Betting Against Beta under Incomplete Information*

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Abstract

We show analytically and empirically that Betting-Against-Beta (BAB) – low beta stocks outperforming high beta stocks – is consistent with market segmentation due to the cost of information acquisition, as in Merton's (1987) model. Consistent with our predictions, expected returns and CAPM alphas from a BAB strategy (long low beta stocks and short high beta stocks) are positive and vary (1) negatively in the cross-section with firm visibility, and (2) positively in the time-series with the portfolio's shadow cost of information and beta spread. These results cannot be fully explained by alternate explanations such as funding illiquidity or preference for lottery-like stocks.

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1. Introduction

The evidence in the extant empirical literature on the relationship between market beta and returns is, at best, mixed. Early empirical studies such as Friend and Blume (1970), Jensen, Black, and Scholes (1972) and Fama and MacBeth (1973) report a positive market beta–return relationship; however, the price of risk (the slope) is much smaller than what is implied by the CAPM. Perhaps surprisingly, later studies such as Fama and French (1992, 1993) report an even flatter market beta–return relationship. More recently, Frazzini and Pedersen (2014) thoroughly investigate these early results and document an interesting finding: an investment strategy that buys low-beta stocks and sells short high-beta stocks, dubbed “betting against beta,” generates an annual alpha of 6.6% over the period of January 1927 – March 2012.

Various explanations for this finding have been proposed. Frazzini and Pedersen (2014) attribute the betting against beta (BAB) result to funding liquidity. They argue that leverage constrained investors tilt their portfolio towards risky, high-beta stocks, creating a demand pressure that results in higher current prices and lower subsequent returns. Alternatively, Bali, Brown, Murray and Tang (2016) argue that BAB is driven by a demand for lottery-like securities, and demonstrate that controlling for the lottery-like feature of a stock eliminates the abnormal returns to a BAB strategy. Cederburg and O’Doherty (2016) attribute the BAB phenomenon to beta measurement error, and show that estimating a conditional beta using instrumental variables eliminates the average relation between beta and abnormal returns. Liu, Stambaugh, and Yuan (2016) argue that BAB can be explained by a combination of firm characteristics-based mispricing and idiosyncratic volatility, and find that BAB is only significant for overpriced stocks during periods of high mispricing and high positive correlation between beta and idiosyncratic volatility.

We provide an alternative explanation for BAB based on the predictions of the Merton (1987) segmented capital markets equilibrium model in which information is costly to collect and process, and it is impractical for investors to track all of the securities in the market. In the model, investors own only known securities and they hold under-diversified portfolios. As a result, the model predicts a flatter security market line with a *higher intercept* (as compensation for the firm specific shadow cost of information) and a *lower slope* than full information CAPM. Merton shows that firms will, in general, earn an apparent "abnormal return" relative to the standard CAPM, and that this alpha will be negatively related to the firm's beta. As such, we argue that the BAB phenomenon is consistent with a flatter security market line caused by the cost of information acquisition. Specifically, we derive from Merton's model the expected excess return and CAPM alpha for a beta-neutral BAB hedge portfolio that takes a long position in low-beta stocks and a short position in high-beta stocks, as in Frazzini and Pedersen (2014). We show that the excess and abnormal return will be positive whenever the cost of information acquisition is positive. Moreover, we show that the performance of the BAB portfolio is negatively related to firm visibility (i.e. how widely a firm is tracked by investors) in the cross-section, which represents the underlying notion of market segmentation in the model. Our empirical results support this prediction.

In particular, visibility represents the degree of market segmentation induced by the cost to investors of gathering and analyzing information. Consistent with this, prior works have shown that the cost of information acquisition is lower for a more visible firm (e.g., Bushee and Miller, 2012). We test the link between BAB and firm visibility using multiple measures of visibility following prior works: (1) the number of analysts following the stock (Diether, Malloy, and Scherbina, 2002), (2) the firm's advertising expense (Grullon, Kanatas, and Weston, 2004), (3) the breadth of institutional ownership (Lehavy and Sloan, 2008), and (4) the number of institutional shareholders that own the firm (Bushee and Miller, 2012). Additionally, we isolate the common variance among these proxies using a principal component factor analysis, and construct a fifth measure of visibility as the first principal component of the four individual proxies.[1] Because each of these visibility measures starts at different time period, we construct five data samples – one sample for each visibility measure.

After documenting the BAB result in each of our subsamples, we examine the prediction that BAB performance will vary with firm visibility. We use a five-by-five sequential double sort strategy, sorting firms first by visibility, then by market beta. Within in visibility quintile, we calculate the returns to a beta-neutral portfolio that takes a long position in the lowest beta quintile portfolio and a short position in the highest beta quintile portfolio. We find that BAB performance is negatively related to firm visibility, regardless of the measure of visibility used. Averaging across our measures of visibility, we find that the beta-neutral BAB portfolio formed within the lowest visibility quintile generates approximately 1.71% excess return per month during our sample period. A beta-neutral BAB portfolio formed within the highest visibility quintile generates an average excess return of 0.73% per month, or less than half of the return among the most neglected stocks. In each case, BAB performance differs significantly between the low and high visibility quintiles. Results are similar if we examine CAPM alphas rather than excess returns.

We next examine whether BAB performance varies over time in a way that is consistent with our propositions. We argue that BAB performance should be positively related to the portfolio's shadow cost of information and beta spread in the time-series, and should have decreased over time as information has become less costly to collect and analyze. We first perform two related tests, examining whether BAB performance has decreased over time during our sample period (as

[1] As detailed below, we perform this analysis using the correlation matrix of the visibility measures, rather than the covariance matrix, as the correlation matrix method is not sensitive to differences in scale across the variables of interest.

technology has improved) or over the lifetime of the firm, as the cost of information acquisition is likely to be higher for newer firms. We find that BAB performance exhibits a significantly negative time trend, but does not completely disappear during our sample period. Similarly, we find that BAB performance is highest among the youngest quintile of firms, producing approximately 60 basis points greater excess returns per month than a BAB portfolio formed within the oldest quintile of sample firms.

To further examine the time-series implications of our predictions, we use pooled time-series regressions to investigate the link between BAB performance and the shadow cost of information over time. We perform this analysis using both an unconditional BAB portfolio (formed among all available sample stocks) and five BAB portfolios formed within firm visibility quintiles, and present results with and without controls for alternate explanations for BAB. Consistent with our predictions, we find a positive relation between BAB performance and the portfolio's shadow cost of information. We also document a positive relation between BAB performance and the portfolio's beta spread after controlling for the shadow cost of information. This may help shed light on the insignificant relation between BAB and beta spread documented by Frazzini and Pedersen (2014), inconsistent with the predictions of their model.

We then take a number of steps to differentiate our results from those documented by previous studies, as the previously proposed drivers of BAB could be correlated with firm visibility and the shadow cost of information in the Merton (1987) model and our framework. However, if firm visibility is the fundamental issue that generates both BAB and its possible correlation with the firm characteristics examined in prior works, the link between firm visibility and BAB should not be subsumed by these alternate explanations. Thus, we examine the importance of firm visibility as a driver of the BAB phenomenon while accounting for the impact of these alternate explanations.

To do so, we rank-orthogonalize our principal component (PC) visibility proxy by (1) funding liquidity constraints (Frazzini and Pedersen, 2014), (2) leverage constraint tightness (Boguth and Simutin, 2016), (3) lottery-like stock characteristics (Bali et al., 2016), (4) idiosyncratic volatility, (5) stock mispricing rankings (Jiang and Lin, 2016; Liu, Stambaugh, and Yuan, 2016), (6) firm size, and (7) all of these. We then perform our double-sort tests by sorting firms into visibility quintiles based on the orthogonalized proxies, removing the possible impact of these alternate explanations for BAB. We continue to find that BAB generates larger abnormal returns among less visible stocks. Further tests examine whether our findings could be the result of beta measurement error (Cederburg and O'Doherty, 2016). We repeat our analysis using our principal component measure and well as the PC measure orthgonalized to the full set of alternate explanations for BAB listed above, but perform the analysis using alphas from a conditional CAPM. We continue to find BAB portfolios formed using neglected firms earn more than twice the abnormal returns earned by BAB portfolios within highly visible firms, with an average difference in alphas of 87 basis points.

Lastly, we examine whether factors designed to capture these alternate explanations can explain the relation between BAB and firm visibility. When added to a Fama-French-Carhart four-factor model, factors for leverage constraint tightness, lottery preferences, and the combined effects of mispricing and idiosyncratic volatility appear to explain the performance of an unconditional BAB portfolio. That is, there is no longer a significant alpha for a BAB portfolio formed using all stocks, and ignoring firm visibility, when this benchmark model is used. However, when BAB portfolios are formed within visibility quintiles, we continue to find that BAB generates a significant alpha within neglected firms, alpha decreases monotonically as visibility increases, and the insignificant alpha for highly visible firms is nevertheless significantly different from the alpha for neglected firms. These results hold whether the model is implemented traditionally, or following Cederburg and O'Doherty's (2016) IV approach. Taken together, these tests help to rule out these potential alternate explanations for our results.

Our findings make a number of interesting contributions to the literature. First, we provide the first evidence that BAB is driven in large part by the cost of information acquisition, consistent with the Merton (1987) model. This has the additional benefit of being an independent model that was not written with the purpose of explaining BAB. Our results also contribute to the literature on the relationship between firm visibility (or investor base) and returns, commonly called the investor recognition hypothesis. Prior literature has documented that events that increase firm visibility – such as increases in advertising expenditure (Grullon, Kanatas and Watson, 2004) and the initiation of analyst coverage (Irvine, 2003) – increase firm values and decrease subsequent returns. We add to this literature by showing that firm visibility affects the relationship between beta and returns. Finally, our analysis provides the first comprehensive test of the ability of the recently proposed drivers of betting against beta to explain its performance across firm types.

The remainder of this paper is organized as follows. We provide background information and theoretical predictions in Section 2. We describe the data and variable construction, and discuss summary statistics in Section 3. We present the main findings in Section 4, and perform additional tests for robustness in Section 5. Finally, we provide concluding remarks in Section 6.

2. Betting Against Beta and the Merton (1987) Model

We start with a slightly modified version of Merton's (1987) model of capital market equilibrium under incomplete information. Merton demonstrates that, relative to the complete information case (i.e., the CAPM), firms will earn an apparent abnormal return when information is costly to acquire. The underlying intuition is that investors will require compensation for the cost expended to receive and interpret information about a stock, leading to a security market line with a higher intercept and lower slope than under complete information. Merton further notes that this alpha relative to the CAPM will be decreasing in beta, generating a prediction similar to the empirically observed "betting against beta."

Frazzini and Pedersen (2014) approach betting against beta from an alternate angle. The authors theoretically model stock returns when investors suffer from funding liquidity or leverage constraints, which limit potential investment choices. The authors show theoretically that a beta-neutral strategy of taking a long position in low-beta stocks and a short position in high-beta stocks will generate a positive return, and this return will increase as constraints tighten. The authors further document empirical evidence consistent with this argument.

Blending these two theoretical analyses, we examine whether the incomplete information framework of the Merton model generates predictions regarding the beta-neutral strategy of the Frazzini-Pedersen model. We begin with Merton's equation (25):

$$E[R_i] - R_f = \beta_i\big(E[R_m] - R_f - \lambda_m\big) + \lambda_i \tag{1}$$

where $E[R_i]$, β_i and λ_i are the expected return, market-beta, and the "shadow cost" of information for stock i, and λ_m and R_f are the aggregate shadow cost of information and risk free rate, respectively. Following Frazzini and Pedersen's (2014), we construct a beta-neutral (market neutral) betting against beta (BAB) hedge portfolio which has the expected excess return

$$E(R_t^{BAB}) = \frac{1}{\beta_t^L}\big[E(R_t^L) - R_f\big] - \frac{1}{\beta_t^H}\big[E(R_t^H) - R_f\big] \tag{2}$$

where β_t^L and β_t^Hdenote the portfolio betas for the low- and high-beta portfolios, respectively ($\beta_t^L < \beta_t^H$). Inserting equation (1) into equation (2) for the low- and high-beta portfolios

$$E(R_t^{BAB}) = \frac{1}{\beta_t^L}\left[\beta_t^L\left(E[R_m] - R_f - \lambda_m\right) + \lambda_t^L\right] - \frac{1}{\beta_t^H}\left[\beta_t^H\left(E[R_m] - R_f - \lambda_m\right) + \lambda_t^H\right] \quad (3)$$

where λ_t^L (λ_t^H) is the shadow cost of information for the low-beta (high-beta) portfolio. With the assumption that $E(\lambda_i|\beta_i) = E(\lambda_i)$, on average $\lambda_t^L = \lambda_t^H = \lambda_t^{BAB}$, and this further simplifies to

$$E(R_t^{BAB}) = \frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H}\lambda_t^{BAB} \quad (4)$$

which is both positive ($\beta_t^L < \beta_t^H$ and $\lambda_t^{BAB} > 0$) and increasing in $\beta_t^H - \beta_t^L$ and λ_t^{BAB}. This leads to Proposition 1:

Proposition 1*: A beta-(market-)neutral hedge portfolio taking a long position in low-beta and a short position in high-beta stocks will generate a positive return that is increasing in the difference between portfolio betas and in the portfolios' shadow costs of information.*

This is observationally equivalent to Frazzini and Pedersen's (2014) equation (10), with the shadow cost of information taking the place of funding tightness. However, while the Frazzini-Pedersen (2014) model links the expected excess return to aggregate funding tightness, our prediction depends on the shadow cost of information that is specific to the hedge portfolio. Thus, our proposition has both time-series and cross-sectional properties; we can examine the cross-sectional implications of BAB, similar to Frazzini and Pedersen's (2014) analysis of investor-level constraints.

Specifically, we focus on the implications of cross-sectional differences in firm visibility/investor base. This is most closely related to Merton's (1987) underlying notion of segmentation due to incomplete information. From Merton's equations (15) and (19), we can re-write λ_i as

$$\lambda_i = \frac{1 - q_i}{q_i}(x_i \sigma_i^2 \delta) \tag{5}$$

where λ_i is the firm's "shadow cost" of information, q is the firm's visibility/investor base, x_i is the firm's market capitalization relative to the market total, σ_i^2 is the firm's idiosyncratic volatility, and δ captures investor risk preferences. Substituting this definition into equation (4) yields

$$E(R_t^{BAB}) = \frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H} \frac{1 - q_t^{BAB}}{q_t^{BAB}}(x_t^{BAB} \sigma_t^{BAB^2} \delta) \tag{6}$$

As Merton (1987) notes, β_i is not a function of q_i, and thus for a cross-section of securities with the same values of *x* and σ^2,

$$\frac{\partial E(R_t^{BAB})}{\partial q_t^{BAB}} = \frac{q_t^{BAB} - 1}{q_t^{BAB^2}} \delta * \frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H} \mathrm{x}_t^{BAB} \sigma_t^{BAB^2} \leq 0 \tag{7}$$

because $q_i \in [0,1]$ by definition, and all other quantities are positive. This leads to Proposition 2:

Proposition 2*: The positive expected excess return to a beta-(market-)neutral BAB portfolio will be negatively related to firm visibility in the cross-section of stocks.*

We note that in the full information case (i.e., $q_i = 1$), equations (6) and (7) reduce to zero. In other words, betting against beta exists in this framework when a firm is not perfectly visible or held by all investors, making firm visibility/investor base a critical underlying driver of these predictions, consistent with Merton's model. This provides a plausible alternative to the Frazzini-Pedersen model prediction linking betting against beta to funding constraints.

It is also straight-forward to show that the same results obtain if the BAB portfolio performance is evaluated as an alpha relative to the CAPM. Define the BAB portfolio's CAPM alpha as

$$E(\alpha_t^{BAB}) = \frac{1}{\beta_t^L}[E(R_t^L) - E^{CAPM}(R_t^L)] - \frac{1}{\beta_t^H}[E(R_t^H) - E^{CAPM}(R_t^H)] \tag{8}$$

Inserting the standard formula for the expected return under the CAPM and equation (1) above

$$E(\alpha_t^{BAB}) = \frac{1}{\beta_t^L}\left[\beta_t^L\left(E[R_m] - R_f - \lambda_m\right) + \lambda_t^L - \beta_t^L\left(E[R_m] - R_f\right)\right] \tag{9}$$

$$- \frac{1}{\beta_t^H}\left[\beta_t^H\left(E[R_m] - R_f - \lambda_m\right) + \lambda_t^H - \beta_t^H\left(E[R_m] - R_f\right)\right]$$

which reduces to

$$E(\alpha_t^{BAB}) = \frac{\beta_t^H - \beta_t^L}{\beta_t^L \beta_t^H}\lambda_t^{BAB} \tag{10}$$

under the same assumptions listed above. Thus, the same predictions hold for the BAB portfolio's performance whether performance is measured using excess returns or alpha relative to the CAPM.[2]

Similar to Frazzini and Pedersen (2014), our next proposition considers how the BAB portfolio's performance will vary over time. In equations (4) and (10), it is clear that the performance of the BAB portfolio is predicted to vary positively with the shadow cost of information. Thus, a negative shock to the shadow cost of information should reduce the performance of the BAB portfolio. Formally,

Proposition 3*: The positive expected excess return to a beta-(market-)neutral BAB portfolio will decrease over time as the average shadow cost of information decreases.*

As we discuss below, one might argue that the cost of collecting and analyzing information has decreased over time with advances in technology, or will decrease over the life of the firm. Thus, we expect that the BAB portfolio's performance will decrease in magnitude on average over time, and will have a negative cross-sectional relation with firm age. We next examine empirical evidence related to Propositions 1 and 2, and consider whether this evidence could be consistent

[2] A similar prediction cannot be made when expanded benchmark return models are used. This is particularly important for the predictions made by Proposition 2, as typical expanded models (i.e., Fama-French 3-factor or Fama-French-Carhart 4-factor) include factors that may capture some of the effects of the shadow cost of information, such as firm size and value.

with alternate explanations for betting against beta.

3. Data and Variable Description

We construct our sample using all common stocks with CRSP share code 10 and 11 that are traded on the major exchanges (NYSE, AMEX, and NASDAQ; CRSP exchange codes 1, 2, and 3) from 1971 to 2016. We merge this sample with COMPUSTAT, and exclude observations with missing data that is necessary to construct the visibility measures, as defined below. The different visibility measures cover different time periods beginning between 1971 and 1980, and ending in 2016. This results in samples ranging from 407,344 to 1,653,473 firm-month observations with all data necessary to conduct our tests.

Using this data, we calculate a number of variables of interest. We first calculate each stock's market beta ($\widehat{\beta_i}$) at the beginning of each month following Frazzini and Pedersen (2014).

$$\widehat{\beta_i} = \hat{\rho}_{i,m} \frac{\hat{\sigma}_i}{\hat{\sigma}_m} \quad (11)$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the volatilities for stock *i* and the market, and they are calculated as the standard deviations of daily stock returns over the previous year (in natural log form) for stock *i* and the market, respectively. $\hat{\rho}_{i,m}$ is the correlation between stock *i* and the market, and it is calculated using three-day overlapping log stock returns over the previous five years.[3] We exclude all firm-months with less than 200 valid daily stock return observations during the volatility estimation period, and firms-months with less than 1000 valid daily stock return observations during the correlation estimation period.

[3] As Frazzini and Pedersen (2014) note, the five-year horizon used to estimate the correlation is selected to account for the relatively slow change in correlation with the market over time. Three-day overlapping returns are used in this calculation to account for nonsynchronous trading.

3.1 Measuring Visibility

In Merton's (1987) model, visibility is the fraction of investors in the economy that are *informed* (know) about a security, and, indirectly, represents the cost of information acquisition. We consider four different proxies to measure visibility: (1) the number of analysts following the stock and (2) the firm's advertising expense, (3) breadth of institutional ownership and (4) number of institutional shareholders. We also measure visibility using the first principal component of these four measures.

The four proxies for visibility are constructed as follows. First, we follow Chichernea et al. (2015) and Diether, Malloy, and Scherbina (2002) and estimate the number of analyst following a stock in month t as the number of analysts who provide fiscal year-end earnings estimates that month in the Institutional Brokers Estimate System (IBES) database. Analyst coverage is available during the period from 1976 to 2016. Analyst coverage is a particularly relevant measure of visibility in the context of the Merton (1987) model, as it is related to the attention or recognition that the firm receives (Hou and Moskowitz, 2005) and the speed at which the market price of the stock incorporates new information (Hong, Lim, and Stein, 2000).

The second proxy, advertising expense, is collected from COMPUSTAT. We transform the annual advertising expense into a monthly measure by assigning the amount at the end of year t to each of the 12 months of the year t.[4] This measure is available from 1971 to 2016. As Chichernea et al. (2015) note, evidence suggests that advertising impacts both investors' portfolio choices (Cronqvist, 2006) and the firm's breadth of ownership (Grullon, Kanatas, and Weston, 2004).

Third, we calculate the breadth of institutional ownership (Lehavy and Sloan, 2008) using quarterly institutional transaction data from the Thomson CDA/Spectrum 13F institutional

[4] Alternately, we could assume that the advertising expense is spent equally throughout the year, and calculate the monthly expense as the yearly expense divided by twelve. Because this would simply divide our advertising expense by twelve for each observation, it would be equivalent to the measure presented.

transaction database. Breadth of institutional ownership is calculated as the ratio of the number of 13F filers that hold a long position in the stock to the total number of 13F filers in the sample for that quarter. We transform this into a monthly measure by assuming that the breadth of ownership stays constant during the months of a quarter.[5] Finally, we obtain the number of institutional shareholders (Bushee and Miller, 2012) as the total number of 13F filers. We transform this into a monthly measure by assuming that it stays constant during the months of a quarter. We focus on institutional owners as institutions tend to be informed investors (Hendershott, Livdan, and Schurhpoff, 2015). Furthermore, Merton (1987) notes that institutional ownership is likely to proxy for market segmentation and investor base in his model. Breadth of institutional ownership and the number of institutional owners are available from 1980 to 2016.

To further refine our measure of visibility, we conduct a principal component analysis to directly estimate the common portion of the four visibility measures. If each of our measures primarily reflects visibility and the shadow cost of information, the common portion should be the cleanest proxy for visibility. To isolate the principal component, we follow a procedure similar to that of Bushman, Chen, Engel, and Smith (2004). We examine whether any underlying component loads significantly and with the same sign for all of the four measures, and has an eigenvalue greater than one.[6] We perform this analysis based on the correlation, rather than covariance, matrix of the visibility measures, as this does not require the measures to be of the same scale (Jolliffe, 2014). We find that the first component is the only factor with an eigenvalue greater than one, and explains approximately 72% of the variation in the four visibility measures. Each of the four individual proxies is positively and significantly correlated with the principal component, with correlations of 0.58 or greater. This analysis suggests that the single principal component provides

[5] For robustness, we also used interpolation and assumed that the variable changes linearly through the months of the quarter. Results are qualitatively similar and are available upon request.
[6] An eigenvalue greater than one is a necessary and sufficient condition for the factor to be reliable (Kaiser, 1960).

a reliable measure of visibility underlying the four individual measures. As such, our fifth measure is the principal component (PC) created from the four visibility measures.

Although the primary variables of interest (i.e., market beta and returns) are available for longer sample periods, the visibility proxies limit the time period that can be used in our tests. To use the longest possible sample period that is as similar as possible to prior studies, we create five samples – one for each visibility proxy – and use each sample to study the impact of visibility on the relationship between market beta and returns. The details regarding the sample period coverage of each of these subsamples are available in Table I.

3.2 Summary Statistics

Table I shows that the sample firms during the full sample period earned a mean (median) stock return of 1.21% (0.37%) per month, and a mean (median) excess return of 0.81% (-0.02%) per month. This is similar to the magnitude of excess returns (approximately 1% per month) earned by the sample of U.S. stocks analyzed by Frazzini and Pederson (2014). The average (median) firm in our sample has a beta of 1.00 (0.97) and idiosyncratic volatility of 2.46% (1.99%) per month. Finally, the average (median) firm has a market capitalization of $2 billion ($218 million).

Additionally, Table II provides correlation matrices between the primary variables of interest and firm characteristics. We find that visibility is generally positively correlated with both beta and size, and negatively correlated with idiosyncratic volatility. Importantly, all of the visibility measures are positively correlated, with correlations ranging from 0.20 to 0.93, and each is most highly correlated with the PC measure. This is consistent with the measures each proxying, to a large extent, for the underlying visibility of the stock. The visibility measures are positively correlated with funding liquidity and negatively correlated with lottery-like characteristics, further suggesting the need to consider these explanations when analyzing the impact of visibility on BAB.

4. Empirical Results

4.1 The BAB Phenomenon

We begin our analysis by first confirming the BAB phenomenon (Proposition 1) across our four different samples created by restrictions due to the availability of visibility proxy data and the overlapping portion of these four samples. Specifically, we sort stocks in each sample into quintiles based on their market beta at time *t-1*. We then calculate the excess return of each quintile, as well as a beta-neutral low-minus-high market beta hedge portfolio.[7] These results are presented in Table III. We find that the hedge portfolio excess returns range from 91 to 113 basis points per month, depending on the sample examined, and are statistically significant in each case. Having confirmed that BAB exists with similar magnitude in each of the samples, we next examine the impact of visibility on BAB abnormal returns.

4.2 The Cross-Sectional Effect of Visibility on BAB

The tests above confirm that the BAB phenomenon exists in our subsamples, consistent with Proposition 1 and prior works. We next analyze the impact of visibility on BAB (Proposition 2) by performing a dependent double-sorting procedure, where stocks are first sorted into visibility quintile portfolios, and then sorted into beta quintile portfolios within each visibility portfolio.[8] We examine the excess returns to beta-neutral, value weighted BAB hedge portfolios across levels of visibility. The BAB excess returns and associated t-statistics for each visibility quintile, along with the difference in BAB performance between low and high visibility quintiles, are presented

[7] We begin with excess rather than abnormal returns relative to a benchmark model as the predictions in Section 2 based on Merton's (1987) model are made based on excess returns. We note that predictions remain unchanged if we instead consider abnormal returns relative to the CAPM, and later present related tests as a part of our analysis. While explicit predictions are not made for abnormal returns relative to a Fama-French-Carhart four-factor or similarly expanded model, we examine results under alternate models in Section 5, and note that our conclusions are not affected by the selection of a particular model.

[8] Our results are qualitatively similar if we use equal weighting rather than value weighting when forming the BAB portfolios, or independent rather than dependent sorts.

in Table IV. These results are presented for each of the five visibility proxies. For brevity, we primarily discuss the results using the principal component (PC) visibility proxy, with a brief discussion of the individual visibility measures.

Consistent with Proposition 2, we find that stocks in the lowest visibility quintile (neglected stocks) have significant BAB excess returns of 170 basis-points per month (t-statistic of 3.55). However, the BAB excess return decreases in magnitude monotonically as visibility increases, generating 75 basis-points (t-statistic of 3.08) in the highest visibility quintile. The difference of 95 basis-points between the low and high visibility quintiles is both economically meaningful (greater than 50% reduction) and statistically significant (t-statistic of 2.10).

We see the same pattern with each of the alternate proxies for visibility. In each instance, we find that the BAB excess return in the highest visibility quintile is both statistically and economically smaller in magnitude than in the lowest visibility quintile. Using the analyst following proxy, we find a difference of 109 basis-points per month between BAB portfolios formed among neglected and highly visibility stocks. Results are similar when we use the Advertising Expense proxy (127 basis-point difference), the Breadth of Ownership proxy (81 basis-point difference), or the Number of Institutional Owners proxy (75 basis-point difference). These results provide strong initial support for Proposition 2.

We next examine the prediction that BAB abnormal returns relative to CAPM decreases as firm visibility increases. To do so, we repeat the tests presented in Table IV, but estimate the CAPM alpha for each BAB portfolio as the intercept from a regression of the portfolio's excess return on the excess return to the market.[9] We present these results in Table V. For brevity, we again discuss the results primarily for the PC visibility measure. Consistent with the excess return

[9] Similar to Frazzini and Pedersen (2014), this may differ slightly from the excess return to the beta-neutral portfolio as the portfolio formation and benchmark model betas are estimated using different time periods and approaches. In any case, no look ahead bias is introduced.

results in Table IV, we find that BAB abnormal returns are largest among neglected stocks (175 basis-points per month, t-statistic of 3.48) and smallest among highly visible stocks (96 basis-points per month, t-statistic of 3.98). We also find that the difference between BAB alphas for the low and high visibility firms is economically large and statistically significant (79 basis points per month, t-statistic of 1.78). Results are similar when each of the individual visibility proxies is used. In one case, when the number of institutional owners is used to proxy for visibility, the difference between high and low visibility BAB alphas becomes marginally statistically insignificant (t-statistic of 1.64), but remains economically significant at 65 basis points per month. Taken together, the results from using excess returns (Table IV) and alphas (Table V) strongly support the prediction that that BAB varies with visibility (Proposition 2).

4.3 BAB Over Time

As noted in Section 2, BAB is predicted to decrease in magnitude as information becomes less costly to acquire on average (Proposition 3). For instance, advances in computer technology, which provided investors greater access to and efficient use of information, could substantially reduce the shadow cost of information and market segmentation due to firm visibility over time (Chichernea et al., 2015). As such, it seems straightforward to predict that the abnormal returns to BAB will move towards zero with technological advances (Proposition 3). An important caveat is that a number of factors could offset the gains from advances in technology over time. First, in the Merton (1987) model, the shadow cost of information increases with firm size, but decreases with investor base/visibility. Thus, the impact of an increase in investor base with advances in technology may be offset as firm size has also increased over time. Second, as computing power has increased, so generally has the number of available market-traded assets. Considering only common stocks traded on major exchanges, the number of available assets increased from approximately 5,000 at the beginning of our sample period (early 1980's) to a peak of 9,000 in the early 2000's. This increase is in addition to the proliferation of derivative securities such as credit default swaps that substantially increased the number of possible assets investors need to track. Third, the amount of potentially relevant information to be collected and interpreted by investors has grown, due to greater disclosure requirements, media coverage of firms, press releases, proxy advisory services, etc. Thus, as computing power has increased, so have processing needs. Fourth, while technological advances have improved the efficiency of data aggregation, ignoring purely algorithmic trades, the investor must use the aggregated information to make investment decisions. The ability to track and interpret the information for a large number of potential investments may be constrained by the cognitive ability of the investor, rather than the available computing resources. Taking these offsetting effects into consideration, we expect that BAB will have decreased over time, but do not argue that it will have been driven to zero by advances in technology.

We first examine this prediction graphically in Figure I. Each month, we calculate the average BAB excess return and associated t-statistic based on the 60-month period ending in that month.[10] For ease of presentation, we then average the monthly excess returns and t-statistics over the calendar year. We graph the average excess and t-statistics, as well as the associated linear trend lines, in Figure I. While there is substantial variance in the performance of BAB over time, there are two notable results in the figure. First, BAB has not completely disappeared over time, but continues to generate significant excess returns at the end of the sample period. Second, the trends in excess returns and t-statistics suggest that the performance of BAB has decreased over time as technology has advanced, with the average t-statistics decreasing in magnitude from

[10] Results are substantively unchanged if excess returns are replaced with CAPM alphas.

approximately -2.5 to -1.5 during the sample period. These results are consistent with Proposition 3. This is also consistent with the findings of Chichernea et al. (2015), who note that offsetting effects of increased investor base and increased firm size lead to a stable idiosyncratic volatility risk premium over time, consistent with Merton's model. Similarly, our results are consistent with Chen, Noronha, and Singal (2004), who document that the shadow cost of information was relevant in explaining firm abnormal returns around S&P500 index inclusion, even in the later part of their sample period (1989-2000).

We examine this prediction further by regressing the returns to the BAB hedge portfolio in our overlapping sample on variables designed to capture the trend in performance over time, similar to McLean and Pontiff (2016). We define two variables to examine possible time trends. First, Time is defined as the number of months since the beginning of the sample period (1980), divided by the total number of months in the sample. Second, Ln(Time) is defined as the natural log of the Time variable. We then examine how the performance of BAB has changed over time using both excess returns and CAPM alphas. We present these results in Panel A of Table VI. We find that BAB performance exhibits a significant negative trend over time. Whether we examine the time trend in linear or log-linear form, we find a negative and significant coefficient on the time variable for both excess returns and CAPM alphas. This provides further evidence that BAB performance has decreased over time, consistent Proposition 3.

Relatedly, one might expect that BAB should be negatively related to firm age in the cross-section, as the cost of information acquisition is likely higher among younger firms that are new to the market. Thus, we also perform a double-sort to examine the relation between firm age and BAB performance. Specifically, we first sort firms into quintiles based on the age of the firm, defined as the number of months since the firm first appeared in the CRSP database. We then sort firms on beta within each firm age quintile, and calculate the excess returns to the beta-neutral BAB hedge portfolios. We present these results in Panel B of Table VI.

Consistent with Proposition 3, we find that BAB produces the largest excess returns among the youngest firms (133 basis points per month, t-statistic of 3.82), and the smallest excess returns among the oldest firms (76 basis points, t-statistic of 3.30). This generates a statistically significant difference in BAB performance of 57 basis points per month (t-statistic of 1.85) between the youngest and oldest firms in our sample. A possible shortcoming of these tests is that multiple reasons for such a time trend may exist, and may not be specific to the model in question. We continue our analysis by further examining our cross-sectional and time-series predictions with a focus on separating the cost of information acquisition from alternate explanations for BAB.

An additional implication of Propositions 1 and 3 is that the performance of BAB should be higher during periods when the portfolio's shadow cost of information (Lambda) and beta spread are higher. Table VII presents regression-based-tests of this prediction for both unconditional and visibility-ranked BAB portfolios. Our primary variable of interest is the value-weighted average shadow cost for each BAB portfolio each month (Lambda). We calculate the shadow cost of information for each stock following equation (5) above, using a similar procedure to that of Kadlec and McConnell (1994), with *q* measured by institutional ownership. A secondary variable of interest is Beta Spread, defined as the difference between the betas of the high and low beta portfolios, scaled by the product of the two betas (eq. (4) above). We then regress BAB portfolio returns on the Lambda and Beta Spread.

Column 1 presents the results for the unconditional BAB portfolio. Consistent with Eq. (4) above, we find that BAB returns are significantly positively related to Lambda, the measure of the cost of information acquisition. While the coefficient on Beta Spread is positive as predicted, we do not find it is statistically significant in this case. Similar to Frazzini and Pedersen (2014), our predictions are based on partial derivatives, assuming that all else is equal. As this may not be the case empirically, we include a number of controls to limit the possibility of omitted variable bias. The first set of controls follow from Frazzini and Pedersen (2014) and include the lagged TED spread, the contemporaneous change in TED spread, the market return, the lagged BAB return, and portfolio's beta spread. We also control for the average idiosyncratic volatility of the stocks in the BAB portfolio, and note that results are similar if we instead control for the within-sample difference in returns between high and low idiosyncratic volatility stocks. The second set of controls aims to address the possibility that the cost of information may be correlated with other proposed explanations for BAB. These include the average mispricing rank (MISP) of the firms in the BAB portfolios (Stambaugh et al., 2012) and the average highest daily return over the previous month (MAX) for the firms in the BAB portfolios (Bali et al., 2016). Due to data availability limits, this analysis uses observations from 1986 through 2013. Column 2 presents the regressions results with added controls. After controlling for these possibly confounding effects, we find that the coefficients on both Lambda and Beta Spread are positive and significant, supporting Propositions 1 and 3.

Table VII also presents the results from a pooled regression in which the dependent variable is the return to one of five BAB portfolios formed within visibility quintiles. In each case, the portfolio-level independent variables are calculated for the specific BAB portfolio in question. Following Frazzini and Pedersen (2014), we include fixed effects for each portfolio and cluster the standard errors by sample month. These results without and with additional controls are presented in Columns 3 and 4, respectively. In each case, we find that the coefficients on Lambda and Beta Spread are positive and statistically significant. Consistent with Frazzini and Pedersen (2014), the results suggest a negative relation between the TED spread and BAB, whether we examine the lagged TED spread or the change in TED spread; however, this cannot explain the relation between BAB and Lambda. Taken together, these results provide further support for Propositions 1 and 3, and the link between BAB and the cost of information acquisition.

5. Additional Tests and Robustness

We perform a number of additional tests to determine the robustness of our results. We first note that our results are generally robust to the use of four alternate proxies for visibility as well as their common component, the principal component measure. Our results are also qualitatively similar if we create equal-weighted rather than value-weighted BAB portfolios. Additionally, we find similar results when we do independent rather than dependent sorts, addressing a potential concern that our results may reflect the difference in the variance or spread of the firm betas across visibility quintiles. Analysis of dollar-neutral rather than beta-neutral BAB portfolios likewise leads to similar conclusions, with BAB generating significant abnormal returns primarily among low visibility firms.

5.1 Funding Liquidity/Leverage Constraint Tightness

We take numerous steps to remove the possible influence of alternate proposed explanations for BAB on our results. We first examine whether our results could be caused by differences in funding illiquidity across firm visibility levels (Frazzini and Pedersen, 2014). Frazzini and Pedersen (2014) argue that funding-constrained investors will overweight risky, high-beta stocks in their portfolios, creating a demand pressure that leads to higher current prices and lower subsequent returns for high-beta stocks. This, in turn, creates a negative relation between beta and alpha, consistent with BAB. To remove the potential impact of funding illiquidity on our results, we create an orthogonalized version of the PC measure to proxy for visibility that is uncorrelated with funding liquidity constraints. We first rank firms into 100 categories based on the firm-level proxies for funding liquidity constraints used by Frazzini and Pedersen (2014).[11] These include (1) β_{TED}, a regression coefficient of the stock's monthly excess return on TED, (2) β_{VOLTED}, a regression coefficient of the stock's monthly excess return on the volatility of TED SPREAD, and (3) β_{TBILL}, a regression coefficient of the stock's monthly excess return on the three-month US Treasury Bill rate.[12] To create a single ranking to represent funding liquidity, we then rank firms into 100 categories based on their aggregate rank across the three measures of funding illiquidity. Similarly, we independently rank firms into 100 categories based on the PC visibility measure. Finally, we regress the visibility ranking on the aggregate funding illiquidity ranking, and take the residual as a measure of visibility that is orthogonal to funding illiquidity. We then repeat the double-sorting procedure using this orthogonalized measure of visibility. These results are presented in Row (1) of Table VIII. Similar to the results presented above, we continue to find that BAB generates a positive and significant alpha among neglected firms (112 basis points, t-statistic of 1.98), which decreases in magnitude nearly monotonically as visibility increases, with a more than 50% reduction in the highest visibility quintile (55 basis points).

Similarly, Boguth and Simutin (2016) argue that the demand for beta among actively managed funds provides a stronger measure of the type of leverage constraints proposed by the Frazzini and Pedersen (2014) model, and demonstrate that leverage constraint tightness (LCT) has predictive power for BAB returns. As such, we next rank-orthogonalize visibility to each firm's sensitivity to constraint tightness (β_{LCT}), the coefficient from a regression of the firm's returns on Boguth and

[11] We perform all of our orthogonalization procedures using ranks to be consistent with the orthogonalization of visibility proxies to mispricing rankings, presented below. All of our results are qualitatively similar if we using rankings based on 50 categories rather than 100.
[12] Each is estimated from a rolling window using the prior 60-month data. The volatility of TED SPREAD is calculated as the standard deviation of daily TED SPREAD data within a month.

Simutin's (2016) LCT, using the rank-orthogonalization procedure described above.[13] We then analyze BAB performance within each LCT-orthogonalized visibility quintile in Row (2) of Table VIII. In this case, we find even stronger evidence that BAB varies with firm visibility. We find that BAB earns an excess return of 176 basis per month among neglected firms (t-statistic of 3.50), and this performance decreases nearly monotonically as visibility increases. BAB produces a 76 basis point excess return in the highest visibility quintile, generating a statistically and economically significant difference of 100 basis points per month between the highest and lowest visibility quintiles (t-statistic of 2.05). Taken together, these findings demonstrate that our results are not driven by a correlation between visibility and funding illiquidity or similar constraints on investors.

5.2 Lottery-Like Stock Characteristics

We next examine whether our results could be driven by a correlation between visibility and lottery-like characteristics. Bali et al. (2016) argue that BAB is driven by a demand for lottery-like securities. If investors prefer stocks with lottery-like payoffs, and if there is a positive correlation between beta and lottery-like payoff characteristics of a stock, then a demand pressure for lottery-like stocks generates negative correlation between beta and alpha. To remove the effect of lottery preferences on our results, we rank-othogonalize our PC visibility measure to firm lottery-like characteristics using the procedure described above. We follow Bali et al. (2016) and measure lottery-like characteristics of a stock using the firm's highest daily stock return over the prior month (MAX). We again repeat the double-sorting procedure using this orthogonalized measure of visibility, and present the results in Row (3) of Table VIII. Our results are again substantively unchanged. We find that BAB generates a large positive and significant excess return among

[13] We thank Professor Mikhail Simutin for making this data available for download at: http://www-2.rotman.utoronto.ca/simutin/research.asp.

neglected stocks (157 basis points, t-statistic of 3.56), and the performance of BAB decreases monotonically as visibility increases, resulting in a 76 basis point excess return among highly visible stocks. This leads to a statistically and economically significant difference of 81 basis points per month between the low and high visibility quintiles (t-statistic of 1.83). This suggests that our results are not driven by a correlation between visibility and lottery-like stock characteristics.

5.3 Idiosyncratic Volatility and Mispricing

Alternatively, Jiang and Lin (2016) and Liu, Stambaugh, and Yuan (2016) suggest that the returns to the BAB strategy could be driven by mispricing and/or idiosyncratic volatility, as these may be correlated with firm betas. To examine this possibility further, we first rank-orthogonalize our PC measure to firm-level idiosyncratic volatility following the procedure described above, and present the updated double-sorting results in Row (4) of Table VIII.[14] Similar to the results described above, we find that BAB performance decreases monotonically from 159 basis points per month (t-statistic of 3.63) among neglected firms to 81 basis points per month (t-statistic of 3.40) among highly visible firms. This difference is again both economically and statistically significant (78 basis points per month, t-statistic of 1.79).

Next, we rank-orthogonalize our PC measure to Stambaugh, Yu, and Yuan (2012)'s mispricing index[15] and orthogonalize firm betas to firm-level idiosyncratic volatility, following a procedure similar to Liu et al. (2016) in their Table 6. We then examine BAB excess returns across visibility

[14] To make sure that our results are comparable with that of Liu et al. (2016), we measure idiosyncratic volatility as the standard deviation of the daily residuals within a month from a Fama-French three factor model. Using other measures of idiosyncratic volatility does not change our results qualitatively.

[15] The index includes financial distress (Campbell, Hilscher, and Szilagyi, 2008), O-score probability of bankruptcy (Ohlson, 1980), net stock issues (Ritter, 1991), composite equity issuance (Daniel and Titman, 2006), total accruals (Sloan, 1996), net operating assets (Hirshleifer, Hou, Teoh, and Zhang, 2004), momentum (Jegadeesh and Titman, 1993), profitability (Novy-Marx, 2010), asset growth (Cooper, Gulen, and Schill, 2008), ROA (Fama and French, 2006), and investment-to-assets ratio (Titman, Wei, and Xie, 2004). We thank Professor Yu Yuan for making this data available for download at: http://www.saif.sjtu.edu.cn/facultylist/yyuan/.

quintiles using these updated visibility and beta measures in Row (5) of Table VIII. In this case, we find some evidence of larger excess returns among low visibility firms (104 vs. 87 basis points per month for low and high visibility firms, respectively), but the strongest performance appears to be among firms in the second lowest visibility quintile (159 basis points, t-statistic of 5.48). While we continue to find some evidence of the predicted relation between visibility and BAB, the difference between high and low visibility BAB excess returns is not statistically significant in this case.[16]

5.4 Firm Size

An additional complicating factor in our analysis is that each of the proxies for visibility are likely to be correlated with the size of the firm. This may be particularly concerning for the PC measure, as the common variance in the individual proxies could be largely driven by the size of the firm. While we note that size is one of the three components of the shadow cost of information (λ) from Merton's (1987) model and thus may also impact BAB, it is important nonetheless to determine whether our results are driven by a pure size effect rather than firm visibility. Thus, we again repeat the double-sorting procedure using our PC visibility measure rank-orthogonalized to firm size, and present the results in Row (6) of Table VIII. Our results are again substantively unchanged. We find that BAB generates approximately 2% excess returns per month among neglect stocks, decreasing in magnitude to 93 basis points per month among highly visible stocks, for a significant difference of more than 1% per month (t-statistic of 3.45). This helps to rule out firm size as the driver of our results.

5.5 Combined Effects

[16] We note, however, that untabulated results show that the difference is positive and statistically significant when any of the individual visibility measures are used instead of their principal component.

While these tests have largely ruled out the concern that our results could be driven by firm visibility capturing any of the alternate explanations for BAB individually, a possible concern is that visibility captures a portion of each of these explanations. This could allow our results to survive individual orthogonalization procedures. Thus, we examine whether our results are robust to orthogonalizing visibility to all of the alternate explanations simultaneously. To perform this test, we repeat the rank-orthogonalization procedure described above, but include in the regression the firm rankings for funding liquidity/leverage constraints, lottery-like characteristics, mispricing, and firm size. We further orthgonalize firm betas to idiosyncratic volatility, following Liu et al. (2016). We then sort firms in quintiles based on the fully-orthogonalized visibility measure, and estimate BAB hedge portfolio excess within each quintile, presenting these results in Row (7) of Table VIII. Similar to the results above, we find that BAB generates 133 basis points (t-statistic of 2.96) among neglected firms, but only 48 basis points (t-statistic of 1.42) among highly visible firms. The difference between the high and low visibility quintiles is again statistically and economically significant (85 basis points per month, t-statistic of 1.90).

5.6 Beta Measurement Error

We also examine whether our results can be explained by beta measurement error, as proposed by Cederburg and O'Doherty (2016). Specifically, the authors find that abnormal returns to a BAB hedge portfolio are no longer significant after addressing beta measurement error using an instrumental variable (IV) specification of the benchmark return model. The authors include historical, time-varying measures of beta, the aggregate dividend yield, and the default spread as instrumental variables for standard beta. More specifically, the authors estimate for each firm a 3- and 36-month beta, calculated over the period immediately prior to the formation period during which the "sorting" beta is estimated. By using this specification, the authors avoid overlap between the periods used to calculate the IV beta estimates and the standard beta estimate used to sort firms to form the BAB hedge portfolio.

To examine this possibility, we follow the IV procedure to re-estimate the abnormal returns to the BAB hedge portfolio within each visibility quintile. These results are presented in Row (8) of Table VIII (Panel B). Similar to the results above, we find that the hedge portfolio abnormal return is positive and significant for each visibility quintile, with neglected firms earning significantly larger alphas than highly visible firms. BAB generates an average abnormal return of 170 basis points (t-statistic of 3.70) among neglected stocks, decreasing to an alpha of 85 basis points (average t-statistic of 3.87) among highly visible stocks. Additionally, we examine whether beta measurement error in combination with the other alternate explanations for BAB can explain the abnormal returns across the visibility quintiles. Thus, we repeat the conditional CAPM tests, but employ as the proxy for visibility the PC measure orthogonalized to all of the alternate explanatory variables described above. We present these results in Row (9) of Table VIII. We find that BAB generates a significant alpha among neglected firms (135 basis points, t-statistic of 3.08), and alpha decreases monotonically as visibility increases, leading to an insignificant alpha among the most visible firms (46 basis points, t-statistic of 1.37). This generates a difference in performance of 89 basis points between the neglected and highly visible stocks, but the difference is marginally insignificant (t-statistic of 1.61). Taken together, these tests suggest that our cross-sectional results are not driven by beta measurement error or any of the alternate explanations for BAB, but are consistent with market segmentation due to the cost of information acquisition, as in Merton (1987).

5.7 Expanded Benchmark Return Models

Lastly, we perform two additional tests to document the relation between BAB and the cost of information acquisition, removing the effects of alternate explanations for BAB. We next examine whether BAB generates abnormal performance beyond what can be explained by return factors designed to capture the effects of leverage constraints, lottery preferences, mispricing, and idiosyncratic volatility. We re-estimate an unconditional (on visibility) BAB alpha as well as BAB alphas within each visibility quintiles using our PC measure under a number of alternate benchmark return models. These models include (1) a Fama-French-Carhart four-factor model, (2) a four-factor model plus a leverage constraint tightness (FLCT) factor (Boguth and Simutin, 2016), (3) a four-factor model plus a lottery-like characteristics (FMAX) factor (Bali et al., 2016), (4) a four-factor model plus an idiosyncratic volatility factor (IVOL), (5) a four-factor model plus mispricing (MGMT, PERF) factors (Stambaugh and Yuan, 2017), (6) a four-factor model plus IVOL, MGMT, and PERF, and (7) a model that includes all of the above factors. For brevity, we present only the alphas for models (1)-(6) in Panel A of Table IX, and report full results for model (7) in Panel B of Table IX.

These tests lead to a number of interesting results. First, we find little evidence that a four-factor model substantially reduces BAB performance, regardless of whether BAB portfolios are formed within visibility quintiles or across the entire sample (Panel A, Row 1). We then augment the four-factor model with a factor designed to capture the effect of leverage constraint tightness. We define this factor (FLCT) as the return to a high-minus-low quintile hedge portfolio from sorting stocks on their sensitivities to leverage constraint tightness (LCT), estimated using 60-month rolling window regressions. The BAB alphas from this updated factor model are presented in Row 2 of Table IX. Similar to the results using the four-factor model, we find that BAB generates a significant alpha in each case, with a near-monotonic negative relation between BAB alphas and firm visibility.

We next examine whether a four-factor model plus FMAX (Bali et al., 2016), a factor designed to capture the effect of investor preference for stocks with lottery-like characteristics, can explain the BAB alphas. The results are presented in Row 3. Consistent with Bali et al. (2016), we find no significant alpha for the unconditional BAB portfolio. However, when BAB portfolios are formed within visibility quintiles, we continue to find significantly positive alphas for the two lowest visibility quintiles, and a monotonically negative relation between BAB alphas and firm visibility. Thus, while lottery preferences may influence BAB performance, this cannot explain our finding of stronger BAB among less-visible firms.

We next examine the influence of idiosyncratic volatility and mispricing. In Row 4, we analyze BAB alphas from an FF4 model plus IVOL, the return to a high-minus-low quintile portfolio of firms sorted on idiosyncratic volatility. We find that idiosyncratic volatility helps to explain unconditional BAB, primarily through its effect among high visibility firms. We continue to find significant BAB alphas across three of the five visibility quintiles. In Row 5, we examine alphas from an FF4 model plus MGMT and PERF (mispricing factors).[17] Similar to the results in Row 4, we find that these help to explain unconditional BAB, primarily through their impact within the high visibility quintile. We continue to find significant BAB alphas in the remaining visibility quintiles. In Row 6, we investigate whether an FF4 model plus IVOL, MGMT, and PERF can explain BAB alphas across visibility levels. Consistent with Liu et al. (2016), we find that this model does reduce unconditional BAB alpha, as well as BAB alphas across the majority of visibility quintiles. However, we continue to find a significant alpha of more than 1% per month (t-statistics of 2.31) among neglect stocks, and the alpha estimate decrease monotonically as visibility increases.

[17] We thank Professor Yu Yuan for making these factors available for download (http://www.saif.sjtu.edu.cn/facultylist/yyuan/).

Finally, we analyze BAB alphas in an FF4 factor model, augmented with FLCT, FMAX, IVOL, MGMT, and PERF, and show the results in Panel B of Table IX (with all the parameter estimates of the factors for illustration). Consistent with the results of prior works, we find that the alpha for the unconditional BAB portfolio is not statistically different from zero (10 basis points, t-statistics of 0.45). However, these factors cannot explain the abnormal performance of the BAB portfolio among neglected stocks. Within the set of neglected firms, we find that BAB earns 92 basis point abnormal return per month (t-statistics of 2.06). Among the most visible firms, BAB alpha is found to be both economically and statistically insignificant (-7 basis points, with a t-statistics of -0.37).

We also note that the difference in BAB alphas between the low and high visibility quintiles is of similar magnitude to that found in our previous results. We find that the difference in alphas ranges between 63 and 104 basis points per month, depending on the benchmark model considered, and is statistically significant in the majority of cases. This documents that the relation between BAB and the cost of information acquisition cannot be explained by the previously proposed causes of the BAB phenomenon. In untabulated tests, we examine whether our results are similar if we implement a conditional benchmark model following Cederburg and O'Doherty's (2016) IV procedure, and find our results to be substantively unchanged. This provides additional evidence that our findings are distinct from those documented by earlier works.

5.8 Beta Spread and Alternate Explanations

Finally, we consider whether our results could be explained purely by the beta spreads across visibility quintiles, as the beta spread is also expected to be positively related to BAB portfolio returns under some of the alternate explanations discussed above (e.g., Frazzini and Pedersen, 2014). We first note that the additional results presented in Table VIII are inconsistent with our results being driven by the previously proposed explanations for BAB. The time series results presented in Table VII help to further distinguish our results from alternate explanations. In particular, we document that BAB portfolio returns are significantly related to Lambda, measuring the cost of information acquisition, after removing the effects of Beta Spread and variables specific to each alternate explanation for BAB, consistent with our predictions. Finally, we note that in untabulated tests we replicate the results in Table IV using independent double-sorts (holding the beta spread constant across visibility levels), and find qualitatively similar results to those presented. Taken together, these tests help to further distinguish our results from alternate explanations for BAB.

6 Conclusion

We examine an explanation for the Betting-Against-Beta (BAB) phenomenon using Merton's (1987) capital markets equilibrium theoretical model. In Merton's model, information is costly to acquire and it is impractical for investors to track all of the securities in the market. Because investors purchase only known securities, this leads investors to hold under-diversified portfolios, causing idiosyncratic volatility to be priced. In turn, this generates a flatter security market line with a higher intercept as compensation for the cost of information acquisition and idiosyncratic risk. This also leads the security market line to have lower slope than in the CAPM – the full information case. We demonstrate analytically that a beta-neutral hedge portfolio constructed out of a long position in low-beta stocks and a short position in high-beta stocks should generate an excess return (or CAPM alpha) that is proportional to the portfolio's "shadow cost of information" and the spread in the beta of the two legs of the portfolio. We further show that this abnormal performance should vary cross-sectionally with the visibility levels of the firms.

Consistent with these predictions, we find that betting against beta (BAB) produces a substantially larger (approximately 100% larger, on average) excess and abnormal returns among neglected stocks relative to highly visible stocks. The returns to the BAB strategy also declined over time with the likely decrease in the cost of information due in part to the proliferation of computing resources. We further distinguish our explanation from existing explanations by demonstrating that the pattern in BAB abnormal performance, even after removing the effects of lottery preferences, funding illiquidity/leverage constraints, firm characteristics-based mispricing, and beta measurement error. Taken together, our results support market segmentation due to costly information acquisition as a primary driver of the BAB phenomenon.

Our work makes a number of contributions to the literature. First, we provide the first evidence that BAB is driven in part by the cost of information acquisition, consistent with the Merton (1987) model. This is particularly interesting as the Merton model was not written with the purpose of explaining the BAB phenomenon documented by Frazzini and Pedersen (2014). Our results also contribute to the literature on the relationship between firm visibility (or investor base) and returns, commonly called the investor recognition hypothesis. Prior works have shown that events that increase firm visibility – such as increases in advertising expenditure (Grullon, Kanatas and Watson, 2004) and initiation of analyst coverage (Irvine, 2003) – increase firm values and decrease subsequent returns. We add to this literature by documenting that firm visibility also affects the relationship between market beta and returns. In particular, our empirical results support Merton's theoretical notion that investors' cognizance of a security is an important determinant of its returns. Finally, our analysis provides the first comprehensive test of the ability of the recently proposed drivers of betting against beta to explain its performance across firm types.

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Figure I: BAB performance over time

We plot the excess returns to a beta-neutral BAB hedge portfolio (low-minus-high beta quintile portfolio) and associated t-statistics over time. We first estimate the average excess returns and t-statistics on a monthly basis using 60 month rolling window ending with the month of interest. We then calculate the yearly averages of the monthly returns and associated t-statistics. The lines are time-trends for the average excess returns and t-statistics.

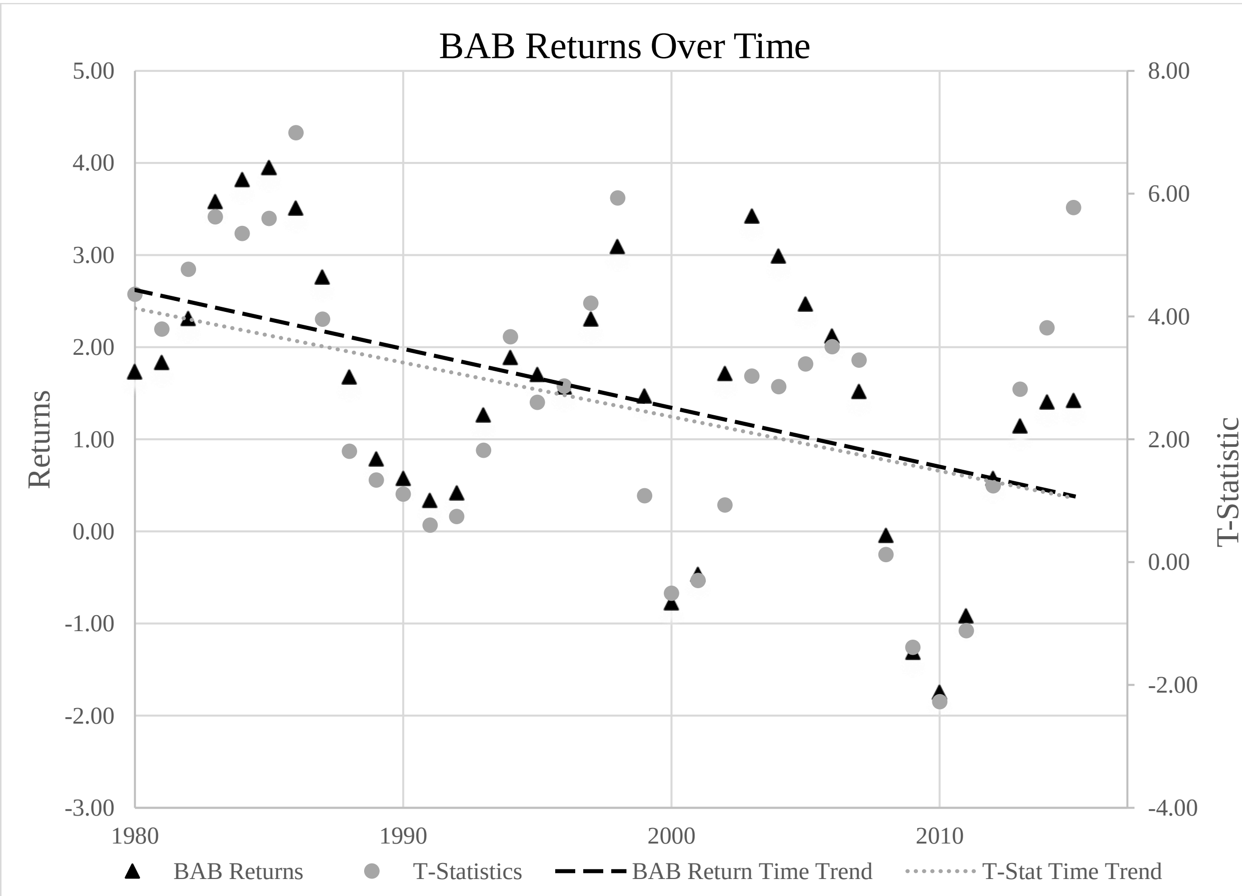

Table I: Summary Statistics

This table provides descriptive statistics for the variables used in our analysis. Every month, we calculate the cross-sectional **Mean, Std Dev, Median, Q1,** and **Q3** for each variable and report the time series averages. Panel A presents the summary statistics for the longest subsample of firms. **RETURN (%)** is the percentage return, **EXRET(%)** is the percentage excess return, **IVOL(%)** is the firm's idiosyncratic volatility estimated each month from a Fama-French three-factor model using daily returns within the month. **BETA** is the stock's correlation with the market times the ratio of standard deviations of the stock and the market, following Frazzini and Pedersen (2014). **SIZE** is the firm's market capitalization. $\boldsymbol{\beta_{TED}}$, $\boldsymbol{\beta_{VOLTED}}$, $\boldsymbol{\beta_{TBILL}}$, and $\boldsymbol{\beta_{LCT}}$ are calculated as univariate a regression coefficient of the stock's monthly excess return on, respectively, TED SPREAD, volatility of TED SPREAD, the three-month US Treasury Bill rate, and leverage constraint tightness from Boguth and Simutin (2016) from a rolling window using the prior 60-month data. **MAX** is the maximum daily return in a given month following Bali et al. (2011). **Mispricing** is the mispricing score from Stambaugh, Yu, and Yuan (2012). Panel B presents summary statistics and sample period details for the visibility measures. **AdExpense** is the firm's advertising expense. **#Analyst** is the number of analyst providing an earnings estimate for the firm. **Breadth** is the ratio of the number of 13F filers that hold a long position in the stock to the total number of 13F filers in that quarter. **#InstSHs** is the firm's number of institutional shareholders. **PC** is the first principal component from a principal component analysis of AdExpense, #Analyst, Breadth, and #InstSHs, which explains more than 70% of the variation of these measures.

Panel A: Descriptive Statistics for the Full Sample (July 1971 to Dec 2016)

Variables	**Mean**	**Std Dev**	**Median**	**Q1**	**Q3**
RETURN (%)	1.205	13.124	0.374	-5.467	6.631
EXRET(%)	0.813	13.124	-0.018	-5.859	6.239
IVOL(%)	2.464	1.863	1.991	1.302	3.075
BETA	1.000	0.321	0.967	0.761	1.201
SIZE ($ mill)	2,034.861	8,910.839	218.219	55.389	929.557
β_{TED}	-0.027	0.090	-0.025	-0.070	0.016
β_{VOLTED}	-0.188	0.590	-0.171	-0.463	0.104
β_{TBILL}	0.008	0.055	0.006	-0.017	0.031
β_{LCT}	0.014	0.242	0.004	-0.106	0.122
MAX (%)	6.629	6.469	5.017	3.179	8.044
Mispricing	49.657	13.050	49.135	40.434	58.387

Panel B: Visibility Proxies						**Sample Period of Visibility**		
Variables	**Mean**	**Std Dev**	**Median**	**Q1**	**Q3**	**Time Period**	**Freq.**	**Avg. No. Firms**
AdExp ($ mill)	50.361	213.888	2.456	0.470	15.850	1976-2016	Monthly	1,289
#Analyst	7.505	7.105	4.925	2.148	10.683	1971-2016	Yearly	2,149
Breadth (%)	37.792	25.099	36.778	16.340	57.194	1980-2016	Quarterly	3,001
#InstSHs	89.895	126.054	47.877	17.782	105.042	1980-2016	Quarterly	2,891
PC	0.017	0.954	-0.243	-0.625	0.341	1980-2016	Monthly	739

Table II: Correlation Table

In this table, we report correlations for the variables of interest in our sample. **RET** is the firm's stock return. **EXRET** is the firm's stock return in excess of the risk free rate. **BETA** is the stock's correlation with the market times the ratio of standard deviations of the stock and the market, following Frazzini and Pedersen (2014). **LN(ME)** the natural logarithm of the firm's market capitalization. **IVOL** is the firm's idiosyncratic volatility estimated each month from a Fama-French three-factor model using daily returns within the month. **MAX** is the maximum daily return in a given month following Bali et al. (2011). **MISP** is Stambaugh, Yu, and Yuan (2012)'s mispricing index. $\boldsymbol{\beta_{TED}}$, $\boldsymbol{\beta_{VOLTED}}$, $\boldsymbol{\beta_{TBILL}}$, and $\boldsymbol{\beta_{LCT}}$ are calculated as univariate a regression coefficient of the stock's monthly excess return on, respectively, TED SPREAD, volatility of TED SPREAD, the three-month US Treasury Bill rate, and leverage constraint tightness from Boguth and Simutin (2016) from a rolling window using the prior 60-month data. **AdExpense** is the firm's advertising expense. **#Analyst** is the number of analyst providing an earnings estimate for the firm. **Breadth** is the ratio of the number of 13F filers that hold a long position in the stock to the total number of 13F filers in that quarter. **#InstSHs** is the firm's number of institutional shareholders. **PC** is the first principal component from a principal component analysis of **AdExpense**, **#Analyst**, **Breadth**, and **#InstSHs**, which explains more than 70% of the variation of these measures.

	RET (%)	EXRET(%)	Beta	Ln(ME)	IVOL	MAX	MISP	β_{TED}	β_{VOLTED}	β_{TBILL}	β_{LCT}	Ad Expense	#Analysts	Breadth	#InstSHs
RET (%)	1.000														
EXRET(%)	1.000	1.000													
BETA	-0.021	-0.021	1.000												
Ln(ME)	0.000	0.000	0.039	1.000											
IVOL	-0.032	-0.032	0.229	-0.137	1.000										
MAX	-0.035	-0.035	0.199	-0.097	0.883	1.000									
MISP	-0.041	-0.041	0.107	-0.102	0.156	0.110	1.000								
β_{TED}	0.000	0.000	-0.026	0.041	-0.087	-0.067	-0.033	1.000							
β_{VOLTED}	-0.001	-0.001	-0.022	0.040	-0.111	-0.091	-0.009	0.597	1.000						
β_{TBILL}	0.005	0.005	-0.013	0.032	-0.074	-0.068	0.013	0.307	0.203	1.000					
β_{LCT}	-0.010	-0.010	0.079	0.008	0.019	0.016	0.021	0.051	0.090	0.130	1.000				
AdExpense	0.001	0.001	0.037	0.676	-0.154	-0.114	-0.130	0.036	0.031	0.044	-0.005	1.000			
#Analysts	-0.005	-0.005	0.156	0.478	-0.259	-0.190	-0.096	0.058	0.074	0.062	0.027	0.455	1.000		
Breadth	0.009	0.009	0.297	0.161	-0.294	-0.216	-0.118	0.064	0.092	0.060	0.009	0.198	0.458	1.000	
#InstSHs	0.005	0.005	0.163	0.759	-0.271	-0.196	-0.168	0.075	0.087	0.064	0.018	0.678	0.784	0.476	1.000
PC	0.005	0.005	0.164	0.721	-0.295	-0.212	-0.238	0.078	0.083	0.071	0.004	0.720	0.887	0.578	0.929

Table III: Betting-Against-Beta in Our Samples

The table reports value weighted beta-neutral portfolio excess returns created from a univariate quintile sort by market beta. To construct the table, each month, we sort stocks into quintiles based on the firm's market beta in month $t-1$. We then form value weighted beta-neutral portfolio excess returns for each quintile. Results are qualitatively similar when we use equal weighting scheme. The last column "Low - High" presents the difference in beta-neutral low beta minus high beta excess returns (i.e. BAB returns). Because the sample periods for the variables measuring visibility start from different time periods and cover different (but partially overlapping) firms, we report results for the four visibility samples, and for the overlapping sample used to form the principal component (PC) measure. **#Analyst** is a sample restricted by the availability of number of analyst who provide earnings estimate in the IBES database. **AdExpense** is a sample restricted by the availability of an advertising expense as reported in the COMPUSTAT database. **Breadth** is a sample restricted by the availability of breadth defined as the ratio of the number of 13F filers that hold a long position in the stock to the total number of 13F filers in that quarter. **#InstSHs** is a sample restricted by the availability of the firm's number of shareholders in CRSP. **PC** is the sample restricted by the availability of all four of the visibility measures noted above. **BETA** is the stock's correlation with the market times the ratio of standard deviations of the stock and the market, following Frazzini and Pedersen (2014). *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Newey-West corrected t-statistics (using 6 lags) are in parenthesis.

	The Samples	Low Beta	2	3	4	High Beta	Low - High
(1)	#Analysts	1.53	1.30	1.03	0.91	0.62	0.91***
		(6.30)	(6.50)	(4.87)	(4.18)	(2.59)	(3.49)
(2)	AdExpense	1.79	1.45	1.01	0.83	0.66	1.13***
		(6.28)	(6.08)	(4.70)	(3.98)	(3.03)	(5.03)
(3)	Breadth	1.71	1.37	1.19	0.93	0.61	1.09***
		(5.51)	(5.97)	(5.58)	(3.94)	(2.40)	(3.64)
(4)	#InstSHs	1.66	1.36	1.17	0.92	0.61	1.06***
		(5.55)	(5.97)	(5.50)	(3.90)	(2.39)	(3.55)
(5)	PC	1.76	1.31	1.14	1.00	0.65	1.11***
		(6.12)	(4.95)	(4.98)	(4.27)	(2.66)	(4.15)

Table IV: Betting-Against-Beta Portfolio Excess Returns from Bivariate Sequential Sort

The table reports value weighted beta neutral low-minus-high beta portfolio returns (i.e. BAB returns) for each of the five visibility samples. In each case, we first form a five by five portfolio (first we sort stocks based on the corresponding visibility measure into quintiles, and then, within each visibility quintile, we sort stocks based on market beta into quintiles). Then, for each visibility quintile, we report value weighted BAB returns. The last column "Low - High" presents the difference between the low visibility and high visibility BAB returns. Results are qualitatively similar when we use independent sorts or equal weighting scheme. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Newey-West corrected t-statistics (using 6 lags) are in parenthesis.

The Samples		Low Visibility	2	3	4	High Visibility	Low - High
(1)	#Analysts	1.77***	1.30***	1.19***	0.84***	0.68***	**1.09*** **
		(5.74)	(4.52)	(4.65)	(3.59)	(2.79)	**(4.18)**
(2)	AdExpense	1.90***	1.65***	1.34***	1.16***	0.63***	**1.27*** **
		(5.02)	(4.40)	(4.45)	(4.89)	(2.79)	**(3.06)**
(3)	Breadth	1.62***	1.81***	1.12***	1.09***	0.81***	**0.81** **
		(3.86)	(5.22)	(3.42)	(3.96)	(3.01)	**(2.31)**
(4)	#InstSHs	1.54***	1.82***	1.49***	1.24***	0.79***	**0.75* **
		(3.45)	(4.50)	(4.59)	(4.67)	(3.02)	**(1.88)**
(5)	PC	1.70***	1.65***	1.31***	1.05***	0.75***	**0.95** **
		(3.55)	(4.44)	(4.70)	(4.02)	(3.08)	**(2.10)**

Table V: Betting-Against-Beta Portfolio Abnormal Returns Relative to CAPM across Visibility Quintiles

The table reports value weighted beta neutral low-minus-high beta portfolio CAPM alphas (i.e. BAB CAPM alphas) for each of the five visibility samples. In each case, we first form a five by five portfolio (first we sort stocks based on the corresponding visibility measure into quintiles, and then, within each visibility quintile, we sort stocks based on market beta into quintiles). Then, for each visibility quintile, we report value weighted BAB CAPM alphas. The last column "Low - High" presents the difference between the low visibility and high visibility BAB CAPM alphas. Results are qualitatively similar when we use independent sorts or equal weighting scheme. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Newey-West corrected t-statistics (using 6 lags) are in parenthesis.

The Samples		Low Visibility	2	3	4	High Visibility	Low - High
(1)	#Analysts	1.87***	1.70***	1.41***	1.20***	0.75***	**1.13*****
		(4.96)	(4.34)	(4.43)	(4.83)	(3.17)	**(2.80)**
(2)	AdExpense	1.91***	1.47***	1.32***	1.03***	0.93***	**0.98*****
		(5.89)	(5.01)	(4.99)	(4.41)	(3.85)	**(3.86)**
(3)	Breadth	1.77***	2.03***	1.27***	1.29***	0.97***	**0.80****
		(3.97)	(5.82)	(3.74)	(4.55)	(3.61)	**(2.21)**
(4)	#InstSHs	1.68***	1.95***	1.67***	1.42***	1.03***	**0.65**
		(3.73)	(4.60)	(5.04)	(5.28)	(4.06)	**(1.64)**
(5)	PC	1.75***	1.69***	1.38***	1.18***	0.96***	**0.79***
		(3.48)	(4.19)	(4.72)	(4.41)	(3.98)	**(1.78)**

Table VI: Betting-Against-Beta Portfolio Performance Over Time

Panel A reports regression results of value weighted low-minus-high beta returns (i.e. BAB returns) and low-minus-high beta CAPM alphas (i.e. BAB CAPM alphas) on a time trend, each in percent scale. BAB CAPM alphas are from a 60-month rolling regression of the BAB return on the market factor. Results are presented using the overlapping (PC) sample, restricted by the availability of all four of the visibility measures noted above. **Time** is the number of months since the beginning of the sample period (1980) scaled by the total number of months in the sample period. **Ln(Time)** is the natural log of **Time**. Panel B reports value weighted BAB returns from a sequential sort by firm age and market beta. **Firm age** is defined as the number of months since the firm first appeared in CRSP. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Newey-West corrected t-statistics (using 6 lags) are in parenthesis.

Panel A: BAB over time

		Excess Returns	Excess Returns	CAPM Alphas	CAPM Alphas
(1)	Time	-1.57**		-2.00***	
		(-2.20)		(-9.54)	
(2)	Ln(Time)		-0.50**		-0.50***
			(-2.35)		(-6.73)
(3)	Constant	1.88***	0.61*	2.50***	1.01***
		(4.93)	(1.67)	(22.43)	(10.29)

Panel B: BAB by Firm Age

		Low Visibility	2	3	4	High Visibility	Low - High
(4)	Firm Age	1.33***	1.55***	1.10***	0.98***	0.76***	**0.57***
		(3.82)	(5.15)	(3.70)	(3.79)	(3.30)	**(1.85)**

Table VII: Time Series Regressions

This table presents time-series regressions of beta neutral low-minus high beta portfolio excess returns (i.e. BAB returns) on portfolio and aggregate market characteristics. Lambda is the cost of information acquisition, defined as in Eq. (5) and operationalized in Kadlec and McConnell (1994). Beta Spread is the scaled spread in portfolio betas, following Eq. (4). Idiosyncratic Volatility, Mispricing, and MAX are each calculated as the value-weighted average of the corresponding stock characteristic, aggregated to the portfolio level. Columns 1 and 2 present results for the unconditional BAB portfolio. Columns 3 and 4 present results from pooled time-series regressions for the five visibility-sorted BAB portfolios, and are estimated with portfolio fixed-effects and standard errors clustered by date. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

	Full Sample	Full Sample	Within Visibility Quintiles	Within Visibility Quintiles
	(1)	(2)	(3)	(4)
Lambda	**0.98****	**1.82****	**0.20*****	**2.90*****
	(2.46)	**(2.12)**	**(3.33)**	**(3.09)**
Beta Spread	1.60	2.96*	2.92**	3.40**
	(1.21)	(1.85)	(2.43)	(2.47)
Lagged BAB Return		-0.05		-0.08
		(-0.64)		(-1.36)
Lagged TED spread		-0.01		-0.02**
		(-0.89)		(-2.35)
Change in TED Spread		-0.01		-0.03**
		(-0.98)		(-2.48)
Market Return		-0.30**		-0.25***
		(-2.57)		(-3.02)
Idiosyncratic Volatility		-0.35		-1.42
		(-1.50)		(-1.08)
Mispricing		-0.01		-0.11
		(-0.06)		(-1.04)
MAX		0.74		0.26
		(1.24)		(0.71)
Fixed Effects?	No	No	Yes	Yes
Observations	438	335	2,190	1,675
R^2	1.02%	7.32%	1.61%	5.93%

Table VIII: BAB Portfolio Excess Returns Across Visibility Quintiles, Removing Relation Between Visibility and Alternate Explanatory Variables

Panel A recreates the results in Tables IV for the overlapping PC sample, after orthogonalizing the PC visibility measure to funding liquidity constraints (FL), leverage constraints (LCT), lottery-like characteristics (MAX), mispricing (MISP), idiosyncratic volatility (IVOL), firm size (SIZE), and to all of these (ALL). Specifically, we first form a five by five portfolio (first we sort stocks based on the orthogonalized PC visibility measure into quintiles, and then, within each visibility quintile, we sort stocks based on market beta into quintiles). Then, for each visibility quintile, we report value weighted beta-neutral low-minus-high beta portfolio returns (i.e. BAB returns). The last column "Low - High" presents the difference between the low visibility and high visibility BAB returns. In Panel B, we present BAB alphas relative to a conditional CAPM (Cederburg and O'Doherty, 2016) for firms sorted on the PC measure, and the PC measure othogonalized to all. Results are qualitatively similar when we use independent sorts or equal weighting scheme. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Newey-West corrected t-statistics (using 6 lags) are in parenthesis.

Panel A: BAB Excess Returns

		Low Visibility	2	3	4	High Visibility	Low - High
(1)	PC-O-FL	1.12**	1.48***	1.14***	0.75**	0.55**	**0.56**
		(1.98)	(3.27)	(3.24)	(2.44)	(2.02)	**(1.05)**
(2)	PC-O-LCT	1.76***	1.85***	1.24***	1.13***	0.76***	**1.00****
		(3.50)	(4.71)	(3.81)	(4.17)	(2.94)	**(2.05)**
(3)	PC-O-MAX	1.57***	1.43***	1.40***	0.89***	0.76***	**0.81***
		(3.56)	(4.30)	(5.25)	(3.56)	(3.05)	**(1.83)**
(4)	PC-O-IVOL	1.59***	1.55***	1.22***	0.81***	0.81***	**0.78***
		(3.63)	(4.34)	(4.60)	(3.31)	(3.40)	**(1.79)**
(5)	PC-O-MISP	1.04**	1.59***	1.16***	0.93***	0.87***	**0.16**
		(2.13)	(5.48)	(3.45)	(3.31)	(3.42)	**(0.33)**
(6)	PC-O-SIZE	2.05***	1.17***	0.97***	0.82***	0.93***	**1.12*****
		(6.31)	(3.03)	(3.32)	(3.14)	(3.07)	**(3.45)**
(7)	PC-O-ALL	1.33***	1.37***	1.10**	0.66**	0.48	**0.85***
		(2.96)	(2.84)	(2.22)	(1.98)	(1.42)	**(1.90)**

Panel B: BAB Conditional CAPM Alphas

		Low Visibility	2	3	4	High Visibility	Low - High
(8)	PC	1.70***	1.55***	1.24***	1.06***	0.85***	**0.85***
		(3.70)	(4.09)	(4.34)	(4.34)	(3.87)	**(1.66)**
(9)	PC-O-ALL	1.35***	1.23***	1.02**	0.49	0.46	**0.89**
		(3.08)	(2.89)	(2.17)	(1.54)	(1.37)	**(1.61)**

Table IX: Betting-Against-Beta Portfolio Abnormal Returns from Expanded Factor Models

This table reports beta neutral low-minus-high beta portfolio CAPM alphas (i.e. BAB CAPM alphas) for both unconditional and visibility-sorted BAB portfolios under alternate benchmark return models. FF4 denotes a Fama-French-Carhart four-factor model. FLCT is a high-minus-low return factor from a univariate sort on the sensitivity to leverage constraint tightness (β_{LCT}) defined in Table I. FMAX is the lottery preference factor created by Bali et al. (2016). IVOL is a high-minus-low return factor from a univariate sort on idiosyncratic volatility. MGMT and PERF are the mispricing factors created by Stambaugh and Yuan (2017). Panel A presents BAB alphas from multiple (reduced) benchmark models. Panel B presents BAB alphas and factor loadings for the full benchmark model. The far-right column presents the difference in alphas between BAB portfolios formed within the low and high visibility quintiles. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Alphas From Reduced Models

		Unconditional BAB	Low Visibility	2	3	4	High Visibility	Low-High Visibility
(1)	FF4	0.84***	1.28***	1.28***	0.91***	0.79***	0.61***	0.67
		(3.17)	(2.94)	(3.44)	(3.16)	(3.32)	(2.69)	(1.35)
(2)	FF4+FLCT	0.75***	1.17**	1.18***	0.78***	0.67***	0.54**	0.63
		(2.71)	(2.53)	(2.92)	(2.59)	(2.77)	(2.22)	(1.21)
(3)	FF4+FMAX	0.19	0.79**	0.67*	0.40	0.18	-0.03	0.82*
		(0.98)	(2.01)	(1.95)	(1.47)	(1.08)	(-0.19)	(1.92)
(4)	FF4+IVOL	0.37	0.94**	0.66*	0.44	0.38**	0.19	0.75
		(1.58)	(2.25)	(1.95)	(1.57)	(2.04)	(1.03)	(1.63)
(5)	FF4+MGMT+PERF	0.34	1.15**	0.75*	0.50*	0.43*	0.12	1.03**
		(1.27)	(2.48)	(1.89)	(1.82)	(1.92)	(0.57)	(2.01)
(6)	FF4+MGMT+PERF	0.21	1.05**	0.56	0.36	0.32	0.01	1.04**
	+IVOL	(0.85)	(2.31)	(1.48)	(1.28)	(1.62)	(0.05)	(2.09)

		Panel B: Full Benchmark Model						
		Unconditional BAB	Low Visibility	2	3	4	High Visibility	Low-High Visibility
(7)	**Alpha**	**0.10**	**0.92****	**0.53**	**0.29**	**0.13**	**-0.07**	**0.99****
		(0.45)	**(2.06)**	**(1.33)**	**(1.04)**	**(0.70)**	**(-0.37)**	**(2.04)**
(8)	MKTRF	0.36***	0.36***	0.51***	0.39***	0.38***	0.30***	
		(4.63)	(2.81)	(4.45)	(4.41)	(7.54)	(5.25)	
(9)	SMB	0.47***	0.20	0.18	0.38***	0.16*	-0.01	
		(3.24)	(1.36)	(0.87)	(3.09)	(1.70)	(-0.10)	
(10)	HML	0.05	0.58***	-0.12	0.27**	0.19	-0.09	
		(0.45)	(2.82)	(-0.57)	(2.25)	(1.47)	(-0.66)	
(11)	UMD	0.20***	0.23**	0.14	0.19	0.13*	0.20***	
		(3.14)	(2.46)	(1.51)	(1.28)	(1.84)	(2.71)	
(12)	FLCT	0.04	0.04	-0.21*	-0.05	-0.09	0.01	
		(0.43)	(0.28)	(-1.90)	(-0.48)	(-1.62)	(0.19)	
(13)	FMAX	-0.79***	-0.66***	-0.36*	-0.42***	-0.77***	-0.88***	
		(-8.76)	(-3.75)	(-1.90)	(-3.14)	(-5.52)	(-9.90)	
(14)	IVOL	-0.04	-0.07	-0.40***	-0.25***	0.03	0.06	
		(-0.55)	(-0.52)	(-3.04)	(-2.62)	(0.37)	(0.89)	
(15)	MGMT	0.04	-0.38*	0.08	-0.07	-0.07	0.11	
		(0.27)	(-1.70)	(0.53)	(-0.47)	(-0.62)	(0.80)	
(16)	PERF	0.10	-0.07	-0.08	0.00	0.16*	0.04	
		(1.04)	(-0.42)	(-0.46)	(0.02)	(1.75)	(0.44)	