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Low-Risk Investing without Industry Bets

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The strategy of buying safe low-beta stocks while shorting (or underweighting) riskier high-beta stocks ("betting against beta") has been shown to deliver significant risk-adjusted returns. Some have suggested, however, that such "low-risk investing" delivers high returns primarily because of industry bets that favor a slowly changing set of stodgy, stable industries. The authors refute this notion by showing that a strategy of betting against beta has delivered positive returns both as an industry-neutral bet within *each industry and as a pure bet* across *industries.*

Low-risk investing is based on the idea that safer stocks deliver higher risk-adjusted returns than do riskier stocks. This notion was first documented by Black, Jensen, and Scholes (1972), who found that the security market line was too flat relative to the capital asset pricing model (CAPM). For many, however, the intuition behind low-risk investing in stocks is captured by going long stodgy (but perhaps ultimately profitable) industries and by the related assumption that the returns are driven by value effects (e.g., Shah 2011).[1]

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

Discussion of findings. In our study, we explicitly tested how much of the benefit of low-risk investing comes from tilts toward or away from industries versus stock tilts within an industry. We found that both types of low-risk investing work. Thus, contrary to conventional wisdom, we found that low-risk investing is *not* driven purely by low-risk industries—not even close—and is *not* driven by the value effect. Among all the low-risk strategies that we considered, those that take no industry bets are among the best.

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There are many closely related forms of low-risk investing that focus on various measures: market beta (Black et al. 1972; Frazzini and Pedersen 2014), total volatility (e.g., Baker, Bradley, and Wurgler 2011), residual volatility (e.g., Falkenstein 1994; Ang, Hodrick, Xing, and Zhang 2006, 2009; Blitz and van Vliet 2007),[2] the minimum-variance portfolio,[3] and other related measures (for connections between these measures, see Clarke, de Silva, and Thorley 2013). In our study, we focused on market beta because it is the original measure and is most closely linked to economic theory.

In particular, we constructed 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 2014). To make the BAB factors market neutral, the safe stocks on the 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 *ex ante* beta of a BAB factor is zero, and so its performance can be ascribed to the efficacy of low-risk investing, not to market movements.

The "regular" BAB factor in the literature is constructed by sorting stocks on their betas without regard to industries; thus, its performance could be driven by industry bets, stock selection within an industry, or a combination of the two. To determine which is more important, we constructed the following two new BAB factors—one with *no* industry bets and the other with *only* industry bets:

- **Industry-neutral BAB.** To see whether BAB works when the effects of industry tilts are eliminated, we constructed an industry-neutral BAB factor by going long and short stocks in a balanced way within each industry. We computed a BAB factor for each industry and diversified across these industries to produce an overall industry-neutral BAB factor. We tested a robust set of methods of diversifying across these essentially separate industry-neutral BAB factors.

- **BAB as a pure industry bet.** To see how well low-risk investing does as a pure industry bet, we considered a BAB strategy that goes long and short industry portfolios. This extreme form of low-risk investing more closely fits the popular perception of a strategy that makes *only* big bets on industries.

By considering the regular BAB, the industry-neutral BAB, and the industry BAB, we sought to determine whether low-risk investing works separately for each decision (industry selection and stock selection within an industry) and to decompose the regular BAB performance into these two components. We found that both types of low-risk investing work. Historically, the industry-neutral BAB factor has realized a higher Sharpe ratio than the industry BAB factor, both in the United States and internationally. Moreover, the industry-neutral bet works not just overall but also remarkably consistently within almost every industry.

We also decomposed the regular BAB into its components and found, unsurprisingly, that it loads on both our new versions. Thus, regular low-risk investing does make industry bets, but it also makes stock selection bets. In fact, we found that the regular BAB loads more on the industry-neutral BAB than on the industry BAB in the United States (thus, the regular BAB is already doing a lot of what the industry-neutral BAB does) and loads about equally in the global sample.

In addition to documenting the high absolute return of the BAB factors, we estimated their alphas, adjusted for the standard four-factor model exposures to size, value (which some say also drives part of the returns to low-risk investing—see, e.g., Scherer 2011; Shah 2011), and momentum. We found that the BAB strategies deliver highly significant returns (adjusted for the four-factor model). Moreover, although the standard BAB has a positive value exposure (as documented in the literature), 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 entirely driven by industry or value exposures. In summary, the regular BAB strategy already makes a significant stock selection bet; the industry-neutral stock selection bet works well, 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 strong performance of the BAB strategy. Black et al. (1972) documented the original evidence for US stocks over 1931–1965. Frazzini and Pedersen (2014) found that the BAB strategy delivered significant returns in the United States over 1926–2012, including the 40-year out-of-sample period since the findings of Black et al. (1972) were first published. In addition, Frazzini and Pedersen (2014) showed that this result is not limited to US stock selection or to stock selection alone, finding that it holds in 19 other global 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 exchange-traded funds (Frazzini and Pedersen 2012) and across asset classes (Asness, Frazzini, and Pedersen 2012). The out-of-sample evidence, over time and across investment types, is exceptionally strong and without serious blemish.

Black (1972) and Frazzini and Pedersen (2014) proposed an explanation for the efficacy of low-risk investing based on leverage constraints. Thus, low-risk investing may have worked persistently over many decades without being arbitraged away because investors face constraints and because betting against this phenomenon involves risk. This theory may also help explain why industry-neutral BAB works particularly well—it requires more leverage because it is more hedged (as we show later in the article).

Further, betting against beta naturally requires portfolio rebalancing, which incurs transaction costs (Li and Sullivan 2010; Li, Sullivan, and Garcia-Feijóo 2014). To study this aspect, we analyzed the performance of the BAB factors net of transaction costs, in both the full universe of stocks and a subsample of the 1,000 largest (and thus highly tradable) stocks. Although focusing on large stocks and returns net of transaction costs naturally diminishes the returns, the performance nevertheless remains significant for the regular BAB, the industry BAB, and the industry-neutral BAB.

Our findings also add to the literature that examines how much risk factors and behavioral anomalies rely on industry selection versus stock selection within industries (Moskowitz and Grinblatt 1999; Asness, Porter, and Stevens 2001). In that spirit, Baker, Bradley, and Taliaferro (2014) studied how much "macro" effects (country and industry) matter versus "micro" effects (stock selection within country and industry) in low-risk investing. Their findings complement ours.

They used a double-sort technique on industries and individual stock betas and also considered country effects, which add to the country results in Frazzini and Pedersen (2014). In contrast, we explicitly constructed industry-neutral BAB portfolios in each industry in the United States and internationally; documented the strong performance of low-risk investing in almost every industry; controlled for standard risk factors, showing how the industry-neutral BAB has even lower risk exposures than the standard BAB (particularly low or negative value exposure, contrary to conventional wisdom); and decomposed the regular BAB strategy into its industry-neutral and industry components.

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 portfolios of Frazzini and Pedersen (2014), we constructed new industry-neutral BAB portfolios and pure industry BAB portfolios.

Data. Our sample includes 57,441 stocks covering 24 countries; summary statistics are reported in **Table 1**. We collected the data from several sources. Stock return data are from the union of the CRSP tape and the Xpressfeed global database. The US equity data include all available common stocks from CRSP between January 1926 and December 2012; we computed stocks' betas with respect to the CRSP value-weighted market index. Our BAB factor returns for the United States start in April 1929 because we needed some initial data to estimate betas. Excess returns are above the US Treasury bill rate. We computed alphas with respect to the market factor and factor returns on the basis of size (SMB), book-to-market (HML), and momentum (UMD).[4]

The global equity data include all available common stocks on the Xpressfeed global daily security file for 24 markets in the MSCI developed universe. As shown in Table 1, Xpressfeed's global coverage starts in 1986 for many countries. Our sample runs from January 1986 to December 2012, and the global BAB factor returns start in January

Table 1. Summary Statistics

Code	Country	Total No. of Stocks	Average No. of Stocks	Company Size (US$ billions)	Weight in Global Portfolio	Start Year	End Year
AUS	Australia	2,142	660	0.63	0.018	1986	2012
AUT	Austria	126	56	0.70	0.002	1990	2012
BEL	Belgium	231	91	2.37	0.009	1990	2012
CAN	Canada	1,901	541	1.08	0.022	1982	2012
CHE	Switzerland	343	135	4.06	0.023	1986	2012
DEU	Germany	1,492	596	3.01	0.061	1989	2012
DNK	Denmark	227	85	1.08	0.004	1986	2012
ESP	Spain	212	82	4.48	0.014	1986	2012
FIN	Finland	202	83	1.66	0.005	1986	2012
FRA	France	1,088	397	2.85	0.044	1986	2012
GBR	United Kingdom	3,312	1,103	1.83	0.095	1986	2012
GRC	Greece	239	132	0.48	0.002	1995	2012
HKG	Hong Kong	1,351	516	1.21	0.026	1989	2012
IRL	Ireland	106	38	1.58	0.002	1987	2012
ISR	Israel	284	97	0.64	0.003	1995	2012
ITA	Italy	356	129	2.37	0.018	1986	2012
JPN	Japan	3,856	1,988	1.29	0.202	1986	2012
NLD	Netherlands	250	109	4.70	0.021	1986	2012
NOR	Norway	429	120	0.96	0.004	1986	2012
NZL	New Zealand	176	69	1.26	0.003	1990	2012
PRT	Portugal	92	38	1.96	0.002	1990	2012
SGP	Singapore	860	353	0.60	0.009	1990	2012
SWE	Sweden	677	203	1.35	0.012	1986	2012
USA	United States	19,356	3,594	1.31	0.399	1951	2012

Notes: This table shows summary statistics as of June of each year. The sample includes all US common stocks (CRSP "shrcd" equal to 10 or 11) and all global stocks ("tcpi" equal to 0) in the merged CRSP/Xpressfeed global databases.

1988. We assigned each stock to its corresponding market on the basis of the location of the primary exchange. We computed betas with respect to the corresponding MSCI local market index. All returns are in US dollars, and excess returns are above the US Treasury bill rate. Following Asness, Frazzini, and Pedersen (2013), we computed alphas with respect to the global market factor and factor returns on the basis of size (SMB), book-to-market (HML), and momentum (UMD).[5]

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

Constructing the Standard BAB Portfolio. We constructed standard BAB portfolios that are long low-beta securities and short high-beta securities, exactly as in Frazzini and Pedersen (2014). To construct each portfolio, we ranked all securities in ascending order on the basis of their estimated beta at the end of each calendar month. We estimated betas as in Frazzini and Pedersen (2014), and the results are robust to using other reasonable methodologies. In particular, we estimated betas as follows:

$$\hat{\beta}_i^{ts} = \hat{\rho}\frac{\hat{\sigma}_i}{\hat{\sigma}_m},$$

where $\hat{\sigma}_i$ and $\hat{\sigma}_m$ are the estimated volatilities for the stock and the market and $\hat{\rho}$ is their estimated correlation. We estimated the volatilities as the one-year daily standard deviations and the correlation as the rolling five-year three-day correlation. For correlations, we used three-day returns (rather than daily returns) to account for nonsynchronous trading across stocks around the world. Further, we considered a longer, five-year horizon because correlations are more stable or harder to estimate. Finally, to account for extreme beta estimates due to noise and biases when we sorted on beta, we followed Vasicek (1973) by shrinking betas toward their cross-sectional mean, which we set to 1:

$$\hat{\beta}_i = 0.6 \times \hat{\beta}_i^{ts} + 0.4 \times 1.$$

The shrinkage did not affect the ranks of the stocks (we based our tests on ordinal sorts); it affected only the leverage of the BAB portfolios (as we discuss later in the article). Naturally, we shrank only the *ex ante* betas used in portfolio formation, not the *ex post* market exposures used in evaluating the performance of the strategies. Of course, any mismeasurement of the *ex ante* betas can lead to *ex post* market exposure, but this aspect is picked up by controlling for the market in our four-factor regressions and would thus be fully accounted for in the realized alphas. Our results are qualitatively similar when using other ways to estimate beta.

We assigned the ranked securities to either a low-beta portfolio or a high-beta portfolio. The low-beta portfolio comprised all stocks with a beta below its country median; the high-beta portfolio comprised all stocks with a beta above its country median. In each portfolio, we weighted securities by the beta ranks. Appendix A provides a simple example of the BAB construction. (Lower-beta securities had larger weights in the low-beta portfolio, and higher-beta securities had larger weights in the high-beta portfolio. Weighting by rank, not by beta itself, allowed us to reduce the impact of potential data errors and reliance on extreme values.) We rebalanced all portfolios every calendar month.

More formally, let z be the $n \times 1$ vector of beta ranks at portfolio formation, $z_i = \text{Rank}(\beta_i)$, where the lowest-beta stock is ranked 1, the second lowest is ranked 2, and so on. Further, 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 1s. The portfolio weights of the low-beta and high-beta portfolios are given by

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

where k is a normalizing constant $k = 2/1_n'\left|z-\bar{z}\right|$ and, for any vector x, x^+ and x^- indicate vectors of positive and negative parts [i.e., $x^+ = \max(0, x)$ and $x^- = \max(0, -x)$]. The weights sum to 1 by construction ($1_n' w_H = 1$ and $1_n' w_L = 1$), and 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 standard BAB portfolio is a self-financing, zero-beta portfolio that is long the low-beta portfolio and short the high-beta portfolio:

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

Note that the BAB factor scales the L and H portfolios by their betas so that both the long and the short sides have a beta of 1 at portfolio formation, which makes the BAB factor market neutral.

Constructing the Industry-Neutral BAB Portfolio. We next constructed an industry-neutral BAB portfolio for each industry. Specifically, we assigned a stock to the high-beta portfolio if its beta was above the median for its industry in its country and to the low-beta portfolio otherwise. For instance, we would assign Toyota to the high-beta portfolio if its beta was above the median among Japanese auto stocks.

For each industry, we constructed a long–short portfolio as in Equation 2, which yielded a set of self-financing, zero-beta BAB portfolios with no industry exposure, one for each industry (49 in the US sample and 70 in the global sample). Our methodology ensured that the industry-neutral BAB had the same number of stocks from each country on the long and short sides, resulting in a limited country exposure. (To keep the analysis simple, we did not require that each country beta be zero.)

We then aggregated these separate BAB portfolios for each industry to arrive at an overall industry-neutral BAB strategy. We computed the overall industry-neutral BAB portfolio, BAB_t^{Intra}, which is simply a portfolio of the individual industry-neutral BABs with weights w_{t-1}^j:

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

To ensure that our results were not driven by a particular weighting scheme, we computed 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 rescaled each portfolio to an *ex ante* annualized volatility of 10% at portfolio formation and took an equal-weighted average of these re-scaled portfolios $\left(w_{t-1}^j = 1/I \times 10\% / \hat{\sigma}_{t-1}\right)$.[6]

Constructing the Industry BAB Portfolio. To construct a pure industry BAB portfolio, we first computed the returns of value-weighted industry portfolios and then computed the industry BAB portfolio by going long and short the industry portfolios (using Equation 2).[7] Thus, our industry BAB factor is long low-beta industries and short high-beta industries. In the global sample, we first computed an industry BAB portfolio for each country and then computed the value-weighted average of these portfolios on the basis of each country's lagged market capitalization. This construction makes our global industry BAB country neutral. We used value weights (and thus gave larger weights to larger countries) to be conservative and make the analysis realistic.

How Much of Low-Risk Investing Is an Industry Bet?

We first examined the level of industry bets in regular low-risk investing (i.e., the regular BAB portfolio). We looked at what industries the regular BAB portfolio typically bets on, how large these average bets are, and how much they change over time.

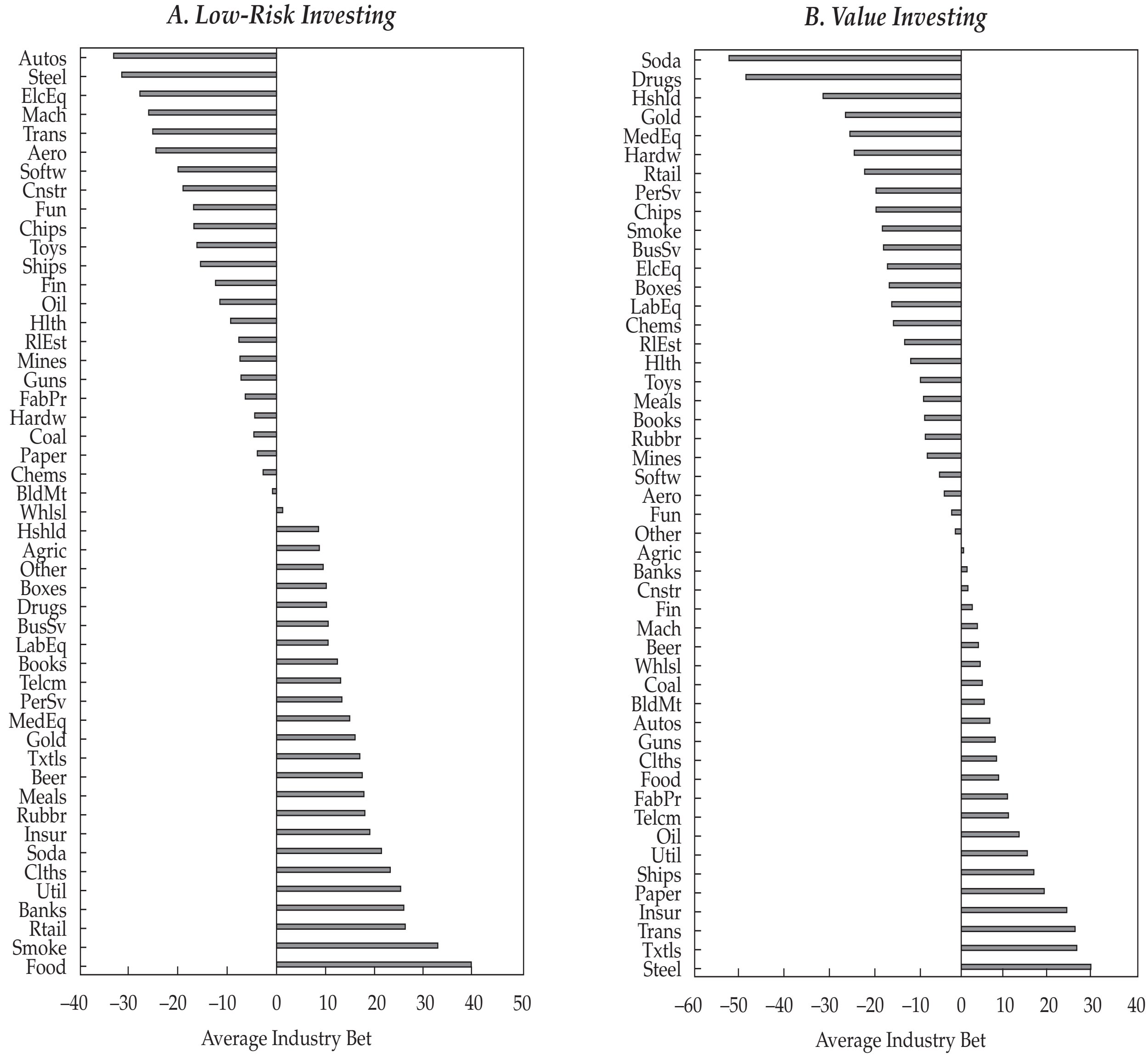
To address these issues, we ran a cross-sectional regression. For the dependent variable, we used the unleveraged weight, w^s, in the BAB portfolio for each stock s, which is proportional to the rank of its beta. Specifically, for low-beta stocks, we let $w^s = w_L^s$ be the weight in the low-beta portfolio; for high-beta stocks (which the BAB factor is short), we let $w^s = -w_H^s$ be the weight in the high-beta portfolio (where w_H and w_L are defined as in Equation 1). Hence, the dependent variable is linearly decreasing in a stock's beta rank, the positive numbers sum to 1, and the negative numbers sum to 1.[8]

The independent variables are simply dummies for whether stock s belongs to any industry indexed by i. We ran these cross-sectional regressions in each month t:

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

Panel A of **Figure 1** depicts the average estimated regression coefficient for each industry dummy divided by its standard deviation—that is, its Fama–MacBeth t-statistic. (We report this measure only for 1951–2012 because we are comparing BAB and value portfolios and the Xpressfeed data on book equity starts in 1951.) A positive number means that the regular (not industry-neutral or industry) BAB portfolio weights tend to be long for the stocks in that industry, whereas a negative number reflects short average exposure for the BAB factor. We can see that the five largest positive exposure t-statistics are in utilities, banks, retail, smoke, and food, which generally fit our intuition of what constitutes safer industries. The five most negative exposures are in cyclical and risky industries—namely, automobiles, steel, electrical equipment, machinery, and transportation. For comparison, Panel B of Figure 1 shows the same exercise for a value factor based on each stock's book-to-price ratio; low-risk investing and value investing make very different industry bets, on average (e.g., steel shows up in the opposite ends of these portfolios).

Figure 1. Industry Bets in Regular Low-Risk Investing: Which Industries Are Long vs. Short?



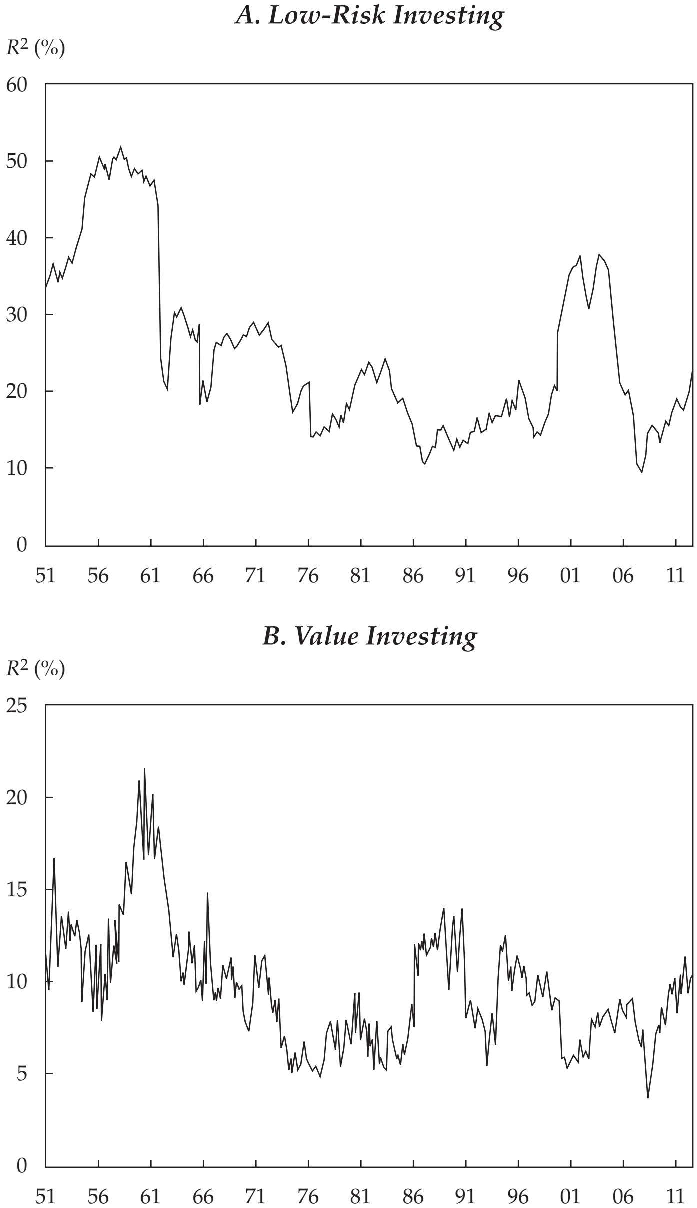
Notes: Panel A reports the results of monthly cross-sectional regressions of the BAB portfolio weights on industry dummies. Each bar represents an industry's average estimated coefficient divided by the standard deviation of its estimates. Positive bars represent industries whose stocks the BAB portfolio tends to be long, whereas negative bars represent industries whose stocks the BAB portfolio tends to be short. Panel B reports the corresponding numbers where the dependent variables are value-investing portfolio weights.

Panel A of **Figure 2** depicts the monthly R^2 from the cross-sectional regressions. The average R^2 is 25%, with a maximum of 52% and a minimum of 10%. Thus, the BAB factor's portfolio weights can be explained by industry exposures to some extent; nevertheless, most of the variation in holdings across stocks is left unexplained by industries. For comparison, Panel B presents the same exercise for the book-to-price factor; the average R^2 is 10%, the maximum is 22%, and the minimum is 4%. We can see that popular intuition—that the low-beta factor is more industry driven than the others—is quite true in this case.

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 does indeed tend to be long the safe industries that one might expect and short the cyclical industries, and these industry exposures explain a nontrivial amount of the variation in stock holdings.

Having studied the BAB factor *holdings*, we next considered its *returns*. We wanted to study how much of the regular BAB factor's performance is driven by industry exposures versus within-industry stock selection. First, we simply considered the correlations

Figure 2. The Magnitude of Industry Bets over Time



Notes: Panel A reports the magnitude of industry bets for low-risk investing; Panel B does the same for value investing. Each panel reports the R^2 of monthly cross-sectional regressions of the portfolio weights on industry dummies. A high (low) R^2 means that the portfolio's industry exposures can explain a large (small) part of its portfolio weights.

between the returns of the regular BAB factor (constructed without regard to industries), the industry-neutral BAB portfolio, and the industry BAB. Panel A of **Table 2** reports the results. Not surprisingly, the returns are all positively correlated. We can see that the regular BAB is most correlated with the industry-neutral BAB in the United States and about equally correlated with the industry-neutral and industry BAB factors in the global sample. Naturally, the lowest pairwise correlation is between the industry-neutral and industry BAB factors. They are constructed so that the weights are essentially orthogonal to each other, and the correlation that remains is a pure result of the economic correlation of the factors. The high correlation between the regular BAB factor and the industry-neutral BAB already suggests that stock selection bets within industries are important for low-risk investing, an aspect we then studied in more detail by decomposing the return of the regular BAB factor into its components.

Specifically, we regressed the returns of the regular BAB factor on the value-weighted[9] version of the industry-neutral BAB portfolio $\left(BAB_t^{Intra}\right)$, the industry BAB portfolio $\left(BAB_t^{Industry}\right)$, and the standard factors related to market risk (MKT), size (SMB), value (HML), and momentum (UMD), as well as subsets of these independent variables:

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

Panel B of Table 2 reports the results of this entire regression as well as regressions on various subsets of the factors. The first specification (column 1) shows a regression of regular BAB on the standard four-factor model, which serves as a reminder of the strong risk-adjusted returns to regular BAB investing, replicating the results of Frazzini and Pedersen (2014). BAB loads positively on value and more positively on momentum, but even accounting for these effects (which, of course, reduces the intercept), both the economic and the statistical significance of the BAB intercept are very strong.[10]

We next added the industry-neutral and industry BAB factors to the right-hand side for the regression specifications in columns 2–4. Obviously, the explanatory power (R^2) goes way up because we are now explaining the regular BAB with two other forms of BAB. More importantly, the loading on the industry-neutral BAB factor is larger than that of the industry BAB (measured by coefficient or *t*-statistic) by a factor of about 2.5 in the United States. To correctly interpret the regression coefficients, however, we must account for the fact that the industry BAB is more volatile. In the United States, the industry-neutral BAB remains the more important, even with adjusting for volatility (which we can see in the *t*-statistics). Indeed, a change

Table 2. Decomposing BAB into Its Industry-Neutral and Industry Components (*t*-statistics in parentheses)

A. Correlations

	US (1926–2012)			Global (1986–2012)		
	BAB	Industry-Neutral BAB	Industry BAB	BAB	Industry-Neutral BAB	Industry BAB
BAB	1			1		
Industry-neutral BAB	0.81	1		0.65	1	
Industry BAB	0.61	0.43	1	0.69	0.55	1

B. Regression of BAB on industry-neutral BAB and industry BAB

	US (1926–2012)				Global (1986–2012)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Alpha	0.55*	0.10*	0.01	0.00	0.47*	0.19*	0.19*	0.18
	(5.64)	(2.00)	(0.16)	(0.06)	(3.72)	(2.10)	(2.12)	(1.94)
Industry-neutral BAB		0.88*	0.94*	0.94*		0.61*	0.63*	0.62*
		(38.46)	(41.43)	(40.01)		(8.72)	(8.46)	(8.18)
Industry BAB		0.35*	0.33*	0.33*		0.39*	0.39*	0.38*
		(18.26)	(17.20)	(17.17)		(10.65)	(9.69)	(9.16)
MKT	–0.01		0.03*	0.03*	0.01		0.00	0.01
	(–0.49)		(2.91)	(2.97)	(0.49)		(–0.16)	(0.26)
SMB	–0.03		–0.04*	–0.04*	0.15*		–0.04	–0.04
	(–1.00)		(–2.35)	(–2.32)	(2.59)		(–0.95)	(–0.87)
HML	0.10*		0.13*	0.14*	0.23*		–0.02	0.00
	(3.61)		(9.60)	(9.32)	(3.91)		(–0.39)	(–0.04)
UMD	0.19*			0.01	0.20*			0.03
	(8.39)			(0.60)	(6.01)			(1.28)
Adjusted R^2	0.07	0.75	0.77	0.77	0.15	0.58	0.58	0.58
No. of observations	1,005	1,005	1,005	1,005	300	300	300	300

Notes: Panel A reports the correlations between the regular BAB factor, the value-weighted industry-neutral BAB, and the industry BAB. Panel B reports the results of a regression of the regular BAB factor on the value-weighted industry-neutral BAB, the industry BAB, and market (MKT), size (SMB), value (HML), and momentum (UMD) returns.
*Significant at the 5% level.

of one standard deviation in the industry-neutral BAB factor has more than twice the effect of the industry BAB in the United States. In the global sample, the volatility-adjusted effects of the two BAB factors are similar, with the industry-neutral BAB having a volatility-adjusted effect of about 80% of that of the industry BAB. These results suggest that the standard BAB effect is due as much to stock selection as to industry selection (and more so in the United States), a rebuke to the idea that BAB is all about industries. We next examined the performances of the different forms of low-risk investing.

BAB Performance within and across Industries

We analyzed how low-risk investing performs as (1) a long–short portfolio that goes long low-beta stocks and short high-beta stocks, ignoring industry exposures (regular BAB); (2) a long–short portfolio within each industry, diversified across industries (industry-neutral BAB); and (3) a long–short portfolio of entire value-weighted industries, going long low-beta industries and short high-beta industries (industry BAB).

Table 3 reports our results for US stocks over 1926–2012 (our longest sample) and for all global stocks over 1986–2012 (our broadest sample). We considered four versions of the industry-neutral BAB that differ in terms of how the individual industry-neutral BAB portfolios are weighted across industries, as previously explained. Our results also hold when considering only US stocks over 1986–2012 or only global stocks (excluding the United States). For brevity, however, we will focus on our findings for the longest and broadest samples.

We can see that all the BAB portfolios for US 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

Table 3. Performance of the Regular BAB, Industry-Neutral BAB, and Industry BAB (*t*-statistics in parentheses)

	US (1926–2012)						Global (1986–2012)					
		Industry-Neutral BAB						Industry-Neutral BAB				
	BAB	Equal Weighted	Value Weighted	No. of Stocks	Equal Risk	Industry BAB	BAB	Equal Weighted	Value Weighted	No. of Stocks	Equal Risk	Industry BAB
Excess return	0.70*	0.65*	0.59*	0.64*	1.19*	0.22*	0.72*	0.50*	0.47*	0.41*	0.74*	0.63*
	(7.20)	(7.76)	(7.93)	(8.45)	(9.47)	(2.47)	(5.47)	(5.37)	(5.60)	(4.86)	(4.45)	(3.89)
CAPM alpha	0.74*	0.66*	0.62*	0.64*	1.17*	0.31*	0.74*	0.49*	0.46*	0.39*	0.72*	0.68*
	(7.53)	(7.85)	(8.31)	(8.37)	(9.23)	(3.56)	(5.62)	(5.23)	(5.53)	(4.70)	(4.29)	(4.30)
Three-factor alpha	0.73*	0.69*	0.66*	0.65*	1.21*	0.32*	0.64*	0.44*	0.41*	0.33*	0.65*	0.47*
	(7.48)	(8.34)	(8.97)	(8.69)	(9.65)	(3.68)	(4.85)	(4.76)	(5.00)	(3.98)	(3.92)	(3.12)
Four-factor alpha	0.55*	0.51*	0.51*	0.50*	1.01*	0.22*	0.47*	0.34*	0.31*	0.22*	0.46*	0.27
	(5.64)	(6.31)	(6.98)	(6.77)	(8.06)	(2.50)	(3.72)	(3.73)	(3.91)	(2.74)	(2.84)	(1.85)
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	–0.02	–0.05	0.00	0.03	–0.15	–0.05	0.03	0.01	0.04	0.06	–0.14
$Short	0.70	0.77	0.75	0.74	1.50	0.79	0.88	0.97	0.93	0.93	2.01	0.90
$Long	1.40	1.34	1.31	1.33	2.58	1.16	1.39	1.33	1.29	1.30	2.78	1.33
Volatility	10.7	9.2	8.2	8.3	13.5	9.9	7.9	5.6	5.0	5.0	9.4	9.7
Skewness	–0.79	–1.10	–1.11	–0.62	–0.92	–0.34	0.21	–0.06	0.18	–0.41	–0.84	0.29
Kurtosis	10.75	14.10	9.84	9.99	8.21	6.58	5.67	5.14	4.58	5.78	6.41	4.64
Sharpe ratio	0.79	0.85	0.87	0.92	1.05	0.27	1.09	1.07	1.12	0.97	0.95	0.78

Notes: This table reports the performance of the regular BAB, four versions of an industry-neutral BAB portfolio (in which each industry is equal weighted, value weighted, weighted by the number of stocks, or equal risk weighted), and the industry BAB (which bets purely across industries). The volatilities and Sharpe ratios are annualized.
*Significant at the 5% level.

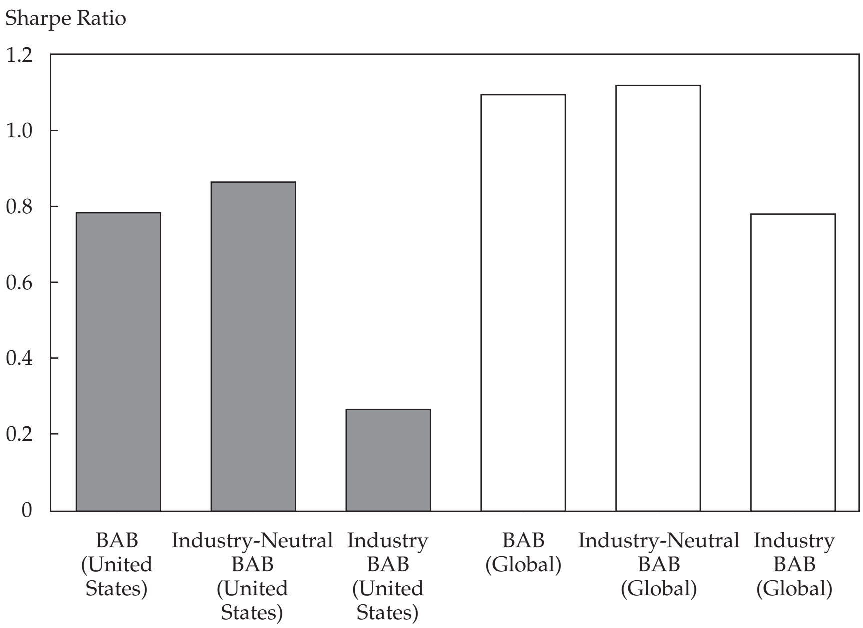
of Table 3 all show positive intercepts and positive *t*-statistics). The Sharpe ratios of the different BAB strategies are illustrated in **Figure 3** for the United States over 1926–2012 and for the global set of countries over 1986–2012. Our results show that low-risk investing works for both selecting industries and selecting stocks within an industry. In fact, industry-neutral BAB portfolios have delivered higher Sharpe ratios and information ratios than have the industry BAB portfolios.

Table 4 reports the four-factor model loadings on the different BAB portfolios. Interestingly, for both the US and the 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 the industry-neutral BAB, in which there is not even a significantly positive value loading to overcome.

A BAB Portfolio for Each Industry. After considering the overall diversified industry-neutral BAB strategy, we thought it would also be 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 that combines all the strategies (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, all 49 Sharpe ratios are positive for the US BAB portfolios, and 26 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 is oddly succeeding (at least by sign) in 49 of 49 industries! The results are also strong for the global industries, where the industry-neutral BAB factor delivers positive returns in 60 of 70 industries.

Hedging Industry Risk and Leverage. Interestingly, by hedging industry risk, the industry-neutral BAB has historically achieved a larger Sharpe ratio than both the industry BAB and the standard BAB for both US 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—or may be implementable

Figure 3. Performance of Regular BAB, Industry-Neutral BAB, and Industry BAB



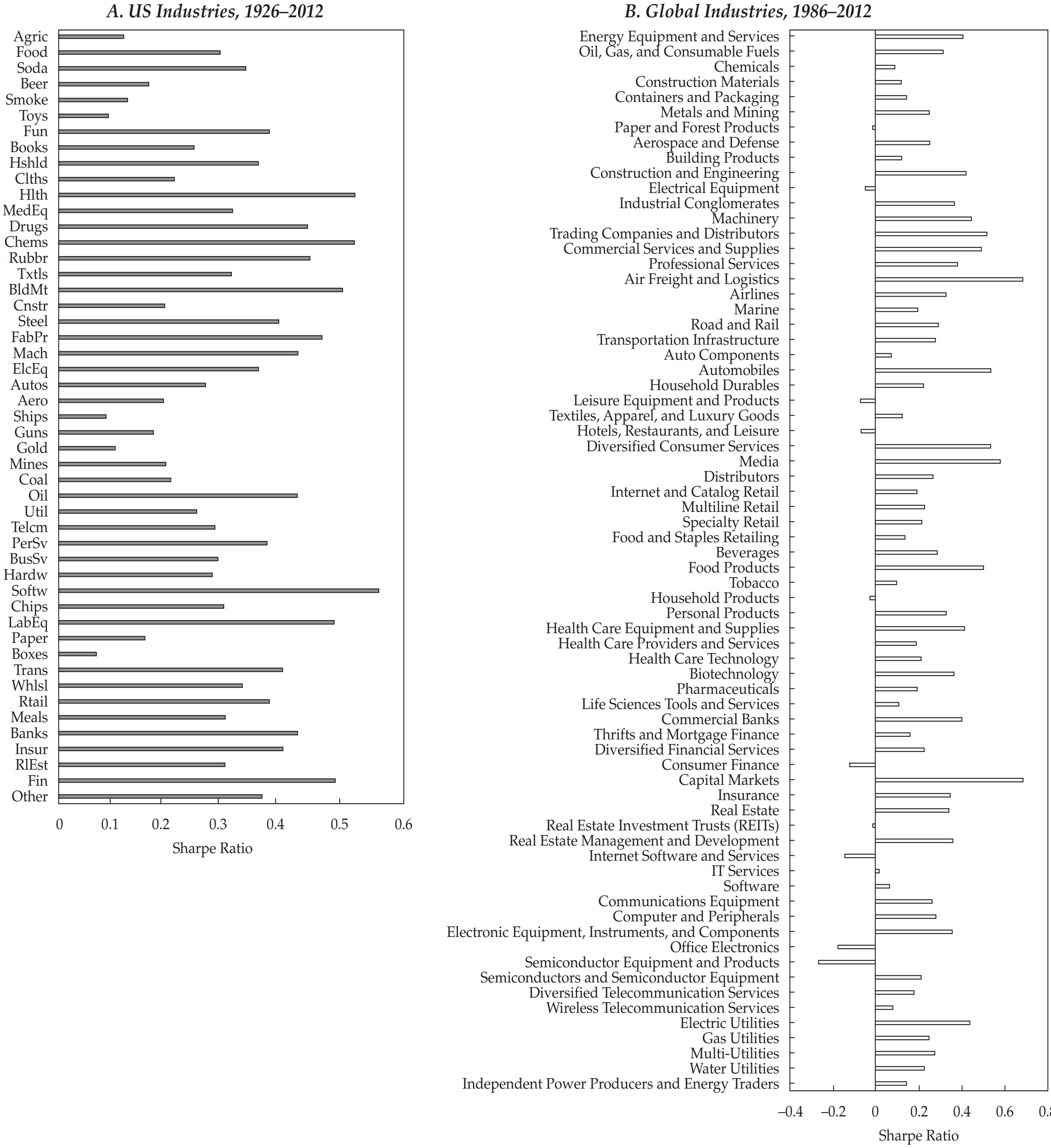
Note: This figure reports the Sharpe ratios for the regular BAB, the value-weighted industry-neutral BAB, and the industry BAB constructed on the basis of US stocks (1926–2012) and global stocks (1986–2012).

Table 4. Factor Loadings
(*t*-statistics in parentheses)

	US (1926–2012)						Global (1986–2012)					
		Industry-Neutral BAB						Industry-Neutral BAB				
	BAB	Equal Weighted	Value Weighted	No. of Stocks	Equal Risk	Industry BAB	BAB	Equal Weighted	Value Weighted	No. of Stocks	Equal Risk	Industry BAB
Excess return	0.70*	0.65*	0.59*	0.64*	1.19*	0.22*	0.72*	0.50*	0.47*	0.41*	0.74*	0.63*
	(7.20)	(7.76)	(7.93)	(8.45)	(9.47)	(2.47)	(5.47)	(5.37)	(5.60)	(4.86)	(4.45)	(3.89)
Alpha	0.55*	0.51*	0.51*	0.50*	1.01*	0.22*	0.47*	0.34*	0.31*	0.22*	0.46*	0.27
	(5.64)	(6.31)	(6.98)	(6.77)	(8.06)	(2.50)	(3.72)	(3.73)	(3.91)	(2.74)	(2.84)	(1.85)
MKT	–0.01	0.01	–0.01	0.03*	0.07*	–0.10*	0.01	0.07*	0.04*	0.08*	0.12*	–0.04
	(–0.49)	(0.70)	(–0.36)	(1.99)	(2.55)	(–5.82)	(0.49)	(3.26)	(2.19)	(4.36)	(3.37)	(–1.25)
SMB	–0.03	0.15*	0.06*	0.12*	0.13*	–0.15*	0.15*	0.15*	0.18*	0.17*	0.31*	0.19*
	(–1.00)	(5.96)	(2.69)	(5.27)	(3.34)	(–5.63)	(2.59)	(3.70)	(5.04)	(4.72)	(4.39)	(2.92)
HML	0.10*	–0.05*	–0.06*	–0.02	–0.07	0.09*	0.23*	0.08	0.09*	0.13*	0.15*	0.48*
	(3.61)	(–2.11)	(–3.00)	(–1.07)	(–1.90)	(3.34)	(3.91)	(1.91)	(2.41)	(3.57)	(2.03)	(6.92)
UMD	0.19*	0.18*	0.16*	0.15*	0.22*	0.10*	0.20*	0.12*	0.12*	0.13*	0.22*	0.24*
	(8.39)	(9.65)	(9.45)	(8.98)	(7.64)	(5.01)	(6.01)	(5.19)	(5.72)	(6.60)	(5.53)	(6.49)
Sharpe ratio	0.79	0.85	0.87	0.92	1.05	0.27	1.09	1.07	1.12	0.97	0.95	0.78
Adjusted R^2	0.07	0.13	0.13	0.11	0.08	0.13	0.15	0.12	0.16	0.20	0.16	0.26
No. of observations	1,005	1,004	1,005	1,005	968	1,005	300	300	300	300	264	300

Notes: This table reports the factor loadings of the regular BAB, four versions of an industry-neutral BAB portfolio (in which each industry is equal weighted, value weighted, weighted by the number of stocks, or equal risk weighted), and the industry BAB (which bets purely across industries). The Sharpe ratios are annualized.
*Significant at the 5% level.

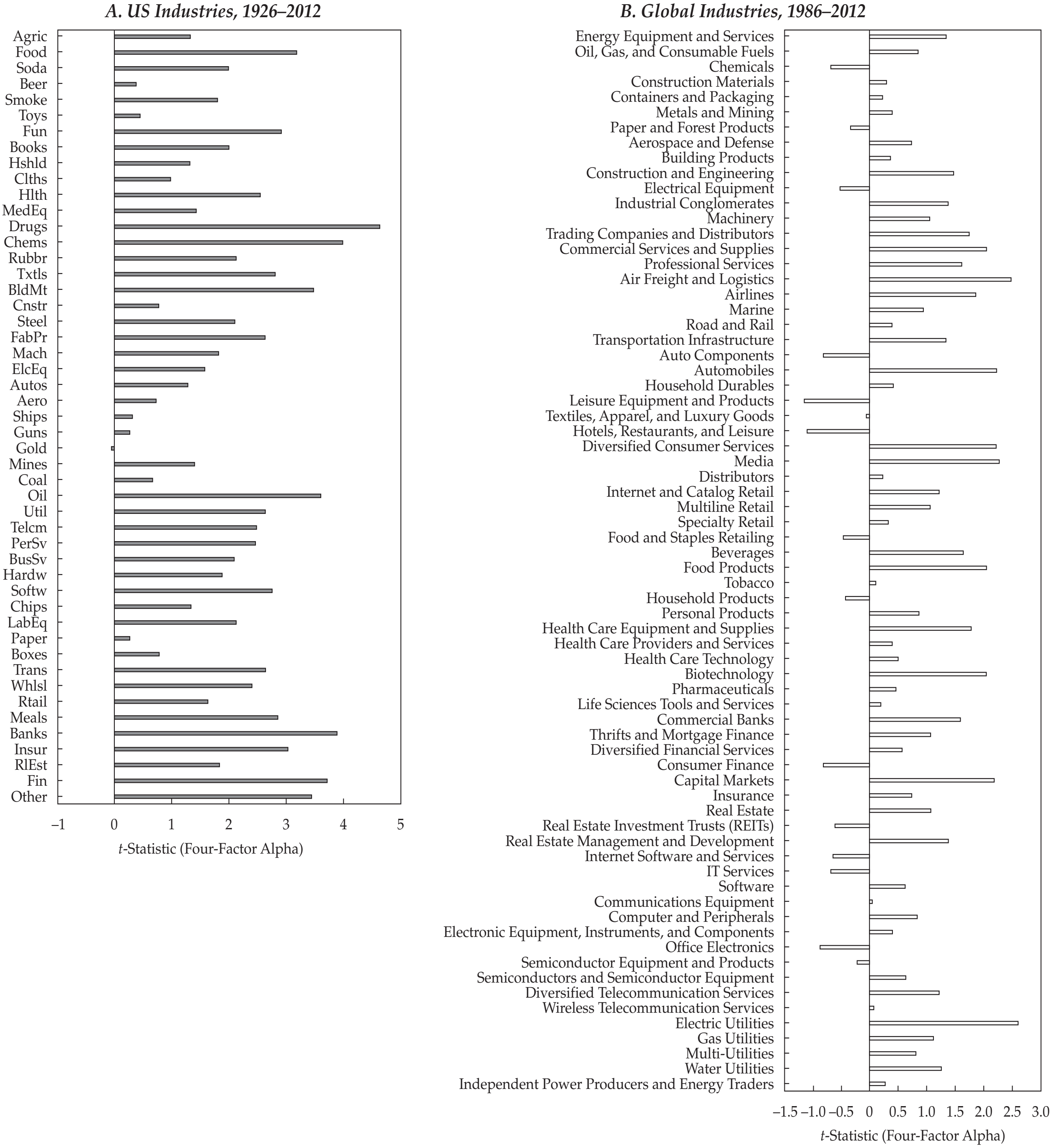
Figure 4. Sharpe Ratios of Industry-Neutral BAB Portfolios in Each Industry



Note: This figure shows the Sharpe ratios for the BAB factors constructed within each industry.

by fewer investors because many cannot tolerate leverage or leverage beyond a certain point, thus raising the required return for leverage-averse investors, consistent with the theories of Black (1972) and Frazzini and Pedersen (2014). Specifically, Table 3 reports the average dollar exposure for the long and short legs of the portfolio (labeled "$Long" and "$Short"), and we can see that the notional exposures required per unit of volatility, ($Long + $Short)/Volatility, are larger for the industry-neutral BAB portfolios. Moreover, the industry-neutral BAB portfolios tend to have more negatively skewed and more kurtotic monthly returns than the industry BAB. Therefore, the overall evidence is very supportive of the leverage constraint models: Low-risk investing works within and across industries, and it delivers a higher Sharpe ratio when more leverage is required per unit of risk.

Figure 5. ***t*-Statistics of Alpha for Industry-Neutral BAB Portfolios in Each Industry**



Notes: This figure shows the t-statistics of alpha with respect to the standard four-factor model for the BAB factors constructed within each industry. Panel A reports the results for US industries, and Panel B reports the results for global industries.

Optimizing Low-Risk Investing within and across Industries. Given that low-risk investing works both within and across industries, we wanted to consider how each strategy should be weighted. For this experiment, we allowed an optimizer to maximize the overall Sharpe ratio by allocating across all three potential BAB factors (regular, industry, and industry neutral) and the four standard factors (market, size, value, and momentum). We constrained the weights to be positive across all seven strategies and used US monthly data back to 1929.

The resulting *ex post* optimal weights are 0% for the regular BAB, 44% for the industry-neutral BAB, 0% for the industry BAB, 11% for the market factor, 24% for HML (value), 4% for SMB (size), and 17%

for UMD (momentum). The weight for the industry-neutral BAB factor is somewhat exaggerated because this factor has a lower volatility than the others (and thus its notional weight must be larger to deliver the same impact as higher-volatility factors). If we scale by *ex post* volatility, instead of 44% of the dollars, the optimizer assigns the industry-neutral BAB factor 30% of the risk taken. This large assigned risk allocation may also be exaggerated because the BAB factors are constructed by using rank weightings, a different methodology than the one used for the other factors. This approach could mean that we end up with a larger weight for BAB versus the four-factor strategies than a more apples-to-apples comparison would yield, but it should not affect the relative weights for different versions of BAB, the focus of our study. The optimizer clearly favors the industry-neutral BAB over the industry BAB.

Looking at the global results for 1986–2012, we can see an *ex post* optimal weight for the industry-neutral BAB of 34% in dollars and 30% in *ex post* risk—again, with no desired weight for the regular BAB and the industry BAB. Essentially, both optimizations prefer only industry-neutral BAB—so much for low risk being mainly about industries.

Finally, we can look at only (non-US) global results for 1986–2012 in order to cherry-pick a sample to find the strongest results for the industry BAB versus the industry-neutral BAB (not shown in Table 3, which reports the global results including the United States). 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 terms of *ex post* volatility), and 0% to the industry BAB. Thus, even in this sample, *ex post* selected as the one most favoring the industry BAB, an optimizer favors adding back the industry-neutral BAB to the regular BAB. This finding means that the regular BAB still has more than the optimal amount of industry betting (or less than the optimal amount of industry-neutral betting).

The evidence points to the industry-neutral BAB as being, if anything, superior to the industry BAB, both in terms of its standalone Sharpe ratio and in terms of a portfolio context. However, investors might still want to rely on the regular BAB or industry BAB factors to limit leverage and transaction costs, among other reasons.

Robustness Analysis

Our results are robust along several dimensions. We have already shown that the industry-neutral BAB portfolios have delivered positive returns in each US industry and in most global industries. Thus, the diversified industry-neutral BAB portfolios perform well with any of the four weighting schemes that we tested.

Table 5 reports an additional robustness analysis for our industry-neutral BAB portfolios and industry BAB portfolios. Panel A shows the robustness with respect to time periods. The US 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 1986. The US 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 of Table 5 shows the robustness with respect to company size, splitting our sample into small-cap stocks and large-cap stocks. For the United States, we defined the large-cap universe as all stocks with market capitalizations above the median for NYSE stocks; for global stocks, we defined the large-cap universe as all stocks larger than the 80th percentile in their respective countries. We can see that low-risk investing has delivered positive returns within both the small-cap and the large-cap stock universes, and it has done so for both industry-neutral and industry BAB portfolios and for both US and global stocks. Panel C shows the performances separately for the long and short sides of the BAB portfolios.

Finally, **Table 6** reports performance net of transaction costs. The transaction cost estimates are from Frazzini, Israel, and Moskowitz (2013), who estimated market impact functions in a sample of a trillion dollars of live trading data from a large institutional money manager. Their estimates provide predicted transaction costs as a function of the time period, aggregate volatility, idiosyncratic volatility, daily volume, size of the stock, and the amount traded.[11] On the basis of these predicted transaction costs for each stock, we computed the net return of our BAB portfolios. We report gross and net returns, average transaction costs, and the breakeven transaction cost (the cost that would drive net returns to zero).

Panel A of Table 6 reports results for the BAB portfolios that are presented in Tables 2, 3, and 4. Panel B reports more-conservative results for BAB portfolios constructed over a highly tradable universe of the largest 1,000 securities in our US and global samples. In the samples of the 1,000 largest stocks, we slowed down the turnover by averaging the portfolio weights of each stock over the past 12 months. This approach is a simple version of transaction cost optimization; see Gârleanu and Pedersen (2013) for a discussion (and a more sophisticated method).

Table 6 shows that transaction costs have only a moderate impact on the returns of BAB portfolios owing to their low turnover. Indeed, the BAB returns net of transaction costs remain positive and large. Stated differently, the estimated transaction

Table 5. Robustness Analysis

				US (1926–2012)						Global (1986–2012)					
					Industry-Neutral BAB						Industry-Neutral BAB				
Universe	Sample	Company Size	Long/ Short	BAB	Equal Weighted	Value Weighted	No. of Stocks	Equal Risk	Industry BAB	BAB	Equal Weighted	Value Weighted	No. of Stocks	Equal Risk	Industry BAB
A. Time period															
US	1926–1945	All	Long/short	0.25	0.18	0.23	0.19	0.46	0.17	1.12	0.83	1.38	1.01	1.81	0.80
US	1946–1965	All	Long/short	0.63*	0.53*	0.43*	0.43*	1.26*	0.49*	5.32	5.53	5.61	6.31	6.41	4.08
US	1966–1985	All	Long/short	0.87*	0.76*	0.65*	0.73*	1.32*	0.39*	5.53	5.71	5.51	5.75	5.10	2.87
US	1986–2009	All	Long/short	0.42*	0.49*	0.52*	0.54*	0.68*	–0.14	2.20	2.86	3.29	3.38	2.76	–0.80
US	2010–2012	All	Long/short	0.96*	0.67*	0.78*	0.76*	1.00*	0.58	3.24	2.94	3.64	3.04	3.09	1.58
Global	1986–2004	All	Long/short	0.54*	0.38*	0.39*	0.23*	0.48*	0.01	3.35	3.22	3.74	2.36	2.39	0.07
Global	2005–2012	All	Long/short	0.32	0.26	0.15	0.18	0.44	0.52*	1.69	1.91	1.30	1.39	1.73	2.57
B. Company size															
US	1926–2012	Small cap	Long/short	0.60*	0.59*	0.59*	0.58*	0.98*	0.27*	5.18	5.70	6.94	6.56	8.82	2.61
US	1926–2012	Large cap	Long/short	0.33*	0.23*	0.23*	0.20*	0.52*	0.28*	3.33	3.87	3.63	3.56	4.93	3.03
Global	1986–2012	Small cap	Long/short	0.52*	0.17	0.12	0.16	0.27	0.42*	3.43	1.50	1.28	1.82	1.91	2.69
Global	1986–2012	Large cap	Long/short	0.37*	0.15*	0.17*	0.09	0.36*	0.24	2.92	1.99	2.46	1.29	2.30	1.63
C. Long/short side															
US	1926–1945	All	Short	–0.24*	–0.19*	–0.23*	–0.22*	–0.08	–0.29*	–4.00	–3.51	–4.78	–4.51	–0.53	–5.93
US	1926–1945	All	Long	0.31*	0.32*	0.28*	0.28*	0.93*	–0.08	3.75	3.64	3.64	3.55	4.80	–1.12
US	1946–1965	All	Long/short	0.55*	0.51*	0.51*	0.50*	1.01*	0.22*	5.64	6.31	6.98	6.77	8.06	2.50
Global	1986–2004	All	Short	–0.27	–0.17	–0.16	–0.24	–0.20	–0.40*	–1.88	–1.38	–1.20	–1.86	–0.77	–3.27
Global	1986–2004	All	Long	0.20	0.18	0.15	–0.03	0.26	–0.12	1.06	1.12	0.88	–0.26	0.78	–0.71
Global	2005–2012	All	Long/short	0.47*	0.34*	0.31*	0.22*	0.46*	0.27	3.72	3.73	3.91	2.74	2.84	1.85

Notes: This table reports the risk-adjusted returns, measured as the four-factor alphas, in subsamples across (A) time, (B) company size, and (C) long/short sides of the portfolio. The table reports these alphas for the regular BAB, our four versions of the industry-neutral BAB portfolio, and the industry BAB (which bets purely across industries).
*Significant at the 5% level.

Table 6. Performance (Net of Trading Costs) of the Regular BAB, Industry-Neutral BAB, and Industry BAB (*t*-statistics in parentheses)

	US (1926–2012)						Global (1986–2012)					
		Industry-Neutral BAB						Industry-Neutral BAB				
	BAB	Equal Weighted	Value Weighted	No. of Stocks	Equal Risk	Industry BAB	BAB	Equal Weighted	Value Weighted	No. of Stocks	Equal Risk	Industry BAB
A. All stocks												
Return (gross)	0.70*	0.65*	0.59*	0.64*	1.19*	0.22*	0.72*	0.50*	0.47*	0.41*	0.74*	0.63*
	(7.20)	(7.76)	(7.93)	(8.45)	(9.47)	(2.47)	(5.47)	(5.37)	(5.60)	(4.86)	(4.45)	(3.89)
Return (net)	0.60*	0.52*	0.49*	0.52*	0.99*	0.18*	0.61*	0.35*	0.34*	0.26*	0.44*	0.55*
	(6.11)	(6.18)	(6.46)	(6.83)	(7.83)	(1.99)	(4.66)	(3.73)	(4.08)	(3.12)	(2.58)	(3.40)
Turnover (monthly)	0.34	0.44	0.40	0.42	0.83	0.31	0.50	0.59	0.56	0.57	1.21	0.45
Average market impact (bps)	30.2	28.6	26.0	28.4	23.7	13.8	20.99	25.57	22.03	25.20	25.23	17.67
Breakeven market impact (bps)	209.2	146.7	147.7	153.6	143.7	71.4	144.03	84.46	82.61	71.57	61.41	138.64
Market impact minus break-even (bps)	–178.96*	–118.16*	–121.67*	–125.17*	–120.04*	–57.62*	–123.04*	–58.89*	–60.58*	–46.37*	–36.18*	–120.98*
	(–10.36)	(–10.06)	(–10.25)	(–10.44)	(–11.37)	(–4.39)	(–5.51)	(–4.91)	(–4.90)	(–4.28)	(–4.22)	(–4.35)
Sharpe ratio (gross)	0.79	0.85	0.87	0.92	1.05	0.27	1.09	1.07	1.12	0.97	0.95	0.78
Sharpe ratio (net)	0.67	0.68	0.71	0.75	0.87	0.22	0.93	0.75	0.82	0.62	0.55	0.68
B. Largest 1,000 stocks												
Return (gross)	0.39*	0.32*	0.29*	0.31*	0.75*	0.21*	0.43*	0.21*	0.18*	0.18*	0.30*	0.53*
	(4.07)	(4.77)	(4.56)	(4.88)	(6.95)	(2.47)	(3.43)	(2.87)	(2.62)	(2.82)	(2.06)	(3.13)
Return (net)	0.35*	0.27*	0.25*	0.26*	0.66*	0.19*	0.41*	0.17*	0.15*	0.15*	0.23	0.49*
	(3.57)	(3.92)	(3.85)	(4.06)	(6.11)	(2.16)	(3.26)	(2.35)	(2.22)	(2.34)	(1.57)	(2.90)
Turnover (monthly)	0.24	0.27	0.25	0.26	0.56	0.20	0.23	0.31	0.27	0.27	0.68	0.34
Average market impact (bps)	19.5	19.8	17.2	19.1	15.3	13.2	9.11	12.29	10.38	11.36	10.40	11.40
Breakeven market impact (bps)	164.1	117.3	115.6	117.3	132.7	106.6	183.18	68.15	68.42	66.20	44.50	157.59
Market impact minus break-even (bps)	–144.60*	–97.44*	–98.40*	–98.20*	–117.38*	–93.38*	–174.07*	–55.86*	–58.04*	–54.84*	–34.10*	–146.19*
	(–7.08)	(–7.55)	(–7.43)	(–7.49)	(–8.93)	(–5.05)	(–4.33)	(–3.07)	(–2.95)	(–3.01)	(–2.23)	(–4.04)
Sharpe ratio (gross)	0.44	0.52	0.50	0.53	0.77	0.27	0.69	0.57	0.52	0.56	0.44	0.63
Sharpe ratio (net)	0.39	0.43	0.42	0.44	0.68	0.24	0.65	0.47	0.44	0.47	0.34	0.58

Notes: This table reports the net performance of the regular BAB, the four versions of the industry-neutral BAB portfolio, and the industry BAB (which bets purely across industries). To compute predicted transaction costs for each stock, we used the coefficients from column 4 of Table 4 in Frazzini, Israel, and Moskowitz (2013). Panel A reports the results for all stocks, and Panel B reports the results for the largest 1,000 stocks. In Panel B, the turnover is slowed down by using the average portfolio weights over the past 12 months.
*Significant at the 5% level.

costs are well below the breakeven cost, and we are able to safely reject the null hypothesis that the two are equal in all specifications.

Conclusion

We have shown that low-risk investing is useful both for selecting stocks within an industry and for selecting industries. Betting against beta earns positive returns for both industry selection and within-industry stock selection, and its risk-adjusted, within-industry returns are especially strong. The industry-neutral BAB factor has delivered positive returns in each of the 49 US industries and in 60 of 70 global industries. Putting those industries together leads to an aggregate industry-neutral BAB factor that performs strongly, either alone or vis-à-vis the four-factor model. Moreover, the regular BAB factor is more dependent on industry-neutral stock selection than on industry selection.

Taken together, our findings disprove the common sentiment that BAB—and low-risk investing in general—is merely an industry bet. It is neither driven purely by industry bets nor more effective for industry bets. In addition, our results support the leverage-aversion theory behind the BAB strategy's efficacy because the higher point estimate of the Sharpe ratio of the industry-neutral BAB comes with higher necessary leverage.

Finally, we note the interesting finding that the industry-neutral form of BAB is also less exposed to the value factor (in fact, not exposed at all in the United States) than either the regular BAB or the industry BAB (put another way, the correlation of BAB and value comes mostly from its industry bets). Thus, we can dispel two notions at once. The economically and statistically strong low-risk phenomenon is driven by neither exposure to value nor betting on industries.

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This article qualifies for 1 CE credit.

Appendix A. Example of the Construction of a BAB Portfolio

To make our construction of betting-against-beta portfolios clear, we consider a simple numerical example in **Table A1**. The example has six stocks, listed in order of their betas. The table shows how we first calculate the ranks of the betas from 1 to 6 (given by z). The average rank is $\bar{z} = 3.5$. Stocks 4–6 naturally belong to the high-beta portfolio, H, whereas Stocks 1–3 belong to the low-beta portfolio, L. The portfolio weights in the high-beta portfolio, w_H, are then calculated as the difference between the beta rank and the average beta rank of 3.5, scaled by k = 0.22 in order to sum to 1. The portfolio weights in the low-beta portfolio, w_L, are computed similarly.

Table A1. Example of BAB Construction

β	z = Rank(β)	$(z-\bar{z})^+$	$(z-\bar{z})^-$	w_H	w_L
0.3	1	0	2.5	0	0.56
0.6	2	0	1.5	0	0.33
0.9	3	0	0.5	0	0.11
1.1	4	0.5	0	0.11	0
1.4	5	1.5	0	0.33	0
1.7	6	2.5	0	0.56	0
Sum		4.5	4.5	1	1

Note: $\bar{z}$ = Average(z) = 3.5; k = 2/9 = 1/4.5 = 0.22.

Notes

1. We reached a different conclusion from that of Shah (2011) because there are several differences between our studies. Whereas Shah considered only long strategies in the top 1,000 US stocks, we considered long–short industry-neutral strategies in a broad selection of stocks in 24 countries (as well as the subset of the top 1,000 US stocks) over a longer period. Further, Shah estimated betas by using only monthly data whereas we used daily data, which produce better beta estimates (Merton 1980).
2. The effect of short-term residual volatility is related to short-term return reversal, and it disappears when controlling for the maximum daily return over the past month (Bali, Cakici, and Whitelaw 2011) and when using other measures of idiosyncratic volatility (Fu 2009); see also Cowan and Wilderman (2011). Our focus on longer-term betas was not subject to these issues.
3. Scherer (2011) found that investing based on the minimum-variance portfolio is subsumed by the other forms of low-risk investing and standard factors.
4. The SMB, HML, and UMD factors for the United States are from Kenneth R. French's data library (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).
5. For a detailed description of these constructions, see Asness, Frazzini, and Pedersen (2013). The factors mimic their US counterparts, following Fama and French (1992, 1993). The

data can be downloaded at www.econ.yale.edu/~af227/data_library.htm.

6. Our equal-risk methodology followed that of Asness, Frazzini, and Pedersen (2012). We also tried weighting by various measures of the dispersion of betas within each industry—to capture the cardinal aspects of beta estimation that our ordinal methodology might have missed—but found no significant differences from the results reported here.
7. Using other weighting methods within industries to form industry returns had little effect on our conclusions.
8. Although the BAB factor applies leverage to the low-beta portfolio and delevers the short high-beta portfolio, it is more natural to use unleveraged versions of these portfolio weights in the cross-sectional regression analysis.
9. We chose to use the value-weighted version of the industry-neutral BAB for the sake of conservatism.
10. The BAB portfolios that we used are rank weighted, not value weighted like the four-factor model. We separately constructed BAB portfolios by following the methodology that Fama and French (1992, 1993) used to construct HML (sort 3 × 2 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 found that this BAB factor also has significantly positive returns.
11. To compute predicted market impact for each stock, we used coefficients from column 4 of Table 4 in Frazzini, Israel, and Moskowitz (2013) and set the trade size (as a fraction of daily volume) equal to the median fraction of daily volume traded in their sample.

References

Ang, A., R.J. Hodrick, Y. Xing, and X. Zhang. 2006. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance*, vol. 61, no. 1 (February):259–299.

———. 2009. "High Idiosyncratic Volatility and Low Returns: International and Further U.S. Evidence." *Journal of Financial Economics*, vol. 91, no. 1 (January):1–23.

Asness, C.S., A. Frazzini, and L.H. Pedersen. 2012. "Leverage Aversion and Risk Parity." *Financial Analysts Journal*, vol. 68, no. 1 (January/February):47–59.

———. 2013. "Quality Minus Junk." Working paper, AQR Capital Management (9 October).

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

Baker, M., B. Bradley, and R. Taliaferro. 2014. "The Low-Risk Anomaly: A Decomposition into Micro and Macro Effects." *Financial Analysts Journal*, vol. 70, no. 2 (March/April):43–58.

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 (January/February):40–54.

Bali, T., N. Cakici, and R. Whitelaw. 2011. "Maxing Out: Stocks as Lotteries and the Cross-Section of Expected Returns." *Journal of Financial Economics*, vol. 99, no. 2 (February):427–446.

Black, F. 1972. "Capital Market Equilibrium with Restricted Borrowing." *Journal of Business*, vol. 45, no. 3 (July):444–455.

Black, F., M.C. Jensen, and M. Scholes. 1972. "The Capital Asset Pricing Model: Some Empirical Tests." In *Studies in the Theory of Capital Markets.* Edited by Michael C. Jensen. New York: Praeger.

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

Clarke, R., H. de Silva, and S. Thorley. 2013. "Minimum Variance, Maximum Diversification, and Risk Parity: An Analytic Perspective." *Journal of Portfolio Management*, vol. 39, no. 3 (Spring):39–53.

Cowan, D., and S. Wilderman. 2011. "Re-Thinking Risk: What the Beta Puzzle Tells Us about Investing." White paper, GMO.

Falkenstein, E.G. 1994. "Mutual Funds, Idiosyncratic Variance and Asset Returns." PhD dissertation, Northwestern University.

Fama, E.F., and K.R. French. 1992. "The Cross-Section of Expected Returns." *Journal of Finance*, vol. 47, no. 2 (June):427–465.

———. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics*, vol. 33, no. 1 (February):3–56.

Frazzini, A., and L.H. Pedersen. 2012. "Embedded Leverage." Working paper, AQR Capital Management and New York University.

———. 2014. "Betting against Beta." *Journal of Financial Economics*, vol. 111, no. 1 (January):1–25.

Frazzini, A., R. Israel, and T.J. Moskowitz. 2013. "Trading Costs of Asset Pricing Anomalies." Working paper, AQR Capital Management and University of Chicago.

Fu, F. 2009. "Idiosyncratic Risk and the Cross-Section of Expected Stock Returns." *Journal of Financial Economics*, vol. 91, no. 1 (January):24–37.

Gârleanu, N., and L.H. Pedersen. 2013. "Dynamic Trading with Predictable Returns and Transaction Costs." *Journal of Finance*, vol. 68, no. 6 (December):2309–2340.

Li, X., and R.N. Sullivan. 2010. "Why Low-Volatility Stocks Outperform: Market Evidence on Systematic Risk versus Mispricing." Working paper, Boston College and CFA Institute (21 December).

Li, Xi, Rodney N. Sullivan, and Luis Garcia-Feijóo. 2014. "The Limits to Arbitrage and the Low-Volatility Anomaly." *Financial Analysts Journal*, vol. 70, no. 1 (January/February):52–63.

Merton, R.C. 1980. "On Estimating the Expected Return on the Market: An Exploratory Investigation." *Journal of Financial Economics*, vol. 8, no. 4 (December):323–361.

Moskowitz, T.J., and M. Grinblatt. 1999. "Do Industries Explain Momentum?" *Journal of Finance*, vol. 54, no. 4 (August):1249–1290.

Scherer, Bernd. 2011. "A Note on the Returns from Minimum Variance Investing." *Journal of Empirical Finance*, vol. 18, no. 4 (September):652–660.

Shah, R.R. 2011. "Understanding Low Volatility Strategies: Minimum Variance." Dimensional Fund Advisors.

Vasicek, O.A. 1973. "A Note on Using Cross-Sectional Information in Bayesian Estimation of Security Betas." *Journal of Finance*, vol. 28, no. 5 (December):1233–1239.