PORTFOLIO
MANAGEMENT
RESEARCH

the journal of
PORTFOLIO
management

MULTI-ASSET
STRATEGIES

volume 46 number 6

MAY 2020

jpm.pm-research.com

AQR

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KEY FINDINGS

- Low-risk investing has historically delivered significant risk-adjusted returns, both in-sample and out-of-sample.
- Low-risk investing can be applied across asset classes, with strong returns in equities, government bonds, credit markets, and beyond.
- Low-risk investing can be applied based on statistical risk measures (e.g., beta) or fundamental risk measures (e.g., stable profits).

ABSTRACT: *Low-risk investing within equities and other asset classes has received a lot of attention over the past decade. An intensive academic debate has spurred, and been spurred by, the growing market for low-risk strategies. This article presents five facts and dispels five fictions about low-risk investing. The facts are as follows: Low-risk returns have been (1) strong historically, (2) highly significant out-of-sample, (3) robust across many countries and asset classes, and (4) backed by strong economic theory but, nevertheless, (5) can be negative when the market is down. The fictions this article dispels are that low-risk investing (1) delivers weaker returns than other common factor premiums, (2) is mostly about betting on bond-like industries, (3) is especially sensitive to transaction costs and only works among small-cap stocks, and (4) has become so expensive that it cannot do well going forward. Lastly, the article dispels the fiction that (5) the capital asset pricing model (CAPM) is dead and so is low-risk investing—this statement is a contradiction. If the CAPM is dead, then low-risk investing is alive.*

TOPICS: ***Factor-based models, style investing, volatility measures****

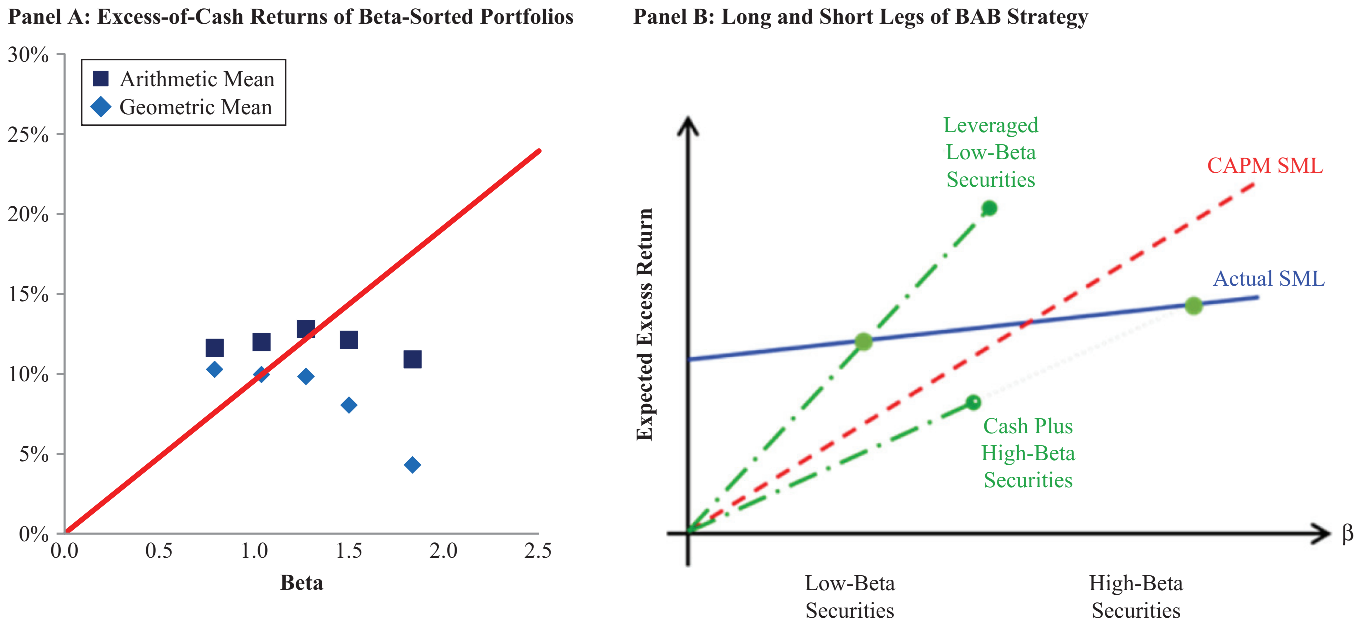
Low-risk investing has received a tremendous amount of attention in the last decade. An intensive academic debate has spurred, and been spurred by, the growing market for low-risk strategies. The debate contains several conflicting arguments, and this article seeks to set the record straight by separating fact from fiction about low-risk investing.

As is clear from its name, low-risk investing means buying securities with low estimated risk. Low-risk investing is based on economic theory and has a strong historical track record, at least as strong and robust as that of any of the other well-known factors, such as value, momentum, and size.[1]

[1] The other factors are surrounded by their own facts and fictions; see Asness et al. (2014, 2015) and Alquist, Israel, and Moskowitz (2018).

Exhibit 1

The Flat Security Market Line and How to Exploit It



Notes: Panel A shows the excess-of-cash returns of five beta-sorted portfolios over our full sample period, January 1931–August 2019. It depicts both arithmetic and geometric mean returns. The red line is the CAPM-predicted relation, in which the slope is the full-sample market risk premium. Panel B depicts the different expected returns of the long and the short legs of the BAB strategy.

Low-risk strategies have delivered large risk-adjusted returns, and this strong risk-adjusted performance has persisted for nearly a century both in-sample and out-of-sample (OOS). The performance is pervasive across countries, industries, country indexes, and asset classes—and even sports betting. Furthermore, the performance of low-risk strategies is strong for different statistical and economic measures of risk, is distinct from other common factors, and survives the exclusion of small-cap stocks and taking account of transaction costs.

The literature on low-risk investing is too extensive for a full survey here,[2] but it is helpful to consider a bit of background. Black, Jensen, and Scholes (1972) first discovered the flatness of the empirical security market line (SML), which depicts the relation between security betas and their returns. When sorting stocks into portfolios based on their risk (as measured by their betas), their long-term average returns are almost the same. That is, there is a relatively flat line when plotting average excess returns versus betas (Exhibit 1, Panel A). This finding is puzzling when viewed through the lens of the capital asset pricing model (CAPM), which predicts an upward-sloping linear relation between expected returns and risk (red line in the Panel A).

How would you exploit a situation in which safe and risky stocks deliver similar returns? Suppose, for instance, you believed that a portfolio of safe stocks has a beta of 0.5 and an expected excess return of 10%, whereas a portfolio of risky stocks has an expected excess return of 12% with a beta of 1.5. Normally, the way investors can exploit an anomaly (i.e., a trading opportunity) is by buying the good stuff and selling the bad stuff, so let us try that here. Here, the good stuff is the safe assets because they deliver returns higher than predicted by the CAPM (i.e., positive alpha as measured by the vertical difference between the realized return and the CAPM line in Exhibit 1). Suppose we buy \$1 worth of safe stocks and sell short \$1 worth of risky stocks. Under the assumptions given, the expected return is 10% − 12% = −2%, so we expect to lose money in

[2] Recent overviews include those by Blitz, Falkenstein, and van Vliet (2013), who focused on explanations for low-risk investing, and Blitz, van Vliet, and Baltussen (2019), who focused on the empirical evidence.

this case. This anomaly is a little different from other ones (and perhaps this is one of the reasons it persists) because its benefit is in risk reduction rather than return enhancement. The problem is that we are buying something safe and selling something risky, so this portfolio is not in balance—that is, it is not market neutral.

To create a market-neutral strategy, we should go long one beta (rather than \$1) and short one beta. This means buying \$2 worth of safe stocks and shorting \$0.67 worth of risky ones, creating an expected excess return of $2 \times 10\% - 0.67 \times 12\% = 12\%$. This so-called *betting-against-beta* (BAB) strategy makes money as long as the SML is flatter than the one implied by the CAPM. The profit of the BAB strategy is illustrated in the Panel B of Exhibit 1. In Panel B, the expected return of the BAB strategy is the vertical distance between the point representing the leveraged low-beta securities and the deleveraged high-beta securities (labeled "cash plus high-beta securities").

We see that a BAB strategy is one way to exploit the low-risk effect, one that generates a market-neutral factor and that directly enhances expected returns. Another way to exploit the effect is to buy a long-only portfolio consisting of low-risk securities while underweighting (or altogether avoiding) high-risk securities. The goal of such a long-only portfolio of safe securities may not be to outperform the market but rather to achieve similar returns at lower risk, thus raising the Sharpe ratio (and perhaps allowing investors to take more rewarded risk elsewhere in the portfolio).

Why does the low-risk effect persist? Black (1972) proposed that the existence of leverage constraints helps to explain the puzzle. Furthermore, he tried to start the market for low-risk investing in the 1970s, although he and others faced significant obstacles at the time.[3] Inspired by Black's insights, Frazzini and Pedersen (2014) extended the leverage-constraint theory and considered more than 40 years of OOS evidence in the United States as well as evidence from many other global markets and asset classes based on their BAB strategy.

Another strand of the literature is inspired by behavioral finance, which predicts that investors overpay for risky stocks owing to lottery demand. This literature considers risk measures such as the short-term (i.e., one-month) idiosyncratic volatility (Ang et al. 2006, 2009), the long-term (36-month) volatility (Blitz and van Vliet 2007), the maximum recent daily return (MAX; see Bali, Cakici, and Whitelaw 2011), and the minimum variance portfolio (Clarke, de Silva, and Thorley 2006). Asness et al. (2020) proposed a betting-against-correlation strategy to disentangle these theories. A final strand of the literature focuses on accounting-based measures of fundamental economic risk rather than return-based measures of statistical risk (see, e.g., Asness, Frazzini, and Pedersen 2019 and the references therein).

In summary, this article presents five facts and five fictions about low-risk investing that shed new light on the diverse and important questions regarding low-risk investing.

DATA AND METHODOLOGY

The general idea of low-risk strategies is to buy or overweight low-risk assets and to sell or underweight high-risk assets. There are many return-based statistical risk metrics (e.g., beta, volatility, correlation) and many fundamental risk metrics (e.g., quality and its subgroups) that one can use, and we will illustrate the performance of some of the most commonly used metrics. As noted in the introduction, there are many ways to construct these strategies. Our empirical analysis will focus on long–short strategies and will emphasize the differences between dollar-neutral and market-neutral designs. We focus on long–short strategies to highlight how low-risk assets perform relative to high-risk assets, but clearly these insights translate to long-only strategies (in which the performance relative to a benchmark corresponds to the performance of a long–short strategy).

We include six statistical risk metrics and four fundamental risk metrics, although to save space we will often focus on a subset. In our main analysis, all metrics will be created by ranking US stocks each month since 1931 for the statistical risk metrics or since 1957 for the fundamental risk measures that have later data availability. The construction of factor portfolios follows the literature—we highlight the key design aspects here, and details are provided in Exhibit A1 in the Appendix.

The first strategy based on a statistical risk metric is the BAB factor from Frazzini and Pedersen (2014). It involves buying stocks with low beta and selling stocks

[3] Mehrling (2011) described how Black could not convince Wells Fargo to pursue low-risk investing, making him so upset that he "stomped out, an event memorable as the nearly unique instance when Fischer lost his cool." The meeting was later referred to as "the day alpha died."

with high beta every month, weighting stocks by the strength of their signal (rank weighting) and targeting market neutrality. That is, the long side of low-beta stocks is levered up and the short side of high-beta stocks is levered down to ensure an ex ante beta of zero for the long–short portfolio. As noted in the introduction, being long $2 worth of a 0.5-beta portfolio against shorting $0.67 of a 1.5-beta portfolio achieves this goal. The beta is estimated by using daily log returns over the past year for volatility and three-day log returns over the past five years for correlations and applying shrinkage to these estimates.

The stable minus risky (SMR) factor also ranks stocks using betas, but it weights them in a dollar-neutral rather than a market-neutral way. No leverage is used, resulting in a net negative beta. We follow a procedure similar to the one used in many papers that double-sort stocks by their market capitalization and some characteristic (here, beta) following Fama and French (1993). We buy a value-weighted portfolio of the 30% of stocks with lowest betas and sell a value-weighted portfolio of the 30% of stocks with highest betas separately for the large- and small-cap universes and then average the returns of the portfolios. We estimate beta in the same way as we did for BAB.

The SMRMN is the market-neutral version of SMR. SMRMN resembles the BAB strategy design in the beta estimation method and market-neutrality target (i.e., levering up low-beta longs and levering down high-beta shorts), but it resembles SMR in the stock weighting design within the long and short legs (value weighting the 30% of the most and the least attractive stocks in large-cap and small-cap universes). SMRMN thus helps us see the separate impact of design decisions used in BAB and SMR.

The remaining statistical risk metrics are betting against correlation (BAC) (Asness et al. 2020), idiosyncratic volatility (IVOL) (Ang et al. 2006), and maximum recent daily return (MAX) (Bali, Cakici, and Whitelaw 2011). BAC uses the design choices of BAB except that it uses correlation rather than beta to guide its tilts; notably, it targets market neutrality and rank weights stocks. In contrast, IVOL and MAX follow SMR in creating dollar-neutral portfolios and in its Fama–French stock weighting design.[4]

Turning to fundamental risk metrics, there is a long list of diverse quality measures in the literature—profitability, earnings quality, credit quality, low leverage, earnings stability, and so on—but we focus on the broad composite series quality minus junk (QMJ), which is based on 16 single metrics, and its subgroups of profitability, growth, and safety, as done by Asness, Frazzini, and Pedersen (2019). These series are constructed similarly to the way SMR was constructed, using the Fama–French dollar-neutral weighting.[5]

LOW-RISK ASSETS OUTPERFORM HIGH-RISK ASSETS ON A RISK-ADJUSTED BASIS (FACT)

We first consider the performance of six statistical low-risk strategies and four fundamental low-risk strategies (as described in the section on methodology). Exhibit 2 presents the evidence, providing a range of performance statistics for each of these 10 long–short strategies. We consider excess returns, alpha with respect to the market factor (i.e., the CAPM alpha), and alpha with respect to a six-factor model (the Fama and French 2015 five-factor model plus momentum). For returns, we consider average returns, its statistical significance (via the *t*-statistic, where absolute numbers greater than two indicate significance), and the Sharpe ratio (SR, excess return divided by volatility). For the alphas, we consider the average alpha, its statistical significance, and the information ratio (IR), which is the SR of the alpha (i.e., alpha divided by residual volatility).

Exhibit 2 clearly shows the historical success of low-risk strategies. Indeed, we see positive alphas for all

[4] Some of our design choices differ from those used in the referenced papers because we try to maintain consistency across the methods used here. For example, our IVOL measure is slower moving than that from Ang et al. (2006) because we use the past year's daily returns data whereas they used only past month's daily return. Overall, the broad results that follow were robust to various changes in our design choices.

[5] We distinguish between statistical and fundamental low-risk series in our analysis. In other work, when we create a parsimonious set of factors, we sometimes combine them. Low risk, or defensive, is a common umbrella term, with statistical and fundamental low risk being the two key subgroups. Specific design choices can give rise to further subgroups, such as low beta, low volatility, or minimum variance investing for statistical risk, and profitability, stable earnings, earnings quality, or low leverage for fundamental risk. Alternatively, one could use quality as the umbrella term (see Asness, Frazzini, and Pedersen 2019) and safety or statistical low risk as one of its subgroups. There is no uniquely correct or established classification scheme.

EXHIBIT 2

Performance of Low-Risk Equity Strategies over Full Sample Period

	Annual Return	t-Statistic	Annual Volatility	SR	Annual Alpha (vs. CAPM)	t-Statistic	Information Ratio (vs. CAPM)	CAPM Beta	t-Statistic	Annual Alpha (vs. FF6)	t-Statistic	Information Ratio (vs. FF6)	Turnover (since 1957)
Statistical													
BAB	8.4%	(7.04)	11.2%	0.75	9.1%	(5.57)	0.82	–0.09	(–1.83)	3.9%	(2.38)	0.44	38%
SMR	0.0%	(–0.02)	18.8%	0.00	6.7%	(5.01)	0.61	–0.84	(–18.19)	3.2%	(2.31)	0.38	39%
SMRMN	7.9%	(6.88)	10.9%	0.73	8.3%	(5.58)	0.76	–0.04	(–0.99)	3.0%	(1.95)	0.33	41%
BAC	8.6%	(6.99)	11.6%	0.74	8.1%	(5.66)	0.70	0.06	(1.49)	5.8%	(4.21)	0.73	42%
IVOL	0.2%	(0.12)	16.0%	0.01	4.5%	(3.14)	0.36	–0.54	(–11.32)	1.7%	(1.50)	0.24	38%
MAX	4.0%	(2.71)	12.3%	0.32	8.1%	(6.15)	0.86	–0.54	(–11.22)	3.1%	(2.89)	0.46	218%
Fundamental													
QMJ	4.4%	(4.68)	7.5%	0.59	6.1%	(6.26)	0.95	–0.26	(–7.93)	3.5%	(6.21)	0.93	34%
PROFIT	3.2%	(3.98)	6.3%	0.50	3.9%	(4.05)	0.65	–0.12	(–4.16)	2.3%	(3.88)	0.64	28%
GROWTH	2.4%	(2.90)	6.4%	0.37	2.2%	(2.44)	0.35	0.02	(0.84)	2.8%	(4.90)	0.78	32%
SAFETY	2.9%	(2.66)	8.6%	0.34	5.1%	(4.98)	0.76	–0.35	(–10.60)	3.3%	(4.18)	0.67	29%

Notes: This exhibit shows performance statistics for six statistical low-risk strategies and four fundamental low-risk strategies. The first section reports excess returns, the next section reports returns controlling for market exposure (CAPM), the third section controls for the five Fama–French (2015) factors and momentum (FF6), and the last section reports annual turnover. The sample period is 1931–2019 for the statistical measures and 1957–2019 for the fundamental measures, and the multifactor regression results in the last panel (FF6) are for 1952–2019 due to data availability. Factor construction details are given in Exhibit A1.

strategies and all methods, and these alphas are statistically significant with only a few exceptions. The annual returns are also significantly positive, except for the dollar-neutral SMR and IVOL strategies. These two strategies provide near-zero average returns and SRs but significantly positive alphas. This difference between their average returns and alphas arises from their negative market betas. For example, SMR has a very large negative beta of −0.84 and IVOL has a beta of −0.54. In other words, the alphas of these strategies are elevated to give credit for the powerful hedging ability implied by the negative market exposure. Similarly, we see that other strategies with negative betas have higher alphas than excess returns.

In later sections, we often restrict our attention to a narrower set of low-risk factors for simplicity, focusing on BAB because of its close connection to theory and applicability to all asset classes.

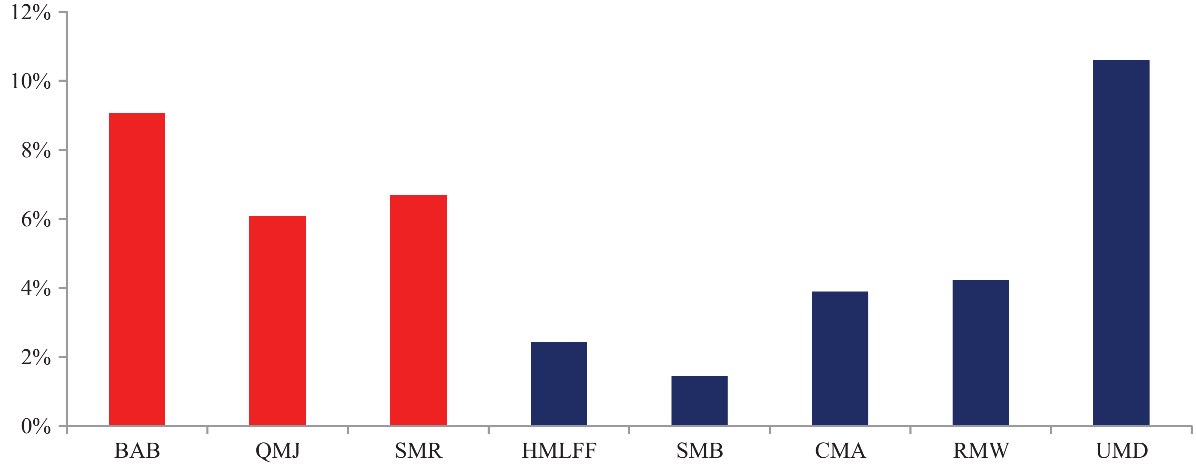
BUT THE LOW-RISK RETURN PREMIUM IS WEAKER THAN OTHER COMMON FACTOR PREMIUMS (FICTION)

It is natural to compare the long-run performance of low-risk strategies to other common factor premiums. We next contrast the historical performance of BAB, QMJ, and SMR portfolios with those of the portfolios in the Fama–French five-factor model—value (high-minus-low or HMLFF), size (small-minus-big, or SMB), investment (conservative-minus-aggressive, or CMA), and profitability (robust-minus-weak, or RMW), excluding the market factor but including momentum (up-minus-down, or UMD).

Exhibit 3 shows the CAPM alphas for each factor over the full sample (since January 1931 for most and since the 1950s for CMA, RMW, and QMJ). The results look visually indistinguishable if we use the common sample starting in 1957. The three low-risk strategies—BAB, SMR, and SMR—have the highest CAPM alphas, except for UMD. (This momentum factor, however, has 2.5 to 4 times higher turnover than the other factors, and we display pre-cost performance here.) Thus, the low-risk return premium is among the highest factor premiums, both for statistical and fundamental risk measures. Therefore, to say the reverse—that the low-risk premium is weaker than other factor premiums—is clearly a fiction.

We note that BAB benefits from its factor construction, but SMR is a very simple Fama–French-style portfolio, which also has a large alpha. The SRs (not shown) are 0.75 for BAB and 0.59 for QMJ but only 0.00 for SMR given its huge negative net beta of −0.8; as noted, SMR's stand-alone performance conceals its

EXHIBIT 3
Alpha of Low-Risk Factors and Other Standard Factors



Notes: The exhibit shows the annual CAPM alpha of three key low-risk factors (in red) and five standard factors (in blue). The low-risk factors are BAB, QMJ, and SMR. The standard factors are those of the Fama–French (2015) five-factor model (dropping the market) plus momentum (UMD). The sample period for most of the factors begins in January 1931. For RMW, it starts in February 1952; for CMA, in July 1952; and for QMJ, in July 1957.

valuable role as a diversifying strategy. For the other series, the SRs range from SMB's 0.25 to UMD's 0.54.

Given the overlap between factors (the highest correlations are corr[HML,CMA] = 0.73, corr[QMJ, CMA] = 0.71, and corr[QMJ,SMR] = 0.62), it is interesting to study which factors provide additional alpha in the presence of multiple other factors. Using the common history since 1957, we regress each of the factors in Exhibit 3 on the market and five other factors. The results of these regressions are depicted in Exhibit 4. All factors except for value deliver positive multifactor alpha over this long history.[6] All three low-risk strategies have multifactor alpha above 3%, led by BAB's 4.1%.

EXHIBIT 4
Marginal Significance of Each Factor Premium

	Annual Multifactor Alpha	*t*-Statistic	Information Ratio	Adj. R^2
Low-Risk Factors				
BAB	4.1%	(2.39)	0.45	29%
QMJ	3.5%	(6.21)	0.93	75%
SMR	3.2%	(2.19)	0.37	70%
Other Factors				
MKTRF	9.9%	(5.25)	0.76	24%
SMB	2.5%	(1.91)	0.30	20%
HMLFF	–0.1%	(–0.15)	–0.03	59%
CMA	2.1%	(2.64)	0.49	59%
RMW	3.3%	(3.28)	0.51	24%
UMD	7.3%	(2.69)	0.58	14%

Notes: To assess the marginal significance of each low-risk factor premium, we compute its alpha and information ratio relative to the Fama–French (2015) five-factor model plus momentum (UMD). Similarly, for the other factors, we compute their marginal significance by computing their alpha relative to the same six factors but excluding the factor itself and adding BAB instead. The sample period is July 1957–August 2019.

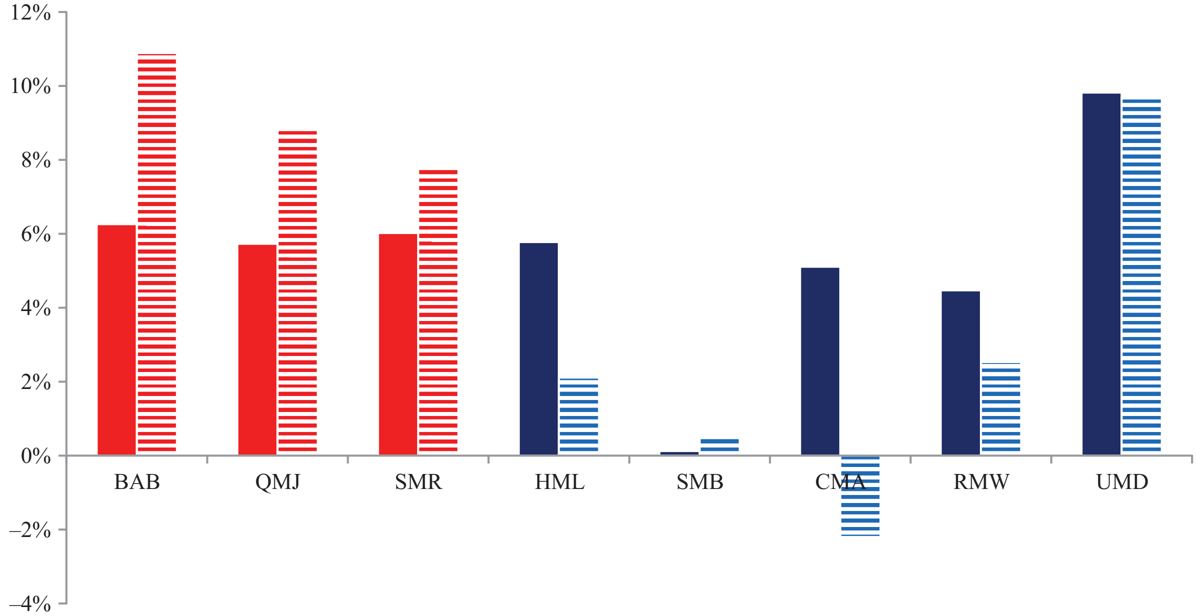
THE LOW-RISK PREMIUM IS SIGNIFICANT OUT-OF-SAMPLE (FACT)

Given the active research by both academics and practitioners to identify profitable trading strategies, there is a natural concern about spurious or data-mined results. Even in the absence of data mining, another concern is that profitable strategies are arbitraged away once investors learn about them. For both concerns, the best empirical answer is OOS evidence of continued success after a strategy has become widely known.

[6] Only the HMLFF is subsumed by the six-factor model, largely through its high correlation with CMA. (As an aside, Asness 2014 resuscitated the value factor in a related multifactor model.) Perhaps surprisingly, the market has the highest multifactor alpha, reflecting its negative correlation with many other factors (only SMB is positively correlated with the market). UMD comes next, followed by BAB and QMJ. QMJ has the highest alpha *t*-statistic, thanks to its large negative correlation with the market and SMB.

Exhibit 5

In-Sample vs. Out-of-Sample Alpha of Major Factors



Notes: This exhibit shows the in-sample (solid bars on the left) and out-of-sample (stripped bars on the right) alphas for three major low-risk factors (in red) and five standard factors (in blue). In-sample periods: BAB: January 1931–December 1965; QMJ: July 1957–January 2012; SMR: January 1931–December 1965; HML: July 1963–December 1990; SMB: January 1936–December 1975; CMA: July 1963–December 2013; RMW: July 1963–December 2013; UMD: January 1965–December 1989. The out-of-sample period begins the month immediately after the in-sample period and ends in August 2019.

For many common factors, subsequent performance has decayed moderately after their past success was highlighted in an academic journal.[7] Low-risk factors are an exception, as Exhibit 5 shows. They have actually performed better during the OOS period than during the in-sample period.

Identifying the in-sample/OOS split based on when a strategy became widely known is inherently debatable for at least two reasons. First, one needs to decide which article made a factor widely known. Second, one needs to decide whether the paper's final publication date, the date the working paper version was first publicly posted, or the end of the sample period in the original paper starts the clock for the OOS evidence. We chose the last approach in our exhibits, but the main finding of low-risk strategies' strong OOS performance is robust to other choices.

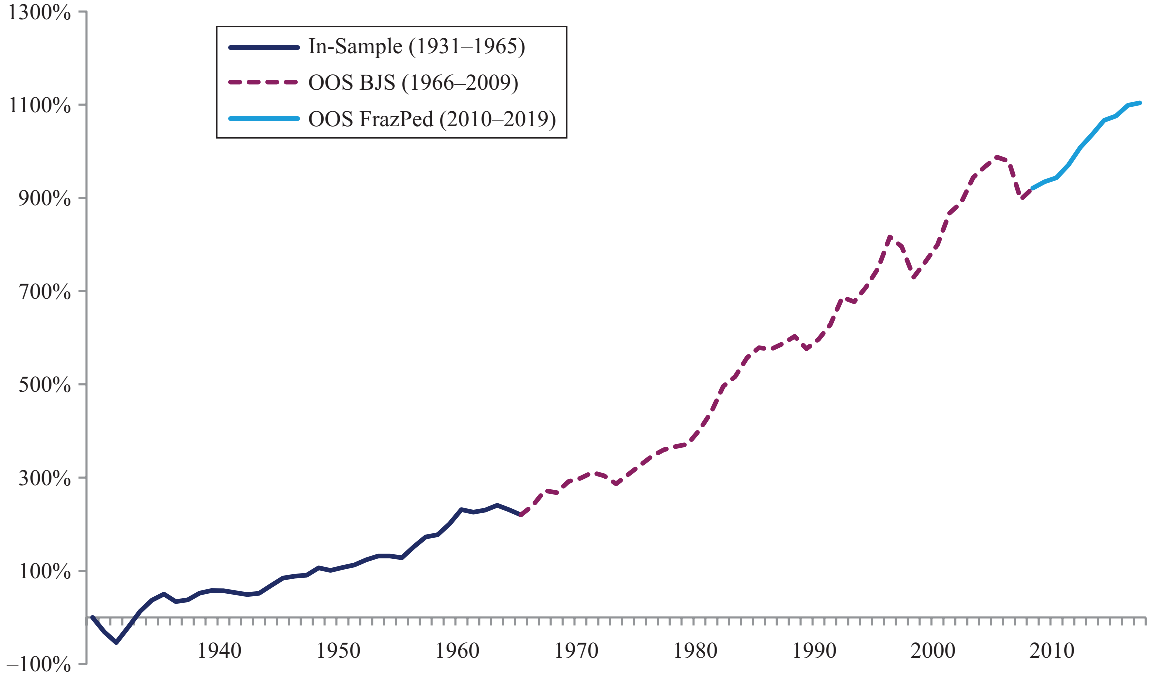
Simple eyeballing of Exhibit 6 confirms this claim. This exhibit plots the cumulative CAPM alpha of the BAB strategy over almost 90 years and depicts the OOS periods for Black, Jensen, and Scholes (1972) and Frazzini and Pedersen (2014) with different colors.[8] The early decades are the in-sample period used in the study by Black, Jensen, and Scholes (1972), with the sample ending in December 1965. This is where we chose to start Black's OOS period, but the OOS performance would look equally good if it had started in 1972. The low-risk anomaly was almost forgotten for decades until it was rediscovered and became more widely known during the past decade or so. We use

[7] For example, McLean and Pontiff (2016) found, on average, roughly one-third lower anomaly or factor returns after publication, reflecting some combination of investor learning or arbitrage forces and data mining or overfitting.

[8] The cumulative excess return of BAB looks similar. The BAB strategy has a modest equity market beta of −0.10, which necessarily implies that the alpha and average excess return are similar to each other.

EXHIBIT 6

BAB Performance: Before Discovery, after Black–Jenson–Scholes and after Frazzini and Pedersen



Notes: This exhibit depicts the cumulative CAPM alpha of the BAB factor for three subperiods: the Black, Jensen, and Scholes (1972) (BJS) original sample, 1931–1965; an out-of-sample period for BJS, 1966–2009; and an out-of-sample period for Frazzini and Pedersen (2014) (FrazPed), 2010–2019.

a second OOS period starting from December 2009, which is the end of the sample period in the first version of the paper by Frazzini and Pedersen (2014) that was posted on SSRN in mid-2010. Again, simple eyeballing shows that a different choice of the OOS period would not change the verdict of strong OOS performance. More generally, the cumulative performance is impressively consistent, even with some meaningful drawdowns in 1931–1932, 1998–1999, and 2008–2009.

LOW-RISK INVESTING IS MOSTLY ABOUT INDUSTRY BETS, BETTING ON BOND-LIKE INDUSTRIES (FICTION)

Although some commentators seem to think that low-risk equity investing is mostly about the outperformance of a few stable industries, this is actually not the case. It is true that BAB works across industries, but it also works reliably within industries. Asness, Frazzini, and Pedersen (2014) focused on this question and showed that the BAB strategy earned a positive SR between 1926 and 2012 within each of the 49 US industries studied. Furthermore, looking at global data since the 1980s, BAB earned a positive SR within most global industries. If anything, industry neutralization, which we do not generally apply in this article, yields even stronger results.

A related claim is that low-risk strategies only work in bond bull markets, perhaps because low-risk industries such as utilities should behave like the lower-risk asset class, bonds. The steady uptrend in Exhibit 6 already contradicts this myth. Yet, it is logically possible that these strategies exhibit some interest rate sensitivity, prompting us to estimate their bond market betas.

Exhibit 7 shows one- and two-factor regression results for three low-risk strategies since 1952.[9]

[9] This sample period is the longest one available that excludes the period between 1941 and 1951 when Treasury yields were regulated.

EXHIBIT 7
Sensitivity of Low-Risk Factors to Interest Rates

	BAB		SMR		SMR Ind.-Neutral	
	(1)	(2)	(3)	(4)	(5)	(6)
Annualized Alpha	10.3%	9.8%	7.5%	6.5%	5.8%	5.6%
	(5.45)	(5.49)	(5.27)	(4.94)	(5.84)	(5.75)
Equity Beta	–0.08	–0.08	–0.76	–0.78	–0.50	–0.50
	(–1.32)	(–1.43)	(–16.68)	(–17.29)	(–14.25)	(–14.00)
Bond Beta		0.30		0.68		0.16
		(2.58)		(9.12)		(2.44)
Adj. R^2	1%	3%	56%	60%	51%	52%

Notes: This exhibit regresses each of three low-risk factors on the equity market and the bond market. The low-risk factors are BAB, SMR, and an industry-neutralized version of SMR (which goes long and short stocks within each industry). The control variables are the CRSP value-weighted equity market index return excess of cash and the US Treasury market return excess of cash (splicing data from CRSP value-weighted Treasuries with maturity over one year until end–1972 with the Barclays Bloomberg Treasury index since then). The sample period is January 1952–August 2019.

The standard BAB, which is not industry neutralized, exhibits no significant equity market beta, but it does have a statistically significant bond beta. These exposures pale in comparison to those of SMR, whose simple dollar-neutral design leaves it with an equity market beta near −0.8 and bond beta near 0.7, with a high R^2. However, an industry-neutral version of SMR has much lower bond beta. In all the regressions, the low-risk strategies have large and statistically significant risk-adjusted returns. The alphas have t-statistics near five, and including the bond factor as a second regressor has only a modest impact on alpha and its t-statistic.[10]

The bottom line is that we find some bond beta in low-risk strategies (less in beta-neutral and industry-neutral variants), but even where it is strongest, it leaves the long-term alpha nearly unchanged.

[10] The results show that SMR's high bond beta can be reduced by overlaying either beta neutrality or industry neutrality; both reduce the bond beta's t-statistic from near 9 to near 2.5. Intuitively, the bond-likeness of the SMR strategy primarily comes from not levering up low-risk stocks, as in BAB (we will argue later that both the BAB premium among stocks and the term premium in Treasuries are boosted by common leverage aversion), or from taking large industry tilts such as buying utilities and consumer staples. Beyond Exhibit 7, we have industry-neutral BAB factor history (only) since 1965. Over that period, this factor had both near-zero equity market beta and near-zero bond beta (t-statistics 1 or lower), and the SR exceeded that of the standard BAB factor (0.93 versus 0.88).

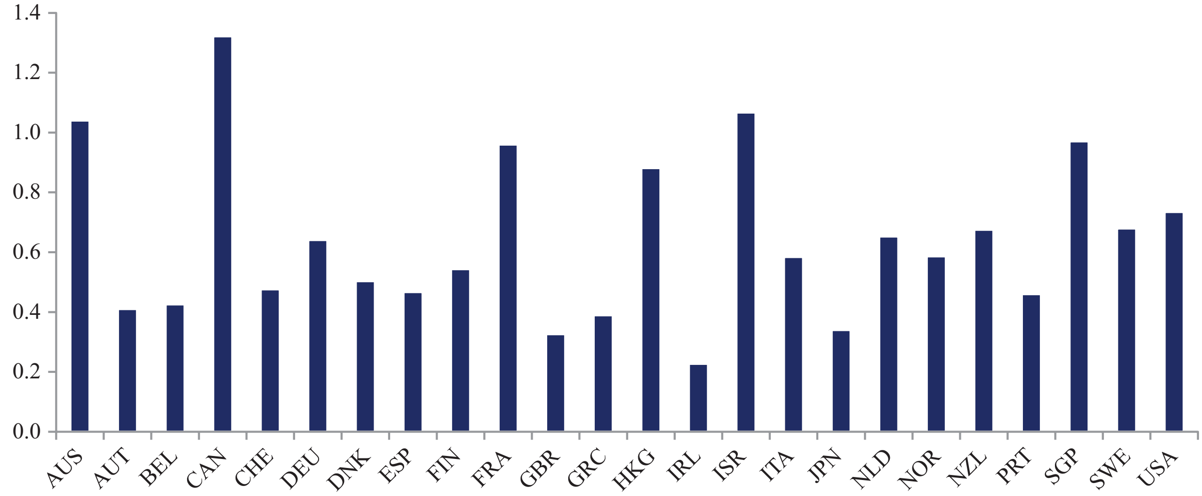
LOW-RISK INVESTING IS ROBUST ACROSS MANY COUNTRIES AND ASSET CLASSES (FACT)

The risk-adjusted performance of low-risk strategies is pervasive across countries and has been robust across many asset classes and even outside financial markets.

Our analysis focuses on stock selection within the US equity market, but Frazzini and Pedersen (2014) showed that the BAB strategy has worked in most of the other countries they studied. Exhibit 8 extends their data to 2019 and finds even more pervasive results: The BAB strategy has worked in stock selection within all 24 countries studied. We show here the SRs but note also that the CAPM alphas ranged between 6% and 20% across these countries, and the six-factor alphas were positive in all countries. Separately, Asness, Frazzini, and Pedersen (2019) showed that the QMJ strategy has delivered positive excess returns and negative market betas in 22 of the 24 countries they studied.

The low-risk effect was first documented for equities (Black, Jensen, and Scholes 1972), but supportive evidence exists across many asset classes. Exhibit 9 highlights strong historical BAB returns in US Treasury bonds, corporate credit indexes, government bonds across countries, and global equity indexes, based on the work by Frazzini and Pedersen (2014). For bonds, low-risk investing means buying short-term bonds while shorting long-term bonds. It may seem puzzling that

EXHIBIT 8
Sharpe Ratio of Equity BAB Factors across Countries



Notes: The universe of stocks in each country is the MSCI universe. The start dates vary by country (1987 to 1991), but there is about a 30-year history for each country (as the end date is August 2019).

EXHIBIT 9
Evidence of BAB Effect across Asset Classes

	Sharpe Ratio	Period
US Treasury Bonds across Maturities	0.81	1953–2012
US Credit Indexes (Treasury-Hedged) across Maturities	1.01	1993–2012
Government Bond Country Allocation	0.14	1989–2012
Equity Index Country Allocation	0.51	1979–2012

Notes: This exhibit shows the performance of BAB strategies across four asset classes: US Treasury bonds across maturities, US credit indexes across maturities (in which the duration risk is hedged using US Treasuries), government bonds across countries, and equity indexes across countries. In each asset class, we consider a BAB strategy that goes long securities with low-beta to that market and shorts securities with high betas, scaling each side to be market neutral. Based on Frazzini and Pedersen (2014) Tables 2, 6, 7, and 8.

this is a profitable strategy because the main result in the fixed-income literature is arguably the existence of a term premium, meaning that long-term bonds have higher average returns than short-term bonds. There is no contradiction, however. The term premium does exist, both for short-term bonds (which deliver higher returns than the money market rate) and even more substantially for long-term bonds, but the new insight is that short-term bonds deliver larger risk-adjusted returns. In other words, the SML for bonds does slope up (this is the term premium), but it is nevertheless too flat—so low-risk investing still works. Applying leverage to short-term bonds such that they reach the same risk as long-term bonds has historically been more profitable than buying long-term bonds.

A similar point applies to credit indexes: Relatively safer credits have lower yields and lower average returns but also much lower risk. Therefore, applying leverage to such low-risk credits has historically outperformed high-risk credits. Findings are similar for country allocation in both government bond and equity markets: Favoring safer countries over beta-matched riskier countries has historically been profitable.[11]

BAB also works across asset classes. Asness, Frazzini, and Pedersen (2012) showed that simple risk-parity portfolios (which ensure that stocks and bonds have balanced risks) have earned higher long-run SRs than the conventional 60/40 portfolios (which are dominated by equity market risk) in all of the countries in their sample. Intuitively, risk parity partly reflects leverage aversion across asset classes: Bonds, the more defensive asset class, have a higher SR than their CAPM

[11] See also Ilmanen et al. (2004), who showed that short-dated high-quality credits provide higher risk-adjusted returns than other market premiums, and Israel, Palhares, and Richardson (2018), who documented strong performance of defensive strategies in corporate bond selection.

beta implies. Bonds have, in fact, a historical SR broadly similar to that of equities. Investors can therefore achieve greater diversification benefits and earn a higher portfolio SR by making balanced risk allocations across the two asset classes with comparable SRs. Investors who are willing and able to apply leverage can convert this SR advantage into an expected return advantage.

The notion that lower-risk assets have higher SRs than their riskier peers extends even beyond financial markets; see Falkenstein (2009) and Ilmanen (2012) for surveys and references. For instance, in sports betting, the *long-shot bias* is a clear example of the low-risk effect. Betting on a favorite is a relatively low-risk bet (a high chance of a small gain) compared to betting on a long shot (a small chance of a large gain, but a large probability of losing the bet). Hence, the low-risk effect is the finding that the favorite offers better odds (and thus returns) than the long shot because bettors overvalue the long shot.

THE CAPM IS DEAD AND SO IS LOW-RISK INVESTING (FICTION)

Robust asset pricing factors are usually not only robust across asset classes and markets but are also grounded in economic theory. Therefore, it is important to consider the economic foundation of low-risk investing. We start with the two death sentences that Fama and French and other researchers have pronounced upon the CAPM and, to some extent, on low-risk investing.

First, Fama and French (1992, 1993, 1996, 2004, 2016) have effectively declared the CAPM dead. For example, Fama and French (2016) stated that the "CAPM is rejected with a GRS p-value that is zero to three decimal places. … CAPM is rejected in the β sorts because the model predicts that the slope in the relation between average excess return and β is the average excess market return, but the actual relation is essentially flat." Second, the same paper nevertheless found that the low-risk stocks do not have alpha with respect to the Fama–French five-factor model.[12]

It is important to recognize that you cannot have it both ways: You cannot simultaneously say that the CAPM is dead and that low-risk investing is unprofitable. If the CAPM does not work because the SML is too flat, then low-risk investing must be profitable.

To see this point graphically, consider the SML depicted in Exhibits 1 and 10. We see that portfolios sorted by beta have delivered similar average excess returns over almost a century. In contrast, the CAPM implies an SML that goes through the origin $(0, 0)$ and increases linearly with beta (as suggested by the red line). The relatively flat SML is not only a rejection of the CAPM, it is also a trading opportunity. To take advantage of this effect, we can just buy low-risk securities, apply leverage, and sell short high-risk securities.[13] As also seen in Exhibit 10, the low-risk effect—that is, the flatness of the SML—has actually become stronger over time, unlike the evidence for many other factors.[14]

In fairness, Fama and French (2016) do not make this blatant contradiction because they find that the CAPM is dead and that the low-beta portfolios have little alpha to their five-factor model, which is not the same as being unprofitable (although others appear to have misinterpreted their conclusion as implying that low-risk investing is unprofitable). Indeed, Fama and French stated that the low-risk effect can be explained[15] by their two newest factors, profitability (RMW) and investment (CMA).

[12] As noted later, our Exhibit 4 provides contrary evidence.

[13] Exhibit 1 in the introduction shows both arithmetic means (AMs) and geometric means (GMs). There is a related fiction that the low-risk anomaly merely reflects compounding (i.e., the mechanical feature that GMs are lower than AMs because of a so-called variance drag). The GMs in Exhibit 1 are indeed lower than the AMs, especially for riskier portfolios, so the SML is even flatter for GMs. However, we also clearly see the low-risk effect for AMs, and the AM is the theoretically consistent object used for tests of the CAPM by us and in most other papers.

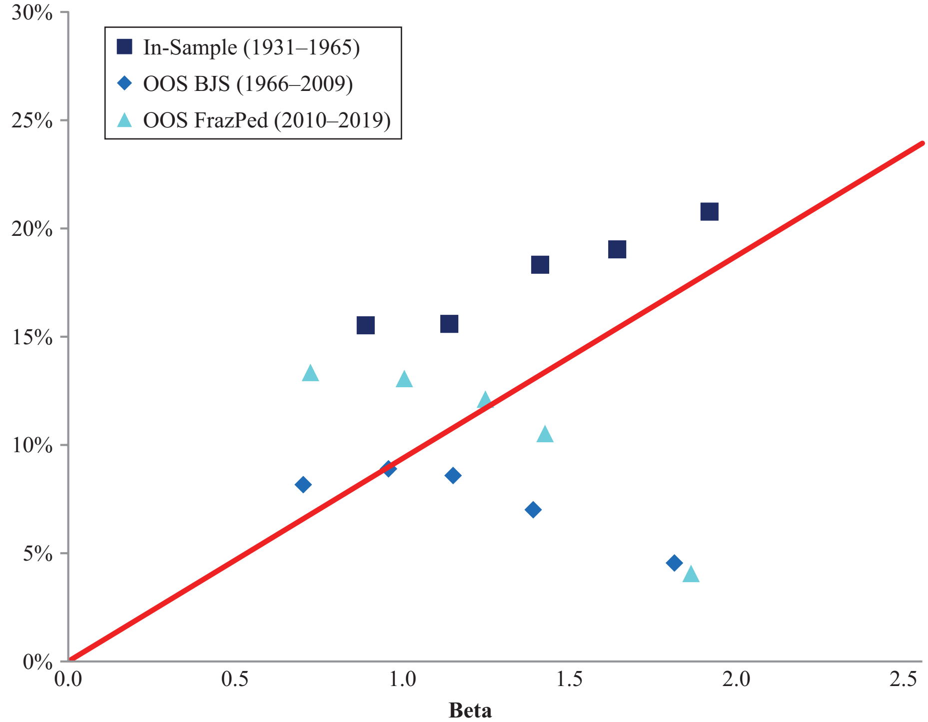
[14] Skeptics of low-risk investing might argue that leverage- and shorting-constrained investors cannot monetize the BAB effect and earn a higher expected return ("you cannot eat Sharpe ratios"). However, such long-only investors can still earn the same long-run return with much lower risk. In practice, investors could have earned the same equity premium as a value-weighted market index with roughly a third lower risk (a beta of 0.67 instead of 1.0 or a volatility of 10% rather than 15%). Not bad—still an anomaly and counts as CAPM alpha. Importantly, reducing risk in one part of the portfolio allows investors to take more risk and earn related premiums in other parts of their portfolio; in this sense, even risk reduction can indirectly boost expected portfolio returns. Thus, even if you are leverage constrained, there are other ways to take up risk, and low-risk strategies increase your risk budget.

[15] For example, Fama and French (2016) stated that:

The five-factor model cures the systematic problems of the CAPM in the tests on the 25 Size-β portfolios. The strong positive CAPM intercepts in the four lower Size and β quintiles disappear in the five-factor results (panel B of Table 4). The negative CAPM intercept for the megacap portfolio in the highest β quintile also becomes inconsequential (−0.06; t = −0.45). The only blemish on the five-factor model is the intercept for the intersection of the fourth Size and fourth β quintiles, −0.24 (t = −2.98).

Exhibit 10

The Security Market Line Is Relatively Flat and Got Flatter



Notes: The exhibit depicts the security market line over three subsamples. In each subsample, stocks are sorted into five portfolios based on their ex ante betas, and the exhibit plots their realized betas and the arithmetic averages of their excess returns. The three subperiods are the Black, Jensen, and Scholes (1972) original sample, 1931–1965; an out-of-sample period for BJS, 1966–2009; and the out-of-sample period for Frazzini and Pedersen (2014), 2010–2019.

Even if true, this means that low-risk investing is profitable but can be explained by fundamental low-risk factors; recall that profitability is one of the fundamental low-risk factors. We are "explaining" low risk using low risk! In other words, low-risk stocks perform well because low-risk stocks perform well.

Aside from this logical issue, there is, in fact, enough empirical difference between low-risk factors based on beta (or other statistical measures) and factors based on fundamental risk. Indeed, as seen in Exhibit 4, BAB has a significant alpha to the Fama–French five-factor model added with momentum.[16]

In sum, you cannot both believe that the CAPM is dead and that low-risk investing does not work. As a matter of logic, something has to give. If you want to argue against BAB, you must either (1) claim that the CAPM holds or (2) claim that BAB is profitable on average but that these profits can be explained by another non-CAPM factor. Hence, the compelling evidence against the CAPM can be viewed as compelling evidence in favor of BAB.

Like any influential research, the low-risk effect has been subject to several criticisms. They fall into the two aforementioned categories (1) and (2). Although Fama and French (2016) fall into (2), an example of (1) is given by Cederburg and O'Doherty (2016). This paper claimed that BAB has a time-varying beta, which can explain the performance. More specifically, the paper claimed that the conditional CAPM holds (a time-varying version of the CAPM), despite much evidence to the contrary (e.g., Lewellen and Nagel 2006 and Gormsen and Jensen 2017). Furthermore, it seems puzzling that the conditional CAPM could help explain the BAB factor because BAB is constructed to have a market beta of zero at

[16] Fama and French (2016) did not actually test BAB and other low-risk factors, instead focusing exclusively on portfolios sorted by size and beta.

each point in time—and zero does not vary over time. Of course, the construction is not perfect, so the true beta might vary a bit over time, but the easiest fix would be to ensure that the beta is zero at each point in time and then to test whether the factor is still profitable. Rather than doing this simple test, Cederburg and O'Doherty (2016) did not use the BAB factor from the literature and instead constructed their own beta factor, which has a time-varying beta; they then failed to reject that the performance is significant. However, finding one weak test is hardly convincing when stronger tests provide significant results. For example, Liu, Stambaugh, and Yuan (2018) confirmed that the low-risk effect cannot be explained by the conditional CAPM.[17]

ALTHOUGH A REJECTION OF THE CAPM, ECONOMIC THEORY UNDERLIES THE LOW-RISK PREMIUM (FACT)

At first glance, it may seem that the efficacy of low-risk investing defies economic theory instead of relying on it. Indeed, the low-beta premium contradicts the standard CAPM, which predicts that expected excess returns are proportional to betas, as discussed in the introduction and in more detail in the previous fiction section. Nevertheless, low-risk investing is consistent with other economic theories, notably including the following:

- The theory of leverage constraints (Black 1972; Frazzini and Pedersen 2014)
- The theory of lottery preferences (Barberis and Huang 2008)

To understand the theory of leverage constraints, suppose you want to beat the market by exploiting the relative flatness of the SML (shown in Exhibit 1 in the introduction). To beat the market (i.e., to earn significantly higher average returns), you need to leverage low-risk securities (as illustrated by the green line in Panel B of Exhibit 1). However, what if some investors cannot, or will not, apply leverage or can only apply a limited amount of leverage? Then they cannot do this trade. Furthermore, if these investors believe that the SML slopes up (less than predicted by the CAPM but still up),[18] they may, in fact, buy the riskier securities. Thus, leverage constraints are both a limit to arbitrage for the low-risk effect and can, simultaneously, cause the low-risk effect. Indeed, extra demand for the most risky securities within an asset class makes these securities expensive; if safer securities are abandoned by leverage-constrained investors, then these securities become cheap, explaining their high returns. Similar leverage aversion logic applies to bond-market and risk-parity evidence described earlier.

A different explanation for why low-risk investing works relies on the theory of lottery preferences. The theory assumes that investors have behavioral biases that make them prefer securities that offer even a small chance of a high return, just like a lottery ticket. Such investors would particularly like securities with a chance of an outsized return, such as a biotech stock bouncing on the news of a drug approval. More generally, they may prefer stocks with positive skewness or high volatility. The demand by such investors drives up the price of risky and lottery-like stocks, according to this theory, implying that such stocks have low future returns. (A similar demand effect would arise if investors overestimated the likelihood of low-probability events.) Bali et al. (2017) found evidence consistent with this theory.

Asness et al. (2020) sought to disentangle these theories and find separate evidence for both, but they documented stronger evidence for leverage constraints. Furthermore, the theory of leverage constraints is supported by direct evidence on the underlying mechanism, not just evidence on returns. Indeed, leverage is

[17] The beta factor of Cederburg and O'Doherty (2016) is weak (has a low CAPM alpha) even before adjusting for time-varying betas owing to their factor construction, the use of quarterly returns, not using the NYSE breakpoints, and their measure of beta. Liu, Stambaugh, and Yuan (2018) slightly varied the methodology of Cederburg and O'Doherty and found that controlling for conditional betas makes the low-risk effect slightly larger (Table A.2).

[18] The SML for equities has empirically been close to flat, but we cannot reject statistically that it slopes up as we would expect (i.e., we would expect that riskier securities have higher required returns than safer ones). Consistent with this idea, Brav, Lehavy, and Michaely (2005) found that analysts' expectations imply a significantly upward-sloping SML. In addition, the SML is upward sloping within bond markets (longer-term bonds have higher average returns than shorter-term ones, and more credit-risky bonds have higher returns than less credit-risky ones), and the SML slopes up when looking across asset classes (e.g., stocks are riskier than bonds, and stocks have higher average returns).

observable, and several papers find a direct link among leverage constraints, portfolios, and returns.[19]

In practice, investors may not care which of these explanations drives the low-risk premium or, in the likely case that they are complementary, what their relative contribution is. The bottom line is that there are at least two good economic theories explaining why the low-risk premium exists and is likely to persist.

LOW-RISK INVESTING IS ESPECIALLY SENSITIVE TO TRANSACTION COSTS AND ONLY WORKS AMONG SMALL-CAP STOCKS (FICTION)

Factors that are successful on paper are sometimes explained away by liquidity-related arguments, which imply that the opportunity is not exploitable in practice. Such criticism tends to have one of the following two dimensions: (1) the strategy's turnover is so large that transaction costs can eliminate its paper gains, or (2) the strategy works only among illiquid securities (e.g., small-cap equities), implying large transaction costs and that the strategy cannot be exploited in scale.

We first note that low-risk investing can be implemented with moderate turnover. All the low-risk equity strategies we study have monthly turnover of around 40% or less, except MAX, which has a large turnover above 200%. As a comparison, the standard Fama–French value factor has a turnover of 26%, and momentum has a turnover of 100%. Hence, BAB and the other low-risk factors clearly have an implementable level of turnover, with the exception of MAX, which may be impractical.

Importantly, it is easy to further reduce the turnover of low-risk strategies by stabilizing the risk measures (e.g., by using more accurate beta estimates, longer estimation windows, or less frequent rebalancing). The economic intuition for the low turnover of these strategies is simple: Securities that are low-risk today tend to remain low risk next month, leading to a low portfolio turnover.

We estimate that, for the BAB equity strategy in US stocks, the breakeven transaction cost (given 8.4% long-run average premium and 38% monthly turnover) is well above 100 bps. This estimate comfortably exceeds the 10- to 20-bps trading cost estimate of Frazzini, Israel, and Moskowitz (2018), suggesting that even a naïve application of the BAB strategy would result in net profits. As noted, in practice, the turnover of the BAB strategy may be reduced with limited loss of gross performance.

Turning to the second issue, we note that low-risk strategies tend to work for both liquid and illiquid securities. For example, we showed strong performance among Treasury bonds and equity country indexes in Exhibit 9. Coming back to individual equities, we can consider the performance separately for small and large stocks. Exhibit 11 reports the performance of BAB, SMR, and QMJ in the large-cap and small-cap universes. We see that the three low-risk strategies have significant CAPM alphas among both large stocks and small stocks, again indicating that these strategies are, in fact, implementable. Yet, all strategies work better in small caps, as most factors do on paper, perhaps because of higher variation in betas and more limits to arbitrage.[20] We repeat this table for two subsamples and find similar results both in-sample and out-of-sample.

In summary, low-risk strategies such as BAB are not more sensitive to transaction costs than other standard premiums. On the contrary, BAB has moderate turnover and has worked among both liquid and illiquid securities.

LOW-RISK INVESTING CAN LOSE MONEY WHEN THE MARKET IS DOWN (FACT)

The accuracy of this claim depends on the portfolio design because the performance during market downturns depends critically on what type of strategy one has in mind:

1. *Beta-neutral strategies*: Strategies like BAB seek to exploit the low-risk effect, but they need not themselves be low risk, nor are they a hedge against

[19] Frazzini and Pedersen (2014) found that mutual funds and individuals who often face leverage constraints, in fact, do overweight risky stocks, whereas investors with access to leverage overweight safer stocks (e.g., leverage buyout firms and Berkshire Hathaway). Adrian, Etula, and Muir (2014) linked the BAB return to financial intermediary leverage. Asness et al. (2020) showed how BAB returns are linked to margin debt (a proxy for leverage constraints), and Jylhä (2018) found consistent evidence based on exogenous changes in margin requirements. Malkhozov et al. (2017) found that international illiquidity predicts BAB. Other theories of the low-risk effect include benchmark effects (Brennan 1993; Baker, Bradley, and Wurgler 2011) and differences of opinions (Hong and Sraer 2016), but most other theories require leverage constraints in addition to other frictions.

[20] See Exhibit 22 by Alquist, Israel, and Moskowitz (2018) for evidence on better performance in small caps than large caps for value, momentum, and profitability factors.

Exhibit 11

Low-Risk Strategy Performance in Large- and Small-Cap Universes

	Annual Return	*t*-Statistic	Annual Volatility	Sharpe Ratio	Annual Alpha (vs. CAPM)	*t*-Statistic	Annual Alpha (vs. FF6)	*t*-Statistic
BAB Large	4.4%	(3.62)	11.5%	0.38	6.1%	(4.36)	1.4%	(0.88)
BAB Small	10.4%	(8.03)	12.2%	0.85	10.0%	(6.12)	4.2%	(2.35)
SMR Large	–0.3%	(–0.36)	9.2%	–0.04	2.8%	(4.09)	1.5%	(1.81)
SMR Small	0.3%	(0.28)	10.4%	0.03	3.9%	(4.95)	1.7%	(2.43)
QMJ Large	1.6%	(0.04)	3.1%	0.39	2.2%	(3.99)	1.7%	(4.00)
QMJ Small	2.9%	(0.05)	5.0%	0.63	3.9%	(6.50)	1.8%	(5.15)

Notes: This exhibit shows the performance of the BAB factor formed using only large stocks and small stocks, respectively, and similarly for the SMR factor (January 1931–August 2019) and for the QMJ factor (July 1957–August 2019). The performance statistics are the annual excess return, volatility, SR, annual alpha relative to the CAPM, and the annual alpha relative to the Fama and French (2015) five-factor model plus momentum (FF6). The sample period for the BAB and SMR multifactor (FF6) alpha is 1952–2019 due to data availability. The t*-statistics are in parentheses.*

market downturns. BAB goes long and short and equal amount of market risk, so BAB is meant to be equally likely to perform well in bull and bear markets. Put differently, BAB is equally likely to lose money in bull or bear markets, assuming that BAB is successfully scaled to be market neutral.

2. *Dollar-neutral strategies*: Strategies like SMR that go long and short an equal notional exposure have a negative market exposure. This means that such strategies are expected to perform well when the market is down. Of course, such strategies are expected to lose when the market is way up, and they are not expected to provide significant positive excess returns. Hence, such strategies are rarely pursued in practice; they are typically statistical tools to analyze alpha (rather than excess returns) in a simple way. Comments[21] about low-risk factors' low long-run average returns are typically based on analyzing risk-reducing strategies like SMR rather than return-enhancing strategies like BAB.
3. *Long-only strategies*: Long-only strategies simply buy low-risk assets, leaving out (or underweighting) high-risk assets. These strategies are said to be defensive because they have a market beta of less than one. Therefore, during significant market downturns, long-only low-risk strategies are also expected to lose money, but less so than the overall market. In other words, such defensive strategies are expected to outperform the market during bear markets.

With this preamble, let us study the performance of various strategies during the 10 worst drawdowns of US equities since 1931. Exhibit 12 shows the performance of the overall market and six different low-risk strategies.

Starting with the long-only version of SMR, we see that this strategy lost money during most of these equity drawdowns but in each case less than the overall market, as expected. As explained, this pattern is not surprising because the long-only version of SMR has a market beta of around 0.6, but it is perhaps surprising that this long-only strategy managed to avoid losing money in one of these bear-market episodes, namely the bust after the tech bubble.

The long–short SMR strategy (third column) has a negative net beta of around −0.8 (because it is a dollar-neutral strategy that goes long low beta and shorts high beta), so it makes sense that it made money in all 10 bear markets. The market-neutral variant SMRMN (fourth column) levers up low-beta stocks to have similar and offsetting beta in its long and short legs, so it is par for the course that it was up in five of the episodes and down in five others.

The QMJ strategy (fifth column) has a small negative beta, so it was expected to make money more often

[21] For example, Arnott et al. (2016) studied a dollar-neutral low-beta strategy, found that it has a modest long-run premium, and further argued that gradual richening explains most of the strategy's long-term performance. This claim is misleading because it only applies to the total returns of dollar-neutral variants (like SMR), which indeed may have a low premium (1.6% per annum)—thus a low bar to explain by richening. Meanwhile, their risk-reduction ability implies a high long-term alpha, a point totally missed by this argument. For BAB-like market-neutral strategies, long-term average returns are high, and valuation changes have had limited impact on them.

EXHIBIT 12
Performance of Low-Risk Strategies during the 10 Worst Equity Market Drawdowns

Peak	Trough	Market Return	SMR Long Only	SMR	SMRMN	QMJ	BAB
February 28, 1931	June 30, 1932	–70%	–56%	46%	–21%	53%	–29%
October 31, 2007	February 28, 2009	–52%	–41%	71%	7%	8%	–31%
February 28, 1937	March 31, 1938	–49%	–45%	46%	–14%	79%	–8%
December 31, 1972	September 30, 1974	–46%	–43%	47%	–12%	33%	–12%
August 31, 2000	September 30, 2002	–45%	21%	111%	144%	7%	159%
November 30, 1968	June 30, 1970	–33%	–30%	47%	5%	0%	10%
August 31, 1987	November 30, 1987	–30%	–21%	19%	–1%	14%	–9%
May 31, 1946	May 31, 1947	–24%	–18%	19%	1%	11%	4%
December 31, 1961	June 30, 1962	–23%	–22%	4%	–11%	15%	–6%
November 30, 1980	July 31, 1982	–18%	–5%	58%	36%	2%	33%
Average Drawdown		*–39%*	*–26%*	*47%*	*13%*	*22%*	*11%*
Freq. of Strategy Losses during Drawdown		*10*	*9*	*0*	*5*	*0*	*6*

Notes: This exhibit shows the performance of the overall market and four different low-risk strategies during the 10 worst drawdowns for the market (January 1931–August 2019). The begin date (peak) and end date (trough) of each date is listed in the first two columns (we note that the event misses the early part of the post-1929 stock market crash because our sample period starts in 1931). The next columns show how much the overall market lost during these periods. The five low-risk strategies are SMR long only (a portfolio that goes long low-beta stocks), the dollar-neutral long–short strategy SMR, the market-neutral SMRMN, the dollar-neutral QMJ, and the market-neutral BAB.

than not in bear markets, but 10 out of 10 is surprisingly consistent; perhaps it also has benefited from a flight to quality. Finally, the market-neutral BAB strategy (last column) was expected to act like SMRMN, and it roughly did (up in four and down in six).

Overall, the drawdown performances of all strategies are in line with their market betas. There is a hint in the data that poor outcomes are a little more likely amid sharp market declines like those in October 1987 and September 2008, reflecting the so-called *beta compression effect* in which all stocks appear to fall by comparable amounts. A related fiction states that the low-risk premium can be fully explained by downside risk (Schneider, Wagner, and Zechner 2016). Asness et al. (2020) showed that downside risk can only explain a small fraction of the low-risk effect, however, because the nonlinearity (or skewness) of returns appears too small to fully account for the large premium.

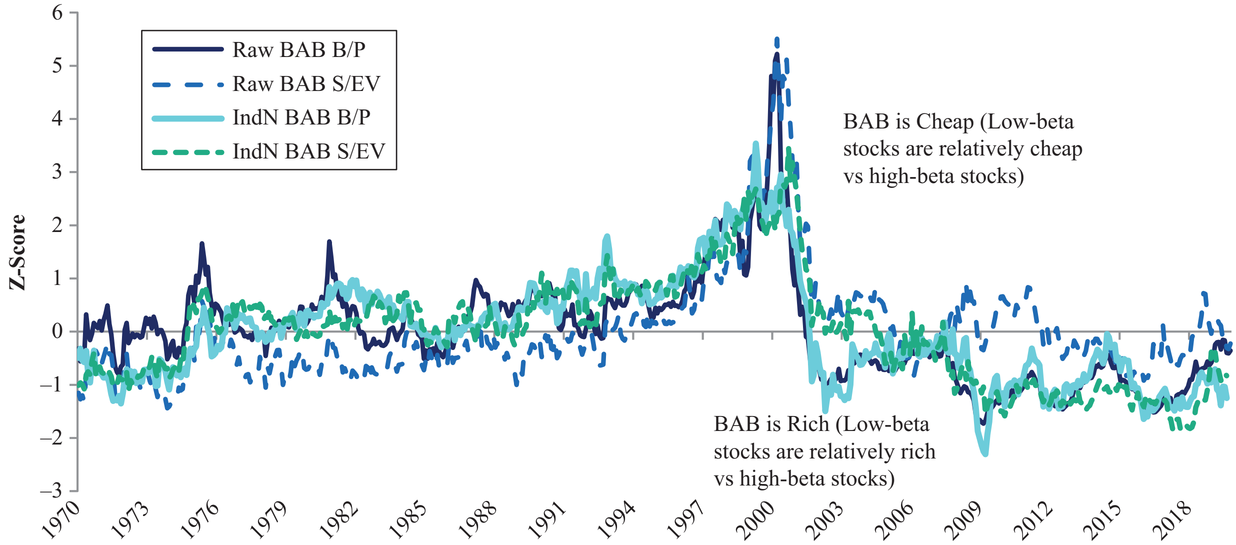
LOW-RISK STRATEGIES HAVE BECOME SO EXPENSIVE THAT THEY CANNOT DO WELL GOING FORWARD (FICTION)

Predictions are always difficult, especially about the future, but it is interesting to consider the valuation of low-risk versus high-risk securities. Indeed, a longstanding concern has been that low-risk stocks have increased in value relative to high-risk stocks, creating a potential headwind for low-risk investing in the future. To analyze this issue, Exhibit 13 tracks several variants of the value spread across beta-sorted stocks over half a century. The value spread measures the relative valuations of low-beta stocks versus high-beta stocks. We see from Exhibit 13 that low-risk stocks do appear relatively expensive by historical standards but that this has been the case for a long time. Indeed, low-beta stocks were extremely cheap during the tech bubble 20 years ago and have looked richer since then. The recent value spreads of the US BAB equity strategy are at a moderately rich level that is similar to the one that prevailed at the end of 2009. Yet, BAB has been among the best-performing factors in the 2010s (SR of 0.89 for the raw BAB and 1.56 for the industry-neutral BAB). This strong performance during a period of moderate richness is an example of factors being difficult to time based on their value spreads.[22] Moreover, investors who are

[22] The strong factor performance amidst rich valuations may seem puzzling. For an even more puzzling example, Ilmanen, Nielsen, and Chandra (2015) highlight the excellent 2013–2014 performance of BAB during a period when the factor was cheapening. The authors explain that so-called wedges weaken the

Exhibit 13

Value Spreads of US BAB Factor over Time



Notes: The exhibit depicts the value spread of the BAB factor, which is the valuation ratio of low-beta stocks divided by the valuation ratio of high-beta stocks, normalized to a Z-score using full-sample mean and volatility. The value spread is computed using two different valuation ratios, book-to-price (B/P) and sales-to-enterprise-value (S/EV), and two different methods, ignoring industries (raw) and industry-neutral (IndN). A high value spread means that low-risk stocks are cheap relative to high-risk stocks by historical standards. The sample period is January 1970–September 2019.

concerned with value spreads can design value-neutral low-risk strategies or even value-positive low-risk strategies—that is, rather than simply buying low-risk assets, you can buy cheap low-risk assets. In any case, low-risk factors may be best used in a diversified combination with other rewarded factors.

CONCLUSION

Low-risk strategies can be seen as testing one of the central issues in finance: the relation between risk and expected return. The strong performance of low-risk strategies means that the risk–return relation is not consistent with the CAPM. Instead, low-risk securities have historically delivered higher risk-adjusted returns than have high-risk assets.

Other facts about low-risk investing show that low-risk strategies have performed well in the out-of-sample period after their discovery, have performed well in many asset classes and countries, are backed by theories of leverage constraints and lottery demand, and could lose money when the market is down (you cannot have everything).

Furthermore, we dispel several fictions about low-risk investing. The low-risk premium is not weaker than other common factors. On the contrary, its empirical record is stronger than that of most other standard factors. Low-risk investing does not require high turnover (because safe securities tend to remain safe for a long time), nor is it only present among securities with high transaction costs. Low-risk strategies are not just an industry bet or a bond market bet, and they are not so expensive as to preclude future outperformance. Furthermore, although some researchers declare the death of the CAPM and are simultaneously skeptical of low-risk investing, they cannot have it both ways. If the CAPM is dead, then BAB is alive. If BAB dies, then the CAPM comes alive. To understand this, note that the SML is either relatively flat (BAB lives) or steep (CAPM lives), but it cannot be both steep and flat.

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contemporaneous correlation between richening valuations and realized performance of long/short factors. These wedges are caused by evolving fundamentals, turnover within the portfolios, and, especially for BAB, different-sized long and short sides. Turning to predictive analysis, Asness et al. (2017) emphasize the difficulty in timing factors based on their value spread. Again, the wedges can make the factor timing task even harder for BAB.

Appendix

Exhibit A1

Portfolio Construction Choices for the Low-Risk Factors

	Statistical Risk Metric	Sampling Frequency	Window Length for Risk Estimate	Weighting	Beta or Dollar Neutral?	Rebalancing Freq.	Notes
BAB	Ex ante beta. Shrinkage: 0.6 × beta + 0.4	Daily. 3d log rets for correls, 1d log rets for vols	1 year for vol, 5 years for correls	Rank-weighted	Beta	Monthly	Frazzini and Pedersen (2014) construction
SMR	Ex ante beta. No shrinkage	Daily. 3d log rets for correls, 1d log rets for vols	1 year for vol, 5 years for correls	Value-weighted based on 6 portfolio size–beta sort 30-40-30 sort	Dollar	Monthly	Asness et al. (2018) construction
SMRMN	Ex ante Beta. Shrinkage: 0.7 × beta + 0.3	Daily. 3d log rets for correls, 1d log rets for vols	1 year for vol, 5 years for correls	Value-weighted based on 6 portfolio size–beta sort 30-40-30 sort	Beta	Monthly	Portfolio is beta neutralized by first constructing 6 FF portfolios, then reweighting the portfolio such that each FF portfolio has a beta of 1
BAC	Correlation with market	Daily. 3d log rets for correls, 1d log rets for vols	1 year for vol, 5 years for correls	Rank-weighted based on 5×2 vol–correl sort. BAC is arithmetic average of 5 long–short portfolios within vol quintiles	Beta	Monthly	Frazzini and Pedersen (2014) construction
IVOL	Idiosyncratic volatility: sqrt (stock_vol^2 – beta^2 × market_vol^2) No shrinkage	Daily. 3d log rets for correls, 1d log rets for vols	1 year for vol, 5 years for correls	Value-weighted based on 6 portfolio size–IVOL sort 30-40-30 sort	Dollar	Monthly	Vols and betas computed using Frazzini and Pedersen (2014) construction.
MAX	Highest daily returns over the last month	Daily	1 month	Value-weighted based on 6 portfolio size–MAXRET sort. 30-40-30 sort	Dollar	Monthly	Follows Asness et al. (2018). The sort differs from Bali, Cakici, and Whitelaw, who do VW and EW decile sorts on raw MAXRET, so long high-risk stocks. AQR portfolio is long low-risk stocks, short high- risk stocks
QMJ	Sum of PROFIT, GROWTH, and SAFETY factors, *z*-scored	Annual	GROWTH: 5-year growth in residual profits	Value-weighted based on 6 portfolio size–QUALITY sort. 30-40-30 sort	Dollar	Monthly	Asness, Frazzini, and Pedersen (2019) construction

Note: The exhibit shows how each low-risk factor is constructed.

ACKNOWLEDGMENTS

We thank Cliff Asness, Ronen Israel, John Liew, Toby Moskowitz, and Scott Richardson for helpful comments and Hernan Gazze for research assistance. AQR Capital Management is a global investment management firm that may or may not apply similar investment techniques or methods of analysis as described herein. The views expressed here are those of the authors and not necessarily those of AQR.

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ADDITIONAL READING

Fact, Fiction, and the Size Effect

Ron Alquist, Ronen Israel, and Tobias Moskowitz
The Journal of Portfolio Management
https://jpm.pm-research.com/content/45/1/34

ABSTRACT: *In the earliest days of empirical work in academic finance, the size effect was the first market anomaly to challenge the standard asset pricing model and prompt debates about market efficiency. The notion that small stocks have higher average returns than large stocks, even after risk adjustment, was a path-breaking discovery, and for decades it has been taken as an unwavering fact of financial markets. In practice, the discovery of the size effect fueled a crowd of small-cap indexes and active funds to the point that the investment landscape is now segmented into large and small stock universes. However, despite its long and illustrious history in academia and its commonplace acceptance in practice, there is still confusion and debate about the size effect. We examine many claims about the size effect and aim to clarify some of the misunderstanding surrounding it by performing simple tests using publicly available data. For one, using 90+ years of U.S. data, there is no evidence of a pure size effect; moreover, it may not have existed in the first place, if not for data errors and insufficient adjustments for risk and liquidity.*

The Volatility Effect

David C. Blitz and Pim van Vliet
The Journal of Portfolio Management
https://jpm.pm-research.com/content/34/1/102

ABSTRACT: *There is empirical evidence that stocks with low historical volatility have high risk-adjusted returns, with annual alpha spreads of global low-versus high-volatility decile portfolios of 12 percentage points over 1986–2006. This volatility effect appears independently in U.S., European, and Japanese markets. It is similar in size to classic effects such as value, size, and momentum, and cannot be explained by implicit loadings on these well-known effects. These results indicate that equity investors overpay for risky stocks. Possible explanations include leverage restrictions, inefficient two-step investment processes, and behavioral biases of private investors. To exploit the volatility effect in practice, investors might include low-risk stocks as a separate asset class in the strategic asset allocation phase of the investment process.*

The Volatility Effect Revisited

David Blitz, Pim van Vliet, and Guido Baltussen
The Journal of Portfolio Management
https://jpm.pm-research.com/content/46/2/45

ABSTRACT: *High-risk stocks do not have higher returns than low-risk stocks in all major stock markets. This article provides a comprehensive overview of this low-risk effect, from the earliest asset pricing studies in the 1970s to the most recent empirical findings and interpretations. Volatility appears to be the main driver of the anomaly, which is highly persistent over time and across markets and which cannot be explained by other factors such as value, profitability, or exposure to interest rate changes. From a practical perspective, low-risk investing requires little turnover, volatilities are more important than correlations, low-risk indexes are suboptimal and vulnerable to overcrowding, and other factors can be efficiently integrated into a low-risk strategy. Finally, there is little evidence that the low-risk effect is being arbitraged away because many investors are either neutrally positioned or even on the other side of the low-risk trade.*