximates the returns on a Credit Default Swap (CDS). We compute market returns by taking the equally weighted average of these hedged returns, and we compute betas and BAB portfolios as before. Abnormal returns are computed with respect to a two-factor model where alpha is the intercept in a regression of monthly excess return on the equally weighted average pseudo-CDS excess return and the monthly return on the (un-hedged) BAB factor for US credit indices in the rightmost column of Table VII Panel B. The addition of the un-hedged BAB factor on the right-hand side is an extra check to test a pure credit version of the BAB portfolio.

The results in Panel B of Table VII tell the same story as Panel A: the CDS BAB portfolio delivers significant returns of 0.08% per month (t-statistics = 3.65) and Sharpe ratios decline monotonically from low-beta to high-beta assets. Figure B5 in the Appendix plots the annual time series of returns.

Last, in Table VIII, we report results where the test assets are credit indexes sorted by rating, ranging from AAA to Ca-D and Distressed. Consistent with all our previous results, we find large abnormal returns of the BAB portfolios (0.56% per month with a t-statistics = 4.02) and declining alphas and Sharpe ratios across beta-sorted portfolios. Figure B6 in the Appendix plots the annual time series of returns.

Equity Indexes, Country Bond Indexes, Currencies, and Commodities

Table IX reports results for equity indexes, country bond indexes, foreign exchange and commodities. The BAB portfolio delivers positive returns in each of the four asset classes, with an annualized Sharpe ratio ranging from 0.22 to 0.51. We are only able to reject the null hypothesis of zero average return for international equity indexes, but we can reject the null hypothesis of zero returns for combination portfolios that include all or some combination of the four asset classes, taking advantage of diversification. We construct a simple equally weighted BAB portfolio. To account for different volatility across the four asset classes, in month t, we rescale each return series to 10% annualized volatility using rolling 3-year estimates up to month t-1, and then we equally weight the return series and their respective market benchmark. This portfolio construction generates a simple implementable portfolio that targets 10% BAB volatility in each of the asset classes. We report results for an *All futures* combo including all four asset classes and a *Country Selection* combo including only Equity indices, Country Bonds and Foreign Exchange. The BAB *All Futures* and *Country Selection* deliver abnormal return of 0.52% and 0.71% per month (t-statistics = 4.50 and 4.42). Figure B7 in the Appendix plots the annual time series of returns.

Betting Against All of the Betas

To summarize, the results in Table III–IX strongly support the predictions that alphas decline with beta and BAB factors earn positive excess returns in each asset class. Figure 1 illustrates the remarkably consistent pattern of declining alphas in each asset class, and Figure 2 shows the consistent return to the BAB factors. Clearly, the relatively flat security market line, documented by Black, Jensen, Scholes (1972) for U.S. stocks, is a pervasive phenomenon that we find across markets and asset classes. Averaging all of the BAB factors produces a diversified BAB factor with a large and significant abnormal return of 0.73% per month (t-statistics of 8.8) as seen in Table IX Panel B.

IV. Time Series Tests

In this section, we test Proposition 3's predictions for the time-series of the BAB returns: When funding constraints become more binding (e.g., because margin requirements rise), the required BAB premium increases, and the realized BAB returns becomes negative.

We take this prediction to the data using the TED spread as a proxy of funding conditions. The sample runs from December 1984 (the first available date for the TED spread) to 2009. Since we expect that funding shocks will affect the overall market return, we confirm that the monthly correlation between the CRSP value-weighted monthly return r_t^m and the monthly innovation in the TED spread (1-month change ΔTED_t) is negative, -26%.

Figure 3 shows the realized return on the U.S. BAB factor and the negative of the TED spread. We plot the 3-year rolling average of both variables. The figure shows that the BAB returns tend to be lower in periods of high TED spread, consistent with Proposition 3. Though consistent with the model, we note that this relationship does not prove causality.

We next test the hypothesis in a regression framework for each of the BAB factors across asset classes, as reported in Table X. In our regression tests, the TED spread is always measured at the beginning of the period (monthly). When proxying for new information that contemporaneously affects returns r_t, we use changes in the TED spread, and we measure them over the same horizon (i.e., a 1-month change).

The first column simply regresses the U.S. BAB factor on the level of the TED spread. Consistent with Proposition 3, we find a negative and significant relationship, confirming the relationship that is visually clear in Figure 3. Column (2) has a similar result when controlling for a number of control variables.

The control variables are the market returns, the 1-month lagged BAB return, the ex-ante *Beta Spread*, the *Short Volatility Returns,* and *Inflation.* The *Beta Spread* is equal to $(\beta_S - \beta_L) / \beta_S \beta_L$ and measures the beta difference between the long and short side of the BAB portfolios. The Short Volatility Returns is the return on a portfolio that short-sells closest-to-the-money, next-to-expire straddles on the S&P500 index. *Inflation* is equal to the 1-year US CPI inflation rate, lagged 1 month.

In columns (3) and (4), we decompose the TED spread into its 1-month lagged level and 1-month change. We see that both the lagged level and contemporaneous change in the TED spread are negatively related to the BAB returns. If the TED spread measures that agents' funding constraints (given by ψ in the model) are tight, then the model predicts a negative coefficient for the change in TED and a positive coefficient for the lagged level. Hence, the coefficient for the lagged level is not consistent with the model under this interpretation of the TED spread. If, instead, a high TED spread indicates that agents' funding constraints are *worsening*, then the results would be easier to understand. Under this interpretation, a high TED spread could indicate that banks are credit-constrained and that banks tighten other investors' credit constraints over time, leading to a deterioration of BAB returns over time (if investors don't foresee this).

Columns (5)-(8) of Table X report panel regressions for international stock BAB factors and columns (9)-(12) for all the BAB factors. These regressions include fixed effects, and standard errors are clustered by date. We consistently find a negative relationship between BAB returns and the TED spread.

In addition to the TED spread, the ex-ante *Beta Spread,* $(\beta_S - \beta_L) / \beta_S \beta_L$, is of interest since Proposition 2 predicts that, unconditionally, the ex-ante beta spread should predict BAB returns positively. Consistent with the model, Table X shows that the estimated coefficient for the *Beta Spread* is positive and statistically significant in all six regressions where it is included.

We see that the inflation rate is not a significant predictor. Hence, our results do not appear to be driven by money illusion (as studied by Cohen, Polk, and Vuolteenaho (2005)).

To ensure that these panel-regression estimates are not driven by a few asset classes, we also run a separate regression for each BAB factor on the TED spread. Figure 4 plots the t-statistics of the slope estimate on the TED spread. Although we are not always able to reject the null of no effect for each individual factor, the slopes estimates display a consistent pattern: we find negative coefficients for most of the asset classes, with fixed income assets being the exceptions (though none of the positive slopes are statistically significant). Obviously, the exceptions could be just noise, but positive returns to the fixed-income BAB portfolios during funding liquidity crises could be related to "flight to quality", either due to some investors switch toward assets that are closer to money-market instruments or due to central banks cutting short-term yields to counteract liquidity crises. Table B10 in the Appendix provides more details on the BAB returns in different environments.

V. Beta Compression

We next test Proposition 4 that betas are compressed toward 1 when funding liquidity risk is high. This model prediction generates two testable hypotheses. The first is that the cross-sectional dispersion in betas should be lower at times when the variance of individual margin requirements is higher. The second is that, while unconditionally beta neutral, a BAB factor should realize a positive conditional market beta when individual credit constraints are more volatile.

Table XI presents tests of these predictions using the TED spread as a proxy of funding liquidity conditions as in Section IV. We use the volatility of the TED spread to proxy for the variation of margin requirements. Volatility in month t is defined as the standard deviation of daily TED spread innovations, $\sigma_t^{\mathrm{TED}} = \sqrt{\sum_{s \in t}(\Delta \mathrm{TED}_s - \overline{\Delta \mathrm{TED}}_t)^2}$. Since we are computing conditional moments, in all our tests, we use the monthly volatility as of the prior calendar month, which ensures that the conditioning variable is known as the beginning of the measurement period. The sample runs from December 1984 to 2009.

Panel A of Table XI shows the cross-sectional dispersion in betas in different time periods sorted by the TED volatility for U.S. stocks, Panel B shows the same for international stocks, and Panel C shows this for all asset classes in our sample. Each calendar month, we compute cross-sectional standard deviation, mean absolute deviation and inter-quintile range in betas for all stocks or assets in the universe. We assign the TED spread volatility into three groups (low, medium, and high) based on full sample breakpoints (top and bottom 1/3) and regress the times series of the cross-sectional dispersion measure on the full set of dummies (without intercept). In Panel C, we compute the monthly dispersion measure in each asset class and average across assets. All standard errors are adjusted for heteroskedasticity and autocorrelation up to 12 months.

Table XI shows that, consistent with Proposition 4, the cross-sectional dispersion in betas is lower when credit constraints are more volatile. The average cross-sectional standard deviation of U.S. equity betas in periods of low spread volatility is 0.44, while the dispersion shrinks to 0.37 in volatile credit environment, and the difference is statistically significant (t-statistics = -3.18). The tests based on the other dispersion measures, the international equities, and the other assets all confirm that the cross-sectional dispersion in beta shrinks at times where credit constraints are more volatile.

Panels D, E, and F report conditional market betas of the BAB portfolios based on the volatility of the credit environment for U.S. stocks, international stocks, and the average BAB factor across all assets, respectively. We run factor regression and allow loadings on the market portfolio (and intercepts) to vary as a function of the realized (lagged) TED spread volatility. The dependent variable is the monthly return of the BAB portfolio. The explanatory variables are the monthly returns of the market portfolio, Fama and French (1993) mimicking portfolios, and Carhart (1997) momentum factor. Market betas are allowed to vary across TED volatility regimes (low, neutral and high) using the full set of TED dummies. We are interested in testing the hypothesis that $\hat{\beta}_{high}^{MKT} > \hat{\beta}_{low}^{MKT}$, where $\hat{\beta}_{high}^{MKT}$ is the conditional market beta in times of high credit constraint volatile and $\hat{\beta}_{low}^{MKT}$ is the beta is times of low credit volatility. Panel B reports loadings on the market factor corresponding to different time periods sorted by the credit environment. We include the full set of explanatory variables in the regression but only report the market loading. The results are consistent with Proposition 4. Although the BAB factor is both ex-ante and unconditionally ex post market neutral, the conditional market loading of the BAB factor varies as a function of the credit environment. Indeed, recall from Table III that the realized average market loading is insignificant, at 0.03, while Table XI shows that when credit constraints are more volatile, the BAB-factor beta rises to 0.44. The rightmost column shows that the difference between low and high credit volatility environment is large (0.60), and we are able to reject the null hypothesis that $\hat{\beta}_{high}^{MKT} = \hat{\beta}_{low}^{MKT}$ (t-statistics 2.72). Controlling for 3 or 4 factors does not alter the results, although loadings on the other factors absorb some of the difference. The results for our sample of international equities (Panel E) and for the average BAB across all assets (Panel F) are similar, but are weaker both in terms of magnitude and statistical significance.

To summarize, the results in Table XI support the prediction of our model that there is beta compression in times of high funding liquidity risk, which can be understood in two ways. First, since the discount rate affects all securities in the same way, higher discount-rate volatility compresses betas. A deeper explanation is that, as funding conditions worsen, all prices tend to go down, but high-beta assets do not drop as much as their ex-ante beta suggests because the securities market line flattens at such times, thereby providing support for high-beta assets. Conversely, the flattening of the security market line makes low-beta assets drop more than their ex-ante betas suggest.

VI. Testing the Model's Portfolio Predictions

The theory's last prediction (Proposition 5) is that more constrained investors hold lower-beta securities than less constrained investors. Consistent with this prediction, Table XII presents evidence that mutual funds and individual investors hold high-beta stocks while LBO firms and Berkshire Hathaway buy low-beta stocks.

Before we delve into the details, let us highlight a challenge in testing Proposition 5. Whether an investor's constraint is binding depends both on the investor's ability to apply leverage (m^i in the model) and its unobservable risk aversion. For example, while a hedge fund may be able to apply some leverage, its leverage constraint could nevertheless be binding if its desired volatility is high (especially if its portfolio is very diversified and hedged).

Given that binding constraints are difficult to observe directly, we seek to identify groups of investors that are plausibly constrained and unconstrained, respectively. One example of an investor who may be constrained is a mutual fund. The 1940 Investment Company Act places some restriction on mutual funds' use of leverage, and many mutual funds are prohibited by charter from using leverage. A mutual funds' need to hold cash to meet redemptions ($m^i > 1$ in the model) creates a further incentive to overweight high-beta securities. Indeed, overweighting high-beta stocks helps avoid lagging their benchmark in a bull market because of the cash holdings (some funds use futures contracts to "equitize" the cash, but other funds are not allowed to use derivative contracts).

A second class of investors that may face borrowing constraints is individual retail investors. Although we do not have direct evidence of their inability to employ leverage (and some individuals certainly do), we think that (at least in aggregate) it is plausible that they are likely to face borrowing restrictions.

The flipside of this portfolio test is identifying relatively unconstrained investors. Thus, one needs investors that may be allowed to use leverage and are operating below their leverage cap so that their leverage constraints are not binding. We look at the holdings of two of groups of investors that may satisfy these criteria.

First, we look at the firms that are the target of bids by Leveraged Buyout (LBO) funds and other forms of "Private Equity." These investors, as the name suggest, employ leverage to acquire a public company. Admittedly, we do not have direct evidence of the maximum leverage available to these LBO firms relative to the leverage they apply, but anecdotal evidence suggests that they achieve a substantial amount of leverage.

Second, we examine the holdings of Berkshire Hathaway, a publicly traded firm run by Warren Buffett that employs leverage (by issuing debt) and that holds a diversified portfolio of stocks. The advantage of using the holdings of a public firm that holds equities like Berkshire is that we can directly observe its leverage. Over the period from 1980 to 2009, its average book leverage, defined as (book equity + total debt) / book equity, was about 1.2, that is, 20% borrowing. It is therefore plausible to assume that Berkshire at the margin could issue more debt but choose not to, making it a likely candidate for an investor whose combination of risk aversion and borrowing constraints made it relatively unconstrained during our sample period.

Table XII reports the results of our portfolio test. We estimate both the ex-ante beta of the various investors' holdings and the realized beta of the time series of their returns. We first aggregate all holdings for each investor group, compute their ex-ante betas (equal and value-weighted, respectively), and take the time series average. To compute the realized betas, we compute monthly returns of an aggregate portfolio mimicking the holdings, under the assumption of constant weight between reporting dates. The realized betas are the regression coefficients in a time series regression of these excess returns on the excess returns of the CRSP value-weighted index.

Panel A shows evidence consistent with the idea that constrained investors stretch for return by increasing their betas. Panel A.1 shows that mutual funds hold securities with betas above 1, and we are able to reject the null hypothesis of betas being equal to 1. These findings are consistent with those of Karceski (2002), but our sample is much larger, including all funds over 30-year period. Panel A.2 presents similar evidence for individual retail investors: individual investors tend to hold securities with betas that are significantly above one.

Panel B.1 reports results for our sample of "Private Equity". For each target stock in our database, we focus on its ex-ante beta as of the month end prior to the initial announcements date. This focus is to avoid confounding effects that result from changes in betas related to the actual delisting event. The first two lines report results of all delisting events. Since we only have partial information about whether each deal is a LBO/MBO, this sample includes LBOs and MBOs, but it also includes other types of deals where a company is taken private. The last two lines in Panel B.1 focus on the subset of deals that we are able to positively identify as a LBO/MBO. The results are consistent with Proposition 5 in that investors executing leverage buyouts tend to acquire (or attempt to acquire in case of a non-successful bid) firms with lower beta, and we are able to reject the null hypothesis of a unit beta.

The results for Berkshire Hathaway are shown in Panel B.2 and show a similar pattern: Warren Buffet bets against beta by buying stocks with betas significantly below one and applying leverage.

VII. Conclusion

All real-world investors face funding constraints such as leverage constraints and margin requirements, and these constraints influence investors' required returns across securities and over time. Consistent with the idea that investors prefer un-leveraged risky assets to leveraged safe assets, which goes back to Black (1972), we find empirically that portfolios of high-beta assets have lower alphas and Sharpe ratios than portfolios of low-beta assets. The security market line is not only flatter than predicted by the standard CAPM for U.S. equities (as reported by Black, Jensen, and Scholes (1972)), but we also find this relative flatness in 18 of 19 international equity markets, in Treasury markets, for corporate bonds sorted by maturity and by rating, and in futures markets. We show how this deviation from the standard CAPM can be captured using betting-against-beta factors, which may also be useful as control variables in future research (Proposition 2). The return of the BAB factor rivals those of all the standard asset pricing factors (e.g., value, momentum, and size) in terms of economic magnitude, statistical significance, and robustness across time periods, sub-samples of stocks, and global asset classes.

Extending the Black (1972) model, we consider the implications of funding constraints for cross-sectional and time-series asset returns. We show that worsening funding liquidity should lead to losses for the BAB factor in the time series

(Proposition 3) and that increased funding liquidity risk compresses betas in the cross section of securities toward 1, leading to an increased beta for the BAB factor (Proposition 4), and we find consistent evidence empirically.

Our model also has implications for agents' portfolio selection (Proposition 5). To test this, we identify investors that are likely to be relatively constrained and unconstrained. We discuss why mutual funds and individual investors may be leverage constrained, and consistent with the model's prediction that constrained investors go for riskier assets, we find that these investor groups hold portfolios with betas above 1 on average.

Conversely, we show that leveraged buyout funds and Warren Buffett's firm Berkshire Hathaway, both of whom have access to leverage, buy stocks with betas below 1 on average, another prediction of the model. Hence, these investors may be taking advantage of the BAB effect by applying leverage to safe assets and being compensated by investors facing borrowing constraints who take the other side. Buffett bets against beta as Fisher Black believed one should.

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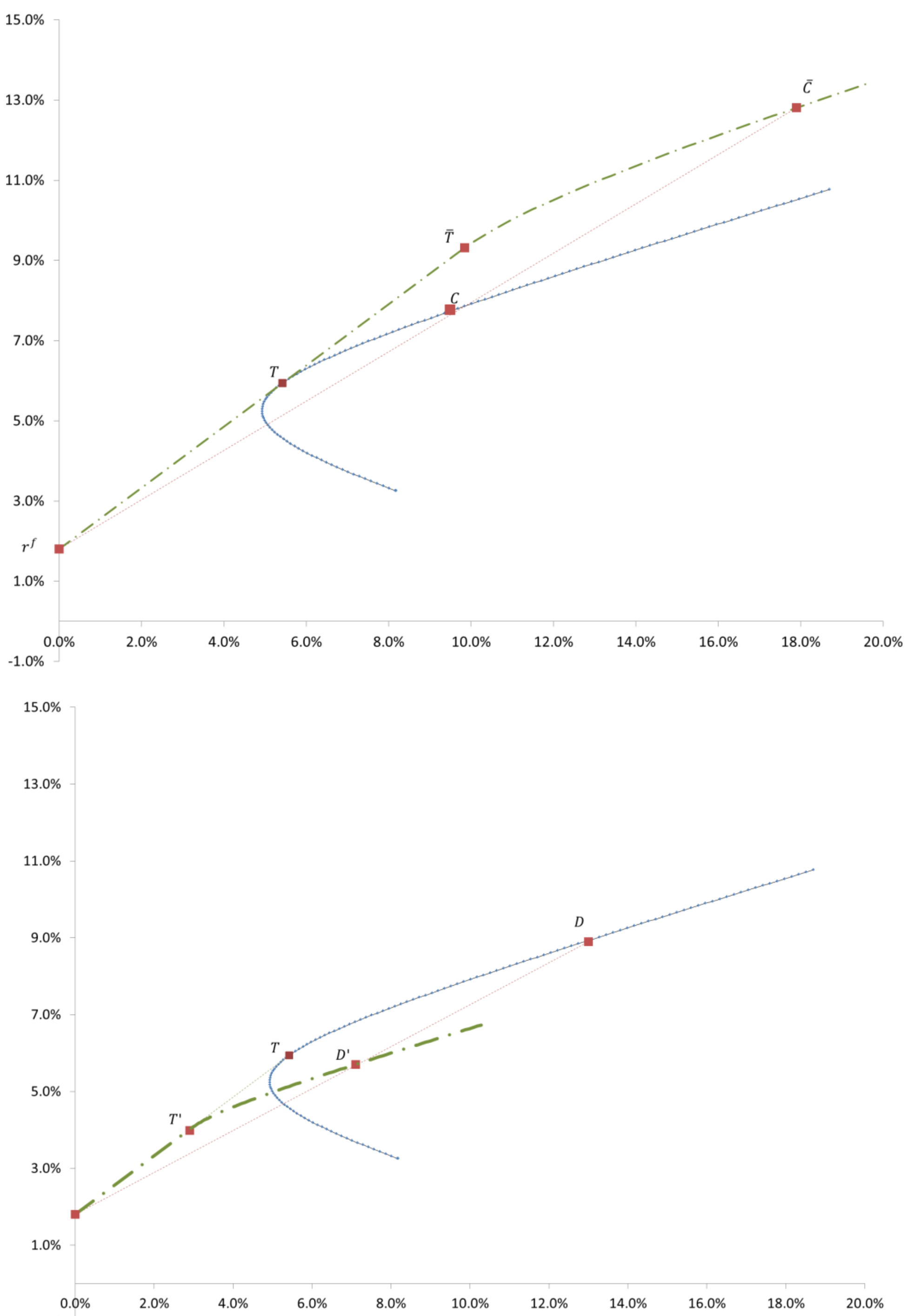
Appendix A: Analysis and Proofs

Before we prove our propositions, we provide a basic analysis of portfolio selection with constraints. This analysis is based on Figure A.1 below. The top panel shows the mean-standard deviation frontier for an agent with $m<1$, that is, an agent who can use leverage. We see that the agent can leverage the tangency portfolio T to arrive at the portfolio $\bar{T}$. To achieve a higher expected return, the agent needs to leverage riskier assets, which gives rise to the hyperbola segment to the right of $\bar{T}$. The agent in the graph is assumed to have risk preferences giving rise to the optimal portfolio $\bar{C}$. Hence, the agent is leverage constrained so he chooses to apply leverage to portfolio C rather than the tangency portfolio.

The bottom Panel of Figure A.2 similarly shows the mean-standard deviation frontier for an agent with $m>1$, that is, an agent who must hold some cash. If the agent keeps the minimum amount of money in cash and invests the rest in the tangency portfolio, then he arrives at portfolio T'. To achieve higher expected return, the agent must invest in riskier assets and, in the depicted case, he invests in cash and portfolio D, arriving at portfolio D'.

Unconstrained investors invest in the tangency portfolio and cash. Hence, the market portfolio is a weighted average of T, and riskier portfolios such as C and D. Therefore, the market portfolio is riskier than the tangency portfolio.

Figure A1. Portfolio Selection with Constraints. The top panel shows the mean-standard deviation frontier for an agent with $m<1$ who can use leverage, while the bottom panel show that of an agent with $m>1$ who needs to hold cash.



Proof of Proposition 1. Rearranging the equilibrium-price Equation (7) yields

$$
\begin{aligned}
E_t\left(r_{t+1}^s\right) &= r^f + \psi_t + \gamma \frac{1}{P_t^s} e_s{}'\Omega x^* \\
&= r^f + \psi_t + \gamma \frac{1}{P_t^s} \operatorname{cov}_t\left(P_{t+1}^s + \delta_{t+1}^s, [P_{t+1} + \delta_{t+1}]' x^*\right) \qquad \text{(A1)} \\
&= r^f + \psi_t + \gamma \operatorname{cov}_t\left(r_{t+1}^s, r_{t+1}^M\right) P_t{}' x^*
\end{aligned}
$$

where e_s is a vector with a 1 in row s and zeros elsewhere. Multiplying this equation by the market portfolio weights $w^s = x^{*s} P_t^s / \sum_j x^{*j} P_t^j$ and summing over s gives

$$
E_t\left(r_{t+1}^M\right) = r^f + \psi_t + \gamma \operatorname{var}_t\left(r_{t+1}^M\right) P_t{}' x^* \qquad \text{(A2)}
$$

that is,

$$
\gamma P_t{}' x^* = \frac{\lambda_t}{\operatorname{var}_t\left(r_{t+1}^M\right)} \qquad \text{(A3)}
$$

Inserting this into (A1) gives the first result in the proposition. The second result follows from writing the expected return as:

$$
E_t\left(r_{t+1}^s\right) - r^f = \psi_t\left(1 - \beta_t^s\right) + \beta_t^s\left(E_t\left(r_{t+1}^M\right) - r^f\right) \qquad \text{(A4)}
$$

and noting that the first term is (Jensen's) alpha. Turning to the third result regarding efficient portfolios, the Sharpe ratio increases in beta until the tangency portfolio is reached, and decreases thereafter. Hence, the last result follows from the fact that the tangency portfolio has a beta less than 1. This is true because the market portfolio is an average of the tangency portfolio (held by unconstrained agents) and riskier portfolios (held by constrained agents) so the market portfolio is riskier than the tangency portfolio. Hence, the tangency portfolio must have a lower expected return and beta (strictly lower iff some agents are constrained).□

Proof of Propositions 2-3. The expected return of the BAB factor is:

$$\begin{aligned} E_t\left(r_{t+1}^{BAB}\right) &= \frac{1}{\beta_t^L}\left(E_t\left(r_{t+1}^L\right)-r^f\right)-\frac{1}{\beta_t^H}\left(E_t\left(r_{t+1}^H\right)-r^f\right) \\ &= \frac{1}{\beta_t^L}\left(\psi_t+\beta_t^L\lambda_t\right)-\frac{1}{\beta_t^H}\left(\psi_t+\beta_t^H\lambda_t\right) \\ &= \frac{\beta_t^H-\beta_t^L}{\beta_t^L\beta_t^H}\psi_t \end{aligned} \tag{A5}$$

Consider next a change in m_t^k. Note first that this does not change the betas. This is because Equation (7) shows that the change in Lagrange multipliers scale all the prices (up or down) by the same proportion. Hence, Equation (11) in the proposition follows if we can show that ψ_t increases in m^k since this lead to:

$$\frac{\partial E_t\left(r_{t+1}^{BAB}\right)}{\partial m_t^k} = \frac{\beta_t^H-\beta_t^L}{\beta_t^L\beta_t^H}\frac{\partial\psi_t}{\partial m_t^k}>0 \tag{A6}$$

Further, since prices move opposite required returns, Equation (11) then follows. To see that an increase in m_t^k increases ψ_t, we first note that the constrained agents' asset expenditure decreases with a higher m_t^k. Indeed, summing the portfolio constraint across constrained agents (where Equation (2) holds with equality) gives

$$\sum_{i \text{ constrained}} \sum_s x^{i,s} P_t^s = \sum_{i \text{ constrained}} \frac{1}{m^i} W_t^i \tag{A7}$$

Since increasing m^k decreases the right-hand side, the left-hand side must also decrease. That is, the total market value of shares owned by constrained agents decreases.

Next, we show that the constrained agents' expenditure is decreasing in ψ.

Hence, since an increase in m_t^k decreases the constrained agents' expenditure, it must increase ψ_t as we wanted to show.

$$\frac{\partial}{\partial \psi}\sum_{i \text{ constrained}} P_t' x^i = \sum_{i \text{ constrained}} \left(\frac{\partial P_t}{\partial \psi}' x^i + P_t' \frac{\partial x^i}{\partial \psi} \right) < 0 \tag{A8}$$

To see the last inequality, note first that clearly $\frac{\partial P_t}{\partial \psi}' x^i < 0$ since all the prices decrease by the same proportion (seen in Equation (7)) and the initial expenditure is positive. The second term is also negative since

$$\begin{aligned}
\sum_{i \text{ constrained}} P_t' \frac{\partial}{\partial \psi} x^i &= \sum_{i \text{ constrained}} P_t' \frac{\partial}{\partial \psi} \frac{1}{\gamma^i} \Omega^{-1} \left(E_t\left(P_{t+1}+\delta_{t+1}\right) - \left(1+r^f+\psi_t^i\right) \frac{E_t\left(P_{t+1}+\delta_{t+1}\right) - \gamma\Omega x^*}{1+r^f+\psi} \right) \\
&= -P_t' \frac{\partial}{\partial \psi} \Omega^{-1} \sum_{i \text{ constrained}} \frac{1}{\gamma^i} \left(1+r^f+\psi_t^i\right) \frac{E_t\left(P_{t+1}+\delta_{t+1}\right) - \gamma\Omega x^*}{1+r^f+\psi} \\
&= -P_t' \frac{\partial}{\partial \psi} \Omega^{-1} \frac{1}{\gamma} \left(q\left(1+r^f\right)+\psi\right) \frac{E_t\left(P_{t+1}+\delta_{t+1}\right) - \gamma\Omega x^*}{1+r^f+\psi} \\
&= -\left(\frac{E_t\left(P_{t+1}+\delta_{t+1}\right) - \gamma\Omega x^*}{1+r^f+\psi} \right)' \frac{\partial}{\partial \psi} \Omega^{-1} \frac{1}{\gamma} \left(q\left(1+r^f\right)+\psi\right) \frac{E_t\left(P_{t+1}+\delta_{t+1}\right) - \gamma\Omega x^*}{1+r^f+\psi} \\
&= -\frac{1}{1+r^f+\psi} \frac{1}{\gamma} \frac{\partial}{\partial \psi} \frac{q\left(1+r^f\right)+\psi}{1+r^f+\psi} \left(E_t\left(P_{t+1}+\delta_{t+1}\right) - \gamma\Omega x^*\right)' \Omega^{-1} \left(E_t\left(P_{t+1}+\delta_{t+1}\right) - \gamma\Omega x^*\right) \\
&< 0
\end{aligned}$$

where we have defined $q = \sum_{i \text{ constrained}} \frac{\gamma}{\gamma^i} < 1$ and used that $\sum_{i \text{ constrained}} \frac{\gamma}{\gamma^i} \psi^i = \sum_i \frac{\gamma}{\gamma^i} \psi^i = \psi$ since $\psi^i = 0$ for unconstrained agents. This completes the proof.□

Proof of Proposition 4. Using the Equation (7) for the price, the sensitivity of with respect to funding shocks can be calculated as

$$\frac{\partial P_t^s}{P_t^s} / \partial \psi_t = -\frac{1}{1+r^f+\psi_t} \tag{A9}$$

which is the same for all securities *s*. Intuitively, shocks that affect all securities the same way compress betas towards one. To see this more rigorously, we write prices as:

$$
\begin{aligned}
P_t^i &= \frac{E_t\left(P_{t+1}^i + \delta_{t+1}^i\right) - \gamma e_i{}'\Omega x^*}{1 + r^f + \psi_t} \\
&= a^i z_t + z_t E_t\left(P_{t+1}^i\right) \\
&= a^i\left(z_t + z_t E\left(z_{t+1}\right) + z_t E\left(z_{t+1}\right) E\left(z_{t+2}\right) + \ldots\right) \\
&= a^i \pi_t
\end{aligned}
\tag{A10}
$$

where

$$
\begin{aligned}
a^i &= E\left(\delta_{t+1}^i\right) - \gamma e_i{}'\Omega x^* \\
z_t &= \frac{1}{1 + r^f + \psi_t} \\
\pi_t &= z_t + z_t E\left(z_{t+1}\right) + z_t E\left(z_{t+1}\right) E\left(z_{t+2}\right) + \ldots
\end{aligned}
\tag{A11}
$$

With these definitions, we can write returns as $r_t^i = \frac{P_t^i + \delta_t^i}{P_{t-1}^i} = \frac{a^i \pi_t + \delta_t^i}{a^i \pi_{t-1}}$ and calculate beta as

$$
\begin{aligned}
\beta_{t-1}^i &= \frac{\mathrm{cov}_{t-1}(r_t^i, r_t^M)}{\mathrm{var}_{t-1}(r_t^M)} \\
&= \frac{\mathrm{cov}_{t-1}\left(\frac{a^i \pi_t + \delta_t^i}{a^i \pi_{t-1}}, \frac{a^M \pi_t + \delta_t^M}{a^M \pi_{t-1}}\right)}{\mathrm{var}_{t-1}\left(\frac{a^M \pi_t + \delta_t^M}{a^M \pi_{t-1}}\right)} \\
&= \frac{a^M}{a^i} \frac{\mathrm{var}\left(\pi_t\right) a^i a^M + \mathrm{cov}(\delta_t^i, \delta_t^M)}{\mathrm{var}(\pi_t)(a^M)^2 + \mathrm{var}(\delta_t^M)}
\end{aligned}
\tag{A12}
$$

We see that the beta depends on security-specific cash flow covariance, $\mathrm{cov}(\delta_t^i, \delta_t^M)$, and market-wide discount rate variance, $\mathrm{var}\left(\pi_t\right)$. The beta approaches 1 when the discount-rate variance increases, $\mathrm{var}\left(\pi_t\right) \to \infty$ (which follows from $\mathrm{var}\left(z_t\right) \to \infty$).

Further, if betas are compressed towards 1 after the formation of the BAB portfolio, then BAB will realize a positive beta as its long-side is more levered than its short side. Specifically, suppose that the BAB portfolio is constructed based on estimated betas (β_t^{L}, β_t^{H}) using data from a period with less variance of ψ_t so that $\beta_t^{L} < \beta_t^L < \beta_t^H < \beta_t^{H}$. Then the BAB portfolio will have a beta of

$$\begin{aligned}\beta_t^{BAB} &= \frac{1}{\operatorname{var}(r_{t+1}^M)} \operatorname{cov}\left(\frac{1}{\beta_t^{L}}\left(r_{t+1}^L - r^f\right) - \frac{1}{\beta_t^{H}}\left(r_{t+1}^H - r^f\right) \ , \ r_{t+1}^M \right) \\ &= \frac{\beta_t^L}{\beta_t^{L}} - \frac{\beta_t^H}{\beta_t^{H}} > 0\end{aligned} \tag{A13}$$

Proof of Proposition 5. To see the first part of the proposition, we first note that an unconstrained investor holds the tangency portfolio, which has a beta less than 1 in equilibrium with funding constraints, and the constrained investors hold riskier portfolios of risky assets, as discussed in the proof of Proposition 1.

To see the second part of the proposition, note that given the equilibrium prices, the optimal portfolio is:

$$\begin{aligned}x^i &= \frac{1}{\gamma^i}\Omega^{-1}\left(E_t\left(P_{t+1}+\delta_{t+1}\right) - \left(1+r^f+\psi_t^i\right)\frac{E_t\left(P_{t+1}+\delta_{t+1}\right)-\gamma\Omega x^*}{1+r^f+\psi_t} \right) \\ &= \frac{\gamma}{\gamma^i}\frac{1+r^f+\psi_t^i}{1+r^f+\psi_t}x^* + \frac{\psi_t-\psi_t^i}{1+r^f+\psi_t}\frac{1}{\gamma^i}\Omega^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right)\end{aligned} \tag{A14}$$

The first term shows that each agent holds some (positive) weight in the market portfolio x^* and the second term shows how he tilts his portfolio away from the market. The direction of the tilt depends on whether the agent's Lagrange multiplier ψ_t^i is smaller or larger than the weighted average of all the agents' Lagrange multipliers ψ_t. A less constrained agent tilts towards the portfolio $\Omega^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right)$ (measured in shares), while a more constrained agent tilts away from this portfolio.

Given the expression (13), we can write the variance-covariance matrix as

$$\Omega = \sigma_M^2 bb' + \Sigma \tag{A15}$$

where Σ=var(e) and $\sigma_M^2 = \text{var}\left(P_{t+1}^M\right)$. Using the Matrix Inversion Lemma (the Sherman–Morrison–Woodbury formula), the tilt portfolio can be written as:

$$\begin{aligned}
\Omega^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right) &= \left(\Sigma^{-1} - \Sigma^{-1}bb'\Sigma^{-1}\frac{1}{\sigma_M^2 + b'\Sigma^{-1}b}\right)E_t\left(P_{t+1}+\delta_{t+1}\right) \\
&= \Sigma^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right) - \Sigma^{-1}bb'\Sigma^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right)\frac{1}{\sigma_M^2 + b'\Sigma^{-1}b} \\
&= \Sigma^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right) - y\Sigma^{-1}b
\end{aligned}$$

where $y = b'\Sigma^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right)/\left(\sigma_M^2 + b'\Sigma^{-1}b\right)$ is a scalar. It holds that $\left(\Sigma^{-1}b\right)_s > \left(\Sigma^{-1}b\right)_k$ since $b^s > b^k$ and since s and k have the same variances and covariances in Σ, implying that $\left(\Sigma^{-1}\right)_{s,j} = \left(\Sigma^{-1}\right)_{k,j}$ for $j \neq s,k$ and $\left(\Sigma^{-1}\right)_{s,s} = \left(\Sigma^{-1}\right)_{k,k} \geq \left(\Sigma^{-1}\right)_{s,k} = \left(\Sigma^{-1}\right)_{k,s}$. Similarly, it holds that $\left[\Sigma^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right)\right]_s < \left[\Sigma^{-1}E_t\left(P_{t+1}+\delta_{t+1}\right)\right]_k$ since a higher market exposure leads to a lower price (see below). So everything else equal, a higher b leads to a lower weight in the tilt portfolio.

Finally, we note that security s also has a higher return beta than k since

$$\beta_t^i = \frac{P_t^M \operatorname{cov}(P_{t+1}^i + \delta_{t+1}^i, P_{t+1}^M + \delta_{t+1}^M)}{P_t^i \operatorname{var}\left(P_{t+1}^M + \delta_{t+1}^M\right)} = \frac{P_t^M}{P_t^i}b^i \tag{A17}$$

and a higher b^i means a lower price:

$$P_t^i = \frac{E_t\left(P_{t+1}^i + \delta_{t+1}^i\right) - \gamma\left(\Omega x^*\right)_i}{1 + r^f + \psi_t} = \frac{E_t\left(P_{t+1}^i + \delta_{t+1}^i\right) - \gamma\left(\Sigma x^*\right)_i - b^i b' x^* \gamma \sigma_M^2}{1 + r^f + \psi_t}$$

□

Appendix B: Additional Empirical Results and Robustness Tests

Tables B1 to B7 and Figures B1 to B7 contain additional empirical results and robustness tests.

- Table B1 reports returns of BAB portfolio in US and International Equities using different window lengths (1, 3, 5 years), different benchmark (local, global), different methods to estimate betas (OLS, Scholes and Williams (1977)) and different risk adjustment (local risk factors, international risk factors). International risk factors are constructed as in Fama and French (1996) using our international sample.

- Table B2 reports returns and factor loadings of US and International BAB portfolios

- Table B3 and B4 report returns of US and International BAB portfolios controlling for idiosyncratic volatility. Idiosyncratic volatility is defined as the standard deviation of the residuals in the rolling regression used to estimated betas. We use conditional sorts: at the beginning of each calendar month stocks are ranked in ascending order on the basis of their idiosyncratic volatility and assigned to one of 10 groups from low to high volatility. Within each volatility deciles, we assign stocks to low and high beta portfolios and compute BAB returns. We report two sets of results: controlling for the level of idiosyncratic volatility and the 1-month change in the same measure.

- Table B5 reports returns of US and International BAB portfolios controlling for size. Size is defined as the market value of equity (in USD). We use conditional sorts: at the beginning of each calendar month stocks are ranked in ascending order on the basis of their market value of equity and assigned to one of 10 groups from small to large based on NSYE breakpoints. Within each size deciles, we assign stocks to low and high beta portfolios and compute BAB returns.

- Table B6 reports returns of US and International BAB portfolios in different sample periods.

- Table B7 reports returns of US and International BAB portfolios using alternative assumption for risk free rates.

- Table B8 reports returns of US Treasury Bonds portfolios using alternative assumption for risk free rates. Table B8 also reports results for BAB factors constructed using 2-year and 30-year Treasury bonds and the corresponding 1-year and 30-year Treasury bond futures over the same sample period. Using futures-based portfolio avoids the need of an assumption about the risk free rate since futures returns are constructed as changes in the futures contract price. We use 2-year and 30-year futures since in our data they are the contract with the longest available sample period.

- Table B9 reports results of global BAB portfolios using beta with respect to a global market index. We use the global market portfolio from Asness, Frazzini and Pedersen (2011). Betas are estimated using use rolling 1- to 5-year windows depending on data availability and we require at least 12 monthly observations.

- Table B10 reports returns of BAB portfolios for all asset classes in different time periods sorted by likelihood of binding credit constraints. At the beginning of each calendar month, we rescale each return series to 10% annualized volatility using rolling 3-year estimate up to moth t-1. We assign the Ted spread into three groups (low, neutral and high) based on full sample breakpoints (top and bottom 1/3) and report returns for each time period.

- Figure B1 plot the Sharpe ratio (annualized) of beta-sorted portfolios for all the asset classes.

- Figure B2 plot alphas (monthly, in percent) of beta-sorted portfolios for all the asset classes.

- Figures B3 to B8 reports calendar time returns of the BAB portfolios.

Table B1
US and International Equities. Robustness: Alternative Betas Estimation and Risk Adjustment

This table shows calendar-time portfolio returns of BAB portfolios for different beta estimation methods and different risk-adjustment. At the beginning of each calendar month within each country stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas (lower beta security have larger weight in the low-beta portfolio and higher beta securities have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the CRSP database, and all available common stocks on the Compustat Xpressfeed Global database for the 19 markets in listed table I. "Beta with respect to" is the index used to compute rolling betas. "Global market index" is the global market portfolio from Asness, Frazzini and Pedersen (2011). "Universe" is the sample universe (US or Global). "Method" is the estimation method used to calculate betas. We use either OLS or the Scholes and Williams (1997) trade-based beta ("SW"). "Risk Factors" is the risk adjustment used to compute alphas. We use either US-based factors (US) or the corresponding international factors. International risk factors are constructed as in Fama and French (1996) using our international sample. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. Returns and alphas are in USD and are expressed in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. *$ Long (Short)* is the average dollar value of the long (short) position. Volatilities and Sharpe ratios are annualized.

Beta with respect to	Universe	Method	Risk Factors	Estimation window (year)	Lagged terms	Excess Return	t-stat Excess Return	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
CRSP - VW index	US	OLS	US	1	1 Week	**0.71**	6.76	**0.55**	5.12	0.71	1.52	11.5	0.75
CRSP - VW index	US	OLS	US	3	1 Week	**0.43**	4.75	**0.43**	4.96	0.73	1.36	9.6	0.53
CRSP - VW index	US	OLS	US	5	1 Week	**0.37**	4.04	**0.42**	5.01	0.76	1.29	9.8	0.46
CRSP - VW index	US	SW	US	1		**0.56**	6.13	**0.42**	4.48	0.73	1.36	10.0	0.67
Local market index	International	OLS	US	1	1 Week	**0.72**	3.79	**0.45**	2.47	0.86	1.51	10.9	0.79
Local market index	International	OLS	International	1	1 Week	**0.72**	3.79	**0.41**	2.48	0.86	1.51	10.9	0.79
Global market index	International	OLS	Global market index	5	1 Month	**1.19**	3.82	**1.08**	3.51	0.62	1.40	16.8	0.85
CRSP - VW index	International	OLS	US	1	1 Week	**0.81**	3.07	**0.39**	1.57	0.98	1.81	15.3	0.64

Table B2
US and International Equities. Factor Loadings

This table shows calendar-time portfolio returns and factor loadings. At the beginning of each calendar month all stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The zero-beta factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the CRSP database, and all available common stocks on the Compustat Xpressfeed Global database for the 19 markets in listed table I. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. International risk factors are constructed as in Fama and French (1996) using our international sample. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Beta (ex ante) is the average estimated beta at portfolio formation. $ Long (Short) is the average dollar value of the long (short) position.

	Excess Return	Alpha	MKT	SMB	HML	UMD	$ Short	$ Long
Panel A: all stocks								
High Beta	**0.97**	0.01	**1.30**	**1.11**	**0.23**	**-0.23**		
Low beta	**0.93**	**0.33**	**0.67**	**0.60**	**0.26**	**-0.05**		
L/S	**0.71**	**0.55**	0.02	**0.13**	**0.10**	**0.11**	0.71	1.52
t-statistics	3.03	0.09	86.35	47.40	10.25	-13.47		
	5.44	6.11	64.04	37.17	16.47	-4.39		
	6.76	5.12	1.13	3.99	3.14	4.39		
Panel B: above NYSE median ME								
High Beta	**0.76**	**-0.15**	**1.41**	**0.62**	**0.05**	**-0.14**		
Low beta	**0.65**	**0.14**	**0.69**	**0.17**	**0.15**	0.02		
L/S	**0.30**	**0.28**	**-0.12**	**-0.20**	**0.13**	**0.13**	0.73	1.35
t-statistics	2.59	-2.15	105.40	29.85	2.34	-8.83		
	4.69	2.79	71.48	11.62	10.12	1.55		
	2.78	2.69	-6.03	-6.47	4.29	5.63		

	Excess Return	Alpha	MKT	SMB	HML	UMD	$ Short	$ Long
Panel C: International Equity								
High Beta	0.20	0.24	**0.85**	**0.21**	-0.16	**-0.35**		
Low beta	0.45	0.31	**0.49**	**0.26**	0.13	-0.07		
L/S	**0.72**	**0.41**	**0.12**	**0.16**	**0.46**	**0.22**	0.86	1.51
t-statistics	0.46	0.83	14.38	1.98	-1.17	-4.40		
	1.66	1.42	11.14	3.26	1.28	-1.16		
	3.79	2.48	3.66	2.68	5.75	4.87		
Panel D: International Equity, above 90% ME by country								
High Beta	0.31	0.26	**0.90**	0.00	-0.08	**-0.22**		
Low beta	0.50	0.32	**0.48**	0.14	0.16	-0.01		
L/S	**0.57**	**0.35**	-0.01	**0.16**	**0.43**	**0.19**	0.87	1.40
t-statistics	0.75	0.92	15.82	0.04	-0.63	-2.89		
	1.94	1.53	11.16	1.80	1.59	-0.18		
	3.10	2.10	-0.28	2.53	5.34	4.16		

Table B3
US Equities. Robustness: Idiosyncratic Volatility.

This table shows calendar-time portfolio returns of BAB portfolios with conditional sort on idiosyncratic volatility. At the beginning of each calendar month stocks are ranked in ascending order on the basis of their idiosyncratic volatility and assign to one of 10 groups. Idiosyncratic volatility is defined as the standard deviation of the residuals in the rolling regression used to estimated betas. Panel A reports results for conditional sorts based on the level of idiosyncratic volatility at portfolio formation. Panel B report results based on the 1-month changes in the same measure. At the beginning of each calendar month, within each volatility deciles stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The zero-beta factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the CRSP database between 1926 and 2009. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. *$ Long (Short)* is the average dollar value of the long (short) position. Volatilities and Sharpe International risk factors are constructed as in Fama and French (1996) using our international sample ratios are annualized.

Panel A: Control for Idiosyncratic volatility	xret	t(xret)	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
Low - volatility	**0.22**	2.04	**0.29**	2.94	1.02	1.65	11.6	0.22
P -2	**0.37**	3.60	**0.38**	3.82	0.91	1.51	11.3	0.40
P -3	**0.50**	4.88	**0.44**	4.46	0.86	1.46	11.1	0.54
P -4	**0.40**	3.66	**0.32**	3.07	0.82	1.42	11.9	0.40
P -5	**0.42**	3.83	**0.30**	2.82	0.79	1.40	11.8	0.42
P -6	**0.48**	4.45	**0.35**	3.30	0.76	1.39	11.8	0.49
P -7	**0.58**	5.18	**0.36**	3.32	0.73	1.38	12.2	0.57
P -8	**0.74**	5.49	**0.41**	3.41	0.70	1.37	14.6	0.61
P -9	**0.94**	5.33	**0.50**	3.51	0.67	1.39	19.3	0.59
High volatility	**1.81**	5.25	**1.16**	3.98	0.63	1.61	37.6	0.58

Panel B: Control for Idiosyncratic volatility changes	xret	t(xret)	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
Low - volatility	**0.46**	3.99	**0.41**	3.64	0.75	1.52	12.6	0.44
P -2	**0.34**	2.98	**0.29**	2.55	0.75	1.49	12.5	0.33
P -3	**0.48**	4.22	**0.40**	3.43	0.74	1.48	12.5	0.47
P -4	**0.59**	5.18	**0.48**	4.26	0.73	1.47	12.3	0.57
P -5	**0.54**	4.63	**0.46**	3.89	0.72	1.47	12.6	0.51
P -6	**0.64**	4.70	**0.44**	3.26	0.71	1.47	14.7	0.52
P -7	**0.60**	4.72	**0.47**	3.56	0.70	1.49	13.8	0.52
P -8	**0.97**	6.25	**0.77**	4.97	0.69	1.51	16.8	0.69
P -9	**1.16**	5.82	**0.93**	4.80	0.68	1.60	21.7	0.64
High volatility	**1.53**	2.61	0.87	1.48	0.68	1.92	63.6	0.29

Table B4
International Equities. Robustness: Idiosyncratic Volatility.

This table shows calendar-time portfolio returns of BAB portfolios with conditional sort on idiosyncratic volatility. At the beginning of each calendar month stocks are ranked in ascending order on the basis of their idiosyncratic volatility and assign to one of 10 groups. Idiosyncratic volatility is defined as the standard deviation of the residuals in the rolling regression used to estimated betas. Panel A reports results for conditional sorts based on the level of idiosyncratic volatility at portfolio formation. Panel B report results based on the 1-month changes in the same measure. Within each volatility deciles stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the CRSP database, and all available common stocks on the Compustat Xpressfeed Global database for the 19 markets in listed table I. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. International risk factors are constructed as in Fama and French (1996) using our international sample Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. *$ Long (Short)* is the average dollar value of the long (short) position. Volatilities and Sharpe ratios are annualized.

Panel A: Control for Idiosyncratic volatility	xret	t(xret)	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
Low - volatility	0.30	1.85	0.19	1.28	1.06	1.56	8.7	0.41
P -2	**0.32**	1.97	0.19	1.23	1.01	1.48	8.7	0.44
P -3	0.17	1.03	0.05	0.29	0.98	1.45	8.6	0.23
P -4	**0.35**	1.96	0.20	1.21	0.95	1.43	9.5	0.44
P -5	**0.38**	2.21	0.34	1.94	0.92	1.41	9.1	0.49
P -6	0.36	1.79	0.21	1.02	0.90	1.39	10.7	0.40
P -7	0.24	1.10	-0.03	-0.16	0.87	1.37	11.9	0.25
P -8	0.05	0.21	0.00	0.01	0.84	1.37	12.6	0.05
P -9	-0.07	-0.23	-0.17	-0.59	0.81	1.36	15.1	-0.05
High volatility	-0.33	-0.93	-0.22	-0.63	0.77	1.41	18.9	-0.21

Panel B: Control for Idiosyncratic volatility changes	xret	t(xret)	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
Low - volatility	**0.47**	2.40	0.37	1.96	0.93	1.49	10.5	0.54
P -2	0.22	1.03	0.06	0.29	0.92	1.48	11.3	0.23
P -3	**0.43**	2.10	**0.46**	2.28	0.92	1.46	11.0	0.47
P -4	**0.45**	2.21	**0.42**	2.07	0.91	1.45	10.9	0.50
P -5	**0.40**	2.03	0.30	1.58	0.90	1.44	10.6	0.45
P -6	**0.60**	2.96	**0.45**	2.30	0.89	1.44	10.8	0.66
P -7	**0.58**	2.79	0.39	1.90	0.88	1.44	11.2	0.62
P -8	0.44	1.77	0.22	0.90	0.87	1.44	13.2	0.40
P -9	**0.45**	2.13	0.33	1.53	0.86	1.44	11.4	0.48
High volatility	-0.02	-0.06	-0.09	-0.31	0.84	1.46	14.2	-0.01

Table B5
US and International Equities. Robustness: Size

This table shows calendar-time portfolio returns of BAB portfolios with conditional sort on size. At the beginning of each calendar month stocks are ranked in ascending order on the basis of their market value of equity (in USD) at the end of the previous month. Stocks are assigned to one of 10 groups based on NYSE breakpoints. Within each size deciles and within each country stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the CRSP database, and all available common stocks on the Compustat Xpressfeed Global database for the 19 markets in listed table I. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. International risk factors are constructed as in Fama and French (1996) using our international sample. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. *$ Long (Short)* is the average dollar value of the long (short) position. Volatilities and Sharpe ratios are annualized.

Panel A: US Equities	xret	t(xret)	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
Small - ME	**1.91**	5.65	**1.32**	4.57	0.69	1.77	36.8	0.62
ME -2	**0.86**	5.40	**0.43**	2.99	0.69	1.47	17.3	0.60
ME -3	**0.64**	5.64	**0.40**	3.56	0.69	1.40	12.4	0.62
ME -4	**0.55**	4.98	**0.41**	3.66	0.69	1.37	12.1	0.55
ME -5	**0.47**	4.22	**0.34**	2.97	0.70	1.35	12.2	0.46
ME -6	**0.39**	3.13	**0.28**	2.21	0.71	1.35	13.5	0.35
ME -7	**0.32**	2.59	**0.29**	2.35	0.72	1.34	13.6	0.29
ME -8	**0.38**	2.95	**0.38**	3.13	0.74	1.33	13.9	0.33
ME -9	**0.29**	2.25	**0.29**	2.37	0.77	1.33	13.9	0.25
Large-ME	0.13	1.01	0.15	1.24	0.81	1.33	13.5	0.11

Panel B: International Equity	Excess Return	T(Excess Return)	4-factor alpha	T(alpha)	$Short	$Long	Volatility	SR
Small - ME	0.98	0.92	1.08	0.92	0.88	1.64	32.1	0.03
ME -2	**0.92**	2.19	0.84	1.95	0.90	1.54	24.0	0.46
ME -3	**0.74**	2.84	**0.55**	2.23	0.90	1.52	14.9	0.60
ME -4	**0.63**	2.84	0.29	1.39	0.89	1.49	12.6	0.60
ME -5	0.45	1.95	0.16	0.76	0.90	1.45	13.2	0.41
ME -6	**0.73**	3.35	0.34	1.72	0.90	1.45	12.5	0.71
ME -7	0.26	1.09	0.08	0.35	0.90	1.43	13.4	0.23
ME -8	**0.62**	2.83	0.36	1.69	0.88	1.36	12.5	0.60
ME -9	**0.49**	2.18	0.33	1.56	0.89	1.36	12.9	0.46
Large-ME	0.35	1.64	0.02	0.10	0.88	1.29	12.0	0.34

Table B6
US and International Equities. Robustness: Sample Period

This table shows calendar-time portfolio returns of BAB portfolios. At the beginning of each calendar month within each country stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the CRSP database, and all available common stocks on the Compustat Xpressfeed Global database for the 19 markets in listed table I. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. International risk factors are constructed as in Fama and French (1996) using our international sample. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. *$ Long (Short)* is the average dollar value of the long (short) position. Volatilities and Sharpe ratios are annualized.

Panel A: US Equities	xret	t(xret)	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
1926 - 1945	**0.55**	2.36	**0.49**	2.18	0.72	1.29	12.0	0.55
1946 - 1965	**0.56**	5.43	**0.56**	4.88	0.79	1.35	5.6	1.22
1966 - 1985	**0.80**	5.02	**0.57**	3.73	0.72	1.31	8.6	1.12
1986 - 2009	**0.90**	3.26	0.33	1.39	0.69	1.42	16.1	0.67

Panel B: International Equity	xret	t(xret)	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
1984 - 1994	0.62	1.67	0.40	1.08	0.87	1.27	12.5	0.59
1995 - 2000	0.41	1.59	0.36	1.24	0.89	1.44	7.6	0.65
2001 - 2009	**1.03**	3.24	**0.81**	2.93	0.86	1.49	11.3	1.09

Table B7
US Equities. Robustness: Alternative Risk-Free Rates

This table shows calendar-time portfolio returns of BAB portfolios. At the beginning of each calendar month within each country stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the CRSP database, and all available common stocks on the Compustat Xpressfeed Global database for the 19 markets in listed table I. We report returns using different risk free rates sorted by their average spread over the Treasury bill. "T-bills" is the 1-month Treasury bills. "Repo" is the overnight repo rate. "OIS" is the overnight indexed swap rate. "Fed Funds" is the effective federal funds rate. "Libor" is the 1-month LIBOR rate. If the interest rate is not available over a date range, we use the 1-month Treasury bills plus the average spread over the entire sample period. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. *$ Long (Short)* is the average dollar value of the long (short) position. Volatilities and Sharpe ratios are annualized.

Rate	spread (annual, Bps)	Excess Return	T(Excess Return)	4-factor alpha	t(alpha)	$Long	$Short	Volatility	SR
T-Bills	0.0	**0.71**	6.76	**0.67**	6.30	1.52	0.71	11.5	0.75
Repo	20.8	**0.70**	6.63	**0.65**	6.18	1.52	0.71	11.5	0.73
OIS	26.1	**0.70**	6.60	**0.65**	6.16	1.52	0.71	11.5	0.73
Fed Funds	41.5	**0.69**	6.51	**0.64**	6.08	1.52	0.71	11.5	0.72
Libor	63.8	**0.67**	6.38	**0.63**	5.95	1.52	0.71	11.5	0.70

Table B8
US Treasury Bonds. Robustness: Alternative Risk-Free Rates

This table shows calendar-time portfolio returns. The test assets are CRSP Monthly Treasury - Fama Bond Portfolios. Only non-callable, non-flower notes and bonds are included in the portfolios. The portfolio returns are an equal weighted average of the unadjusted holding period return for each bond in the portfolios in excess of the risk free rate. To construct the zero-beta BAB factor, all bonds are assigned to one of two portfolios: low beta and high beta. Bonds are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. We report returns using different risk free rates sorted by their average spread over the Treasury bill. "T-bills" is the 1-month Treasury bills. "Repo" is the overnight repo rate. "OIS" is the overnight indexed swap rate. "Fed Funds" is the effective federal funds rate. "Libor" is the 1-month LIBOR rate. If the interest rate is not available over a date range, we use the 1-month Treasury bills plus the average spread over the entire sample period. Alpha is the intercept in a regression of monthly excess return. The explanatory variable is the monthly return of an equally weighted bond market portfolio. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates and 5% statistical significance is indicated in bold. Volatilities and Sharpe ratios are annualized. The top panel reports returns using cash bonds. The bottom panel report returns using 2-year and 30-years cash bonds and 2-year and 30-year bonds futures.

Rate	spread (Bps)	Excess Return	T(Excess Return)	Alpha	t(alpha)	$Long	$Short	Volatility	SR
T-Bills	0.0	**0.16**	6.37	**0.16**	6.27	3.14	0.59	2.3	0.85
Repo	20.5	**0.12**	4.62	**0.12**	4.52	3.14	0.59	2.4	0.61
OIS	25.5	**0.11**	4.28	**0.11**	4.21	3.14	0.59	2.3	0.57
Fed Funds	41.2	**0.08**	2.99	**0.08**	2.89	3.14	0.59	2.4	0.40
Libor	63.3	0.03	1.29	0.03	1.22	3.14	0.59	2.4	0.17

BAB: 2-year and 30-year Treasury Bonds. 1991 to 2009

	Excess Return	T(Excess Return)	4-factor alpha	t(alpha)	$Long	$Short	Volatility	SR
Futures	**0.24**	2.90	**0.24**	2.99	3.56	0.58	4.4	0.67
Cash (using T-bills)	**0.25**	2.89	**0.28**	3.10	4.67	0.57	4.5	0.67

Table B9
All Assets. Robustness: Betas with Respect to a Global Market Portfolio, 1973 – 2009

This table shows calendar-time portfolio returns. The test assets are cash equities, bonds, futures, forwards or swap returns in excess of the relevant financing rate. To construct the BAB factor, all instruments are assigned to one of two portfolios: low beta and high beta. Instruments are weighted by the ranked betas (lower beta security have larger weight in the low-beta portfolio and higher beta securities have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Betas as computed with respect to the global market portfolio from Asness, Frazzini and Pedersen (2011). Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. Alpha is the intercept in a regression of monthly excess return. The explanatory variable is the monthly return of the global market portfolio. *All Bonds and Credit* includes US treasury bonds, US corporate bonds, US credit indices (hedged and unhedged) and country bonds indices. *All Equities* included US stocks, international stocks and equity indices. *All Assets* includes all the assets listed in table I and II. The *All Equities* and *All Assets* combo portfolios have equal risk in each individual BAB and 10% ex ante volatility. To construct combo portfolios, at the beginning of each calendar month, we rescale each return series to 10% annualized volatility using rolling 3-year estimate up to moth *t-1* and then equally weight the return series. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates and 5% statistical significance is indicated in bold. Volatilities and Sharpe ratios are annualized.

Panel A: Global results	Excess Return	T-stat Excess Return	Alpha	T(alpha)	$Short	$Long	Volatility	SR
US Stocks	**0.63**	5.08	**0.59**	4.72	0.50	1.30	0.08	0.91
International Stocks	**1.19**	3.82	**1.08**	3.51	0.62	1.40	0.17	0.85
All Bonds and Credit	**1.33**	2.93	**1.26**	2.74	22.66	25.81	0.32	0.50
All Futures	**1.25**	2.45	**1.10**	2.16	1.22	3.02	0.36	0.41
All Equities*	**0.73**	4.93	**0.62**	4.35			0.10	0.85
All Assets*	**0.66**	4.19	**0.56**	3.65			0.11	0.72

* Equal risk, 10% ex ante volatility

Table B10
BAB Returns and Ted Spread

This table shows calendar-time portfolio returns. The test assets are BAB factors, rescaled to 10% annual volatility. To construct the BAB factor, all instruments are assigned to one of two portfolios: low beta and high beta. Instruments are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. At the beginning of each calendar month, we rescale each return series to 10% annualized volatility using rolling 3-year estimate up to moth *t*-1. We assign the Ted spread into three groups (low, neutral and high) based on full sample breakpoints (top and bottom 1/3) and regress the times series of monthly returns on the full set of dummies (without intercept). Returns are in monthly percent and 5% statistical significance is indicated in bold.

	P1 (low Ted)	P2	P3 (high Ted)	P3 minus P1	t-statitics
AUS	0.84	-0.46	-0.23	-1.07	-1.38
AUT	-0.24	-0.15	-0.04	0.20	0.27
BEL	0.83	0.45	-0.55	-1.37	-1.92
CAN	1.69	0.88	-0.40	**-2.10**	-3.38
CHE	0.72	-0.07	-0.31	-1.03	-1.51
DEU	0.31	0.68	-1.49	**-1.80**	-2.85
DNK	1.02	0.45	-1.17	**-2.19**	-4.72
ESP	1.04	1.01	-0.60	**-1.63**	-2.04
FIN	0.32	0.35	-1.23	**-1.55**	-2.48
FRA	0.90	0.64	-1.09	**-1.99**	-3.00
GBR	0.76	0.45	-2.03	**-2.79**	-4.27
HKG	0.77	0.16	-0.22	-0.99	-1.40
ITA	0.91	0.85	-0.57	**-1.47**	-2.14
JPN	-0.08	0.10	-0.39	-0.31	-0.44
NLD	1.11	0.37	-0.16	**-1.27**	-2.02
NOR	0.26	0.31	-0.33	-0.60	-0.99
NZL	0.99	0.48	-0.26	**-1.25**	-2.16
SGP	0.68	0.72	-0.38	-1.05	-1.79
SWE	0.62	1.12	-0.56	-1.17	-1.86
Commodities	-0.09	-0.32	-0.02	0.08	0.18
Credit Indices	0.83	1.35	1.47	0.63	1.05
Credit - Corporate	-0.04	0.88	0.69	0.73	1.43
Credit - CDS	0.10	0.46	1.18	1.08	1.77
Equity Indices	0.69	-0.38	0.23	-0.46	-0.93
Country Bonds	0.21	0.33	-0.11	-0.32	-0.45
FX	-0.06	-0.03	0.55	0.61	1.17
Global Stocks	1.22	0.99	-0.71	**-1.93**	-4.44
Treasury	0.52	1.26	0.83	0.31	0.59
US Stocks	1.15	1.20	-0.93	**-2.08**	-4.10
Pooled*	0.58	0.54	0.09	**-0.49**	-2.89

Figure B1
Sharpe Ratios of Beta-Sorted Portfolios

This figure shows annual Sharpe Ratios. The test assets are beta-sorted portfolios. At the beginning of each calendar month instruments are ranked in ascending order on the basis of their estimated beta at the end of the previous month. The ranked instruments are assigned to beta-sorted portfolios. This figure plots Sharpe ratios from low beta (left) to high beta (right). Sharpe ratios are annualized.

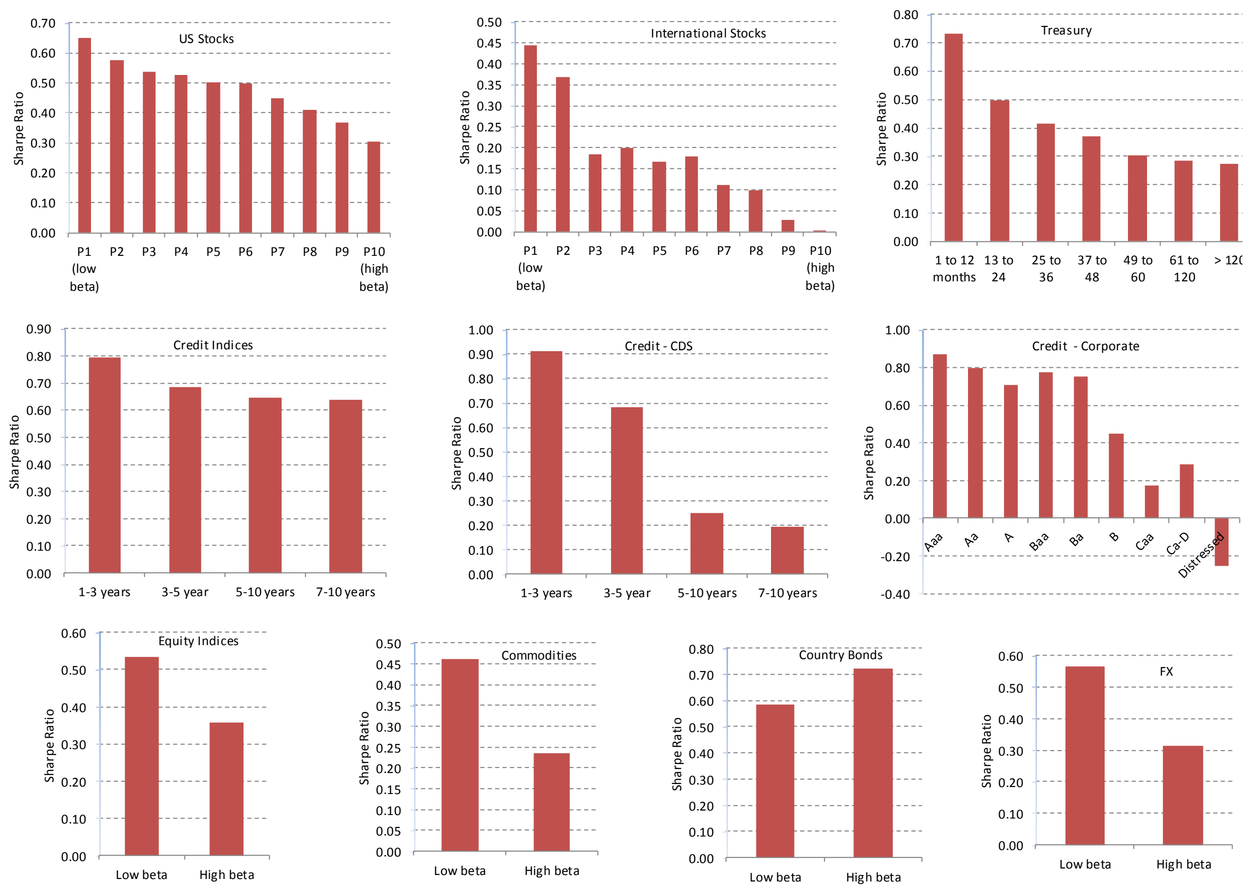


Figure B2
US Equities

This figures shows calendar-time annual abnormal returns. At the beginning of each calendar month all stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This figure plots the annualized intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. A separate factor regression is run for each calendar year. Alphas are annualized.

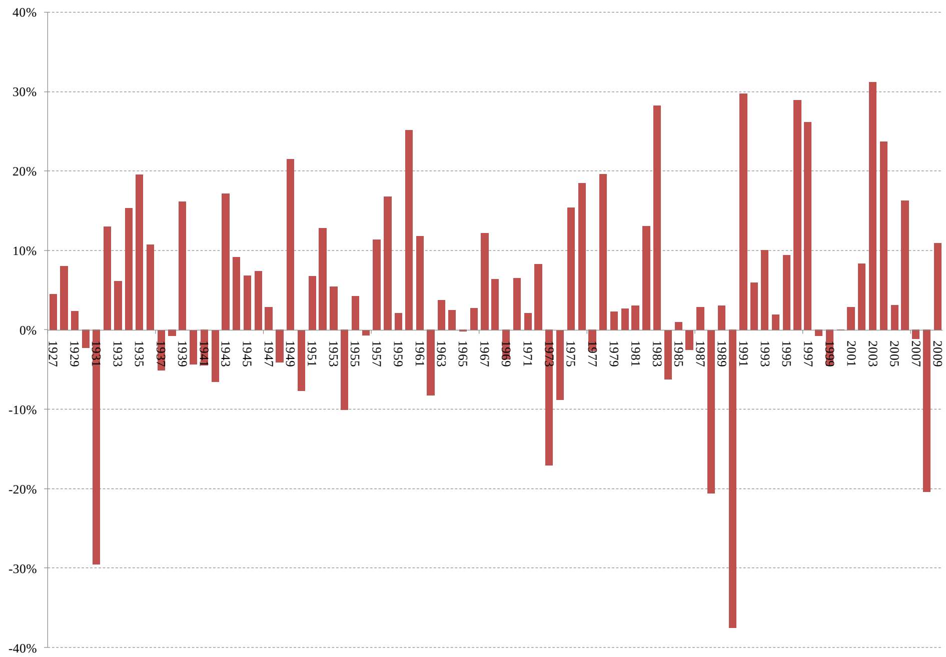


Figure B3
International Equities

This figures shows calendar-time annual abnormal returns. At the beginning of each calendar month all stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The zero-beta factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This figure plots the annualized intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. A separate factor regression is run for each calendar year. Alphas are annualized.

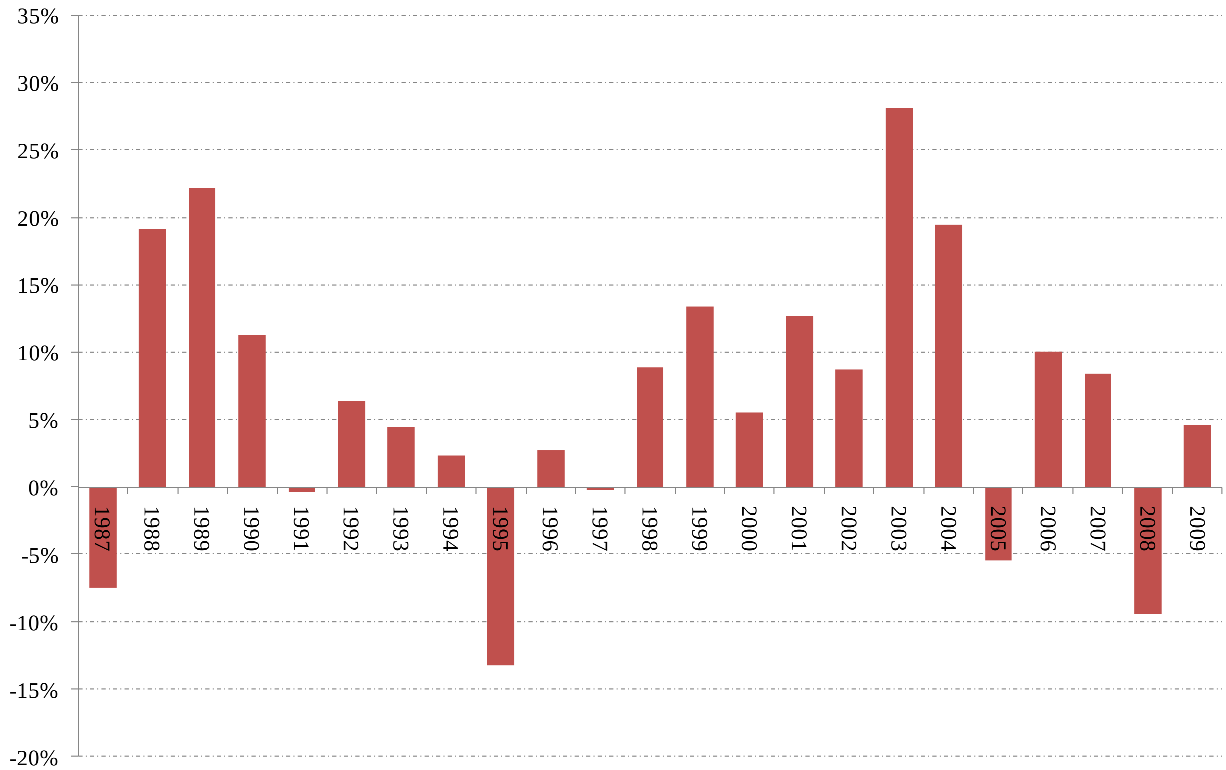


Figure B4
US - Treasury Bonds

This figures shows calendar-time portfolio returns. The test assets are CRSP Monthly Treasury - Fama Bond Portfolios. Only non-callable, non-flower notes and bonds are included in the portfolios. The portfolio returns are an equal weighted average of the unadjusted holding period return for each bond in the portfolios in excess of the risk free rate. To construct the zero-beta BAB factor, all bonds are assigned to one of two portfolios: low beta and high beta. Bonds are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This figure shows annual returns.

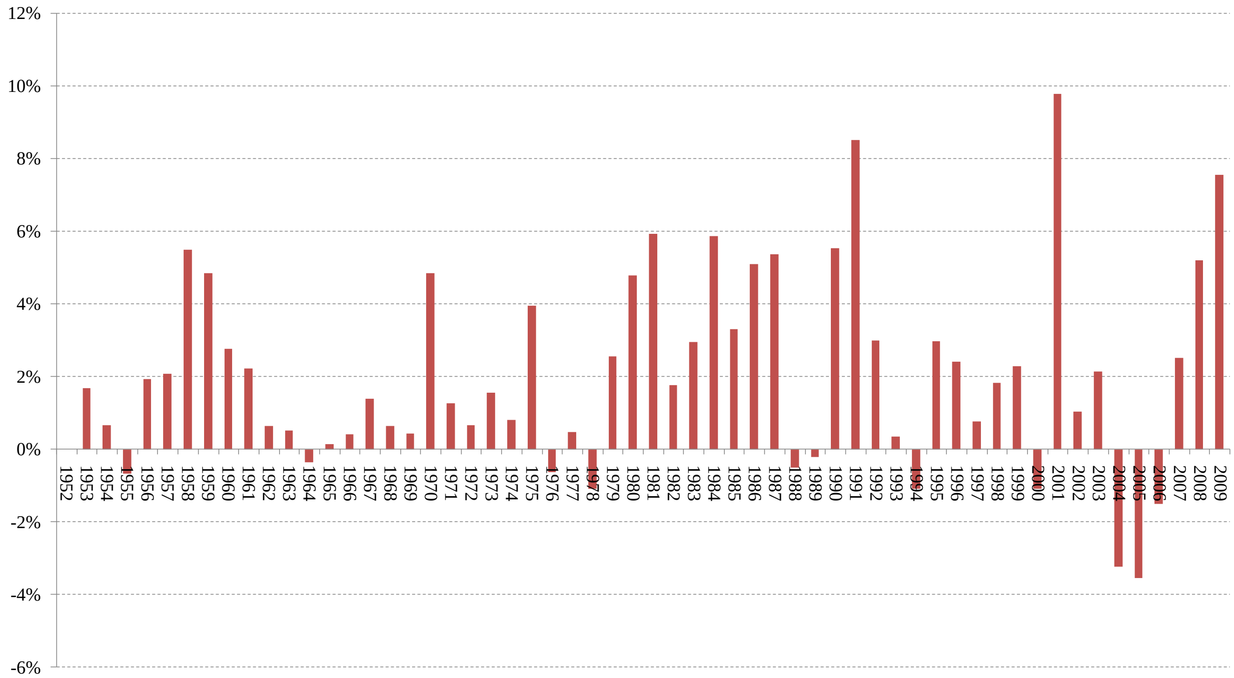


Figure B5
US Credit indices

This figure shows calendar-time portfolio returns. The test assets are monthly returns on corporate bond indices with maturity ranging from 1 to 10 years in excess of the risk free rate. To construct the zero-beta factor, all bonds are assigned to one of two portfolios: low beta and high beta. Bonds are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The zero-beta factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This figure shows annual returns.

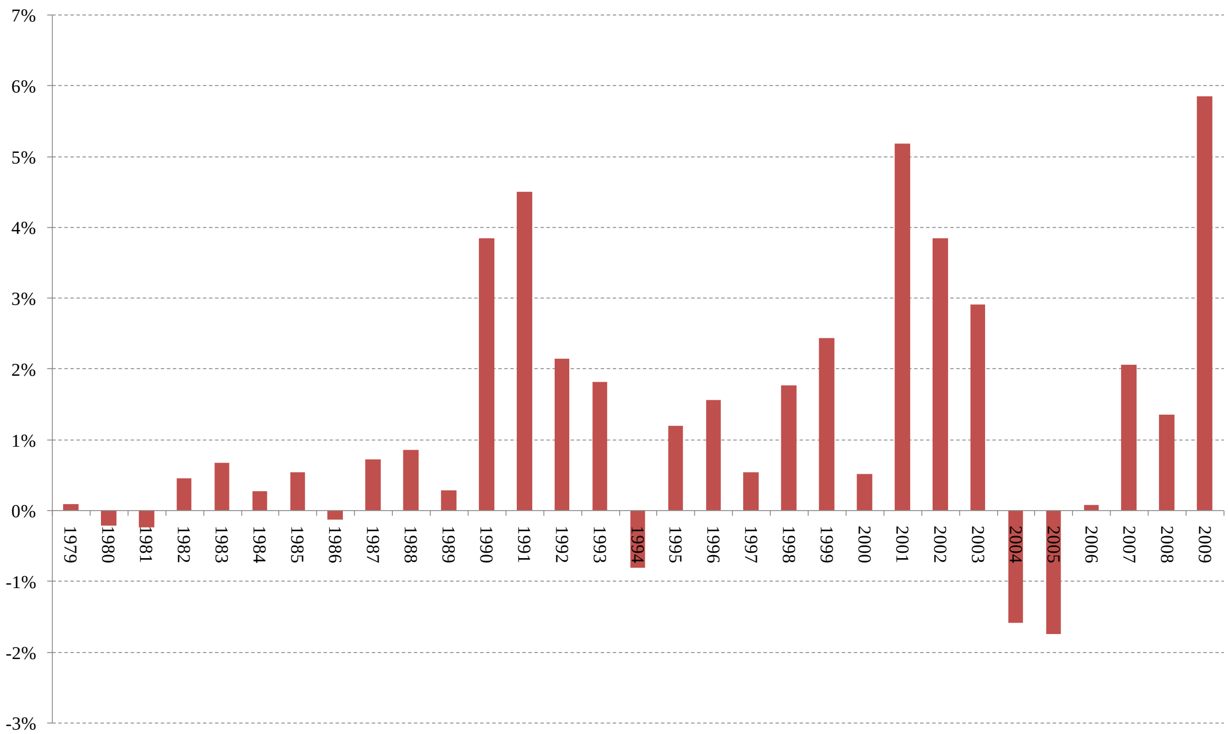


Figure B6
US Corporate Bonds

This figure shows calendar-time portfolio returns. The test assets are monthly returns on corporate bond indices in excess of the risk free rate. To construct the BAB factor, all bonds are assigned to one of two portfolios: low beta and high beta. Bonds are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The zero-beta factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This figure shows annual returns.

Figure B7
Equity indices, Country Bonds, Foreign Exchange and Commodities

This figures shows calendar-time portfolio returns. The test assets are futures, forwards or swap returns in excess of the relevant financing rate. To construct the BAB factor, all instruments are assigned to one of two portfolios: low beta and high beta. Instruments are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This figure shows annual returns of combo portfolios of all futures (Equity indices, Country Bonds, Foreign Exchange and Commodities) with equal risk in each individual BAB and 10% ex ante volatility. To construct combo portfolios, at the beginning of each calendar month, we rescale each return series to 10% annualized volatility using rolling 3-year estimate up to moth *t-1* and then equally weight the return series and their respective market benchmark

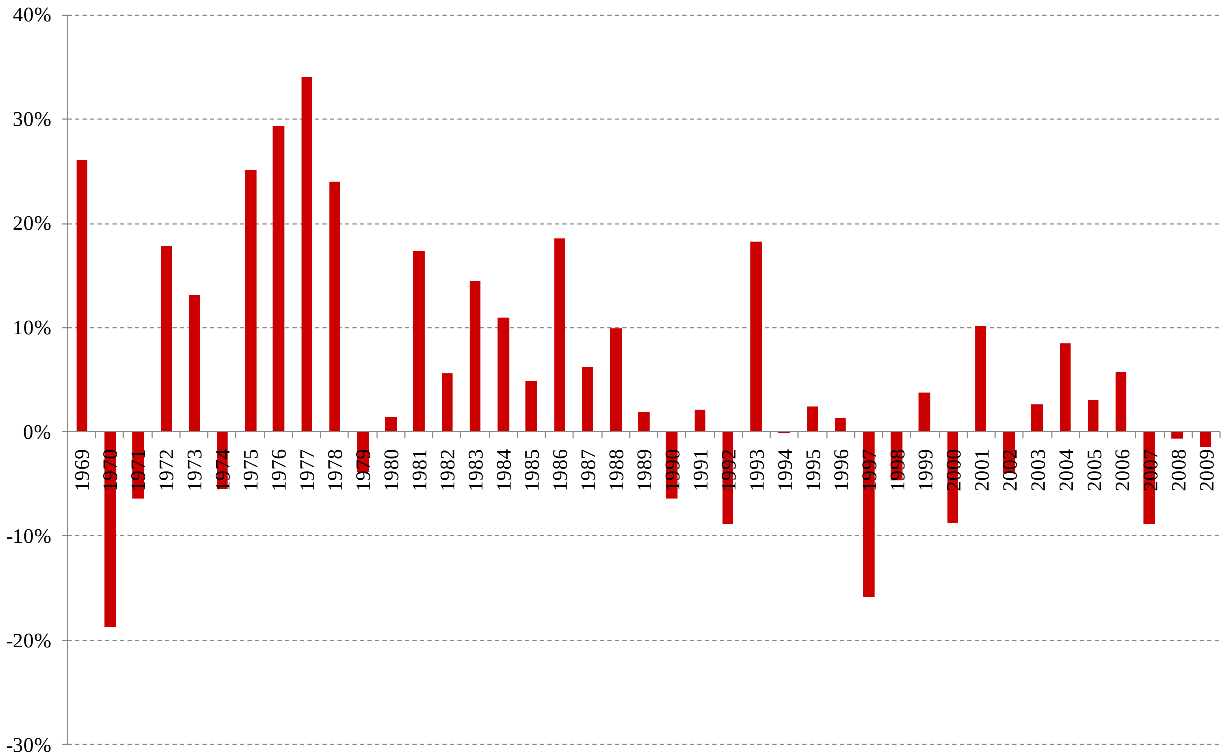


Table I
Summary Statistics: Equities

This table shows summary statistics as of June of each year. The sample include all commons stocks on the CRSP daily stock files ("shrcd" equal to 10 or 11) and Compustat Xpressfeed Global security files ("tcpi" equal to 0). "Mean ME" is the average firm's market value of equity, in billion USD. Means are pooled averages (firm-year) as of June of each year.

Country	Local market index	Number of stocks - total	Number of stocks - mean	Mean ME (firm , Billion USD)	Mean ME (market , Billion USD)	Start Year	End Year
Australia	MSCI - Australia	2,643	841	0.55	460	1989	2009
Austria	MSCI - Austria	197	84	0.72	60	1989	2009
Belgium	MSCI - Belgium	396	142	1.98	279	1989	2009
Canada	MSCI - Canada	4,592	1,591	0.49	566	1984	2009
Denmark	MSCI - Denmark	377	145	0.80	116	1989	2009
Finland	MSCI - Finland	256	111	1.39	154	1989	2009
France	MSCI - France	1,648	596	2.13	1,268	1989	2009
Germany	MSCI - Germany	1,893	701	2.39	1,673	1989	2009
Hong Kong	MSCI - Hong Kong	1,457	636	1.05	663	1989	2009
Italy	MSCI - Italy	563	234	2.12	496	1989	2009
Japan	MSCI - Japan	4,888	2,988	1.20	3,597	1989	2009
Netherlands	MSCI - Netherlands	384	185	3.27	602	1989	2009
New Zealand	MSCI - New Zealand	282	102	0.71	72	1989	2009
Norway	MSCI - Norway	587	162	0.73	117	1989	2009
Singapore	MSCI - Singapore	914	362	0.59	214	1989	2009
Spain	MSCI - Spain	371	152	2.62	398	1989	2009
Sweden	MSCI - Sweden	844	254	1.30	329	1989	2009
Switzerland	MSCI - Switzerland	508	218	2.89	627	1989	2009
United Kingdom	MSCI - UK	5,451	1,952	1.21	2,356	1989	2009
United States	CRSP - vw index	22,575	3,045	0.92	2,803	1926	2009

Table II
Summary Statistics: Asset classes

This table reports the list of instruments included in our datasets and the corresponding date range. *Freq* indicates the frequency (D = Daily, M = monthly)

Asset class	instrument	Freq	Start Year	End Year
Equity Indices	Australia	D	1977	2009
	Germany	D	1975	2009
	Canada	D	1975	2009
	Spain	D	1980	2009
	France	D	1975	2009
	Hong Kong	D	1980	2009
	Italy	D	1978	2009
	Japan	D	1976	2009
	Netherlands	D	1975	2009
	Sweden	D	1980	2009
	Switzerland	D	1975	2009
	United Kingdom	D	1975	2009
	United States	D	1965	2009
Country Bonds	Australia	D	1986	2009
	Germany	D	1980	2009
	Canada	D	1985	2009
	Japan	D	1982	2009
	NW	D	1989	2009
	Sweden	D	1987	2009
	Switzerland	D	1981	2009
	United Kingdom	D	1980	2009
	United States	D	1965	2009
Foreign Exchange	Australia	D	1977	2009
	Germany	D	1975	2009
	Canada	D	1975	2009
	Japan	D	1976	2009
	Norway	D	1989	2009
	New Zealand	D	1986	2009
	Sweden	D	1987	2009
	Switzerland	D	1975	2009
	United Kingdom	D	1975	2009
US - Treasury bonds	0-1 years	M	1952	2009
	1-2 years	M	1952	2009
	2-3 years	M	1952	2009
	3-4 years	M	1952	2009
	4-5 years	M	1952	2009
	4-10 years	M	1952	2009
	> 10 years	M	1952	2009

Asset class	Freq	instrument	Start Year	End Year
Credit indices	M	1-3 years	1976	2009
	M	3-5 year	1976	2009
	M	5-10 years	1991	2009
	M	7-10 years	1988	2009
Corporate bonds	M	Aaa	1973	2009
	M	Aa	1973	2009
	M	A	1973	2009
	M	Baa	1973	2009
	M	Ba	1983	2009
	M	B	1983	2009
	M	Caa	1983	2009
	M	Ca-D	1993	2009
	M	CSFB	1986	2009
Commodities	D	Aluminum	1989	2009
	D	Brent oil	1989	2009
	D	Cattle	1989	2009
	D	Cocoa	1984	2009
	D	Coffee	1989	2009
	D	Copper	1989	2009
	D	Corn	1989	2009
	D	Cotton	1989	2009
	D	Crude	1989	2009
	D	Feeder cattle	1989	2009
	D	Gasoil	1989	2009
	D	Gold	1989	2009
	D	Heat oil	1989	2009
	D	Hogs	1989	2009
	D	Lead	1989	2009
	D	Nat gas	1989	2009
	D	Nickel	1984	2009
	D	Platinum	1989	2009
	D	Silver	1989	2009
	D	Soybeans	1989	2009
	D	Soymeal	1989	2009
	D	Soy oil	1989	2009
	D	Sugar	1989	2009
	D	Tin	1989	2009
	D	Unleaded	1989	2009
	D	Wheat	1989	2009
	D	Zinc	1989	2009

Table III
US Equities. Returns, 1926 - 2009

This table shows calendar-time portfolio returns. Column 1 to 10 report returns of beta-sorted portfolios: at the beginning of each calendar month stocks in each country are ranked in ascending order on the basis of their estimated beta at the end of the previous month. The ranked stocks are assigned to one of ten deciles portfolios based on NYSE breakpoints. All stocks are equally weighted within a given portfolio, and the portfolios are rebalanced every month to maintain equal weights. The rightmost column reports returns of the zero-beta BAB factor. To construct BAB factor, all stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas (lower beta security have larger weight in the low-beta portfolio and higher beta securities have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the CRSP database between 1926 and 2009. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Beta (ex ante) is the average estimated beta at portfolio formation. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	P1 (Low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB Factor
Excess return	**0.99**	**0.90**	**0.92**	**0.98**	**1.04**	**1.12**	**1.07**	**1.07**	**1.03**	**1.02**	**0.71**
	(5.90)	(5.24)	(4.88)	(4.76)	(4.56)	(4.52)	(4.08)	(3.71)	(3.32)	(2.77)	(6.76)
CAPM alpha	**0.54**	**0.39**	**0.35**	**0.35**	**0.34**	**0.37**	**0.26**	0.19	0.09	-0.05	**0.69**
	(5.22)	(4.70)	(4.23)	(4.00)	(3.55)	(3.41)	(2.45)	(1.54)	(0.65)	-(0.29)	(6.55)
3-factor alpha	**0.38**	**0.25**	**0.19**	**0.18**	**0.15**	**0.14**	0.04	-0.07	**-0.18**	**-0.36**	**0.66**
	(5.24)	(4.43)	(3.69)	(3.62)	(2.65)	(2.49)	(0.75)	-(1.06)	-(2.45)	-(3.10)	(6.28)
4-factor alpha	**0.42**	**0.32**	**0.24**	**0.24**	**0.24**	**0.25**	**0.17**	**0.12**	0.04	-0.07	**0.55**
	(5.66)	(5.67)	(4.55)	(4.63)	(4.20)	(4.58)	(3.00)	(1.98)	(0.61)	-(0.59)	(5.12)
5-factor alpha*	**0.23**	**0.23**	**0.17**	**0.16**	**0.16**	**0.20**	**0.22**	0.06	0.11	0.01	**0.46**
	(2.37)	(3.00)	(2.28)	(2.13)	(2.08)	(2.76)	(2.86)	(0.69)	(1.08)	(0.07)	(2.93)
Beta (ex ante)	0.57	0.75	0.84	0.92	0.99	1.06	1.14	1.23	1.36	1.64	0.00
Beta (realized)	0.75	0.86	0.97	1.07	1.18	1.28	1.37	1.50	1.60	1.82	0.03
Volatility	18.2	18.7	20.6	22.4	24.7	27.0	28.4	31.5	33.8	40.0	11.5
Sharpe ratio	0.65	0.58	0.54	0.52	0.50	0.50	0.45	0.41	0.37	0.31	0.75

* Pastor and Stambaugh (2003) liquidity factor only available between 1968 and 2008.

Table IV
International Equities. Returns, 1984 - 2009

This table shows calendar-time portfolio returns. Column 1 to 10 report returns of beta-sorted portfolios: at the beginning of each calendar month stocks are ranked in ascending order on the basis of their estimated beta at the end of the previous month. The ranked stocks are assigned to one of ten deciles portfolios. All stocks are equally weighted within a given portfolio, and the portfolios are rebalanced every month to maintain equal weights. The rightmost column reports returns of the zero-beta BAB factor. To construct the BAB factor, all stocks in each country are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas (lower beta security have larger weight in the low-beta portfolio and higher beta securities have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the Compustat Xpressfeed Global database for the 19 markets listed table I. The sample period runs from 1984 to 2009. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios, Carhart (1997) momentum factor and Pastor and Stambaugh (2003) liquidity factor. All portfolios are computed from the perspective of a domestic US investor: returns are in USD and do not include any currency hedging. Risk free rates and risk factor returns are US-based. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Beta (ex ante) is the average estimated beta at portfolio formation. Beta (realized) is the realized loading on the market portfolio. Volatilities and Sharpe ratios are annualized.

	P1 (Low beta)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high beta)	BAB Factor
Excess return	**0.64**	0.41	0.27	0.26	0.29	0.26	0.21	0.22	0.06	0.04	**0.72**
	(2.64)	(1.66)	(1.04)	(0.93)	(0.99)	(0.81)	(0.62)	(0.57)	(0.15)	(0.08)	(3.79)
CAPM alpha	**0.57**	0.31	0.16	0.13	0.15	0.11	0.05	0.03	-0.15	-0.22	**0.74**
	(2.68)	(1.63)	(0.85)	(0.71)	(0.80)	(0.52)	(0.23)	(0.13)	-(0.55)	-(0.64)	(4.15)
3-factor alpha	**0.53**	0.29	0.09	0.04	0.09	0.04	0.00	0.02	-0.10	-0.06	**0.54**
	(2.52)	(1.51)	(0.49)	(0.25)	(0.49)	(0.22)	-(0.02)	(0.09)	-(0.42)	-(0.19)	(3.16)
4-factor alpha	**0.54**	0.34	0.15	0.11	0.17	0.13	0.15	0.18	0.13	0.28	**0.41**
	(2.50)	(1.75)	(0.82)	(0.66)	(0.98)	(0.73)	(0.76)	(0.94)	(0.59)	(1.00)	(2.48)
5-factor alpha	**0.48**	0.30	0.03	0.02	0.05	0.01	-0.01	0.02	-0.07	0.00	**0.44**
	(2.09)	(1.48)	(0.17)	(0.12)	(0.28)	(0.05)	-(0.03)	(0.11)	-(0.30)	-(0.01)	(2.54)
Beta (ex ante)	0.50	0.65	0.73	0.80	0.87	0.93	1.00	1.08	1.19	1.44	0.00
Beta (realized)	0.38	0.47	0.55	0.63	0.70	0.77	0.83	0.95	1.07	1.30	0.04
Volatility	14.9	14.4	14.9	16.4	16.9	18.7	19.9	21.7	24.8	30.3	10.9
Sharpe ratio	0.44	0.37	0.19	0.20	0.17	0.18	0.11	0.10	0.03	0.00	0.79

* Pastor and Stambaugh (2003) liquidity factor only available between 1968 and 2008.

Table V

International Equities. Returns by Country, 1984 - 2009

This table shows calendar-time portfolio returns. At the beginning of each calendar month all stocks in each country are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The zero-beta BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. This table includes all available common stocks on the Compustat Xpressfeed Global database for the 19 markets in listed table I. The sample period runs from 1984 to 2009. Alpha is the intercept in a regression of monthly excess return. The explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. All portfolios are computed from the perspective of a domestic US investor: returns are in USD and do not include any currency hedging. Risk free rates and factor returns are US-based. Returns and alphas are in monthly percent, and 5% statistical significance is indicated in bold. $ Long (Short) is the average dollar value of the long (short) position. Volatilities and Sharpe ratios are annualized.

	xret	t(xret)	4-factor alpha	t(alpha)	$Short	$Long	Volatility	SR
Australia	0.79	0.66	0.71	0.58	0.80	1.62	63.8	0.15
Austria	-0.26	-0.58	-0.36	-0.77	0.96	1.61	22.8	-0.14
Belgium	0.57	1.53	0.40	1.02	0.95	1.65	16.4	0.42
Canada	**1.66**	4.10	**1.51**	3.52	0.80	1.85	23.1	0.86
Switzerland	0.42	1.46	0.27	0.96	0.90	1.53	15.4	0.33
Germany	0.84	1.77	-0.16	-0.37	0.97	1.78	25.4	0.40
Denmark	**0.95**	2.65	**0.40**	1.12	0.87	1.50	19.3	0.59
Spain	**0.99**	3.08	**0.52**	1.69	0.87	1.52	17.1	0.70
Finland	0.65	1.07	-0.50	-0.90	0.96	1.56	31.6	0.25
France	**0.98**	2.55	0.39	1.06	0.90	1.66	20.5	0.57
United Kingdom	0.23	0.54	-0.19	-0.45	0.89	1.68	23.2	0.12
Hong Kong	0.68	1.96	0.41	1.14	0.89	1.46	17.9	0.45
Italy	**0.88**	3.14	**0.49**	1.77	0.87	1.43	15.0	0.70
Japan	0.03	0.12	-0.43	-1.65	0.82	1.41	14.1	0.03
Netherlands	**1.09**	3.72	**0.76**	2.61	0.86	1.54	15.7	0.83
Norway	0.27	0.69	-0.06	-0.14	0.82	1.37	20.6	0.15
New Zealand	**1.06**	2.54	**0.67**	1.58	1.06	1.66	21.1	0.60
Singapore	**0.74**	2.75	0.41	1.48	0.79	1.32	14.0	0.64
Sweden	**1.11**	2.71	**0.42**	1.07	0.92	1.51	22.0	0.61

Table VI
US Treasury Bonds. Returns, 1952 - 2009

This table shows calendar-time portfolio returns. The test assets are CRSP Monthly Treasury - Fama Bond Portfolios. Only non-callable, non-flower notes and bonds are included in the portfolios. The portfolio returns are an equal weighted average of the unadjusted holding period return for each bond in the portfolios in excess of the risk free rate. To construct the zero-beta BAB factor, all bonds are assigned to one of two portfolios: low beta and high beta. Bonds are weighted by the ranked betas (lower beta bonds have larger weight in the low-beta portfolio and higher beta bonds have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. Alpha is the intercept in a regression of monthly excess return. The explanatory variable is the monthly return of an equally weighted bond market portfolio. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates and 5% statistical significance is indicated in bold. Volatilities and Sharpe ratios are annualized.

	P1 (low beta)	P2	P3	P4	P5	P6	P7* (high beta)	BAB Factor
Maturity (months)	1 to 12	13 to 24	25 to 36	37 to 48	49 to 60	61 to 120	> 120	
Excess return	**0.05**	**0.09**	**0.11**	**0.12**	**0.12**	**0.14**	0.21	**0.16**
	(5.57)	(3.77)	(3.17)	(2.82)	(2.30)	(2.17)	(1.90)	(6.37)
Alpha	**0.03**	**0.03**	**0.02**	0.01	-0.02	**-0.03**	**-0.07**	**0.16**
	(5.87)	(3.42)	(2.21)	(1.10)	-(1.59)	-(2.66)	-(2.04)	(6.27)
Beta (ex ante)	0.14	0.46	0.75	0.99	1.22	1.44	2.17	0.00
Beta (realized)	0.17	0.49	0.77	0.99	1.17	1.43	2.06	0.02
Volatility	0.83	2.11	3.23	4.04	4.76	5.80	9.12	2.32
Sharpe ratio	0.73	0.50	0.42	0.37	0.30	0.29	0.27	0.85

* Return missing from 196208 to 197112

Table VII
US Credit indices. Returns, 1976 - 2009

This table shows calendar-time portfolio returns. The test assets are monthly returns on corporate bond indices with maturity ranging from 1 to 10 years in excess of the risk free rate. To construct the zero-beta factor, all bonds are assigned to one of two portfolios: low beta and high beta. Bonds are weighted by the ranked betas (lower beta security have larger weight in the low-beta portfolio and higher beta securities have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The zero-beta factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. Alpha is the intercept in a regression of monthly excess return. The explanatory variable is the monthly return of an equally weighted corporate bond market portfolio. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates and 5% statistical significance is indicated in bold. Volatilities and Sharpe ratios are annualized. Panel A shows results for unhedged returns. Panel B shows results for return obtained by hedging the interest rate exposure. Each calendar month we run 1-year rolling regressions of excess bond returns on excess return on Barclay's US government bond index. We construct test assets by going long the corporate bond index and hedging this position by shorting the appropriate amount of the government bond index. We compute market returns by taking equally weighted average hedged returns.

	1-3 years	3-5 year	5-10 years	7-10 years	BAB Factor
Panel A: Un-hedged Returns		**0.21**	**0.32**	**0.33**	**0.12**
	(4.64)	(4.01)	(2.76)	(2.96)	(4.91)
Alpha	**0.04**	**0.01**	**-0.05**	**-0.07**	**0.13**
	(2.77)	(0.96)	-(4.01)	-(4.45)	(4.91)
Beta (ex ante)	0.60	0.85	1.39	1.52	0.00
Beta (realized)	0.62	0.85	1.37	1.48	-0.01
Volatility	2.73	3.66	5.91	6.13	1.70
Sharpe ratio	0.79	0.68	0.65	0.64	0.88
Panel B: Hedged Returns		**0.09**	**0.07**	**0.06**	0.05
	(2.61)	(2.25)	(0.97)	(0.82)	(1.77)
Alpha	**0.04**	**0.04**	**-0.03**	**-0.04**	**0.08**
	(3.62)	(3.23)	-(2.38)	-(2.16)	(3.33)
Beta (ex ante)	0.70	0.78	1.14	1.38	0.00
Beta (realized)	0.58	0.72	1.34	1.37	-0.34
Volatility	1.70	2.06	3.77	3.95	1.55
Sharpe ratio	0.62	0.53	0.23	0.19	0.42

Table VIII
US Corporate Bonds. Returns, 1973 - 2009

This table shows calendar-time portfolio returns. The test assets are monthly returns on corporate bond indices in excess of the risk free rate. To construct the BAB factor, all bonds are assigned to one of two portfolios: low beta and high beta. Bonds are weighted by the ranked betas (lower beta bonds have larger weight in the low-beta portfolio and higher beta bonds have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The zero-beta factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. Alpha is the intercept in a regression of monthly excess return. The explanatory variable is the monthly return of an equally weighted corporate bond market portfolio. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates and 5% statistical significance is indicated in bold. Volatilities and Sharpe ratios are annualized.

	Aaa	Aa	A	Baa	Ba	B	Caa	Ca-D	CSFB Distressed	BAB Factor
Excess return	**0.26**	**0.27**	**0.27**	**0.31**	**0.43**	0.33	0.21	0.70	-0.51	0.33
	(4.48)	(4.08)	(3.64)	(3.99)	(3.88)	(2.31)	(0.90)	(1.18)	-(1.23)	(1.74)
Alpha	**0.23**	**0.21**	**0.19**	**0.21**	**0.26**	0.10	-0.13	0.08	**-1.10**	**0.56**
	(4.09)	(3.62)	(3.13)	(3.69)	(4.20)	(1.40)	-(0.95)	(0.26)	-(5.34)	(4.02)
Beta (ex ante)	0.67	0.70	0.72	0.77	0.89	1.01	1.25	1.74	1.66	0.00
Beta (realized)	0.13	0.24	0.33	0.40	0.69	0.95	1.39	2.77	2.49	-0.94
Volatility	3.62	4.11	4.63	4.84	6.79	8.93	14.26	29.15	24.16	11.47
Sharpe ratio	0.87	0.79	0.71	0.78	0.75	0.45	0.17	0.29	-0.25	0.34

Table IX
Equity indices, Country Bonds, Foreign Exchange and Commodities. Return, 1965-2009

This table shows calendar-time portfolio returns. The test assets are futures, forwards or swap returns in excess of the relevant financing rate. To construct the BAB factor, all instruments are assigned to one of two portfolios: low beta and high beta. Instruments are weighted by the ranked betas (lower beta security have larger weight in the low-beta portfolio and higher beta securities have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. Alpha is the intercept in a regression of monthly excess return. The explanatory variable is the monthly return of the relevant market portfolio. Panel A report results for equity indices, country bonds, foreign exchange and commodities. *All Futures* and *Country Selection* are combo portfolios with equal risk in each individual BAB and 10% ex ante volatility. To construct combo portfolios, at the beginning of each calendar month, we rescale each return series to 10% annualized volatility using rolling 3-year estimate up to moth *t-1* and then equally weight the return series and their respective market benchmark. Panel B reports results for all the assets listed in table I and II. *All Bonds and Credit* includes US treasury bonds, US corporate bonds, US credit indices (hedged and unhedged) and country bonds indices. *All Equities* included US stocks, all individual BAB country portfolios, a international stock BAB and equity indices. *All Assets* includes all the assets listed in table I and II. All portfolios in panel B have equal risk in each individual BAB and 10% ex ante volatility. Returns and alphas are in monthly percent, t-statistics are shown below the coefficient estimates and 5% statistical significance is indicated in bold. Volatilities and Sharpe ratios are annualized.

Panel A: Equity indices, country Bonds, Foreign Exchange and Commodities		Excess Return	T-stat Excess Return	Alpha	T(alpha)	$Short	$Long	Volatility	SR
Equity Indices	EI	**0.78**	2.90	**0.69**	2.56	0.93	1.47	18.46	0.51
Country Bonds	CB	0.08	0.99	0.05	0.57	0.95	1.69	4.47	0.22
Foreign Exchange	FX	0.20	1.45	0.23	1.78	0.61	1.61	7.72	0.31
Commodities	COM	0.42	1.44	0.53	1.85	0.78	1.56	22.65	0.22
All Futures*	EI + CB + FX + COM	**0.47**	3.99	**0.52**	4.50			9.02	0.62
Country Selection*	EI + CB + FX	**0.64**	3.78	**0.71**	4.42			11.61	0.66
Panel B: All Assets									
All Bonds and Credit*		**0.73**	6.00	**0.72**	5.88			11.06	0.79
All Equities*		**0.77**	8.10	**0.78**	8.16			10.31	0.89
All Assets*		**0.71**	8.60	**0.73**	8.84			8.95	0.95

* Equal risk, 10% ex ante volatility

Table X
Regression Results

This table shows results from time-series (pooled) regressions. The left-hand side is the month t return on the BAB factors. To construct the BAB portfolios, all instruments are assigned to one of two portfolios: low beta and high beta. Instruments are weighted by the ranked betas (lower beta security have larger weight in the low-beta portfolio and higher beta securities have larger weights in the high-beta portfolio) and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. The explanatory variables include the TED spread (lagged level and contemporaneous changes) and a series of controls. *TED Spread* is the TED spread at the end of month t. "*Change in TED Spread*" is equal to Ted spread at the end of month t minus the median spread over the past 3 years. *"Lagged TED Spread" is* the median Ted spread over the past 3 years. "*Long Volatility Returns*" is the month t return on a portfolio that shorts at-the-money straddles on the S&P500 index. To construct the short volatility portfolio, on index options expiration dates we write the next-to-expire closest-to-maturity straddle on the S&P500 index and hold it to maturity. "*Beta Spread*" is defined as (*HBeta- LBeta*) / (*HBeta* LBeta*) where *HBeta (LBeta)* are the betas of the short (long) leg of the BAB portfolio at portfolio formation. "*Market Return*": is the monthly return of the relevant market portfolio. *Inflation* is equal to the 1-year US CPI inflation rate, lagged 1 month. This table includes all the available BAB portfolios. The data run from December 1984 (first available date for the TED spread) to December 2009. Column 1 to 4 report results for US stocks. Columns 5 to 8 report results for international equities. In these regressions we use each individual country BAB factors as well as an international equity BAB factor. Columns 9 to 12 reports results for all assets in our data. Asset fixed effects are include where indicated, t-statistics are shown below the coefficient estimates and all standard error are adjusted for heteroskedasticity (White (1980)). When multiple assets are included in the regression standard errors are clustered by date. 5% statistical significance is indicated in bold.

LHS: BAB return	US - Stocks				Global Stocks - pooled				All Assets - pooled			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(9)	(9)	(10)	(11)	(12)
TED Spread	**-0.033**	**-0.019**			**-0.020**	**-0.016**			**-0.013**	**-0.011**		
	-(8.29)	-(3.10)			-(4.37)	-(3.63)			-(4.65)	-(3.93)		
Change in TED Spread			**-0.040**	**-0.029**			**-0.017**	**-0.014**			**-0.012**	**-0.010**
			-(3.52)	-(2.50)			-(2.31)	-(2.10)			-(2.73)	-(2.48)
Lagged TED Spread			**-0.031**	**-0.017**			**-0.021**	**-0.017**			**-0.013**	**-0.011**
			-(7.88)	-(2.63)			-(4.12)	-(3.40)			-(4.38)	-(3.62)
Beta Spread		**0.022**		**0.023**		**0.012**		**0.012**		**0.009**		**0.009**
		(2.25)		(2.36)		(2.87)		(2.85)		(4.06)		(4.03)
Lagged BAB return		**0.188**		**0.191**		0.063		0.062		0.073		0.073
		(2.07)		(2.10)		(1.18)		(1.18)		(1.50)		(1.50)
Inflation		-0.070		-0.077		-0.023		-0.029		0.007		0.006
		-(0.25)		-(0.27)		-(0.16)		-(0.20)		(0.08)		(0.06)
Short Volatility Returns		**0.325**		**0.318**		-0.090		-0.092		**-0.093**		**-0.093**
		(2.24)		(2.23)		-(1.34)		-(1.37)		-(1.97)		-(1.98)
Market return		0.000		-0.002		0.022		0.021		0.011		0.011
		(0.00)		-(0.01)		(0.55)		(0.51)		(0.29)		(0.29)
Asset Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Num of observations	294	294	294	294	4,606	4,606	4,606	4,606	7,168	7,168	7,168	7,168
Adjusted R2	0.097	0.199	0.096	0.201	0.013	0.022	0.013	0.022	0.008	0.019	0.008	0.019

Table XI
Beta compression

This table reports results of cross-sectional and time-series tests of beta compression. Panel A, B and C report cross-sectional dispersion of betas in US stocks, International stocks and all asset classes in our sample. The data run from December 1984 (first available date for the TED spread) to December 2009. Each calendar month we compute cross sectional standard deviation, mean absolute deviation and inter-quintile range of betas. In panel C we compute each dispersions measure for each asset class and average across asset classes. All reports times series means of the dispersion measures. P1 to P3 report coefficients on a regression of the dispersion measure on a series of TED spread volatility dummies. TED spread volatility is defined as the standard deviation of daily changes in the TED spread in the prior calendar month. We assign the TED spread volatility into three groups (low, neutral and high) based on full sample breakpoints (top and bottom 1/3) and regress the times series of the cross sectional dispersion measure on the full set of dummies (without intercept). T-statistics are shown below the coefficient estimates, and 5% statistical significance is indicated in bold. Panel D, E and F report conditional market betas of the BAB portfolio based on TED spread volatility as of the prior month. The dependent variable is the monthly return of the BAB portfolios. The explanatory variables are the monthly returns of the market portfolio, Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. Market betas are allowed to vary across TED spread volatility regimes (low, neutral and high) using the full set of dummies. Panel D, E and F report loading on the market factor corresponding to different TED spread volatility regimes. All regressions include the full set of explanatory variables and allow for different intercepts in the 3 regimes but only the market loading is reported. *All Assets* report results for the aggregate BAB portfolio of table IX, panel B. Standard errors are adjusted for heteroskedasticity and autocorrelation using a Bartlett kernel (Newey and West (1987)) with a lag length of 12 months.

Cross sectional Dispersion	Panel A: US Stocks			Panel B: International Stocks			Panel C: All Assets		
	Standard deviation	Mean Absolute Deviation	Interquintile Range	Standard deviation	Mean Absolute Deviation	Interquintile Range	Standard deviation	Mean Absolute Deviation	Interquintile Range
All	0.42	0.33	0.67	0.27	0.21	0.44	0.40	0.31	0.63
P1 (Low Ted Volatility)	0.44	0.35	0.71	0.30	0.23	0.47	0.43	0.34	0.70
P2	0.43	0.34	0.69	0.26	0.21	0.43	0.40	0.30	0.61
P2 (Low Ted Volatility)	0.37	0.29	0.61	0.25	0.19	0.41	0.37	0.28	0.56
P3 minus P1	**-0.07**	**-0.05**	**-0.09**	**-0.05**	**-0.04**	**-0.06**	**-0.06**	**-0.06**	**-0.14**
t-statistics	-(3.18)	-(3.09)	-(2.84)	-(3.99)	-(3.91)	-(3.29)	-(5.39)	-(5.75)	-(5.33)

Conditional Market Beta	Panel D: US				Panel E: International Stocks				Panel F: All Assets			
Ted Volatility	P1 (Low)	P2	P3 (High)	P3 - P1	P1 (Low)	P2	P3 (High)	P3 - P1	P1 (Low)	P2	P3 (High)	P3 - P1
CAPM	-0.16	0.10	**0.44**	**0.60**	0.01	0.01	**0.21**	0.20	-0.03	0.01	**0.08**	**0.12**
	-(0.99)	(0.75)	(2.96)	(2.72)	(0.22)	(0.12)	(2.42)	(1.91)	-(0.80)	(0.27)	(2.07)	(2.05)
Control for 3 Factors	-0.03	**0.32**	**0.49**	**0.53**	0.02	0.04	0.12	0.10				
	-(0.19)	(2.84)	(3.32)	(2.36)	(0.37)	(0.90)	(1.86)	(1.25)				
Control for 4 Factors	0.07	**0.37**	**0.51**	**0.44**	0.04	**0.08**	**0.16**	0.12				
	(0.48)	(3.21)	(3.65)	(2.27)	(0.94)	(2.03)	(2.42)	(1.49)				

Table XII
Testing the Model's Portfolio Predictions, 1963 - 2009

This table shows average ex-ante and realized portfolio betas for different groups of investors. Panel A.1 reports results for our sample of open-end actively-managed domestic equity mutual funds. Panel A.2 reports results a sample in individual retail investors. Panel B.1 reports results for a sample of leveraged buyouts (labeled "Private Equity"). Panel B.2 reports results for Berkshire Hathaway. We compute both the ex-ante beta of their holdings and the realized beta of the time series of their returns. To compute the ex-ante beta, we aggregate all quarterly (monthly) holdings in the mutual fund (individual investors) sample and compute their ex-ante betas (equally weighted and value weighted based on the value of their holdings). We report the time series averages of the portfolio betas. To compute the realized betas we compute monthly returns of an aggregate portfolio mimicking the holdings, under the assumption of constant weight between reporting dates (quarterly for mutual funds, monthly for individual investors). We compute equally weighted and value weighted returns based on the value of their holdings). The realized betas are the regression coefficients in a time series regression of these excess returns on the excess returns of the CRSP value-weighted index. In panel B.1 we compute ex-ante betas as of the month-end prior to the initial takeover announcements date. T-statistics are shows to right of the betas estimates and test the null hypothesis of beta = 1, when computing average ex-ante betas, standard errors are adjusted for heteroskedasticity and autocorrelation using a Bartlett kernel (Newey and West (1987)) with a lag length of 12 months. 5% statistical significance is indicated in bold.

Panel	Investor	Method	Sample Period	Ex Ante Beta of Positions		Realized Beta of Positions	
				Beta	t-statistics (H0: beta=1)	Beta	t-statistics (H0: beta=1)
A)	Investors Likely to be Constrained						
A.1)	Mutual Funds	Value weighted	1980 - 2009	**1.04**	13.14	**1.08**	11.96
	Mutual Funds	Equal weighted	1980 - 2009	**1.06**	15.35	**1.12**	4.08
A.2)	Individual Investors	Value weighted	1991 - 1996	**1.04**	18.14	**1.09**	2.60
	Individual Investors	Equal weighted	1991 - 1996	**1.05**	16.03	1.08	1.17
B)	Investors who use Leverage						
B.1)	Private Equity (All)	Value weighted	1963 - 2009	**0.96**	-2.67		
	Private Equity (All)	Equal weighted	1963 - 2009	**0.92**	-5.40		
	Private Equity (LBO, MBO)	Value weighted	1963 - 2009	**0.83**	-4.01		
	Private Equity (LBO, MBO)	Equal weighted	1963 - 2009	**0.83**	-4.02		
B.2)	Berkshire Hathaway	Value weighted	1980 - 2009	**0.90**	-10.73	**0.78**	-5.53
	Berkshire Hathaway	Equal weighted	1980 - 2009	**0.90**	-13.33	**0.83**	-5.29

Figure 1
Alphas of Beta-Sorted Portfolios

This figure shows monthly alphas. The test assets are beta-sorted portfolios. At the beginning of each calendar month instruments are ranked in ascending order on the basis of their estimated beta at the end of the previous month. The ranked instruments are assigned to beta-sorted portfolios. This figure plots alphas from low beta (left) to high beta (right). Alpha is the intercept in a regression of monthly excess return. For equity portfolios the explanatory variables are the monthly returns from Fama and French (1993) mimicking portfolios and Carhart (1997) momentum factor. For all other portfolios the explanatory variables are the monthly returns on the market factor. Alphas are in monthly percent.

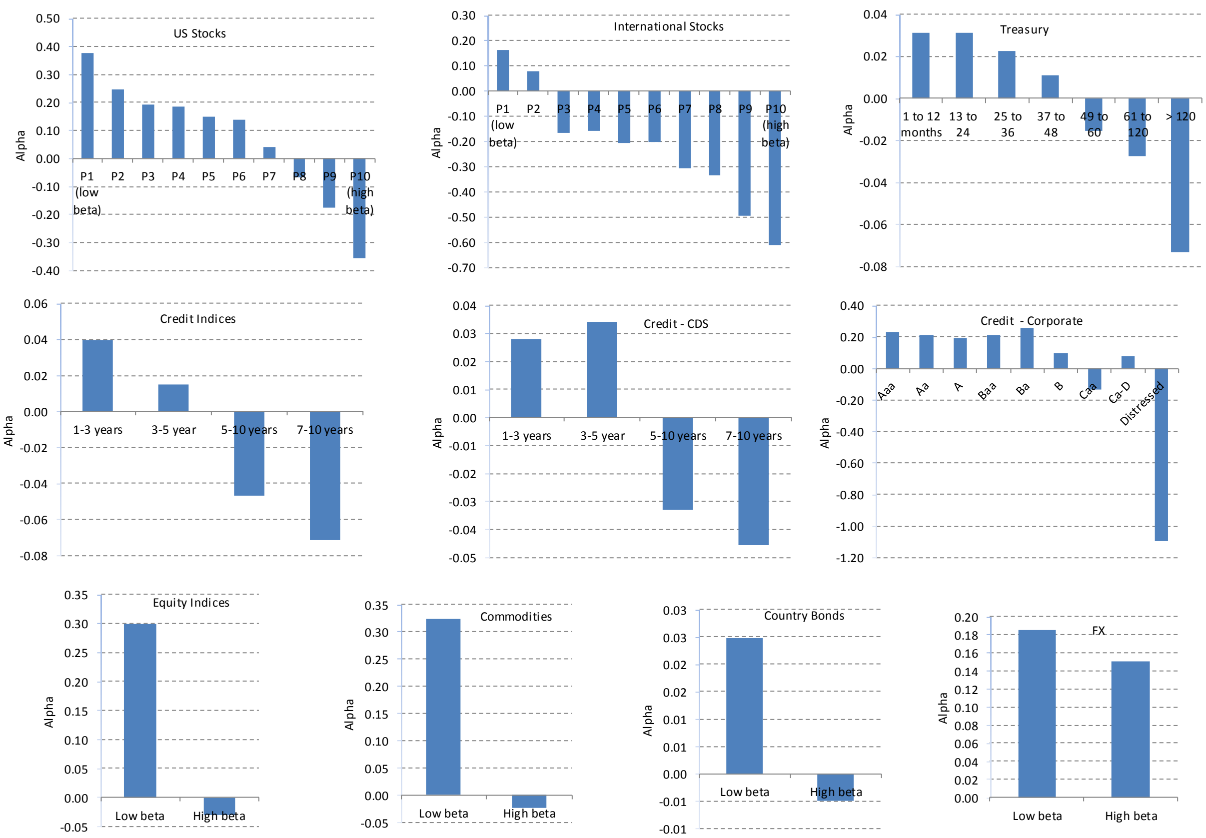


Figure 2
BAB Sharpe Ratios by Asset Class

This figures shows annualized Sharpe ratios of BAB factors across asset classes. To construct the BAB factor, all instruments are assigned to one of two portfolios: low beta and high beta. Instruments are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. Sharpe ratios are annualized.

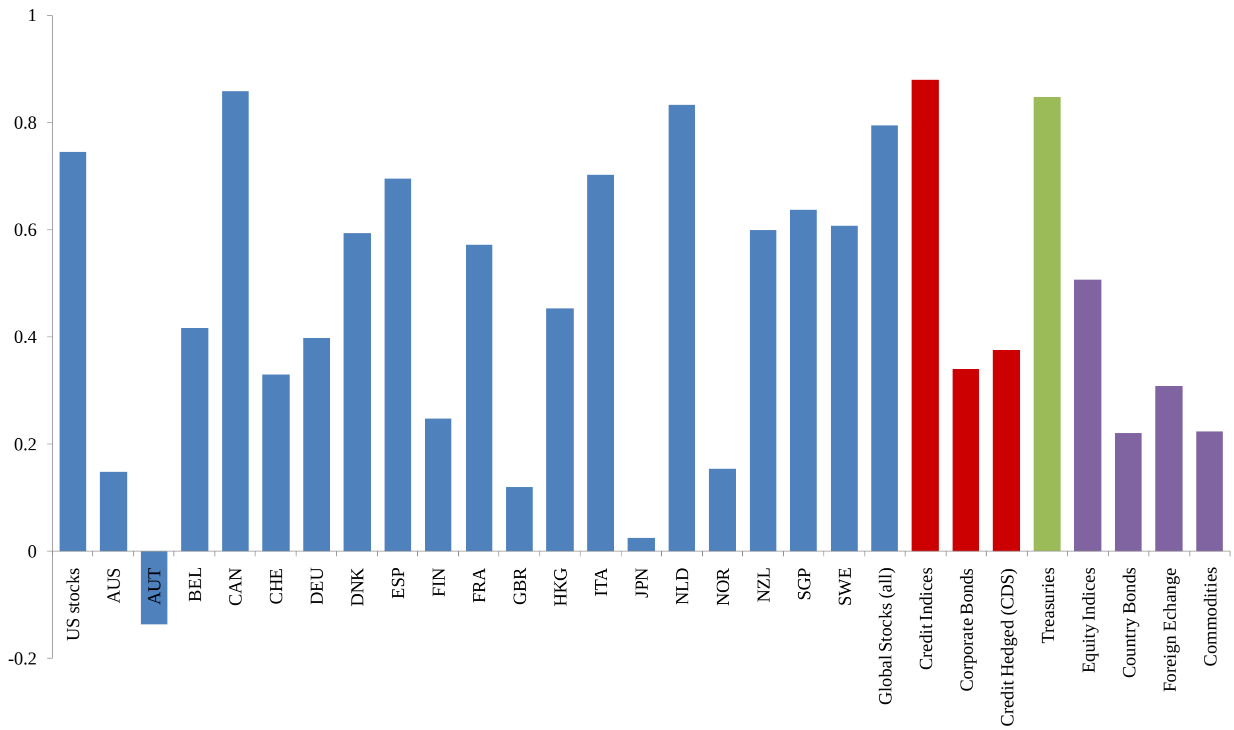


Figure 3
US Stocks BAB and TED Spread

This figures shows annualized 3-year return of the US stocks BAB factor (left scale) and 3-year (negative) average rolling TED spread (right scale) . At the beginning of each calendar month all stocks are assigned to one of two portfolios: low beta and high beta. Stocks are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio.

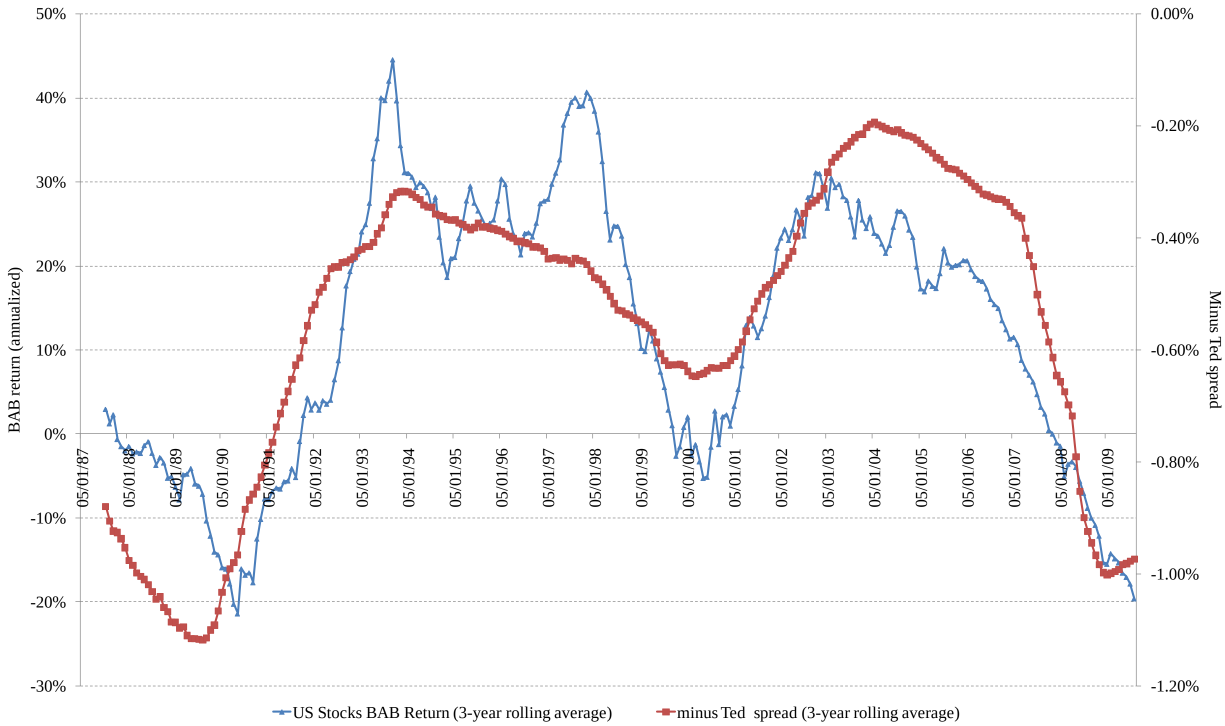


Figure 4
Regression Results: BAB Return on TED, T-statistics.

This figure shows results from time series regressions. The left-hand side is the month t return on the BAB factors. To construct the BAB portfolios, all instruments are assigned to one of two portfolios: low beta and high beta. Instruments are weighted by the ranked betas and the portfolios are rebalanced every calendar month. Both portfolios are rescaled to have a beta of 1 at portfolio formation. The BAB factor is a zero-cost portfolio that is long the low-beta portfolio and shorts the high-beta portfolio. The explanatory variable is the Ted spread at the end of month t-1. A separate regression is run for each BAB portfolio. This figure report t-statistics for each regression