The Unintended Impact of Academic Research on Asset Returns: The CAPM Alpha

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February 15, 2019

(First Draft: October 2017)

Abstract. This paper explores a channel whereby asset-pricing anomalies can appear as investors alter portfolios according to findings in academic research. In particular, I find that assets with low realized CAPM Alphas outperform those with high ones, but only after the CAPM's publication in the 1960s. In a multifactor world the CAPM is misspecified. Then, its widespread application and the multifactor literature that followed generated incentives for fund managers to tilt portfolios systematically away from low CAPM Alpha assets, causing such assets to be undervalued. My results also provide an alternative explanation for existing anomalies based on past return patterns.

Keywords. capital asset pricing model, alpha, benchmarking, mutual funds, smart beta, anomalies.

JEL classification. G10, G12.

*I thank Henrik Cronqvist, Andrew Karolyi, Rajnish Mehra, Salvador Ortigueira, Markus Pelger, Fabricio Perez, Manuel Santos, Jun Tu (discussant), Aurelio Vasquez, and audiences at Wilfrid Laurier University, University of Miami, ITAM, the 2018 Frontier of Factor Investing Conference, the 2018 Citi Quant Conference, the 2018 China International Conference in Finance, and the 2018 European Economic Association Meeting for their helpful comments and suggestions.

1 Introduction

The Capital Asset Pricing Model (henceforth CAPM) developed by Treynor (1962), Sharpe (1964), Lintner (1965), and Mossin (1966) is arguably the most influential model in financial economics. For decades the CAPM has been the building block of finance and business courses, for both undergraduate and graduate students. It still is. Additionally, the asset management industry is comprised of highly specialized individuals, most of them having taken or taught finance courses built on the CAPM. Furthermore, these individuals in the United States are expected to have a thorough understanding of the CAPM, as they are required to take specialized exams provided by the Financial Industry Regulatory Authority.[1] Many financial analysts even take additional exams like the ones provided by the CFA Institute to either signal competence or because they are required by their employers. These exams also require knowledge about the CAPM.[2] Notably, most performance metrics used to evaluate portfolio managers are based on the CAPM. For example, since the seminal paper by Jensen (1968), academics as well as practitioners evaluate the performance of a managed portfolio by its CAPM Alpha. As such, it should not be surprising that knowledge about the CAPM that has spread from academia to the practitioner's world influences portfolio managers' decisions.

The CAPM is a single factor model where all systematic risk is captured by the Market portfolio (henceforth MKT). Unfortunately, in a multifactor world, the CAPM is misspecified, as an extremely large and still growing body of literature documents the existence of multiple factors.[3] This literature shows that the CAPM Alpha can be explained by common risk factors missed by the CAPM's MKT. In this paper I will call any factor other than MKT a *Smart Beta factor*. Performance metrics based on the CAPM generate incentives to avoid buying assets that might generate a negative CAPM Alpha. Therefore, I argue that portfolio managers have a reason to tilt their portfolios away from low CAPM Alpha/Smart Beta assets. I find evidence that this is the case in the data. This in turn creates an anomaly consistent with these low CAPM Alpha/Smart Beta assets being undervalued. I also analyze two other reasons that are consistent with individuals shifting portfolios away from

[1] See http://www.finra.org/industry/qualification-exams.

[2] See https://www.cfainstitute.org/en/programs/cfa/exam.

[3] The theoretical support for the existence of multiple risk factors appeared almost at the same time as the CAPM (e.g., Merton 1972, Ross 1976). Since then, hundreds of factors have been proposed in the literature. For example, Harvey et al. (2016) categorized 314 factors from 311 different papers published in top-tier finance journals and working papers between 1967 and 2014 that generate positive CAPM Alphas.

low CAPM Alpha/Smart Beta assets: Leverage-constraints and overreaction.

More precisely, when I sort US stocks by their realized CAPM Alphas, I find that assets with low alphas have higher ex-post average returns and Sharpe Ratios than assets having high alphas. Moreover, portfolios containing low realized alphas generate positive and statistically significant future alphas when controlling for several benchmark models like the Fama-French Six Factor model (FF6, 2018) augmented with the Long-Term and Short-Term reversal factors. To better capture this reversal pattern, I construct a long-short strategy I call *betting against alpha* (henceforth BAA). This strategy consists of buying a portfolio of low alpha assets and selling a portfolio of high alpha assets.

Interestingly, before the development of the CAPM, there is no difference in performance between the low and high alpha assets. Only after the CAPM was developed in the 1960s did the use of alpha as a performance metric became pervasive, especially after the seminal paper by Jensen (1968). I find that it is only after the CAPM's development that the portfolio of low alpha assets begins to outperform that of high alpha assets. In addition, the differential performance between the two portfolios further increases after the popularization of Smart Beta strategies, which where developed to precisely capture CAPM Alpha.

Consistent with the previous discussion, I find that the BAA strategy's performance can be divided into three clearly distinguishable periods: (i) *The Pre-CAPM era* (before 1965): BAA's cumulative abnormal returns (CAR) generated from the 1930s until 1965 are negligible, (ii) *the CAPM era* (1965-1992): BAA consistently generated positive abnormal returns, and (iii) *the Smart Beta era* (1993 onward): the growth rate of the CAR series generated by BAA further increased with respect to the previous era. This can be clearly seen in Figure 1, which depicts the monthly CAPM's CAR of the BAA strategy calculated using a 5-year rolling regression starting in January 1932 and finishing in December 2015. The dotted line shows the linear trend of the CAR series within each era.

[Insert Figure 1 around here]

Note that the Smart Beta era coincides with the expansion of factor investing as a method for portfolio allocation, for which the seminal papers of Fama and French (1992, 1993) and Jegadeesh

and Titman (1993) undoubtedly played an important role (Dimson et al. 2017).[4]

The CAPM's alpha estimated in a regression setup corresponds to the part of the average return left unexplained by the CAPM model. Then, it is expected that the reversal in alpha I document is at least partially related to anomalies based on past price patterns, like for example the long-term price reversal (LTR) documented by De Bondt and Thaler (1985), which has been attributed to overreaction. However, the overreaction hypothesis cannot fully explain the empirical finding presented in this paper, since my analysis starts in the 1930s but alpha reversal does not appear until the mid 1960s. Additionally, LTR does not perform well before the development of the CAPM either. It is only after the publication of the CAPM that both strategies, BAA and LTR, produce abnormal returns that cannot be accounted for by the CAPM model. Then, this paper not only suggests a new channel whereby anomalies can appear but also provides a complementary explanation for the findings in De Bondt and Thaler (1985) and the related literature that followed. Importantly, I show in this paper that the information contained in LTR does not subsume that in alpha reversal, meaning that reversal in alpha captures relevant information about the cross-section of stock returns that is not contained in LTR.

Can the performance of BAA be linked to the popularity of the CAPM? To investigate this possibility, I calculate the yearly number of academic works containing the phrase "Capital Asset Pricing Model." Consistent with the hypothesis that the performance of BAA is linked to the CAPM's popularity, I find that the rate at which new academic work about the CAPM appears has a trend similar to that of the BAA strategy's CAR: Both increase at a steady pace during the CAPM era and much faster during the Smart Beta era. Furthermore, I find that after 1992 there is a sharp increase in the yearly quantities of academic work produced containing the following three phrases: (i) *Capital Asset Pricing Model*, (ii) *Arbitrage Pricing Theory*, and (iii) *Capital Asset Pricing Model* plus either the words *Anomaly* or *Anomalies*. It seems that the more research that the CAPM model (and its anomalies) attracts, the faster the growth in the CAR series of the BAA strategy. Chordia et al. (2013) and McLean and Pontiff (2016) showed that academic research diminishes or even

[4]There is an upward trend in the CAR series between 1942 and 1953. This trend disappears if we augment the empirical CAPM with the HML factor, suggesting that assets with a high HML beta might have been overvalued in that period. This is consistent with my assumptions and the fact that the Value Premium was known before the development of the CAPM (e.g., Graham and Dodd 1934).

eliminates the predictive power of certain anomalies. My results suggest that academic research might also feed new ones.

The abnormal returns generated by the BAA strategy prior to the CAPM development are close to zero and insignificant. Given that BAA is not pervasive throughout the period of analysis, I called it a "strategy" instead of a factor. Campbell and Vuolteenaho (2004) and Ang and Chen (2007) found that the CAPM worked better before it was published than afterwards, especially for explaining the Value Premium. Interestingly, I find that the CAPM started to correctly price the Value Premium and other factors again during the Smart Beta era (from 1993 onward). Therefore, my results are not driven by overall differential performance of the CAPM through time.

The literature that studies whether fund managers incorporate information about known anomalies in their trades has so far reached ambiguous results. For example, Calluzo et al. (2018) find that institutional investors load in the long arm of an anomaly after it is published in academia, while Edelen et al. (2016) find that institutional investors hold the short-arm of the anomalies. My results are closer to those in Calluzo et al. (2018) but differ methodologically from both aforementioned papers. My paper is based on the estimated CAPM's pricing error to determine whether an asset is overvalued/undervalued, while the other papers focus on the value of some firm characteristic for that assessment. For example, if an asset held by an institutional investor has a relatively low Book to Market value, then the other papers consider that the investor holds an overvalued asset according to that characteristic. Even assuming that an asset with a relatively low Book to Market value has a low Smart Beta value with respect to the value premium factor, that does not imply that the asset has a relatively low CAPM Alpha. This is because in a multifactor world the estimated CAPM Alpha is a linear combination of the asset's Smart Betas times the corresponding Smart Beta factors' risk premiums, not the asset's sensitivity to a single Smart Beta factor. Therefore, my findings are not inconsistent with observing good performance of some Smart Beta strategies individually. In other words, the assets that drive my results need to have a very high or a very low sensitivity to multiple Smart Beta factors simultaneously.[5]

[5]There is an ongoing important debate on whether covariances or characteristics drive stock returns. A recent example on this topic is Kelly et al. (2018). In this paper I abstract from this debate since my assumption, that the widespread use of the CAPM leads to undervaluing low alpha assets, is based on models highlighting the role of covariances.

Finally, my results can explain other interesting patterns. For example, both the low and high alpha portfolios have larger than average volatility. Brunnermeier and Pedersen (2009) showed that the impact of tightening funding conditions is more pronounced in more volatile assets, which require higher margins. Therefore, their result can explain why both portfolios are sensitive to funding liquidity shocks. However, I find that the economic magnitude of funding liquidity shocks is twice as large for the low alpha portfolio than for the high alpha one, despite both portfolios having volatilities of very similar magnitude. This seemingly puzzling result can be rationalized by my hypothesis that the widespread application of the CAPM generated incentives to tilt portfolios away from low alpha assets: In bad times, low alpha assets that are perceived as less desirable and are more prone to be sold command a higher premium. Then, in the long-term these low alpha assets should provide higher expected returns than the high alpha ones. While traditional risk-based models are unable to explain the positive risk-premium of the BAA strategy after the CAPM's development based on the low and high alpha assets' risk profile, the hypotheses developed in this paper can.

The rest of the paper is organized as follows. I discuss the economic channels driving the documented alpha reversal patterns in Section 2 . Then I present in Section 3 the data and detail the construction of the tradable strategy design to capture the alpha reversal patterns: BAA. I study in Section 4 the performance of the BAA strategy before and after the publication of the CAPM. I empirically test the economic drivers of alpha reversal as well as its relationship with LTR in Section 5. I conclude in Section 6. The Online Appendix contains additional robustness checks and analyses.

2 Rationalizing the CAPM Alpha reversal patterns

The CAPM was the first equilibrium model to coherently explain the assets' risk-return relationship. According to the CAPM, in equilibrium all assets should have zero alpha. Then, assets with a negative alpha are overvalued with respect to their equilibrium price while assets with a positive alpha are undervalued. Therefore, a portfolio of low alpha assets should be overvalued relative to a portfolio containing high alpha assets. I find that the opposite holds in real data after the CAPM was developed. Given this counter-intuitive finding, it is important to rationalize why this pattern

might appear. For simplicity, let's assume that assets' returns in equilibrium are generated according to a multifactor asset pricing model with k orthogonal factors, including the CAPM's factor, MKT. Then, the expected excess return of an asset i can be described by the following pricing equation:

$$E(r_i - r_f) = \beta_{MKT,i}\gamma_{MKT} + B'_{Smart,i}\Gamma_{Smart}, \tag{1}$$

where r_i is the return on asset i, r_f is the risk-free return, $\beta_{MKT,i}$ is the MKT beta of asset i, γ_{MKT} is the MKT risk premium, $B_{Smart,i}$ is a $(k-1)$ vector of *Smart Beta factors' betas* (henceforth Smart Betas) of asset i, and Γ_{Smart} is a $(k-1)$ vector of Smart Beta factors' risk premiums.[6] If we use the CAPM for asset pricing — a misspecified model under the multifactor assumption — then the expected value of the estimated parameter for the pricing error of an asset i is

$$E\left(\hat{\alpha}_i^{CAPM}\right) = B'_{Smart,i}\Gamma_{Smart}. \tag{2}$$

Consistent with the previous discussion, I found in the literature at least three possible explanations regarding why assets with a low $\hat{\alpha}_i^{CAPM}$ could systematically outperform assets with a high one.

Hypothesis 1: Incentives to bid up high CAPM Alpha assets related to performance metrics.

(a) Non-Market Betas interpreted as CAPM Alpha: Barber et al. (2016) show that when evaluating a mutual fund's performance, investors act as if the CAPM is the relevant model, rewarding mutual funds with positive CAPM Alpha by increasing the flow of funds toward them. Agarwal et al. (2017) reach a similar conclusion when they analyze hedge fund flows. According to equation (2), their finding implies that an asset with a high (low) combination of Smart Betas is interpreted by investors as an asset having a high (low) CAPM Alpha. Consequently, fund managers might have incentives to tilt their portfolios toward assets with high CAPM Alpha/Smart Betas to signal

[6]For example, if asset prices were generated according to FF6, then Γ_{Smart} would contain the risk premiums of the SMB, HML, RMW, CMA, and Momentum factors.

superior performance and increase the flow of capital toward their funds.

(b) Benchmarking: The large body of empirical and theoretical literature on benchmarking attests to the fact that mutual fund managers have incentives to tilt their portfolios toward high MKT beta stocks, even if these assets are overpriced (e.g., Karceski 2002). Baker et al. (2011) argued that "a typical contract for institutional equity management contains an implicit or explicit mandate to maximize the *information ratio* relative to a specific, fixed capitalization-weighted benchmark without using leverage. For example, if the benchmark is the S&P 500 Index, the numerator of the information ratio (IR) is the expected difference between the return earned by the investment manager and the return on the S&P 500. The denominator is the volatility of these returns' difference, also called the tracking error." More specifically, suppose that R_A represents the returns on an active portfolio while R_{MKT} represents the returns on an index used as a benchmark. Then, the information ratio of the active portfolio is

$$IR_A = \frac{E(R_A - R_{MKT})}{\sigma_{(R_A - R_{MKT})}}. \tag{3}$$

Note that given equation (1), in a multifactor world the numerator of IR_A is $B'_{Smart,A}\Gamma_{Smart} + (\beta_{MKT,A} - 1)\gamma_{MKT}$. It follows that controlling for the MKT beta and tracking error, assets with a high combination of Smart Beta, and thus a higher CAPM Alpha, will increase the numerator of the IR. Then, benchmarked fund managers also have incentives to tilt their portfolio toward assets with high CAPM Alpha/Smart Betas.

Hypothesis 2: Incentives to bid up high CAPM Alpha assets because of leverage constraints.

Frazzini and Pedersen (2014) show theoretically that leverage-constrained investors bid up high MKT beta assets to augment the expected returns of their portfolios. Consequently, high MKT beta stocks are overpriced relative to low MKT beta stocks. These results are further corroborated by Christoffersen and Simutin (2017). However, if leverage-constrained investors know that expected returns are generated by a multifactor model like the one described in equation (1), then they also have incentives to bid up assets with high Smart Betas to augment expected returns. Therefore, according to equation (2), this is equivalent to bidding up assets with a high $\hat{\alpha}_i^{CAPM}$.

Hypothesis 3: Overreaction.

De Bondt and Thaler (1985) documented that past long-term winners underperform past long-term losers. They attribute this result to investors overreacting to extreme price changes. The literature provides several behavioral explanations for the observed overreaction based on how investors form beliefs when new information is available as well as on how they extrapolate past prices into the future. Theoretical foundations on the drivers of long-term overreaction and short-term underreaction can be found in Barberis et. al (1998), Hong and Stein (1999), and more recently Barberis et. al (2015). Similarly, investors chasing alpha might also overreact to extreme values of realized alphas, leading to the alpha reversal phenomenon documented in this paper.[7] However, as I will show throughout the paper, the overreaction hypothesis can not fully explain alpha reversal, since my empirical analysis starts in the 1930s and alpha reversal does not show up until the CAPM was developed in the mid 1960s. Therefore, we have a period of 30 years in which overreaction is not present in alphas. In fact, long-term price reversal does not seem to work well until the mid-1960s either. As such, this paper not only suggests a new channel for anomalies to appear but also provides a complementary explanation to the overreaction literature.

I test the previous three hypotheses in US stock returns data in Section 5. Regarding fund managers' trading behavior, I find that they trade not only high beta assets but also high alpha assets, and the assets they sell have, on average, a lower CAPM Alpha than the assets they buy (Section 5.1), which supports Hypothesis 1. I also find that alpha reversal is related to changes in funding liquidity conditions (Section 5.2), which supports Hypothesis 2. With respect to the overreaction hypothesis, I find that there are commonalities between alpha reversal and price reversal. Importantly, in Section 5.3 I also find that there is information in alpha reversal about the cross-section of stock returns not contained in long-term price reversal. To sum up, the empirical observation that assets with a low $\hat{\alpha}_i^{CAPM}$ outperform those with a high one originates from a combination of economic incentives that arose with the development of the CAPM.

To finalize this Section I would like to emphasize that according to equations (1) and (2) the

[7] In this paper I use the most common time frame and frequency to estimate the parameters of the CAPM: 5 years of monthly data returns (e.g., Black et al. 1972, Banz 1981, Fama-French 1992, 1993, 2018 just to mention some). Hühn and Scholz (2018) use one year of daily data to estimate the CAPM parameters and find that there is momentum in alpha. Their results are consistent with short-term underreaction.

estimated CAPM Alpha is a linear combination of an asset's vector of Smart Beta factor loadings multiplied by the vector of Smart Beta factors' risk premiums. Therefore, BAA is not inconsistent with observing good performance of individual Smart Beta strategies. As such, this paper does not contradict results that show good predictive power of strategies based on extreme values of a single Smart Beta.

3 Data and construction of the Betting Against Alpha strategy

3.1 Data

I use data on US individual stock returns from the Center for Research in Security Prices (CRSP) from January 1927 until December 2015. The returns include dividends and correspond to common stocks traded on the NYSE, NASDAQ, and AMEX, excluding REITs and ADRs. Data on the factors used in the benchmark models are from Kenneth French's website except for the Betting Against Beta factor (BAB) that is from AQR's webpage.[8,9] The models I used to control for common risk are the CAPM, Carhart model (1997), Fama-French Six Factor model (FF6, 2018), FF6 augmented with reversal factors (FF6+REV) and FF6+REV augmented with the Betting Against Beta factor (FF6+REV+BAB). The CAPM contains only the Market factor (the return on the CRSP value-weighted portfolio minus the return on the 1-month Treasury bill). The Carhart model augments the CAPM with the Small Minus Big factor (SMB), High Minus Low factor (HML), and the Momentum factor (MOM, which consists of selling losers and buying winners from the prior 6 to 12 months). The FF6 model augments Carhart's model with the Robust Minus Weak (RMW) and Conservative Minus Aggressive (CMA) factors.[10] The FF6+REV model augments FF6 with the Long-term Reversal factor (LTR, which consists of buying losers and selling winners from the prior 13 to 60 months) and the Short-term Reversal factor (STR, which consists of buying losers and selling winners from the prior month).

[8] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[9] https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly

[10] For a detailed explanation on how SMB, HML, RMW, and CMA are constructed, please see Fama and French (2018).

3.2 Construction of the Betting Against Alpha strategy

The Betting Against Alpha strategy (BAA) consists of selling a portfolio made of high CAPM Alpha stocks and buying a portfolio made of low CAPM Alpha stocks. I construct this strategy following a similar technique to that of Frazzini and Pedersen (FP, 2014) that has two desirable properties for the purpose of this paper. First, it maximizes the weights of the low (high) alpha assets in the low (high) alpha portfolio. Second, it reduces the correlation between the long-short strategy and the Market factor, rendering BAA a self-financing strategy with a zero Market Beta at the moment of portfolio formation.

To construct the BAA strategy I assign assets with α_i lower (higher) than the median alpha to the low (high) alpha portfolio and weight the assets according to their rank in the portfolio. More precisely, let nl be the number of assets in the low alpha portfolio and zl^{α} be the $nl \times 1$ vector of alpha ranks (in ascending order) such that $zl_i^{\alpha} = rank(\alpha_i)$. The weight of an asset i in the low alpha portfolio is given by $wl_i^{\alpha} = (nl - zl_i^{\alpha} + 1)/\sum zl_i^{\alpha}$. Similarly, let nh be the number of assets in the high alpha portfolio and zh^{α} be the $nh \times 1$ vector of alpha ranks (in ascending order) in this portfolio, where $zh_i^{\alpha} = rank(\alpha_i)$. The weight of an asset i in the high alpha portfolio is given by $wh_i^{\alpha} = zh_i^{\alpha}/\sum zh_i^{\alpha}$. Note that $\sum wl_i^{\alpha} = \sum wh_i^{\alpha} = 1$. Figure 2 below shows graphically the relationship between the assets' alphas and their weight in the low and high alpha portfolios.

[Insert Figure 2 around here]

To assign assets to the low and high alpha portfolios I will use the estimated α_i from the CAPM model using the most common time span and frequency observed in the literature: 5 years of monthly data (e.g., Black et al. 1972; Banz 1981; Fama-French 1992, 1993, 2018). The returns of the low and high alpha portfolios are $r^{\alpha,L} = \sum wl_i^{\alpha} r_i^L$ and $r^{\alpha,H} = \sum wh_i^{\alpha} r_i^H$, respectively.

Now let's define $\beta^{\alpha,L} = \sum wl_i^{\alpha} \beta_i^M$ and $\beta^{\alpha,H} = \sum wh_i^{\alpha} \beta_i^M$, where β_i^M is the Market Beta of asset i calculated using the same CAPM regression used to calculate the α_i's.[11] To construct the BAA strategy the low and high alpha portfolios are rescaled to have a Market Beta of 1 at the moment

[11] FP use a different method to calculate β_i^M. Using their method all qualitative results in this paper remain unchanged. For ease of exposition, I decided to keep the simplest possible version of the BAA strategy in the main body of the paper. Changing the way in which the parameters are calculated, as well as the holding-period returns for example, can improve the performance of the BAA strategy (see for example Online Appendix B).

of portfolio formation. Then, the BAA strategy rebalanced yearly at the end of December – the benchmark scenario I use in this paper – is

$$r_{t+s}^{BAA} = \frac{1}{\beta_t^{\alpha,L}}(r_{t+s}^{\alpha,L} - r_{t+s}^{f}) - \frac{1}{\beta_t^{\alpha,H}}(r_{t+s}^{\alpha,H} - r_{t+s}^{f}), \tag{4}$$

where $s = 1, ..., 12$ and t corresponds to December. Interestingly, for the period of analysis (January 1932 - December 2015), $T^{-1}\sum_t \beta_t^{\alpha,L} = 1.20$ and $T^{-1}\sum_t \beta_t^{\alpha,H} = 1.19$, which implies that on average there is negligible leverage applied to the BAA strategy. It also shows, as I will corroborate in Section 4.3, that both low alpha and high alpha assets have larger than average Market Betas (and volatilities). Therefore, as I show in Section 4.3, the BAA strategy not only has very low correlation with the Market factor but also with the Betting Against Beta factor (BAB) of FP.

Finally, it is important to mention that although rescaling the portfolios has the desirable property of reducing the correlation between the BAA strategy and the Market factor, throughout the paper I will show that all results hold independently of whether I rescale the strategy or not. As such, in most Sections I will also present the results for the low and high alpha portfolios' excess returns separately, prior to multiplying them by $1/\beta^{\alpha,L}$ and $1/\beta^{\alpha,H}$. In Section 5.3 I also present the results from a BAA strategy constructed without rescaling the low and high alpha portfolios.

4 The CAPM Alpha across time

In this Section I study the performance of the BAA strategy as well as that of the low and high alpha portfolios separately between January 1932 and December 2015. Section 4.1 studies the evolution of the BAA strategy and several other factors through time to assess whether differential explanatory power of the CAPM across time can drive the results in this paper. Section 4.2 studies the evolution of the low and high alpha portfolios through time using the entire CRSP database and a reduced sample with only NYSE data. A more detailed analysis of the size effect is in the Online Appendix A. Section 4.3 presents a study of the popularity of the literature related to the CAPM to assess if the patterns observed in the BAA strategy could be related to the model's popularity across time.

Finally, Section 4.4 focuses on the period in which the alpha reversal patterns became evident (after the development of the CAPM) to assess if there is information about the cross-section of stocks returns contained in the BAA strategy that is not contained in popular benchmark models.

4.1 Factors' performances through time and the CAPM

Researchers have found that the CAPM performs better in the Pre-CAPM era than afterwards, especially for pricing the Value Premium (e.g., Campbell and Vuolteenaho 2004 and Ang and Chen 2007). To assess the impact of this reported stylized fact I will now study how well the CAPM prices the BAA strategy as well as other factors for which data is available from January 1927 until December 2015. The factors included in the analysis are BAB, SMB, HML, MOM, LTR, and STR.

The BAA strategy is constructed under the following benchmark scenario: (i) The holding period return for the BAA strategy is 12 months, where betas and alphas are estimated at the end of December. Then, portfolios are formed on the first trading day of January and maintained for 12 months until the last trading day of December. (ii) Portfolios are formed using the entire universe of the CRSP database and assets are weighted as explained in Section 3.1. (iii) The alphas used for assigning assets to the short and long portfolios and the betas used to construct the weights to scale the portfolios for the BAA strategy are estimated using the standard CAPM. (iv) The period of analysis is 1927-2015; thus, the BAA strategy spans the 1932-2015 period since the first five years of data are needed for estimating the initial realized alphas.

As a first pass to the data, Figure 3 shows the monthly cumulative abnormal returns (CAR) series for all factors when regressed against the Market factor using a 5-year rolling regression starting in January 1932 and finishing in December 2015. Panel (a) of the figure shows all the factors' CAR series across the three eras defined in the Introduction: *The Pre-CAPM era* (before 1965), *the CAPM era* (1965-1992), and *the Smart Beta era* (1993 onward). Panels (b) through (c) of Figure 3 show the CAR series generated separately during each era.

[Insert Figure 3 around here]

From Panel (a) we observe that the various factors' CAR series behaved quite differently during the three eras. Panel (b) shows that during the Pre-CAPM era BAA, SMB, HML, and LTR per-

formed quite poorly, while BAB, MOM, and STR performed quite well. In fact, in this era STR outperformed all other factors. At the same time, during the Pre-CAPM era [Panel (b)] the BAA strategy is the one that performed the worst.[12] The patterns observed during the CAPM era are quite different. As reported in the literature and shown in Panel (c), HML performed well during the CAPM era. During this era BAB and MOM were the best performer, followed closely by STR. The BAA strategy consistently produced positive abnormal returns during this era and performed as well as HML. Overall, all factors show an upward trend in their CAR series during the CAPM era, corroborating the results in Campbell and Vuolteenaho (2004) and Ang and Chen (2007) stating that the CAPM worked better before its publication than after. Interestingly, during the Smart Beta era the patterns change again. Panel (d) shows that the best overall performer of the previous two eras, STR, generated a flat CAR series during the Smart Beta era. SMB shows a similar pattern while HML shows some positive performance but lower than that of the CAPM era. In this latter era, BAA is the one that performs the best.

[Insert Table 1 around here]

This table shows the results from a CAPM regression using the seven factors of Figure 1 as response variables for the entire period and the three sub-periods of interest. Three of the seven factors present statistically significant pricing errors at the 1% level of significance during the Pre-CAPM period: MOM, BAB, and STR. During the CAPM era all the factors except SMB and LTR present statistically significant pricing errors at the 1% level of significance, while that of LTR is significant at the 5% level. This confirms that the CAPM performed better prior to 1965 as documented in previous research. However, like in the Pre-CAPM era, during the Smart Beta era only three of the seven factors present statistically significant pricing errors at the 1% level of significance: BAA, BAB, and MOM. Given these results, it is not possible to affirm that the CAPM worked better during the Pre-CAPM era than during the Smart Beta era. At the same time, the table shows that the CAPM Alpha generated by the BAA strategy is insignificant for the Pre-CAPM era, while it is statistically significant (t-stat of 3.69) and economically relevant (0.54% monthly) for

[12] In unreported results available upon request I found that during the Pre-CAPM era the BAA strategy does not generate a single pricing error statistically different from zero at the 1% level when using a 5-year rolling CAPM regression. All other factors, with different frequencies, do.

the CAPM era. The magnitude of the CAPM Alpha generated by the BAA strategy increases by more than 50% – to 0.88% monthly with a t-stat of 4.79– in the Smart Beta era with respect to the CAPM era. Therefore, the patterns observed for the BAA strategy's CAR series are not driven by the differential overall performance of the CAPM through the eras.

4.2 NYSE data and the CAPM Alpha

In this Section I study the impact of an important change that happened to the CRSP database. More precisely, the CRSP database experienced two expansions during the period of analysis. The AMEX data was incorporated in 1962 and the NASDAQ data in 1972. These expansions augmented the number of small companies in the sample, which researchers have found to be an important driver of most anomalies (e.g., Fama and French 2008). For this purpose, I will study the performance of the low and high alpha portfolios separately. Remember that these portfolios are not pre-multiplied by the beta weights $1/\beta^{\alpha,L}$ and $1/\beta^{\alpha,H}$ described in Section 3.2. Figure 3 below shows the cumulative abnormal returns (CAR) for the portfolios regressed against the Market factor using a 5-year rolling regression starting in January 1932 and finishing in December 2015. Panel (a) shows the CAR series for the low and high alpha portfolios created using the entire CRSP database while Panel (b) shows the results using only NYSE data.

[Insert Figure 4 around here]

Several interesting patterns arise from the figure across the three eras. First, during the pre-CAPM era, the CAR series for both the low and high alpha portfolios have a flat trend. Second, during the CAPM era, the CAR series of the low alpha portfolio disentangles from that of the high alpha portfolio and presents a clear upward trend, whether we use the entire CRSP database (Panel a) or just NYSE stocks (Panel b). The CAR series of the high alpha portfolio during the CAPM era remains relatively flat. Third, the magnitude of the wedge is larger when using for calculations the entire CRSP database, which implies that the size effect is relevant for the BAA strategy, but does not subsume it as it is still present in the NYSE data. I discuss again the impact of size on the alpha portfolios and the BAA strategy in Section 4.3 and perform a detailed analysis in Online Appendix A. Fourth and finally, the wedge between the portfolios' CAR series increases even more

during the Smart Beta era.

Overall, the patterns observed in the BAA strategies are also present in the low alpha and high alpha portfolios separately. Most of the alpha reversal effect is captured by the low alpha portfolio, which contains the assets neglected by fund managers according to the hypotheses presented in Section 2 and corroborated later in Section 5.1. Finally, the patterns remain if I use only NYSE data to construct the portfolios.

4.3 The CAPM Alpha eras and the CAPM literature

In the previous sections I analyzed the performance of the BAA strategy during the three eras described in the Introduction. In this Section, I will analyze the BAA strategy's performance in relation to the popularity of the CAPM literature, which I propose to measure by the yearly quantity of scientific output related to it.

The beginning of the CAPM era coincides with the theoretical development of the model in the mid-1960s (e.g., Sharpe 1964, Lintner 1965, Mossin 1966). The starting point of the Smart Beta era coincides with the publication of the seminal papers by Fama and French (1992, 1993) and Jeegadesh and Titman (1993), which lead to a substantial expansion in the research for new Smart Beta factors as well as to an expansion in the application of factor investing in the practitioners' world (Dimson et al. 2017).

Now I will show that the performance of the BAA strategy can be linked to the popularity of the CAPM in the academic literature, which undoubtedly spread to the practitioners' world as it became the benchmark model to evaluate fund managers' performances (e.g., Jensen 1968, Baker et al. 2011, Barber et al. 2016). To capture the popularity of the CAPM in the academic literature, I count the yearly number of scholarly works produced that contain the phrase "Capital Asset Pricing Model" between 1956 and 2008 using the Google Scholar search engine.[13] I restrict the sample to academic works having at least one citation according to the search engine. Figure 5 shows the yearly number of works containing this phrase (solid line) as well as a linear trend calculated separately for the three different eras (dotted line).

[13]See Online Appendix C for a detailed explanation on how the calculations were done.

[Insert Figure 5 around here]

The Figure shows that during the CAPM era (1965-1992) the yearly number of new works with at least one citation containing the phrase "Capital Asset Pricing Models" increased from 4 to 484. After 1992 the trend increases and by 2008 there were almost 1000 new yearly works related to the CAPM.

Restricting the analysis to works published with the words "Capital Asset Pricing Model" might omit other important literature related to the drivers of BAA. Therefore, I will now analyze the popularity of the multifactor asset pricing model's literature, which supports the existence of Smart Beta factors. For this purpose, in Panel (a) of Figure 6 I plot the number of scholarly works with at least one citation in Google Scholar when searching for the phrase "Arbitrage Pricing Theory," as well as its trend. Unsurprisingly, the number starts to increase after the publication of Ross's seminal paper in 1976. As with the CAPM case, the trend becomes much steeper during the Smart Beta era. A similar pattern can be observed when searching for academic works with the phrase "Capital Asset Pricing Model" with the added condition that at least one of the following two words should also appear in the publication: "Anomaly" or "Anomalies." The results are shown in Panel (b) of Figure 6. Between 1980 and 1992 the number of yearly works produced containing these words increased from 5 to 97. By the year 2008 there were already 407 new works produced yearly. Thus, the upward trend appears during the CAPM era and becomes much steeper during the Smart Beta era.

[Insert Figure 6 around here]

The trend of the BAA strategy's CAR series is strikingly similar to those of the variables used to capture the popularity of the CAPM, multifactor asset pricing models, and the CAPM anomalies literature: All of them have an upward trend during the CAPM era and show sharp breaks at the beginning of the Smart Beta era. Overall, these results suggest that popular academic research might have a non-negligible impact on the financial markets in a way not documented before. Previous work showed that academic research reduces or even eliminates the predictive power of certain anomalies (Chordia et al. 2013 and McLean and Pontiff 2016). My results suggest that academic research can also originate new anomalies.

4.4 The CAPM Alpha after the Pre-CAPM era

It is clear from sections 4.1 and 4.2 that the BAA strategy did not perform well during the Pre-CAPM era (1932-1965) but did afterwards. In this Section I will assess the economic magnitude of BAA's performance after 1968, the year in which alpha was suggested as a performance metric (Jensen 1968). Therefore, in this Section I construct the BAA strategy using data from January 1968 until December 2015. Since five years of data are needed for estimating the initial realized alphas and betas, the first observation for the BAA strategy corresponds to January 1973.

It is important to remember that the main objective of this paper is to analyze a new channel that might feed new anomalies: The dissemination of academic knowledge. It is in that spirit that I suggest the reader to consider Section 4.4 as simply robustness checks. Further robustness checks are available in the Online Appendix.

I start the analysis by showing in Table 2 the summary statistics for the excess return of the low alpha portfolio over the risk free asset, excess return of the high alpha portfolio over the risk free asset, and the BAA strategy. While the BAA strategy is constructed using scaled portfolio returns, the results for the individual low and high alpha portfolios show the performance metrics on the unscaled returns. I report the monthly Sharpe Ratios, average monthly excess return, monthly CAPM Alpha, monthly Carhart alpha, monthly FF6 alpha, monthly FF6+Rev alpha, and monthly FF6+Rev+BAB alpha.[14] The final line of the table reports the average market capitalization of the weighted portfolios in thousands of 2010 US dollars (Size) at the time of rebalancing. Heteroskedastic robust t-statistics are in parenthesis below each model's estimated alpha.

[Insert Table 2 around here]

The first line of Table 2 shows that the Sharpe Ratio decreases when we move from the low to the high portfolio. The BAA strategy's monthly Sharpe Ratio is 0.22. It has a higher monthly Sharpe Ratio than the Market (0.11), SMB (0.07), HML (0.12), RMW (0.11), CMA (0.17), MOM (0.16), LTR (0.10), and STR (0.13) factors. The only factor with a higher monthly Sharpe Ratio than the BAA strategy is BAB (0.25).

[14] To avoid aggregation issues, I do not annualize the estimated monthly Sharpe Ratios (see Lo 2002).

The BAA strategy produces abnormal returns across all models used to control for systematic risk, with t-statistics easily surpassing the hurdle of 3.0 suggested by Harvey et al. (2016). So does the (unscaled) portfolio of low alpha assets while the portfolio of high alpha assets seems correctly priced by all models. The latter is expected given the results in Section 4.2 (see Figure 4). Additionally, in the Online Appendix D I used the rank estimation method developed in Ahn et al. (2018) to further corroborate that the BAA strategy captures information about the cross-section of stock returns missed by the other factors.

I now analyze the correlation between BAA and the factors used to control for systematic risk in this paper (Market, SMB, HML, RMW, CMA, MOM, LTR, STR, and BAB factors). Results are shown in Table 3.

[Insert Table 3 around here]

The Pearson's correlation coefficient (henceforth correlation) between the BAA strategy and the Market factor is only -0.08 as expected by the factor's construction. Interestingly, the BAA correlation with the BAB factors is quite low too, only 0.06, which implies that betting against alpha is not the same as betting against beta. Note that the correlation between BAA and LTR is quite high (0.53), suggesting that there are commonalities between alpha reversal and price reversal. I will explore the relationship between these two patterns in depth in Section 5.3.

Finally, Table 4 presents performance metrics for the dataset divided into decile portfolios sorted on realized CAPM Alphas. Assets within each portfolio are equally weighted.

[Insert Table 4 around here]

The first two lines of the table show that Sharpe Ratios and excess returns decrease in alpha. The last column of the table shows the results from using a low minus high strategy corresponding to using only the highest and lowest decile portfolios.[15] As expected, the ninth line of the table shows that Average Realized CAPM Alpha increases for portfolios sorted by this variable. Additionally, the third to fifth lines of the table show that the portfolios' alphas with respect to the benchmark

[15]Note that here the long-short strategies use only the largest and smallest decile portfolios (20% of the available stock returns data). See Section 5.3 for the results of the long-short strategy using the same alpha portfolios as in BAA but without being rescaled.

models are decreasing in assets sorted in ascending order by realized CAPM Alpha. Then, a low realized CAPM Alpha implies a future high alpha.

Lines seven and eight show that the relationship between realized alphas and volatility presents a U-shape, suggesting that reversal in alpha is not related to the low-volatility anomaly. The relationship between realized alpha and realized beta is also U-shaped as shown in line ten. This result further corroborates the result on Table 3 showing that betting against alpha is not the same as betting against beta.

Finally, the last line of the table shows that the relationship between market capitalization (Size) and Average Realized CAPM Alpha has an inverted U-shape. Thus, as confirmed in Online Appendix A, removing small stocks from the sample negatively impacts the performance metrics of the BAA strategy since it is equivalent to removing assets from both extreme decile portfolios. Additionally, this inverted U-shape between market capitalization and realized alpha implies that using value-weighted portfolios to construct the strategy should have a negative impact on its performance metrics too: While the BAA strategy should overweigh the assets in the extreme range of the alpha values, a value-weighted version would overweight the assets in the middle of the range. According to Hypothesis 1 to 3, the assets in the middle of the range – those with intermediate values of alpha – are not the ones driving alpha reversal. Thus, a strategy constructed using value-weighted portfolios will overweight alphas close to zero, which is exactly the opposite of what my assumptions suggest.[16]

5 Empirical analysis of the economic channels driving the CAPM Alpha reversal patterns

In this section I empirically test the three hypotheses suggested in Section 2 as economic drivers of the BAA strategy. First, I check in Section 5.1 if fund managers' trading behavior is consistent with Hypothesis 1, which suggests that institutional investors have incentives to tilt their portfolios

[16] As explained in this paragraph, using value-weighted portfolios or any other type of weights violates the strategy's premises of overweighting low alpha assets in the low alpha portfolio, while underweighting this type of asset in the high alpha portfolio. Thus, results with equally-weighted (or value-weighted) portfolios should be considered of second order importance. Studying the impact of size is important, but should be performed taking into account the strategy's premises. This can be done by studying the performance of the strategies across sets of assets belonging to different market capitalization ranges, which I do in the Online Appendix A.

toward high CAPM Alpha assets and away from low alpha ones. Then I study in Section 5.2 if alpha reversal is related to funding liquidity shocks as suggested by Hypothesis 2. Finally, I explore Hypothesis 3 in Section 5.3 by studying in depth the relationship between alpha reversal and long-term price reversal.

5.1 The CAPM Alpha and mutual fund trading

In this Section I study if the trading behavior of mutual funds is consistent with the hypotheses stated in Section 2 suggesting that managers have incentives to tilt their portfolios toward assets with a high CAPM Alpha. Recent research shows that managers have incentives to tilt their assets toward high Market Betas (e.g., Christoffersen and Simutin 2017), however, this is the first paper suggesting that managers also have incentives to tilt their portfolios toward high CAPM Alphas. Note that the empirical implications of Hypothesis 1 about managers' behaviors should hold independently of whether they face leverage constraints or not. I analyze the impact of changing funding liquidity conditions in the next Section.

I obtain the change in mutual funds' holdings from the Thomson-Reuters Mutual Fund Ownership database. This database provides quarterly data on all funds' holdings since 2003 and at a more sparse holding period for some funds since 1980. Following the cleaning process suggested by Kacperczyk et al. (2008), I exclude transaction data for all non-equity funds from my sample. For each asset bought or sold by mutual fund managers I retrieve the CAPM Alphas and betas from the Beta Suite by WRDS, where these metrics are calculated using 60 months of consecutive data. I also calculate the prior 13- to 60-month returns and the posterior cumulative 12 months returns using the CRSP database. The results are presented in Table 5 below. The column Selling Portfolio shows the average CAPM Alpha, average CAPM beta, average prior 13- to 60-month returns, and average posterior cumulative 12 month returns for the assets sold by the mutual funds. The column Buying Portfolio shows the metrics for the assets bought by mutual funds. The column CRSP database shows the average value for the alphas and betas in the CRSP database for the period 1980-2015.

[Insert Table 5 around here]

The results for Avg. Alpha corroborate what is stated in the hypotheses: Mutual fund managers

buy stocks with larger (monthly) realized CAPM Alpha (0.72%) than those sold (0.52%). In fact, the average alpha of stocks bought and sold is higher than the average alpha of all the available stocks in the market (0.46%). Therefore, mutual fund transactions seem dominated by assets with larger than average alphas.

The results for Avg. Beta corroborate prior findings in the literature: Mutual funds tend to buy stocks with higher CAPM beta (1.09) than those sold (1.05). Similar to the alpha case, mutual fund transactions are dominated by stocks with a larger than average Market Beta (1.00). Results for Avg. monthly Returns (-13 to -60 months) also confirm previous results in the literature interpreted as mutual funds' price overreaction (e.g., Brown et al. 2013): Assets bought tend to have better past performance than assets sold. Consistent with prior results in the literature, the variable Avg. cumulative returns (12-month holding period) shows that assets sold by mutual fund tend to outperform those bought by mutual fund when held for a year (e.g., Dasgupta et al. 2011).[17] Additionally, the literature on mutual funds finds that these institutional investors generally produce alphas close to zero (e.g., Barras et al. 2010). My results are coherent with this as I showed in Section 4.2 (Figure 4) and Section 4.4 (Table 2) that high alpha assets do not necessarily produce future negative performance metrics. In fact, the high alpha portfolio of the BAA strategy seems well arbitraged.

Overall, I find that mutual funds trade stocks with values of realized CAPM Alphas above market average. Additionally, assets bought by mutual fund managers have on average higher alphas than assets sold. Thus, the results in this Section show that mutual fund managers do tilt their portfolios away from low alpha assets as suggested by the hypotheses discussed in Section 2.

5.2 The CAPM Alpha and funding liquidity shocks

Hypothesis 2 in Section 2 states that funding liquidity shocks might be fueling the reversal pattern observed in alphas. To empirically test this hypothesis, I study the impact of funding liquidity shocks on the BAA strategy and the portfolios used to construct it. As a proxy for funding conditions, I use two variables. One is the TED spread (ΔTED, change in the Treasury-Eurodollar spread

[17] The difference in values between the metrics reported for the Selling Portfolio and the Buying Portfolio are all highly statistically significant, with a t-stat of 71.62 for Avg. Alpha, 32.09 for Avg. Beta, 54.23 for Avg. monthly returns (-13 to -60 months), and -14.80 for Avg. cumulative returns (12-month holding period).

from the FRED website), which was already used in Frazzini and Pedersen (FP, 2014) for the same purpose. Since ΔTED is only available starting in 1986, I also used a second variable already used in Boyson et al. (2010) that is available for the entire period after the Pre-CAPM era, the credit spread (ΔCredit, change in Baa to 10-year Constant Maturity Treasury rate from the FRED website).

Table 6 shows results using as response variables the BAA strategy as well as the low and high alpha portfolios. I add the portfolios to the analysis to study if the effect of funding liquidity shocks comes from the long or short arm of the strategy. Column (1) shows the results for the period January 1986 - December 2015 (where liquidity shocks are captured by ΔTED) while Column (2) shows the results for the period January 1972 - December 2015 (where liquidity shocks are captured by ΔCredit). I add several independent variables to the regressions to partially control for the omitted variable bias that I borrow from FP.[18] More precisely, I add the one-period lagged value of the dependent variable to account for possible short-term momentum or reversal, the lagged inflation rate to account for the possible effects of money illusion (where inflation is the yearly change in the CPI index from the FRED website), and the Market returns.

[Insert Table 6 around here]

The table shows that the BAA strategy is affected by funding liquidity shocks as predicted by Hypothesis 2 in Section 2, since both ΔTED and ΔCredit show statistically significant coefficients. Moreover, the sign of the effect coincides with the theoretical predictions by FP.[19] In addition, the table also shows that funding liquidity shocks affects negatively the returns of both, the low and high alpha portfolios, and that the effect is statistically significant. However, the economic magnitude of the effect is twice as large for the low alpha portfolios, explaining the contraction of the BAA strategy's returns in periods in which funding liquidity is tighter.

These results can be partially rationalized in the context of the theory developed by Brunnermeier and Pedersen (2009). They showed that the impact of tightening funding conditions is more

[18] While FP also control for the volatility risk premium (return on a portfolio that short-sells closest-to-the-money, next-to-expire straddles on the S&P500 index) I do not. This is because I do not have access to data on this variable for the period of analysis.

[19] FP find that in periods in which funding liquidity constraints become more binding, the returns of their BAB factor should decrease. Their result implies that ΔTED should have a negative coefficient on a strategy fueled by constrained investors bidding up high Market Beta to augment expected returns. Similarly, the returns of a strategy fueled by constrained investors bidding up high CAPM Alpha/Smart Beta to augment expected returns should also present a negative coefficient when regressed onto ΔTED (or ΔCredit).

pronounced in more volatile assets which require higher margins. Table 4 shows that low alpha stocks and high alpha stocks are both high-volatility stocks. Therefore, according to their theory, it is expected for both types of assets to be negatively impacted by funding liquidity shocks. However, what is surprising and cannot be rationalized by their theory is that the economic magnitude of funding liquidity shocks is twice as large for low alpha assets than for high alpha ones, despite both types of assets having similar volatilities – the monthly standard deviation after the Pre-CAPM era for the low and high alpha portfolio returns are 0.62 and 0.59, respectively. This seemingly puzzling result is explained by the hypothesis corroborated in Section 5.1 about managers tilting portfolios away from low alpha assets. In periods of stringent liquidity, tilting portfolios away from the less desirable low alpha assets (i.e. selling these assets) requires the sellers to absorb a higher premium.

Overall, my results are consistent with the existence of liquidity constrained investors tilting away their portfolios from low alpha assets, which fuels the alpha reversal patterns.

5.3 The CAPM Alpha and Long-Term Price Reversal

Table 3 in Section 4.4 shows that LTR is relatively highly correlated with the BAA strategy (0.53). As such, it is relevant to study whether alpha reversal captures different information than price reversal despite the commonalities. Before continuing with the analysis, it is important to remember that both BAA and LTR did not work prior to the development of the CAPM (see Section 4.1). Then, there exists a possibility that prior research at least partially confounded agents tilting portfolios away from low alpha assets for the reasons I just discussed with price overreaction. Therefore, the results in this paper can also be considered complementary to those in De Bondt and Thaler (1985) and the literature that followed.

That alpha reversal and price reversal share information should not be surprising. This can be easily seen by analyzing the fitted equation from the estimated CAPM model

$$\bar{\mu}_i = \hat{\alpha}_i + \hat{\beta}_i \times \bar{\mu}_{Market}, \tag{5}$$

where $\bar{\mu}_i$ is the average excess return over r_f for asset i and $\bar{\mu}_{Market}$ is the Market portfolio's average risk premium. While LTR consists of sorting assets based on the cumulative returns over a long

period of time[20], BAA consists of sorting assets on the unexplained part of the average returns $\bar{\mu}_i$ by the CAPM ($\hat{\alpha}_i$). Then, price overreaction might be confounded with agents tilting portfolios away from low alpha assets, and agents tilting portfolios away from low alpha assets might be confounded with overreaction.

To separate the information in alpha reversal from LTR, I will perform two exercises. In the first one I will create a betting against alpha strategy based on double-sorting assets on CAPM Alpha and past long-term returns. In the second one I will run Fama-MacBeth regression of individual stock returns onto their lagged alphas and lagged past long-term cumulative returns.

Let's start now with the first exercise using double-sorted portfolios. For this purpose, I now divide the data into two samples at the moment of rebalancing: High prior return assets (those with $\bar{\mu}_i$ above the median) and low prior return assets (those with $\bar{\mu}_i$ below the median). Then, I divide each sample again into two subsamples, one with $\hat{\alpha}_i$ above the median alpha and one with $\hat{\alpha}_i$ below the median. Therefore, now I have four double-sorted portfolios: high prior returns with low alpha ($r^{\alpha,L}_{\bar{\mu},H}$), high prior returns with high alpha ($r^{\alpha,H}_{\bar{\mu},H}$), low prior returns with low alpha ($r^{\alpha,L}_{\bar{\mu},L}$), and low prior returns with high alpha ($r^{\alpha,H}_{\bar{\mu},L}$). Within each of portfolio assets are weighted according to the rank of $\hat{\alpha}_i$ as explained in Section 3.2.

Using these double-sorted portfolios I will construct an alpha reversal strategy with a reduced exposure to price reversal (BAA*), where both the short and long arms of the alpha strategy contain high and low past return assets. To abstract from the possible impact of betas on the correlation between alpha reversal and price reversal, I will not rescale this strategy. For comparison purposes, in this Section I will not rescale the original BAA strategy either. More precisely, I now create two strategies that are self-financed and can be defined as

$$r^{BAA^*} = 0.5\left(r^{\alpha,L}_{\bar{\mu},L} + r^{\alpha,L}_{\bar{\mu},H}\right) - 0.5\left(r^{\alpha,H}_{\bar{\mu},L} + r^{\alpha,H}_{\bar{\mu},H}\right), \tag{6}$$

$$r^{BAA^+} = r^{\alpha,L} - r^{\alpha,H}, \tag{7}$$

[20]For example, a classical LTR strategy consists of sorting assets by $\prod(1+\mu_{it})-1$, from $t-60$ to $t-13$, where μ_{it} is the return of asset i in month t.

where BAA$^+$ is simply the BAA strategy without the rescaling weights $1/\beta^{\alpha,L}$ and $1/\beta^{\alpha,H}$.

The correlation coefficient for the period January 1932 - December 2015 between BAA$^+$ and LTR (0.56) is 40% larger than that of BAA* and LTR (0.34). Therefore, the applied double-sorting reduces the correlation between alpha reversal and price reversal. To better understand the relationship between these strategies and the rest of the factors, Table 7 shows the results from regressing BAA* and BAA$^+$ onto the FF6+Rev+BAB model after the CAPM was developed.[21]

[Insert Table 7 around here]

The table shows that controlling (at least partially) for price reversal reduces the performance of alpha reversal. However, the pricing error from BAA* is still economically relevant and statistically significant. Second, the sensitivity of BAA$^+$ to LTR is 50% larger than that of BAA*, showing that double sorting partially controls for price reversal. The table also shows that the Market Beta is statistically significant for BAA$^+$, confirming that the weights created in Section 3.2 work well in reducing the impact of the Market factor (see Table 2).[22]

Overall, the results from constructing a strategy double-sorting on alpha and long-term past retunrs show that the alpha reversal strategy remains relevant once we control for price reversal. However, the results also show that even after double-sorting, price reversal remains correlated with alpha reversal, although to a much lesser degree. This should not be surprising as discussed at the beginning of this Section when I presented equation (5). Therefore, I provide below another test to better understand the relationship between these confounding effects.

Now I move to the second test to disentangle alpha reversal from price reversal based on Fama-MacBeth regressions. I use as dependent variables individual stock's excess returns while my independent variables of interest are the one-period lagged CAPM Alpha [Alpha (t-1)] and the one-period lagged long-term price reversal [Returns -13 to -60 (t-1)]. Additionally, I add as controls the other one-period lagged CAPM variables: CAPM beta [Beta (t-1)] and CAPM idiosyncratic volatility [Ivol (t-1)]. The last control I use is the one-period lagged log market capitalization [Size (t-1)] since

[21] Like the BAA strategy, both BAA$^+$ and BAA* present almost negligible excess returns and non-significant pricing errors during the Pre-CAPM era.

[22] Note that comparing the results of Table 7 with those on Table 2, the pricing error of BAA is around 50% larger than that of BAA$^+$ or BAA*.

size has a non-negligible impact on BAA as shown throughout the paper and further discussed in Online Appendix A. Results are presented in Table 8 below. Column 1 of the table shows results for alpha reversal and the control variables, Column 2 shows results for long-term price reversal and the controls, and Column 3 shows results using the two variables of interest as regressors plus all the controls. Finally, I divided the data into two periods: Pre CAPM (prior to 1965) and Post CAPM (1965 onward).

[Insert Table 8 around here]

The table shows that prior to the CAPM development (Pre CAPM era), both CAPM Alpha and long-term price reversal have some predictive power, but with limited statistical significance. Once both are use in tandem (Column 3) both variables become non-significant, suggesting they do capture quite similar information in the period prior to the publication of the CAPM. This is consistent with my results in Section 4.1 (Figure 3 and Table 1) where I show that during the Pre-CAPM era both BAA and LTR's series of cumulative abnormal returns have a flat trend. The patterns change after the CAPM's publication in the mid 1960s. During the Post CAPM era, both variables become highly significant when used individually. Additionally, when I use lagged CAPM Alpha and lagged long-term reversal together (Column 3 of Table 8), the lagged CAPM Alpha's explanatory power is the one that survives, although its t-statistic diminishes with respect to using it without long-term price reversal. Overall, Table 8 shows that after the publication of the CAPM, alpha reversal contains additional information about the cross-section of stock returns not in long-term price reversal.

Overall, my analysis shows that, as expected, there are commonalities between alpha reversal and long-term price reversal. Importantly, it also shows that there are differences and that long-term price reversal cannot subsume all the information about the cross-section of stock returns contained in alpha reversal. Again, the disentanglement between both strategies appears after the development of the CAPM, while there seems to be little to no reversal effect prior to this event, confirming the hypothesis studied in this paper about the widespread dissemination of academic research as a channel through which anomalies might appear.

6 Concluding remarks

I find that assets having low realized CAPM Alphas outperform those having high ones. My hypothesis is that this counterintuitive stylized fact arose from the widespread use of performance metrics in the practitioners' world based on the CAPM – a misspecified model under the assumption that multiple risk factors coexist – generating incentives to tilt portfolios toward assets with high CAPM Alpha/Smart Betas. To do this, agents must tilt their portfolios away from low CAPM Alpha/Smart Betas assets, causing such assets to be undervalued. This behavior is consistent with (i) managers being benchmarked with respect to the CAPM, (ii) investors facing leverage constraints, and (iii) overreaction to extreme values of realized alphas or long-term cumulative returns. The data supports hypotheses (i) and (ii) but opens a question regarding hypothesis (iii): Why did investors not overreact prior to the development of the CAPM? As such, my results are also complementary to the literature on price reversal started by De Bondt and Thaler (1985). My results can also explain other empirical findings, like for example why funding liquidity shocks have differential impact on two sets of assets with similar betas and overall volatilities: The low alpha and high alpha assets.

The CAPM was published in the 1960s and immediately became a central topic in the asset pricing literature. By the year 2009 there were more than 1,000 new scientific works produced per year related to the CAPM with at least one citation and more than 450 new yearly works related to the CAPM's anomalies. Undoubtedly, its development led to the widespread use of alpha as a performance metric, especially after the work of Jensen (1968). I find that after the CAPM's publication, assets having a low realized CAPM Alpha started to consistently outperform those with a high one. The differential performance between these assets further increases after 1992, coinciding with a sharp expansion of academic research related to Smart Beta factors, which led to the explosion of factor investing in the practitioners' world (Dimson et al. 2017). Previous work showed that academic research diminishes or even eliminates the predictive power of certain anomalies (e.g., Chordia et al. 2013 and McLean and Pontiff 2016). In this paper I show that the channel in which academic research and anomalies interact goes both ways: The widespread dissemination of scholarly generated ideas can also generate new anomalies.

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Online Appendix

A Betting Against Alpha across size

Most long-short strategies that produce abnormal returns show decreasing performance as companies with low market capitalization values are removed from the sample (e.g., Fama and French 2008). In fact, the positive risk premiums generated by many factors disappear once small companies (or even micro cap companies) are removed from the sample. Therefore, it is important to study the performance of strategies for different levels of market cap.

Before performing the analysis separating companies by market capitalization, it is important to remember that the relationship between size and realized alpha has an inverted U-shape form.[23] This means that there are small stocks at both extremes of the alpha range. Thus, removing small stocks will negatively affect the BAA strategy's performance metrics.

Using the NYSE 30th and 70th percentile for market capitalization cutoff values, every December, I divide the dataset into three categories: (i) *30% Small*, which contains all firms whose market cap is equal to or below the 30th percentile; (ii) *40% Medium*, which contains all firms whose market cap is greater than the 30th percentile and lower than or equal to the 70th percentile; and (iii) *30% Big*, which contains those firms with a market cap value greater than the 70th percentile. For each group, I construct the BAA strategy and run the same performance metrics as in the main body of the paper. As in the benchmark scenario, I use a 12-month holding period.[24] Results are presented in Table A1.

[Insert Table A1 around here]

Sharpe Ratios decrease as the market capitalization value of the companies used to construct the strategy increases. However, an important desirable property is maintained: the Sharpe Ratio of the low portfolio surpasses that of the large one across all size groups. When looking at average returns, BAA produces positive risk premiums across size groups too. In fact, the low alpha portfolio generates higher average returns than the high alpha portfolio across all size groups.

[23] See Table 4 in Section 4.4 and the corresponding discussion in the last paragraph of that section.

[24] Results improve for the BAA strategy when using a 24-month holding period.

For the 30% Small stocks and the 40% Medium stocks groups, the BAA strategy produces abnormal returns that are significant at the 1% level of significance or less for all benchmark asset pricing models. When restricting the sample to the stocks belonging to the highest 30% percentile by market capitalization, the BAA strategy still generates statistically significant abnormal returns for the CAPM and Carhart models (at the 5% or less level of significance) but not for FF6 or the augmented versions of the FF6 model. This is not surprising for two reasons: First, as shown in Table 4, most large companies present realized alpha that are in the middle of the alpha distribution, therefore the alpha reversal effect should be less prominent for these companies. Additionally, the factors used to control for common risks in the benchmark models contain the entire universe of stocks. Then, when trying to price a factor constructed with a smaller subset of stocks, these benchmark models should perform better. However, the fact that the BAA strategy constructed with stocks in the 40% medium range by market cap generates abnormal returns across all benchmark models and that the BAA strategy with only very large stocks is still not priced by the CAPM or Carhart model shows that alpha reversal is not simply driven by small stocks. This is further corroborated in the Fama-MacBeth regressions presented in Section 5.4 of the paper.

Overall, I find that the BAA strategy maintain desirable properties across all size groups, like decreasing Sharpe Ratios from the low-alpha portfolio to the high-alpha one as well as a positive risk premiums. As I include more factors in the empirical asset pricing model used to test the strategies, abnormal returns for strategies using only very large stocks diminish, and for the FF6 model or its augmented versions disappear.

B Betting Against Alpha for different holding periods

In this Section I analyze the performance of the different strategies when rebalancing them every 1-month, 6-month, 12-month (benchmark scenario), 24-month, and 48-month period. As in the main body of the paper, I use the same weights for every strategy, where I recalculate the weights at the end of each holding period using the formulas presented in Section 3.2.

Table B1 presents the performance metrics across holding period returns for the BAA strategy.

[Insert Table B1 around here]

The BAA strategy shows its best performance when rebalancing portfolios every 24 months. Interestingly, this result is consistent with the empirical results of Dasgupta et al. (2011) about trading persistence in mutual funds and institutional herding. In fact, Dasgupta et al. (2011) also find that their results about underperformance of stocks bought by institutional investors (high-alpha assets in the case of my paper) are stronger using a 24-month holding period.

C Construction of the citations' indices

This Section describes the construction of the citation indices depicted in Figure 5 and Figure 6. The source data is extracted from Google Scholar search engine results using Harzing's (2007) program *Publish or Perish* version 6.27.6194. This program allowed me to create Excel spreadsheets with the yearly outcomes from the Google Scholar search engine. In my calculations I only kept those works having at least one citation in Google Scholar. Since Google Scholar limits the results of any search to the 1000 most cited papers, I stopped my search when the yearly results showed 1000 works with at least 1 citation. For the case when searching for the phrase "Capital Asset Pricing Model," this limit was reached in 2009. Therefore, I stopped in 2008.

To calculate the number of academic works containing the phrase "Capital Asset Pricing Model" presented in Figure 5, I searched this phrase yearly starting in 1950. However, focusing on just this phrase left out of the sample important works like Mossin (1966). This is because the name Capital Asset Pricing Model became popular by the end of the 1960s. For this reason, I added to the sample the results of searches for "Capital Asset Prices" between 1920 and 1975, while removing entries already obtained when searching for "Capital Asset Pricing Model" to avoid double counting.

I followed a similar procedure to calculate the number of academic works containing the phrase "Arbitrage Pricing Theory" and the phrase "Capital Asset Pricing Model" plus either the word "Anomaly" or "Anomalies." For these two searches, the limit of 1000 results with at least one citation in a year was never reached.

D Betting Against Alpha as a different source of stock returns' comovement

In Section 4.4 of the paper I showed that after the Pre-CAPM era, the BAA strategy is not priced by either the CAPM, Carhart, FF6, FF6+Rev, or FF6+Rev+BAB models. However, that a variable generates significant pricing errors when regressed against other factors is not sufficient evidence about that variable capturing a missing dimension in the space of stock returns. For example, using rank estimation methods, Ahn et al. (2018) found that 26 commonly used factors capture at most five independent vectors in the space of stock returns.

Therefore, in this Section I will study whether the BAA strategy captures different information about the comovement of stock returns, as well as information missed by the FF6+Rev+BAB factors. A natural way to answer this question is to estimate the rank of the beta matrix generated by these strategies when they are used as regressors. As Ahn et al. (2018) point out, "the rank of the beta matrix corresponding to a set of factors equals the number of factors whose prices are identifiable." In other words, the rank of the beta matrix will tell us the number of different sources of stock returns' comovements captured by a set of factors.

First I will test whether BAA and BAB produce a full rank beta matrix when used together as regressors. This will allow me to assess whether they are capturing a different dimension in the space of stock returns. Then, I will use the BAA strategy to augment the CAPM, Carhart, FF6, FF6+Rev, and FF6+Rev+BAB models to analyze if the BAA strategy contains information missed by these empirical models.

As the tests' response variables, I will use portfolio returns.[25] Following the suggestion of Lewellen et al. (2010), I consider the combined set of the 25 Size and Book to Market portfolios with the 30 Industrial portfolios, which generates a better dispersion of the estimated betas.

While many alternative rank estimators are available in the literature, they are designed for the analysis of data with a small number of cross section units (N). Consequently, they may not be

[25] Portfolio returns contain a stronger factor structure than individual stock returns. Ahn et al. (2018) show that a higher signal to noise ratio of the factors with respect to the response variables increases the accuracy of their rank estimator.

appropriate for the estimation of the beta matrix with large N. Ahn et al. (2018), however, found that a restricted version of the BIC (RBIC) rank estimator of Cragg and Donald (1997) has good finite-sample properties if the return data used contains the time series observations of at least 240 months ($T \geq 240$) over individual portfolios whose number does not exceed one half of the time series observations ($N \leq T/2$). My data fits the desirable properties for the RBIC rank estimator since the time span is January 1973 - September 2015 ($T = 516$) and the number of cross-sectional units is $N = 55$.

Table D1 presents the rank estimations' results. Each row corresponds to a set of k factors used as regressors to generate the estimated beta matrix (or matrix of factor loadings). Thus, k corresponds to the maximum rank attainable by the beta matrix.

[Insert Table D1 around here]

The results in the first two lines correspond to using only BAA and BAB. Both strategies capture a relevant source of comovement according to the RBIC estimator: The estimated rank equals 1 for the BAB factor alone and increases to 2 when BAA is added. The rest of the table shows that the BAA strategy increases the rank of the beta matrix when added to any empirical model.

In summary, this Online Appendix shows that after 1968 the BAA strategy captures information missed by the nine factors in the FF6+Rev+BAB model.

Figure 1: Cumulative abnormal returns from the Betting Against Alpha strategy

This figure shows the CAPM's cumulative abnormal returns (CAR) from the Betting Against Alpha (BAA) strategy. It also shows the linear trend in the CAR series (dotted line) for three different time periods: Pre-CAPM (before 1965), CAPM (1965-1992), and Smart Beta (1993 onward). The monthly abnormal returns are estimated by OLS using a 5-year rolling regression. I use monthly data corresponding to the period January 1927 – December 2015 to construct the BAA strategy for the period January 1932 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM's Market factor comes from Kenneth French's webpage.

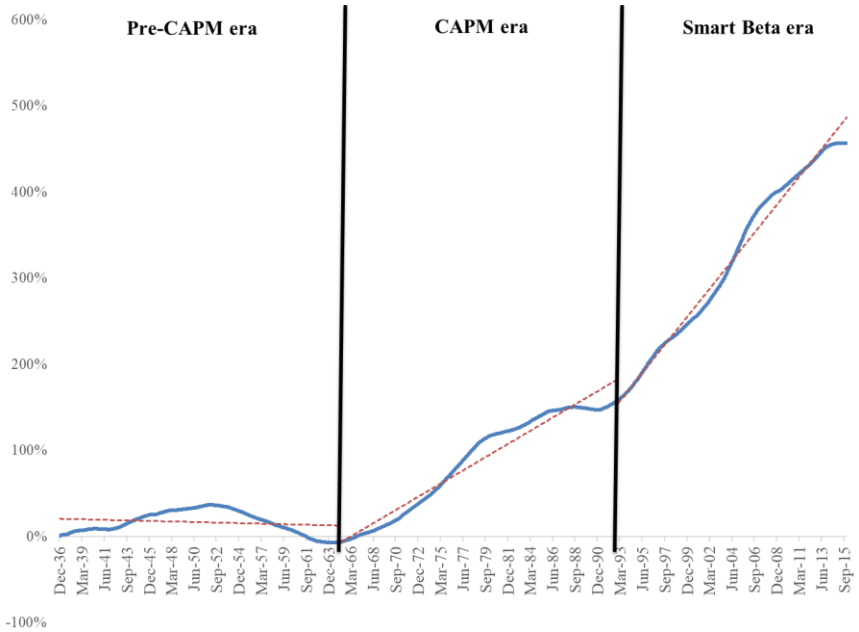


Figure 2: Relationship between an asset's alpha and its weight on the low or high alpha portfolio

This figure shows the relationship between an asset's alpha and its weight on the low (high) alpha portfolio if the asset's alpha is smaller (larger) than the median alpha at the time of rebalancing.

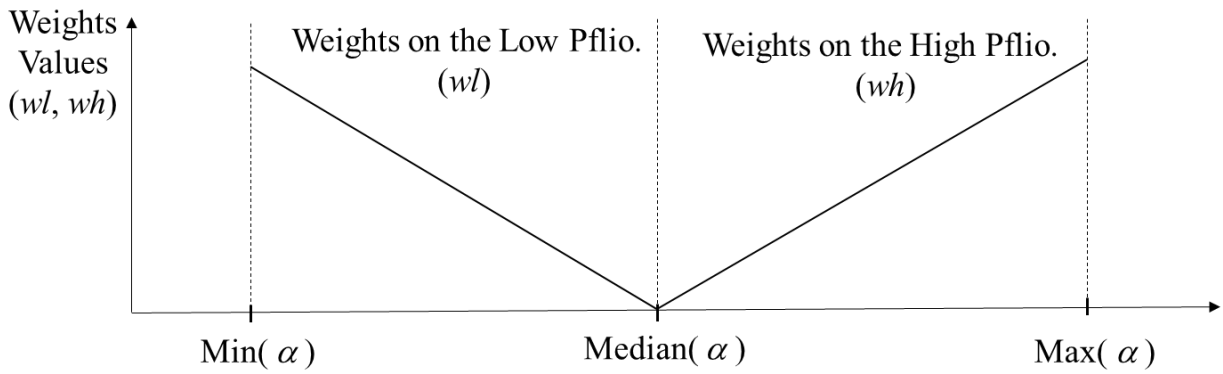
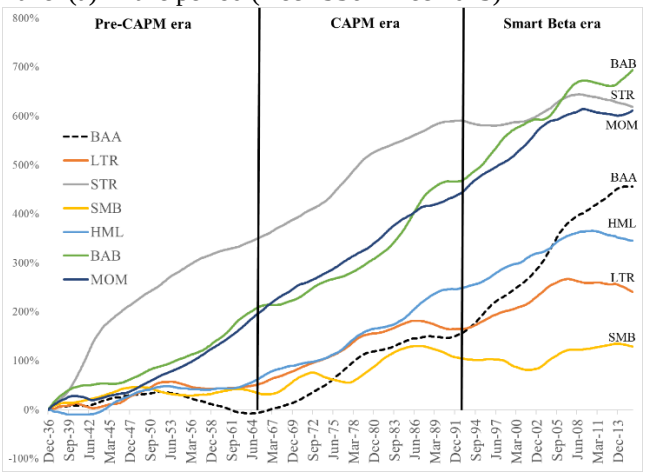


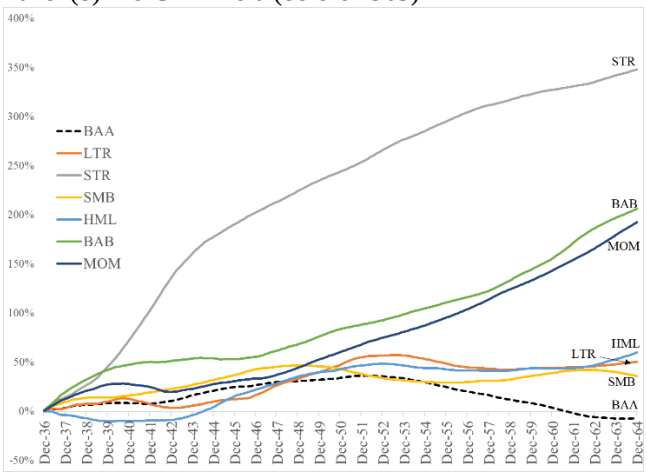
Figure 3: Cumulative abnormal returns from several factors

This figure shows the CAPM's cumulative abnormal returns (CAR) from various factors during the period December 1936 – December 2015. Panel (a) shows data for the entire period while panels (b) to (d) show data for three different periods separately: Pre-CAPM era (before 1965), CAPM era (1965-1992), and Smart Beta era (1993 onward). The factors analyzed are Betting Against Alpha (BAA), Small Minus Big (SMB), High Minus Low (HML), Momentum (MOM), Long-Term Reversals (LTR), Short Term-Reversals (STR), and Betting Against Beta (BAB). The monthly abnormal returns are estimated by OLS using a 5-year rolling regression. I use monthly data corresponding to the period January 1927 – December 2015 to construct the BAA strategy for the period January 1932 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the other factors comes from Kenneth French's webpage and that of the BAB factor comes from AQR's webpage.

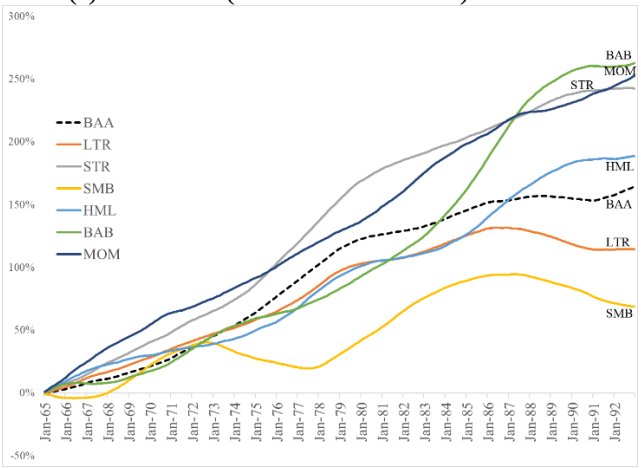
Panel (a) Entire period (Dec 1936 – Dec 2015)



Panel (b) Pre-CAPM era (before 1965)



Panel (c) CAPM era (Jan 1965 – Dec 1992)



Panel (d) Smart Beta era (1993 onward)

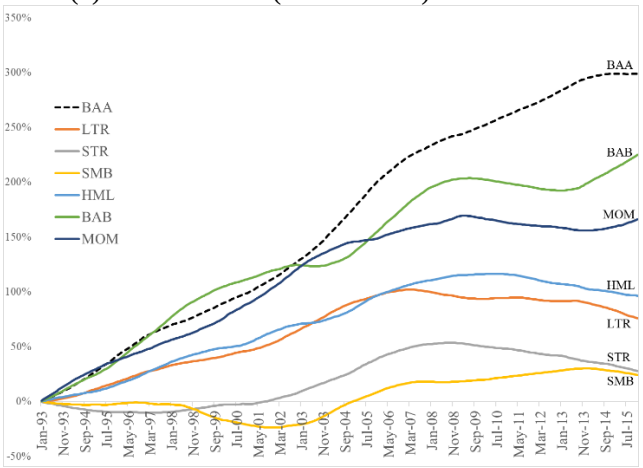
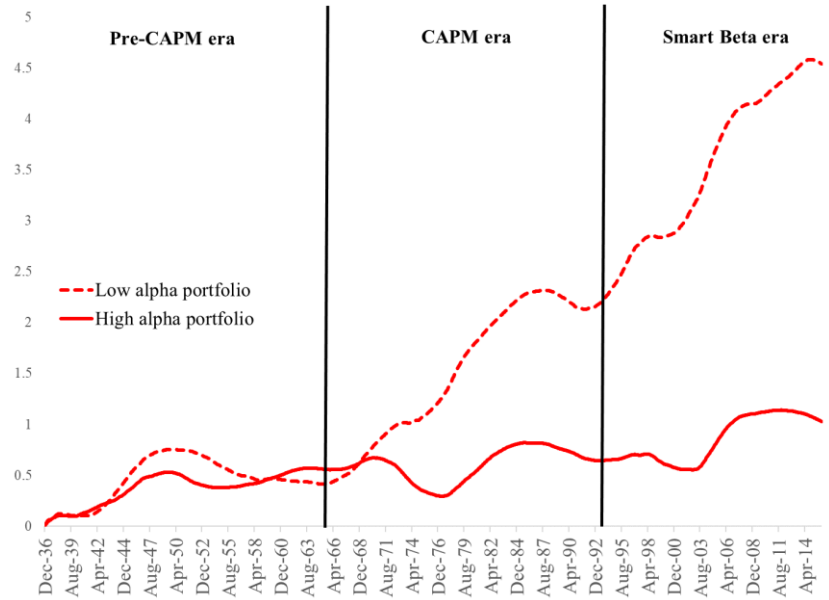


Figure 4: Cumulative abnormal returns for the low and high alpha portfolios constructed using the entire CRSP database and only NYSE stocks

This figure shows the CAPM's cumulative abnormal returns (CAR) obtained from the excess returns over the risk-free rate of the long and short alpha portfolios used to construct the Betting Against Alpha (BAA) strategy. These portfolios have been constructed using the entire CRSP database (NYSE+NASDAQ+AMEX) in Panel (a) and using only NYSE data in Panel (b). The Low (High) alpha portfolio contains assets with realized alphas below (above) the median alpha value at the moment of rebalancing. Alphas used to create the low and high portfolios are estimated with OLS regressions using the CAPM model. I use 5-year data to calculate alphas and rebalance the portfolios yearly, at the end of December. The monthly abnormal returns are estimated by OLS using a 5-year rolling regression. I use monthly data corresponding to the period January 1927 – December 2015 to construct the portfolios for the period January 1932 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the risk-free rate (one-month T-bill) and the CAPM comes from Kenneth French's webpage.

Panel (a) Results using the entire CRSP database



Panel (b) Results using only NYSE stocks

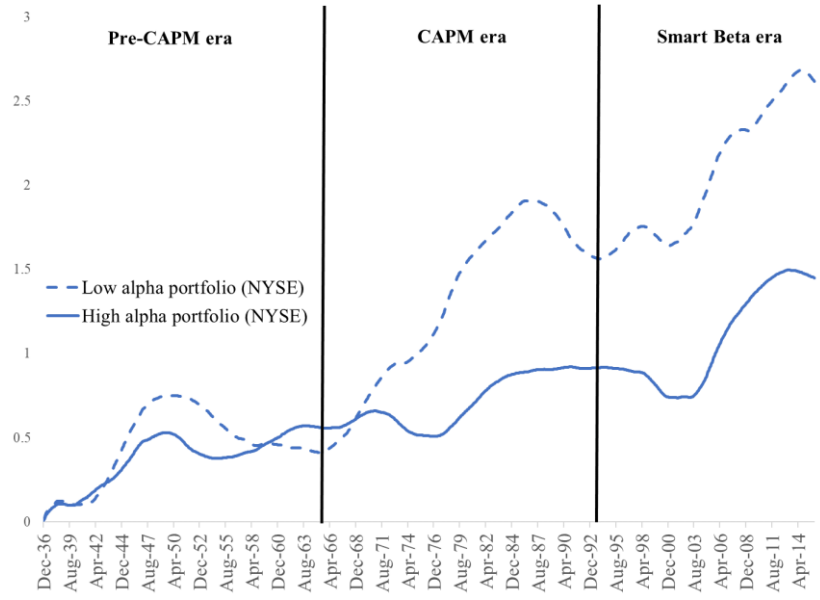


Figure 5: Scholarly work on the Capital Asset Pricing Model

This figure shows the yearly number of academic works containing the phrase "Capital Asset Pricing Model" with at least 1 citation according to the Google Scholar search engine. The solid line shows the number of academic projects, while the dotted line shows the linear trend calculated for the three different eras separately: Pre-CAPM era (before 1965), CAPM era (1965-1992), and Smart Beta era (1993 onward). To retrieve the data from Google Scholar I used Harzing's (2007) *Publish or Perish* program version 6.27.6194.

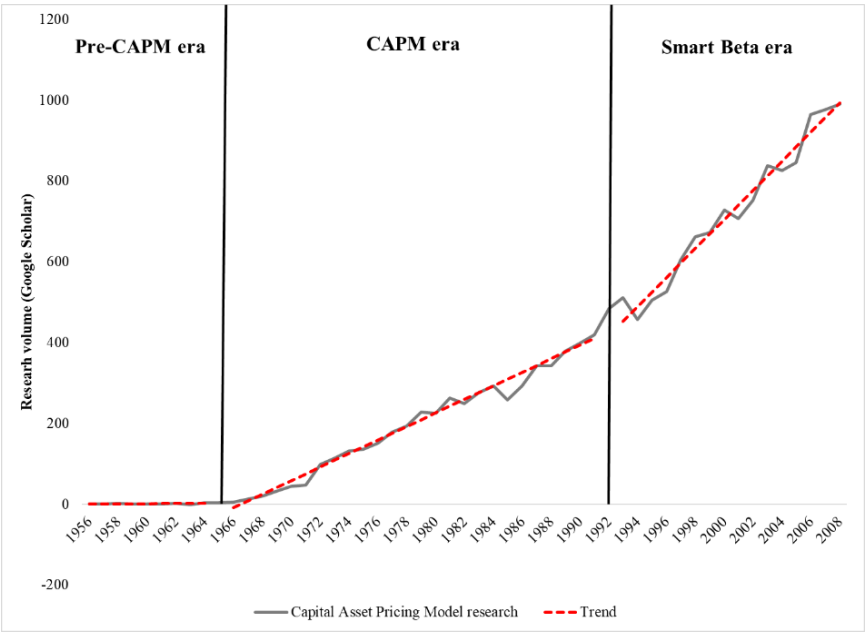
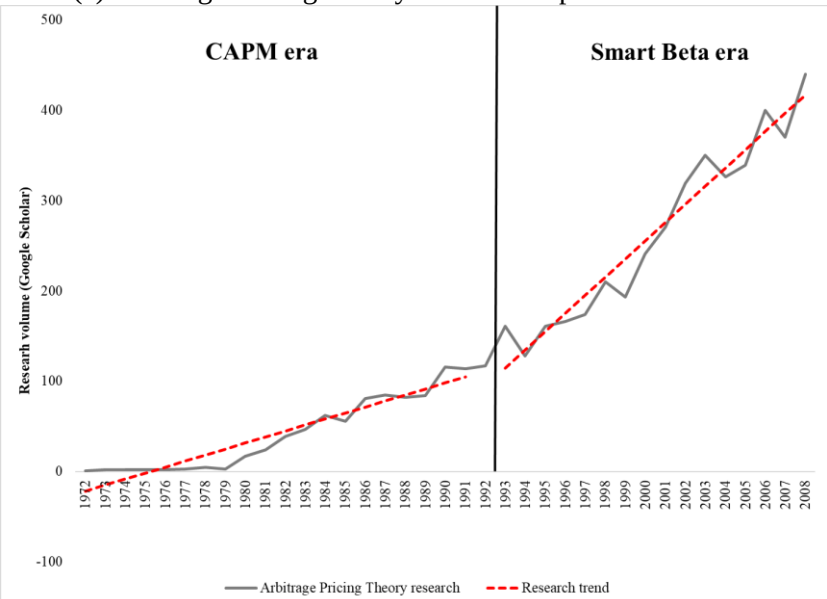


Figure 6: Scholarly work on the Arbitrage Pricing Theory and the CAPM anomalies

The first Panel of this figure shows the yearly number of academic works containing the phrase "Arbitrage Pricing Theory" with at least 1 citation according to the Google Scholar search engine. The solid line shows the number of academic projects while the dotted line shows the linear trend calculated for two different periods separately: the CAPM era (before 1993), and the Smart Beta era (1993 onward). Similarly, Panel (b) shows the yearly number of academic works with at least 1 citation containing the phrase "Capital Asset Pricing Model" and at least one of the following two words: "Anomaly" or "Anomalies." To retrieve the data from Google Scholar I used Harzing's (2007) *Publish or Perish* program version 6.27.6194.

Panel (a) Arbitrage Pricing Theory research output



Panel (b) Capital Asset Pricing Model plus anomalies research output

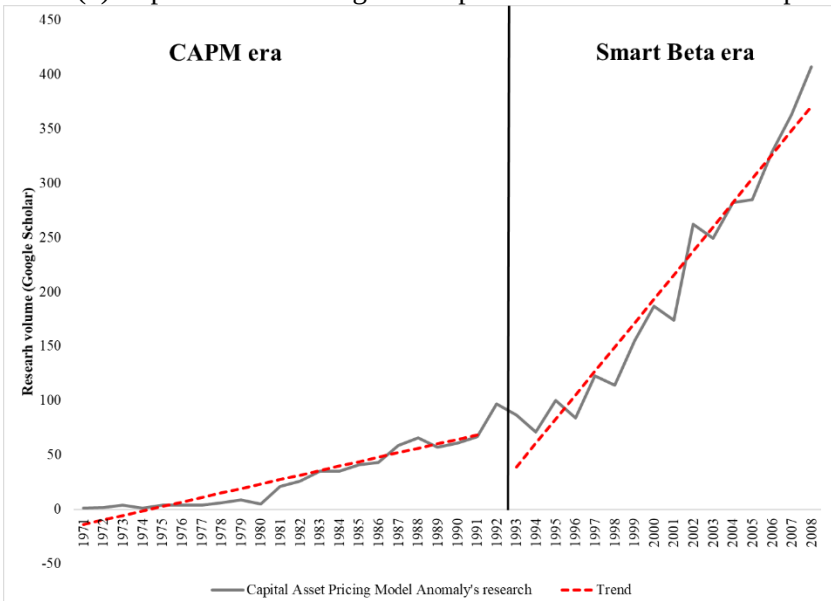


Table 1: Pricing of several factors by the CAPM across eras

This table presents the results from regressing the BAA strategy and several other factors onto the CAPM. The CAPM alpha and Market beta are estimated by OLS, and the t-statistics reported in parenthesis are calculated using heteroskedastic robust standard errors. I use monthly data corresponding to the period January 1927 – December 2015 to construct the BAA strategy for the period January 1932 – December 2015. I run the regression for the entire period and then for three subperiods: (i) the Pre-CAPM era using data from January 1932 to December 1964, (ii) the CAPM era using data from January 1965 to December 1992, and (iii) the Smart Beta era using data from January 1993 to December 2015. Individual data on stock returns comes from the CRSP database, the data for the CAPM model and other factors (SMB, HML, MOM, LTR, and STR) comes from Kenneth French's webpage and the data for the BAB factor comes from AQR's webpage.

		BAA	**SMB**	**HML**	**MOM**	**BAB**	**LTR**	**STR**
1932-2015	**CAPM Alpha**	**0.41%**	**0.11%**	**0.33%**	**0.80%**	**0.77%**	**0.21%**	**0.66%**
		(4.61)	(1.22)	(3.28)	(6.34)	(7.81)	(2.15)	(6.77)
	Market Beta	0.09	0.22	0.15	-0.28	-0.09	0.16	0.12
		(1.78)	(5.83)	(2.51)	(-3.39)	(-2.07)	(2.55)	(2.22)
	R^2	0.02	0.12	0.05	0.10	0.02	0.06	0.03
Pre-CAPM era (1932-1964)	**CAPM Alpha**	**-0.04%**	**0.06%**	**0.13%**	**0.87%**	**0.66%**	**0.06%**	**1.11%**
		(-0.32)	(0.44)	(0.79)	(4.59)	(4.79)	(0.31)	(7.17)
	Market Beta	0.22	0.23	0.43	-0.41	-0.11	0.31	0.04
		(2.90)	(3.62)	(5.68)	(-3.25)	(-1.69)	(3.18)	(0.51)
	R^2	0.15	0.17	0.36	0.23	0.05	0.17	0.01
CAPM era (1965-1992)	**CAPM Alpha**	**0.54%**	**0.22%**	**0.51%**	**0.83%**	**0.79%**	**0.32%**	**0.61%**
		(3.69)	(1.49)	(3.93)	(4.36)	(5.67)	(2.31)	(4.47)
	Market Beta	-0.03	0.24	-0.21	0.01	0.11	-0.04	0.16
		(-0.51)	(5.36)	(-5.18)	(0.20)	(2.29)	(-0.80)	(3.57)
	R^2	0.00	0.13	0.14	0.00	0.04	0.01	0.08
Smart Beta era (1993-2015)	**CAPM Alpha**	**0.88%**	**0.05%**	**0.30%**	**0.75%**	**0.98%**	**0.24%**	**0.10%**
		(4.79)	(0.26)	(1.52)	(2.67)	(4.17)	(1.50)	(0.47)
	Market Beta	-0.09	0.16	-0.11	-0.31	-0.30	0.02	0.26
		(-1.52)	(3.71)	(-1.80)	(-3.28)	(-3.90)	(0.33)	(3.67)
	R^2	0.02	0.04	0.02	0.07	0.11	0.00	0.09

Table 2: Betting Against Alpha and Betting Against Beta factors' performance metrics

This table presents monthly performance metrics for the excess returns of the low alpha portfolio over the risk-free rate, excess returns of the high alpha portfolio over the risk-free rate, and the Betting Against Alpha (BAA) strategy. These metrics are the monthly Sharpe Ratios, monthly average Excess Returns, and abnormal returns for the CAPM, Carhart (1997), Fama-French Six Factor (FF6, 2018), FF6 plus reversal factors (FF6+Rev), and the FF6+Rev augmented with the Betting Against Beta (FF6+Rev+BAB) factor models. The CAPM model contains only the Market factor. Carhart augments the CAPM with the SMB, HML, and MOM factors. FF6 augments the Carhart model with the RMW and CMA factors. FF6+Rev augments the FF6 model with the long-term reversal (LTR) and short-term reversal (STR) factors. The abnormal returns are estimated by OLS and the t-statistics reported in parenthesis are constructed using heteroskedastic robust standard errors. The variable Size corresponds to the market cap value of the portfolios in 2010 US dollars. The column Low (High) Alpha shows the results for the portfolio containing assets with realized alphas below (above) the median alpha value at the moment of rebalancing. Assets' alphas used to assign them to the low and high portfolios are estimated with OLS regressions using the CAPM model. I use 5-year data to calculate alphas and rebalance the portfolios yearly, at the end of December. I use monthly data corresponding to the period January 1968 – December 2015 to construct portfolios and strategies for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the risk-free rate (one-month T-bill), CAPM, Carhart, FF6, and FF6+Rev models comes from Kenneth French's webpage and the data for the BAB factor comes from AQR's webpage.

	Low alpha pflio	High alpha pflio	**BAA**
Sharpe Ratio	0.18	0.12	**0.22**
Excess Return	1.15%	0.67%	**0.68%**
CAPM Alpha	0.60%	0.10%	**0.71%**
	(3.47)	(0.90)	(5.43)
Carhart Alpha	0.55%	0.06%	**0.67%**
	(4.18)	(0.86)	(5.03)
FF6 Alpha	0.55%	0.05%	**0.64%**
	(4.01)	(0.63)	(4.39)
FF6+Rev Alpha	0.52%	0.01%	**0.65%**
	(4.10)	(0.13)	(4.81)
FF6+Rev+BAB Alpha	0.48%	-0.01%	**0.63%**
	(3.72)	(-0.21)	(4.49)
Size	$2,337,982	$3,325,571	

Table 3: Correlation between factors

This table presents the correlation coefficient between the Betting Against Alpha strategy (BAA), Betting Against Beta factor (BAB), Fama-French six factors (Market, SMB, HML, RMW, CMA, MOM), and reversal factors (LTR and STR). I use 5-year data to calculate the parameters used to construct BAA, which is rebalanced yearly, at the end of December. I use monthly data corresponding to the period January 1968 – December 2015 to construct BAA for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for Fama-French six factors and the reversal factors comes from Kenneth French's webpage and the data for the BAB factor comes from AQR's webpage.

	BAA	BAB	Market	SMB	HML	RMW	CMA	MOM	LTR	STR
BAA	**1**									
BAB	0.06	**1**								
Market	-0.08	-0.10	**1**							
SMB	0.15	-0.04	0.23	**1**						
HML	0.43	0.33	-0.29	-0.08	**1**					
RMW	-0.05	0.33	-0.25	-0.38	0.16	**1**				
CMA	0.32	0.29	-0.40	-0.04	0.69	0.05	**1**			
MOM	-0.38	0.20	-0.14	-0.02	-0.17	0.09	0.03	**1**		
LTR	0.53	0.02	0.02	0.39	0.42	-0.27	0.44	-0.06	**1**	
STR	0.14	-0.07	0.29	0.16	0.00	-0.09	-0.14	-0.31	0.10	**1**

Table 4: Portfolio deciles sorted on alphas and betas

This table presents the monthly performance metrics for decile portfolios based on pre-sorted realized alphas. These metrics are the monthly Sharpe Ratios; average monthly Excess Returns; and abnormal returns for the CAPM, Carhart (1997), Fama-French Six Factor (FF6, 2018), and FF6 plus reversal factors (FF6+Rev) models. The CAPM model contains only the Market factor. Carhart augments the CAPM with the SMB, HML, and MOM factors. FF6 augments the Carhart model with the RMW and CMA factors. FF6+Rev augments the FF6 model with LTR and STR. The abnormal returns are estimated by OLS and their significance levels are calculated using heteroskedastic robust standard errors. The last column Low-High shows the performance metrics for the long-short strategy using the extreme portfolios (P10-P1). Assets within a portfolio are equally weighted. The row Average Realized CAPM Alpha (Mkt Beta) corresponds to the average realized alpha (beta) value of the assets in a given portfolio at the moment of rebalancing. Average Total Volatility corresponds to the average standard deviation of the assets' excess returns. Average Idios. Volatility corresponds to the average standard deviation of the assets' excess returns minus their betas multiplied by the Market factor's risk premium. Alphas to assign assets to the different portfolios are estimated with OLS regressions using the CAPM model. I use 5-year data to calculate alphas and rebalance the portfolios yearly, at the end of December. I use monthly data corresponding to the period January 1968 – December 2015 to construct portfolios for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database. The CAPM, Carhart, FF6, and FF6+Rev models come from Kenneth French's webpage and the data for the BAB factor comes from AQR's webpage.

	P1 (low)	P2	P3	P4	P5	P6	P7	P8	P9	P10 (high)	Low-High
					(a) Portfolios sorted on CAPM alphas						
i) Sharpe Ratio	0.19	0.16	0.16	0.17	0.18	0.17	0.17	0.17	0.13	0.07	0.19
ii) Excess Return	1.56%	0.98%	0.83%	0.82%	0.83%	0.77%	0.81%	0.84%	0.72%	0.51%	1.05%
iii) CAPM Alpha	0.93%***	0.44%***	0.35%***	0.37%***	0.38%***	0.31%***	0.32%***	0.33%***	0.16%*	-0.16%	1.09%***
iv) Carhart Alpha	0.95%***	0.35%***	0.27%***	0.26%***	0.25%***	0.14%**	0.16%***	0.19%***	0.09%	-0.05%	1.00%***
v) FF6 Alpha	1.00%***	0.34%***	0.24%***	0.21%***	0.17%***	0.06%	0.07%	0.12%**	0.04%	0.02%	0.99%***
vi) FF6+Rev Alpha	0.97%***	0.31%***	0.20%**	0.18%**	0.15%**	0.02%	0.04%	0.08%*	0.01%	-0.03%	1.00%***
vii) Average Total Volatility	38.32%	34.49%	32.61%	31.24%	30.83%	31.26%	32.22%	33.86%	36.75%	43.57%	
viii) Average Idios. Volatility	36.41%	32.49%	30.62%	29.26%	28.89%	29.37%	30.35%	31.98%	34.86%	41.82%	
ix) Average Realized CAPM Alpha	-2.10%	-0.90%	-0.40%	-0.05%	0.25%	0.53%	0.85%	1.24%	1.83%	3.43%	
x) Average Realized Mkt. Beta	1.26	1.10	1.00	0.94	0.91	0.91	0.95	1.00	1.12	1.29	
xi) Size	$1,414,290	$2,588,140	$2,848,926	$3,497,599	$3,763,370	$4,060,580	$3,882,981	$3,759,830	$3,728,933	$2,512,400	

* 10%, ** 5%, *** 1%

Table 5: Mutual fund's alphas, betas, and returns

This table shows several metrics retrieved from mutual fund trading activity between the first quarter of 1980 and the last quarter of 2015. Mutual fund trading data comes from the Thomson-Reuters Mutual Fund Ownership database, which contains quarterly data on mutual fund activity since 2003 and sometimes sparser data before this date. For each mutual fund at each reported date I select the sold and bought assets. For each of these assets I retrieve their CAPM Alphas and Market Betas from the Beta Suite by WRDS. I also calculate traded assets' prior 13- to 60-month returns and the next 12-month returns using the CRSP database. The column Selling Portfolio shows the average CAPM Alpha, average Market Beta, average prior 13- to 60-month returns, and average cumulative 12 month returns for the assets sold by the mutual funds. The column Buying Portfolio shows the same statistics for the assets bought by the mutual funds. The last column (CRSP database) shows the average CAPM Alpha and average Market Beta for all the assets in the CRSP database. Alphas and betas are calculated using 60 months of data. Standard deviations are in parenthesis.

	Selling Portfolio	Buying Portfolio	CRSP database
Avg. CAPM Alpha	0.52%	0.72%	0.46%
	(0.0148)	(0.0152)	(0.0174)
Avg. Market Beta	1.05	1.09	1.00
	(0.668)	(0.707)	(0.734)
Avg. returns (-13 to -60 months)	1.45%	1.62%	
	(0.0169)	(0.0175)	
Returns (+12 month holding period)	14.55%	12.99%	
	(0.587)	(0.521)	
Number of Transactions	453681	777668	
Value of Transactions (billions)	10341	39988	

Table 6: Betting Against Alpha and funding liquidity conditions

This table presents results from regressing the Betting Against Alpha (BAA) strategy, the excess returns of the low alpha portfolio over the risk-free rate, and the excess returns of the high alpha portfolio over the risk-free rate, on a set of variables capturing changing funding liquidity conditions and some controls. The variables capturing changes in funding liquidity condition are change in the TED spread (ΔTED) and the Credit Spread (ΔCredit), where the TED spread is the change in the Treasure-Eurodollar spread from the FRED website (data available since January 1986) and the Credit Spread is the change in Baa to 10-year Constant Maturity Treasury rate from the FRED website (data available for the period January 1972 – December 2015). The control variables are the one-period lagged value of the dependent variable, one-period lagged inflation (yearly change in the CPI index from the FRED website), and Market returns. Columns 1 show the results using ΔTED to capture funding liquidity shocks while columns (2) shows the results using ΔCredit to capture funding liquidity shocks. Alphas to create the low and high portfolios of the BAA and BAB strategies are estimated with OLS regressions using the CAPM model. I use 5-year data to calculate alphas and rebalance the portfolios yearly, at the end of December. The t-statistics reported in parenthesis are constructed using heteroskedastic robust standard errors. I use monthly data corresponding to the period January 1968 – December 2015 to construct portfolios and strategies for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the risk-free rate (one-month T-bill) and the Market factor comes from Kenneth French's webpage.

	BAA		Low alpha portfolio		High alpha portfolio	
	(1)	(2)	(1)	(2)	(1)	(2)
ΔTED	-0.026		-0.039		-0.017	
	(-2.62)		(-3.72)		(-2.75)	
ΔCredit		-0.044		-0.057		-0.028
		(-2.36)		(-2.35)		(-2.01)
BAA(-1)	0.246	0.170				
	(3.50)	(2.76)				
Low alpha pflio(-1)			0.219	0.150		
			(5.84)	(3.45)		
High alpha pflio(-1)					0.103	0.088
					(3.36)	(3.72)
Inflation(-1)	-0.129	-0.010	-0.098	0.062	-0.042	0.068
	(-0.80)	(-0.13)	(-0.61)	(0.74)	(-0.58)	(2.06)
Market returns	-0.061	0.000	0.968	1.049	1.028	1.115
	(-1.13)	(0.00)	(19.79)	(17.84)	(33.55)	(42.11)
R^2	0.094	0.046	0.66	0.62	0.80	0.83

Table 7: Betting against alpha controlling for long-term price reversal

This table presents the results from regressing two version of the BAA strategy in which the low and high alpha portfolios are not rescaled: one version controls for long-term price reversal (BAA*) and another is simply a long-short strategy of the low and high alpha portfolios (BAA^+). For the BAA* strategy I first construct four portfolios: From the assets with average prior returns (-13 to -60 months) below the average ($\bar{\mu}$) I construct two portfolios: One with assets having an alpha below the median within this portfolio ($r_{\mu,L}^{\alpha,L}$) and one with assets above the median alpha ($r_{\mu,L}^{\alpha,H}$). From the assets with average prior returns (13 to 60 months) above the average I construct another two portfolios: One with assets having an alpha below the median within this portfolio ($r_{\mu,L}^{\alpha,H}$) and one with assets above the median within this portfolio ($r_{\mu,H}^{\alpha,H}$). BAA* is the following long-short strategy $r^{BAA*} = 0.5(r_{\mu,L}^{\alpha,L} + r_{\mu,H}^{\alpha,L}) - 0.5(r_{\mu,L}^{\alpha,H} + r_{\mu,H}^{\alpha,H})$. Similarly, $r^{BAA^+} = r^{\alpha,L} - r^{\alpha,H}$, where $r^{\alpha,L}$ and $r^{\alpha,H}$ are the low alpha and high alpha portfolios from the original BAA strategy. The CAPM are estimated by OLS and the t-statistics reported in parenthesis are calculated using heteroskedastic robust standard errors. I use monthly data corresponding to the period January 1968 – December 2015 to construct the BAA^+ and BAA* strategies for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database. The CAPM, Carhart, FF6, and FF6+Rev models come from Kenneth French's webpage and the data for the BAB factor comes from AQR's webpage.

	BAA^+	BAA*
Constant (alpha)	0.46%	0.42%
	(3.70)	(3.21)
Market Beta	-0.15	-0.02599
	(-3.88)	(-0.73)
SMB Beta	0.11	0.12
	(2.14)	(2.54)
HML Beta	0.22	0.21
	(2.55)	(2.65)
RMW Beta	0.13	0.07
	(2.24)	(1.30)
CMA Beta	-0.40	-0.38
	(-3.07)	(-3.28)
MOM Beta	-0.26	-0.33
	(-6.01)	(-7.91)
LTR Beta	0.68	0.43
	(8.51)	(6.16)
STR Beta	0.02	0.01
	(0.37)	(0.18)
BAB Beta	0.08	0.03
	(1.53)	(0.52)
R^2	0.50	0.50

Table 8: Fama-MacBeth regressions

This table presents the results from Fama-MacBeth regressions using individual stocks excess returns as dependent variables and the following independent ones: one-period lagged CAPM alpha [Alpha (t-1)], one-period lagged long-term price reversal [Returns -13 to -60 (t-1)], one-period lagged CAPM beta [Beta (t-1)], one-period lagged CAPM idiosyncratic volatility [Ivol (t-1)], and one-period lagged log market capitalization [Size (t-1)]. Alphas and betas are estimated by OLS using the CAPM model using 5-year data. Standard errors in parenthesis are heteroskedastic robust and are calculated using two lags. Individual data on stock returns comes from the CRSP database.

	Pre CAPM era (1932-1964)			**Post CAPM era (1965 - 2015)**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Alpha (t-1)	-0.2116		-0.1799	-0.1483		-0.1227
	(-1.97)		(-1.28)	(-3.06)		(-1.87)
Returns -13 to -60 (t-1)		-0.1046	0.05625		-0.0530	-0.0035
		(-1.69)	(0.89)		(-3.74)	(-0.18)
Beta (t-1)	0.0023	0.0005	0.00379	0.0014	0.0014	0.0018
	(0.77)	(0.22)	(1.17)	(1.25)	(1.30)	(1.63)
Ivol (t-1)	0.0251	0.0010	0.0295	0.0008	-0.0132	-0.0018
	(0.96)	(0.05)	(1.08)	(0.06)	(-1.06)	(-0.12)
Size (t-1)	-0.0017	-0.0023	-0.0017	-0.0012	-0.0016	-0.0012
	(-3.58)	(-3.42)	(-3.57)	(-5.23)	(-5.51)	(-5.23)
Average R^2	0.090	0.082	0.097	0.051	0.046	0.054
# time periods		395			636	

Online Appendix Figures and Tables

Table A1: BAA for different ranges of market capitalization

This table presents the monthly performance metrics for the excess returns over the risk-free rate of the low alpha portfolio, the excess returns over the risk-free rate of the high alpha portfolio, and low minus high strategy used to construct Betting Against Alpha (BAA) strategy for sets containing assets grouped by their market capitalization value. These metrics are the monthly Sharpe Ratios; monthly Excess Returns over the one-month T-bill; and abnormal returns for the CAPM, Carhart (1997), Fama-French Six Factor (FF6, 2018), FF6 plus reversal (FF6+Rev), and the FF6+Rev augmented with the Betting Against Beta (FF6+Rev+BAB) factor models. The Carhart model augments the CAPM with the SMB, HML, and MOM factors. FF6 augments the Carhart model with the RMW and CMA factors. FF6+Rev augments the FF6 model with the LTR and STR factors. The abnormal returns are estimated by OLS and their significance levels are calculated using heteroskedastic robust standard errors. The column Low (High) shows the results for the portfolio containing assets with realized alphas below (above) the median alpha value. Alphas used to assign assets to the low and high alpha portfolios are estimated with OLS regressions using the CAPM model. I use 5-year data to calculate alphas and rebalance the portfolios yearly, at the end of December. Additionally, at the moment of rebalancing, I use NYSE break points to create three sets of data: (i) 30% Small, which contains all firms whose market cap is equal to or below the 30th percentile; (ii) 40% Medium, which contains all firms whose market cap is greater than the 30th percentile and lower than or equal to the 70th percentile; and (iii) 30% Big, which contains those firms with a market cap value greater than the 70th percentile. I use monthly data corresponding to the period January 1968 – December 2015 to construct portfolios and factors for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, FF6, and FF6+Rev models comes from Kenneth French's webpage and the data for the BAB factor comes from AQR's webpage.

	Low	High	BAA
		Sharpe Ratio	
30% Small	0.19	0.13	0.22
40% Medium	0.13	0.10	0.15
30% Big	0.13	0.09	0.08
		Average Returns	
30% Small	1.44%	0.80%	0.80%
40% Medium	0.76%	0.59%	0.38%
30% Big	0.64%	0.52%	0.24%
		CAPM Alpha	
30% Small	0.88%***	0.26%**	0.84%***
40% Medium	0.21%*	-0.02%	0.39%***
30% Big	0.12%*	-0.07%	0.26%**
		Carhart Alpha	
30% Small	0.82%***	0.17%*	0.79%***
40% Medium	0.13%**	-0.05%	0.33%***
30% Big	0.08%*	0.03%	0.18%**
		FF6 Alpha	
30% Small	0.87%***	0.16%*	0.72%***
40% Medium	0.08%	-0.07%	0.28%***
30% Big	0.01%	0.04%	0.10%
		FF6+Rev Alpha	
30% Small	0.83%***	0.10%	0.75%***
40% Medium	0.05%	-0.09%	0.29%***
30% Big	-0.01%	0.02%	0.11%
		FF6+Rev+BAB Alpha	
30% Small	0.78%***	0.06%	0.82%***
40% Medium	0.04%	-0.09%	0.29%***
30% Big	-0.10%	0.02%	0.11%

* 10%, ** 5%, *** 1%

Table B1: BAA constructed using different holding periods for the assets

This table presents the monthly performance metrics over different holding periods for the excess returns over the risk-free rate of the low alpha portfolio, the excess returns over the risk-free rate of the high alpha portfolio, and low minus high strategy used to construct Betting Against Alpha (BAA) strategy. These metrics are the monthly Sharpe Ratios; monthly Excess Returns over the one-month T-bill; and abnormal returns for the CAPM, Carhart (1997), Fama-French Six Factor (FF6, 2018), FF6 plus reversal (FF6+Rev), and the FF6+Rev augmented with the Betting Against Beta (FF6+Rev+BAB) factor models. The Carhart model augments the CAPM with the SMB, HML, and MOM factors. FF6 augments the Carhart model with the RMW and CMA factors. FF6+Rev augments the FF6 model with the LTR and STR factors. The abnormal returns are estimated by OLS and their significance levels are calculated using heteroskedastic robust standard errors. The column Low (High) Alpha shows the results for the portfolio containing assets with realized alphas below (above) the median alpha value. Alphas used to assign assets to the low and high alpha portfolios are estimated with OLS regressions using the CAPM model. I use 5-year data to calculate alphas and rebalance the portfolios using the following frequencies: 1, 6, 12, 24, and 48 months. I use monthly data corresponding to the period January 1968 – December 2015 to construct the portfolios and the BAA strategy for the period January 1973 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, FF6, and FF6+Rev models comes from Kenneth French's webpage and the data for the BAB factor comes from AQR's webpage.

	Low Alpha	High Alpha	BAA
		Sharpe Ratio	
1 month	0.17	0.13	**0.14**
6 month	0.16	0.13	**0.15**
12 month	0.18	0.12	**0.22**
24 month	0.20	0.12	**0.28**
48 month	0.21	0.13	**0.19**
		Average Returns	
1 month	1.10%	0.77%	**0.50%**
6 month	1.07%	0.75%	**0.60%**
12 month	1.15%	0.67%	**0.68%**
24 month	1.25%	0.64%	**0.82%**
48 month	1.23%	0.72%	**0.42%**
		CAPM Alpha	
1 month	0.55%***	0.19%**	**0.52%***
6 month	0.52%***	0.17%*	**0.55%***
12 month	0.60%***	0.10%	**0.71%***
24 month	0.69%***	0.08%	**0.83%***
48 month	0.69%***	0.14%*	**0.46%***
		Carhart Alpha	
1 month	0.55%***	0.12%**	**0.60%***
6 month	0.49%***	0.12%**	**0.55%***
12 month	0.55%***	0.06%	**0.67%***
24 month	0.61%***	0.07%	**0.75%***
48 month	0.60%***	0.12%**	**0.42%***
		FF6 Alpha	
1 month	0.56%***	0.14%**	**0.55%***
6 month	0.49%***	0.12%*	**0.51%***
12 month	0.55%***	0.05%	**0.64%***
24 month	0.62%***	0.02%	**0.78%***
48 month	0.56%***	0.10%**	**0.36%***
		FF6+Rev Alpha	
1 month	0.49%***	0.12%**	**0.51%***
6 month	0.45%***	0.09%	**0.51%***
12 month	0.52%***	0.01%	**0.65%***
24 month	0.59%***	-0.02%	**0.80%***
48 month	0.53%***	0.07%	**0.36%***
		FF6+Rev+BAB Alpha	
1 month	0.45%***	0.01%*	**0.53%***
6 month	0.41%***	0.07%	**0.54%***
12 month	0.48%***	0.01%	**0.63%***
24 month	0.56%***	-0.05%	**0.82%***
48 month	0.50%***	0.04%	**0.36%***

* 10%, ** 5%, *** 1%

Table D1: Estimation of the rank of the beta matrix

This table presents the results using Ahn et al.'s (2018) RBIC rank estimator to test the rank of beta matrices generated by different sets of factors. Each line specifies the set of factors used to generate the beta matrix, which are combinations of the Betting Against Alpha strategy (BAA), Betting Against Beta factor (BAB), CAPM factor (Market), Carhart factors (Market, SMB, HML, MOM), the Fama-French six factors (FF6: Carhart, RMW, and CMA) and FF6+Rev (FF6, LTR, and STR). The value in parenthesis *k* indicates the total number of factors used in the estimation and is equivalent to the maximum rank attainable by the estimated beta matrix. The matrix of estimated factor betas is calculated using 55 portfolios as response variables: 25 Size and Book to Market portfolios together with the 30 Industrial portfolios. I use monthly data from January 1968 – December 2015 to construct the BAA strategy for the period January 1973 – December 2015, corresponding to 516 monthly observations. Individual data on stock returns comes from the CRSP database, while the data for the CAPM, Carhart, FF6, and FF6+Rev models and portfolio returns comes from Kenneth French's webpage and the data for the BAB factor comes from AQR's webpage.

		Rank Estimation
(i)	BAA (k=1)	**1**
(ii)	BAB + BAA (k=2)	**2**
(iii)	CAPM (k=1)	**1**
(iv)	CAPM + BAA (k=2)	**2**
(v)	Carhart (k=4)	**3**
(vi)	Carhart + BAA (k=5)	**4**
(vii)	FF6 (k=6)	**4**
(viii)	FF6 + BAA (k=7)	**5**
(ix)	FF6 + Rev (k=8)	**4**
(x)	FF6 + Rev + BAA (k=9)	**5**
(xi)	FF6 + Rev + BAB (k=9)	**4**
(xii)	FF6 + Rev + BAB + BAA (k=10)	**5**