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Research

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When Equity Factors Drop Their Shorts

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Although factor premiums originate in both long and short legs of factor portfolios, we found that (1) most added value comes from the long legs, (2) the long legs offer more diversification than the short legs, and (3) the performance of the short legs is generally subsumed by that of the long legs. These results are robust over size, time, and markets and cannot be attributed to differences in tail risk. We also found that the claim that the value and low-risk factors are subsumed by the new (post-2015) Fama–French factors does not hold for the long legs of these factors.

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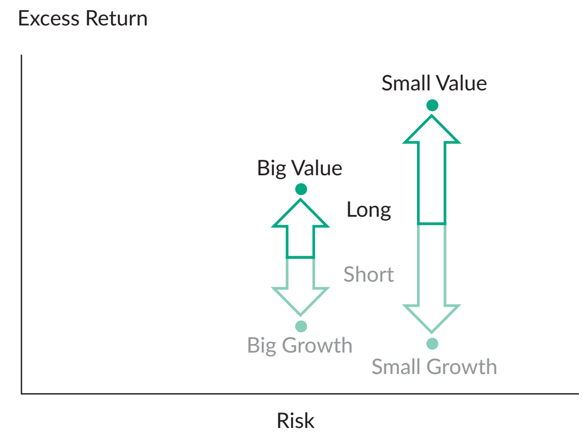
We examined the long and short sides of Fama–French factor portfolios and found that the added value of common factors is generally concentrated in the long legs. Evidence for the existence of various factor premiums in the equity market—such as the value, momentum, and low-risk premiums—is abundant.[1] Standard academic factor portfolios take hypothetical long positions in stocks with attractive characteristics and combine them with short positions in stocks with unattractive characteristics. Therefore, factor premiums can be disentangled into a long-leg premium and a short-leg premium. For example, the Fama and French (1993) value factor (high book-to-market stock minus low book-to-market stock, or HML) assumes long positions in large-capitalization (or "big") and small-capitalization value stocks combined with short positions in large- and small-cap growth stocks, as illustrated in **Figure 1**. In this way, the portfolio captures not only the outperformance of value stocks but also the underperformance of growth stocks. The Fama–French momentum factor (winners minus losers, or WML), profitability factor [robust (high) operating profitability minus weak (low) operating profitability, or RMW], and investment factor (companies that invest conservatively minus companies that invest aggressively, or CMA) are constructed by using the same approach, which ensures that factors are (more or less) orthogonal to the broad equity market and to the performance of small-cap versus large-cap stocks.

The long–short approach assumes that both legs contain information that is relevant for investor portfolios and for understanding asset prices. The legs may be subject to different dynamics and asset pricing implications, however. Numerous papers have made the argument that short selling faces constraints, which implies that mispricing on the side of overvaluation is considerably harder to correct than mispricing on the side of undervaluation; see, for example, Miller (1977). Similarly, Shleifer and Vishny (1997); Chen, Hong, and Stein (2002); and Stambaugh, Yu, and Yuan (2012, 2015) argued that factor premiums increase with limits to arbitrage, which are, arguably, more binding on the short side. Consequently, one might expect factor premiums to be stronger on the short side.

Figure 1. How Long Legs and Short Legs Are Constructed



Notes: In this illustration, the long leg is invested 50/50 in the large-cap and small-cap portfolios and hedges out the average of the large-cap growth and small-cap growth portfolios. The short leg mirrors the long leg.

Empirical studies have found that the importance of the long and short legs does, indeed, differ and that their relationship is not symmetrical. For instance, Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) found that extreme negative returns of the momentum factor are mainly driven by the short side, and Ang, Hodrick, Xing, and Zhang (2006) found that the idiosyncratic volatility anomaly is mostly a short-side phenomenon. Stambaugh et al. (2012) reported that abnormal returns were stronger for the short-leg portfolios for 11 anomalies selected in their study. Furthermore, Stambaugh et al. (2012) and Chu, Hirshleifer, and Ma (forthcoming) showed that short-sale constraints have an asymmetrical effect on the two legs of equity factor premiums.

In practice, shorting individual stocks is not without frictions. One consideration is that short positions involve additional costs—in particular, borrowing fees. Diether, Lee, and Werner (2009) found that short positions are significantly less liquid than long positions, with a typical short volume of about 24% for NYSE stocks and 31% for Nasdaq stocks. Investors also face various implementation hurdles because many stocks can be sold short only to a limited extent, other stocks cannot be shorted at all, and existing short positions may unexpectedly be recalled; see, for example, D'Avolio (2002) and Geczy, Musto, and Reed (2002). In addition, the stocks that are designated for shorting (i.e., the short legs) are typically the stocks that are harder and more expensive to short. For example, Drechsler and Drechsler (2016) found that shorting fees are more than three times higher than normal for the short leg of value, momentum, volatility-related, and profitability portfolios. They argued that anomalies disappear, in fact, for stocks with low lending fees. Beneish, Lee, and Nichols (2015) showed that the short returns of several accounting-based anomalies are attributable to hard-to-borrow stocks. Short selling also entails additional risks, such as (1) the potential for unlimited losses, (2) "short squeeze" scenarios (in which investors are unable to close their short positions), (3) counterparty risk, and (4) reputational risk (because the media can take a critical stance toward short sellers; see, for example, Angel and McCabe 2009). Finally, legal impediments to short selling may exist. For instance, many countries have either a partial or a full ban on short selling.

In light of these theoretical and practical considerations, we argue that examining the long and short dimensions of factor premiums separately is important for a proper understanding of factor premiums and how to build efficient factor portfolios. The issues involved with shorting individual stocks can be solved effectively by hedging the market beta of a long-only factor portfolio with liquid derivatives on broad market indexes. With this approach, one captures the performance of the long legs of factor premiums. The performance of the short legs can be isolated in a similar fashion—that is, by considering the short portfolio in combination with an offsetting long position in broad market indexes that brings the market beta to zero. How both legs contribute to factor premiums depends on the relative contribution of each leg to total performance and also on the correlation between the two legs.

Breaking down commonly studied equity factor premiums over the 1963–2018 period, we found that the long-minus-market approach has offered more value than the full-fledged long–short approach for individual factors and even more so for a multifactor combination. This key result is summarized in the first three bars in **Figure 2**. Factors can be harvested in both long legs and short legs with positive premiums. As Figure 2 shows, however, Sharpe ratios have been highest for the long legs of factors and lowest for the short legs. We found that a key driver of the higher risk-adjusted returns for long legs is that individual factors have close to zero correlation on their long sides while being positively correlated on their short sides. Consequently, long legs offer better diversification across factors. Further tests revealed that short legs typically have zero or negative alpha after controlling for the long legs. In contrast, long legs generally have a significantly positive alpha that cannot be explained by the short legs. Spanning and optimization tests show that short legs typically do not improve portfolios containing long legs. In other words, the dominant part of factor premiums is generally on the long side and the short legs of factor premiums are subsumed by their long-leg counterparts.

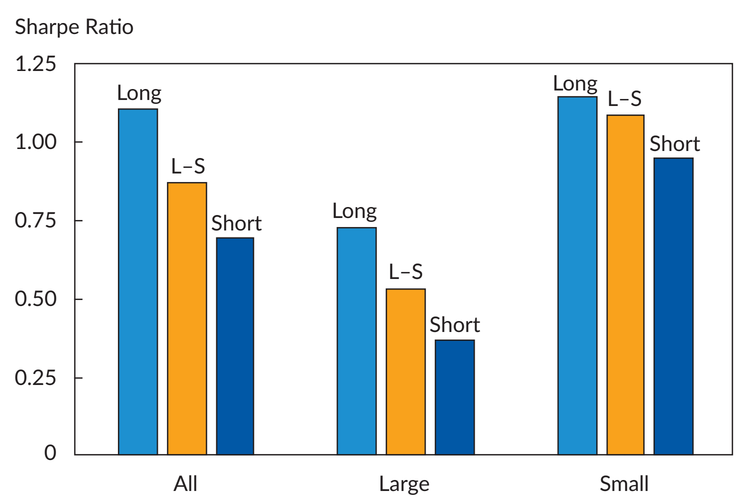
We also examined the role of size because limits to arbitrage are generally higher in small caps and many studies have shown that factor premiums tend to be larger in the small-cap space than in the large-cap (or "big" in Fama–French terms) space.[2]

We confirmed these authors' results, as summarized in Figure 2. Furthermore, we found that the long side of factor strategies exhibits stronger performance and subsumes the short legs both in the large-cap space and in the small-cap space. Moreover, starting from the long side of factors in the large-cap space, a bigger gain can be obtained by adding the long side in the small-cap space than by adding the short side in the large-cap space. Similarly, portfolio tests revealed that short legs are of limited value to most investors whereas long legs in small caps add significant value.

We found our results to be robust and consistent over time as to size considerations and in relation to a range of methodological choices. We also found similar results internationally—for various regions around the world and for global versions of the factor strategies. Moreover, the results cannot be explained by tail risk.

Our breakdown of factor strategies into their long and short legs also yielded new insights into the low-risk and value premiums. The low-risk premium, which was documented in Blitz and van Vliet (2007); Baker, Bradley, and Wurgler (2011); and Frazzini and Pedersen (2014), derives from the finding that low-risk stocks earn high risk-adjusted returns whereas high-risk stocks earn low risk-adjusted returns. The result is a significant alpha for low-risk stocks that is not explained by such classic factors as market, size, value, and momentum. Novy-Marx (2014) argued,

Figure 2. The Long and Short of Equity Factors, July 1963–December 2018



Note: Shown are the Sharpe ratios for the equal-weighted combinations of HML, WML, RMW, CMA, and VOL (low volatility vs. high volatility) factor portfolios, split per long leg ("Long"), long–short ("L–S"), and short leg ("Short") and for all stocks, large-cap stocks, and small-cap stocks.

however, that the low-risk premium is explained by the profitability factor introduced in Novy-Marx (2013). Similarly, Fama and French (2016) found that the low-risk premium is subsumed by their recently introduced profitability and investment factors. Early findings for the value factor premium have also come under attack. Fama and French (2015) showed that their classic value factor based on book-to-market ratios (HML) is rendered redundant by the new investment and profitability factors. Neither the Novy-Marx (2013, 2014) studies nor the Fama–French (2015) study made a distinction, however, between the long legs and the short legs of the low-risk and value factors.

Breaking down factor portfolios into their long and short legs, we found that the conclusions of Novy-Marx (2014) and Fama and French (2015, 2016) regarding the low-risk and value factors are entirely driven by the short sides of these strategies. The short sides of low risk and value are indeed subsumed by the other factors—in particular, (low) profitability and (high) investment. In other words, the poor performance of high-risk and growth stocks can be explained by their resemblance to "junk." The performance of the long sides of low-risk and value strategies cannot be explained, however, by the long sides of other factors, including (high) profitability and (low) investment. This asymmetrical result implies that low risk and value are distinct factors on the long side and that the long–short results for these factors are dominated by their different behavior on the short side.

For factor-based investors, our results indicate that because the short legs of Fama–French-style portfolios provide no unique alpha, an efficient approach to factor investing is simply to concentrate on the long legs and hedge out the market beta with liquid market index derivatives. However, we need to mention a couple of caveats here. First, investing in just the long legs gives only about half the raw return, so double the amount of gross leverage is needed to attain the original return level. Second, the impact of costs should be accounted for. Considering all relevant costs, however, we believe that our conclusions are unlikely to change fundamentally. Most important in this regard are the magnitude of shorting costs and the feasibility of shorting. Finally, we caution against overgeneralizing our conclusions. Our analysis was limited to the recognized academic factors and extended to the q-factors of Hou, Xue, and Zhang (2015); it does not necessarily carry over to the many other factors that have been proposed in the asset pricing literature or to portfolios optimized on individual stocks after accounting for various factor- and risk-based constraints.

Data and Methodology

Most of our data came from the online data library of Professor Kenneth French.[3] From that source, we obtained monthly returns for the 2×3 portfolios behind the value (HML), momentum (WML), profitability (RMW), and investment (CMA) factors for the US market for the period July 1963 through December 2018. We did not include the size factor in our analyses because it was already constructed in a long-minus-market fashion.

We augmented the Fama–French factors with a low volatility versus high volatility (VOL) factor, based on the work of Ang, Hodrick, Xing, and Zhang (2006); Blitz and van Vliet (2007); and many subsequent studies. For an overview, see Blitz, van Vliet, and Baltussen (2019). Inclusion of the VOL factor was inspired by the betting-against-beta (BAB) factor of Frazzini and Pedersen (2014), but our construction of it was closer to the Fama–French construction methodology to prevent the issues identified by Novy-Marx and Velikov (2018), who found that a large part of the BAB premium stems from dynamic hedging and shorting highly illiquid microcaps. Our choice to use volatility rather than beta had no material impact on our conclusions, as we discuss later.

The VOL factor is based on 2×3 portfolio sorts, like the other long–short Fama–French equity factors. Every month, we classified all stocks in the CRSP database as either large or small on the basis of the NYSE median market capitalization as the breakpoint. Next, we sorted stocks within the size groups on their past 36-month volatility, and we assigned them to low-, mid-, or high-risk portfolios on the basis of the NYSE 30th and 70th percentiles as breakpoints. We value-weighted all the portfolios, and each portfolio was levered up or down to a market beta of 1.0 to make the VOL factor market neutral.

For simplicity, we estimated full-sample market betas against the Fama–French market portfolio. (But note that the results did not change when we used a rolling-window estimate.) The 30-day T-bill rate is the borrowing and savings rate. This beta adjustment is our only departure from the standard Fama–French construction methodology. The VOL factor was created by taking a 50/50 long position in large-cap low-volatility and small-cap low-volatility stocks, combined with a 50/50 short position in large-cap high-volatility and small-cap high-volatility stocks. Data for this VOL factor are from Robeco (http://www.robeco.com/data).

Based on the underlying 2×3 portfolios, we were able to break down all long–short factors in two ways. One breakdown is into the large-cap and small-cap components. For the value factor, for example, the full-fledged long–short value strategy is the Fama–French HML portfolio, which is long 50% large-cap value (high book to price) and 50% small-cap value and short 50% large-cap growth and 50% small-cap growth (low book to price). The large-cap component is long the large-cap value portfolio and short the large-cap growth portfolio, and the small-cap component is long the small-cap value portfolio and short the small-cap growth portfolio. Note that a 50/50 combination of these large-cap and small-cap components yields the original HML factor.

Another breakdown of the standard long–short factors is into their long and short legs, where, again, we strove for consistency with the Fama–French methodology. For value as an example again, we constructed the long leg by going long the "high" component of the HML portfolio (i.e., 50% large-cap value and 50% small-cap value) and short a neutral hedging portfolio. For the short leg, we were short the "low" component of the HML portfolio (i.e., 50% large-cap growth and 50% small-cap growth) and long the same neutral hedging portfolio. Note that with the long and short legs defined in this way, taking the sum of the two legs yields the original HML factor. We used the same approach for the other factors. This approach is visually illustrated in Figure 1, where the top arrows represent the long leg and the bottom arrows, the short leg.

A natural candidate for the neutral hedging portfolio would be the cap-weighted market portfolio. With that choice, however, all the results would be distorted by the size effect because the long leg is 50% long in small-cap stocks and the short leg is 50% short in small-cap stocks. To prevent such size distortions, using the two components of the Fama and French (2015) SMB (small minus big) factor, we defined the neutral hedging portfolio as 50% large-cap stocks (Big) plus 50% small-cap stocks (Small). The Fama–French large-cap and small-cap portfolios are derived from the 2×3 size/value, 2×3 size/profitability, and 2×3 size/investment sorted portfolios, with the large-cap portfolio being the simple average of the nine large-cap stock portfolios and the small-cap portfolio being the simple average of the nine small-cap stock portfolios. With this choice for the neutral hedging portfolio, we ensured that all long and short legs would have a net zero exposure to large-cap and small-cap stocks. Although this process did not ensure exact size neutrality (because a factor strategy might prefer the larger or smaller stocks within the large-cap and small-cap universes), it produced a much better approximation than using the cap-weighted market portfolio. In a robustness analysis, we show that our conclusions remained unchanged when we made other choices for the neutral hedging portfolio. Note that, in practice, highly liquid and cost-efficient derivatives, such as S&P 500 and Russell 2000 index futures, can be used to hedge factor portfolios in a size-neutral fashion.

Throughout most of our analysis, we used Sharpe ratios—that is, volatility-adjusted returns—as the key evaluation metric. In unreported tests, we found similar results when we used alphas—that is, market-beta-adjusted returns—instead of Sharpe ratios. The intuition behind this similarity is that the *ex post* betas of our test portfolios are close to zero, which means that CAPM (capital asset pricing model) alphas are similar to raw returns. Thus, our Sharpe ratios can also be interpreted as Treynor and Black's (1973) appraisal ratios—that is, volatility-adjusted alphas—and when the (annualized) Sharpe ratios are multiplied by a constant (the square root of the number of years in our sample), they are approximately equal to the *t*-values of the alphas. For our 1963–2018 sample, therefore, a Sharpe ratio greater than 0.26 is statistically significant at the 5% level.

The Long and Short Sides of Factor Premiums

Panel A of **Table 1** shows the performance of the long legs of the five factors based on the standard Fama–French methodology. The individual Sharpe ratios range from 0.31 to 0.61, but for an equally weighted portfolio of the five long legs, the Sharpe ratio increases to 1.10 because of diversification. In Panel B of Table 1, the short legs of the five factors are shown. As was the case for the long legs, factor premiums are positive for the short legs. Furthermore, the magnitude of the factor returns is similar for the long and the short legs. That said, note that the short legs have a higher volatility than the long legs, causing three of the five factors (value, momentum, and investment) to have a lower Sharpe ratio on the short side than on the long side.

Table 1. Breakdown of Factor Premiums, July 1963–December 2018

	HML	WML	RMW	CMA	VOL	All
A. Long leg of factors						
Return (%)	2.1	3.6	1.0	1.6	3.7	2.4
Volatility (%)	5.3	5.9	3.3	3.2	6.9	2.2
Sharpe ratio	0.40	0.61	0.31	0.49	0.53	1.10
B. Short leg of factors						
Return (%)	1.8	4.4	2.1	1.8	2.7	2.5
Volatility (%)	4.8	9.5	4.8	4.6	4.9	3.7
Sharpe ratio	0.37	0.46	0.43	0.40	0.54	0.69
C. Long–short factors						
Return (%)	3.9	8.0	3.1	3.4	6.3	4.9
Volatility (%)	9.7	14.5	7.5	6.9	11.0	5.7
Sharpe ratio	0.40	0.55	0.41	0.49	0.58	0.86

Notes: All factors are market neutral. In Panels A and B, each leg is an equal 50/50 combination of the large-cap and small-cap portions, minus the market (50/50 Big/Small portfolios), to neutralize market and size tilts. Panel C is the sum of Panels A and B and the classical way of presenting long–short factors.

The short leg of the momentum factor exhibits particularly high volatility, consistent with the finding of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016) that momentum crashes stem from the short legs. For the two other factors (profitability and low risk), the short side appears to be a little stronger. When all five factors are combined (as in the last column), the long side—with a Sharpe ratio of 1.10 versus only 0.69 for the short side—clearly emerges as the winner. This result indicates that the long legs diversify much better than the short legs.

Panel C of Table 1 shows the combination of the long and short legs—that is, the standard long–short factors. The results are in between those in Panels A and B, with Sharpe ratios for the individual factors varying between 0.40 and 0.58 and a combined Sharpe ratio of 0.86.

Table A1 in Appendix A shows that these conclusions carry over to the q-factors (profitability and low investment) introduced by Hou et al. (2015); that is, the long legs of these factors also offer higher Sharpe ratios and better diversification than the short legs. In other words, factor premiums are in general more attractive on the long side.

Table 2, by reporting for each factor its average correlation with the other factors, provides insight into factor diversification on the long side versus on the short side. For example, value stocks (the long leg of HML) are shown to have an average correlation of 0.04 with the other long factor legs. In contrast, growth stocks (the short leg of HML) have an average correlation of 0.38 with the other short legs. In other words, growth stocks comove with risky/unprofitable/loser stocks whereas value

Table 2. Diversification Benefits of Factors: Correlations, July 1963–December 2018

	HML	WML	RMW	CMA	VOL	All
Long leg	0.04	−0.16	−0.09	−0.05	0.08	−0.04
Short leg	0.38	0.12	0.32	0.42	0.34	0.31
Long–short	0.26	−0.03	0.14	0.25	0.31	0.19

Note: Shown is the average pairwise correlation of each factor with the other factors for each leg and the long–short portfolio.

stocks are virtually uncorrelated with stable/profitable/winner stocks. The average correlation among all long legs is negative, −0.04; the corresponding number for the short legs is positive, 0.31. Thus, the diversification benefits of factors are asymmetrical. They are more powerful on the long side than on the short side.

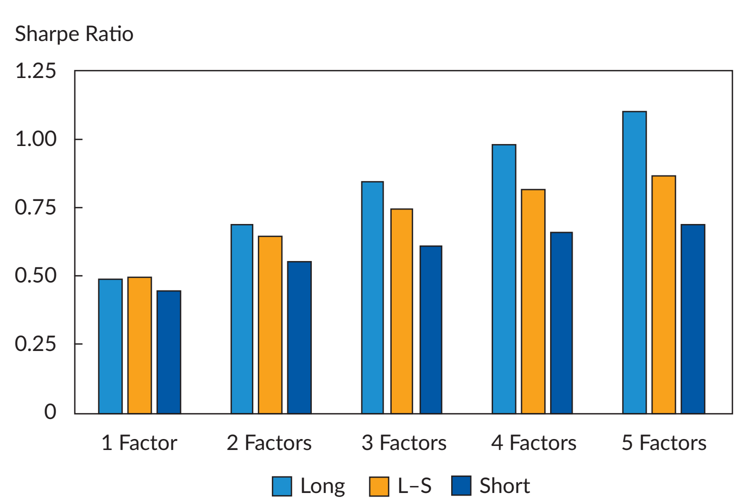
Although the 0.35 difference in correlation between long legs and short legs might not seem that large, it compounds to sizable risk-adjusted return differences when multiple factors are combined. **Figure 3** shows that the average Sharpe ratio for single factors is about 0.5, both on the long side and on the short side. When three factors are combined, however, the Sharpe ratio goes up to 0.8, on average, for the long legs versus only 0.6 for the short legs. This gap widens when all five factors are combined; the long portfolio reaches a Sharpe ratio of 1.1, but the ratio is less than 0.7 for the short portfolio.

The results so far indicate that because of lower correlations between the long legs of factors, factors are better rewarded on the long side than on the short side. Investors might still leave some performance on the table, however, by ignoring the short legs altogether. To address this concern, we directly examined the added value of factors on the long and short sides. We started by examining the correlations between the long and short legs, as shown in the top row of **Table 3**. Correlations are generally high, ranging between 0.59 and 0.85 for individual factors. The correlation increases to 0.87 for the multifactor combination, which also explains why, in Table 1, the volatilities of the long-leg portfolio (2.2%) and the short-leg portfolio (3.7%) almost fully add up to the volatility of the long–short portfolio (5.7%). These numbers show that the long legs and short legs offer closely related exposures, especially when factors are combined.

The question is, then, what do the long legs and short legs each contribute when the "other" leg has been controlled for? To find an answer, we separately regressed each individual factor leg on all flip-side legs. These tests examine the added value of long-leg and short-leg portfolios and have *t*-values that reflect the Treynor–Black (1973) appraisal ratio (see De Roon, Nijman, and Werker 2001). Specifically, in previous tests of Sharpe ratios, we compared the performance of different portfolios, whereas the regressions reported in Table 3 indicate the potential improvement in performance when one particular leg is included in the portfolio. The results, shown in Panel B, reveal that the alpha of the long leg of each factor is positive and mostly significant at the 5% level. In contrast, the alpha of each short leg ranges from nearly zero to significantly negative. In other words, none of the short-leg factor exposures adds significant value over the long legs.

Next, using a spanning test of all the intercepts jointly being nonnegative, following Gibbons, Ross, and Shanken (1989) and Kan and Zhou (2012), we tested whether the short legs (long legs) are jointly spanned by the other legs. The last column of Table 3 reveals that spanning cannot be rejected for the short legs. In other words, short-leg positions in the recognized factors do not improve the opportunity set of investors.

Figure 3. Diversification Benefits of Long Legs and Short Legs of Equity Factors, July 1963–December 2018



Note: Shown are the Sharpe ratios of the average portfolio over all possible single-factor and multiple-factor portfolios for 1-2-3-4-5 factor combinations.

Table 3. Added Value of Long Legs and Short Legs, July 1963–December 2018 (*t*-statistics in parentheses)

	HML	WML	RMW	CMA	VOL	All
A. Correlations between long and short leg	0.85	0.75	0.70	0.59	0.74	0.87
B. Alphas						
Long leg over short leg	0.70%	2.70%	0.51%	1.19%	0.39%	1.09%
	(1.82)	(6.44)	(2.21)	(3.83)	(0.76)	(7.44)
Short leg over long leg	−0.57%	−3.07%	−0.70%	−0.94%	0.15%	−1.00%
	(–1.86)	(–4.04)	(–2.07)	(–2.91)	(0.33)	(–3.89)
C. Maximum-Sharpe-ratio portfolio						
	HML	WML	RMW	CMA	VOL	Spanning Test *p*-Value
Weight of long leg	11.0%	23.7%	20.6%	31.0%	11.0%	0.00
Weight of short leg	0.0%	0.0%	0.0%	0.0%	2.6%	0.87

Notes: For the individual factors shown in Panel B, we regressed the long- or short-leg returns on the returns on the other factors of the opposite leg. For the combined factor portfolio, we regressed the returns of one leg on those of the other leg. Panel C shows the optimal weights in each of the 2×5 legs in the maximum-Sharpe-ratio portfolio, as well as the *p*-value of the spanning test of the long or short legs of the individual factors jointly being nonnegative.

We examined the robustness of this conclusion by constructing the maximum-Sharpe-ratio portfolio based on the 2×5 factor legs. The weights were required to be nonnegative and to sum to 100%. Panel C of Table 3 shows that the optimal portfolio, the one with the highest return per unit of risk, contains positions in each of the five long legs, with weights varying between 11.0% and 31.0%. In contrast, only 2.6% would be allocated to a single short leg (high volatility). When we included (in unreported tests) the equity market and/or bond market, the allocation to short legs dropped to zero. This finding provides confirmation that virtually none of the short sides of factors is able to offer any value on top of the performance that can be obtained by investing in just the long sides of factors. That said, keep in mind that these optimizations assume an investor can leverage to scale the maximum-Sharpe-ratio (or long-leg) portfolio to the desired risk level. For an investor facing leverage constraints, short legs could add more value than shown here because they offer higher volatility and higher return.

Finally, we regressed the long leg of the multifactor portfolio on its short leg and vice versa. In line with the preceding analyses, we found that the alpha of the long-leg portfolio—that is, the performance that remained after we adjusted for the exposures to the short-leg portfolio—was positive (1.09%) and statistically significant (*t*-statistic of 7.44). In contrast, the short-leg portfolio had a statistically significant negative alpha (–1.00%, *t*-statistic of –3.89). The explanation for this result is that the short legs had weaker performance than the long legs, and on top of that, they barely provided any diversification to the long legs.

All these tests show that the long-leg portfolio is superior to the short-leg portfolio and that nothing essential is lost by ignoring the short side of factors altogether. In a nutshell, the short legs are fully subsumed by the long legs and provide no added value whatsoever.

Factor Premiums in Large Caps and Small Caps

Many studies show that factor premiums tend to be larger in small-cap stocks than in large-cap stocks.[4] A possible mechanism for the difference is limits to arbitrage, which are generally higher in small caps. Factor premiums are thought to increase with limits to arbitrage. Consequently, size is an important dimension in factor premiums. This issue is addressed in the standard academic factors, such as HML, by averaging over a large-cap leg and a small-cap leg to mitigate potential size effects. Thus, the standard factors can be broken down not only into long and short legs but also into large-cap and small-cap components. In this section, we examine these large-cap and small-cap parts of factors separately.

Table 4 contains the results. Consistent with the literature, we found that factor performance is generally stronger among small caps than among large caps. Panel A shows a higher Sharpe ratio in the small-cap space than in the large-cap space. The equally weighted portfolio of the five factors has a Sharpe ratio of 1.08 in the small-cap space versus just 0.53 in the large-cap space. The long legs of the five factors have a higher combined Sharpe ratio than the short legs for both large caps and small caps. For large caps, the Sharpe ratio is 0.72 versus 0.36; for small caps, it is 1.13 versus 0.94. In both size segments, the correlations between the long legs are lower than the correlations between the short legs. The Panel B regression of the long legs on the short legs again shows a significantly positive alpha for the long legs. In contrast, neither short leg displays a significant positive alpha. As previously, spanning tests of the large-cap and small-cap multifactor portfolios reveal that spanning cannot be rejected for the short legs.

To examine whether the small-cap short legs perhaps still contain some unique alpha, we again optimized for the maximum-Sharpe-ratio portfolio. Panel C of Table 4 shows that most weight is allocated to the long legs—17.8% for large caps and 64.9% for small

Table 4. Small Caps vs. Large Caps, July 1963–December 2018 (*t*-statistics in parentheses)

	Long Leg	Short Leg	Long–Short
A. Sharpe ratios			
Large caps	0.72	0.36	0.53
Small caps	1.13	0.94	1.08
All caps	1.10	0.69	0.86

B. Alphas and spanning

	Long Leg		Short Leg	
	Large Caps	Small Caps	Large Caps	Small Caps
Alpha over other legs	0.67%	1.24%	–1.95%	–0.04%
	(3.11)	(5.18)	(–5.68)	(–0.15)
Spanning (*p*-value)	0.00		0.84	

C. Maximum-Sharpe-ratio portfolio

	Long Leg		Short Leg	
	Large Caps	Small Caps	Large Caps	Small Caps
Large caps (5×2 portfolios)	97.5%	—	2.5%	—
Small caps (5×2 portfolios)	—	74.8%	—	25.2%
All caps (5×2×2 portfolios)	17.8%	64.9%	0.0%	17.4%

Notes: In Panel B, the *p*-value is for the spanning test of either the long or short legs jointly being non-negative. Panel C shows the optimal weights in the maximum-Sharpe-ratio portfolio when each factor is considered individually.

caps. The remaining weight, 17.4%, is concentrated in the small-cap short legs of investment and volatility. For small caps only, the optimal allocation to the short legs becomes 25.2%. Thus, short legs are able to add some value after all, but only in the small-cap space. That space is also, however, where limits to arbitrage are most prevalent. Shorting small-cap stocks can be particularly expensive and is difficult, if not impossible, to implement on a large scale, as we discuss in the section "The Role of Costs and Investment Frictions." When we optimized only over large caps, the allocation to the short legs dwindled to a mere 2.5%, in line with our base-case results in the previous section.

Robustness Tests

In this section, we analyze how the results reported so far varied when we considered different time frames, whether the results proved to be robust to the choice of the neutral hedging portfolio, and whether the results were robust to using more granular (5×5) sorts for the portfolios. We also examine asymmetrical risk measures and consider whether our results carry over to international markets.

Subsample Results. We conducted a decade-by-decade analysis. Panel A of **Figure A1** shows the Sharpe ratios of the combined five long legs and the combined five short legs for six subperiods. In each of the subperiods, the long legs have higher Sharpe ratios than the short legs, indicating that our main result is highly robust over time. The magnitude of the difference varies—being smaller in the 1970s and 2000s and bigger in the 1960s and 2010s—but without any clear trend over time. Panel B of Figure A1 shows the *t*-values of the alphas of the long (short) portfolio regressed on the short (long) portfolio. Confirming our full-sample results, the added value of the long legs is consistently positive and significant while the short legs consistently do not add alpha over the long legs.

To further examine the dynamics between the long and short legs, we plotted the 10-year rolling correlation of each long and short leg. The resulting plot is shown in **Figure A2**.

Correlations between the legs, which were high throughout our sample period, vary between 68% and 93% in Figure A2. We also examined the alpha of the long legs over the short legs, and vice versa, for the same 10-year rolling subperiods. **Figure A3** reports the resulting *t*-values of the alphas for the multifactor portfolios. The alpha of long legs over short legs is consistent over time; the short legs fail to display significant added value in every 10-year subperiod. In other words, these dynamics suggest no specific episodes in which short legs dominated.

Choice of Hedging Portfolio. We also examined the robustness of our results to the choice of hedging portfolio. Our base-case definition of the hedging portfolio was 50% large-cap stocks (Big) plus 50% small-cap stocks (Small), where the Big and Small portfolios are the same as in the Fama and French (2015) SMB size factor. Our first alternative was to define the hedging portfolio as a 50/50 mix of the two "neutral" portfolios in the standard 2×3 sorts. Taking the value factor as an example, the process was to hedge the long leg, which consisted of 50% large-cap value (top 30% based on book-to-market data) and 50% small-cap value, with 50% large-cap neutral (the middle 40% of stocks based on book-to-market data) and 50% small-cap neutral. For the short leg, which consisted of 50/50 short positions in large-cap growth and small-cap growth (bottom 30% based on book-to-market data), we took an offsetting 50/50 long position in the same two neutral portfolios.

Panels A and B of **Table A2** report the Sharpe ratios for our base-case approach and the alternative hedging approach just described. The alternative hedge leads to lower Sharpe ratios for both the long legs and the short legs, but the multifactor short portfolio is hit harder than the multifactor long portfolio. As a result, our conclusion that the long side of factor premiums dominates the short side remains unchanged—actually, is strengthened.

In another robustness test, we departed from the standard 2×3 Fama–French construction methodology, which gives a disproportionately high weight to small-cap stocks. Following Cremers, Petajisto, and Zitzewitz (2013), we considered factor portfolios that were fully market-cap weighted. Taking the value factor as an example again, the process resulted in the long leg consisting of a cap-weighted long position in the top 30% of stocks measured by book-to-market ratio across the full universe. The short leg took a cap-weighted short position in the bottom 30% of stocks by book-to-market ratio across the full universe. For the hedging portfolio, we considered two alternatives—namely, (1) the cap-weighted market portfolio and (2) the neutral portfolio for the factor under consideration (i.e., for the value factor, the cap-weighted middle 40% of stocks by book-to-market ratio across the full universe). The results of these tests are reported in Panels C and D of Table A2. The cap-weighted factor portfolios produced lower Sharpe ratios across the board, as expected on the basis of our earlier finding that factors are stronger in the small-cap space. The short legs of the value and investment factors were hit particularly hard by the alternative methodologies; they barely remain positive. When we compare the performance of the multifactor long and short portfolios, our conclusions remain unchanged. If anything, the performance gap seems to widen a little; the multifactor long portfolios exhibit Sharpe ratios that are approximately double those of the multifactor short portfolios.

In summary, the test results in Table A2 show that our conclusions are robust to methodological choices regarding the neutral hedging portfolio and factor portfolio weighting.

Results for 5×5 Portfolios. The standard 2×3 Fama–French construction methodology splits the investment universe into two parts on the basis of equity market capitalization (size). This methodology mitigates a potential size bias in factor portfolios, but second-order size effects may still arise within these two segments. For instance, the value factor tends to go long the smaller stocks within each of the two segments, whereas the profitability and low-risk factors tend to go long the larger stocks. For the momentum factor, the preference for large or small stocks is highly time varying. Regressing the multifactor long- and short-leg returns on the SMB factor (results not tabulated), we observed *ex post* factor loadings on SMB amounting to –0.04 for the long legs and –0.09 for the short legs.

To further control for the effect of size, and also to examine the robustness of our results to more methodological choices, we repeated our main tests on more granular, 5×5 portfolios sorted on the size factor. For the value, profitability, investment, and momentum factors, the data are from French's data library, and we followed the same methodology to construct the low-risk factor. So, every month, we independently double-sorted all stocks on size and past 36-month volatility; we used NYSE breakpoints for the five size quintiles and the five volatility quintiles. For each factor, we created long and short legs within each of the five size buckets. A long leg is the top quintile in a size bucket minus the average of the five quintiles in that size bucket, and the short leg is the average of the five quintiles in the size bucket minus the bottom quintile.

The Sharpe ratios for the 5×5 approach are summarized in **Table A3**. In line with our previous findings, we observe that the general effectiveness of factors increases as the size segment becomes smaller. Performance is strongest among microcap stocks. This result is consistent with the existing literature and also with the results shown in Table 4. In each of the five size segments, the combined Sharpe ratio for the long legs is higher than that for the short legs; the long–short Sharpe ratios are in between. Although microcaps provided the highest risk-adjusted returns, the lack of diversification among the short legs of the factors in the microcap segment is striking. The individual microcap short legs have high individual Sharpe ratios, but the combined short portfolio has only a slightly better performance, which indicates considerable overlap in the microcap short-leg portfolios. In contrast, the long legs have lower individual Sharpe ratios, but the combined long portfolio has by far the highest Sharpe ratio. Overall, our results for the 5×5 portfolios are in line with our base-case results for the 2×3 portfolios: The long legs are superior to the short legs, and adding the short legs to the long legs merely detracts from risk-adjusted performance.

We further examined the attractiveness of the long legs versus the short legs by using mean–variance optimization. In Panel A of **Table A4,** we show results for maximum-Sharpe-ratio portfolios within each of the five size buckets separately. We observe that among the largest (megacap) stocks, the optimal portfolio consists almost exclusively (97.6%) of long legs. As we descend into smaller-cap buckets, the short legs become more attractive. In the microcap space, the optimal portfolio has 46.1% of its weight in short legs. Panel B of Table A4 shows the results for portfolios optimized on the long and short legs of the top two size buckets, the top three size buckets, and so forth. Here, we also see that most of the weight is allocated to long legs but short legs increasingly make it into the optimal portfolio as smaller-cap buckets are added. When all long and short legs from all size buckets are included, 32.4% of the weight goes to short legs, mostly (28.2%) in the microcap space.

The main takeaway from Table A4 is that the long legs generally dominate the short legs but that among the smallest stocks in the universe, the short legs offer some unique added value. These short positions are concentrated in microcap stocks with poor profitability, high investment, and high risk. This result is consistent with the finding of Fama and French (2015) that, although their five-factor model generally does a good job, it fails to explain the exceptionally low return of microcap junk stocks—that is, very small risky stocks with low profitability and aggressive investment. Unfortunately, these stocks are precisely the kind of short positions that are most difficult and most expensive to take on in reality. We discuss costs and feasibility further in the section on practical implications, "The Role of Costs and Investment Frictions."

Asymmetrical Risk Measures. A potential explanation of the results so far might be that risks are asymmetrical. (For this argument, see, for example, Bawa and Lindenberg 1977 or, for a more recent example, Ang, Chen, and Xing 2006.) In other words, the long legs may be less attractive than the short legs from a tail-risk perspective. In light of these concerns, we examined tail risk, measured in terms of cumulative drawdowns, of the long and short legs over time. **Figure A4** shows that the long legs exhibited a consistently lower drawdown risk than the short legs. The short legs were often twice as risky as the long legs and experienced significantly deeper drawdowns.

An explanation for Figure A4 may be that factor performance was generally weak during the dot-com bubble of the late 1990s, but the losses on the short legs (risky, unprofitable, growth stocks) exceeded the losses on the long legs (stable, profitable, value stocks). Also, in the aftermath of the global financial crisis of 2007–2009, most factors underperformed; the momentum factor performed particularly poorly. Again, however, the losses of the short legs were up to three times larger than the losses of the long legs in 2009. In other words, when factors fail, the short legs tend to be hit harder. These results are consistent with those of Daniel and Moskowitz (2016), who found that the momentum factor is vulnerable to crash risk and that this risk mainly arises from the short side of the factor.

Table A5 reports various nonsymmetrical risk statistics for the multifactor combination of the long and short legs, thereby providing additional confirmation of this result. The short legs exhibit a more negative skewness and a higher excess kurtosis than the long legs. They also have a higher semi-deviation (2.4% vs. 1.3%) and a much higher 95% VAR (value at risk). Some of this downside risk is idiosyncratic, but the systematic contribution to downside risk is also higher for short legs, as shown by the higher downside betas. Ang, Chen, and Xing (2006) showed that a lower-partial-moment (LPM) (0) beta provides a better description of the risk and return of stocks than does standard deviation. Lettau, Maggiori, and Weber (2014) used LPM (1 sigma) beta to understand the risk/return relationship in currency and other markets. Although Levi and Welch (2020) showed that downside risk measures are not always better than standard deviation in predicting downside risk, downside risk measures are still useful for evaluating the risk of a particular strategy. The downside betas of the short legs are, at best, slightly lower than those of the long legs, but the differences are tiny.

In summary, a downside risk perspective seems unlikely to explain the finding that the long side of factors dominates the short side.

International Evidence. Several papers have documented the existence of factor premiums in international samples.[5] To examine the robustness of our findings, we considered the international evidence. We followed the same testing approach as previously but applied it to the international 2×3 portfolios from French's data library, and we used the volatility factor from Hanauer and Windmueller (2019). We considered four regions (North America, Europe, Japan, Asia ex Japan), similarly to Fama and French (2012), and a global portfolio. We studied the maximum available sample period, July 1990–December 2018. **Table 5** shows the results. Consistent with our findings for the United States, we found that for North America, Europe, Asia ex Japan, and the global portfolio, the long legs tend to have higher Sharpe ratios than the short legs. Only for Japan do the short legs appear to be slightly stronger than the long legs. In the global sample, for example, the long legs have a Sharpe ratio of 1.19 versus 0.66 for the short legs. For this sample, the correlation between the long and short legs is 0.80, indicating very similar exposures and warning that limited diversification is possible between long legs and short legs. Furthermore, the long legs consistently have positive alphas (i.e., add value over the short legs) in all the portfolios, whereas the reverse does not hold true. For example, the alpha of the global long legs is significantly positive (1.56%, *t*-statistic of 5.75) and cannot be explained by the short legs; the short alpha of the global portfolio is significantly negative (–0.89%, *t*-statistic of –2.37),

Table 5. International Results, July 1990–December 2018 (*t*-statistics in parentheses)

	North America	Europe	Japan	Asia ex Japan	Global
A. Annualized Sharpe ratio					
Long leg	0.88	1.19	0.33	1.10	1.19
Short leg	0.50	0.92	0.35	0.99	0.66
Long–short	0.69	1.12	0.39	1.14	0.94
B. Alphas					
Alpha long leg over short leg	1.44	1.21	0.39	1.28	1.56
	(5.14)	(3.91)	(0.89)	(3.02)	(5.75)
Alpha short leg over long leg	–1.15	0.11	0.53	0.86	–0.89
	(–3.34)	(0.28)	(1.12)	(1.76)	(–2.37)

Note: All factors are market neutral.

which is, again, in line with the results for the US market.

The global results are also consistent over time. Panel A of **Figure A5** shows that in each of three subperiods (i.e., decades) in our sample, the long legs have higher Sharpe ratios than the short legs. Similarly, Panel B of Figure A5 shows that the long legs add consistent alpha over the short legs during each decade in the international sample, while short legs consistently do not add alpha over the long legs. In summary, the long legs of factors dominate the short legs also in international markets.

Asset Pricing Implications

We investigated the asset pricing implications of our findings. Recent studies (e.g., Fama and French 2015) have argued that the value and low-risk factors are subsumed by the new Fama–French factors—profitability and investment. We found, however, that the results reported in these studies are entirely driven by the short legs of these factors. The long legs of the value and low-risk factors offer distinct premiums that cannot be explained by the long legs of other factors.

Growth Is Junk, but Value Is Not Quality.

Fama and French (2015) found that their classic value factor (HML) is rendered redundant by the profitability and investment factors in their five-factor model. We reevaluated this result in light of our findings that factor premiums predominantly originate on the long side and that correlations of HML with the other factors are materially lower on the long side (0.04) than on the short side (0.38) or in the long–short combination (0.26; see Table 2). In our tests, we followed Fama and French (2015) by using a time-series regressions approach. Panel A of **Table 6** shows that the value factor had a highly significant CAPM alpha over the 1963–2018 period. The multifactor regressions reveal that this alpha, 4.91%, did, indeed, fall to an insignificant −0.13% when we controlled for the loadings of HML on the other four factors that nowadays compose the Fama–French five-factor model. The biggest hit came from a very high loading on the CMA (investment) factor, which has a coefficient close to 1.0 and an associated *t*-statistic greater than 20. This finding is robust to adding WML (momentum) and VOL as additional control factors.

Our breakdown of factors into their long and short sides enabled us to provide a fresh perspective on the HML factor. Panel B of Table 6 shows that the alpha of the long leg of HML remained strong (+1.98%) and highly significant when we controlled for the long legs of all other Fama–French factors. One reason for this result is that the loading on the CMA factor became much lower than it had been, and another reason is that the loading on RMW went from positive to negative. Panel C of Table 6 shows the results for the short leg (growth part) of HML. For this short leg, the alpha vanished completely (−0.22%) after we adjusted for exposure to the short sides of other factors. Especially significant was the exposure to the short leg of CMA (that is, aggressive

Table 6. HML and Long versus Short Legs (*t*-statistics in parentheses)

	Alpha	Mkt – Rf	SMB	RMW	CMA	WML	VOL
A. HML							
CAPM	4.91%	–0.16					
	(3.87)	(–6.88)					
Four factors	–0.13%	0.02	0.03	0.14	1.00		
	(–0.13)	(1.00)	(1.08)	(3.50)	(23.66)		
Six factors	0.66%	–0.07	0.11	–0.03	0.76	–0.11	0.28
	(0.73)	(–3.42)	(4.08)	(–0.67)	(16.64)	(–6.63)	(8.99)

B. Long leg (value)

	Alpha	Mkt – Rf	SMB	Robust	Conservative	Winner	Low Volatility
CAPM	2.49%	–0.06					
	(3.51)	(–4.52)					
Four factors	1.98%	–0.05	0.00	–0.23	0.44		
	(2.89)	(–3.64)	(–0.14)	(–3.60)	(6.39)		
Six factors	1.21%	–0.04	0.10	–0.32	0.31	–0.16	0.35
	(2.00)	(–3.78)	(5.65)	(–5.49)	(5.19)	(–5.20)	(12.44)

C. Short leg (growth)

	Alpha	Mkt – Rf	SMB	Weak Operating Profitability	Aggressive Investment	Momentum Loser	High Volatility
CAPM	2.41%	–0.10					
	(3.98)	(–9.08)					
Four factors	–0.22%	0.03	0.02	0.06	0.90		
	(–0.59)	(3.80)	(1.54)	(2.26)	(34.25)		
Six factors	0.11%	0.00	0.02	0.03	0.85	–0.06	0.09
	(0.31)	(0.31)	(1.87)	(1.11)	(27.51)	(–5.39)	(2.93)

D. Subperiods

	1963–1990			1991–2018		
	HML	Long	Short	HML	Long	Short
CAPM alpha	6.12%	3.36%	2.76%	3.48%	1.44%	2.04%
	(3.82)	(3.75)	(3.54)	(1.78)	(1.36)	(2.15)
Four-factor alpha	2.76%	3.24%	0.24%	–2.52%	0.60%	–0.84%
	(2.31)	(4.43)	(0.47)	(–1.76)	(0.50)	(–1.56)
Six-factor alpha	1.80%	1.80%	0.48%	–1.20%	0.12%	–0.36%
	(1.49)	(2.43)	(0.88)	(–0.91)	(0.11)	(–0.73)

Notes: The sample period for Panels A–C is July 1963–December 2018. Mkt – Rf is exposure to the market: the market return minus the risk-free rate. Panel A shows the long–short results for HML (value), Panel B shows the long leg (value) results, and Panel C shows the short leg (growth) results. Panel D shows the robustness of the tests in the subsample periods: July 1963–December 1990 and January 1991–December 2018.

investment), with a *t*-statistic greater than 30. Again, this result is robust to adding the WML and VOL factors to the analysis, as shown in the six-factor findings in Panel C.

In other words, the poor performance of growth stocks can be fully explained by their resemblance to junk, but the strong performance of value stocks cannot be attributed to quality characteristics. Thus, value is not the simple inverse of growth. Altogether, we found that the finding of Fama and French (2015) is entirely driven by the short leg of HML and that their conclusions do not hold for the long leg of HML. The long side of value holds its ground as a distinct factor that is not subsumed by the long sides of other factors.

To examine the robustness of our findings, we repeated all tests we had carried out for the full sample period in subperiods, July 1963–December 1990 and January 1991–December 2018. The first subperiod is the exact same period that was used in the seminal Fama and French (1992) study. Panel D of Table 6 shows the corresponding alphas and *t*-statistics. Recall that for the full sample, we found that, although the standard value premium was explained by the new Fama–French factors, the long side of the value premium was *not* explained by the long sides of the other factors. As Panel D shows, for the first subperiod, the standard value premium remained significant after we controlled for the other Fama–French factors. This result is, again, fully driven by the long leg; the short leg is subsumed by the short legs of the other factors. In the second subperiod, the raw value premium is not even significant. The long side again appears to be stronger than the short side, but both were not significantly different from zero during this period. These results imply that if the value premium manifests itself, the unique alpha is coming from the long side but if the value premium does not materialize, the investor does not have much left to salvage.

High Risk Is Junk, but Low Risk Is Not Quality. Novy-Marx (2014) found that the low-risk anomaly is subsumed by the profitability factor of Novy-Marx (2013). In a similar spirit, Fama and French (2016) found that the low-risk anomaly is explained by the five-factor model that includes the profitability and investment factors. We reevaluated this result in light of our finding that factor premiums tend to be stronger and less correlated on the long side.

Similarly to our analysis for value, we separately considered the long and short legs of the VOL (low volatility) factor and used time-series regressions for the evaluation. Panel A of **Table 7** shows that the highly significant CAPM alpha of the long–short volatility factor fell to 0.58% when we controlled for exposure to the current Fama–French factors—because of, in particular, highly significant loadings on the RMW (profitability), CMA (investment), and HML (value) factors. As we found for HML, a different picture emerged when we broke down the VOL factor into its long and short legs and analyzed low risk and high risk separately.

Panels B and C of Table 7 show that low risk and high risk each have a highly significant CAPM alpha, with *t*-statistics greater than 3. Panel B shows that, although the alpha of the long leg of the volatility factor became somewhat smaller when we controlled for the long legs of the other Fama–French factors, it remained highly significant. The main reasons are that the loading on the long leg of the CMA factor (conservative) became small and insignificant and that the loading on RMW hurt less because the RMW premium was rather small on the long side (1.0%; see Table 1). For the short leg of the volatility factor, however, the alpha vanished completely and even turned negative after we adjusted for exposure to the short sides of other factors, as shown in Panel C of Table 7. A high-volatility portfolio loads heavily on the short legs of the RMW, CMA, and WML factors.

As noted previously, high-risk stocks perform like junk but the performance of low-risk stocks cannot be attributed to "quality" features of these stocks. These results held when we dropped momentum from the regression. We carried out this same analysis but used BETA instead of VOL (as reported in **Table A6**) and found that, although the alphas were generally lower for the BETA factor, a similar asymmetry occurred between the long-leg and short-leg results.

Novy-Marx (2014) observed that the high-risk portfolio is strongly tilted toward small and unprofitable growth companies, and our results confirm this finding. The long–short results are fully driven, however, by this relationship on only the short side of the factor. The long-leg results show a completely different picture. Put differently, the *high-risk* anomaly may not be a distinct phenomenon, but the time-series regression indicates that the *low-risk* anomaly is. Cross-sectional (Fama and MacBeth 1973)

Table 7. Volatility and Long Legs vs. Short Legs (*t*-statistics in parentheses)

	Alpha	Mkt – Rf	SMB	HML	RMW	CMA	WML
A. VOL							
CAPM	6.35%	0.00					
	(4.26)	(0.00)					
Six factors	0.58%	0.26	−0.28	0.40	0.60	0.40	0.03
	(0.54)	(11.72)	(−9.14)	(8.99)	(13.95)	(6.36)	(1.22)

B. Long (low volatility)

	Alpha	Mkt – Rf	SMB	High Book Value	Robust Operating Profitability	Conservative Investment	Momentum Winner
CAPM	4.10%	−0.07					
	(4.46)	(−4.05)					
Six factors	3.12%	0.02	−0.24	0.54	0.53	0.07	−0.19
	(4.16)	(1.30)	(−11.50)	(12.44)	(7.54)	(0.94)	(−5.08)

C. Short (high volatility)

	Alpha	Mkt – Rf	SMB	Low Book Value	Weak Operating Profitability	Aggressive Investment	Momentum Loser
CAPM	2.24%	0.07					
	(3.46)	(5.75)					
Six factors	−0.82%	0.22	−0.05	0.14	0.40	0.42	0.11
	(−1.87)	(21.71)	(−3.97)	(2.93)	(13.10)	(7.78)	(7.53)

D. Subperiods

	1963–1990			1991–2018		
	VOL	Long	Short	VOL	Long	Short
CAPM alpha	6.12%	3.48%	2.64%	7.20%	5.04%	2.16%
	(3.76)	(3.26)	(3.92)	(2.96)	(3.43)	(1.98)
Six-factor alpha	4.20%	4.56%	0.96%	−0.48%	3.00%	−1.68%
	(3.10)	(5.26)	(1.64)	(−0.30)	(2.61)	(−2.37)

Notes: Panels A–C are for the full July 1963–December 2018 period. Panel A shows the long–short results for VOL, Panel B shows the long leg (low volatility) results, and Panel C shows the short leg (high volatility) results. Panel D shows the robustness of the results in the subsample periods: July 1963–December 1990 and January 1991–December 2018.

regressions also support the notion that low risk is a distinct factor not explained by the five-factor model (see Blitz and Vidojevic 2017).

To examine the robustness of our findings, we repeated all the tests for the July 1963–December 1990 subperiod and the January 1991–December 2018 subperiod. Panel D of Table 7 shows the corresponding alphas and *t*-statistics. The results for the low-risk factor are very robust for both subsamples. In the first subperiod, the standard low-risk factor is not even explained by the Fama–French factors;

the unique alpha comes from the long side. In the second subperiod, the standard factor is explained, but the long side remains unexplained. Thus, the long side of the low-risk factor offers a consistent unique alpha.

The Role of Costs and Investment Frictions

Our results show that the long side of factor premiums offers stronger risk-adjusted returns than the short side, but that conclusion comes before considering the impact of transaction costs, shorting costs, and other implementation frictions. In this section, we discuss whether costs and frictions might lead to different conclusions. The challenge in such an analysis is that gauging exact transaction and shorting costs is hard over a sample period that spans more than half a century. Moreover, transaction costs and shorting costs are investor specific. That said, several recent studies have extensively analyzed real-life transaction costs. Novy-Marx and Velikov (2016), studying the transaction costs of trading anomalies, found that since 1963, following an SMB strategy costs 5.66 basis points (bps) per month; HML, 5.45 bps; and WML, 48.4 bps. Furthermore, Novy-Marx and Velikov (2019) showed that costs for trading anomalies in small-cap stocks are approximately double the costs for trading anomalies in large-cap stocks. In addition, Novy-Marx and Velikov (2016) showed that the average trading costs are higher for high-volatility stocks and small-cap stocks.

These studies typically focused on (effective) bid–ask spreads—that is, costs that resemble what the average investor would pay. Frazzini, Israel, and Moskowitz (2018) challenged these estimates by showing that real-life trading costs are substantially lower for sophisticated institutional investors, who operate as arbitrageurs or "factor investors" in markets. Frazzini et al. estimated average transaction costs at 10 bps for large-cap stocks and 20 bps for small-cap stocks, regardless of whether the trade is a buy or a short sell.

Because most stocks in our study were held, on average, for more than a year (the exception being stocks involved in a momentum factor strategy), the general impact of trading costs on the factor premiums we studied would have been limited. Furthermore, the added value of the long legs in small-cap stocks can be expected to exceed transaction costs.

Short legs also involve shorting costs, of course, as well as severe practical limitations historically. Shorting is not always feasible because of unreasonably high shorting costs or insufficient volume availability. Several studies have revealed that shorting costs can be substantial. Using data from an institutional lender in a sample covering the 2000–01 period, D'Avolio (2002) found that the cost of borrowing a value-weighted loan portfolio in that period was 25 bps a year. Kolasinski, Reed, and Ringgenberg (2013) found annual costs generally above 100 bps between 2003 and 2007. Porras Prado, Saffi, and Sturgess (2016) found average value-weighted loan fees of 116 bps per year between 2006 and 2010, but fees were 23–35 bps when the available lending supply was plentiful (i.e., in the top three quintiles of lending supply). Cohen, Diether, and Malloy (2007) used proprietary lending data from a large institution and found average loan fees of around 400 bps for small-cap stocks and 40 bps for large-cap stocks in the 1999–2003 period. Kim and Lee (2019) reported a mean (median) borrowing fee for the easiest-to-borrow stocks of 42.3 bps (37.5 bps) per year between 2006 and 2017. Using a similar database, Beneish et al. (2015) found a mean (median) loan fee of 33.2 bps (27.5 bps) for the 10% easiest-to-borrow stocks between 2004 and 2013; the amount quadrupled for the next 10% easiest-to-borrow stocks. In summary, since the 2000s, shorting costs are estimated to have been above 25 bps but only for the easily shortable large-cap stocks.

That said, several studies have found that the stocks that are designated for shorting by a factor strategy (i.e., the short legs) are the harder and more expensive stocks to short. Geczy et al. (2002) showed that growth stocks, loser stocks, and small-cap stocks are significantly harder to short than other stocks. Drechsler and Drechsler (2016) found more than triple the shorting fees for the short-leg value, momentum, volatility-related, and profitability portfolios. Beneish et al. (2015) found that the short returns for several accounting-based anomalies are attributable to special stocks; the short sides of the profitability and investment stocks were present only among hard-to-borrow stocks, and their returns became statistically indistinguishable from zero once shorting costs were accounted for. Drechsler and Drechsler showed that shorting costs are high for several anomalies and that constraints on shorting execution substantially reduce the profitability on the short side; profits disappear altogether for stocks with low lending fees. Chu et al. (forthcoming) found that relaxing short-sale constraints reduced the profitability of several stock anomalies by 77 bps per month. Kim and Lee (2019) found that shorting fees are twice as high for the short legs of many anomalies, including unprofitable, high-investment, and loser companies. Furthermore, they showed that stocks in the short legs are substantially more difficult to short.

Shorting involves frictions in addition to cost and difficulty, such as the unavailability of stocks in the short leg. Beneish et al. (2015) showed that shares are often least available to borrow when the stocks are most attractive to short sellers. Kim and Lee (2019) showed that stocks in short legs are substantially more difficult to short than those in long legs would be. They estimated that shorting frictions (i.e., the unavailability of stocks in the short leg to sell short, as well as loan fees actually paid to stock lenders), as obtained from the IHS Markit database, amount to 10.4 bps per month, or about 40% of the gross short profits for 14 anomalies. In their study, shorting fees amounted to 7.5 bps per month and unavailability costs, 2.9 bps. In summary, shorting costs are substantial on the short side of factor investing, especially when tilting to small-cap stocks. Overall, these results suggest that our conclusions are likely to strengthen when the impact of costs is accounted for.

A final remark is in order: Investing only in the long side of factors offers roughly half of the raw returns to be gained from the long–short approach. Thus, a position in the long factor legs needs to be levered up by approximately a factor of 2 to maintain a similar absolute return, and this higher leverage may require increased funding. Some investors face constraints on leverage and/or funding, and these limits to arbitrage might prevent them from investing only in the long sides of factors, even if these offer higher risk-adjusted returns. The long–short approach gives an investor more return per unit of cash, although, as highlighted in this article, these returns are partly beyond the reach of investors because of shorting costs and limitations.

Conclusion and Practical Implications

Factor portfolios are typically constructed by combining a long leg and a short leg under the assumption that the two legs are complementary drivers of factor premiums. We critically examined this assumption by decomposing five Fama–French-style portfolios (value, momentum, profitability, investment, and low risk) into their long and short legs. We found that factor premiums originate in both legs but are typically stronger on the long side. Short legs usually add less value for investor portfolios. In fact, the short legs are generally subsumed by the long legs because the short legs provide lower risk-adjusted returns and less diversification benefit. This outcome is especially driven by a high common risk in short legs, as is evident from relatively high correlations (1) between the short legs of various factors and (2) between the short legs and long legs of individual factors. These results hold across large- and small-cap stocks; the long legs in both the large-cap space and the small-cap space provide most of the contribution to factor premiums. Our findings are robust over time, cannot be attributed to differences in tail risk, and hold internationally across various regions. In summary, factor premiums tend to be most attractive on the long side. The long legs are crucial for understanding factor premiums, and no essential information is lost by dropping the short legs. The short legs offer essentially the same exposure as the long legs but with lower rewards.

We also shed light on previous findings regarding the value and low-risk factor premiums because we found their correlation structures to be materially different on the long and short sides. Some recent studies have argued that these factors are subsumed by the new Fama–French factors—profitability and investment—but we showed that these new results are entirely driven by the short legs of the new factors. The long legs of both the value and low-risk factors offer distinct premiums that cannot be explained by the long legs of other factors.

Our findings have important practical implications. Factor premiums are present in the long and short legs, in both large-cap and small-cap stocks, but turn out to be most attractive on the long side, especially in small-cap stocks. Investors may thus efficiently capture the premiums offered by factors by focusing on the long legs of factors and using highly liquid market index futures to hedge out the market exposure. Some important caveats apply, however.

First, the long-leg approach may interfere with investor-specific constraints—in particular, leverage constraints—for a given absolute-return objective. As a consequence, for leverage-constrained investors, shorting recognized factors may be optimal.

Second, the impact of costs, liquidity, and capacity limits should be carefully accounted for. Not only short-leg stocks but also small-cap stocks tend to have higher costs and lower liquidity. Short selling involves stock-lending fees and missed opportunities from stocks that are not available for shorting, but the long-leg approach also involves additional costs. Moreover, the long-leg approach requires more leverage to achieve the same amount of factor exposure. We argue that investment frictions are unlikely to change our conclusions but they may alter the magnitude of the performance advantage of the long legs over the short legs and of factor strategies in large-cap versus small-cap stocks. That said, we stress that our results by no means imply that investors should ignore factor strategies in large-cap investing because these strategies offer attractive factor premiums, their long legs did add value in our tests, and they face fewer investment frictions.

Third, the conclusions of our analysis should not necessarily be overgeneralized to the notion that shorting does not add value in general. Our analysis is limited to the long and short legs of five widely used academic factor premiums with portfolios constructed via standard sorting procedures. Although the factors in our study are widely considered to be among the most important drivers of stock returns, we acknowledge that hundreds of alternative factors have been documented and that some of them may obtain most of their performance from the short side. Also, we have not examined portfolios optimized at the level of individual stocks while accounting for various factor- or risk-based constraints. Follow-up research should reveal whether short positions can add value to models with long legs.

Appendix A. Additional Tests

Table A1. Breakdown of q-Factor Premiums, January 1967–December 2018

	Investment to Assets	Return on Equity	All
A. Long leg of q-factors			
Return (%)	3.0	3.2	3.1
Volatility (%)	3.7	3.9	2.3
Sharpe ratio	0.80	0.82	1.35
B. Short leg of q-factors			
Return (%)	2.6	3.4	3.0
Volatility (%)	4.0	5.2	3.6
Sharpe ratio	0.65	0.65	0.82
C. Long–short of q-factors			
Return (%)	5.6	6.6	6.1
Volatility (%)	6.3	8.7	5.1
Sharpe ratio	0.88	0.75	1.19

Notes: These q-factors from Hou et al. (2015) are market neutral and constructed from a triple 2×3×3 sort on size, investment to assets, and return on equity. To neutralize market and size tilts, each leg is an equal 50/50 combination of the large-cap leg and small-cap leg, minus the market (50/50 Big/Small portfolios). Panel C is the sum of Panels A and B and the classical way of presenting long–short factors.

Figure A1. Subperiod Results

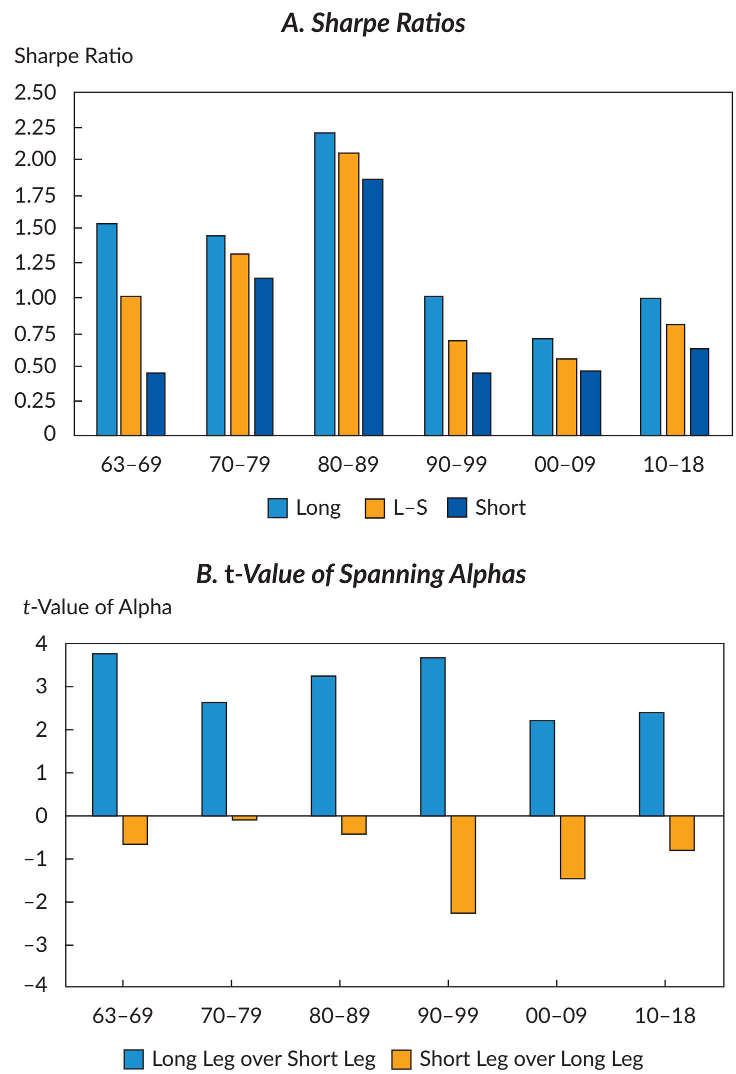
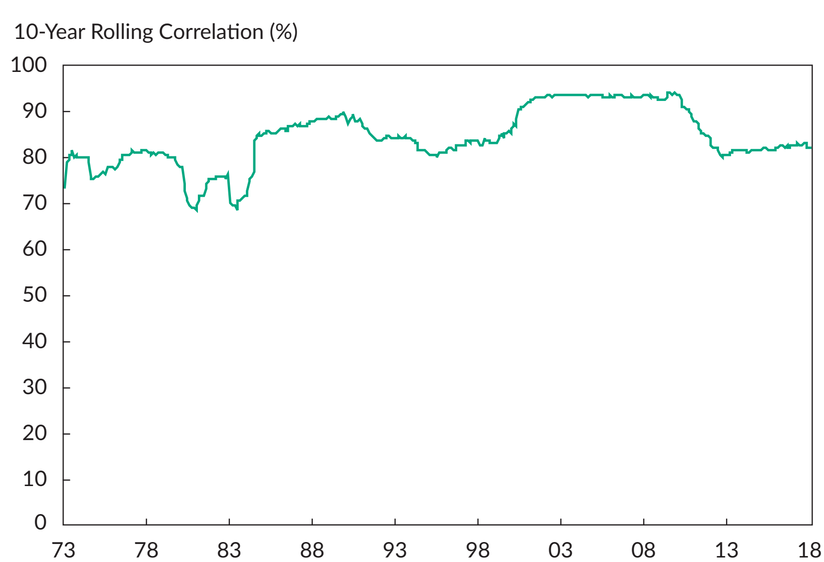
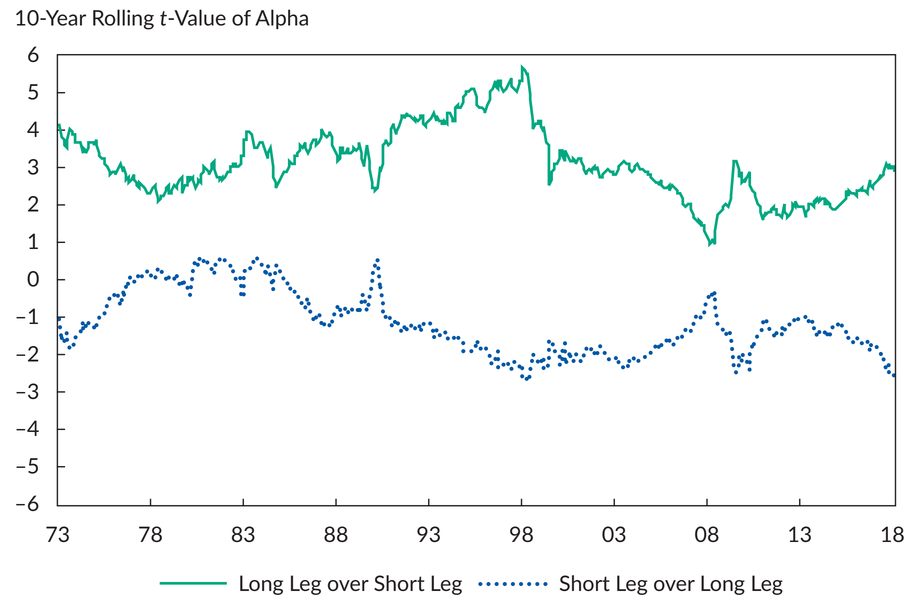


Figure A2. Rolling (10-Year) Correlation between Long Leg and Short Leg



Note: The sample period is July 1963–December 2018.

Figure A3. Rolling (10-Year) Alpha of Long Legs vs. Short Legs



Notes: Shown is the *t*-value of the 10-year rolling alpha of each leg of the combined factor portfolio over the other leg. The sample period is July 1963–December 2018.

Table A2. Robustness to Definition of Factor Legs: Sharpe Ratios, July 1963–December 2018

	HML	WML	RMW	CMA	VOL	All
A. Standard factors (2×3) minus equal-weighted Big and Small portfolios						
Long leg	0.40	0.61	0.31	0.49	0.53	1.10
Short leg	0.37	0.46	0.43	0.40	0.54	0.69
Long–short	0.40	0.55	0.41	0.49	0.58	0.86
B. Standard factors (2×3) minus equal-weighted neutral portfolios						
Long leg	0.35	0.49	0.29	0.21	0.48	0.95
Short leg	0.29	0.41	0.30	0.37	0.49	0.49
Long–short	0.40	0.55	0.41	0.49	0.58	0.86
C. Cap-weighted factors minus market portfolio						
Long leg	0.41	0.59	0.37	0.43	0.32	0.81
Short leg	0.05	0.34	0.27	0.11	0.30	0.41
Long–short	0.31	0.47	0.32	0.30	0.33	0.67
D. Cap-weighted factors minus neutral portfolios						
Long leg	0.38	0.45	0.28	0.33	0.25	0.88
Short leg	0.08	0.33	0.19	0.12	0.33	0.32
Long–short	0.31	0.47	0.32	0.30	0.33	0.67

Notes: The hedge portfolio in Panel A is a 50/50 mix of the Small and Big portfolios as defined in SMB; in Panel B, the hedge is a 50/50 mix of the two neutral portfolios. Panels C and D show results for fully cap-weighted factor portfolios. The hedge portfolio is the cap-weighted market portfolio in Panel C and the relevant cap-weighted neutral portfolio in Panel D.

Table A3. Sharpe Ratios for Long vs. Short Legs Based on 5×5 Portfolios, July 1963–December 2018

	HML	RMW	CMA	WML	VOL	All
Mega						
Long leg	0.14	0.29	0.29	0.35	0.24	0.67
Short leg	0.06	0.17	0.09	0.32	0.05	0.26
Long–short	0.12	0.25	0.21	0.37	0.15	0.47
Large						
Long leg	0.17	0.28	0.13	0.43	0.41	0.78
Short leg	0.12	0.20	0.22	0.46	0.38	0.42
Long–short	0.17	0.27	0.22	0.49	0.43	0.61
Mid						
Long leg	0.39	0.36	0.19	0.55	0.58	1.13
Short leg	0.35	0.25	0.44	0.47	0.66	0.59
Long–short	0.41	0.34	0.42	0.57	0.67	0.87
Small						
Long leg	0.32	0.35	0.16	0.56	0.52	1.03
Short leg	0.40	0.28	0.53	0.68	0.72	0.71
Long–short	0.41	0.36	0.50	0.71	0.67	0.96
Micro						
Long leg	0.58	–0.03	0.23	0.77	0.75	1.32
Short leg	0.71	0.40	0.97	0.87	0.88	0.99
Long–short	0.70	0.29	0.87	0.95	0.88	1.32

Note: The long leg of a factor in a size bucket is defined as the top quintile of the factor in that size bucket minus the average of the five quintiles in that size bucket, and the short leg of a factor in a size bucket is defined as the average of the five quintiles in that size bucket minus the bottom quintile of the factor in that size bucket.

Table A4. Portfolio Optimization Results for 5×5 Portfolios, July 1963–December 2018

	Percentage Allocation				
	Mega	Large	Mid	Small	Micro
A. Separate optimization					
Long legs	97.6	89.1	72.8	63.1	53.9
Short legs	2.4	10.9	27.2	36.9	46.1
Total	100.0	100.0	100.0	100.0	100.0
B. Additive optimization					
	Mega	+Large	+Mid	+Small	+Micro
Long legs	97.6	93.1	81.3	78.7	67.6
Short legs	2.4	6.9	18.7	21.3	32.4
Total	100.0	100.0	100.0	100.0	100.0

Notes: Shown are the results for maximum-Sharpe-ratio optimizations based on the 5×5 portfolios sorted on the size factor. Each column refers to a separate optimization. For each optimization in Panel A, five long legs and five short legs were used as inputs. In Panel B, the process was to start from the megacaps segment and then add the other size segments one by one. Each cell shows the optimal allocation to all long legs and all short legs combined.

Figure A4. Drawdowns of Factor Portfolios, July 1963–December 2018

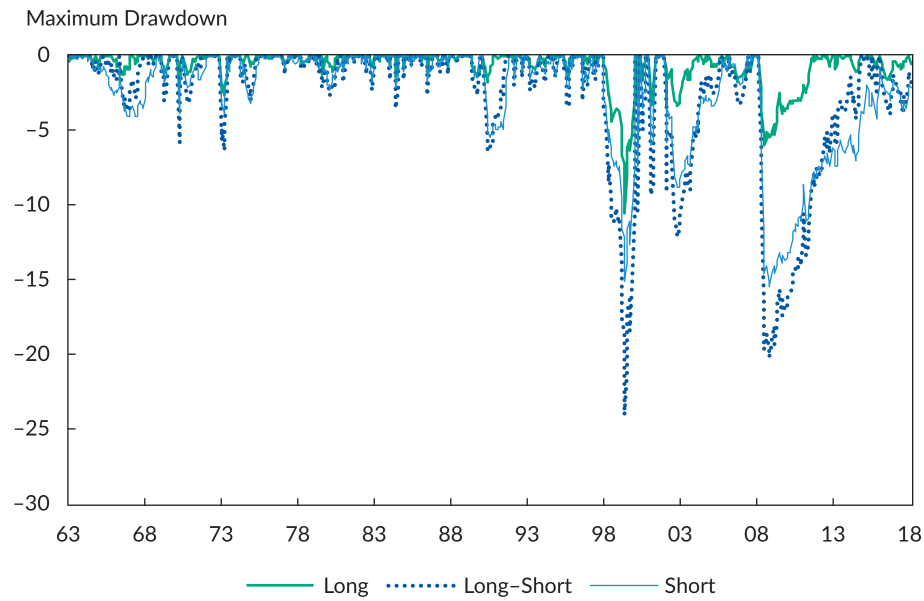
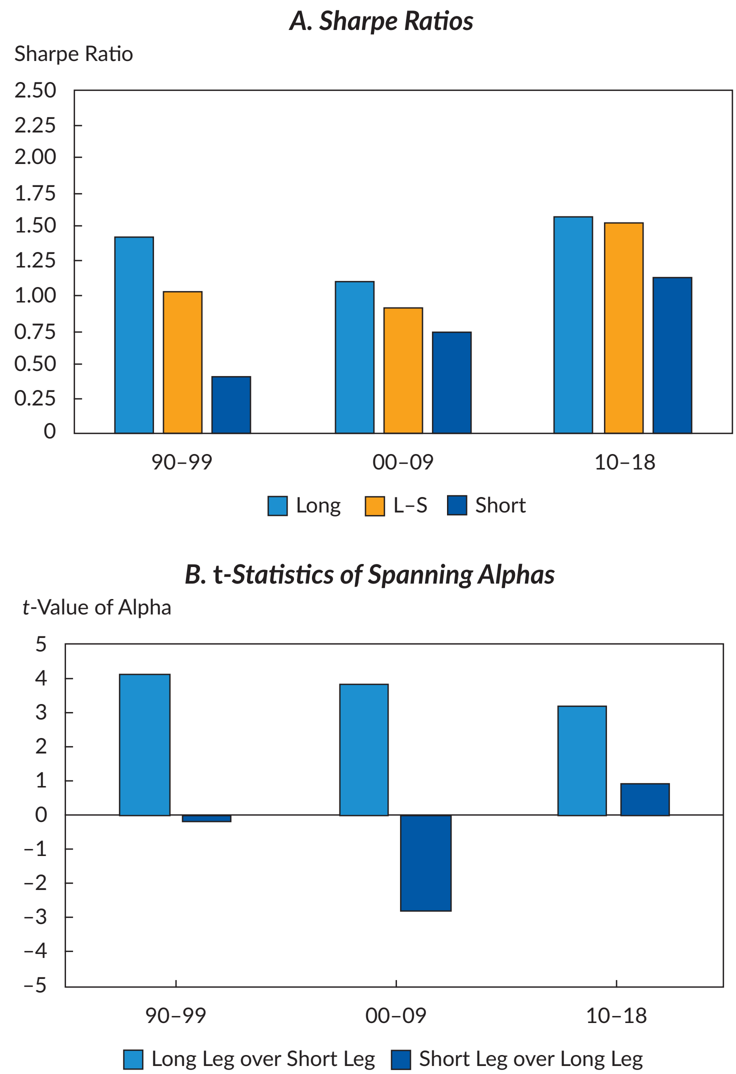


Table A5. Downside Risk Perspectives, July 1963–December 2018

	Long Leg	Short Leg	Long–Short
A. Risk			
Volatility	2.2%	3.7%	5.7%
Skewness	−0.1	−0.3	−0.2
Excess kurtosis	7.0	10.1	8.9
Semi-deviation	1.3%	2.4%	3.5%
VAR (95%)	−2.7%	−4.9%	−7.3%
Maximum drawdown	−10.5%	−15.5%	−24.2%
Regular beta	−0.02	−0.08	−0.11
LPM (0) beta	−0.02	−0.06	−0.08
LPM (1 sigma) beta	−0.01	−0.03	−0.04
B. Return/risk			
Sharpe ratio	1.10	0.69	0.86
Adjusted Sharpe ratio	0.69	0.52	0.60
Sortino ratio	1.88	1.07	1.39
Return/VAR	0.90	0.52	0.68

Notes: VAR = value at risk; LPM = lower partial moment. The data are for the long leg and short leg of the combined factor portfolio. Panel A shows data for volatility and various downside risk measurements. The LPM (0) beta is similar to the downside beta used by Ang, Chen, and Xing (2006), and the LPM (1 sigma) beta was used by Lettau, Maggiori, and Weber (2014). The return/risk statistics in Panel B include measures that account for nonnormal returns. The adjusted Sharpe ratio corrects for skewness and kurtosis (Pézier and White 2008), and the Sortino ratio uses downside volatility as the risk measure.

Figure A5. Global Sample Subperiod Results, July 1990–December 2018



Note: Data are for the multifactor long-leg, short-leg, and long–short portfolios by decade.

Table A6. BETA and Long Legs vs. Short Legs

	Alpha	Mkt – Rf	SMB	HML	RMW	CMA	WML
A. BETA							
CAPM	5.01%	0.00					
(*t*-value)	(3.88)	(0.00)					
Six-factor	−0.74%	0.20	−0.11	0.29	0.43	0.40	0.12
(*t*-value)	(−0.69)	(9.29)	(−3.70)	(6.72)	(10.08)	(6.44)	(5.89)

(continued)

Table A6. BETA and Long Legs vs. Short Legs (continued)

B. Long legs (low beta)

	Alpha	Mkt – Rf	SMB	High	Robust	Conservative	Winner
CAPM	2.87%	−0.07					
(*t*-value)	(3.47)	(−4.51)					
Six-factor	1.28%	0.00	−0.17	0.44	0.48	0.22	−0.03
(*t*-value)	(1.70)	(−0.18)	(−8.00)	(10.02)	(6.79)	(2.93)	(−0.83)

C. Short legs (high beta)

	Alpha	Mkt – Rf	SMB	Low	Weak	Aggressive	Loser
CAPM	2.14%	0.07					
(*t*-value)	(3.86)	(6.72)					
Six-factor	−0.62%	0.17	0.03	0.14	0.20	0.32	0.18
(*t*-value)	(−1.44)	(18.47)	(2.62)	(2.97)	(6.79)	(6.23)	(13.79)

D. Subperiods

	July 1963–December 1990			January 1991–December 2018		
	BETA	Long	Short	BETA	Long	Short
CAPM alpha	5.52%	2.88%	2.64%	5.16%	3.24%	1.92%
(*t*-value)	(3.76)	(3.15)	(4.47)	(2.44)	(2.41)	(2.06)
Six-factor alpha	2.40%	3.12%	0.48%	−2.04%	0.72%	−1.32%
(*t*-value)	(1.87)	(3.68)	(0.92)	(−1.23)	(0.61)	(−2.00)

Notes: The BETA factor replaces 36-month volatility with 36-month BETA to construct 2×3 portfolios similar to the Fama–French portfolios—a process identical to the construction of the VOL factor. The BETA factor resembles the Frazzini and Pedersen (2014) BAB factor, but to address the Novy-Marx and Velikov (2018) critique, it does not give more or less weight to illiquid small caps than do the Fama–French factors. Panel A shows the long-leg/short-leg results (BETA); Panel B provides the long-leg (low-beta) results; Panel C provides the short-leg (high-beta) results. Panel D shows the robustness of the results by breaking them down into two subperiods.

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Notes

1. See, for example, Fama and French (1992, 1993, 2006, 2008, 2012, 2015, 2016); Jegadeesh and Titman (1993, 2001); Asness, Moskowitz, and Pedersen (2013); Ang, Hodrick, Xing, and Zhang (2006); Blitz and van Vliet (2007); and Frazzini and Pedersen (2014).

2. For example, see Fama and French (1992, 1993, 2006, 2008, 2012, 2015, 2017) and Israel and Moskowitz (2013).

3. Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

4. See, among others, Fama and French (1992, 1993, 2006, 2008, 2012, 2015) and Israel and Moskowitz (2013).

5. For example, Fama and French (1998, 2012, 2017); Asness et al. (2013).

References

Ang, A., J. Chen, and Y. Xing. 2006. "Downside Risk." *Review of Financial Studies* 19 (4): 1191–239.

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang. 2006. "The Cross-Section of Volatility and Expected Returns." *Journal of Finance* 61 (1): 259–99.

Angel, J. J., and D. M. McCabe. 2009. "The Business Ethics of Short Selling and Naked Short Selling." *Journal of Business Ethics* 85 (Supplement 1): 239–49.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. "Value and Momentum Everywhere." *Journal of Finance* 68 (3): 929–85.

Baker, M., B. Bradley, and J. Wurgler. 2011. "Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly." *Financial Analysts Journal* 67 (1): 40–54.

Barroso, P., and P. Santa-Clara. 2015. "Momentum Has Its Moments." *Journal of Financial Economics* 116 (1): 111–20.

Bawa, V. S., and E. B. Lindenberg. 1977. "Capital Market Equilibrium in a Mean–Lower Partial Moment Framework." *Journal of Financial Economics* 5 (2): 189–200.

Beneish, M. D., C. M. Lee, and D. C. Nichols. 2015. "In Short Supply: Short-Sellers and Stock Returns." *Journal of Accounting and Economics* 60 (2–3): 33–57.

Blitz, D., and P. van Vliet. 2007. "The Volatility Effect: Lower Risk without Lower Return." *Journal of Portfolio Management* 34 (1): 102–13.

Blitz, D., P. van Vliet, and G. Baltussen. 2019. "The Volatility Effect Revisited." *Journal of Portfolio Management* 46 (2) Quantitative Special Issue: 45–63.

Blitz, D., and M. Vidojevic. 2017. "The Profitability of Low-Volatility." *Journal of Empirical Finance* 43 (September): 33–42.

Chen, J., H. Hong, and J. C. Stein. 2002. "Breadth of Ownership and Stock Returns." *Journal of Financial Economics* 66 (2–3): 171–205.

Chu, Y., D. Hirshleifer, and L. Ma. Forthcoming. "The Causal Effect of Limits to Arbitrage on Asset Pricing Anomalies." *Journal of Finance*.

Cohen, L., K. B. Diether, and C. J. Malloy. 2007. "Supply and Demand Shifts in the Shorting Market." *Journal of Finance* 62 (5): 2061–96.

Cremers, M., A. Petajisto, and E. Zitzewitz. 2013. "Should Benchmark Indices Have Alpha? Revisiting Performance Evaluation." *Critical Finance Review* 2 (1): 1–48.

Daniel, K., and T. Moskowitz. 2016. "Momentum Crashes." *Journal of Financial Economics* 122 (2): 221–47.

D'Avolio, G. 2002. "The Market for Borrowing Stock." *Journal of Financial Economics* 66 (2–3): 271–306.

De Roon, F. A., T. E. Nijman, and B. J. M. Werker. 2001. "Testing for Mean–Variance Spanning with Short Sales Constraints and Transaction Costs: The Case of Emerging Markets." *Journal of Finance* 56 (2): 721–42.

Diether, K. B., K. H. Lee, and I. M. Werner. 2009. "Short-Sale Strategies and Return Predictability." *Review of Financial Studies* 22 (2): 575–607.

Drechsler, I., and Q. S. Drechsler. 2016. "The Shorting Premium and Asset Pricing Anomalies." Working paper. Available at https://ssrn.com/abstract=2387099.

Fama, E. F., and K. R. French. 1992. "The Cross-Section of Expected Stock Returns." *Journal of Finance* 47 (2): 427–65.

———. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33 (1): 3–56.

———. 1998. "Value versus Growth: The International Evidence." *Journal of Finance* 53 (6): 1975–99.

———. 2006. "The Value Premium and the CAPM." *Journal of Finance* 61 (5): 2163–85.

———. 2008. "Dissecting Anomalies." *Journal of Finance* 63 (4): 1653–78.

———. 2012. "Size, Value, and Momentum in International Stock Returns." *Journal of Financial Economics* 105 (3): 457–72.

———. 2015. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics* 116 (1): 1–22.

———. 2016. "Dissecting Anomalies with a Five-Factor Model." *Review of Financial Studies* 29 (1): 69–103.

———. 2017. "International Tests of a Five-Factor Asset Pricing Model." *Journal of Financial Economics* 123 (3): 441–63.

Fama, E. F., and J. D. MacBeth. 1973. "Risk, Return, and Equilibrium: Empirical Tests." *Journal of Political Economy* 81 (3): 607–36.

Frazzini, A., R. Israel, and T. J. Moskowitz. 2018. "Trading Costs." Working paper. Available at https://ssrn.com/abstract=3229719.

Frazzini, A., and L. H. Pedersen. 2014. "Betting against Beta." *Journal of Financial Economics* 111 (1): 1–25.

Geczy, C. C., D. K. Musto, and A. V. Reed. 2002. "Stocks Are Special Too: An Analysis of the Equity Lending Market." *Journal of Financial Economics* 66 (2–3): 241–69.

Gibbons, M. R., S. A. Ross, and J. Shanken. 1989. "A Test of the Efficiency of a Given Portfolio." *Econometrica* 57 (5): 1121–52.

Hanauer, M. X., and S. Windmueller. 2019. "Enhanced Momentum Strategies." Working paper. Available at https://ssrn.com/abstract=3437919.

Hou, K., C. Xue, and L. Zhang. 2015. "Digesting Anomalies: An Investment Approach." *Review of Financial Studies* 28 (3): 650–705.

Israel, R., and T. J. Moskowitz. 2013. "The Role of Shorting, Firm Size, and Time on Market Anomalies." *Journal of Financial Economics* 108 (2): 275–301.

Jegadeesh, N., and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48 (1): 65–91.

———. 2001. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *Journal of Finance* 56 (2): 699–720.

Kan, Raymond, and Guofu Zhou. 2012. "Tests of Mean–Variance Spanning." *Annals of Economics and Finance* 13 (1): 145–93.

Kim, D., and B. Lee. 2019. "Shorting Costs and Profitability of Long–Short Strategies." Working paper. Available at https://ssrn.com/abstract=3519706.

Kolasinski, A. C., A. V. Reed, and M. C. Ringgenberg. 2013. "A Multiple Lender Approach to Understanding Supply and Search in the Equity Lending Market." *Journal of Finance* 68 (2): 559–95.

Lettau, M., M. Maggiori, and M. Weber. 2014. "Conditional Risk Premia in Currency Markets and Other Asset Classes." *Journal of Financial Economics* 114 (2): 197–225.

Levi, Y., and I. Welch. 2020. "Symmetric and Asymmetric Market Betas and Downside Risk." *Review of Financial Studies* 33 (6): 2772–95.

Miller, E. M. 1977. "Risk, Uncertainty, and Divergence of Opinion." *Journal of Finance* 32 (4): 1151–68.

Novy-Marx, R. 2013. "The Other Side of Value: The Gross Profitability Premium." *Journal of Financial Economics* 108 (1): 1–28.

——. 2014, "Understanding Defensive Equity." NBER Working Paper 20591.

Novy-Marx, R., and M. Velikov. 2016. "A Taxonomy of Anomalies and Their Trading Costs." *Review of Financial Studies* 29 (1): 104–47.

——. 2018. "Betting against Betting against Beta." Working paper. Available at https://ssrn.com/abstract=3300965.

——. 2019. "Comparing Cost-Mitigation Techniques." *Financial Analysts Journal* 75 (1): 85–102.

Pézier, J., and A. White. 2008. "The Relative Merits of Alternative Investments in Passive Portfolios." *Journal of Alternative Investments* 10 (4): 37–49.

Porras Prado, M., P. A. Saffi, and J. Sturgess. 2016. "Ownership Structure, Limits to Arbitrage, and Stock Returns: Evidence from Equity Lending Markets." *Review of Financial Studies* 29 (12): 3211–44.

Shleifer, A., and R. W. Vishny. 1997. "The Limits of Arbitrage." *Journal of Finance* 52 (1): 35–55.

Stambaugh, R. F., J. Yu, and Y. Yuan. 2012. "The Short of It: Investor Sentiment and Anomalies." *Journal of Financial Economics* 104 (2): 288–302.

——. 2015. "Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle." *Journal of Finance* 70 (5): 1903–48.

Treynor, J. A., and F. Black. 1973. "How to Use Security Analysis to Improve Portfolio Selection." *Journal of Business* 46 (1): 66–86.