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The Volatility Effect Revisited

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KEY FINDINGS

- This article provides a comprehensive overview of the low-risk anomaly, from the earliest asset pricing studies in the 1970s to the most recent empirical findings and interpretations.
- The main driver of the anomaly appears to be volatility. The alpha is highly persistent over time and across markets and cannot be explained by other factors such as value, profitability, or exposure to interest rate changes.
- 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. Low-risk indexes, however, are vulnerable to overcrowded positions.

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.*

TOPICS: ***Volatility measures, exchanges/markets/clearinghouses, risk management****

*All articles are now categorized by topics and subtopics. **View at PM-Research.com.**

This article provides a comprehensive overview of the low-risk effect (i.e., the empirical finding that higher risk is not rewarded with a higher return in global stock markets or within other asset classes). Although the main driver of the low-risk effect appears to be volatility, which implies that it is essentially a low-volatility effect, we will use the more neutral term *low-risk effect* throughout this article. In the first section, we review the empirical evidence for the low-risk effect. In the next section, we argue that the low-risk effect cannot be explained by factors such as value, profitability, or exposure to interest rate changes. After this, we make the step from theory to practice and discuss the key considerations that come into play when investing based on the low-risk effect using real money. We next argue that there is little evidence that the low-risk effect is being arbitraged away because many investors turn out to be either neutrally positioned or even on the other side of the low-risk trade. The final section gives our conclusions.

EMPIRICAL EVIDENCE FOR THE LOW-RISK EFFECT

In this section, we review the empirical evidence for the low-risk effect, going back all the way to the very first empirical asset pricing studies in the 1970s and now consisting of an extensive stream of literature that also extends to asset classes other than equities. We also outline the various metrics used to measure risk and discuss commonly cited explanations for the existence of the low-risk effect.

History of the Low-Risk Effect

The roots of the low-risk effect can be traced back to the very first empirical tests of the capital asset pricing model (CAPM). The CAPM predicts a linear relation between a security's systematic risk, measured by its beta against the market portfolio, and its return. The first empirical tests of the CAPM by Black, Jensen, and Scholes (1972), Miller and Scholes (1972), and Fama and MacBeth (1973) found that, although higher risk is rewarded with higher return, it is not rewarded enough. In other words, the empirical security market line (SML) was observed to be flatter than expected. Haugen and Heins (1975) first recognized the existence of a low-risk anomaly, concluding that "our empirical efforts do not support the conventional hypothesis that risk—systematic or otherwise—generates a special reward. Indeed, our results indicate that, over the long run, stock portfolios with lesser variance in monthly returns have experienced greater average returns than their 'riskier' counterparts." Such findings were not interpreted as a major cause for concern though. The general consensus was that, although it was maybe not perfect, the CAPM did an adequate job at explaining stock prices. The first serious challenge to the CAPM was the finding of Banz (1981) that small stocks had higher returns than large stocks, even after correcting for the fact that the average small stock is more risky than the average large stock.

It took until the 1990s for the true failure of the CAPM to become clearly visible. Fama and French (1992) found that market beta is entirely unpriced in the cross section of stock returns when size and market beta are properly disentangled from each other. Quoting from the abstract of their paper: "When the tests allow for variation in beta that is unrelated to size, the relation between market beta and average return is flat, even when beta is the only explanatory variable." Whereas anomalies such as size and value imply that the CAPM may need to be augmented with some additional factors, the low-risk anomaly challenges the heart of the CAPM—that is, the very notion that higher risk should be rewarded with higher return in the cross section.

Unknown at the time, all these studies suffered from a delisting bias in the data that had not been identified and resolved. Shumway (1997) and Shumway and Warther (1999) found that stocks that are delisted (e.g., due to bankruptcy) tend to have very negative returns in the month of delisting that were either not at all or incorrectly recorded in old CRSP tapes. This bias caused stock returns in general to be overestimated, particularly so the returns of small and risky stocks, because the probability of delisting is higher for such stocks (see Cochrane 1999). As a result, the relation between risk and return appeared to be more positive than it actually was, and the magnitude of the size premium was overestimated.

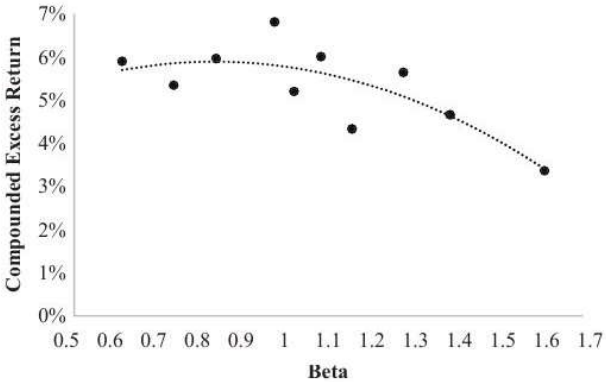
The Kenneth French data library[1] currently contains bias-free historical return series for US stock portfolios sorted on 60-month market beta, with data going back to July 1963. In Exhibit 1, we plot the performance of 10 decile portfolios sorted on beta, and in Exhibit 2, we plot the performance of the 5 × 5 size/beta portfolios that are also available from this source. All exhibits are based on publicly available data only and include a second-order polynomial trend line. The graphs clearly show a flat, or even slightly negative, relation between risk and return, which implies that, over a sample period that is by now twice as long, the conclusion of Fama and French (1992) that beta is not a priced factor still holds.

The rejection of the CAPM relation by Fama and French (1992) was confirmed by several studies that appeared shortly afterward. Black (1993) found that the raw relation between beta and return became flat in the decades following the sample period covered in the Black, Jensen, and Scholes (1972) study. Falkenstein (1994) even reported a negative relation between risk

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

EXHIBIT 1

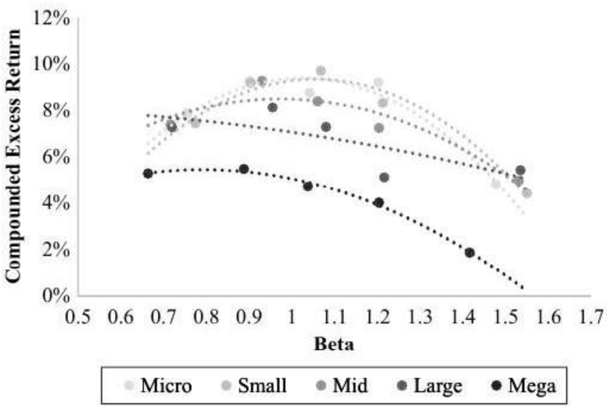
10 Portfolios Sorted on 60-Month Beta, 1963–2018



Source: Prepared by the authors from data sourced from the Kenneth French data library.

EXHIBIT 2

5 × 5 Portfolios Sorted on Size and 60-Month Beta, 1963–2018



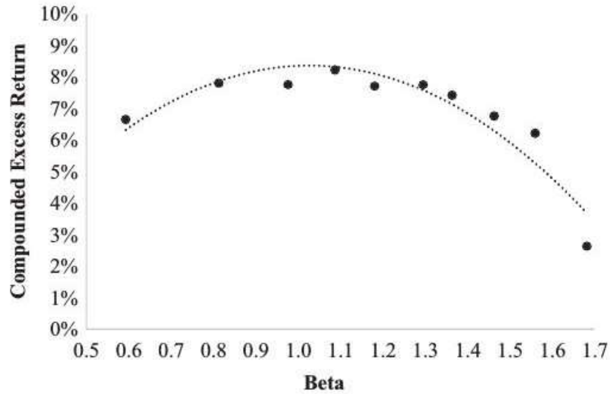
Source: Prepared by the authors from data sourced from the Kenneth French data library.

and return when applying the crucial control for the size effect. Despite this compelling empirical evidence, the academic community did not abandon the CAPM relation between beta and return, and the investment community ignored the investment opportunity offered by these insights.

Fifteen years after the seminal Fama and French (1992) study, Blitz and van Vliet (2007) took a fresh look

EXHIBIT 3

10 Portfolios Sorted on 36-Month Volatility, 1929–2018



Source: Prepared by the authors from data sourced from paradoxinvesting.com.

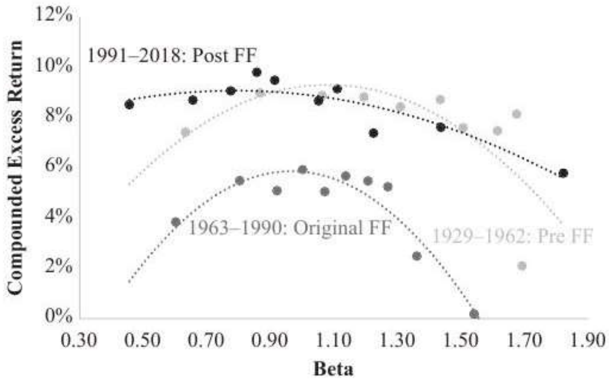
at the low-risk effect and found that, if anything, it has become even stronger over time. Over their 20-year sample period, the relation between risk and return is not merely flat but even outright inverted, with a top-minus-bottom CAPM-alpha spread of 12% per annum. They also found that total volatility appears to be at least as effective as beta and that the effect is not only present in the US equity market but also in international equity markets.

The Paradox Investing website[2] contains publicly available data for volatility-sorted deciles portfolios. These portfolios are constructed by sorting the 1,000 largest US stocks on their past 36-month volatility, with data starting in January 1929, as done by van Vliet and de Koning (2017). Exhibit 3 shows that the full-sample relation between risk and return is clearly flat instead of upward sloping and even becomes inverted in the highest-risk spectrum. Exhibit 4 shows that this result is robust over time when we separately consider the 1963–1990 sample period of Fama and French (1992), the pre-1963 presample period that resembles the original sample period used by Black, Jensen, and Scholes (1972), and the post-1990 out-of-sample period.

Subsequent studies by Baker, Bradley, and Wurgler (2011), Baker and Haugen (2012), and Frazzini and Pedersen (2014) all confirmed and extended these empirical results, using various definitions of risk and proposing

[2] https://www.paradoxinvesting.com/data.

EXHIBIT 4
10 Portfolios Sorted on 36-Month Volatility, Subperiods



Source: Prepared by the authors from data sourced from paradoxinvesting.com.

various explanations for the findings. A parallel stream of literature examined the empirical performance of the theoretical minimum-variance portfolio and also found clear evidence for the existence of a low-risk anomaly (see Haugen and Baker 1991, 2010; Clarke, de Silva, and Thorley 2006, 2011). Following these studies, dedicated low-risk investing gradually evolved into a widely accepted investment approach, typically labeled *low volatility*, *managed volatility*, *minimum volatility*, *minimum variance*, *defensive*, or *conservative*. Still, theoretical thinking continues to be shaped by the CAPM. For example, although academics disagree about the specific set of factors that should be included in asset pricing models, the classic CAPM relation between market beta and expected return remains the starting point in all such models.

The Low-Risk Effect Is Universally Present

The low-risk effect is remarkably robust from a geographic perspective (present in all major developed and emerging markets), from an industry perspective (present within and across industries), and from a time perspective (consistent over time). Blitz and van Vliet (2007) showed that the anomaly exists in the US, European, and Japanese equity markets, and Blitz, Pang, and van Vliet (2013) documented the low-risk anomaly for emerging equity markets. The low-risk effect is further confirmed in international samples by Baker and Haugen (2012), Frazzini and Pedersen (2014), and Walkshäusl (2014). Recently, Han, Li, and Li (2018) and Chen, Pong, and Wang (2018) found that the low-risk anomaly is also present in the local Chinese (A shares) equity market, and Joshipura and Joshipura (2016) documented the anomaly for the Indian stock market.

If the relation between risk and return is flat, then a long low-risk and short high-risk hedge portfolio will show an average return of zero and a strong negative CAPM beta. Frazzini and Pedersen (2014) constructed a so-called betting-against-beta (BAB) factor that is designed to turn this into a positive premium with zero beta by dynamically levering the long low-risk portfolio up, to a beta of 1, and delevering the short high-risk portfolio down, also to a beta of 1. Exhibit 5 shows that the BAB premium is positive in all 24 countries for which data are available online.[3] The BAB study helped to popularize the low-risk effect, especially among academics. Recently, however, the methodological assumptions behind BAB have been criticized by Novy-Marx and Velikov (2018), who argued that a large part of the premium is driven by dynamic hedging and shorting highly illiquid micro caps.

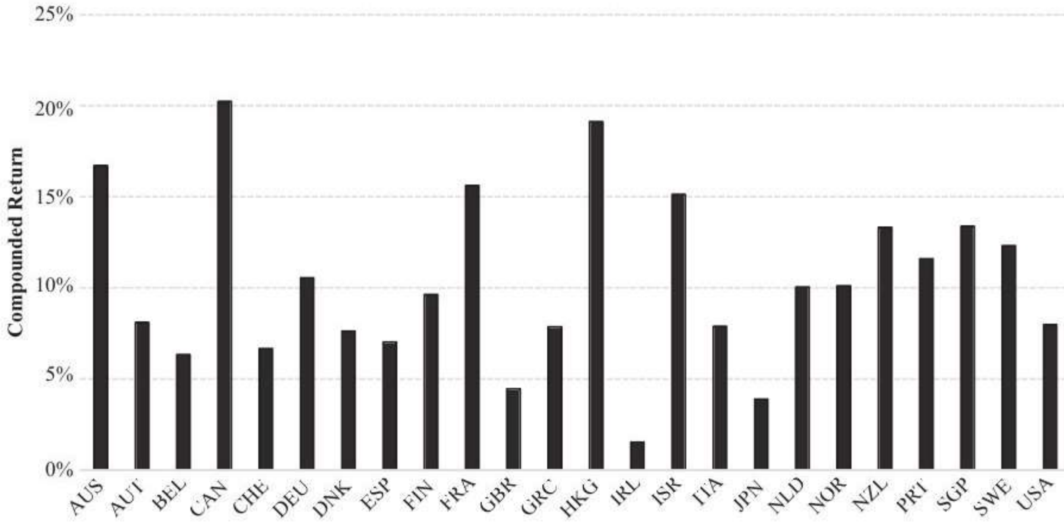
The previously mentioned Paradox Investing website contains a US volatility factor portfolio that addresses this concern by staying close to the factor construction methodology of Fama and French (1993, 2015). To construct this volatility factor (VOL), every month, all stocks in the CRSP database are first classified as either large or small, using the NYSE median market capitalization as breakpoint; next, value-weighted low-, mid-, and high-volatility portfolios are created within both of these size groups using past the 36-month volatility and the NYSE 30th and 70th percentiles as breakpoints. The long leg of the factor takes a 50-50 mix of the large-cap low-volatility and small-cap low-volatility portfolios and the short leg a 50-50 mix of the large-cap high-volatility and small-cap high-volatility portfolios. The only deviation from the standard Fama–French factor construction methodology is that the VOL factor is made beta neutral by first levering each sub-portfolio up or down to a market beta of 1. Without beta neutrality, the VOL factor would have a highly negative beta to the market factor.

Exhibit 6 shows the annualized premiums of the volatility factor and the factors in the Fama and French (2015)

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

EXHIBIT 5

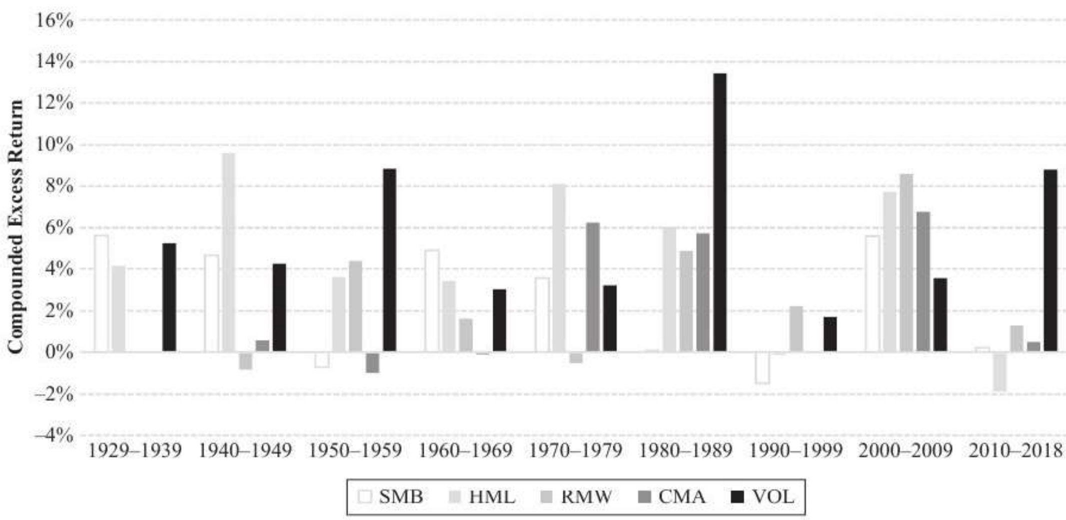
BAB Premium around the World, Various Start Dates until End-2018 (maximum available history for each country)



Source: Prepared by the authors from data sourced from the AQR data library.

EXHIBIT 6

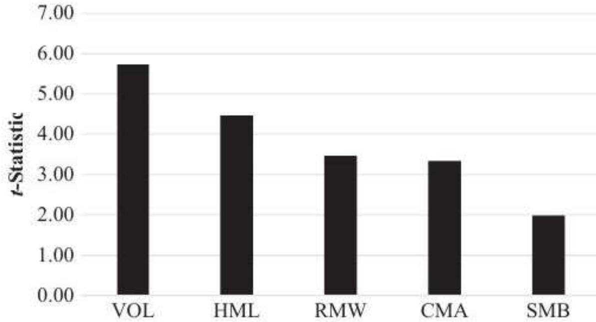
Factor Premiums by Decade



Source: Prepared by the authors from data sourced from the Kenneth French data library, paradoxinvesting.com, and the Journal of Financial Economics *website.*

EXHIBIT 7

Strength of Factor Premiums, 1940–2018



Source: Prepared by the authors from data sourced from the Kenneth French data library, paradoxinvesting.com, and the Journal of Financial Economics *website.*

model by decade since 1940. The data for the profitability (RMW) and investment (CMA) factors over the 1940–1963 period are obtained from Wahal (2019).[4] The graph shows that the volatility factor is the only factor that has generated a positive premium in every decade. Unreported tests show that the volatility factor has even been positive in every 120-month moving window period. It is also the only factor that has delivered a solid premium over the most recent decade.

Compared to the Fama–French factors, the volatility premium is not only stable through time but also large in magnitude. Over the full sample period, the average premium is 5.8% per annum with a volatility of 9.0%. This translates into an annualized Sharpe ratio of 0.65 and an accompanying t-statistic of 5.7, well above all common thresholds for statistical significance. To put the statistical strength of the volatility premium into perspective, Exhibit 7 shows the t-statistics of the other factor premiums. On a stand-alone basis, the volatility premium is the strongest factor, whereas the size premium is the weakest factor.

Many anomalies are known to be concentrated in small-cap stocks and therefore difficult to exploit in reality, but Auer and Schuhmacher (2015) showed that the low-risk anomaly is strongly present among the largest, most liquid US stocks. Asness, Frazzini, and Pedersen (2014) and Baker, Bradley, and Taliaferro (2014) showed that the low-risk effect exists within industries and countries and across industries and countries. Annaert and Mensah (2014) documented a clear low-risk effect for the Brussels stock exchange in the decades before World War I, when this was one of the biggest stock markets.

Further evidence for the low-risk effect is coming from studies on other asset classes. Carvalho et al. (2014) and Israel, Palhares, and Richardson (2018) documented a low-risk effect within the investment-grade corporate bond market, and Houweling and Van Zundert (2017) showed that the effect is not only present among investment-grade corporate bonds but also among high-yield corporate bonds. Falkenstein (2009) documented over 20 occurrences of the low-risk effect, including some more exotic ones such as the options market, movie production (De Vany and Walls 2002), and sports books (Snowberg and Wolfers 2010). Eraker and Ready (2015) found that very risky over-the-counter stocks have very poor average returns; Moskowitz and Vissing-Jorgensen (2002) found a low-risk anomaly for private business returns, Adhami, Gianfrate, and Johan (2019) observed an inverse relation between risk and return in the crowdlending market; and Jordan and Riley (2015) found that the low-risk anomaly is also present in the cross section of mutual fund returns. Altogether, there appears to be a low-risk effect within every asset class. The relation between risk and return only seems to be positive across entire asset classes because stocks have higher returns than bonds, and corporate bond returns are higher than government bond returns in the long run.

Low Volatility or Low Beta?

Is the low-risk anomaly primarily a low-volatility or a low-beta anomaly? The first thing to note in this regard is that volatility and beta are closely related metrics because the beta of a stock to the market index is equal to its volatility times its correlation with the market index, divided by the volatility of the market. In cross-sectional comparisons, the latter term is a constant and hence irrelevant. As such, defining low-risk based on volatility or beta is effectively a choice on the added value of correlations. Blitz and van Vliet (2007) and Baker, Bradley, and Wurgler (2011) found slightly stronger results for volatility than for beta, although these differences are relatively small. More recently,

[4] http://jfe.rochester.edu/data.htm.

Liu, Stambaugh, and Yuan (2018) also found weaker results for beta.

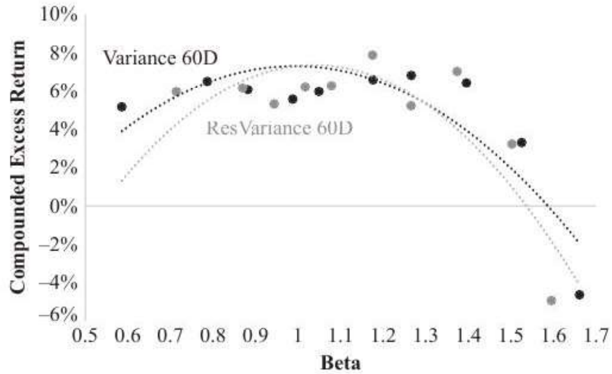
Asness et al. (2019) directly disentangled the two driving components of beta, volatility and correlation. They found that there is a clear alpha when stocks are sorted on volatility and that next to that there is an alpha when stocks are sorted on correlation within volatility buckets. In other words, correlation matters, but only among stocks that have a similar level of volatility. These results suggest that volatility is the main driver of the low-risk effect and that the added value of correlations is a second-order effect.

All studies mentioned so far typically estimate risk using metrics such as beta or volatility, estimated on one, three, or five years of historical data. A closely related phenomenon is the idiosyncratic volatility (iVol) effect of Ang et al. (2006, 2009), which they estimated using daily return data over the past one month. This one-month lookback period for risk estimation, in combination with a standard one-month holding period, resulted in one of the most powerful manifestations of the low-risk anomaly on paper, but one that is less suitable for practical applications because of the amount of turnover (and hence transaction costs) involved. Another practical concern is that Ang et al. (2006) found that most of the alpha of their strategy comes from the short side (i.e., very poor performance of the recently most risky stocks). In reality this alpha may be beyond the reach of many investors because of limits to arbitrage; see also the next section.

The previously mentioned Kenneth French data library also contains data for portfolios sorted by 60-day variance and 60-day residual variance. The reason for the use of an approximately three-month lookback period instead of the one-month lookback period of Ang et al. (2006) is unclear, but the results appear generally similar. Exhibit 8 shows the full-sample performance of decile portfolios sorted on the short-term risk measures. Once again we observe that the risk–return relation goes from flat to inverted at the far end. The very low returns for the most risky stocks are particularly striking. Sorting on 60-day variance or 60-day residual variance seems to make little difference. All these results are consistent with Ang et al. (2006), who also reported dismal performance for the most risky stocks and very similar results for sorting on past one-month total return volatility and past one-month idiosyncratic volatility.

EXHIBIT 8

10 Portfolios Sorted on 60-Day Variance and 60-Day Residual Variance, 1963–2018



Source: Prepared by the authors from data sourced from the Kenneth French data library.

Yet another manifestation of the low-risk effect, one could argue, is the finding of Campbell, Hilscher, and Szilagyi (2008), who found that financially distressed stocks have delivered anomalously low returns.

Explanations

We continue with discussing the most popular explanations for the low-risk effect. For the purposes of this article, we group these explanations into five main categories: (1) constraints, (2) relative performance objectives, (3) agency issues, (4) skewness preference, and (5) behavioral biases. For a more extensive overview of explanations we refer to Blitz, Falkenstein, and van Vliet (2014).

Constraints. The low-risk effect has been linked to the limits to arbitrage that arise from various practical constraints, in particular shorting and leverage constraints. Heterogeneous beliefs cause the investors with the most optimistic expectations to drive up the price of risky assets. Miller (1977) argued that in the absence of enough short sellers, this *winners' curse* flattens the risk–return relation. For many investors, the possibility to sell short or use leverage is restricted by mandate or means. Theoretically, Brennan (1971) and Black (1972) showed that the SML may become flatter than predicted by the CAPM in the presence of leverage constraints. Black (1993) argued that, if anything, leverage constraints have tightened over time. The intuition behind this explanation is as follows. In the world of the CAPM, there is only one efficient portfolio, and investors simply lever or delever this portfolio based on their degree of risk aversion. In the presence of leverage constraints, however, investors looking to increase their return are forced to tilt their portfolios toward high-beta securities. This extra demand for high-beta securities and reduced demand for low-beta securities may explain a flattening of the SML. In support of this explanation, Frazzini and Pedersen (2014) found that, when leverage constraints are tighter, the low-risk anomaly tends to be stronger.

Relative performance objectives. A second explanation for the low-risk effect is a focus on performance relative to others instead of absolute performance. The CAPM assumes that investors only care about absolute returns, but in reality many investors focus on beating the market average. Blitz and van Vliet (2007), Falkenstein (2009), and Baker, Bradley, and Wurgler (2011) argued that, if the CAPM holds, then low-risk stocks are unattractive for benchmark-relative investors because they involve high tracking error and lower expected return. Brennan (1993) and Brennan, Cheng, and Li (2012) assumed the simultaneous presence of absolute and relative return-oriented investors and showed that this implies a partial flattening of the SML, with the degree of flattening depending on the number of relative-return investors versus the number of absolute-return investors. Falkenstein (2009) showed that, if investors only care about performance relative to others, then in equilibrium the relation between risk and return is flat. Within this relative utility framework, there are no risk premiums left at all, which is at odds with the existence of a global equity premium. Blitz (2014) reconciled the simultaneous existence of a positive equity risk premium and absence of a risk premium within asset classes by considering a two-stage investment process, wherein investors first make asset allocation decisions based on absolute performance criteria and next switch to a relative performance objective when trying to identify the best managers or securities within each asset class. This explanation assumes a mental accounting bias, as in the two-layer portfolio model of Shefrin and Statman (2000), where the low-aspiration layer is designed to avoid poverty and the high-aspiration layer aims for a shot at riches.

Agency issues. The low-risk effect has also been attributed to agency issues. Karceski (2002) argued that profit-maximizing asset managers have a strong incentive to create high-beta products owing to the highly asymmetric nature of the flow-performance relationship documented by Sirri and Tufano (1998): Most flows are attracted by funds with the best performance in asset classes that also had a good performance. Falkenstein (1996) showed that mutual fund managers, who have an incentive to attract investor flows, have a preference for stocks with higher idiosyncratic volatility, and Agarwal, Jiang, and Wen (2018) found that smaller, younger mutual funds with poor recent performance own more risky lotterylike stocks, arguably to attract capital. Such tournament behavior may also be present among analysts; Hsu, Kudoh, and Yamada (2013) provided evidence that sell-side analysts prefer high-volatility stocks. Baker and Haugen (2012) generalized this agency problem and argued that all portfolio managers and their analysts implicitly or explicitly have optionlike reward structures, which incentivizes them to focus on high-risk assets. A lab-in-the field experiment by Kirchler, Lindner, and Weitzel (2018) with a large group of professional investors supports the notion that ranking and tournament incentives are important drivers of risk taking.

Skewness preference. Another explanation for the low-risk effect is a preference for lotterylike payoffs or positive skewness (see Blitz and van Vliet 2007; Baker, Bradley, and Wurgler 2011; Ilmanen 2012; and Hsu and Chen 2017). Kumar (2009) showed that many investors participate in the stock market to gamble. Bali, Cakici, and Whitelaw (2011) tested the stocks-as-lotteries hypothesis of Barberis and Huang (2008) and used this to explain the very low returns of the most risky stocks. High-risk stocks are attractive to lottery-seeking investors because they offer limited downside risk combined with unlimited upside potential. A preference for skewness can even support the existence of an inverse risk–return relationship; that is, instead of requiring a compensation for taking on risk, investors may actually be willing to pay a premium for it.

Behavioral biases. A fifth explanation for the low-risk effect is behavioral biases, such as attention-grabbing bias, representativeness bias, and overconfidence, which cause investors to irrationally prefer higher-risk stocks over lower-risk stocks (see, e.g., Blitz and van Vliet 2007; Baker, Bradley, and Wurgler 2011). For example, investors pay more attention to stocks that are very visible than to stocks that remain more under the radar. High-risk stocks are more likely to experience extreme returns that grab the attention of investors, which creates excessive buying pressure on these stocks (Barber and Odean 2008). With representativeness bias or overconfidence, investors may become too optimistic about the future prospects of volatile stocks that might be the next Amazon or Google, causing these stocks to become overpriced and generate lower subsequent returns. Behavioral explanations can also support the existence of an inverse risk–return relationship.

The Low-Risk Effect is not a Data Fluke

Harvey (2017) argued that a serious concern in finance, and in science in general, is *p-hacking*. Scientists are subject to statistical testing limitations and have several degrees of freedom (on areas such as data manipulation, statistical method, and results chosen for presentation), publications are biased toward positive results, and scientists have an incentive to publish. As a consequence, the possibility exists that evidence for the low-risk effect might actually be a false positive. As a case in a point, Harvey, Liu, and Zhu (2016) found a clear publication bias pattern in the top finance journals and that many of the 300+ documented stock-level anomalies become questionable after analysis in a rigorous testing framework that allows for multiple hypotheses testing bias.

For the low-risk effect, we deem the *p-hacking* explanation unlikely for the following reasons. First, the effect did not originate from research that tested dozens or hundreds of different potential alpha factors but from research that aimed to confirm the basic predictions of the CAPM. Moreover, the anomaly was ignored for many decades until it simply could not be ignored anymore. Second, the low-risk effect is not about a slight failure of the CAPM but about the total absence of a positive relation between risk and return. Many studies even find the relation to be clearly inverted. Furthermore, as discussed earlier, there is also a clear economic rationale for these findings. Third, the effect is shown to be very robust over different samples, initially observed in the United States over half a century ago and then out of sample in many studies covering different time periods and/or markets. These studies include more recent decades and all main regions, including emerging markets, as outlined previously. Fourth, as shown in Exhibit 6, the effect is remarkably robust over subperiods, even more so than widely accepted factors such as size and value. Fifth, the effect is also present in other asset classes where the same economic mechanisms are present, such as corporate bonds.

IS LOW-RISK A DISTINCT EFFECT?

In this section, we discuss the most important challenges to the low-risk effect, in particular whether it might be a manifestation of interest rate exposure or if it can be explained by other factors such as value or profitability. We review the studies that have specifically addressed these concerns and conclude that, at best, they can explain only a small part of the low-risk effect or performance over a very specific subperiod. None, however, can provide a comprehensive explanation for the low-risk anomaly.

Low-Risk is not Explained by Interest Rate Risk

Some have suggested that the low-risk effect may be explained by an implicit exposure to interest rate risk. Standard asset pricing models only use equity-based factors, but Baker and Wurgler (2012) showed that low-risk stocks have pronounced bond-like features. De Franco, Monnier, and Rulik (2017) formally examined this issue and concluded that, although low-risk stocks have a statistically significant exposure to interest rate risk, this only explains a very small part of their alpha. This is not really surprising because the bond premium is relatively small, so the loading of low-risk stocks on bonds would have to be extremely large for the alpha to be fully explained. Another reason why it is implausible that the alpha of low-risk stocks is driven by interest rate exposure is that the low-risk anomaly is not merely a phenomenon of recent decades, during which interest rates were falling, but was present in earlier decades, during which interest rates were stable or even rising. Moreover, the interest rate risk explanation does not carry over to the low-risk anomaly in corporate bonds because low-risk corporate bonds have short maturities and hence lower instead of higher exposure to interest rate changes. van Vliet (2011) and Coqueret, Martellini, and Milhau (2017) argued that from an ALM perspective the interest rate exposure of low-risk stocks is actually a desirable feature because it implies better liability-hedging properties compared to a standard equity portfolio.

Low-Risk is Distinct from the Value Effect

In the mid-2000s many investors wondered whether the low-risk effect was simply a manifestation of the well-known value effect. Like generals preparing for the next war by training to fight the previous war again, investors had the technology bubble fresh in their minds. The technology stocks that soared during the late 1990s and crashed in the early 2000s were unattractive from both a value and a low-risk perspective, whereas so-called old economy stocks were both cheaper and less risky. Blitz and van Vliet (2007), Frazzini and Pederson (2014), and Walkshäusl (2014) all found that the alpha of low-risk stocks is not explained when controlling for value (and other factors) for the universes and sample periods in their studies.

That said, the alpha of a plain-vanilla US low-risk strategy seems to be explained by an implicit loading on the classic HML value factor in time-series regressions over the commonly used post-1963 period. Blitz (2016) examined this issue in detail and found that the value effect failed to explain the performance of large-cap low-risk strategies in the United States pre-1963 and post-1984, when the Fama–French value factor itself ceased to be effective in the large-cap segment of the market. Moreover, the value effect cannot explain the performance of small-cap low-risk strategies during any period. In other words, the value factor can explain only the performance of US large-cap low-volatility strategies during a period roughly in the middle of the CRSP sample, which makes up less than a quarter of the entire CRSP sample. These results reject the notion that low-risk might simply be value in disguise.

After the global financial crisis of the late 2000s, the criticism that low-risk may be value waned because low-risk stocks began trading at higher multiples than the market. In other words, investors were willing to pay up for defensiveness. This is not unprecedented; the same happened in the wake of the Great Depression in the 1930s. Nevertheless, it fueled a new criticism by Arnott et al. (2016), who argued that low-risk (and other smart beta) indexes have been designed based on relatively short backtest periods and obtained a large part of their return from multiple expansion of their holdings, which is not sustainable in the long run. Although they documented that multiple expansion can indeed be a significant explanatory factor for performance in the short run, it cannot explain the long-run success of low-risk strategies. Nevertheless, investors should be aware that low-risk stocks can go through long cycles of being either value or growth tilted.

Low-Risk is Distinct from the Profitability Effect

A more recent challenge to the low-risk anomaly is that it is explained by profitability factors. This argument was first made by Novy-Marx (2014) using the gross profitability factor of Novy-Marx (2013) and subsequently by Fama and French (2016) using the slightly different profitability factor of the Fama and French (2015) five-factor model. Despite the unequivocal conclusion of Fama and French (1992) that market beta is not a priced factor in the cross section of stock returns, Fama and French (1993) chose to retain the fundamental CAPM relation between market beta and return as the basis for their three-factor model. The Fama and French (2015) five-factor model adds profitability and investment factors to the three-factor model, again without changing the CAPM basis of the model. This time, however, they specifically addressed whether this is justified in light of the low-risk anomaly. Fama and French (2016) argued that with the new factors included in the five-factor model, they are able to explain the performance of risk-sorted portfolios in time-series regressions.

Blitz and Vidojevic (2017) acknowledged that the low-risk effect appears to be subsumed by the profitability factor in time-series regressions. They went on to argue, however, that if it were true that the CAPM relation holds when accounting for interactions with the profitability factor, then it should be possible to construct portfolios that exhibit a clear positive relation between market beta and return, provided one controls for the profitability characteristics of these portfolios. They argued that this can be tested by running Fama and MacBeth (1973) cross-sectional regressions because the returns estimated with these regressions can be interpreted as the reward to a unit exposure to a factor, controlling for the exposures to all other factors included in the analysis. Applying this approach, they found that all factors in the five-factor model are priced, except market beta. In other words, it is not possible to construct high-beta portfolios with a high return and low-beta portfolios with a low return, whether one controls for profitability or not. Based on this finding, they concluded that it is premature to assume that the low-risk effect is explained by profitability or other factors.

Additional evidence was provided by Blitz, Baltussen, and van Vliet (2019), who examined how the long legs and short legs of classic factor strategies separately contribute to performance. They found that the long legs of factors tend to have a stronger risk-adjusted performance than the short legs. Moreover, although the short side of a low-risk strategy (i.e., high risk) can be explained by the short side of the new Fama–French factors (e.g., poor profitability), the long side is not explained (i.e., the alpha of low-risk stocks cannot be explained by the alpha of high-profitability stocks). In other words, the results of Novy-Marx (2014) and Fama and French (2016) are entirely driven by the short sides of factors. In a long-only setting, which is the preferred approach of many investors in practice (see next section), low-risk clearly stands its ground as a distinct factor.

Blitz, Baltussen, and van Vliet (2019) also observed that even the long–short low-risk factor is not explained by the new Fama–French factors over the 1963–1990 subsample period, which is the period used by Fama and French (1992) to establish their classic size and value factors. Based on the data in Exhibit 6, the long–short low-risk factor is also not explained by the other Fama–French factors pre-1963 and post-2010. Altogether this implies that the conclusions of Novy-Marx (2014) and Fama and French (2016) are entirely driven by the 20-year period surrounding the turn of the century.

CAPTURING THE LOW-RISK EFFECT

In this section, we make the step from theory to practice, discussing the key considerations that come into play when investing based on the low-risk effect with real money. We first discuss why investors who aim to profit from the low-risk effect typically use a long-only approach. We then discuss the optimal amount of turnover needed to capture the low-risk anomaly, the role of correlations, how to deal with currency risk, the pros and cons of passively following a generic low-risk index, and whether to combine low-risk with other factors.

Low-Risk Strategies Tend to Be Long-Only in Practice

Theoretical studies typically consider long–short portfolios. For instance, the Fama–French factors for size, value, momentum, profitability, and investment all assume a long portfolio of stocks with good factor characteristics and a matching short portfolio of stocks with bad factor characteristics. In practice, however, factor investing is often implemented using a long-only approach—witness, for instance, the popularity of smart beta exchanged-traded funds (ETFs) that track (long-only) factor indexes. Not only the index-based but also the most popular active offerings that target the low-risk effect tend to follow a long-only approach.

In principle, the low-risk effect can also be targeted with a long–short approach, in which one not only goes long the lowest-risk stocks but simultaneously short in the highest-risk stocks. Perhaps certain individual hedge funds follow such a long–short approach, but overall it seems to be far less popular than a more straightforward long-only approach. One reason for this may be management fees: Long-only funds tend to charge considerably lower fees than long–short hedge funds. Another reason may be that shorting the most risky stocks can be difficult and expensive in practice. In fact, shorting costs tend to increase (substantially) with a stock's volatility (see Drechsler and Drechsler 2016), and the probability of recall increases with a stock's volatility (see D'Avolio 2002). Moreover, shorting high-risk stocks is relatively risky because the price of these stocks can suddenly increase substantially over short periods of time. Beta management (i.e., making sure that the long position in low-risk stocks and the short position in high-risk stocks has zero net beta) is also challenging because volatility levels are highly time varying with occasional spikes. Given that long-only appears to be the preferred way to harvest the low-risk effect in practice, we will take this as the starting point for the remainder of this section.

Low-Risk Requires Low Turnover

The literature on low-risk investing reports annual turnover levels ranging from less than 20% to over 100%. A wide dispersion can also be observed in the turnover levels of the low-risk strategies offered by asset managers and index providers. This gives rise to the question of how much turnover is needed to efficiently harvest the low-risk premium. Li, Sullivan, and Garcia-Feijóo (2014) argued that high turnover and implementation costs could be a serious restriction for investors looking to profit from the low-risk anomaly. On the other hand, Novy-Marx and Velikov (2015) found that, with smart trading rules, most anomalies remain profitable after costs, except for those that involve very high amounts of turnover. Frazzini, Israel, and Moskowitz (2012) also examined implementation strategies designed to reduce turnover and argued that actual trading costs are oftentimes lower than assumed in the literature. van Vliet (2018) conducted a meta-analysis of the low-risk literature and considered various historical portfolio simulations to conclude that an efficient low-risk strategy does not require more than 30% turnover per annum.

One way to control turnover is to estimate risk using medium or long lookback periods. For instance, the one-month iVol effect of Ang et al. (2006) may look great in theoretical tests with one-month holding periods, but it is not particularly suitable for a real-life investment strategy that involves transaction costs. Another crucial aspect in controlling turnover is not to create an entirely fresh portfolio every month but to take the existing portfolio into account and only replace those holdings that are most in need of replacement. Clarke, de Silva, and Thorley (2006) found that a naïve minimum-volatility approach with monthly rebalancing results in an annual turnover of 143% but that performance is hardly affected if turnover is reduced to 56%. The MSCI Minimum Volatility indexes impose constraints that explicitly limit annual turnover to just 20%, without significantly diluting the exposure to the low-risk effect. In sum, the low-risk anomaly does not require a high turnover, but a naïve implementation can result in excessive turnover and hence unnecessary transaction costs.

Low-Risk or Minimum Risk: Mainly Semantics

Although low-risk and minimum-risk approaches are closely related, there are also subtle differences. The most important difference is that a low-risk approach will only select stocks that each have a low-risk individually, whereas a minimum-risk approach may additionally select stocks that have a medium or even high risk on their own but help to reduce risk at the portfolio level owing to their low correlation with other stocks. Stocks of gold-mining companies are a classic example of high-risk but low-correlation stocks, given the role of gold as a catastrophe hedge. This raises the question of whether the alpha of low-risk strategies is concentrated in stocks that have a low-risk on their own or whether there is also alpha in risky stocks that have low correlations with other stocks. Soe (2012) empirically compared low-volatility and minimum-volatility strategies based on the constituents of the S&P 500 index and found that the two approaches exhibit very similar performance characteristics. Carvalho, Lu, and Moulin (2012) investigated five popular risk-based approaches and found that they generally load on low-beta and low-volatility factors. Scherer (2011) and Chow et al. (2014) came to the same conclusion. In other words, differences between low-risk and minimum-risk are mostly semantics.

Currency Risk

A related question is how to deal with currencies, because the volatilities and correlations of stocks can change when returns are measured in a different currency. The key question here is whether a low-risk strategy should be optimized toward the base currency of an investor or whether it should be base-currency agnostic. To illustrate, MSCI offers, among others, USD-optimized, EUR-optimized, JPY-optimized, GBP-optimized, and AUD-optimized versions of its commonly used global Minimum Volatility indexes. In other words, its optimal minimum-volatility portfolio is different for investors with different base-currency perspectives. Alonso and Barnes (2017) empirically investigated this issue and found that optimizing toward a base-currency results in a very large bias toward the home market of the investor. The intuition behind this result is that investing in foreign markets is more risky than investing in the home market because in addition to share price volatility in the local currency, it also exposes the investor to exchange rate volatility. This currency risk is reduced by creating a home-market bias. However, this is probably not the most efficient way to deal with currency risk. Investors can also create a base-currency agnostic low-risk portfolio that only considers the risk of stocks measured in their local currency and use derivatives to directly hedge out any undesired foreign exchange rate risk.

Low-Risk Indexes: Beware of the Pitfalls

Low-risk investing is essentially active investing because one intentionally deviates from the capitalization-weighted market portfolio. Because the riskiness of stocks can change over time, low-risk investing is also not a buy-and-hold strategy but requires (at least some) turnover. Furthermore, a wide range of active choices is required, such as the choice of risk metric, choice of lookback period, choice of weighting rules, choice of rebalancing frequency, concentration limits on, for example, countries or sectors, and so on (see also Alighanbari, Doole, and Shankar 2016). For these reasons, there is no such a thing as a passive approach toward low-risk investing. Investors can choose to passively replicate a smart beta low-risk index, but this does not change the fact that the index itself is not passive in these cases. The main benefit of index-based low-risk investing is that it may be cheaper than an outright active approach because index replication typically involves lower management fees than active management. Investors also appreciate the transparency of low-risk indexes because the index methodology is fully specified and public.

However, there is also a flipside to these advantages. Although low-risk indexes can be suitable for tracking the hypothetical performance of a generic low-risk investment approach, they are less suitable for large-scale replication with real money. In particular, low-risk indexes tend to use simplistic rebalancing rules that are fine for back-testing purposes (i.e., on paper) but that are clearly suboptimal when it comes to actual money management. The popular MSCI Minimum Volatility indexes, for instance, conduct all their trades on just two days of the year, the last business day of May and the last business day of November. Blitz and Marchesini (2019) showed that this can easily result in trades that are 10 or even 100 times the average daily volume of the stocks in question, which implies high expected market impact costs and the risk of ending up in overcrowded positions. They argued that the larger the amount of money invested in a low-risk strategy, the more important it is to apply a trading strategy that makes efficient use of the liquidity that the market has to offer throughout the year. This means continuously trading in small amounts, rather than infrequently trading big chunks.

The full transparency of low-risk indexes is also a double-edged sword because it makes the investors in these strategies vulnerable to index arbitrage, which is a common strategy among hedge funds. The time gap between the announcement of the new index composition and the effectuation of these changes also offers opportunities for passive managers to game the index. By already buying stocks that enter the index between the announcement and effective dates, the more one pushes up the price of these stocks, the worse the price at which the index will buy the stock at the effective date. Huij and Kyosev (2016) empirically investigated the price effects of stocks entering and exiting during MSCI Minimum Volatility index rebalances and estimated a hidden cost to investors tracking these indexes amounting to about 16 bps per annum.

Low-Risk Can Be Combined Efficiently with Other Factors

There is a lot of evidence for the low-risk anomaly and for other factor premiums such as size, value, momentum, profitability, and investment. When setting up a low-risk investment strategy, investors need to decide whether to ignore or also do something with these other factors. Haugen and Baker (1996) developed a multifactor model that generates higher return than the market, with lower risk. Furthermore, Garcia-Feijóo et al. (2015) found that the performance of a low-risk strategy is higher when valuation levels are lower.

A concern may be that incorporating other factors into a low-risk strategy leads to a dilution of the amount of low-risk exposure and an increase in trading costs. van Vliet (2018) addressed these concerns and found that with just a little bit of additional trading, the exposure to other factors in a low-risk strategy can be increased sharply, especially when using negatively correlated factors such as value and momentum. Blitz and van Vliet (2018) showed that a multifactor strategy that uses three simple price-based metrics (36-month volatility, net payout yield, and 12-minus-1-month price momentum) is able to give investors simultaneous exposure to all major factor premiums. This conservative formula beats not only the market index by a wide margin but also a generic low-volatility approach and a wide range of other single-factor indexes. Thus, the low-risk anomaly lends itself well to combination with other factors.

Alighanbari, Doole, and Melas (2017) showed that environmental, social, and governance (ESG) factors can also be efficiently integrated into a low-risk strategy. For instance, they reported that improving the portfolio level ESG score by 30% comes at the cost of only a 0.5% increase in volatility.

THE LOW-RISK EFFECT IS NOT ARBITRAGED AWAY

The first dedicated low-risk products were introduced in the mid-2000s, but only after the global financial crisis of the late-2000s did investors begin to show serious interest in these products. Within the space of just a decade, low-risk investing has developed into a widely accepted investment style. The approach is so well known now that many investors are concerned it might become a victim of its own success. In this section, we look for tangible evidence that the low-risk effect is already in the process of being arbitraged away, in particular by investors in mutual funds, ETFs, and hedge funds, and find little justification for such concerns.

Mutual Funds—Typically on the Other Side

Falkenstein (1996) and Sias (1996) found that mutual funds have a negative exposure toward low-risk stocks. Beveratos et al. (2017) also found that mutual funds are tilted toward smaller stocks with higher volatility. Ang, Madhavan, and Sobcyzk (2017) examined the aggregate assets of all US active mutual funds since the late 1990s and found that that mutual funds have a consistently negative exposure toward low-volatility stocks. Although low-volatility investing became more popular during this period, mutual fund managers did not change their investment behavior and continued to underweight low-risk stocks. Christoffersen and Simutin (2017) argued that, in an effort to beat benchmarks, fund managers tend to increase their exposure to high-risk stocks, while aiming to maintain tracking errors around the benchmark. These results are consistent with the benchmark-relative objectives explanation for the low-risk anomaly discussed earlier. Altogether, it seems that mutual funds are more drawn toward high-risk stocks than toward low-risk stocks.

ETFs—On Aggregate Neutral on Low-Risk

One commonly heard concern with low-risk investing is that the sizable assets in dedicated low-risk ETFs currently may imply that the anomaly is rapidly being arbitraged away. Ang, Madhavan, and Sobcyzk (2017) reported that US$24 billion was invested in low-volatility ETFs at the end 2016. Blitz (2017) directly addressed this concern by examining the factor exposures of all US-listed ETFs investing in US equities. The study found that there are indeed quite a few ETFs that offer a large exposure to the low-risk factor. This includes dedicated low-risk ETFs, but also some high-dividend ETFs and some sector ETFs on typical low-risk sectors such as utilities. Many other ETFs, however, have a clear high-risk profile. This may not be evident to investors because, for obvious reasons, these ETFs are typically not marketed as high-risk funds. On aggregate, when all ETFs are lumped together into one big total portfolio, the sizable low-risk and sizable high-risk exposures, which are so strongly present at the individual fund level, almost perfectly cancel out. In other words, ETF investors have zero net exposure to low- and high-risk stocks. The conclusion of this analysis is that, although some ETF investors are targeting the low-risk anomaly, either explicitly or implicitly, just as many other ETF investors do precisely the opposite, and these two groups keep each other nicely in check. Based on these findings there is little cause for concern that ETF investors are arbitraging the low-risk anomaly away.

Hedge Funds—Typically on the Other Side

One can also wonder if hedge funds are perhaps exploiting the low-risk effect, especially if leverage and benchmark constraints are at the root of the anomaly. These constraints are much less of an issue for hedge funds because the flexibility to use leverage is one of the defining features of hedge funds and because hedge funds typically have an absolute-return objective. In other words, the limits to arbitrage that hamper many investors do not apply to hedge funds. Blitz (2018) investigated whether hedge funds are indeed exploiting the low-risk anomaly but found strong evidence for the exact opposite: Hedge funds have higher returns when high-risk stocks outperform low-risk stocks, instead of the other way around. These results suggest that, instead of arbitraging the low-risk anomaly away, hedge funds may actually be helping to create and sustain it. Put differently, hedge funds seem to be on the other side of the low-risk trade. Asness et al. (2015) also found that hedge funds are positioned against the low-risk anomaly. Perhaps hedge funds have a preference for high-risk stocks because their optionlike incentive structures reward risk-seeking behavior, as suggested by Baker and Haugen (2012).

Institutional Investors—Discouraged by Regulation

Other important market participants are institutional investors such as insurance companies, pension funds, and banks. Low-risk stocks are potentially very interesting for institutional investors because of their downside protection and liability-hedging properties. However, regulatory frameworks, such as Solvency II for insurance companies (and similar local regulation for pension funds) and Basel III for banks, do not incentivize low-risk investing; they require the same capital charges for low-risk stocks as for high-risk stocks. Swinkels et al. (2018) examined this issue in detail and argued that current regulation is sustaining the low-risk effect rather than encouraging investors to benefit from it.

CONCLUSION

In this article, we have reviewed the key insights into the low-risk (or low-volatility) effect. A low-risk approach has been effective for as far as the data go back, across all major stock markets, from developed to emerging, within and across industries, across various market regimes, and using different measures of risk. The effect is also present in other asset classes, such as corporate bonds. The low-risk effect is commonly attributed to the existence of leverage constraints, a focus on benchmark-relative instead of absolute performance, agency issues, skewness preference, and various behavioral biases. As with any other anomaly, only time will tell if the low-risk effect will persist going forward. The concern that the anomaly is already being rapidly arbitraged away by, for example, mutual funds, ETFs, or hedge funds, does not appear to be justified by the empirical evidence, which more often finds such investors to be on the other side of the low-risk trade.

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ADDITIONAL READING

Managing Risks Beyond Volatility

MEHDI ALIGHANBARI, STUART DOOLE, AND DIMITRIS MELAS

The Journal of Index Investing

https://jii.pm-research.com/content/8/2/68

ABSTRACT: *Minimum volatility strategies enjoy broad support in the academic literature and have been applied extensively by institutional investors to reduce portfolio volatility. In this article, the authors discuss how such strategies can adapt to address risks beyond price volatility. Specifically, concentration, sustainability, and crowding risks could be mitigated using appropriate but simple optimization constraints. However, adding a diversification constraint increased exposure to residual volatility and had a negative impact on risk reduction and risk-adjusted performance. In contrast, to help manage environmental, social, and governance (ESG) risks, adding a significant sustainability constraint had only a small effect on the risk reduction properties. Finally, introducing constraints on the value exposure ensured the market-relative valuations of the strategy remained attractive for only a small increase in realized volatility. The authors show that simple constraints could be used effectively in minimum volatility strategies to manage risks beyond volatility.*

Designing Low-Volatility Strategies

MEHDI ALIGHANBARI, STUART DOOLE, AND DURGA SHANKAR

The Journal of Index Investing

ABSTRACT: *Since the Global Financial Crisis hit in 2008, low volatility has garnered increased attention from institutional investors. In this article, the authors delve into the practicalities of low-volatility investing, including construction issues, their performance in different market regimes, and the effect of recent increased demand on the strategy's behavior. They discuss that although heuristic approaches tend to be simpler, only optimization-based approaches can take full advantage of the correlation between stocks. Constraints are essential in creating a well-behaved and investable low-volatility index. The authors show how different constraints can improve a minimum volatility strategy without having a significant impact on its volatility. Via attribution analyses, they analyze the sources of long-term outperformance of a minimum volatility index and discuss the valuation of minimum volatility indexes after the recent increases in demand and outperformance.*

What Is Missing in Common Minimum Volatility Strategies? *The Ignored Impact of Currency Risk*

NICK ALONSO AND MARK BARNES

The Journal of Index Investing

https://jii.pm-research.com/content/8/2/77

ABSTRACT: *Many investors that adopt minimum volatility strategies are inadvertently allowing unnecessary volatility in their minimum volatility allocations by ignoring the underlying currency assumptions used in building their portfolios. Specifically, portfolio country weights can vary widely depending on the currency used in calculating risk. In this article, the authors provide empirical evidence that the currency of the risk calculation should match the currency used in evaluating the portfolio's performance. In practice, many investors are well aware of the latter but unaware of the former, which can be embedded in commonly available benchmarks and investment vehicles. Any mismatch can lead to increased volatility.*