Low-Risk Investing Without Industry Bets

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Abstract

The strategy of buying safe low-beta stocks while shorting (or underweighting) riskier high-beta stocks has been shown to deliver significant risk-adjusted returns. However, it has been suggested that such "low-risk investing" delivers high returns primarily due to its industry bet, favoring a slowly changing set of stodgy, stable industries and disliking their opposites. We refute this. We show that a betting against beta (BAB) strategy has delivered positive returns both as an industry-neutral bet *within* each industry and as a pure bet *across* industries. In fact, the industry-neutral BAB strategy has performed stronger than the BAB strategy that only bets across industries and it has delivered positive returns in *each* of 49 U.S. industries and in 61 of 70 global industries. Our findings are consistent with the leverage aversion theory for why low beta investing is effective.

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1. Introduction

Low-risk investing is based on the idea that safer stocks deliver higher risk-adjusted returns than riskier stocks. This was first documented by Black, Jensen, and Scholes (1972), who found that the security market line was flat relative to the Capital Asset Pricing Model (CAPM). However, for many the intuition behind low-risk investing in stocks is captured in going long stodgy (but perhaps ultimately profitable!) industries and by an assumption that the returns are driven by value effects. For example:

> ***…low volatility strategies have substantial industry tilts that, when removed, substantially reduce volatility-adjusted returns. Second, low volatility strategies have higher exposure to the value premium***
>
> ***— Shah (Dimensional Fund Advisors, 2011)***

While there is nothing per se wrong with a factor that bets on industries, the tone of this criticism often conveys the idea that such bets, particularly when passive (going the same direction for long periods), are perhaps either the result of path-dependent data mining or that industry bets will somehow be particularly dangerous going forward. In any event, it's a common sentiment regarding these strategies and it is meant to call into question their robustness and efficacy.

We explicitly test how much of the benefit of low-risk investing comes from tilts toward and away from industries versus stock tilts within an industry. We find that both types of low-risk investing work. However, counter to conventional wisdom, we find that low-risk investing is *not* driven by low-risk industries — not close — and is *not* driven by the value effect. Among all the low-risk strategies that we consider, the best ones take no industry bets at all!

There are many closely related forms of low-risk investing. Some focus on market beta (Black, Jensen, and Scholes (1972), Frazzini and Pedersen (2010)), some focus on total volatility (e.g., Baker, Bradley, and Wurgler (2011)), some on residual volatility (e.g., Falkenstein (1994), Ang et. al. (2006, 2009)), and some on still other related measures. We focus on market beta since this is the original measure which is linked to economic theory.

In particular, we construct Betting Against Beta (BAB) factors that invest long in a portfolio of low-beta stocks while short selling a portfolio of high-beta stocks (following Frazzini and

Pedersen (2010)). To make the BAB factors market neutral, the safe stocks on long side of the portfolio are leveraged to a beta of 1 and, similarly, the short side of the portfolio is deleveraged to a beta of 1. Hence, the overall beta of a BAB factor is zero so that its performance can be ascribed to the efficacy of low-risk investing, not market movements.

The "regular" BAB factor in the literature is constructed by sorting stocks on their beta without regard to industries — hence, its performance could be driven by industry bets, or stock selection within industry, or a combination. To determine which is more important, we consider the following new BAB factors, constructed to have minimum and maximum industry bets:

- **Industry-Neutral BAB.** To see whether BAB works when we *eliminate* the effects of industry tilts, we construct an industry-neutral BAB factor by going long and short stocks in a balanced way within each industry. This way, we compute a BAB factor for each industry and diversify across these to produce an overall industry-neutral BAB factor.
- **BAB as a *Pure* Industry Bet.** To see how well low-risk investing does as a pure industry bet, we consider a BAB strategy that goes long and short industry portfolios. This is an extreme form of the low-risk strategy fitting the popular perception, one that *only* makes big bets on industries.

By comparing the regular BAB, the industry-neutral BAB and the industry BAB, we seek to determine whether low-risk investing works separately for each decision (industry selection and stock selection within industries), and which is better. We find that the industry-neutral BAB works the best. Moreover, the industry-neutral bet works not just overall but within almost every industry, which is a remarkable consistency. We also decompose the regular BAB into its components and find that it loads three times more on the industry-neutral BAB than the industry BAB (so regular BAB is already doing mostly industry-neutral BAB).

In addition to documenting the high absolute return of the BAB factors, we estimate their alpha adjusted for the standard four-factor model exposures to size, value (which some also say drives low-risk investing, e.g., Shah (2011)), and momentum. We find that the BAB strategies deliver highly significant returns adjusted for the four-factor model and, moreover, the industry-neutral BAB strategies have very low — and sometimes *negative* — loadings on the value factor, thus strongly rejecting the notion that low-risk investing is driven by industry or value exposures.

In summary, the regular BAB strategy is already mostly a stock-selection (not industry) bet, the industry-neutral stock-selection part is the bet that works the best, and it is not a value bet.

Our finding that low-risk investing works in almost every industry adds to the mounting evidence of the ubiquitous performance of the BAB strategy. Black, Jensen, and Scholes (1972) document the original evidence for U.S. stocks 1931-1965. Frazzini and Pedersen (2010) find that the BAB strategy delivers significant returns in the U.S. from 1926 to the present, including the 40-plus year out-of-sample period since the findings were first published in 1972. In addition, they show that the result is not particular to U.S. stock selection or stock selection itself, finding it holds in 19 other international stock markets, in stock market country selection, across and within bond markets, and in credit markets. Low-risk investing also works across options and leveraged ETFs (Frazzini and Pedersen (2011)) and across asset classes (Asness, Frazzini, and Pedersen (2012)). The out-of-sample evidence, through time and across investment types, is exceptionally strong and without serious blemish.

Black (1972) and Frazzini and Pedersen (2010) propose an explanation for the efficacy of low-risk investing based on leverage constraints. This theory may also help explain why industry-neutral BAB works particularly well, namely because it requires more leverage since it is more hedged, as we show.

Our paper also adds to the broader literature (Moskowitz and Grinblatt (1999), Asness, Porter, and Stevens (2001)) examining how much risk factors and behavioral anomalies rely on industry selection versus stock selection within industries. In this spirit, Baker, Bradley, and Taliaferro (2013) independently of our paper study how much "macro" effects (country and industry) matter versus "micro" effects (stock selection within these) in low-risk investing. Their findings complement ours. They use a double-sort technique on industries and individual stock betas and also consider country effects, which add to the country results in Frazzini and Pedersen (2010). In contrast, we explicitly construct industry-neutral BAB portfolios in each industry in the U.S. and globally, we document strong performance of low-risk investing in almost every industry, we control for standard risk factors and show how the industry-neutral BAB has even lower risk exposures than the standard BAB (in particular low or negative value exposure counter to conventional wisdom), and we decompose the regular BAB strategy into its industry-neutral and industry components.

The rest of the paper is organized as follows. Section 2 describes our data and portfolio-construction methodology. Section 3 decomposes the regular BAB portfolio holdings and returns into their stock-selection versus industry-selection components. Section 4 reports the performance of low-risk investing within and across industries, and Section 5 shows that these results are robust. Section 6 concludes.

2. Data and Methodology

In this section we describe our data and the methodology for constructing a betting against beta portfolio. In addition to the "regular" BAB portfolio of Frazzini and Pedersen (2010), we also construct new industry-neutral BAB portfolios and a pure industry BAB portfolio.

Data

Our sample includes 55,600 stocks covering 20 countries, and summary statistics are reported in Table I. The data in this study are collected from several sources. Stock return data are from the union of the CRSP tape and the Xpressfeed Global database. The U.S. equity data include all available common stocks on CRSP between January 1926 and March 2012, and stocks' betas are computed with respect to the CRSP value-weighted market index. Our BAB factor returns for the U.S. start in April 1929 since we need some initial data to estimate betas. Excess returns are above the U.S. Treasury bill rate. We compute alphas with respect to the market factor and factor returns based on size (SMB), book-to-market (HML) and momentum (UMD).[1]

The global equity data include all available common stocks on the Xpressfeed Global daily security file for 20 markets belonging to the MSCI developed universe. The sample runs between January 1985 and Match 2012 and the global BAB factor returns start in December 1987. We assign each stock to its corresponding market based on the location of the primary exchange. Betas are computed with respect to the corresponding MSCI local market index. All returns are in USD, and excess returns are above the U.S. Treasury bill rate. We compute alphas with

[1] The SMB, HML, and UMD factors for the U.S. are from Ken French's data library.

respect to the global market factor and factor returns based on size (SMB), book-to-market (HML) and momentum (UMD) from Asness and Frazzini (2011).[2]

For our industry analysis, we assign stocks in our U.S. sample to one of 49 industries based on their primary SIC code, following the classification of Fama and French (1992). In the global sample we use 73 industries based on the Global Industry Classification Standard (GICS) industries from Xpressfeed.

Constructing the Standard Betting-Against-Beta (BAB) Portfolio

We construct standard BAB portfolios that are long low-beta securities and short sell high-beta securities exactly as in Frazzini and Pedersen (2010). To construct each portfolio, we rank all securities in ascending order on the basis of their estimated beta at the end of each calendar month. Betas are estimated as in Frazzini and Pedersen (2010) and, as shown there, the results are robust to using other reasonable methodologies. In particular, betas are estimated based on the product of the rolling one-year daily standard deviation and the rolling five-year three-day correlations. For correlations, we use three-day returns to account for nonsynchronous trading and a longer horizon because correlations are more stable. The ranked securities are assigned to one of two portfolios: low-beta and high-beta. The low-beta portfolio is comprised of all stocks with a beta below its country median; the high-beta portfolio of all stocks above its country median. In each portfolio, securities are weighted by the beta ranks. (Lower-beta security have larger weight in the low-beta portfolio and higher-beta securities have larger weights in the high-beta portfolio. Weighting by ranks not betas themselves allows us to reduce the impact of potential data errors and reliance on extreme values.) All portfolios are rebalanced every calendar month.

More formally, let z be the $n \times 1$ vector of beta ranks $z_i = rank(\beta_i)$ at portfolio formation, and let $\bar{z} = 1_n' z/n$ be the average rank, where n is the number of securities and $1_n'$ is an $n \times 1$ vector of ones. The portfolio weights of the low-beta and high-beta portfolios are given by

[2] We refer to Asness and Frazzini (2011) for a detailed description of their constructions. These factors mimic their U.S.-based counterparts, following Fama and French (1992, 1993, 1996).

$$
\begin{aligned}
w_h &= k(z-\bar{z})^{+} \\
w_L &= k(z-\bar{z})^{-}
\end{aligned}
\tag{1}
$$

where k is a normalizing constant $k = 1_n'|z - \bar{z}|/2$ and x^+ and x^- indicate the positive and negative elements of a vector x. The weights add to one by construction, $w_H = 1$ and $1_n' w_L = 1$, so we can construct the return of a low-beta portfolio (*L*) as $r_{t+1}^L = r_{t+1}' w_L$ and that of a high-beta portfolio (*H*) as $r_{t+1}^H = r_{t+1}' w_H$. Portfolio *L* has a beta of $\beta_t^L = \beta_t' w_L$ and portfolio *H* has a beta of $\beta_t^H = \beta_t' w_H$.

The BAB is a self-financing zero-beta portfolio that is long the low-beta portfolio and that short-sells the high-beta portfolio.

$$
r_{t+1}^{BAB} = \frac{1}{\beta_t^L}(r_{t+1}^L - r^f) - \frac{1}{\beta_t^H}(r_{t+1}^H - r^f) \tag{2}
$$

The BAB factor scales the *L* and *H* portfolios by their betas so that both the long and short sides have a beta of one at portfolio formation, which makes the BAB factor market neutral.

Constructing Industry-Neutral BAB Portfolios

We next construct an industry-neutral BAB portfolio for each industry. Specifically, for each industry we assign stocks with betas above their country median to the high-beta portfolio, those with betas below the median to the low-beta portfolio, and construct a long-short portfolio as in (2). This yields a set of self-financing zero-beta BAB portfolios (49 of them in the U.S.) with no industry exposure (and limited country exposure), one for each industry.

We next must aggregate these separate BAB portfolios for each industry to get an overall industry-neutral BAB strategy. We compute the overall industry-neutral BAB portfolio BAB^{Intra} is simply a portfolio of the individual industry-neutral BABs with weighs w_{t-1}^j:

$$
BAB_t^{Intra} = \sum_j w_{t-1}^j \, BAB_t^j \tag{3}
$$

To ensure that our results are not driven by a particular weighting scheme, we compute four versions of BAB_t^{Intra}: equal-weighted ($w_{t-1}^j = 1/I$, where I is the number of industries), value-weighted (weighted by each industry's lagged market capitalization), name-weighted (weighted by the number of stocks in each industry), and equal risk weighted. To compute the equal risk weights, we rescale each portfolio to an ex-ante annualized volatility of 10% at portfolio formation and take an equal-weighted average of these ($w_{t-1}^j = 1/I \times 10\%/\hat{\sigma}_{t-1}$).[3]

Constructing Industry BAB Portfolios

To construct a pure industry BAB portfolio, we first compute the returns of value-weighted industry portfolios and then compute the industry BAB portfolio by going long and short the industry portfolios using (2).[4] Hence, the industry BAB factor is long low-beta industries and short high-beta industries. In the global sample, we compute an industry BAB portfolio for each country and compute the value-weighted average of these based on each country's lagged market capitalization. Hence, the industry BAB portfolio is constructed to be country neutral.

3. How Much of Low-Risk Investment Is an Industry Bet?

We first examine the level of industry bets in regular low-risk investing, i.e., the regular BAB portfolio. We look at what industries the regular BAB portfolio is typically betting on, how large these average bets are, and how much they change through time.

To address these issues, we run a cross-sectional regression. The dependent variable is weight w^s in the BAB portfolio for each stock *s*, which is proportional to the rank of its beta.[5] The independent variables are simply dummies for whether stock *s* belongs to any industry indexed by *i*. We run these cross-sectional regressions for in each month *t*:

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[3] The equal risk methodology follows that of Asness, Frazzini and Pedersen (2012). We also try weighting by various measures of the dispersion of betas within each industry, to try and capture the cardinal aspects of beta estimation our ordinal methodology might miss, but find no significant differences than the results we report.

[4] Using weighting methods within industries other than value-weighted to form industry returns had no effect on our conclusions.

[5] Specifically, we let $w^s = w_H^s$ for high-beta stocks and $w^s = w_L^s$ for low-beta stocks, where w_H and w_L are defined in equation (1).

$$w_t^s = \sum_i d_{i,t} 1_{\{\text{stock } s \text{ is in industry } i \text{ at time } t\}} + \varepsilon_t^s$$

Figure 1A reports the average estimated regression coefficient for each industry dummy, divided by its standard deviation, i.e., its Fama-MacBeth t-statistic. (We report this only over the 1951-2012 period since we are comparing BAB and Value portfolios and the Xpressfeed data on book equity starts in 1951.) A positive number means that the BAB portfolio weights tend to be long for the stocks in that industry, while a negative number reflects short average exposure by the BAB factor. We see that the five largest positive exposures are in utilities, beer, food, banks, and soda. These generally fit our intuition of what constitutes safer industries. On the flip side, the five most negative exposures are in cyclical and risky industries, namely automobiles, chips, hardware, transportation, and aerospace. For comparisons sake, we also report in Figure 1B the same exercise for a value factor based on stocks book-to-price.

Figure 2A reports the monthly R-squared from the cross-sectional regressions. We see that the R-squared are 25% on average, reaching a maximum of 52% and a minimum of 10%. This shows the BAB factor's portfolio weights can be explained by industry exposures to some extent, but, nevertheless, most of the variation of holdings across stocks is left unexplained by industries. For comparison, Figure 2B presents this same exercise again for the book-to-price factor. Here the average R-squared is 10%, the maximum 22%, and the minimum 4%. We see that popular intuition, that the low beta factor is more industry-driven than others, is quite true in this case. Of course we have not yet tested whether this affects the efficacy of the factor itself.

In summary, our analysis of the stock holdings of the BAB factor does not disappoint those who think that low-risk investing is driven by stodgy industries. The BAB factor indeed tends to be long the safe industries that one might expect, short the cyclical industries, and these industry exposures explain a non-trivial amount of the variation in stock holdings. However, the stock selection bets reflected in the holdings that *cannot* be explained by industries turn out to be successful and important, as we shall see.

Having studied the BAB factors *holdings*, we next consider its *returns*. We want to study how much of the regular BAB factor's performance is driven by industry exposures versus within-industry stock selection. To address this, we regress the returns of the regular BAB factor (constructed without regard for industries) on the value-weighed[6] version of the industry-neutral BAB portfolio (BAB_t^{intra}), the industry BAB portfolio ($BAB_t^{industry}$), and the standard factors related to market risk (*MKT*), size (*SMB*), value (*HML*) and momentum (*UMD*), as well as subsets of these independent variables:

$$BAB_t = \alpha + \beta_1 BAB_t^{intra} + \beta_2 BAB_t^{industry} + \beta_3 MKT_t + \beta_4 SMB_t + \beta_5 HML_t + \beta_6 UMD_t + \varepsilon_t$$

Table II reports the results. The first specification (1) shows a regression of regular BAB on the standard four-factor model, which serves as a reminder of the risk-adjusted returns to regular BAB investing, replicating the results of Frazzini and Pedersen (2010). BAB loads positive on value, more positively on momentum, but, even accounting for these effects, the economic and statistical significance of the BAB intercept is very strong.[7]

Regressions (2)-(4) next add the industry-neutral and industry BAB factors to the right-hand side. Obviously, the explanatory power (R-squared) goes way up as we are now explaining the regular BAB with two other forms of BAB. More importantly, the loading on the industry-neutral BAB factor is about three times that of the industry BAB (measured in coefficient or t-statistic), suggesting that the standard BAB is in fact more due to stock-selection than to industry selection, already a rebuke to the idea that BAB is all about industries. We next examine which forms of BAB perform better.

4. BAB Performance Within and Across Industries

We are ready to analyze how low-risk investing performs as (i) a long-short portfolio that goes long low-beta stocks and short high-beta ones, ignoring industry exposures (regular BAB); (ii) a long-short portfolio within each industry, diversified across industries (industry-neutral

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[6] We choose to use the value-weighed version of industry-neutral BAB for conservatism. Other choices do not affect our results.

[7] The BAB portfolios we use here are rank weighted not value weighted like the four-factor model. We have separately constructed BAB portfolios following the methodology Fama and French use to construct HML (sort 3x2 by beta and market cap, take high beta minus low beta within small and large, use value weighted returns, go long and short, leveraged to be market neutral) and find this BAB factor also has significantly positive returns.

BAB); and (iii) a long-short portfolio of entire value-weighted industries, going long low-beta industries and short high-beta ones (industry BAB).

Table III reports our results for U.S. stocks over the full 1926-2012 period (our longest sample) and for all global stocks for 1985-2012 (our broadest sample). We consider four versions of the industry-neutral BAB that differ in terms of how the individual industry-neutral BAB portfolios are weighted across industries as explained in Section 2. Our results also hold if we restrict attention to just U.S. stocks over the 1985-2012 time period or to just international stocks (i.e., excluding the U.S.). However, for brevity we focus on the findings over the longest and broadest samples.

We see that all the BAB portfolios for U.S. and global stocks have delivered significantly positive returns and significantly positive alphas with respect to the CAPM, the three factor model, and the four factor model (i.e., the first four rows all show positive intercepts and positive t-statistics). The Sharpe ratios of the different BAB strategies are illustrated in Figure 3 for the U.S. over the full 1926-2012 sample and the global set of countries over the common 1985-2012 sample. Our results show that low-risk investing works both for selecting industries and for selecting stocks within an industry. However, the performance of the industry-neutral BAB portfolios are far stronger than those of the industry BAB portfolios and, in the U.S. sample, stronger than the regular BAB itself, indicating that ex-post regular BAB has "too much" industry BAB versus within-neutral BAB.

Table IV reports the four-factor model loadings on the different BAB portfolios. Interestingly, for both the U.S. and global stocks, the standard BAB factor has a positive loading on the value factor HML and this positive HML loading is even stronger for the industry BAB, but the industry-neutral BAB portfolios have small HML loadings that are sometimes even negative. These small HML loadings and the highly significant alphas soundly reject the notion that low-risk investing is just a variation of value investing, especially for industry-neutral BAB.

A BAB Portfolio in Each Industry

Above we considered the overall diversified industry-neutral BAB strategy, but it is also interesting to consider each industry's individual industry-neutral BAB portfolio. Of course, each of these 49 strategies should deliver, on average, a lower risk-adjusted return than the portfolio of them all (our overall industry-neutral BAB). Figure 4 shows the Sharpe ratios of each of these industry-neutral BAB portfolios and Figure 5 shows the corresponding t-statistics of their four-factor alphas. Remarkably, each Sharpe ratio is positive for the U.S. BAB portfolios, and 26 of them have statistically significant positive alphas. It is quite rare to see such consistent results for any method of investing. If low-risk investing is largely an industry bet it's oddly succeeding *within* 49 of 49 industries! The results are also strong for the global industries, where the industry-neutral BAB factor delivers positive returns in 61 of 70 industries.

Hedging Industry Risk and Leverage

It is interesting that, by hedging industry risk, the industry-neutral BAB can achieve a larger Sharpe ratio than both the industry BAB and the standard BAB for U.S. and global stocks. This ability of the industry-neutral BAB to contribute to a better BAB portfolio reflects a more general phenomenon, namely that when more risk is hedged, one can often achieve higher risk-adjusted returns. However, the reason may be deeper than simply reflecting risk reduction. The more-hedged strategies require more leverage and may be associated with more tail risk, thus raising their required return for leverage-averse investors, consistent with the theories of Black (1972) and Frazzini and Pedersen (2010). Specifically, Table III reports the average dollar exposure for the long and short legs of the portfolio (labeled "$Long" and "$Short") and we see that the notional exposures required per unit of volatility, ($Long+$Short)/Volatility, are larger for the industry-neutral BAB portfolios. Further, the industry-neutral BAB portfolios tend to have more negatively skewed and more kurtotic monthly returns than the industry BAB. The overall evidence is therefore very supportive of the leverage constraint models: Low-risk investment works within and across industries and it works better when more leverage is required per unit of risk.

Optimizing Low-Risk Investing Within and Across Industries

Given that low-risk investing works both within and across industries, it is interesting to consider how each of them should be weighted. For this experiment, we allow an optimizer to maximize the overall Sharpe by allocating across all three potential BAB factors (regular, industry and industry-neutral) and the four standard factors (market, size, value and momentum). We constrain the weights to be positive across all the seven strategies and use U.S. monthly data back to 1929.

The resulting ex post optimal weights are 0% regular BAB, 45% industry-neutral BAB, 0% industry BAB, 10% market, 24% HML (value), 2% SMB (size), and 18% UMD (momentum). The weight on the industry-neutral BAB factor is somewhat exaggerated as this is a lower-volatility factor than the others. If we scale by ex post volatility, instead of 45% of the dollars, the optimizer assigns the industry-neutral BAB factor 31% of the risk taken. This large assigned risk allocation may also be exaggerated as the BAB factors are constructed using rank-weighting, a different methodology than that used for the other factors. This could mean that we end up with a larger weight on BAB versus the four-factor strategies than a more apples-to-apples comparison would yield, but it should not affect the relative weights on different versions of BAB, which is all we are interested in here.

Similarly looking at the global results 1985-2012, we find an ex post optimal weight of 52% in industry-neutral BAB in dollars and 37% in ex post risk, again with no weight desired in regular BAB and industry BAB. Essentially, both optimizations only want industry-neutral BAB. Again, so much for low risk being about industries!

Finally, we can look at only non-U.S. international results 1985-2012 in order to cherry-pick a sample where we find the strongest industry BAB versus industry-neutral BAB results (not shown in Table III). Here we find that the ex post optimal allocations are 21% to the regular BAB (18% in terms of ex post volatility), 21% to the industry-neutral BAB (12% in ex post volatility), and 0% to the industry BAB. Hence, even in this sample, an optimizer favors adding back industry-neutral BAB. This means that regular BAB still has more than the optimal amount of industry betting.

The evidence clearly points to the industry-neutral BAB as superior to the industry BAB, both in terms of absolute performance and in a portfolio context. However, investors might still want to rely on the regular or industry BAB factors to limit leverage and transaction costs, among other reasons.

5. Robustness Analysis

Our results are very robust. We have already shown that the industry-neutral BAB portfolios deliver positive returns in each U.S. industry and most global industries. As a result, the diversified industry-neutral BAB portfolios perform well for any for the four weighting schemes that we tested.

Table V shows additional robustness analysis for our industry-neutral BAB portfolios and industry BAB portfolios. Panel A shows the robustness with respect to time periods. The U.S. industry-neutral BAB portfolio has delivered positive returns in each 20-year period since 1929 and the global industry-neutral BAB has delivered positive returns in each decade since 1985. The U.S. industry BAB has delivered positive returns in four out of five 20-year periods since 1929 and the global industry BAB has delivered positive returns in each subsample.

Panel B shows the robustness with respect to firm size, splitting our sample into small-cap stocks and large-cap stocks. For the U.S., we define the large-cap universe as all stocks with market capitalization above the median for NYSE stocks, and, for global stocks, we define the large-cap universe as all stocks larger than the 80th percentile in its country. We see that low-risk investing has delivered positive returns both within the small-cap and large-cap stock universes, and it has done so for both industry-neutral and industry BAB portfolios and for both U.S. and global stocks.

6. Conclusion

This paper shows that low-risk investing works both for selecting stocks within an industry and for selecting industries. Although betting against beta works both for industry selection and for within-industry stock selection, its risk-adjusted returns are considerably stronger within-industry. The industry-neutral BAB factor has delivered positive returns in each of the 49 U.S. industries and in 61 of 70 global industries. Putting together those industries leads to an aggregate industry-neutral BAB factor that performs very strongly — alone or versus the four-factor model. Moreover, the regular BAB factor is in fact more dependent on the industry-neutral stock selection than on industry selection.

Together these utterly disprove the common sentiment that BAB — and low-risk investing in general — is really just an industry bet. It’s neither driven by industry bets nor is it more effective for industry bets. In fact, for both, the opposite is true.

In addition our results support the leverage aversion theory behind the BAB strategy’s efficacy, as the higher Sharpe ratios of intra-industry BAB come with higher necessary leverage.

Finally, we note the interesting result that the more-effective industry-neutral form of BAB is also less exposed to the value factor (in fact, not at all exposed in the U.S.) than regular or industry BAB (put another way, the correlation of BAB and value is mostly coming from lower Sharpe ratio industry bets). Thus we can dispel two wrong notions at once. The economically and statistically strong low-risk phenomenon is neither driven by exposure to value nor, again, by betting on industries.

References

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2006), "The Cross-Section of Volatility and Expected Returns", *The Journal of Finance,* vol. LXI, no. 1, pp. 259-299.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang (2009), "High idiosyncratic volatility and low returns: International and further U.S. evidence", *Journal of Financial Economics,* vol. 91, no. 1, pp. 1-23.

Asness, C. S., R. B. Porter, and R. L. Stevens (2001), "Predicting Stock Returns Using Industry-Relative Firm Characteristics", working paper, AQR Capital Management, LLC, The Warrington College of Business at the University of Florida.

Asness, C. S. (1995), "The Power of Past Returns", working paper, AQR Capital Management, LLC.

Asness, C., A. Frazzini, and L. H. Pedersen (2012a), "Leverage Aversion and Risk Parity", *Financial Analysts Journal*, 68(1), 47-59..

Asness, C., A. Frazzini, and L. H. Pedersen (2012b), "Quality Investment", working paper, AQR Capital Management, New York University.

Baker, M., B. Bradley, and R. Taliaferro (2013), "The Low Risk Anomaly: A Decomposition into Micro and Macro Effects", working paper, Harvard Business School, National Bureau of Economic Research, Acadian Asset Management.

Baker, M., B. Bradley, and J. Wurgler (2011), "Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly", *Financial Analysts Journal*, vol. 67, no. 1, pp. 40-54.

Baker, N. L. and R. A. Haugen (2012), "Low Risk Stocks Outperform within All Observable Markets of the World", working paper, Guggenheim Partners Asset Management LLC, Haugen Custom Financial Systems, LowVolatilityStocks.com.

Black, F. (1972), "Capital market equilibrium with restricted borrowing," *Journal of Business,* 45, 3, pp. 444-455.

Black, F., M.C. Jensen, and M. Scholes (1972), "The Capital Asset Pricing Model: Some Empirical Tests." In Michael C. Jensen (ed.), Studies in the Theory of Capital Markets, New York, pp. 79-121.

Banner, A. (2012), Essentials of Low Volatility Investing, A Primer, Intech.

Blitz, D.C and P. van Vliet (2007), "The Volatility Effect", *The Journal of Portfolio Management,* vol. 34, no. 1, pp. 102-113.

Carhart, M. (1997), "On persistence in mutual fund performance", *Journal of Finance* 52, 57–82.

Chow, T., J. Hsu, V. Kalesnik, and B. Little (2011), "A Survey of Alternative Equity Index Strategies", *Financial Analysts Journal,* vol. 67, no. 5, pp. 37-57.

Clarke, R., H. de Silva, and S. Thorley (2011), "Minimum Variance, Maximum Diversification and Risk Parity: An Analytic Perspective", working paper, Analytic Investors, LLC, BYU.

Cowan, D. and S. Wilderman (2011), “Re-Thinking Risk: What the Beta Puzzle Tells Us About Investing”, white paper, GMO.

Crill, W. and J. L. Davis (2012), “Beta and Expected Return”, Dimensional Fund Advisors.

Crill, W. and R. R. Shah (2012), “Residual Volatility and Average Returns”, research paper, Dimensional Fund Advisors.

Fama, E. F. and K. R. French (1992), “The Cross-Section of Expected Returns”, *The Journal of Finance*, vol. XLVII, no. 2, pp. 427-465.Fama, E.F. and French, K.R. (1993), "Common risk factors in the returns on stocks and bonds", *Journal of Financial Economics* 33, 3–56.

Falkenstein, E. (2013), “Dimensional’s Latest on Low-Vol”, http://falkenblog.blogspot.com/.

Falkenstein, E. G. (1994), “Mutual Funds, Idiosyncratic Variance and Asset Returns”, Ph.D. Dissertation, Northwestern University.

Frazzini, A. and L. H. Pedersen (2010), “Betting Against Beta”, working paper, AQR Capital Management, New York University and NBER (WP 16601).

Frazzini, A. and L. H. Pedersen (2012), “Embedded Leverage”, working paper, AQR Capital Management, New York University.

Graham, B. and D. L. Dodd (1934), “Security Analysis,” McGraw Hill.

Jegadeesh, N. and S. Titman (1993), “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency,” *The Journal of Finance*, vol. 48, no. 1, pp. 65-91.

Kacperczyk, M., C. Sialm, and L. Zheng (2008), “Unobserved Actions of Mutual Funds,” Review of Financial Studies, 21, 2379-2416.

Lee, W. (2010), “Risk-Based Asset Allocation: A New Answer to an Old Question?”, working paper, Neuberger Berman.

Li, X. and R. Sullivan (2010), “Why Low-Volatility Stocks Outperform: Market Evidence on Systematic Risk versus Mispricing”, working paper, Boston College, CFA Institute.

Moskowitz, T. J. and M. Grinblatt (1999), “Do Industries Explain Momentum?”, *The Journal of Finance*, vol. 54, no. 4, pp. 1249-1290.

Shah, R.R. (2011), “Understanding Low Volatility Strategies: Minimum Variance,” Dimensional Fund Advisors.

Table I
Summary Statistics

This table shows summary statistics computed as pooled averages as of June of each year. The sample includes all U.S. common stocks on the CRSP daily stock files ("shrcd" equal to 10 or 11) and all global stocks in the Xpressfeed Global security files ("tcpi" equal to 0). "Mean ME" is the average market value of equity, in billion USD.

Country	Local market index	Number of stocks - total	Number of stocks - mean	Mean ME (firm , Billion USD)	Mean ME (market , Billion USD)	Start Year	End Year
Australia	MSCI - Australia	3,057	892	0.58	501	1985	2012
Austria	MSCI - Austria	211	81	0.75	59	1985	2012
Belgium	MSCI - Belgium	428	139	1.80	245	1985	2012
Canada	MSCI - Canada	5,756	1,232	0.99	544	1964	2012
Denmark	MSCI - Denmark	413	146	0.83	119	1985	2012
Finland	MSCI - Finland	293	109	1.39	143	1985	2012
France	MSCI - France	1,814	588	2.12	1,222	1985	2012
Germany	MSCI - Germany	2,166	724	2.48	1,785	1985	2012
Hong Kong	MSCI - Hong Kong	1,792	673	1.22	799	1985	2012
Italy	MSCI - Italy	609	224	2.12	470	1985	2012
Japan	MSCI - Japan	5,011	2,907	1.19	3,488	1985	2012
Netherlands	MSCI - Netherlands	411	166	3.33	552	1985	2012
New Zealand	MSCI - New Zealand	318	97	0.87	81	1985	2012
Norway	MSCI - Norway	661	164	0.76	121	1985	2012
Singapore	MSCI - Singapore	1,056	374	0.63	239	1985	2012
Spain	MSCI - Spain	371	135	3.04	398	1985	2012
Sweden	MSCI - Sweden	1,060	264	1.30	334	1985	2012
Switzerland	MSCI - Switzerland	566	210	3.06	633	1985	2012
United Kingdom	MSCI - UK	6,113	1,763	1.23	2,247	1984	2012
United States	CRSP - vw index	23,538	3,183	0.99	3,209	1925	2012

Table II
Decomposing BAB into its Industry-Neutral and Industry Components

This table reports the result of a regression of the regular BAB factor (constructed without regards to industries) on the value-weighted industry-neutral BAB, the industry BAB, and the standard factors for the market (MKT), size (SMB), value (HML), and momentum (UMD). Regressions (1)-(4) consider the U.S. BAB and risk factors from 1926 to 2012, while regressions (5)-(8) consider global BAB and risk factors from 1985 to 2012. Standard errors are reported in parenthesis.

Left-hand side: BAB	**U.S. (1926 - 2012)**				**Global (1985 - 2012)**			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Alpha	**0.55**	0.01	-0.01	-0.02	**0.33**	0.05	0.05	0.04
	(5.59)	(0.13)	-(0.28)	-(0.44)	(2.58)	(0.69)	(0.73)	(0.55)
Industry-neutral BAB		**0.95**	**1.01**	**1.00**		**0.72**	**0.89**	**0.87**
		(55.34)	(58.52)	(56.37)		(11.53)	(13.87)	(13.44)
Industry BAB		**0.39**	**0.33**	**0.33**		**0.43**	**0.34**	**0.33**
		(26.05)	(20.97)	(20.98)		(11.52)	(8.70)	(8.36)
MKT	-0.01		**-0.02**	**-0.02**	0.01		**-0.08**	**-0.07**
	-(0.47)		-(2.90)	-(2.51)	(0.27)		-(4.76)	-(3.92)
SMB	-0.02		**-0.10**	**-0.10**	**0.16**		**-0.09**	**-0.09**
	-(0.80)		-(7.94)	-(7.82)	(2.91)		-(2.82)	-(2.73)
HML	**0.10**		**0.07**	**0.08**	**0.31**		0.05	0.07
	(3.50)		(6.89)	(6.87)	(5.37)		(1.64)	(1.94)
UMD	**0.19**			0.01	**0.21**			0.03
	(8.33)			(1.06)	(6.38)			(1.42)
Adjusted R2	0.07	0.85	0.86	0.86	0.21	0.72	0.76	0.76
Nobs	996	996	996	996	269	269	269	269

Table III
Performance of the Regular BAB, Industry-Neutral BAB, and Industry BAB

This table reports the performance of the regular BAB, four versions of an industry-neutral BAB portfolio (where each industry is either equal weighted, value weighted, weighed by the number of stocks, or equal-risk weighed), and the industry BAB (which purely bets across industries). We report the results for the U.S. from 1926-2012 and for global stocks from 1985-2012. The CAPM alpha is the intercept from a regression on the market, the three-factor alpha also controls for size and value exposures, and the four-factor alpha further controls for momentum. Beta (ex ante) is the average estimated beta at portfolio formation and beta (realized) is the realized loading on the market portfolio. $ Long (Short) is the average dollar value of the long (short) position. Volatilities and Sharpe ratios are annualized and standard errors are reported in parenthesis.

	U.S. (1926 - 2012)						Global (1985 - 2012)					
	BAB	Industry-Neutral BAB				Industry BAB	BAB	Industry-Neutral BAB				Industry BAB
		Equal Weighted	Value Weighted	Num of stocks	Equal Risk			Equal Weighted	Value Weighted	Num of stocks	Equal Risk	
Excess return	**0.70**	**0.60**	**0.64**	**0.60**	**1.19**	**0.23**	**0.67**	**0.46**	**0.43**	**0.46**	**0.71**	**0.57**
	(7.12)	(7.85)	(8.36)	(7.85)	(9.43)	(2.61)	(4.90)	(5.09)	(4.49)	(5.09)	(4.18)	(3.73)
CAPM alpha	**0.73**	**0.62**	**0.64**	**0.62**	**1.17**	**0.28**	**0.61**	**0.39**	**0.38**	**0.39**	**0.68**	**0.62**
	(7.44)	(8.22)	(8.27)	(8.22)	(9.17)	(3.31)	(4.43)	(4.47)	(4.20)	(4.47)	(4.02)	(4.13)
3-factor alpha	**0.73**	**0.66**	**0.65**	**0.66**	**1.21**	**0.27**	**0.51**	**0.34**	**0.32**	**0.34**	**0.60**	**0.46**
	(7.39)	(8.84)	(8.56)	(8.84)	(9.58)	(3.22)	(3.74)	(4.01)	(3.67)	(4.01)	(3.58)	(3.23)
4-factor alpha	**0.55**	**0.50**	**0.50**	**0.50**	**1.01**	**0.20**	**0.35**	**0.24**	**0.22**	**0.24**	**0.43**	**0.30**
	(5.59)	(6.88)	(6.67)	(6.88)	(8.00)	(2.35)	(2.70)	(2.96)	(2.62)	(2.96)	(2.62)	(2.17)
Beta (ex ante)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Beta (realized)	-0.06	-0.05	0.01	-0.05	0.03	-0.10	-0.07	0.01	0.05	0.01	0.06	-0.10
$Short	0.70	0.75	0.75	0.75	1.50	0.79	0.88	0.95	0.94	0.95	1.97	0.87
$Long	1.40	1.32	1.34	1.32	2.58	1.16	1.41	1.31	1.32	1.31	2.73	1.22
Volatility	10.7	8.3	8.4	8.3	13.6	9.5	8.1	5.3	5.7	5.3	9.4	9.1
Skewness	-0.79	-1.13	-0.63	-1.13	-0.91	-0.07	0.31	0.08	-1.14	0.08	-0.63	0.47
Kurtosis	10.70	9.92	10.11	9.92	8.12	6.63	5.81	5.37	9.61	5.37	5.96	5.27
Sharpe ratio	0.78	0.86	0.92	0.86	1.05	0.29	0.99	1.03	0.91	1.03	0.91	0.76

Table IV
Factor Loadings

This table reports the factor loadings of the regular BAB, four versions of an industry-neutral BAB portfolio (where each industry is either equal weighted, value weighted, weighed by the number of stocks, or equal-risk weighed), and the industry BAB (which purely bets across industries). We report the results for the U.S. from 1926-2012 and for global stocks from 1985-2012. The alpha is the intercept and the factor loadings are the coefficients from a regression on the market (MKT), size (SMB), value (HML), and momentum (UMD). The Sharpe ratios are annualized and standard errors are reported in parenthesis.

	U.S. (1926 - 2012)						Global (1985 - 2012)					
	BAB	Industry-Neutral BAB				Industry BAB	BAB	Industry-Neutral BAB				Industry BAB
		Equal Weighted	Value Weighted	Num of stocks	Equal Risk			Equal Weighted	Value Weighted	Num of stocks	Equal Risk	
Excess return	**0.70**	**0.60**	**0.64**	**0.60**	**1.19**	**0.23**	**0.67**	**0.46**	**0.43**	**0.46**	**0.71**	**0.57**
	(7.12)	(7.85)	(8.36)	(7.85)	(9.43)	(2.61)	(4.90)	(5.09)	(4.49)	(5.09)	(4.18)	(3.73)
Alpha	**0.55**	**0.50**	**0.50**	**0.50**	**1.01**	**0.20**	**0.35**	**0.24**	**0.22**	**0.24**	**0.43**	**0.30**
	(5.59)	(6.88)	(6.67)	(6.88)	(8.00)	(2.35)	(2.70)	(2.96)	(2.62)	(2.96)	(2.62)	(2.17)
MKT	-0.01	0.00	**0.03**	0.00	**0.07**	**-0.07**	0.00	**0.05**	**0.09**	**0.05**	**0.13**	-0.02
	-(0.47)	-(0.18)	(2.16)	-(0.18)	(2.81)	-(3.99)	(0.06)	(2.50)	(4.88)	(2.50)	(3.34)	-(0.52)
SMB	-0.02	**0.06**	**0.12**	**0.06**	**0.13**	**-0.16**	**0.18**	**0.17**	**0.19**	**0.17**	**0.34**	**0.26**
	-(0.80)	(2.65)	(5.31)	(2.65)	(3.37)	-(5.92)	(3.01)	(4.73)	(5.25)	(4.73)	(4.70)	(4.21)
HML	**0.10**	**-0.07**	-0.03	**-0.07**	**-0.08**	**0.15**	**0.26**	**0.11**	**0.13**	**0.11**	**0.19**	**0.38**
	(3.50)	-(3.12)	-(1.22)	-(3.12)	-(2.13)	(6.03)	(4.38)	(3.06)	(3.58)	(3.06)	(2.65)	(6.14)
UMD	**0.19**	**0.16**	**0.15**	**0.16**	**0.22**	**0.07**	**0.20**	**0.12**	**0.13**	**0.12**	**0.21**	**0.21**
	(8.33)	(9.47)	(9.00)	(9.47)	(7.59)	(3.60)	(5.97)	(6.12)	(5.99)	(6.12)	(5.20)	(5.92)
Sharpe ratio	0.78	0.86	0.92	0.86	1.05	0.29	0.99	1.03	0.91	1.03	0.91	0.76
Adjusted R2	0.07	0.13	0.11	0.13	0.08	0.10	0.18	0.19	0.23	0.19	0.17	0.25
Nobs	996	996	996	996	960	996	292	292	292	292	256	292

Table V.
Robustness Analysis.

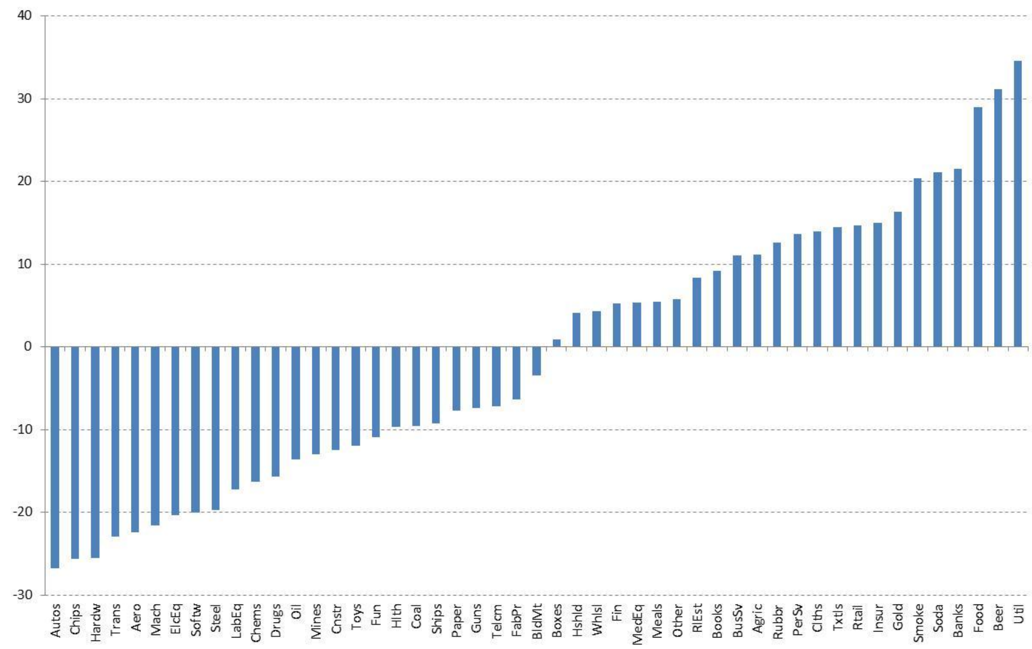
This table reports robustness analysis for our four versions of the industry-neutral BAB portfolio (where each industry is either equal weighted, value weighted, weighed by the number of stocks, or equal-risk weighed) and the industry BAB (which purely bets across industries). Panel A shows the robustness over time, proving the four-factor alphas (computed as in Tables III and IV) over different sub-periods for U.S. and global stocks. Panel B reports the robustness by the size of the stocks used in portfolio formation, separating the sample into small stocks and large stocks for U.S. and global stocks.

Panel A: by Time Period			**4-factor alphas**					**t-statistics**				
			Industry-Neutral BAB				**Industry BAB**	**Industry-Neutral BAB**				**Industry BAB**
Universe	Sample	Firm Size	Equal Weighted	Value Weighted	Num of stocks	Equal Risk		Equal Weighted	Value Weighted	Num of stocks	Equal Risk	
U.S.	1926 - 1945	All	0.21	0.16	0.21	0.42	0.11	1.23	0.87	1.23	1.69	0.56
U.S.	1946 - 1965	All	**0.43**	**0.44**	**0.43**	**1.27**	**0.50**	5.65	6.35	5.65	6.45	4.14
U.S.	1966 - 1985	All	**0.65**	**0.73**	**0.65**	**1.33**	**0.35**	5.53	5.77	5.53	5.14	2.78
U.S.	1986 - 2009	All	**0.51**	**0.54**	**0.51**	**0.67**	-0.12	3.27	3.35	3.27	2.74	-0.69
U.S.	2010 - 2012	All	**0.99**	**0.89**	**0.99**	**1.24**	0.81	3.64	2.69	3.64	3.04	1.82
Global	1985 - 2004	All	**0.29**	**0.24**	**0.29**	**0.48**	**0.48**	2.89	2.38	2.89	2.49	2.46
Global	2005 - 2012	All	0.15	0.20	0.15	0.39	**0.52**	1.12	1.39	1.12	1.37	2.45

Panel B: by Firm's Size			**4-factor alphas**					**t-statistics**				
			Industry-Neutral BAB				**Industry BAB**	**Industry-Neutral BAB**				**Industry BAB**
Universe	Sample	Firm Size	Equal Weighted	Value Weighted	Num of stocks	Equal Risk		Equal Weighted	Value Weighted	Num of stocks	Equal Risk	
U.S.	1926 - 2012	Small Cap	**0.59**	**0.58**	**0.59**	**0.98**	**0.22**	6.81	6.44	6.81	8.79	2.09
U.S.	1926 - 2012	Large Cap	**0.23**	**0.20**	**0.23**	**0.52**	**0.25**	3.60	3.51	3.60	4.92	2.76
Global	1985 - 2012	Small Cap	0.13	0.17	0.13	**0.35**	**0.35**	1.45	1.90	1.45	2.36	2.57
Global	1985 - 2012	Large Cap	0.08	0.03	0.08	0.17	0.27	1.17	0.48	1.17	1.12	1.82

Figure 1. The Industry Bets in Regular Low-Risk Investing: Which Industries Are Long vs. Short? Panel A reports the average industry bets for low-risk investing while Panel B does this for value investing. Specifically, each figure reports the results of monthly cross-sectional regressions of the BAB portfolio weights (i.e., ranked betas across stocks, minus the average rank) on industry dummies. Each bar represents an industry's average estimated coefficient divided by the standard deviation of its estimates. Positive bars represent industries whose stocks the BAB factor tends to be long, while negative bars represent industries that the BAB factor tends to be short.

Panel A. Average Industry Bets: Low-Risk Investing.



Panel B. Average Industry Bets: Value Investing.

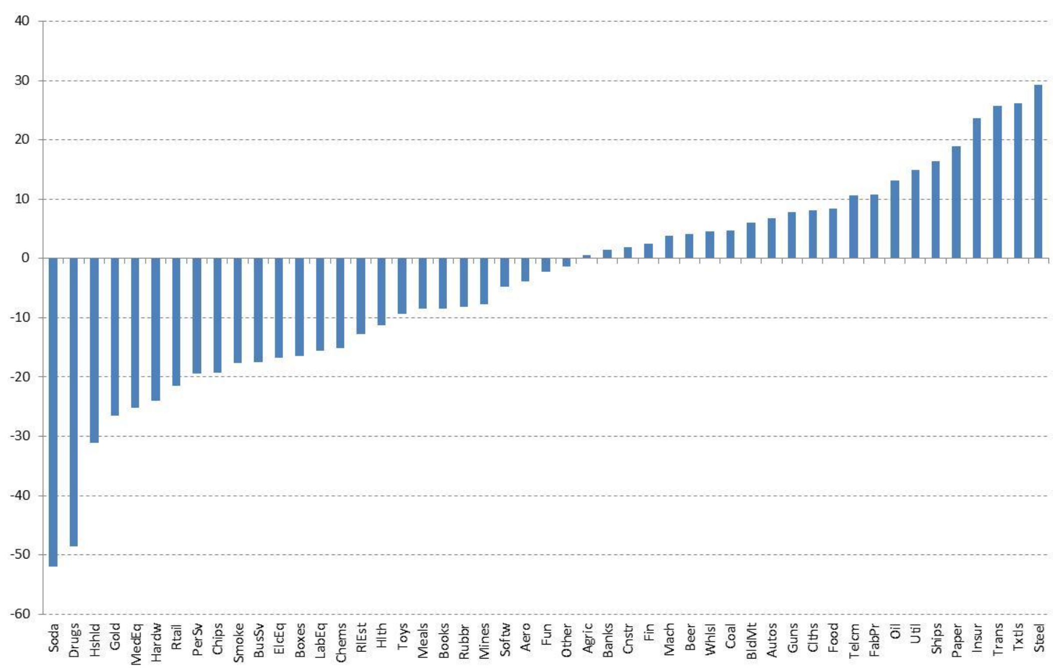
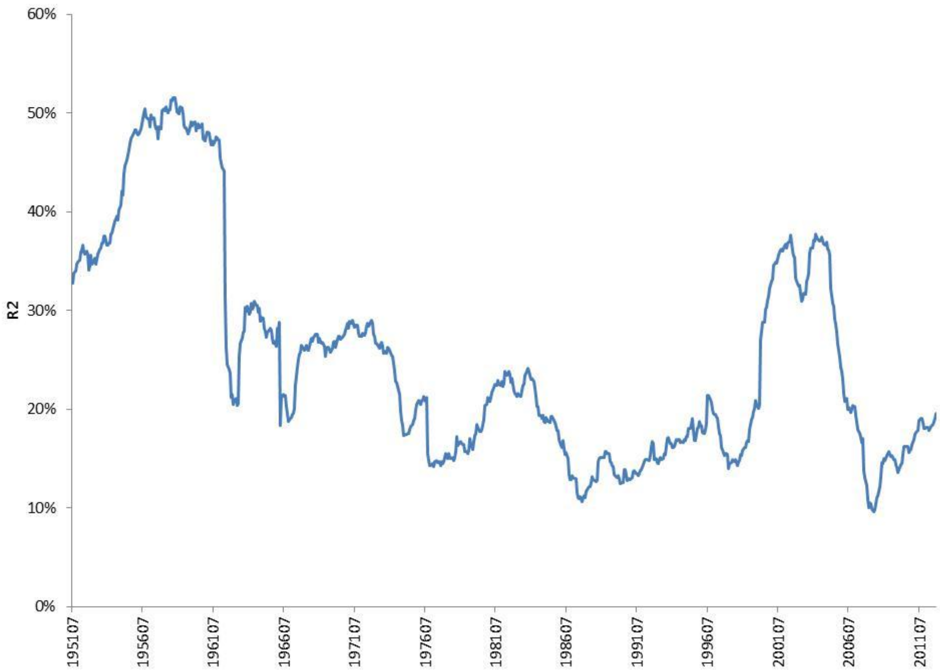


Figure 2. The Magnitude of Industry Bets Over Time. Panel A reports the magnitude of industry bets for low-risk investing while Panel B does this for value investing. Specifically, each figure reports the R2 of monthly cross-sectional regressions of the BAB portfolio weights (i.e., ranked betas across stocks, minus the average rank) on industry dummies. A high (low) R2 means that the BAB factor's industry exposures can explain a large (small) part of its portfolio weights.

Panel A. R2 of Industry Bets: Low-Risk Investing.



Panel B. R2 of Industry Bets: Value Investing.

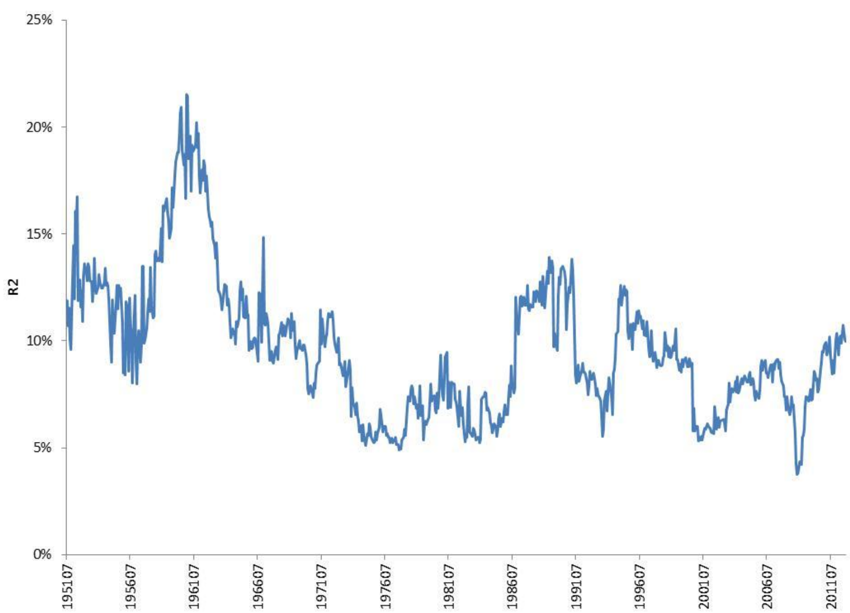


Figure 3. Performance of Regular BAB, Industry-Neutral BAB, and Industry BAB. This figure reports the Sharpe ratios for the regular BAB, the value-weighted industry-neutral BAB, and the industry BAB constructed based on U.S. stocks 1926-2012 and global stocks 1985-2012, respectively.

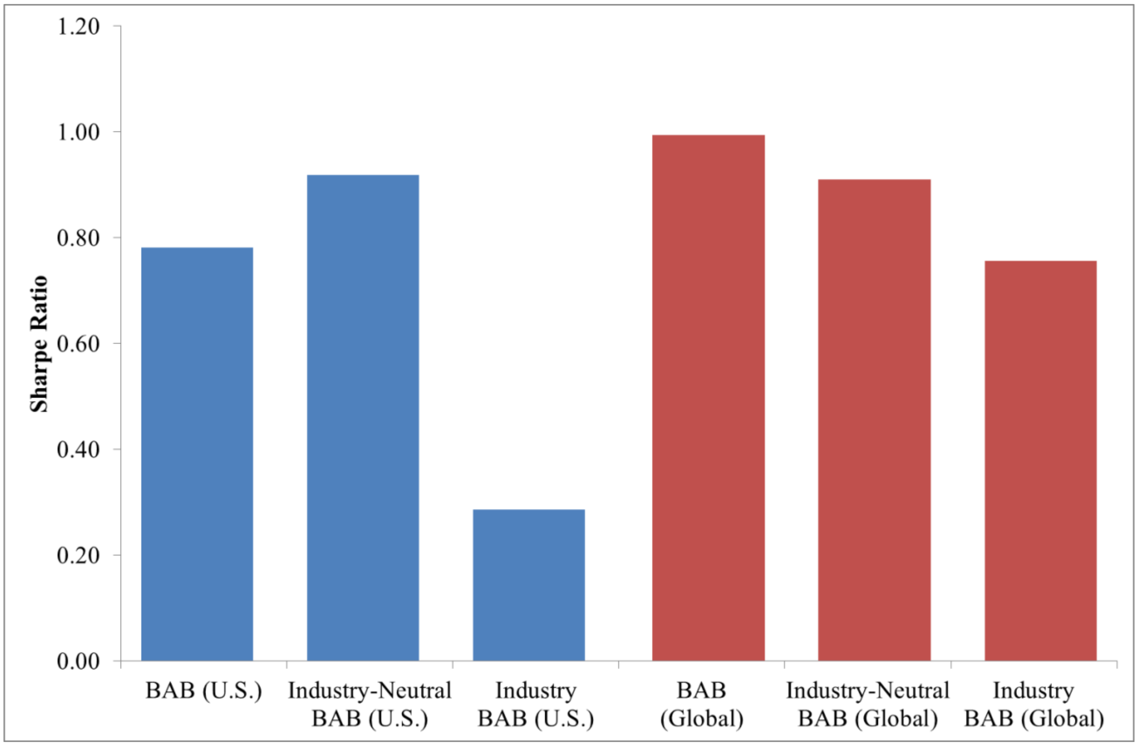
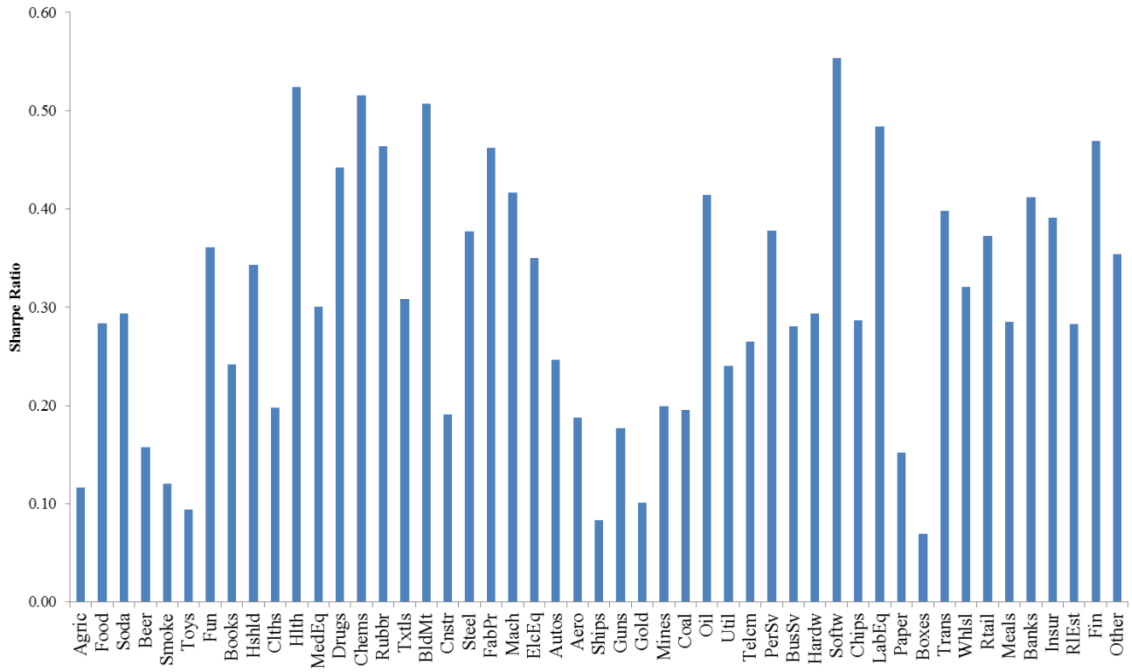


Figure 4. Sharpe Ratios of Industry-Neutral BAB Portfolios in Each Industry. This figure shows the Sharpe ratios for the BAB factors constructed within each industry. Panel A reports the results for the U.S. and Panel B for global industries.

Panel A: Sharpe Ratios for U.S. Industries, 1926-2012



Panel B: Sharpe Ratios for Global Industries, 1985-2012

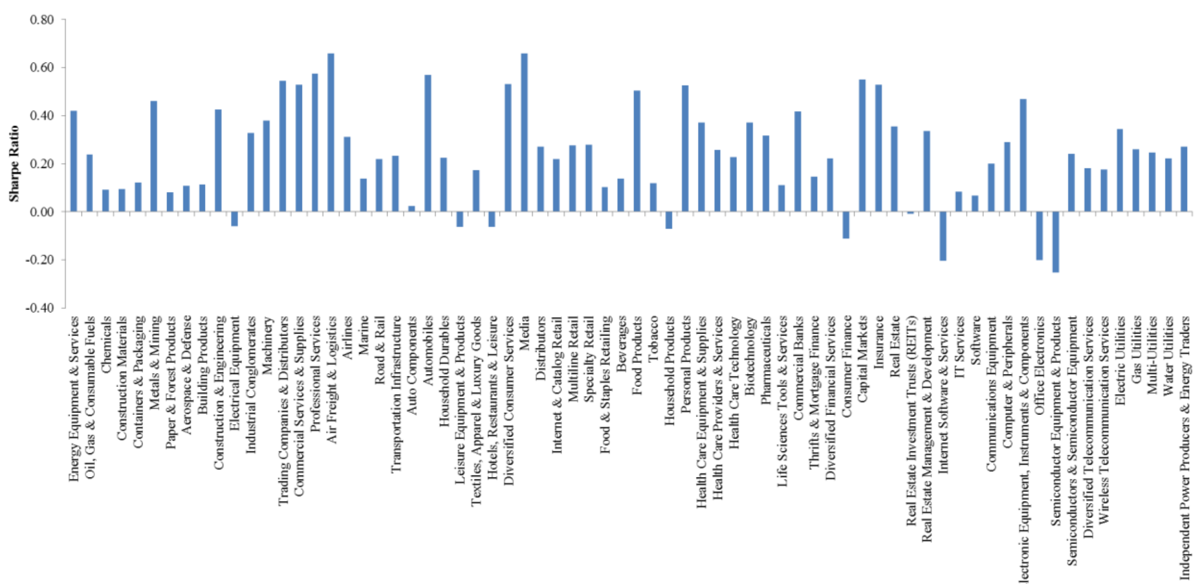
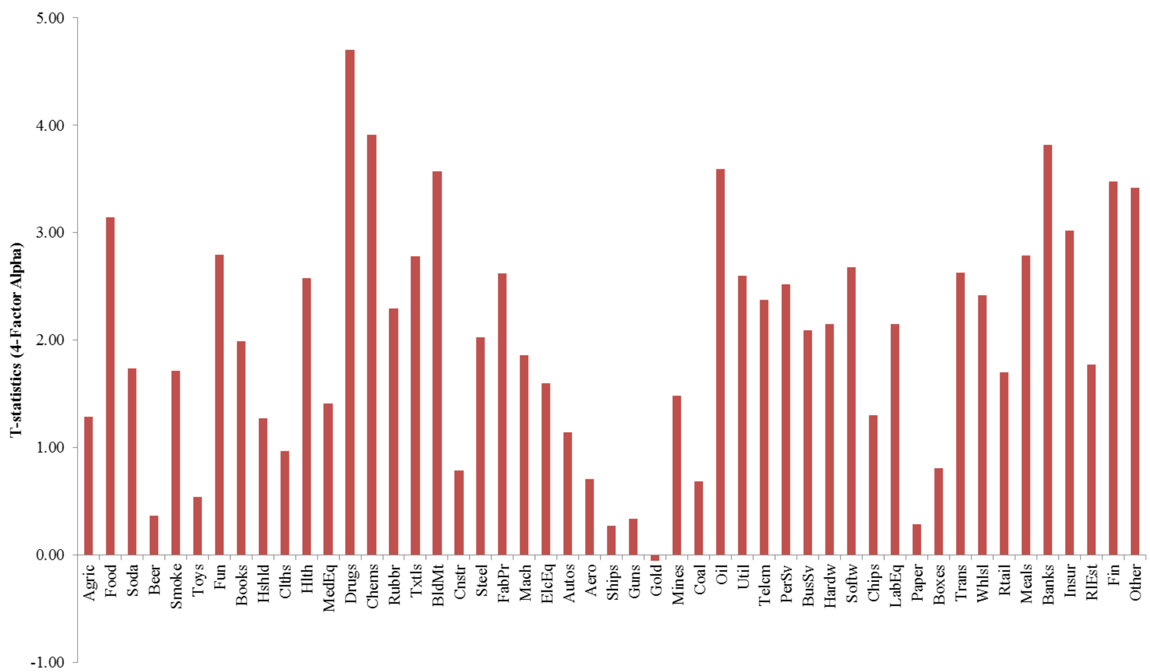


Figure 5. T-statistic of Alpha for Industry-Neutral BAB Portfolios in Each Industry. This figure shows the t-statistic for the alpha with respect to the standard four-factor model for the BAB factors constructed within each industry. Panel A reports the results for the U.S. and Panel B for global industries (where the four-factor model uses global risk factors).

Panel A: T-Stats for U.S. Industries, 1926-2012



Panel B: T-Stats for Global Industries, 1985-2012