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

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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 this finding only appears after the CAPM's publication in the 1960s. I find evidence consistent with the widespread application of the CAPM model generating incentives to tilt portfolios systematically away from low CAPM Alpha assets, causing such assets to be undervalued.

Keywords. betting against alpha, capital asset pricing model, extrapolative beliefs.

JEL classification. G10, G12.

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1 Introduction

The Capital Asset Pricing Model (CAPM), arguably the most influential model in financial economics, is more than fifty years old (Treynor 1962, Sharpe 1964, Lintner 1965, and Mossin 1966). Its influence throughout the years has been demonstrably overarching. Over the years, the CAPM has become the building block of finance undergraduate and graduate education, giving it extraordinary academic exposure to generations of finance and business professionals. Also, most notably, CAPM Alpha became a critical metric for evaluating the performance of portfolio managers since the seminal paper by Jensen (1968). It would hardly be an exaggeration to say that the CAPM's impact on an entire industry and, by extension, on the national economy is enormous.

Performance metrics based on the CAPM generate incentives to avoid assets with a negative CAPM Alpha. The literature has documented that a large proportion of participants in the stock market form beliefs by extrapolating past data into the future, including CFOs and professional investors (e.g., Greenwood and Shleifer 2014). Therefore, benchmarked portfolio managers as well as any leveraged constrained investors with extrapolative beliefs have a reason to tilt their portfolios away from low CAPM Alpha assets. Additionally, managers window-dressing their portfolios by overselling underperforming stocks could exacerbate these patterns (e.g., Lakonishok et al. 1991). This in turn can create an anomaly consistent with low CAPM Alpha assets being undervalued.

Consistent with the previous discussion, 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 assets with low realized CAPM Alphas generate positive and statistically significant future alphas.

The use of alpha as a performance metric became pervasive after the CAPM was developed in the 1960s. Interestingly, before the development of the CAPM, there was no difference in performance between the low and high alpha assets. The portfolio of low alpha assets outperforms that of high alpha assets only after the CAPM appeared. McLean and Pontiff (2016) showed that academic research diminishes or even eliminates the predictive power of certain anomalies. My results suggest that academic research might also feed new anomalies.

To study these patterns I construct several self-financed strategies I call *betting against alpha* (henceforth BAA). The abnormal returns generated by the BAA strategy prior to the CAPM development are close to zero and insignificant. Starting in the mid-1960s the BAA strategies generate positive abnormal returns. Given that BAA is not pervasive throughout the period of analysis, I call it a *strategy* instead of a *factor*.

The benchmark BAA strategy used in this paper is constructed with rank-weighted portfolios, a technique that is becoming popular in the literature (e.g., Frazzini and Pedersen 2014, Asness et al. 2017, Kelly et al. 2018, Kozak et al. 2018). However, given that strategies constructed using rank-weighted portfolios can have a large exposure to assets with low market cap values (see Novy-Marx and Velikov 2018), I also construct BAA strategies using size-robust methodologies.

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 performance of extreme alpha assets (henceforth *alpha reversal*) I document is related to the (model-free) long-term price reversal (LTR) anomaly documented by De Bondt and Thaler (1985) and attributed to overreaction. However, overreaction to past prices cannot fully explain my results since my analysis starts in the 1930s but alpha reversal does not appear until more than three decades later.

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 has documented the existence of multiple factors.[1] In this paper I will call any factor other than MKT a *Smart Beta factor*. I also find evidence of changing patterns in the BAA strategy around 1993 after the popularization of Smart Beta strategies, which were developed to precisely capture CAPM Alpha. This also 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) played an important role (Dimson et al. 2017).[2]

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,

[1] 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.

[2] I show in Online Appendix A that the popularity of the academic literature related the CAPM experienced further increases after 1993.

I corroborate the aforementioned result between 1965 and 1992 but I find that the CAPM started to correctly price the Value Premium and other popular factors again after 1993. Therefore, my results are not driven by overall differential performance of the CAPM through time.

This paper relates to recent work concerned with observable patterns in stock returns' pricing errors and their relationship to stock return predictability. Hühn and Scholz (2018) use one year of daily data to estimate Fama-French three-factor alpha and find that there is alpha-momentum. Based on this paper's results as well as those in Hühn and Scholz (2018), Zaremba et al. (2019) document alpha momentum and alpha reversal in international stock returns. He et al. (2019) uncover predictive patterns of pricing errors as evidence that multifactor models fail to properly price asset returns and even to outperform the CAPM. My paper separates from the aforementioned papers in three important ways. First, I document alpha reversal using the most common estimation method, time frame, and frequency available in the literature to calculate the parameters of the CAPM: OLS regressions with 5 years of monthly data returns (e.g., Black et al. 1972, Banz 1981, Fama-French 1992, 1993, 2018 just to mention some). Second, I focus on the low and high CAPM Alpha assets' differential performance before and after the CAPM development. I show that the reversal patterns arose after the CAPM was developed. Third and finally, I suggest a new mechanism for these predictable patterns (and possibly others) to arise: The widespread dissemination and application of academic knowledge.

The rest of the paper is organized as follows. Section 2 presents the data and methods to construct the BAA strategy. Sections 3 and 4 analyze the main empirical findings. Section 5 discusses the possible economic channels driving alpha reversal. Section 6 concludes. The Online Appendix contains several additional analyses.

2 Data and construction of the Betting Against Alpha strategy

2.1 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), which is from AQR's webpage.[3,4] 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 (MKT). The Carhart model augments the CAPM with the Small Minus Big factor (SMB), High Minus Low factor (HML), and the Momentum factor (MOM). The FF6 model augments Carhart's model with the Robust Minus Weak (RMW) and Conservative Minus Aggressive (CMA) factors. The FF6+REV model augments FF6 with the Long-term Reversal factor (LTR) and the Short-term Reversal factor (STR).

2.2 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 the benchmark strategy using the method of Frazzini and Pedersen (FP, 2014). This method divides the sample into two portfolios by the median CAPM Alpha at the moment of rebalancing and rank-weights the assets within each portfolio. The details are in Online Appendix F. For this paper's purpose, FP's method has the desirable property of maximizing the weights of the low (high) alpha assets in the low (high) alpha portfolio. This method also reduces the correlation between the long-short strategy and MKT by rescaling the portfolios by the inverse of their MKT Beta. Thus, it generates a self-financing strategy with a zero MKT Beta at the moment of portfolio formation.

Throughout the paper I show that all results hold independent of whether I rescale the strategy or not. As such, in most Sections I also present the results for the low and high alpha portfolios' excess returns separately and without rescaling. In addition, in Section 3 I show all results hold when the BAA strategy is constructed using traditional size-weighted double-sorted portfolios by CAPM Alpha and market capitalization.

[3] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[4] https://www.aqr.com/Insights/Datasets/Betting-Against-Beta-Equity-Factors-Monthly

3 The CAPM Alpha before and after the CAPM

3.1 Betting Against Alpha

In this Section I will study in detail the economic magnitude of the tradable strategy I create to capture the alpha reversal patterns. For that purpose, I will first divide the analysis into *Pre-CAPM era (before 1965)* and *Post-CAPM era (1965 onward)*.[5]

The benchmark BAA strategy is constructed under the following 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 all common stocks in the CRSP database (NYSE, Nasdaq, and AMEX), and assets are rank-weighted as explained in Section 2.2 and Online Appendix F. (iii) CAPM Alphas and Betas used to construct the BAA strategy are estimated by OLS using 5-year data. (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 1 below depicts the monthly CAPM's cumulative abnormal returns (CAR) for the low and high alpha portfolios calculated using a 5-year rolling regression.

[Insert Figure 1 around here]

From the figure it is clear that the low and high CAPM Alpha portfolios present strikingly different patterns before and after the development of the CAPM: While the portfolio of high CAPM Alpha assets has a fairly flat CAR series for the whole period of analysis, the low CAPM Alpha portfolio shows a clear upward trend after the CAPM was developed in the mid 1960s.

Table 1 presents the summary statistics for the excess return of the low CAPM Alpha portfolio over the risk free asset, excess return of the high CAPM Alpha portfolio over the risk free asset, and the BAA strategy. I report the monthly Sharpe Ratios, average monthly excess return, monthly

[5] 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). To address this issue, Section 3.2 of the paper focuses on the impact of size on the BAA strategy. Additionally, Online Appendix C shows results restricted to using only NYSE data.

CAPM Alpha, monthly Carhart Alpha, monthly FF6 Alpha, monthly FF6+Rev Alpha, and monthly FF6+Rev+BAB Alpha.[6] Data for the last three models is only available for the Post-CAPM era.

[Insert Table 1 around here]

The table confirms the discussion from Figure 1. During the Pre-CAPM era there was no substantial difference between the Sharpe Ratio of the low and high alpha portfolios, as well as no significant alpha generated by the BAA strategy. The results for the Post-CAPM era are strikingly different. The first line in Panel (b) of Table 1 shows that during this second era the Sharpe Ratio diminishes almost by half when we move from the low to the high alpha portfolio. The BAA strategy's monthly Sharpe Ratio is 0.22. It has a higher monthly Sharpe Ratio than MKT (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).

During the Post-CAPM era 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. The portfolio of low alpha assets also produces statistically significant abnormal returns across all models. On the other hand, the portfolio of high alpha assets is correctly priced by all models. The latter corroborates the results of Figure 1. Additionally, in Online Appendix D I use 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 all the factors used to control for systematic risk in this paper (MKT, SMB, HML, RMW, CMA, MOM, LTR, STR, and BAB factors). Results for the Pre-CAPM and Post-CAPM eras are shown in panels (a) and (b) of Table 2, respectively.

[Insert Table 2 around here]

During the Pre-CAPM era, the Pearson's correlation coefficients (henceforth correlation) between the BAA strategy and many other factors are quite high, especially those with respect to SMB, HML, MOM, and LTR. During this era BAA did not perform well as I already showed in Table 1. During the Post-CAPM era the correlation between BAA and all other factors decreases, most notably the

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

one with respect to SMB. The correlation between BAA and MKT is only -0.08 as expected by the factor's construction. Interestingly, the correlation between BAA and BAB is quite low, too, only 0.08, which implies that betting against alpha is not the same as betting against beta. Note that the correlation between BAA and LTR is still quite high (0.53) in the Post-CAPM era, suggesting that there are commonalities between alpha reversal and the model-free long-term price reversal patterns. I will explore the relationship between these two patterns in depth in Section 3.3.

Finally, Table 3 presents performance metrics for the dataset divided into decile portfolios sorted on realized CAPM Alphas for the two eras. Assets within each portfolio are equally weighted.

[Insert Table 3 around here]

Note that the Sharpe Ratios across portfolios are almost the same during the Pre-CAPM era [Panel (a)] while they decrease for the high-alpha portfolio deciles during the Post-CAPM era [Panel (b)]. As expected, the sixth line of the table shows that Average Realized CAPM Alpha increases for portfolios sorted by this variable.

The third line of the panels shows that when regressing the decile portfolios onto the CAPM, the abnormal returns increase as the portfolio CAPM Alpha at formation decreases only during the Post-CAPM era. Then, it is only in this era that a low realized CAPM Alpha implies a future high abnormal return.

Additionally, the fourth to eighth lines of both panels show that low alpha and high alpha assets' characteristics were the same during both eras: both low and high CAPM Alpha assets have relatively large total volatility and idiosyncratic volatility, relatively large MKT Betas, and relatively small size. In other words, the characteristics of the low and high alpha assets remained unchanged during both eras; however, their performance did not.

The fact that both low and high alpha assets have larger than average volatilities and MKT Betas suggests that alpha reversal is not related to the low-volatility anomaly. This result further corroborates the results in Table 1, Table 2, and Online Appendix D showing that BAA and BAB are not capturing the same source of returns' comovement.

Finally, as previously mentioned, the last line of the panels shows that the relationship between market capitalization (Size) and Average Realized CAPM Alpha has an inverted U-shape. Therefore, the size effect should be analyzed in depth to corroborate that the alpha reversal pattern is pervasive and not just an anomaly present on small size assets. This is the objective of the next Section and Online Appendix E.

3.2 Betting Against Alpha and market capitalization

Most tradable 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. Therefore, it is important to study the performance of new strategies for different levels of market capitalization. Additionally, like the BAA strategy developed in this paper, several new papers construct tradable strategies using rank-weighted portfolios instead of using the classical double-sorted size-weighted portfolios advanced by Fama and French since 1992 (e.g., Frazzini and Pedersen 2014, Asness et al. 2017, Kelly et al. 2018, and Kozak et al. 2018). These rank-weighted strategies might be justified if the researcher's objective is to maximize the exposure of a strategy to a certain parameter or characteristic; however, new research has raised concerns on their robustness to more traditional weighting schemes (e.g., Novy-Marx and Velikov 2018).

In light of the above discussion, in this Section I construct two additional betting against alpha strategies based on double-sorted portfolios by market cap and CAPM Alpha, where assets are size-weighted within each portfolio.[7]

Using the NYSE 30th and 70th percentile for market capitalization cutoff values, every December I assign assets to three groups: (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. Then, I construct two new BAA strategies. For the first strategy I divide assets into three groups based on their CAPM Alphas and form nine portfolios as the intersection of the size and alpha groups. I also construct

[7] In Online Appendix E, I further analyze the impact on the rank-weighted BAA strategy of micro cap and small cap assets (Appendix E1) as well as the rank-weighted strategy's performance when constructed using stocks grouped by their NYSE market cap percentile (Appendix E2).

a second set of fifteen portfolios as the intersection of the three size groups and five alpha groups to create a larger spread in alpha. This second set is justified by the prior results in Table 3 where I show that the relationship between alpha and size is inverted U-shaped. Then, a size-weighted strategy might overweight assets with alphas around the median if we use too few alpha groups. The excess returns and Sharpe Ratios for the two sets of portfolios are in Table 4. Like in the previous analyses, results are divided into Pre-CAPM [Panel (a)] and Post-CAPM era [Panel (b)].

[Insert Table 4 around here]

The table shows that looking at portfolio excess returns there does not seem to be a clear difference between the Pre-CAPM and Post-CAPM era: Low alpha assets have higher returns than high alpha assets for both eras. However, looking at Sharpe Ratios is considerably more informative. Sharpe Ratios are quite flat across alpha sorted portfolios during the Pre-CAPM era (except for the largest stocks, in which high alpha assets show higher Sharpe Ratios than low alpha assets). This pattern completely changes during the Post-CAPM era, in which low alpha portfolios have much higher Sharpe Ratios than high alpha portfolios across all size groups. The table also shows that the wedge in Sharpe Ratios between low and high alpha portfolios increases when we divide assets into five alpha groups instead of using three.

The portfolios' analysis suggests different behavior between low and high CAPM Alpha assets before and after the CAPM was developed, even when using value weighted portfolios. Now I will use these portfolios to construct and test two additional strategies using double-sorted size-weighted portfolios as in the Fama-French factors: (i) $\text{BAA}^{5\times3}$, constructed using the intersection of assets assigned to the three Size groups and five CAPM Alpha groups and (ii) $\text{BAA}^{3\times3}$, constructed using the intersection of assets assigned to three Size groups and three CAPM Alpha groups. Both strategies are constructed as the equally weighted returns of the three size-weighted portfolios of low alpha assets (small size and low alpha, medium size and low alpha, big size and low alpha) minus the equally weighted returns of the three size-weighted portfolios of high alpha assets (small size and high alpha, medium size and high alpha, big size and high alpha). Table 5 shows the performance of these strategies for the Pre-CAPM and Post-CAPM periods using several models to control for common risks. The first column of the table shows the benchmark rank-weighted BAA strategy for comparison purposes.

[Insert Table 5 around here]

The results show again that no BAA strategy produces abnormal returns during the Pre-CAPM era, while all of them produce highly significant abnormal returns during the Post-CAPM era. The performances of BAA and BAA$^{5\times3}$ are very similar while, as expected, the economic magnitude of the abnormal returns diminishes for BAA$^{3\times3}$.

The results in this section show that BAA is robust to size – controlling for size sometimes reduces but never eliminates the abnormal returns generated by BAA in the Post-CAPM era. Furthermore, Online Appendix E1 shows that the rank-weighted BAA strategy is not priced by any model during the CAPM era even after removing micro cap and small stocks. Online Appendix E2 shows that when restricting the sample to the stocks belonging to the highest 30% NYSE percentile by market capitalization, the rank-weighted 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. Importantly, I find that no matter how I construct the BAA strategy, it maintains desirable properties across all size groups, like decreasing Sharpe Ratios from the low-alpha portfolio to the high-alpha one as well as positive risk premiums.

3.3 Betting Against Alpha and Long-Term Price Reversal

Table 2 in Section 3.1 shows that BAA is relatively highly correlated with LTR. As such, it is relevant to study whether alpha reversal captures different information than price reversal despite the commonalities. In fact, it should not be surprising that alpha reversal and the model-free price reversal anomalies share information. This fact becomes obvious when analyzing the fitted equation from the estimated CAPM model

$$\bar{\mu}_i = \hat{\alpha}_i + \hat{\beta}_i \times \bar{\mu}_{MKT}, \tag{1}$$

where $\bar{\mu}_i$ is the average excess return over r_f for asset i and $\bar{\mu}_{MKT}$ 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[8], BAA consists of sorting assets on the unexplained part of the average returns $\bar{\mu}_i$ by the CAPM ($\hat{\alpha}_i$). Then, model-free price reversal might be confounded with agents tilting portfolios away from low CAPM Alpha assets.

To separate the information in alpha reversal from that in price reversal, I will study betting against alpha strategies constructed in the same fashion as LTR (i.e., using double-sorted size-weighted portfolios). More precisely, Fama-French's LTR factor is constructed as the intersection of variables sorted by long-term price reversal (three groups) and size (two groups).[9] I already created similar BAA strategies in Section 3.2, BAA$^{3\times3}$ and BAA$^{5\times3}$. Unfortunately, I cannot create an LTR factor with similar numbers of groups as the aforementioned BAA strategies because some portfolios end up unpopulated in many time periods.[10] Therefore, I now create BAA$^{3\times2}$ by dividing assets into three groups by CAPM Alpha and two groups by size. The correlation between LTR and the three double-sorted size-weighted BAA strategies is around 0.59, which is similar to that of the benchmark rank-weighted BAA strategy and LTR (0.53).

Barillas and Shanken (2017) show that when using alphas for comparing asset pricing models with tradable factors, all that is needed is to check a model's ability to price the factors in the other models. Therefore, I now analyze whether the BAA strategies can be priced by LTR and vice versa. Table 6 presents the results of regressing BAA onto LTR while Table 7 shows the results of regressing LTR onto BAA. I add MKT as regressor to better control for common risk.

[Insert tables 6 and 7 around here]

From Table 6 we can observe that no double-sorted size-weighted BAA strategy produces abnormal returns in the Pre-CAPM era while all of them do in the Post-CAPM era. We can also observe that controlling by LTR has a sizable impact on the economic magnitude of the pricing error, but it remains highly significant for BAA$^{3\times3}$ and BAA$^{5\times3}$ while it is still marginally significant

[8]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.

[9]See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_lt_rev_factor.html.

[10]This situation arises because portfolios with extreme model-free price realizations contain a larger proportion of small-cap assets than portfolios with extreme CAPM Alpha realizations.

for BAA$^{3\times2}$. On the other hand, Table 7 shows that all pricing information in LTR is contained in BAA. This is further supported by the Fama-MacBeth regressions in Online Appendix G.

Overall, my analysis shows that, as expected, there are commonalities between BAA and LTR. Importantly, it also shows that there are differences and that the information in LTR does not subsume that in BAA. Again, the disentanglement between both strategies happened after the development of the CAPM, while there seems to be little to no reversal effect prior to this event.

3.4 Multifactor models' alpha strategies and the Smart Beta era

After CAPM, another breakthrough occurred around 1993 when Fama and French developed an empirical multifactor model that became the new benchmark in academic work and fostered *Factor Investing* (Dimson et al. 2017). The main idea of Factor Investing is to decompose the CAPM Alpha into *Smart Betas*, which are the sensitivities of an asset to factors not captured by the CAPM model.

For exposition purposes, 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:

$$E(r_i - r_f) = \beta_{MKT,i}\gamma_{MKT} + B'_{Smart,i}\mathit{\Gamma}_{Smart}, \tag{2}$$

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 $\mathit{\Gamma}_{Smart}$ is a $(k-1)$ vector of Smart Beta factors' risk premiums.[11] 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

$$E\left(\hat{\alpha}_i^{CAPM}\right) = B'_{Smart,i}\mathit{\Gamma}_{Smart}. \tag{3}$$

As a consequence, investors willing to outperform the CAPM got a new tip to decrease the likelihood

[11] For example, if asset prices were generated according to FF3, then $\mathit{\Gamma}_{Smart}$ contains the risk premiums of the SMB and HML.

of underperforming: Avoid low Smart Beta assets. Then, I hypothesize that the widespread use of factor investing – together with the expansion of the mutual fund industry – had an impact on assets with extreme alpha realizations.[12] I test this hypothesis comparing betting against alpha strategies based on alphas from different empirical multifactor models and dividing the Post-CAPM era (1965-2015) in two periods: *the CAPM era (1965-1992)* and *the Smart Beta era (1993-2015).*

Note that if we include Smart Beta factors as independent variables in the CAPM regression, then we remove their impact from the estimated Alpha. For example, if all the factors in FF3 are common sources of risk, then the estimated CAPM Alpha includes a linear combination of HML and SMB while the alpha generated by FF3 does not. More precisely, $E\left(\hat{\alpha}_i^{CAPM}\right) \approx E\left(\hat{\alpha}_i^{FF3}\right) + \beta_{SMB,i}\gamma_{SMB} + \beta_{HML,i}\gamma_{HML}$ (in a world with orthogonal factors this holds with equality).

Despite the advances in multifactor models after 1993 as evidence that the CAPM is a misspecified model, the CAPM Alpha is still a fundamental performance metric for portfolio managers.[13] If avoiding low sensitivities to specific factors like HML and SMB became more prevalent after 1993, increasing the possibility of observing mispricing in assets with extreme low values of $\beta_{SMB}\gamma_{SMB}+\beta_{HML}\gamma_{HML}$, then we should expect that sorting assets on $\hat{\alpha}_i^{CAPM}$ outperforms sorting assets on $\hat{\alpha}_i^{FF3}$. This is because the latter need not capture the additional source of mispricing.

To further study the impact of factor investing on alpha reversal I construct three new betting against alpha strategies, where I use three popular models to estimate alpha: Fama-French Three Factor model (1993), Carhart model (1997), and Fama-French Six Factor model (2018). I call these strategies BAA^{FF3}, $\text{BAA}^{Carhart}$, and BAA^{FF6}, respectively.

The strategies are constructed using the benchmark rank-weighted methodology used for BAA since my intention is to overweight assets with extreme realizations of Alpha. As discussed above, I expect that assets with an extremely low combination of popular Smart Betas are more likely to be mispriced after Fama and French (1992, 1993).[14] At the same time, these assets are more likely to

[12]For example, Bogle (2005) documents that at the beginning of the 1990s around 8% of US stocks where managed by US mutual funds. That percentage increased to 25% by the early 2000s.

[13]For example, most managers are benchmarked against an index or some metric related to the CAPM, like the Information Ratio (Baker et al. 2011, Ma et al. 2019), or are rewarded with inflow of capital based on the CAPM Alpha (Barber et al. 2016).

[14]Table I1 in Online Appendix I shows that the Sharpe Ratio of SMB decreased from 0.11 to 0.04 between the CAPM era and the Smart Beta era while that of HML decreased from 0.16 to 0.08. Table 9 in the next Section shows that the CAPM Alpha of HML was statistically significant during the CAPM era but not in the Smart Beta era (the

appear in extreme low CAPM Alpha than in extreme low multifactor Alpha. Moreover, the CAPM is nested in FF3, FF3 is nested in Carhart, and Carhart is nested in FF6. Then, after 1993, we should expect the following relationship for the factors' performances: BAA$\geqslant$BAA$^{FF3}\geqslant$BAA$^{Carhart}\geqslant$BAA^{FF6}. Table 8 below shows that this is the case when comparing risk-premiums. Table H2 in Online Appendix H shows the relationships also holds when comparing risk-adjusted performance.

The next step is to check whether BAA contains information missed by the different multifactor BAA strategies, especially after 1993. Following Barillas and Shanken (2017) as in Section 3.3, Table 8 shows the results from regressing the BAA strategy onto MKT and each of the mutifactor BAA (BAA^{FF3}, BAA^{Carhart}, and BAA^{FF6}) during the CAPM and Smart Beta eras. It also shows results from regressing the multifactor BAA strategies onto MKT and BAA.

[Insert Table 8 around here]

Note that while the pricing information in BAA was similar to that of the multifactor BAA strategies during the CAPM era, it definitely had more pricing information during the Smart Beta era. In fact, the table shows that during the Smart Beta era, the more information I remove from the estimated alpha by augmenting the number of factors in a model, the higher the difference in performance with BAA. This is consistent with the previous discussion about extreme CAPM Alpha realizations containing more information about possible mispricing than the specific multifactor alphas, especially during the Smart Beta era. The table also shows that every multifactor BAA strategy is subsumed by BAA. Online Appendix H shows that there is differential performance for each strategy in the two eras (all strategies but BAA^{FF6} perform better in the Smart Beta era) and that there is a sharp break in the series of cumulative abnormal returns of the BAA strategy in the Smart Beta era. Online Appendix A analyzes the popularity of the CAPM model and related research in the academic literature constructing several citation indices. I find a sharp break in the growth rate of academic papers produced in relationship to the CAPM around 1993.

Overall, the results are consistent with my hypothesis that assets with an extreme combination

CAPM Alpha of SMB is not significant in both eras). This is consistent with an increment in the relative performance of the short arm of popular Smart Beta strategies. As Schwert (2003) pointed out almost two decades ago, "the size effect and the value effect seem to have disappeared after the papers that highlighted them were published. At about the same time, practitioners began investment vehicles that implemented the strategies implied by the academic papers."

of Smart Beta realizations had a higher effect on BAA during the Smart Beta.

3.5 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, Ang and Chen 2007). To assess the relative impact of this reported stylized fact on the BAA strategy, 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 other factors included in the analysis are BAB, SMB, HML, MOM, LTR, and STR.

[Insert Table 9 around here]

Table 9 shows the results from CAPM regressions using the seven factors as response variables and three sub-periods: The Pre-CAPM era, the CAPM era, and the Smart Beta era. Three of the seven factors present statistically significant pricing errors at the 1% level of significance during the Pre-CAPM era: 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 the pricing error of LTR is significant at the 5% level. This confirms that the CAPM pricing power was 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.[15] 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 and economically relevant for the CAPM era (0.54% monthly return with a t-stat of 3.69) and the Smart Beta era (0.88% monthly returns with a t-stat of 4.79). 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.

[15]Note that the behavior of short-term price reversal is the opposite to that of alpha reversal. STR was the most profitable strategy during the Pre-CAPM era while its predictive power disappeared during the Smart Beta era. As such, short-term price reversal is consistent with the channel studied in McLean and Pontiff (2016): Once the anomaly was published (Jegadeesh 1990), its predictive power disappeared.

4 CAPM Alpha, mutual funds, and funding liquidity shocks

4.1 The CAPM Alpha and mutual fund trading behavior

In this Section I study the trading behavior of mutual funds' managers and find evidence that they tilt their portfolios away from low CAPM Alpha assets. The result is consistent with Calluzo et al. (2018) who find that institutional investors load in the long arm of an anomaly after it is published in academia, suggesting that institutional investors avoid low Smart Beta assets. I further discuss why investors avoid low CAPM Alpha assets in Section 5.

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 MKT 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 month returns using the CRSP database. The results are presented in Table 10 below. The column Selling Portfolio shows data for the assets sold by the mutual funds while the column Buying Portfolio shows the metrics for the assets bought. The column CRSP database shows the average value for the alphas and betas in the CRSP database for the period 1980-2015.

[Insert Table 10 around here]

The results for Avg. Alpha corroborate my hypothesis: Mutual fund managers buy stocks with larger 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 tilted toward assets with larger than average alphas.

The results for Avg. MKT Beta corroborate prior findings in the literature (e.g. Christoffersen and Simutin 2017): Mutual funds tend to buy stocks with higher CAPM beta (1.09) than those sold (1.05).[16] Similar to the alpha case, mutual fund transactions are tilted toward stocks with a

[16] The difference in values between the metrics reported for the Selling Portfolio and the Buying Portfolio are all

larger than average MKT 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 documenting lack of skills in the mutual fund industry (e.g., Malkiel 1995, Gruber 1996, Wermers 2000, Fama and French 2010, Dasgupta et al. 2011, and Song 2017), the variable Avg. cumulative returns (12-month holding period) shows that assets sold by mutual funds tend to outperform those bought by mutual funds when held for a year.[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 consistent with this as I showed in Section 3.1 (Figure 1 and Table 1) that high CAPM Alpha assets do not necessarily produce future negative performance metrics. In fact, as shown throughout the paper, the high CAPM Alpha portfolio of the BAA strategy seems fairly priced.

Overall, I find that mutual funds trade stocks with values of realized CAPM Alphas above average. Additionally, assets bought by mutual fund managers have on average a higher CAPM Alpha than assets sold. This evidence suggests that mutual fund managers do tilt their portfolios away from low CAPM Alpha assets.

4.2 The CAPM Alpha and funding liquidity shocks

Brunnermeier and Pedersen (BP, 2009) show that it is expected for tightening funding conditions to negatively affect the returns of high volatility stocks. Table 3 shows that extreme low and high CAPM Alpha assets have relatively high volatilities – the monthly average total volatility for the individual assets in the lowest and highest alpha portfolio during the Post-CAPM era is 15.3% and 18.6%, respectively. For the rank-weighted low and high alpha portfolio, the total volatility during the Post-CAPM era is 6.2% and 5.8%, respectively. Then, we should expect a similar impact of a tightening funding condition on both types of assets.

highly statistically significant, with a t-stat of 71.62 for Avg. CAPM Alpha, 32.09 for Avg. MKT Beta, 54.23 for Avg. monthly returns (-13 to -60 months), and -14.80 for Avg. cumulative returns (12-month holding period).

[17] There is also literature that documents skills in the mutual fund industry (e.g., Cremers and Petajisto 2009, Kacperczyk et al. 2014). Consistent with the existence of both skilled and unskilled fund managers, Song (2017) documents that both types of managers coexist in the market. Importantly, he documents that managers in the largest mutual funds are the ones that more frequently underperform.

Therefore, I now 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 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 11 shows results using as response variables the BAA strategy and the low and high CAPM 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 (when liquidity shocks are captured by ΔTED) while Column (2) shows the results for the period January 1972 - December 2015 (when 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 MKT.

[Insert Table 11 around here]

The table shows that the BAA strategy is affected by funding liquidity shocks as suggested at the beginning of this Section, since both ΔTED and ΔCredit show statistically significant coefficients. Moreover, the sign of the effect coincides with the theoretical predictions by BP. In addition, the table also shows that funding liquidity shocks negatively affect 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 when funding liquidity is tighter.

Overall, the results in Table 11 can be partially rationalized in the context of the theory developed

[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.

by BP. However, what 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 having similar volatilities and MKT betas. This puzzling result can be explained by the hypothesis advanced in this paper about agents tilting portfolios away from low alpha assets. In periods of stringent liquidity, selling low CAPM Alpha assets requires sellers to absorb a higher premium.

5 Discussion

The CAPM was the first equilibrium model to coherently relate assets' risk and return. According to the CAPM, in equilibrium all assets should have zero alpha. Consequently, 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 have shown comprehensive evidence that the opposite holds in real data after the CAPM was developed using the most common estimation method for alpha. Given this counter-intuitive finding, it is important to rationalize why this pattern might appear.

A fully rational expectations model without frictions cannot accommodate these results as investors would be systematically tilting portfolios away from overperforming assets. However, these results can be understood in relation to a behavioral model in which investors have extrapolative beliefs (e.g., Barberis et al. 2015, 2018). In these models, extrapolative investors' expectations about future market values are positively correlated with past observable data. In fact, Greenwood and Shleifer (2014) analyze survey data from 1963 until 2011 and find that "a substantial share of investors, including individuals, CFOs, and professional investors hold extrapolative expectations about returns." Then, if investors value positive CAPM Alpha, it cannot be discarded that they also hold extrapolative beliefs about this metric. Greenwood and Shleifer (2014) also find that extrapolative beliefs are negatively correlated with future stock market performance.

There are several specific reasons as to why investors with extrapolative beliefs could be tilting their portfolios away from assets with low realized CAPM Alpha. First, 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."[19] It follows that when we control for the tracking error, assets with a high CAPM Alpha increase the information ratio, while assets with a low CAPM Alpha reduce it. Second, Frazzini and Pedersen (2014) argue that leverage-constrained investors bid up high MKT Beta assets to augment their portfolios' expected returns. If leverage-constrained investors believe expected returns are generated by a multifactor model like the one described in Equation (2), then they also have incentives to bid up assets with high CAPM Alpha/Smart Betas to augment expected returns. Third, 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. Consequently, fund managers with extrapolative beliefs have incentives to tilt their portfolios away from low CAPM Alpha. Additionally, managers window-dressing their portfolios by overselling underperforming stocks could reinforce the alpha reversal patterns (e.g., Lakonishok et al. 1991).

A relevant question is why mispricing is persistent in low CAPM Alpha assets. My results and the existing literature can also shed light on this issue. The persistence of undervaluation on low alpha assets could be explained by the relatively high downside-risk these assets contain (see Table 11). Then, even if there are (risk-averse) rational investors coexisting with extrapolative ones, they might not fully take advantage of the apparent opportunity to avoid the high penalty these assets command in bad states of nature. Additionally, Barberis et al. (2015) show that even if there are rational investors coexisting with extrapolative ones, they might not fully counteract the mispricing generated by extrapolators because the latter can keep prices disconnected from fundamentals in the near future.

Another relevant question is why managers buying high CAPM Alpha assets survive. I find that high CAPM Alpha assets underperform low CAPM Alpha assets but not the Market. More precisely, the portfolio of high realized CAPM Alpha assets generates a flat CAR series (see Figure 1). This is consistent with empirical evidence in the literature (e.g., Malkiel 1995, Fama and French

[19] 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 $IR_A = \frac{E(R_A - R_{MKT})}{\sigma_{(R_A - R_{MKT})}}$. Note that given Equation (2), in a multifactor world the numerator of IR_A is $B'_{Smart,A}\Gamma_{Smart} + (\beta_{MKT,A} - 1)\gamma_{MKT}$.

2010) showing that most managers do not outperform the Market.

Finally, it is important to point out that most of the analysis hinges on studying long-term trends in time-series data. This type of analysis has weaknesses, such as the possibility that the observed patterns are driven by alternative events. Therefore, I have tried to minimize the possibility of a false positive by performing a thorough analysis of the time-series trends as well as additional analyses that either support my hypotheses or rules out alternative ones. Some of the alternative analyses are those of mutual fund managers trading behavior, the time-varying risk exposure of the BAA strategy, the relationship of the BAA strategy with long-term reversal (and other factors' long-term trends) and its disconnection after the CAPM was developed, and the analysis of BAA strategies using alphas from multifactor models. I also present additional evidence and robustness checks in the Online Appendix, for example the analysis of the evolution of the popularity of the CAPM in the academic literature (Online Appendix A), and the study of BAA as a different source of comovement using rank estimation methods (Online Appendix D).

6 Concluding remarks

Having been so successful and arriving at the half-century mark, the CAPM was bound to affect the behavior of market participants, the collective outcomes of decisions made by individual players and, in the aggregate, the economic activity of a critical national industry. The research presented here reflects my original intention to evaluate the CAPM's effects in a rigorous manner.

Once published in the mid 1960s, CAPM immediately became a central topic in the asset pricing literature. By 2009 there were more than 1,000 new CAPM related scientific works produced per year having 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).

Contrary to the model's prediction, I find that assets having low realized CAPM Alphas outperform those having high ones, but only after the CAPM was developed. My hypothesis is that this counterintuitive stylized fact arose from the widespread dissemination of CAPM knowledge and its applications, generating incentives to tilt portfolios away from low CAPM Alpha assets, causing such assets to be undervalued. This behavior is consistent with participants in the stock markets forming beliefs by extrapolating past data into the future (Greenwood and Shleifer 2014). These participants can be managers being benchmarked with respect to the CAPM and investors facing leverage constraints. Managers window dressing their portfolios can reaffirm these patterns (Lakonishok et al. 1991). I also show evidence that the fast expansion of factor investing starting in 1993 (Dimson et al. 2017) had non-negligible impact in the alpha reversal patterns presented in this paper. Previous work showed that academic research diminishes or even eliminates the predictive power of certain anomalies (e.g., 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 might also generate new anomalies.

References

[1] Agarwal V., T. Green, and H. Ren, 2017, Alpha or beta in the eye of the beholder: What drives hedge fund flows?, *Journal of Financial Economics* 127, 417-434.

[2] Ahn S., A. Horenstein, and N. Wang, 2018, Beta matrix and common factors in stock returns, *Journal of Financial and Quantitative Analysis* 53, 1417-1440.

[3] Ang A. and J. Chen, 2007, CAPM over the long run: 1926–2001, *Journal of Empirical Finance* 14, 1-40.

[4] Asness C., A. Frazzini, N. Gormsen, and L. Pedersen, 2017, Betting against correlation: Testing theories of the low-risk effect, *working paper available at SSRN*: https://ssrn.com/abstract=2913508

[5] Baker M., B. Bradley, and J. Wurgler, 2011, Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly, *Financial Analysts Journal* 67, 40-54.

[6] Banz R., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

[7] Barber B., X. Huang, and T. Odean, 2016, Which factors matter to investors? Evidence from mutual fund flows, *Review of Financial Studies* 29, 2600-2642.

[8] Barberis N., R. Greenwood, L. Jin and A. Shleifer, 2015, X-CAPM: An extrapolative capital asset pricing model, *Journal of Financial Economics* 129, 203-227.

[9] Barberis N., R. Greenwood, L. Jin and A. Shleifer, 2018, Extrapolation and bubbles, *Journal of Financial Economics* 129, 203-227.

[10] Barillas F. and J. Shanken, 2017, Which alpha?, *Review of Financial Studies* 30, 1316-1338.

[11] Barras L., O. Scaillet, and R. Wermers, 2010, False discoveries in mutual fund performance: Measuring luck in estimated alphas, *Journal of Finance* 65, 179-216.

[12] Black F., M. Jensen, and M. Scholes, 1972, The capital asset pricing model: Some empirical tests, *working paper available* https://ssrn.com/abstract=908569

[13] Bogle J., 2005, The mutual fund industry 60 years later: For better or worse? *Financial Analysts Journal* 61, 15-24.

[14] Boyson N., C. Stahel, and R. Stultz, 2010, Hedge fund contagion and liquidity shocks, *Journal of Finance* 65, 1789-1816.

[15] Brown N., K. Wei, and R. Wermers, 2013, Analyst recommendations, mutual fund herding, and overreaction in stock prices, *Management Science* 60, 1-264.

[16] Brunnermeier M. and L. Pedersen, 2009, Market Liquidity and Funding Liquidity, *Review of Financial Studies* 22, 2201–2238.

[17] Calluzzo P., F. Moneta, and S. Topaloglu, 2018, When anomalies are publicized broadly, do institutions trade accordingly? Forthcoming *Management Science*.

[18] Campbell J. and T. Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249-1275.

[19] Carhart M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

[20] Cremers M. and A. Petajisto, 2009, How active is your fund manager? A new measure that predicts performance, *Review of Financial Studies* 22, 3329-3365.

[21] Christoffersen S. and M. Simutin, 2017, On the demand for high-beta stocks: Evidence from mutual funds, *forthcoming Review of Financial Studies*.

[22] Dasgupta A., A. Prat, and M. Verardo, 2011, Institutional trade persistence and long-term equity returns. *Journal of Finance* 66, 635–653.

[23] DeBondt W. and R. Thaler, 1985, Does the stock market overreact?, *Journal of Finance*, 40, 793-805.

[24] Dimson E., P. Marsh, and M. Staunton, 2017, Factor-based investing: The long-term evidence, *Journal of Portfolio Management* 43, 15-37.

[25] Fama E. and K. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

[26] Fama E. and K. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

[27] Fama E. and K. French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653-1678.

[28] Fama E. and K. French, 2010, Luck versus skill in the cross-section of mutual fund returns, *Journal of Finance* 65, 1915-1947.

[29] Fama E. and K. French, 2018, Choosing factors, *Journal of Financial Economics* 128, 234-252

[30] Frazzini A. and L. H. Pedersen, 2014, Betting against beta, *Journal of Financial Economics* 111, 1-25.

[31] Greenwood R. and A. Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714-746.

[32] Gruber M., 1996, Another puzzle: The growth in actively managed mutual funds, *Journal of Finance* 51, 783-810.

[33] Harvey C., Y. Liu, and H. Zhu, 2016, ... and the cross-section of expected returns, *Review of Financial Studies* 29, 5-68.

[34] He A., D. Huang, and G. Zhou, 2019, New factors wanted: Evidence from a simple specification test, *working paper available at SSRN*: https://ssrn.com/abstract=3143752

[35] Hühn L. and H. Scholz, 2018, Alpha momentum and price momentum, *International Journal of Financial Studies* 6, 1-28.

[36] Jegadeesh N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

[37] Jegadeesh N. and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

[38] Jensen M., 1968, The performance of mutual funds in the period 1945–1964, *Journal of Finance* 23, 389– 416.

[39] Kacperczyk M., C. Sialm, and L. Zheng, 2008, Unobserved actions of mutual funds, *Review of Financial Studies*, 21, 2379-2416.

[40] Kacperczyk M, S. Van Nieuwerburgh, and L. Veldkamp, 2014, Time-varying fund manager skill, *Journal of Finance* 69, 1455-1484.

[41] Kelly B., S. Pruitt, and Y. Su, 2018, Characteristics are covariances: A unified model of risk and return, forthcoming *Journal of Financial Economics.*

[42] Kozak S., S. Nagel, and S. Santosh, 2018, Shrinking the cross section, forthcoming *Journal of Financial Economics.*

[43] Lakonishok J., R. Thaler, A. Shleifer, and R. Vishny, 1991, Window dressing by pension fund managers, *American Economic Review P&P* 81, 227-231.

[44] Lintner J., 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economic and Statistics* 47, 13-37.

[45] Lo A., 2002, The statistics of Sharpe Ratios, *Financial Analysts Journal* 58, 36-52.

[46] Ma L., Y. Tang, and J. Gomez, 2019, Portfolio manager compensation in the U.S. mutual fund industry, *Journal of Finance* 74, 587-638.

[47] Malkiel B., 1995, Returns from investing in equity mutual funds 1971 to 1991, *Journal of Finance* 50, 549-572.

[48] McLean R. and R. Pontiff, 2016, Does academic research destroy stock return predictability?, *Journal of Finance* 71, 5-32.

[49] Merton R., 1972, An intertemporal capital asset pricing model, *Econometrica* 41, 867–887.

[50] Mossin J., 1966, Equilibrium in a capital asset market, *Econometrica* 35, 768-783.

[51] Novy-Marx R. and M. Velikov, 2018 Betting against betting against beta, *working paper available at SSRN*: https://ssrn.com/abstract=3300965

[52] Ross S., 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13, 341–360.

[53] Schwert G., 2003, Anomalies and market efficiency, in George M. Constantinides, Milton Harris, and Rene Stulz eds., *Handbook of the Economics of Finance*, 937-972.

[54] Sharpe W., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-442.

[55] Song Y., 2017, The mismatch between mutual fund scale and skill, *working paper available at SSRN*: https://ssrn.com/abstract=3065700

[56] Treynor J. Toward a theory of market value and risky assets. Unpublished manuscript. Final version in *Asset Pricing and Portfolio Performance*, 1999, Robert A. Korajczyk ed., London: Risk Books, 15-22.

[57] Wermers R., 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transaction costs, and expenses, *Journal of Finance* 55, 1655-1695.

[58] Zaremba A., M. Umutlu, and A. Karathanasopoulos, 2019, Alpha momentum and alpha reversal in country and industry equity indexes, *Journal of Empirical Finance* 53, 144-161.

Figure 1: Cumulative abnormal returns for the low and high alpha portfolios

This figure shows the CAPM's cumulative abnormal returns from the low and high alpha portfolios' excess returns. I use 5-year data to calculate CAPM Alphas and rebalance the portfolios yearly, at the end of December. Each year, assets with a CAPM Alpha below (above) the sample median CAPM Alpha are assigned to the low (high) alpha portfolio. Alphas are estimated with OLS regressions using the CAPM model. Assets within each portfolio are rank-weighted. 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. These portfolios are constructed using individual data on common stock returns from the CRSP database. The data for the risk-free rate (one-month T-bill) and the CAPM comes from Kenneth French's webpage.

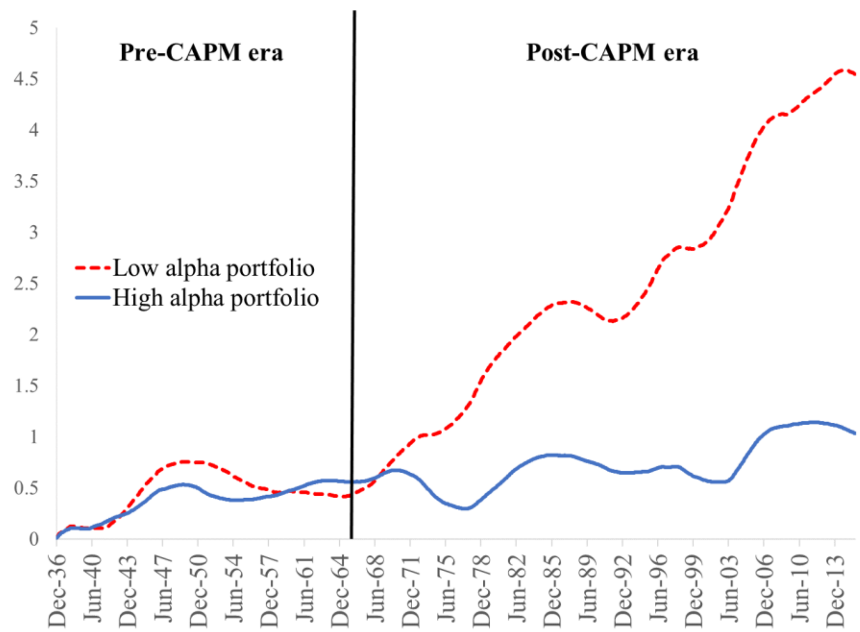

Table 1: Betting Against Alpha performance metrics during the Pre- and Post-CAPM eras

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. 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 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), 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. Heteroskedastic robust standard errors are reported in parenthesis.

	(a) Pre-CAPM era (1932-1964)			**(b) Post-CAPM era (1965-2015)**		
	Low alpha portfolio	High alpha portfolio	**BAA**	Low alpha portfolio	High alpha portfolio	**BAA**
Sharpe Ratio	0.17	0.18	**0.06**	0.18	0.10	**0.22**
Excess Return	1.82%	1.55%	**0.20%**	1.12%	0.59%	**0.66%**
CAPM Alpha	0.15%	0.06%	**-0.05%**	0.60%***	0.03%	**0.69%*** **
	(0.0020)	(0.0012)	(0.0014)	(0.0015)	(0.0010)	(0.0011)
Carhart Alpha	0.19%**	0.00%	**0.02%**	0.49%***	-0.04%	**0.64%*** **
	(0.0009)	(0.0007)	(0.0010)	(0.0011)	(0.0007)	(0.0012)
FF6 Alpha		-		0.47%***	-0.06%	**0.60%*** **
				(0.0012)	(0.0007)	(0.0013)
FF6+Rev Alpha		-		0.42%***	-0.07%	**0.58%*** **
				(0.0011)	(0.0007)	(0.0017)
FF6+Rev+BAB Alpha		-		0.36%***	-0.10%	**0.57%*** **
				(0.0011)	(0.0007)	(0.0012)

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

Table 2: Correlation between factors during the Pre- and Post-CAPM eras

This table presents the correlation coefficient between the Betting Against Alpha strategy (BAA), Betting Against Beta factor (BAB), Fama-French six factors (MKT, SMB, HML, RMW, CMA, MOM), and reversal factors (LTR and STR) during the Pre-CAPM (1932-1964) and Post-CAPM (1965-2015) eras. 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 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 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.

(a) Pre-CAPM era (1932-1964)

	BAA	BAB	Market	SMB	HML	RMW	CMA	MOM	LTR	STR
BAA	**1**									
BAB	-0.32	**1**								
MKT	0.38	-0.21	**1**							
SMB	0.58	-0.03	0.41	**1**						
HML	0.74	-0.52	0.60	0.46	**1**					
MOM	-0.58	0.46	-0.48	-0.31	-0.58	**1**				
LTR	0.78	-0.28	0.42	0.54	0.75	-0.35	**1**			
STR	0.04	-0.06	0.07	0.17	0.03	-0.03	-0.03	**1**		
RMW	-	-	-	-	-	-	-	-	-	
CMA	-	-	-	-	-	-	-	-	-	-

(b) Post-CAPM era (1965-2015)

	BAA	BAB	Market	SMB	HML	RMW	CMA	MOM	LTR	STR
BAA	**1**									
BAB	0.08	**1**								
MKT	-0.08	-0.08	**1**							
SMB	0.13	-0.07	0.29	**1**						
HML	0.44	0.33	-0.27	-0.21	**1**					
MOM	-0.38	0.17	-0.13	0.01	-0.18	**1**				
LTR	0.54	0.05	-0.03	0.26	0.45	-0.06	**1**			
STR	0.14	-0.05	0.28	0.16	0.00	-0.29	0.08	**1**		
RMW	-0.07	0.29	-0.24	-0.41	0.08	0.11	-0.29	-0.08	**1**	
CMA	0.33	0.31	-0.39	-0.17	0.69	-0.01	0.48	-0.13	-0.04	**1**

Table 3: Portfolio deciles sorted on alphas

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 (MKT). 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 1927 – December 2015 to construct the portfolios for the period January 1932 – 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)
					(a) Pre-CAPM era (1932-1964)					
i) Sharpe Ratio	0.17	0.18	0.16	0.17	0.17	0.19	0.19	0.18	0.18	0.16
ii) Excess Return	2.20%	1.79%	1.47%	1.44%	1.42%	1.64%	1.46%	1.58%	1.53%	1.56%
iii) CAPM Alpha	0.33%	0.15%	-0.05%	0.03%	0.01%	0.17%	0.13%	0.10%	0.10%	-0.03%
iv) Average Total Volatility	13.33%	11.98%	11.24%	10.71%	10.77%	10.88%	10.92%	11.62%	12.55%	16.74%
v) Average Idios. Volatility	10.10%	8.70%	8.17%	7.66%	7.77%	7.89%	7.95%	8.52%	9.46%	13.68%
vi) Average Realized CAPM Alpha	-1.32%	-0.59%	-0.28%	-0.03%	0.19%	0.43%	0.63%	0.89%	1.22%	2.20%
vii) Average Realized MKT Beta	1.44	1.32	1.23	1.18	1.16	1.13	1.11	1.14	1.19	1.37
viii) Size	$428,439	$900,074	$1,255,365	$1,366,351	$1,509,483	$1,353,721	$1,692,217	$1,561,486	$1,395,376	$901,276
					(b) Post-CAPM era (1965-2015)					
i) Sharpe Ratio	0.17	0.16	0.17	0.17	0.18	0.17	0.16	0.16	0.12	0.06
ii) Excess Return	1.42%	0.96%	0.87%	0.82%	0.83%	0.78%	0.79%	0.82%	0.68%	0.42%
iii) CAPM Alpha	0.83%***	0.46%***	0.40%***	0.39%***	0.40%***	0.34%***	0.32%***	0.32%***	0.13%	-0.21%
iv) Average Total Volatility	15.33%	12.15%	10.86%	10.06%	9.79%	10.07%	10.64%	11.73%	13.59%	18.86%
v) Average Idios. Volatility	13.98%	10.85%	9.59%	8.83%	8.58%	8.87%	9.43%	10.47%	12.24%	17.41%
vi) Average Realized CAPM Alpha	-1.64%	-0.71%	-0.30%	0.00%	0.24%	0.49%	0.75%	1.09%	1.58%	2.89%
vii) Average Realized MKT Beta	1.26	1.09	1.01	0.96	0.93	0.95	0.98	1.04	1.15	1.32
viii) Size	$1,115,768	$1,782,175	$2,309,880	$2,357,915	$2,735,528	$2,971,247	$2,882,941	$2,942,423	$2,741,645	$1,999,256

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

Table 4: Double-sorted size-weighted portfolios by CAPM Alpha and market capitalization

This table presents the average monthly excess returns and monthly Sharpe Ratios of portfolios constructed as the intersection of the assets' market capitalization value (Size) and CAPM Alpha. Assets within each portfolio are size weighted. At the moment of rebalancing, I use NYSE break points to assign assets to three Size groups: (i) 30% Small, which contains all firms whose market cap is equal to or below the 30th NYSE percentile; (ii) 40% Medium, which contains all firms whose market cap is greater than the 30th NYSE 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 NYSE percentile. At the moment of rebalancing I also divide assets by their CAPM Alpha into three groups and five groups. The two sets of portfolios are the intersection of the Size groups and the three and five CAPM Alpha groups. Alphas to assign assets to the different groups 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 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 CAPM's Market factor and risk-free rate (one-month T-bill) comes from Kenneth French's webpage.

				Excess Returns						
				a) Pre-CAPM era (1932-1964)						
		CAPM Alpha						CAPM Alpha		
		1	2	3		1	2	3	4	5
	1	2.09%	1.76%	1.82%	1	2.33%	1.58%	1.94%	1.77%	1.82%
Size	2	2.15%	1.72%	1.76%	2	2.35%	1.79%	1.77%	1.70%	1.79%
	3	1.62%	1.41%	1.54%	3	1.86%	1.42%	1.43%	1.50%	1.54%
				b) Post-CAPM era (1965-2015)						
		1	2	3		1	2	3	4	5
	1	1.65%	1.05%	0.91%	1	1.99%	1.16%	1.06%	1.02%	0.82%
Size	2	1.52%	1.14%	1.29%	2	1.90%	1.18%	1.15%	1.20%	1.36%
	3	1.28%	1.04%	1.16%	3	1.63%	1.07%	1.03%	1.09%	1.24%
				Sharpe Ratios						
				a) Pre-CAPM era (1932-1964)						
		1	2	3		1	2	3	4	5
	1	0.17	0.16	0.15	1	0.17	0.14	0.16	0.16	0.15
Size	2	0.20	0.20	0.19	2	0.20	0.19	0.19	0.19	0.19
	3	0.21	0.23	0.24	3	0.20	0.21	0.21	0.25	0.23
				b) Post-CAPM era (1965-2015)						
		1	2	3		1	2	3	4	5
	1	0.25	0.21	0.14	1	0.26	0.21	0.21	0.18	0.12
Size	2	0.26	0.24	0.22	2	0.28	0.23	0.24	0.23	0.21
	3	0.25	0.24	0.23	3	0.25	0.24	0.23	0.24	0.21

Table 5: BAA strategies constructed using double-sorted size-weighted portfolios

This table presents monthly performance metrics for the rank-weighted Betting Against Alpha (BAA) strategy and two additional versions: (i) BAA^{5x3}, constructed using the intersection of assets assigned to three Size groups and five CAPM Alpha groups and (ii) BAA^{3x3}, constructed using the intersection of assets assigned to three Size groups and three CAPM Alpha groups. At the moment of rebalancing, I use NYSE break points to assign assets to three Size groups: (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. At the moment of rebalancing I also divide assets by their CAPM Alpha into three groups and five groups. Both strategies, BAA^{5x3} and BAA^{3x3}, are constructed as the equally weighted returns of the three size-weighted portfolios of low alpha assets (small size and low alpha, medium size and low alpha, big size and low alpha) minus the equally weighted returns of the three size-weighted portfolios of high alpha assets (small size and high alpha, medium size and high alpha, big size and high alpha). The performance metrics reported are the 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 (RMW and CMA are not available for the Pre-CAPM era). 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. I rebalance the portfolios yearly, at the end of December. 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), 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. Heteroskedastic robust standard errors are reported in parenthesis.

		BAA	**BAA^{5x3}**	**BAA^{3x3}**
Pre-CAPM era (1932-1964)	**CAPM Alpha**	-0.05%	0.24%	0.10%
		(0.0014)	(0.0018)	(0.0010)
	Carhart Alpha	0.02%	0.35%*	0.18%%
		(0.0010)	(0.0016)	(0.0011)
Post-CAPM era (1965-2015)	**CAPM Alpha**	0.69%***	0.73%***	0.39%***
		(0.0011)	(0.0016)	(0.0011)
	Carhart Alpha	0.64%***	0.63%***	0.35%***
		(0.0012)	(0.0013)	(0.0010)
	FF6 Alpha	0.60%***	0.58%***	0.34%***
		(0.0013)	(0.0014)	(0.0010)
	FF6+Rev Alpha	0.58%***	0.56%***	0.32%***
		(0.0017)	(0.0011)	(0.0007)
	FF6+Rev+BAB Alpha	0.57%***	0.57%***	0.33%***
		(0.0012)	(0.0011)	(0.0007)

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

Table 6: Double-sorted size-weighted BAA strategies regressed onto LTR

This table presents results from regressing three betting against alpha strategies constructed using size-weighted double sorted portfolios onto the LTR factor. The three strategies are (i) BAA^{3x2}, constructed using the intersection of assets assigned to two Size groups and three CAPM Alpha groups; (ii) BAA^{3x3}, constructed using the intersection of assets assigned to three Size groups and three CAPM Alpha groups; and (iii) BAA^{5x3} constructed using the intersection of assets assigned to three Size groups and five CAPM Alpha groups. At the moment of rebalancing, I use NYSE break points to assign assets to three Size groups: (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. At the moment of rebalancing I also divide assets by their CAPM Alpha into three groups and five groups. Both strategies, BAA^{5x3} and BAA^{3x3}, are constructed as the equally weighted returns of the three size-weighted portfolios of low alpha assets (small size and low alpha, medium size and low alpha, big size and low alpha) minus the equally weighted returns of the three size-weighted portfolios of high alpha assets (small size and high alpha, medium size and high alpha, big size and high alpha). BAA^{3x2} is constructed as the equally weighted returns of the two size-weighted low alpha groups (small size and low alpha, big size and low alpha) minus the equally weighted returns of the two size-weighted high alpha groups (small size and high alpha, big size and high alpha). I use 5-year data to calculate the parameters used to construct the different betting against alpha strategies, which is rebalanced yearly, at the end of December. I use monthly data corresponding to the period January 1960 – December 2015 to construct the portfolios for the period January 1965 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for LTR and the Market factor (MKT) comes from Kenneth French's webpage. Heteroskedastic robust standard errors are reported in parenthesis.

		BAA^{3x2}		**BAA^{3x3}**		**BAA^{5x3}**	
Pre-CAPM era (1932-1964)	**Alpha**	0.00%	-0.02%	0.10%	0.08%	0.25%	0.22%
		(0.0010)	(0.0011)	(0.0013)	(0.0011)	(0.0018)	(0.0014)
	MKT Beta	0.15**	0.04	0.12**	0.02	0.19**	0.05
		(0.0729)	(0.0528)	(0.0568)	(0.0394)	(0.0872)	(0.0620)
	LTR Beta	-	0.36***	-	0.36***	-	0.48***
		-	(0.0590)	-	(0.0756)	-	(0.1299)
	R^2	0.09	0.32	0.07	0.32	0.08	0.31
Post-CAPM era (1965-2015)	**Alpha**	0.37%***	0.13%*	0.39%***	0.17%**	0.73%***	0.41%***
		(0.0012)	(0.0008)	(0.0011)	(0.0008)	(0.0016)	(0.0011)
	MKT Beta	-0.064	-0.51*	-0.06	-0.06**	-0.05	-0.03
		(0.0420)	(0.0260)	(0.0401)	(0.0250)	(0.0536)	(0.0355)
	LTR Beta	-	0.81***	-	0.77***	-	1.06***
		-	(0.0590)	-	(0.0550)	-	(0.0858)
	R^2	0.01	0.48	0.01	0.47	0.00	0.43

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

Table 7: LTR regressed onto double-sorted size-weighted BAA strategies

This table presents results from regressing the LTR factor onto three betting against alpha strategies constructed using size-weighted double sorted portfolios: (i) BAA^{3x2}, constructed using the intersection of assets assigned to two Size groups and three CAPM Alpha groups; (ii) BAA^{3x3}, constructed using the intersection of assets assigned to three Size groups and three CAPM Alpha groups; and (iii) BAA^{5x3}, constructed using the intersection of assets assigned to three Size groups and five CAPM Alpha groups. At the moment of rebalancing, I use NYSE break points to assign assets to three Size groups: (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. At the moment of rebalancing I also divide assets by their CAPM Alpha into three groups and five groups. Both strategies, BAA^{5x3} and BAA^{3x3}, are constructed as the equally weighted returns of the three size-weighted portfolios of low alpha assets (small size and low alpha, medium size and low alpha, big size and low alpha) minus the equally weighted returns of the three size-weighted portfolios of high alpha assets (small size and high alpha, medium size and high alpha, big size and high alpha). BAA^{3x2} is constructed as the equally weighted returns of the two size-weighted low alpha groups (small size and low alpha, big size and low alpha) minus the equally weighted returns of the two size-weighted high alpha groups (small size and high alpha, big size and high alpha). I use 5-year data to calculate the parameters used to construct the different betting against alpha strategies, which is rebalanced yearly, at the end of December. I use monthly data corresponding to the period January 1960 – December 2015 to construct the portfolios for the period January 1965 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for LTR and the Market factor (MKT) comes from Kenneth French's webpage. Heteroskedastic robust standard errors are reported in parenthesis.

		LTR			
Pre-CAPM era (1932-1964)	**Alpha**	0.06%	0.06%	-0.01%	-0.07%
		(0.0020)	(0.0016)	(0.0016)	(0.0016)
	MKT Beta	0.31***	0.20**	0.22**	0.21*
		(0.0983)	(0.0997)	(0.0938)	(0.1169)
	BAA^{3x2} Beta	-	0.69***	-	-
		-	(0.1010)	-	-
	BAA^{3x3} Beta	-	-	0.74***	-
		-	-	(0.0906)	-
	BAA^{5x3} Beta	-	-	-	0.51***
		-	-	-	(0.0982)
	R^2	0.17	0.38	0.40	0.38
Post-CAPM era (1965-2015)	**Alpha**	0.28%***	0.07%	0.05%	0.01%
		(0.0010)	(0.0007)	(0.0007)	(0.0008)
	MKT Beta	-0.02	0.02	0.22	0.00
		(0.0338)	(0.0213)	(0.0213)	(0.0229)
	BAA^{3x2} Beta	-	0.58***	-	-
		-	(0.0464)	-	-
	BAA^{3x3} Beta	-	-	0.60***	-
		-	-	(0.0485)	-
	BAA^{5x3} Beta	-	-	-	0.40***
		-	-	-	(0.0407)
	R^2	0.00	0.47	0.46	0.43

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

Table 8: Differential pricing information between the benchmark BAA strategy and betting against alpha strategies constructed using alphas from multifactor models.

This table presents results from regressing the BAA strategy constructed using CAPM Alphas onto BAA strategies constructed with alphas from multifactor models, and vice-versa. The table also presents the risk-premium of the strategies. The sample period is divided into the CAPM era (1965-1992) and Smart Beta era (1993-2015). The strategies analyzed are the rank-weighted betting against alpha strategies constructed using estimated alphas from the CAPM (BAA), the Fama-French Three Factor model (BAA^{FF3}), the Carhart model (BAA^{Carhart}), and the Fama-French Six Factor model (BAA^{FF6}). I use 5-year data to calculate the parameters used to construct the different betting against alpha strategies, which is rebalanced yearly, at the end of December. I use monthly data corresponding to the period January 1960 – December 2015 to construct the portfolios for the period January 1965 – December 2015. Individual data on stock returns comes from the CRSP database. Heteroskedastic robust standard errors are reported in parenthesis.

			BAA		**BAA^{FF3}**	**BAA^{Carhart}**	**BAA^{FF6}**
CAPM era (1965-1992)	**Risk Premium**		0.53%		0.54%	0.52%	0.48%
	Alpha	0.13%*	0.16%**	0.01%	0.03%	0.02%	0.15%
		(0.0008)	(0.0008)	(0.0010)	(0.0010)	(0.0011)	(0.0011)
	MKT Beta	0.21	0.00	0.16***	-0.04	-0.02	-0.19***
		(0.0329)	(0.0368)	(0.0489)	(0.0385)	(0.0457)	(0.0538)
	BAA Beta	-	-	-	1.00***	0.97***	0.78***
		-	-	-	(0.0448)	(0.0475)	(0.0535)
	BAA^{FF3} Beta	0.71***	-	-	-	-	-
		(0.068)	-	-	-	-	-
	BAA^{Carhart} Beta	-	0.68***	-	-	-	-
		-	(0.074)	-	-	-	-
	BAA^{FF6} Beta	-	-	0.91***	-	-	-
		-	-	(0.097)	-	-	-
	R^2	0.71	0.66	0.71	0.71	0.66	0.74
Smart Beta era (1993-2015)	**Risk Premium**		0.82%		0.59%	0.52%	0.14%
	Alpha	0.35%***	0.43%***	0.69%***	0.03%	0.04%	0.05%
		(0.0012)	(0.0014)	(0.0018)	(0.0015)	(0.0016)	(0.0023)
	MKT Beta	0.11***	0.09**	0.13**	-0.22***	-0.22***	-0.59***
		(0.0353)	(0.0384)	(0.0560)	(0.0422)	(0.0453)	(0.0647)
	BAA Beta	-	-	-	0.85***	0.75***	0.55***
		-	-	-	(0.1261)	(0.1323)	(0.1845)
	BAA^{FF3} Beta	0.69***	-	-	-	-	-
		(0.052)	-	-	-	-	-
	BAA^{Carhart} Beta	-	0.64***	-	-	-	-
		-	(0.046)	-	-	-	-
	BAA^{FF6} Beta	-	-	0.34***	-	-	-
		-	-	(0.076)	-	-	-
	R^2	0.59	0.49	0.20	0.63	0.54	0.46

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

Table 9: Pricing of several factors by the CAPM across eras

This table presents the CAPM regression's results for the BAA strategy and several other factors. The CAPM alpha and MKT 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 following 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 data comes from AQR's webpage. Heteroskedastic robust standard errors are reported in parenthesis.

		BAA	SMB	HML	MOM	BAB	LTR	STR
Pre-CAPM era (1932-1964)	**Alpha**	**0.04%**	**0.06%**	**0.13%**	**0.87%*** **	**0.66%*** **	**0.06%**	**1.11%*** **
		(0.0014)	(0.0010)	(0.0016)	(0.0018)	(0.0013)	(0.0019)	(0.0015)
	MKT Beta	0.22***	0.23***	0.43***	-0.41	-0.11*	0.31***	0.04
		(0.0762)	(0.0620)	(0.0749)	(0.1266)	(0.0630)	(0.0980)	(0.0839)
	R^2	0.15	0.17	0.36	0.23	0.05	0.17	0.01
CAPM era (1965-1992)	**Alpha**	**0.54%*** **	**0.22%**	**0.51%*** **	**0.83%*** **	**0.79%*** **	**0.32%** **	**0.61%*** **
		(0.0014)	(0.0014)	(0.0012)	(0.0019)	(0.0013)	(0.0013)	(0.0014)
	MKT Beta	-0.03	0.24***	-0.21	0.01	0.11**	-0.04	0.16***
		(0.0570)	(0.0438)	(0.0406)	(0.0644)	(0.0480)	(0.0490)	(0.0439)
	R^2	0.00	0.13	0.14	0.00	0.04	0.01	0.08
Smart Beta era (1993-2015)	**Alpha**	**0.88%*** **	**0.05%**	**0.30%**	**0.75%*** **	**0.98%*** **	**0.24%**	**0.10%**
		(0.0018)	(0.0019)	(0.0019)	(0.0027)	(0.0023)	(0.0015)	(0.0020)
	MKT Beta	-0.09	0.16***	-0.11*	-0.31***	-0.30***	0.02	0.26***
		(0.0579)	(0.0437)	(0.0620)	(0.0940)	(0.0759)	(0.0469)	(0.0720)
	R^2	0.02	0.04	0.02	0.07	0.11	0.00	0.09

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

Table 10: 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 MKT 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 MKT 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 MKT Beta for all the assets in the CRSP database. Alphas and betas are calculated using 60 months of data.

	Selling Portfolio	Buying Portfolio	CRSP database
Avg. CAPM Alpha	0.52%	0.72%	0.46%
Avg. MKT Beta	1.05	1.09	1.00
Avg. returns (-13 to -60 months)	1.45%	1.62%	
Returns (+12 month holding period)	14.55%	12.99%	
Number of Transactions	453681	777668	
Value of Transactions (billions)	10341	39988	

Table 11: 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. CAPM Alphas 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 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 (MKT) comes from Kenneth French's webpage.

	BAA		Low alpha portfolio		High alpha portfolio	
	(1)	(2)	(1)	(2)	(1)	(2)
ΔTED	-0.022***		-0.039***		-0.017***	
	(0.0083)		(0.0104)		(0.0063)	
ΔCredit		-0.038**		-0.057**		-0.028**
		(0.0157)		(0.0240)		(0.0140)
BAA(-1)	0.22***	0.16**				
	(0.0709)	(0.0600)				
Low alpha pflio(-1)			0.219***	0.150***		
			(0.0375)	(0.0435)		
High alpha pflio(-1)					0.103***	0.088***
					(0.0306)	(0.0237)
Inflation(-1)	-0.129	-0.011	-0.098	0.062	-0.042	0.068**
	(0.1383)	(0.0630)	(0.1589)	(0.0839)	(0.0731)	(0.0330)
MKT	-0.109**	-0.056	0.968***	1.049***	1.029***	1.115***
	(0.0466)	(0.0480)	(0.0489)	(0.0588)	(0.0306)	(0.0264)
R^2	0.096	0.047	0.66	0.62	0.80	0.83

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

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

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A The CAPM Alpha eras and the CAPM literature

In sections 4.4 and 4.5 of the paper I analyze the BAA strategy during three differentiated eras: (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. In this Online Appendix, I will assess if the popularity of the CAPM literature presents similar patterns across the eras. I propose to measure this popularity 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 popularity of the CAPM in the academic literature increased rapidly during the CAPM era and even more during the Smart Beta era. This literature undoubtedly spread to the practitioners' world as the CAPM 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.[1] I restrict the sample to academic works having at least one citation according to the search engine.[2] Figure A1 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).

[Insert Figure A1 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 A2 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

[1] 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.

[2] To calculate the number of academic works containing the phrase "Capital Asset Pricing Model" presented in Figure A1, 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.

should also appear in the publication: "Anomaly" or "Anomalies." The results are shown in Panel (b) of Figure A2. 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 A2 around here]

The trend of the BAA strategy's CAR series (see Figure H1 in Online Appendix H) 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 further suggest that popular academic research might have a non-negligible impact on the financial markets in a way not documented before.

B Betting Against Alpha for different holding periods

In this Section I analyze the performance of the benchmark rank-weighted BAA strategy when rebalancing it every 1-month, 6-month, 12-month (benchmark scenario), 24-month, and 48-month period. As in the main body of the paper, I recalculate the weights at the end of each holding period using the formulas presented in Online Appendix F.

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.

Finally, the impact of transaction costs on the BAA strategy are quite low. In the benchmark case where I rebalance the low and high alpha portfolios yearly, the average *yearly* turnover between

1965 and 2015 is 22% (minimum is 17% and maximum is 28%). Novy-Marx and Velikov (2016) show that transaction costs affect mostly anomalies with a *monthly* turnover of 50% or more. Moreover, in this Appendix I show that the BAA strategy performs even better when portfolios are rebalanced every 24 months, which further reduces the impact of transaction costs on the strategy.

C NYSE data and the CAPM Alpha

In this Section I study the impact of an important change that happened to the CRSP database in the 1960s and 1970s. 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 Online Appendix F. Figure C1 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 C1 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 the entire CRSP database for calculations, which implies that the size effect is relevant for the BAA strategy as shown in Section 3.2 and Online Appendix E below.

Overall, the patterns observed in the BAA strategies are also present in the low and high alpha portfolios separately. Most of the alpha reversal effect is captured by the low alpha portfolio, which contains the assets avoided by fund managers as discussed in Section 5 and corroborated in Section 4.1.

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

In Section 3.4 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.[3] 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

[3]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.

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 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.

E Further robustness checks for the impact of size on the BAA strategy

E1 Betting Against Alpha using rank-weighted portfolios without micro cap and small stocks

In this Online Appendix I will test the performance of two additional betting against alpha strategies constructed with the rank-weighted method explained in Online Appendix F but removing assets below the NYSE 20th and NYSE 50th percentile of market capitalization at the moment of portfolio formation. More precisely, removing assets below the NYSE 20th percentile I construct BAA^{Ex20}, which eliminates micro cap and penny stocks. Removing assets below the NYSE 50th percentile I also construct BAA^{Ex50}, which further eliminates small cap stocks, leaving in the sample big and mega cap stocks. Table E1 below shows the performance of these strategies controlling for common risk using several models for the Pre-CAPM and Post-CAPM eras. The first column of the table shows the benchmark BAA strategy for comparison purposes.

[Insert Table E1 around here]

As expected, the table shows that there is no alpha reversal effect during the Pre-CAPM era independently of the sample used to construct BAA. More importantly, it shows that during the Post-CAPM era removing small stocks reduces the economic magnitude of the BAA strategy but does not make it disappear. Note that once the LTR factor is added and only big and mega cap assets are used to construct the strategy (BAA^{Ex50}), the economic significance becomes marginal (unreported p-value of 0.065).

E2 Betting Against Alpha using rank-weighted portfolios across different NYSE market capitalization cutoff values

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. Results are presented in Table E2.

[Insert Table E2 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 alpha portfolio surpasses that of the high alpha 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.

For the 30% Small stocks and the 40% Medium stocks groups, the BAA strategy produces abnormal returns 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 3, 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 Online Appendix G1.

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.

F Detailed construction of the rank-weighted Betting Against Alpha strategy

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 F1 below shows graphically the relationship between the assets' alphas and their weights in the low and high alpha portfolios.

[Insert Figure F1 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 MKT Beta of asset i calculated using the same CAPM regression used to calculate the α_i's.[4] To construct the BAA strategy the low and high alpha portfolios are rescaled to have a MKT Beta of 1 at the moment of portfolio formation. Then, the BAA strategy rebalanced yearly at the end of December – the benchmark scenario I use in this paper – is

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

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 corroborate in Section 3.1, that both low alpha and high alpha assets have larger than average MKT Betas (and volatilities). Therefore, as I show in Section 3.1, the BAA strategy not only has very low correlation with the Market factor but also with the Betting Against Beta factor (BAB) of FP.

[4]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).

G Long-term reversal vs alpha reversal: More results

G1 Analysis of long-term reversal and alpha reversal using Fama-MacBeth regressions

The exercise in this Appendix aims at disentangling alpha reversal from model-free price reversal using Fama-MacBeth regressions. I use as dependent variables individual stocks' excess returns while my independent variables of interest are the one-period lagged CAPM Alpha [CAPM 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 [MKT 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 size has a non-negligible impact on BAA as shown in Section 3.2. Results are presented in Table G1 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, as in the previous tables I divided the data into two periods: Pre-CAPM era (1932-1964) and Post-CAPM era (1965-2015).

[Insert Table G1 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 (p-values of 0.05 and 0.09, respectively). Once both are used 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 3.5 (Table 9) 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 (with t-statistics above 3.0). Additionally, when I use lagged CAPM Alpha and lagged long-term reversal variables together (Column 3 of Table G1), the lagged CAPM Alpha's explanatory power is the one that survives, although its statistical significance diminishes (p-value of 0.06). Overall, Table G1 shows that after the publication of the CAPM, alpha reversal contains additional information about the cross-section of stock returns not contained in long-term price reversal.

G2 Sharpe Ratios and the mean-variance optimal portfolio between BAA and LTR

Table G2 below presents the Sharpe Ratios for the different BAA strategies and LTR. It also shows the weigh of each BAA strategy in the mean-variance optimal portfolio (MVOP) when is combined with LTR, and the Sharpe Ratio of MVOP.[5] I present the results for both the Pre-CAPM era (1932-1964) and the Post-CAPM era (1965-2015).

[Insert Table G2 around here]

The table shows that BAA became more important in the MVOP during the Post-CAPM era. For example, the weights in the MVOP of BAA and BAA$^{3\times2}$ where 0% and 9.82% in the Pre-CAPM era, respectively. Later in the Post-CAPM era, their weights increased to 100% and 49.33%, respectively. The other BAA strategies (BAA$^{5\times3}$ and BAA$^{3\times3}$) also increased their weight in the MVOP during the Post-CAPM era.

Additionally, all BAA strategies show a steep increased in their Sharpe Ratios between the eras. The Sharpe Ratio of BAA increased by almost 300%, BAA$^{5\times3}$ by 54%, BAA$^{3\times3}$ by 57%, and BAA$^{3\times2}$ by 105%. In contrast, LTR increased only by 25%.

Finally, combining a BAA strategy with LTR during the Post-CAPM era sometimes lead to a MVOP's Sharpe Ratio considerable higher (BAA and BAA$^{5\times3}$) while in other cases the increment is not too large (BAA$^{3\times3}$ and BAA$^{3\times2}$). The later result is not surprising as my results in Section 3.3 and Online Appendix G1 show that empirically and by construction, there is some commonality between alpha reversal and long-term price reversal. Nevertheless, it is clear from the data in the previous table as well as that in Section 3.3 and Online Appendix G1 that the long-term patterns in alpha reversal and long-term price reversal are sufficiently different, with alpha reversal performing better in the Post-CAPM era while similar or worse during the Pre-CAPM era.

[5] I present results for an optimal portfolio in which short positions are not allowed. Results when short positions are allowed are qualitatively the same for all BAA strategies. Quantitatively, results are the same for all strategies except the benchmark rank-weighted BAA.

H The Smart Beta era: Further results

Table H1 below presents the correlations between BAA and the multifactor alpha strategies (BAA^{FF3}, BAA^{Carhart}, and BAA^{FF6}) developed in Section 3.4 during the CAPM and Smart Beta eras.

[Insert Table H1 around here]

There are two patterns worth noticing. First, as more factors are added to control for common risks, the correlation decreases. Second and more important, the decrease in the correlation coefficients is much sharper during the Smart Beta era than during the CAPM era. This suggests that controlling for an additional factor (and thus removing its impact from the CAPM Alpha) has a larger effect during the Smart Beta era, which is the era in which the tradable versions of these additional factors were developed.

Equations (2) and (3) in Section 3.4 show that in a multifactor world the CAPM Alpha is a linear combination of Smart Betas times their risk premiums. Therefore, BAA includes the possible effects of BAA^{FF3} as well as those due to agents tilting portfolios away from assets with low sensitivities to SMB and HML. More precisely, $E\left(\hat{\alpha}_i^{CAPM}\right) \approx E\left(\hat{\alpha}_i^{FF3}\right) + \beta_{SMB,i}\gamma_{SMB} + \beta_{HML,i}\gamma_{HML}$ (in a world with orthogonal factors this holds with equality). Similarly, BAA^{FF3} includes the information on BAA^{Carhart} and MOM, and the latter includes the information on BAA^{FF6} as well as CMA and RMW. As discussed in Section 3.4, we should expect that controlling for the additional factors has a higher impact in the Smart Beta era than in the CAPM era. Then, it should not be surprising that during the Smart Beta era BAA performs equally or better than BAA^{FF3} since BAA contains additional information about possible misvalued assets due to agents tilting portfolios away specifically from low SMB and low HML assets. Similarly, we should expect BAA^{FF3} to perform equally or better than BAA^{Carhart} and that the latter performs equally or better than BAA^{FF6}. Table H2 below shows that this is the case during the Smart Beta era.

[Insert Table H2 around here]

Finally, Figure H1 shows the evolution of the BAA strategy's cumulative abnormal returns (CAR) between 1932 and 2015. The dotted line shows the linear trend of the CAR series within each era.

[Insert Figure H1 around here]

Similarly to the results in Online Appendix A about the popularity of the CAPM in the literature, the figure presents a sharp break in the CAR series trend around 1993. The result is consistent with the hypothesis that what further fuels the BAA strategy in the Smart Beta era is the explosion in factor investing, the expansion in the asset management industry, and the fact that most managers are benchmarked against an index or some metric related to the CAPM, like the Information Ratio (e.g., Baker et al. 2011, Ma et al. 2019).

I Sharpe Ratios of all the long-short strategies used in the paper

Table I1 below present the Sharpe Ratios of all the strategies used in this paper during the Pre-CAPM era (1932-1964), CAPM era (1965-1992), and Smart Beta era (1993-2015).

[Insert Table I1 around here]

References

[1] Ahn S., A. Horenstein, and N. Wang, 2018, Beta matrix and common factors in stock returns, *Journal of Financial and Quantitative Analysis* 53, 1417-1440.

[2] Baker M., B. Bradley, and J. Wurgler, 2011, Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly, *Financial Analysts Journal* 67, 40-54.

[3] Banz R., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

[4] Barber B., X. Huang, and T. Odean, 2016, Which factors matter to investors? Evidence from mutual fund flows, *Review of Financial Studies* 29, 2600-2642.

[5] Black F., M. Jensen, and M. Scholes, 1972, The capital asset pricing model: Some empirical tests, *working paper available* https://ssrn.com/abstract=908569

[6] Carhart M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

[7] Cragg J. and S. Donald, 1997, Inferring the rank of a matrix, *Journal of Econometrics* 76, 223–250.

[8] Dasgupta A., A. Prat, and M. Verardo, 2011, Institutional trade persistence and long-term equity returns. *Journal of Finance* 66, 635–653.

[9] Dimson E., P. Marsh, and M. Staunton, 2017, Factor-based investing: The long-term evidence, *Journal of Portfolio Management* 43, 15-37.Fama E. and K. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

[10] Fama E. and K. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

[11] Fama E. and K. French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653-1678.

[12] Fama E. and K. French, 2018, Choosing factors, *Journal of Financial Economics* 128, 234-252

[13] Harzing A., 2007, Publish or perish, available from http://www.harzing.com/pop.htm

[14] Jegadeesh N. and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

[15] Jensen M., 1968, The performance of mutual funds in the period 1945–1964, *Journal of Finance* 23, 389– 416.

[16] Lewellen, J., S. Nagel, and J. Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175–194.

[17] Lintner J., 1965, The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets, *Review of Economic and Statistics* 47, 13-37.

[18] Ma L., Y. Tang, and J. Gomez, 2019, Portfolio manager compensation in the U.S. mutual fund industry, *Journal of Finance* 74, 587-638.

[19] Mossin J., 1966, Equilibrium in a capital asset market, *Econometrica* 35, 768-783.

[20] Novy-Marx R. and M. Velikov, 2018 Betting against betting against beta, *working paper available at SSRN*: https://ssrn.com/abstract=3300965

[21] Ross S., 1976, The arbitrage theory of capital asset pricing, *Journal of Economic Theory* 13, 341–360.

[22] Sharpe W., 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425-442.

Online Appendix

Figures and Tables

Figure A1: 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.

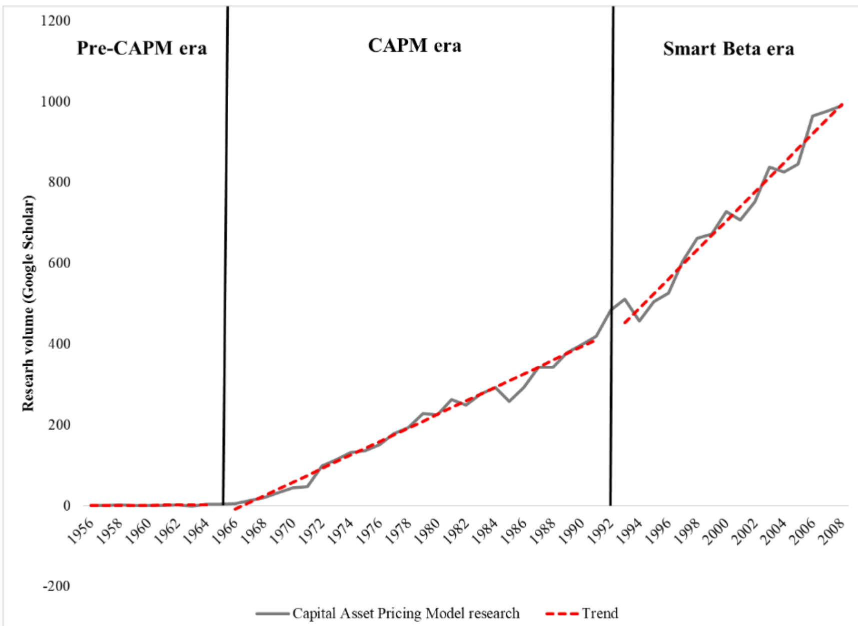
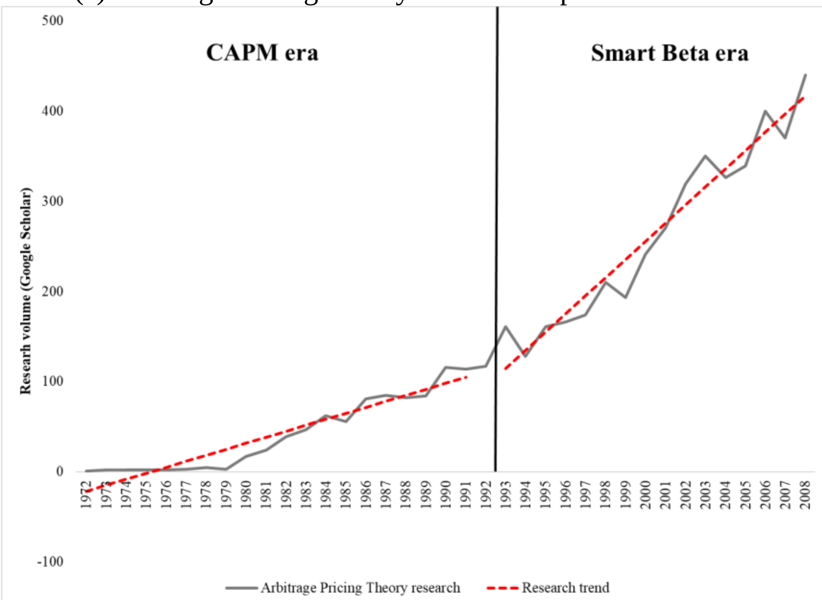


Figure A2: Scholarly work on the Arbitrage Pricing Theory and the CAPM anomalies

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

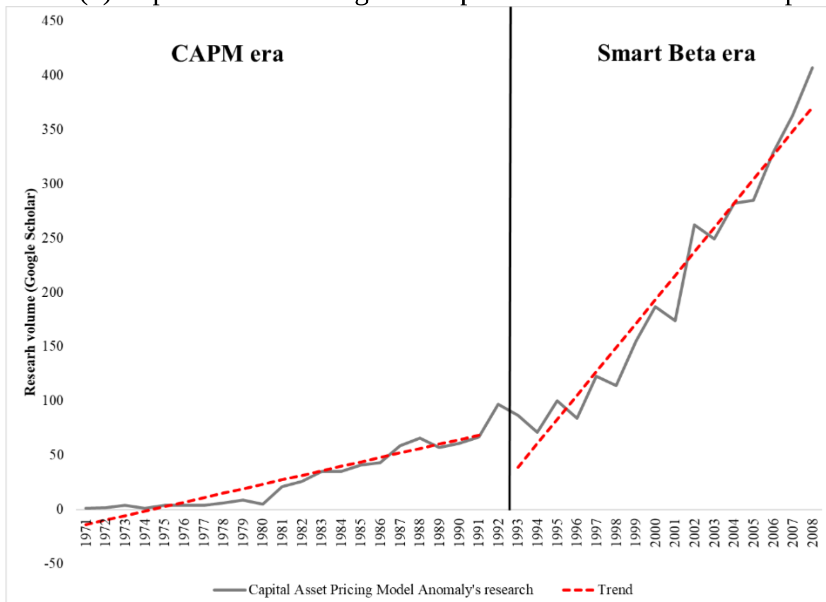


Figure C1: Cumulative abnormal returns for the low and high alpha portfolios constructed using the entire CRSP database and only NYSE stocks

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

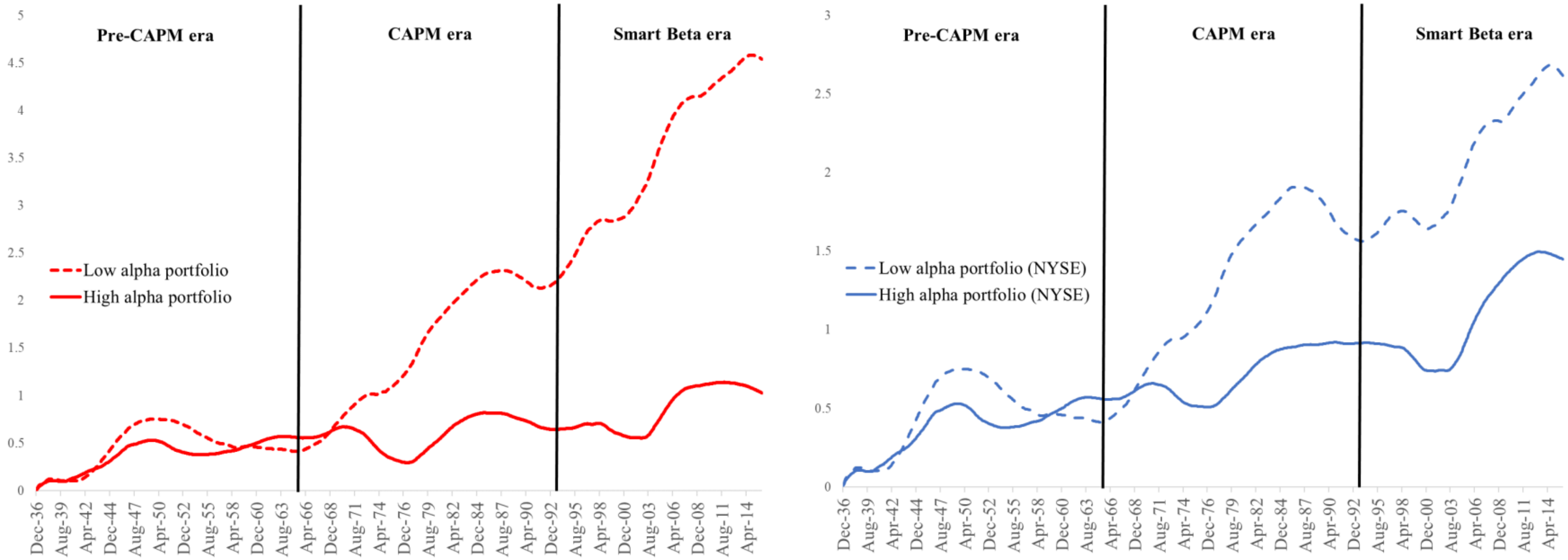


Figure F1: Relationship between an asset's alpha and its weight on the low or high alpha portfolio

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.

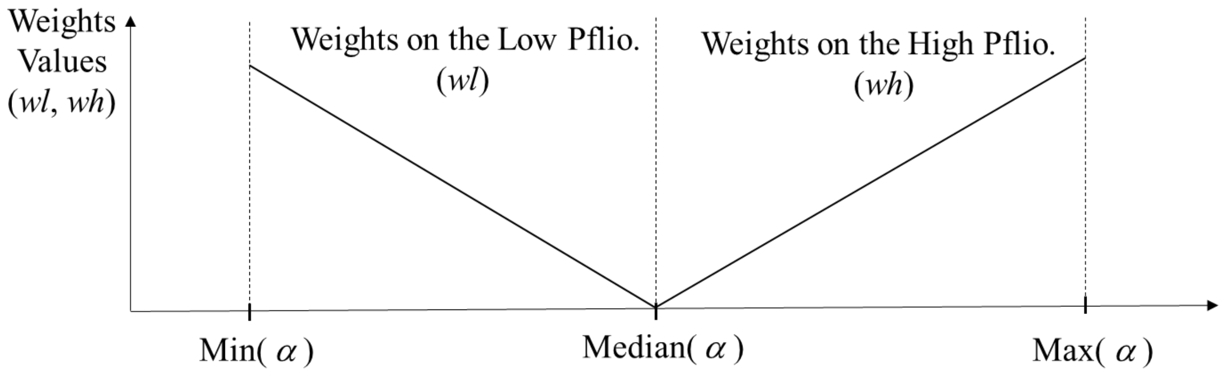


Figure H1: Cumulative abnormal returns from the Betting Against Alpha strategy

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.

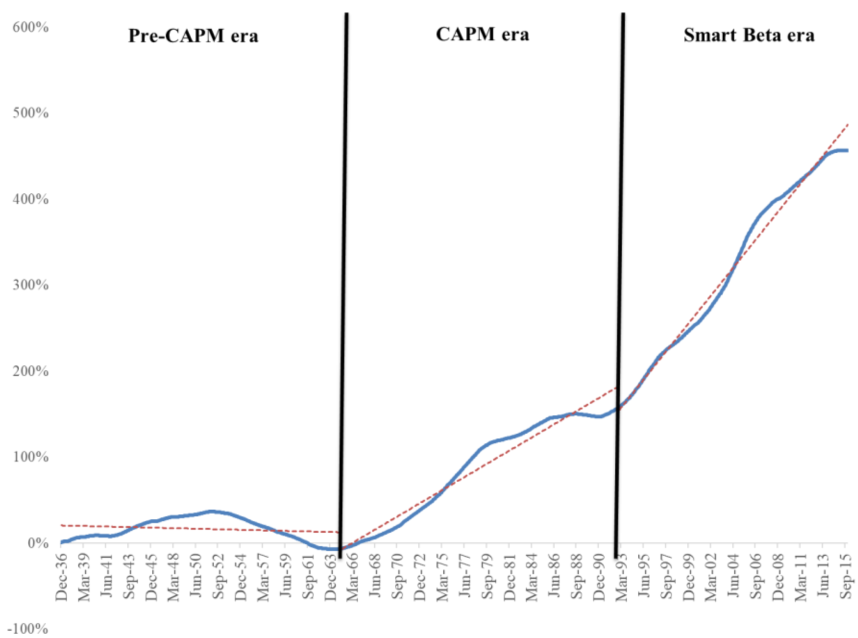


Table B1: BAA constructed using different holding periods for the assets

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%*** **

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

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**

Table E1: Rank-weighted Betting Against Alpha without small stocks

This table presents monthly performance metrics for the Betting Against Alpha (BAA) strategy and two additional versions: (i) BAA^{EX20}, constructed removing assets with market capitalization values below the NYSE 20th percentile and (ii) BAA^{EX50}, constructed removing assets with market capitalization values below the NYSE 50th percentile. These metrics are the 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 (RMW and CMA are not available for the Pre-CAPM era). 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. 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 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), 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. Heteroskedastic robust standard errors are in parenthesis.

		BAA	**BAA^{EX20}**	**BAA^{EX50}**
Pre-CAPM era (1932-1964)	**CAPM Alpha**	-0.05%	-0.17%	-0.15%
		(0.0014)	(0.0013)	(0.0013)
	Carhart Alpha	0.02%	-0.09%	-0.02%
		(0.0010)	(0.0010)	(0.0010)
Post-CAPM era (1965-2015)	**CAPM Alpha**	0.69%***	0.39%***	0.28%***
		(0.0011)	(0.0010)	(0.0011)
	Carhart Alpha	0.64%***	0.33%***	0.22%***
		(0.0012)	(0.0008)	(0.0008)
	FF6 Alpha	0.60%***	0.28%***	0.16%**
		(0.0013)	(0.0008)	(0.0008)
	FF6+Rev Alpha	0.58%***	0.27%***	0.13%*
		(0.0017)	(0.0007)	(0.0007)
	FF6+Rev+BAB Alpha	0.57%***	0.27%***	0.13%*
		(0.0012)	(0.0007)	(0.0007)

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

Table E2: 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 G1: 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 [CAPM Alpha (t-1)], one-period lagged long-term price reversal [Returns -13 to -60 (t-1)], one-period lagged CAPM Beta [MKT 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 and 5-year data. The heteroskedastic robust standard errors reported in parenthesis 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)**
CAPM Alpha (t-1)	-0.2116**		-0.1799	-0.1483***		-0.1227*
	(0.1073)		(0.1403)	(0.0484)		(0.0658)
Returns -13 to -60 (t-1)		-0.1046*	0.0563		-0.0530***	-0.0035
		(0.0621)	(0.0629)		(0.0142)	(0.0207)
MKT Beta (t-1)	0.0023	0.0005	0.00379	0.0014	0.0014	0.0018
	(0.0030)	(0.0024)	(0.0032)	(0.0011)	(0.0011)	(0.0011)
Ivol (t-1)	0.0251	0.0010	0.0295	0.0008	-0.0132	-0.0018
	(0.0261)	(0.0184)	(0.0273)	(0.0141)	(0.0124)	(0.0145)
Size (t-1)	-0.0017***	-0.0023***	-0.0017***	-0.0012***	-0.0016***	-0.0012***
	(0.0005)	(0.0007)	(0.0005)	(0.0002)	(0.0003)	(0.0002)
Average R^2	0.090	0.082	0.097	0.051	0.046	0.054
# time periods		395			636	

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

Table G2: Sharpe Ratios and mean-variance optimal portfolio for BAA and LTR

This table presents Sharpe Ratios for four alpha reversal strategies as well as LTR, and statistics for the mean-variance optimal portfolio (MVOP) between each individual alpha reversal strategy and LTR. These statistics are the weight of the alpha reversal strategy in the MVOP and the Sharpe Ratio of the MVOP. The MVOP is constructed without short-selling and investing 100% of the available funds. The four alpha reversal strategies analyzed are (i) the benchmark rank-weighted BAA strategy (see Section 2.2), (ii) BAA^{3x2}, constructed using the intersection of assets assigned to two Size groups and three CAPM Alpha groups; (iii) BAA^{3x3}, constructed using the intersection of assets assigned to three Size groups and three CAPM Alpha groups; and (iv) BAA^{5x3} constructed using the intersection of assets assigned to three Size groups and five CAPM Alpha groups. At the moment of rebalancing, I use NYSE break points to assign assets to three Size groups: (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. At the moment of rebalancing I also divide assets by their CAPM Alpha into three groups and five groups. Both strategies, BAA^{5x3} and BAA^{3x3}, are constructed as the equally weighted returns of the three size-weighted portfolios of low alpha assets (small size and low alpha, medium size and low alpha, big size and low alpha) minus the equally weighted returns of the three size-weighted portfolios of high alpha assets (small size and high alpha, medium size and high alpha, big size and high alpha). BAA^{3x2} is constructed as the equally weighted returns of the two size-weighted low alpha groups (small size and low alpha, big size and low alpha) minus the equally weighted returns of the two size-weighted high alpha groups (small size and high alpha, big size and high alpha). Weight BAA corresponds to the weight of each BAA strategy separately in the MVOP constructed with LTR. I use 5-year data to calculate the parameters used to construct the different betting against alpha strategies, which is rebalanced yearly, at the end of December. I use monthly data corresponding to the period January 1960 – December 2015 to construct the portfolios for the period January 1965 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for LTR and the Market factor comes from Kenneth French's webpage.

	Pre-CAPM era (1932-1964)			Post-CAPM era (1965-2015)		
	Sharpe Ratio	weight BAA (MVOP with LTR))	Sharpe Ratio (MVOP with LTR)	Sharpe Ratio	weight BAA (MVOP with LTR))	Sharpe Ratio (MVOP with LTR)
BAA	0.06	0.00%	0.09	0.22	100.00%	0.22
BAA^{5x3}	0.11	71.32%	0.11	0.17	92.97%	0.17
BAA^{3x3}	0.08	52.45%	0.10	0.13	64.90%	0.13
BAA^{3x2}	0.05	9.82%	0.09	0.11	49.33%	0.12
LTR	0.09			0.11		

Table H1: Correlation between the benchmark BAA strategy and betting against alpha strategies constructed using alphas obtained from different multifactor factor models.

This table presents the correlation coefficient between the Betting Against Alpha strategy constructed using estimated alphas from the CAPM (BAA) and Betting Against Alpha strategy constructed using estimated alphas from the Fama-French Three Factor model (BAA^{FF3}), Carhart model ($BAA^{Carhart}$), and Fama-French Six Factor model (BAA^{FF6}). Correlations have been estimated for the CAPM era (1965-1992) and Smart Beta era (1993 onward). The abnormal returns are estimated by OLS. Assets' alphas used to assign them to the different portfolios are estimated with OLS regressions using the corresponding models. I use 5-year data to calculate the parameters used to construct the different betting against alpha strategies, which is rebalanced yearly, at the end of December. I use monthly data corresponding to the period January 1960 – December 2015 to construct the portfolios for the period January 1965 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for the Fama-French six factors comes from Kenneth French's webpage.

	CAPM era (1965-1992)	**Smart Beta era (1993-2015)**
BAA^{FF3}	0.93	0.75
$BAA^{Carhart}$	0.90	0.69
BAA^{FF6}	0.81	0.42

Table H2: Performance of the benchmark BAA strategy and betting against alpha strategies constructed using alphas from different multifactor models.

This table presents results from regressing several rank-weighted betting against alpha strategies on the CAPM model during the CAPM era (1965-1992) and Smart Beta era (1993 onward). The strategies analyzed are the Betting Against Alpha strategies constructed using estimated alphas from the CAPM (BAA), the Fama-French Three Factor model (BAA^{FF3}), the Carhart model ($BAA^{Carhart}$), and the Fama-French Six Factor model (BAA^{FF6}). I use 5-year data to calculate the parameters used to construct the different betting against alpha strategies, which is rebalanced yearly, at the end of December. I use monthly data corresponding to the period January 1960 – December 2015 to construct the portfolios for the period January 1965 – December 2015. Individual data on stock returns comes from the CRSP database, while the data for Fama-French six factors comes from Kenneth French's webpage. Heteroskedastic robust standard errors are reported in parenthesis.

		BAA	**BAA^{FF3}**	**$BAA^{Carhart}$**	**BAA^{FF6}**
CAPM era (1965-1992)	**Alpha**	**0.54%*****	**0.57%*****	**0.54%*****	**0.56%*****
		(0.0014)	(0.0018)	(0.0018)	(0.0016)
	MKT Beta	-0.03	-0.07	-0.05	-0.21***
		(0.0570)	(0.0701)	(0.0730)	(0.0780)
	R^2	0.00	0.01	0.00	0.11
Smart Beta era (1993-2015)	**Alpha**	**0.88%*****	**0.77%*****	**0.69%*****	**0.53%****
		(0.0018)	(0.0021)	(0.0020)	(0.0024)
	MKT Beta	-0.09	-0.29***	-0.29***	-0.64***
		(0.0579)	(0.0655)	(0.0620)	(0.0744)
	R^2	0.02	0.13	0.12	0.33

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

Table I1: Factors' Sharpe Ratios during the Pre-CAPM (1932-1964), CAPM (1965-1992), and Smart Beta (1993-2015) eras

This table presents the Sharpe Ratios of all factors presented in the paper during three different time periods: Pre-CAPM (before 1965), CAPM (1965-1992), and Smart Beta (1993-2015). The factors are the rank-weighted Betting Against Alpha strategy (BAA); Betting Against Alpha strategy constructed using estimated alphas from the Fama-French Three Factor model (BAA^{FF3}), Carhart model ($BAA^{Carhart}$), and Fama-French Six Factor model (BAA^{FF6}); BAA^{EX20}, constructed removing assets with market capitalization values below the NYSE 20th percentile and BAA^{EX50}, constructed removing assets with market capitalization values below the NYSE 50th percentile; BAA^{5x3}, size-weighted strategy constructed using the intersection of assets assigned to three Size groups and five CAPM Alpha groups; BAA^{3x3}, size-weighted strategy constructed using the intersection of assets assigned to three Size groups and three CAPM Alpha groups; and BAA^{3x2}, size-weighted strategy constructed using the intersection of assets assigned to two Size groups and three CAPM Alpha groups; Betting Against Beta factor (BAB); Fama-French six factors (MKT, SMB, HML, RMW, CMA, MOM), and reversal factors (LTR and STR). I use 5-year data to calculate the parameters used to construct all BAA strategies, which is rebalanced yearly, at the end of December. 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 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.

	Sharpe Ratio		
	Pre-CAPM era (1932-1964)	CAPM era (1965-1992)	Smart Beta era (1993-2015)
BAA	0.06	0.18	0.27
BAA^{FF3}	0.10	0.16	0.16
$BAA^{Carhart}$	0.10	0.15	0.15
BAA^{FF6}	NA	0.15	0.03
BAA^{EX20}	0.03	0.12	0.19
BAA^{EX50}	0.03	0.10	0.11
BAA^{5x3}	0.11	0.19	0.15
BAA^{3x3}	0.08	0.15	0.10
BAA^{3x2}	0.05	0.13	0.09
BAB	0.18	0.27	0.25
MKT	0.18	0.08	0.14
SMB	0.09	0.11	0.04
HML	0.14	0.16	0.08
MOM	0.08	0.24	0.11
LTR	0.09	0.12	0.10
STR	0.32	0.25	0.07
RMW	NA	0.13	0.10
CMA	NA	0.16	0.14