Routledge
Taylor & Francis Group

Financial Analysts Journal

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ufaj20

Is Sector Neutrality in Factor Investing a Mistake?

Sina Ehsani, Campbell R. Harvey & Feifei Li

To cite this article: Sina Ehsani, Campbell R. Harvey & Feifei Li (2023) Is Sector Neutrality in Factor Investing a Mistake?, Financial Analysts Journal, 79:3, 95-117, DOI: 10.1080/0015198X.2023.2196931

To link to this article: https://doi.org/10.1080/0015198X.2023.2196931

Financial Analysts Journal | A Publication of **CFA Institute**
https://doi.org/10.1080/0015198X.2023.2196931

Research

Is Sector Neutrality in Factor Investing a Mistake?

Sina Ehsani, Campbell R. Harvey, and Feifei Li

Sina Ehsani is an assistant professor of finance at Northern Illinois University and a consultant to Research Affiliates, LLC. Campbell R. Harvey is a professor of finance at the Fuqua School of Business, Duke University, and a research associate at the National Bureau of Economic Research. Feifei Li, PhD, FRM, is chief investment officer of Kavout Algo Financial and a partner of Research Affiliates, LLC. Send correspondence to Campbell R. Harvey at cam.harvey@duke.edu.

Stock characteristics have two sources of predictive power. First, a characteristic might be valuable in identifying high or low expected returns across industries. Second, a characteristic might be useful in identifying individual stock expected returns within an industry. Past studies generally find that the firm-specific component is the strongest predictor, leading many to sector neutralize their factor exposures. We show both analytically and empirically that the average long–short investor is more likely to benefit from hedging out sector bets, whereas the long-only investor should, on average, avoid sector neutralization.

Keywords: Equity factors; factor zoo; industry factors; sector bet; sector neutral; sector tilt; portfolio management; sector neutralization; smart beta

Disclosure: No potential conflict of interest was reported by the authors.

PL Credits: 2.0

Introduction

Firm characteristics such as size, book-to-market ratio, and momentum are often correlated with expected returns (Banz 1981; Basu 1983; Rosenberg, Reid, and Lanstein 1985; Fama and French 1993; Jegadeesh and Titman 1993). The market-wide predictive power of these characteristics may stem from their industry component, their firm-specific component, or both. Moskowitz and Grinblatt (1999), for example, argue that momentum in stocks stems from the industry component. Other studies such as Asness, Porter, and Stevens (2000), Asness, Frazzini, and Pedersen (2014), Bender, Mohamed, and Sun (2019), Blitz and Hanauer (2020), Israel, Laursen, and Richardson (2020), Kessler, Scherer, and Harries (2019), and Novy-Marx (2013) find that the firm-specific component of characteristics contains most of the information, suggesting that an investor benefits from forming portfolios that neutralize sector exposures. Baker, Bradley, and Taliaferro (2014) find that both the stock component and the country and industry components contribute to the profits of the low-risk factor. These papers study the impact of sector exposures on a factor's risk–return profile by focusing on long–short factor portfolios.

In this paper, we first confirm that the *within* (firm-specific) component of stock characteristics contains on average more information about the cross-section of expected returns than the *across* (sector) component. We then derive a condition that determines when the weaker component of a predictor should be omitted. Using aggregate values for Sharpe ratios and correlation coefficients, we predict that this condition—which identifies whether the across-sector component is redundant—will be met frequently in long–short portfolios; therefore,

We thank William Goetzmann (Executive Editor), Daniel Giamouridis (Co-Editor), Christoffer Grände, two anonymous referees, and the participants at the Bernstein 6th Annual Quantitative Finance Conference in Boston for useful feedback. Kay Jaitly, CFA, provided editorial assistance.

the long–short investor likely gains from sector neutralization. In contrast, the same condition is unlikely to hold in long-only portfolios; therefore, the long-only factor investor gains more from investing in the as-is factor. Empirical bootstraps of historical factor data, constructed using various portfolio construction techniques, show that our predictions are accurately reflected in the actual data.

To illustrate, assume that signal S consists of two parts, $S = W + A$. If S is the book-to-market ratio, then W is its within-sector component and A the across-sector component. The investor can use the signal as it stands and earn a return of $S \times r = (W + A) \times r$, or they can use W or A independently to earn $W \times r$ or $A \times r$. If W predicts returns more accurately than A, then the risk–return profile of $W \times r$ dominates that of $A \times r$. Should the mean-variance investor form portfolios based on W or $W + A$? This problem, the value of predictor A in the presence of W, is equivalent to a static two risky-asset problem. The next section shows that the redundancy of the weaker predictor, A, can be evaluated using the inequality

$$\frac{\mathrm{SR_A}}{\mathrm{SR_W}} \leq \rho, \qquad (1)$$

where SR_A and SR_W denote the Sharpe ratios of the resulting portfolios, $A \times r$ and $W \times r$, respectively, and ρ is the correlation coefficient between the two portfolios. The inequality in (1) states that the trade-off between diversification benefits and mean-variance efficiency determines whether a predictor is redundant. The weaker predictor should be ignored when its relative Sharpe ratio is lower than its diversification benefits. Otherwise, the optimal portfolio is a blend of the within and sector components.

It is important to note that the condition in (1) is the minimum threshold for pursuing sector neutrality. If (1) holds, sector neutrality certainly increases the Sharpe ratio. Even if (1) does not hold, however, sector neutrality could still increase the factor's Sharpe ratio if the factor's sector exposure is much larger than its optimal weight. For example, suppose that the optimal sector bet of a factor portfolio is 5%; that is, the factor benefits from taking on a small amount of sector exposure. Also assume that this factor has 50% sector exposure, which is far more than the optimal amount of 5%. In this case, although the optimal amount is positive and the inequality recommends to not neutralize, neutralization increases the portfolio's Sharpe ratio because of the large difference between the optimal (5%) and actual (50%) sector exposure. What factors are more likely to have large sector exposures? Long–short factors have far more sector exposures than long-only factors. Therefore, the inequality underestimates the benefits of neutrality for long–short factors. In contrast, long-only factors have minimal sector exposures: The condition is an accurate decision-making criterion for long-only factors, which are the focus of this study.

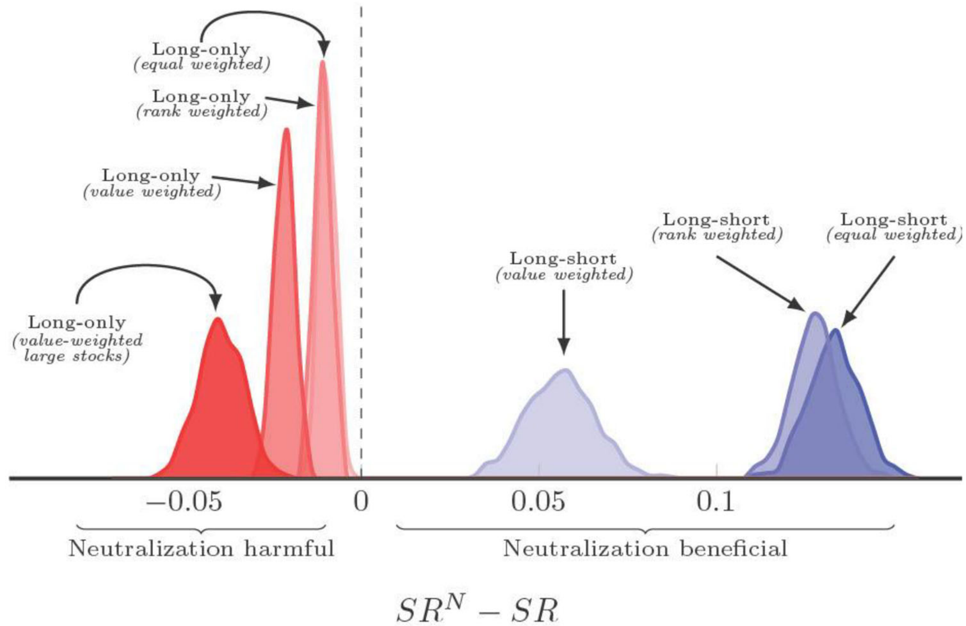
Our empirical work shows that the Sharpe ratio is the main determinant of the predictor redundancy problem of (1). In long–short portfolios, the Sharpe ratios of the within and across components differ substantially, and there is a high chance that the ratio in (1) becomes small. Therefore, an investor can improve the risk–return profile of the long–short portfolio by neutralizing its sector bets. In contrast, Sharpe ratios of the across and within components of long-only factors are very similar. In this case, the inequality rarely holds because the left side, which is close to 1.0, cannot be less than the correlation coefficient, which is usually less than 0.8. Therefore, the long-only investor is better off investing in the as-is factor, which contains both components.

With the aggregate values of Sharpe ratios and correlation coefficients, we predict that using the across signal in addition to the within signal (i.e., avoiding sector neutralization) increases the Sharpe ratios of long–short and long-only factors with probabilities of 29% and 78%, respectively. Historical bootstraps of factor data suggest that our analytical probabilities are reasonably accurate: Keeping the sector component produces better long–short factors in only 20% of the trials, while doing so produces better long-only factors in 78% of the trials.

Figure 1 shows the summary of our empirical results, specifically the difference between the Sharpe ratios of two implementations of the factors. SR^N is the Sharpe ratio of the factor constructed using only the within signal (i.e., sector-neutralized factor), and SR is the Sharpe ratio of the standard factor that sorts on the original signal, which consists of both across and within components.

We use bootstraps to compute 1,000 differences in Sharpe ratios for the average factor of each construction method. A positive difference indicates that on average the sector-neutral factor dominates the original factor. Figure 1 shows that the average change is positive for long–short factors regardless of the construction method. Thus, the long–short

Figure 1. Impact of Removing Sector Exposures on Sharpe Ratios of Equity Factors



Note: We form two versions of each of the size, value, profitability, investment, and momentum factors. The first version sorts stocks based on firm characteristics; the second version sorts stocks based on firm characteristics minus their industry average. We compute the Sharpe ratio of the factors resulting from each version and compute their difference. SR^N is the Sharpe ratio of the factor constructed using only the within signal (i.e., sector-neutralized factor), and SR is the Sharpe ratio of the standard factor that sorts on the original signal, which consists of both across and within components. The factors are long–short or long-only, and the weighting schedules are equal, rank, or value. The number of industry sectors is 5, 10, 12, 17, 30, 38, 48, or 49 based on the industry portfolio classifications of Fama and French (Kenneth R. French Data Library). The data are from 1963 to 2020. We compute the distributions by bootstrapping the factor return data by month.

investor benefits from sector neutralization. In contrast, average changes are negative for long-only factors: The long-only investor benefits more from investing in the as-is factor. The largest reduction in Sharpe ratio from sector neutralization happens for the value-weighted long-only factors that trade large stocks, arguably the most investable portfolio depicted in the figure.

We find that the inferences from individual factors carry over to multi-factor portfolios. We use spanning tests that regress each sector-neutral factor on all standard factors and vice versa. We find that a model consisting of the market and five sector-neutral long–short factors explains the average return of each long–short standard factor, whereas a model of standard long–short factors does not explain the average returns of individual sector-neutral factors. Therefore, a multi-factor long–short investor can expand their portfolio's mean-variance boundary more by investing in sector-neutral factors. In contrast, a portfolio of standard long-only factors explains the returns to each sector-neutral factor better than vice versa. We conclude that the multi-factor long-only investor gains the most by investing in the as-is factors.

Analytics of Sector Bets

A Mean-Variance Condition for Redundancy of a Predictor.

A tech firm may have a high book-to-market ratio (BM) relative to other tech firms, but a low BM relative to a non-tech firm. Although the firm would be considered a value company compared to other tech firms, a long–short sort on BM will short this firm because firms in the tech sector generally have a lower BM. In this context, the predictive power of the market-wide BM results because sector BMs predict the cross-section of sector returns, firm-specific BMs predict the cross-section of firm-specific returns, or a combination of both. By extension, the return to a portfolio sorted on BM stems from its (a) sector exposure and (b) sector-neutralized (firm-specific) component. We follow the literature and use the terms *across* and *within* to refer to the sector and the sector-neutralized components, respectively. The next section shows that the return to a sort on a characteristic can be precisely decomposed as

$$r_{factor} = r_{within} + r_{across}. \quad (2)$$

If the within component of BM predicts returns better than the across component, trading based on the within component will be more profitable than trading based on the across component, and we will have $SR_{within} > SR_{across}$. The question becomes whether a mean-variance investor should use the original signal, which has both components, or invest *only* using the component that predicts returns more accurately? Notice that because this is a static problem, we can view the portfolio that results from trading based on a predictive signal, such as sector BMs, as an asset whose existence is contingent on trading the signal. The answer to the problem of using or neglecting the signal should be settled by studying the properties of the signal's resulting portfolio.

Our mean-variance investor seeks to maximize the overall Sharpe ratio of their portfolio, which has the well-known solution of $\frac{\Sigma^{-1}\mu}{1'\Sigma^{-1}\mu}$ (Ingersoll 1987). In the case of the two assets generated by the within and across signals, denoted by subscripts *w* and *a*, respectively, the solution to optimal allocation to the across asset is[1]

$$\text{optimal weight (across component)} = \frac{\mu_a\sigma_w^2 - \mu_w \mathrm{COV}(r_w, r_a)}{\mu_a\sigma_w^2 + \mu_w\sigma_a^2 - (\mu_w + \mu_a)\mathrm{COV}(r_w, r_a)}, \quad (3)$$

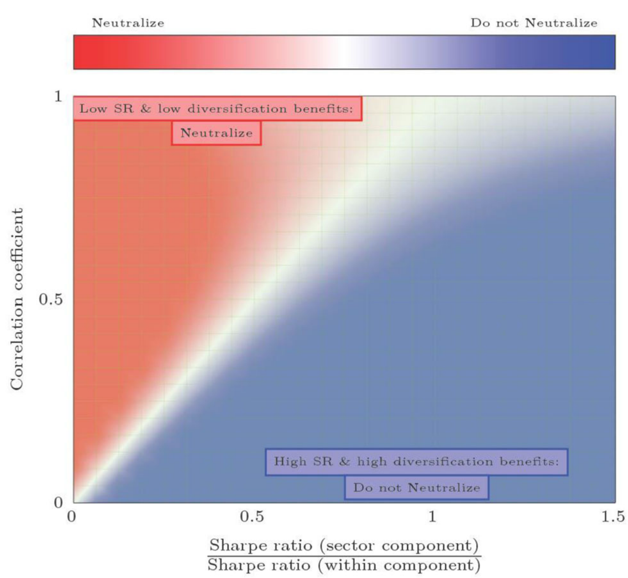
where μ and σ are mean and standard deviation, respectively, and $\mathrm{COV}(r_w, r_a)$ is the covariance between returns. An optimal weight of zero means that the Sharpe ratio–maximizing strategy is to invest in the within component exclusively and earn the Sharpe ratio of the within component. When the optimal weight is negative, the Sharpe ratio–maximizing strategy would be to invest in the within component and *short* the across component. Therefore, when (3) is nonpositive, the sector component is at best redundant and the mean-variance investor benefits from sector neutralizing the factor.

With positive correlations and means, the sign of the equation in (3) has an exact solution. The optimal weight in (3) is nonpositive when[2]

$$\frac{SR_a}{SR_w} \leq \rho. \quad (4)$$

We plot this inequality in Figure 2 by varying the correlation coefficient between 0 and 1 and the relative Sharpe ratios between 0 and 1.5. The figure shows that sector neutrality or sector tendency are both possible outcomes. Reducing the Sharpe ratio of the

Figure 2. The Sign of the Optimal Allocation to the Sector Component



Note: The figure shows the sign of the optimal allocation to the sector component as a function of (a) its Sharpe ratio relative to the Sharpe ratio of the within component ($\frac{SR_a}{SR_w}$) and (b) the correlation between the two components (ρ). The area where optimal allocation to the sector bet is positive (negative) is shown in blue (red). The white area indicates an allocation of zero.

sector component or increasing its correlation with the within component pushes the optimal allocation into deep red (sector neutrality) and changing the parameters in the opposite direction lifts the optimal allocation to solid blue (sector tendency).

The inequality in (4) is a tradeoff between the efficiency and diversification benefits of the across component. If the across component is not correlated with the within component ($\rho = 0$), the across component brings large diversification benefits and will enter the portfolio even if it is associated with a small Sharpe ratio. But if the two components are highly correlated ($\rho \approx 1$), the across component can only enter the portfolio if it has a Sharpe ratio as high as the within component. In summary, the across component would have to have a low Sharpe ratio, a high correlation with the within component, or both to be redundant.

The inequality allows us to discipline the across-versus-within problem. If the ratio of the two components' Sharpe ratios is less than their correlation coefficient, the investor should sector neutralize the factor. Otherwise, using the standard factor, akin to investing in both components, is *likely* the most mean-variance efficient.[3]

It is important to emphasize that the inequality's prediction is accurate when it recommends neutralization: Neutralization certainly enhances the factor if the ratio of Sharpe ratios is less than the correlation. Even when the inequality recommends not pursuing neutralization, however, sector-neutrality can still be beneficial if sector exposures are too large. Suppose a scenario exists in which the optimal weight to the sector component is positive but small, while the factor's actual sector exposure is far above its optimal value. In this case, the inequality recommends *not* pursuing neutralization, but sector neutrality may still be beneficial because the actual allocation is much larger than the optimal amount. Empirically, the inequality always gives an accurate assessment for long-only portfolios because long-only portfolios have small sector exposures. The divergence between the inequality and the exact solution only happens for long–short factors because they have large sector exposures. Appendix B provides more details on this issue.[4]

Decomposing Signals and Their Returns.

We analytically decompose the signals and returns. Following Ehsani, Hunstad, and Mehta (2020), we denote the signals by C and returns by r and index sectors and stocks by subscripts s and n, respectively. The average characteristic value and the average return of sector s are

$$C_s = \frac{1}{N}\sum_{n=1}^{N} C_{n,s} \;\; and \;\; r_s = \frac{1}{N}\sum_{n=1}^{N} r_{n,s}, \qquad (5)$$

where N is the number of stocks in a sector, and $C_{n,s}$ and $r_{n,s}$ are the characteristic and return of stock n in sector s, respectively. The return to the standard factor is

$$r_{factor} = \frac{1}{S \times N}\sum_{s}\sum_{n}\left(C_{n,s} - \overline{C}\right) r_{n,s}, \qquad (6)$$

where S is the number of sectors and $\overline{C}$, the average of the characteristics in the cross-section, is defined as follows:

$$\overline{C} = \frac{1}{SN}\sum_{s}\sum_{n} C_{n,s} = \frac{1}{S}\sum_{s=1}^{S} C_s. \qquad (7)$$

The sector-neutralized factor invests in each stock based on its characteristic relative to the average characteristic of sector s. The return to the factor is

$$r_{within} = \frac{1}{SN}\sum_{s}\sum_{n}\left(C_{n,s} - C_s\right) r_{s,n}, \qquad (8)$$

where C_s is the characteristic score of sector s. We decompose factor returns as follows:

$$\begin{aligned} r_{factor} &= \frac{1}{SN}\sum_{s}\sum_{n}\left(C_{n,s} - \overline{C}\right) r_{n,s} \\ &= \frac{1}{SN}\sum_{s}\sum_{n}\left(C_{n,s} - \overline{C} + C_s - C_s\right) r_{n,s} \end{aligned} \qquad (9)$$

$$\underbrace{\frac{1}{SN}\sum_s\sum_n\left(C_{n,s} - \overline{C}\right) r_{n,s}}_{r_{factor}} = \underbrace{\frac{1}{SN}\sum_s\sum_n\left(C_{n,s} - C_s\right) r_{n,s}}_{r_{within(sector\text{-}neutralized)}} + \underbrace{\frac{1}{SN}\sum_s\sum_n\left(C_s - \overline{C}\right) r_{n,s}}_{r_{across}}. \qquad (10)$$

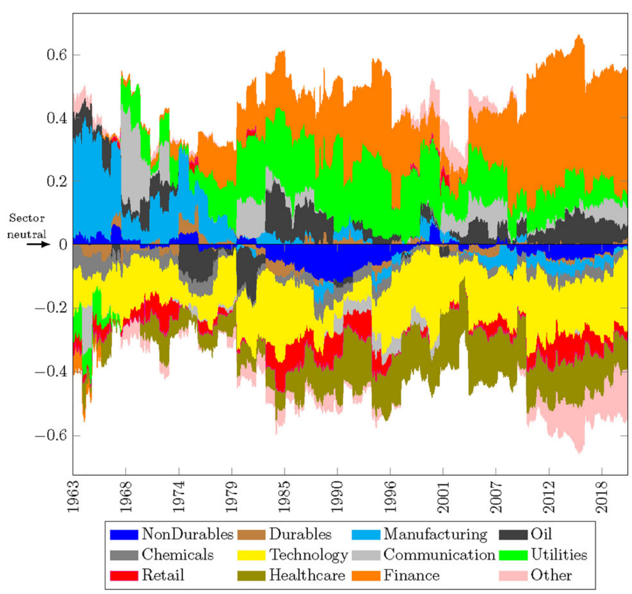
Empirical Results

We implement the decomposition in (10) for rank-weighted, equal-weighted, and value-weighted portfolios. Although the decomposition of (10) is motivated using the actual level of the characteristic, $C_{n,s}$, it can be applied to any weighting scheme. For example, for rank- or value-weighted portfolios, we just need to substitute $C_{n,s}$ with the normalized rank or market value of the stock; for equal-weighted portfolios, $C_{n,s}$ is the reciprocal of the number of stocks in the portfolio.

An Illustration of Sector Bets. Total exposure of a factor to sectors can be computed using the second term of the decomposition, $\frac{\sum_s \sum_n (C_{n,s} - \bar{C})}{SN}$. We show the time series of sector exposures for the long–short value factor (the high-minus-low, or HML, factor) in Figure 3. Over the 60-year period of our study, the standard value factor has consistently invested large amounts in the finance and utilities sectors and at the same time has shorted large amounts in the technology and healthcare sectors. Figure 4 shows the time series of net sector exposures computed by the sum of absolute values of the sector exposures in Figure 3. Figure 4 shows that the overall net sector exposure of the value factor is large and time-varying. Static or time-varying exposure to any risky asset, such as an equity sector, comes with volatility. The premium associated with this extra risk, and its covariance with the rest of the portfolio, determines its overall contribution to the factor's risk–return profile. We can construct the standard value factor with the sector exposures of Figure 3 or we can form a value factor using the within characteristics, such that the overall exposure to any one of the sectors is always zero. The sector-neutral value factor is likely less volatile than the standard value factor because it offsets the positive sector exposure of the long leg with an equal amount of negative exposure in the short leg.

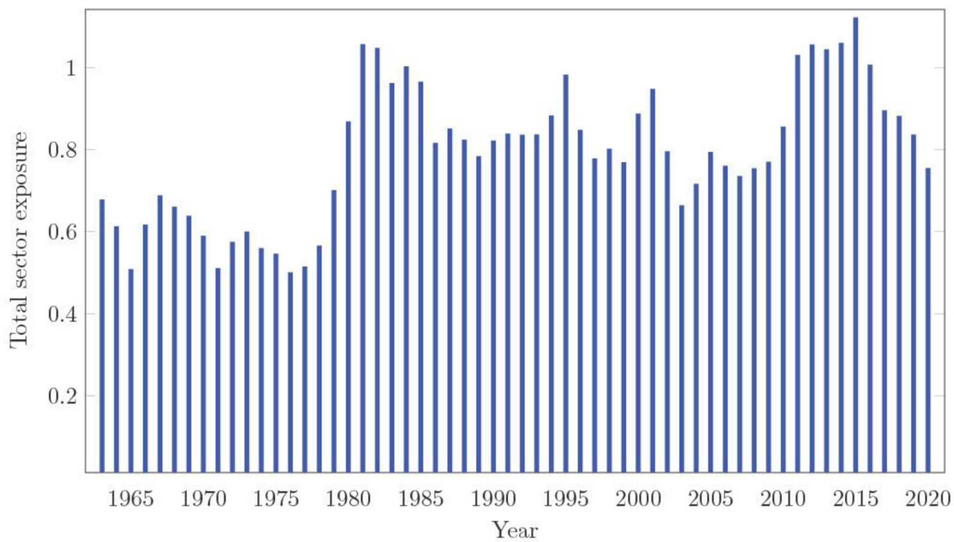
Empirical Return Decomposition. We decompose the returns of equity factors using (10) at the intersection of the following factor construction techniques: long–short and long-only and equal, rank, and value weighted. We set the stage by reporting the summary of results for the two parameters of the condition in (4) for the average factor. Table 1 reports the results. Panel A shows the Sharpe ratios

Figure 3. Sector Bets of the Long–Short Value Factor



Note: The figure shows the exposures of the long–short value-weighted value factor over the 1963–2020 period to the 12 industry classifications of Fama and French. We estimate the net exposure to a sector by computing $\frac{\sum_s \sum_n (C_{n,s} - \bar{C})}{SN}$, where $C_{n,s}$ is the weight (based on market capitalization) of stock n in industry s. The y-axis displays the net exposure to a sector. A positive (negative) net exposure means that more stocks from that sector are in the long (short) leg than in the short (long) leg. An exposure of zero or close to zero means that the net long–short exposure to that sector is zero.

Figure 4. Aggregate Sector Bets of the Long–Short Value Factor



Note: The figure shows the total sector exposure of the long–short value-weighted value factor over the 1963–2020 period. Sectors are defined by the 12 industry classifications of Fama and French. We estimate total exposure by summing the absolute values of all net exposures to the sectors every month. The figure shows the average of monthly total net exposures for each year.

for the across and within components, their ratio, and the correlation between across and within components for the average factor. According to (4), the across component is redundant if the ratio of Sharpe ratios is less than the correlation coefficient. Panel A shows that for the average long–short factor, the ratio of the Sharpe ratios of the across component to the within component is 0.18 and the correlation between them is 0.46. Because 0.18 is less than 0.46, the long–short investor benefits from neutralizing sector exposures.

The pattern in statistics of the average long-only factor is quite different. The Sharpe ratios of the within and across components are similar with a ratio of 0.93. This means that the across component of the long factor is just slightly less mean-variance efficient than the within component. The average correlation between the returns of the across and within components is 0.75. Because 0.93 is not less than 0.75, the inequality will not hold true and the optimal decision is to invest in the as-is factor. In summary, omitting the sector component is more likely to improve the long–short factor and degrade the long-only factor.

The ratio of Sharpe ratios is larger than the correlation coefficient for several long–short factors—rank-weighted momentum and value-weighted profitability, investment, and momentum—implying that neutralization will likely degrade these factors. Table 2 shows, however, that neutralization does not reduce the Sharpe ratios of these factors (the Sharpe ratio of the value-weighted investment factor even increases). These examples illustrate the divergence between the inequality and the exact solution: If the sector exposure of a factor is far larger than its optimal amount, then neutralization is beneficial even if the optimal weight is positive. Appendix B shows that the conflict between the inequality and the exact solution only occurs in long–short factors because they have large sector exposures. The inequality and the exact solution are in harmony for long-only factors because long-only factors have small sector exposures.

We next present the factor-by-factor results for the 12 sector classifications. Table 2 shows the factor-by-factor decomposition results for value-weighted factors.[5] The columns on the left in Table 2 show the returns to each long–short factor, the return to its across component, and the return to its within component. Our focus is on the Sharpe ratios (*t*-values) of the factors and components. If the *t*-value of the within component is larger than that of the factor, the mean-variance investor is better off trading the within component only and sector neutralizing.

Table 1. Sharpe Ratios and the Correlation Coefficient

	Long–short factors					Long-only factors			
	SR_{across}	SR_{within}	Ratio	ρ		SR_{across}	SR_{within}	Ratio	ρ
Panel A: Average of all factors' construction methods									
	0.10	0.53	0.18	0.46		0.50	0.54	0.93	0.75
Panel B: Equal weighted									
Size	−0.29	0.30	−0.97	0.18	Size	0.45	0.47	0.95	0.89
Value	0.05	0.82	0.06	0.64	Value	0.61	0.64	0.97	0.69
Profitability	0.15	0.24	0.64	0.64	Profitability	0.52	0.53	0.98	0.87
Investment	0.12	0.97	0.13	0.48	Investment	0.46	0.61	0.75	0.67
Momentum	0.37	0.57	0.64	0.68	Momentum	0.39	0.53	0.73	0.61
Panel C: Rank weighted									
Size	−0.26	0.24	−1.07	0.23	Size	0.43	0.42	1.03	0.90
Value	0.03	0.86	0.04	0.65	Value	0.60	0.65	0.93	0.70
Profitability	0.09	0.27	0.35	0.70	Profitability	0.52	0.53	0.98	0.85
Investment	0.21	1.05	0.20	0.50	Investment	0.46	0.59	0.78	0.68
Momentum	0.41	0.57	0.72	0.67	Momentum	0.53	0.58	0.91	0.73
Panel D: Value weighted									
Size	−0.27	0.26	−1.03	−0.17	Size	0.47	0.42	1.12	0.87
Value	0.01	0.46	0.03	0.43	Value	0.57	0.51	1.11	0.71
Profitability	0.25	0.46	0.54	0.31	Profitability	0.56	0.53	1.05	0.83
Investment	0.15	0.41	0.37	0.31	Investment	0.44	0.54	0.80	0.59
Momentum	0.39	0.53	0.73	0.61	Momentum	0.53	0.55	0.96	0.65

Note: The table shows Sharpe ratios of the across and within components of factors, the ratio of the Sharpe ratios (across to within), and their correlation coefficient. The factors are constructed using the Fama and French (2015) methodology. At the end of every June, we use accounting data for the fiscal year of the previous year to form 2 × 3 portfolios sorted on size and characteristic. The size breakpoint is the NYSE median market capitalization, and the characteristic breakpoints are the NYSE 30th and 70th percentiles. We compute two HML returns for small and big stocks and compute the long–short factor return as the average of the two. The long-only factor is constructed by averaging the returns of the high-large and high-small portfolios. The within and across components are obtained from (10). We use the 12 sector classifications of Fama and French. Data are monthly from July 1963 to December 2020 (690 months).

Indeed, consistent with Asness, Porter, and Stevens (2000), Blitz and Hanauer (2020), Ehsani, Hunstad, and Mehta (2020), Israel, Laursen, and Richardson (2020), Kessler, Scherer, and Harries (2019), and Novy-Marx (2013), we find that the within component of almost every long–short factor earns a larger *t*-ratio than the factor. Size, value, and investment factors produce the largest gains. The equal-weighted value-weighted sector-neutral factor earns about a 20% (7.94/6.67) higher Sharpe ratio than its standard version. The last row shows the premium to the bottom-up multi-factor portfolio and its two components. We construct the bottom-up multi-factor portfolio and its components in three steps:

1. Assign characteristic ranks to each stock based on the stock's characteristic value in the cross-section. After this step each stock has a value ranking, a momentum ranking, and so on.
2. Average the characteristic rankings to find the stock's final ranking.
3. Form the bottom-up multi-factor portfolio by sorting stocks based on their final ranking.
4. Estimate the across and within components of the bottom-up multi-factor portfolio by substituting the final ranking for $C_{n,s}$ in equation (10).

The estimates in the last row of the table show that the long–short sector-neutral bottom-up portfolio earns 17% (6.40/5.46) higher Sharpe ratio than its standard version.[6]

The columns on the right in Table 2 show the results for long-only factors. The pattern in *t*-values of long factors is the opposite of the long–short factors. Here, the as-is factor always earns a higher *t*-value than its sector-neutral version. For both the average factor and the bottom-up factor, the *t*-value of the sector component is as large as the within component, indicating that the long-only investor should *not* seek to invest exclusively in the within component.[7] We find similar results for equal- and rank-

Table 2. Return Decompositions

	Long–short factors				Long-only factors		
	Factor	Across	Within		Factor	Across	Within
Size	0.19	−0.06	0.25	Size	0.79	0.09	0.70
	(1.51)	(−2.02)	(1.97)		(3.26)	(3.56)	(3.18)
Value	0.23	0.01	0.22	Value	0.82	0.20	0.61
	(2.07)	(0.09)	(3.52)		(4.22)	(4.33)	(3.90)
Profitability	0.30	0.07	0.23	Profitability	0.81	0.13	0.67
	(3.53)	(1.89)	(3.51)		(4.14)	(4.21)	(4.01)
Investment	0.21	0.04	0.16	Investment	0.81	0.07	0.73
	(2.82)	(1.17)	(3.13)		(4.19)	(3.30)	(4.11)
Momentum	0.59	0.18	0.41	Momentum	0.94	0.19	0.75
	(3.98)	(2.93)	(3.99)		(4.43)	(4.03)	(4.20)
Multi-factor	0.30	0.05	0.25	Multi-factor	0.83	0.14	0.69
(EW)	(6.67)	(1.99)	(7.94)	(EW)	(4.14)	(5.15)	(3.93)
Multi-factor	0.57	0.15	0.43	Multi-factor	0.98	0.16	0.82
(bottom-up)	(5.46)	(2.79)	(6.40)	(bottom-up)	(5.26)	(5.32)	(4.99)

Note: The table shows mean returns and *t* values to value-weighted factor returns and their within and across components using the decomposition of (10). The construction method for the five equity factors is as in Table 1. The equal-weighted multi-factor portfolio invests equally in the five factors. The bottom-up multi-factor portfolio is a sort on the average ranking of the characteristic rankings. We use the 12-sector classification of Fama and French to compute the across and within components. Data are monthly from June 1963 to December 2020 (690 months). EW = Equal weighted.

weighted long-only portfolios in Appendix C. Neither of the across components of long-only factors meets condition (4). Therefore, the long factor investor is better off investing in the factor that sorts on the characteristic as it stands.[8]

Sector-Level Decompositions. Table 3 provides a detailed decomposition of the long–short value returns at the sector level. We present the average exposure to each sector and the resulting return and variance contributions to the overall return and variance of the portfolio.[9] We report the results for the original factor in panel A and the results for its two components, sector and within, in panels B and C, respectively. By construction, exposures and returns of the original factor equal the sum of the exposures and returns of the sector and within components. The variances of the sector and within components do not sum to the variance of the original factor because of their covariance.

An interesting finding is that the within returns of panel C are positive for every sector. As a result, the total contribution of the within component is significant (0.22% with a *t*-value of 3.52). The net return emerging from the sector component, reported in Panel B, is close to zero. For example, trading BM within the cross-section of every sector is highly profitable, while trading BM in the cross-section of sectors is not. This observation suggests that the entire predictive power of market-wide BM stems from the information in its firm-specific component. A long–short investor who sorts stocks based on a raw BM signal contaminates the useful within-sector information by the noise of the across-sector component. Once again, consider the example of tech firms. The standard value factor shorts technology because most tech companies are considered growth companies when compared to the average company. Therefore, the standard approach does not exploit the variation of BM *within* the tech sector because tech stocks are all sent to the short leg of the portfolio. Table 3 shows, however, that BM appears to be priced in the cross-section of tech companies with a premium of 0.04% (*t*-value of 2.07). This result explains our earlier findings: The long–short factor sorted on the raw characteristic is less efficient than an alternative sort on the within component because the raw characteristic is contaminated with the noise from the across component.

Tables 4 and 5 show sector-level decompositions for the long-only value factor and the short-only value factor, respectively. Table 4 shows that, as expected, the standard long value factor has positive sector exposures to all sectors, and as a result, each sector contributes positively to its total return of 0.82% (*t*-value of 4.22). Panel B of Table 4 shows the contribution of each sector to the sector component of long value.[10] The sector component earns a large

Table 3. Exposure and Return Contribution by Each Sector to the Long–Short Value Factor

	NonDur	Dur	Manufac	Oil	Chemical	Tech	Comm	Util	Retail	Health	Finance	Other	Total
Panel A: Factor													
Average	−0.02	−0.01	0.04	0.03	−0.03	−0.15	0.03	0.12	−0.04	−0.11	0.17	−0.02	0.00
Exposure	(−2.87)	(−1.86)	(2.30)	(2.95)	(−9.74)	(−15.28)	(2.37)	(8.06)	(−6.79)	(−13.04)	(6.85)	(−1.98)	
Average	0.00	0.01	0.08	0.06	−0.01	−0.07	0.01	0.09	−0.01	−0.09	0.18	−0.01	0.23
Return	(−0.38)	(1.19)	(3.00)	(2.53)	(−1.25)	(−1.38)	(0.49)	(4.35)	(−0.51)	(−2.91)	(3.28)	(−0.36)	(2.07)
Variance	0.32	0.22	0.58	0.49	0.15	2.62	0.28	0.41	0.51	1.03	1.14	0.88	8.64
Panel B: Sector component													
Average	−0.02	−0.01	0.04	0.03	−0.03	−0.15	0.03	0.12	−0.04	−0.11	0.17	−0.02	0.00
Exposure	(−2.87)	(−1.86)	(2.30)	(2.95)	(−9.74)	(−15.28)	(2.37)	(8.06)	(−6.79)	(−13.04)	(6.85)	(−1.98)	
Average	−0.01	0.00	0.04	0.02	−0.02	−0.11	0.00	0.09	−0.01	−0.12	0.16	−0.03	0.01
Return	(−1.58)	(0.56)	(2.04)	(0.80)	(−3.78)	(−2.09)	(−0.24)	(4.70)	(−1.42)	(−4.00)	(3.49)	(−2.01)	(0.09)
Variance	0.05	0.03	−0.01	0.16	0.05	1.86	0.05	0.18	0.11	0.82	−0.08	−0.01	3.20
Panel C: Within component													
Average	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Exposure	.	.	.	.	.	.	.	.	.	.	.	.	
Average	0.01	0.01	0.03	0.04	0.01	0.04	0.01	0.00	0.01	0.04	0.02	0.02	0.22
Return	(1.46)	(0.95)	(1.97)	(4.37)	(2.77)	(2.07)	(0.85)	(−0.19)	(0.70)	(3.16)	(0.98)	(1.34)	(3.52)
Variance	0.13	0.15	0.43	0.12	0.10	0.41	0.21	0.05	0.26	0.20	0.38	0.50	2.94

Note: The table shows the average sector exposure and the resulting variance and returns from these exposures by each sector for the long–short value-weighted value factor. We report the sector contributions for the overall factor and for its two components. Data are monthly from July 1963 to December 2020 (690 months).

Table 4. Exposure and Return Contribution by Each Sector to the Long-Only Value Factor

	NonDur	Dur	Manufac	Oil	Chemical	Tech	Comm	Util	Retail	Health	Finance	Other	Total
Panel A: Factor													
Average	0.06	0.04	0.15	0.07	0.02	0.05	0.06	0.14	0.07	0.02	0.23	0.11	1.00
Exposure	(10.36)	(8.64)	(7.05)	(10.87)	(9.86)	(10.29)	(5.98)	(10.56)	(19.80)	(9.39)	(9.31)	(18.06)	
Average	0.05	0.03	0.12	0.06	0.02	0.06	0.02	0.09	0.06	0.02	0.20	0.10	0.82
Return	(3.25)	(2.50)	(2.78)	(2.65)	(2.94)	(3.38)	(1.26)	(4.10)	(3.16)	(3.82)	(3.34)	(3.38)	(4.22)
Variance	1.56	1.24	4.28	1.89	0.57	1.64	0.96	1.41	2.11	0.46	6.85	3.56	26.53
Panel B: Sector component													
Average	0.01	0.00	0.03	0.03	0.00	−0.03	0.02	0.12	−0.01	−0.01	0.13	−0.01	0.26
Exposure	(2.36)	(−0.52)	(3.02)	(4.77)	(−6.25)	(−16.94)	(2.92)	(8.70)	(−2.89)	(−10.06)	(6.35)	(−2.44)	
Average	0.01	0.00	0.04	0.01	−0.01	−0.04	0.00	0.09	0.00	−0.03	0.12	−0.01	0.20
Return	(1.79)	(0.64)	(3.15)	(0.97)	(−3.21)	(−4.72)	(−0.09)	(4.61)	(0.80)	(−5.04)	(3.49)	(−2.13)	(4.33)
Variance	0.02	0.00	0.09	0.26	−0.03	−0.10	0.06	0.41	−0.01	−0.04	0.95	−0.09	1.53
Panel C: Within component													
Average	0.06	0.04	0.12	0.05	0.02	0.07	0.04	0.02	0.07	0.03	0.10	0.12	0.75
Exposure	(18.45)	(12.24)	(12.73)	(13.92)	(13.64)	(17.26)	(11.02)	(10.56)	(43.30)	(13.32)	(19.09)	(23.47)	
Average	0.04	0.03	0.08	0.05	0.02	0.10	0.02	0.00	0.05	0.05	0.08	0.11	0.61
Return	(3.28)	(2.44)	(2.37)	(3.31)	(3.25)	(3.99)	(1.73)	(0.17)	(2.98)	(4.79)	(2.69)	(3.45)	(3.90)
Variance	1.08	1.02	2.97	0.87	0.61	2.19	0.63	0.12	1.80	0.73	2.54	3.20	17.74

Note: The table shows the average sector exposure and the resulting variance and returns from these exposures by each sector for the long-only value-weighted value factor. We report the sector contributions for the overall factor and for its two components. Data are monthly from July 1963 to December 2020 (690 months).

t-ratio of 4.33 that is larger than the *t*-ratio of 3.90 earned by the within component shown in panel C. In fact, the Sharpe ratio–maximizing optimal mix of the sector and within components would be to put 86% in the sector component and 14% in the within component; this long-only "factor" would have earned a *t*-value of 4.50. The main takeaway from Table 4 is that both across and within components contribute to the returns of long-only factors.

Table 5 shows the same results for the short-only value factor. The standard short value factor is a short position in stocks with a BM below the average BM. Panel A shows that this portfolio loses an

Table 5. Exposure and Return Contribution by Each Sector to the Short-Only Value Factor

	NonDur	Dur	Manufac	Oil	Chemical	Tech	Comm	Util	Retail	Health	Finance	Other	Total
Panel A: Factor													
Average	0.08	0.05	0.12	0.04	0.05	0.20	0.03	0.01	0.10	0.13	0.06	0.13	1.00
Exposure	(16.25)	(9.64)	(15.32)	(6.44)	(15.57)	(18.77)	(9.52)	(2.95)	(28.72)	(15.06)	(12.91)	(12.81)	
Average	0.05	0.02	0.04	0.01	0.02	0.13	0.02	0.00	0.06	0.10	0.03	0.10	0.59
Return	(3.26)	(1.90)	(1.44)	(0.28)	(2.55)	(2.11)	(1.89)	(0.30)	(2.71)	(3.29)	(2.09)	(2.73)	(2.75)
Variance	1.86	1.28	3.65	1.35	1.10	8.12	0.97	0.15	3.01	3.58	1.55	4.84	31.47
Panel B: Sector component													
Average	0.03	0.01	−0.01	−0.00	0.03	0.13	−0.01	−0.01	0.03	0.10	−0.05	0.01	0.27
Exposure	(4.98)	(3.18)	(−1.16)	(−0.13)	(12.24)	(13.30)	(1.17)	(−1.30)	(8.08)	(17.15)	(−7.85)	(1.68)	
Average	0.02	−0.00	−0.00	−0.00	0.02	0.07	0.00	−0.00	0.02	0.09	−0.04	0.02	0.20
Return	(3.24)	(−0.17)	(−0.26)	(−0.18)	(3.05)	(1.58)	(0.20)	(−0.42)	(2.14)	(3.46)	(−3.00)	(1.76)	(2.72)
Variance	0.16	0.05	−0.01	0.14	0.16	2.12	−0.02	−0.08	0.24	1.07	−0.38	0.14	3.59
Panel C: Within component													
Average	0.06	0.04	0.12	0.05	0.02	0.07	0.04	0.02	0.07	0.02	0.10	0.12	0.74
Exposure	(18.45)	(11.09)	(12.73)	(13.69)	(12.53)	(16.51)	(12.20)	(11.16)	(43.30)	(10.75)	(18.37)	(23.47)	
Average	0.03	0.02	0.04	0.01	0.01	0.06	0.02	0.00	0.05	0.01	0.06	0.09	0.39
Return	(2.39)	(2.03)	(1.30)	(0.58)	(1.37)	(2.34)	(1.30)	(0.51)	(2.66)	(1.06)	(2.74)	(2.58)	(2.57)
Variance	1.03	0.91	3.01	0.76	0.39	1.68	0.82	0.32	1.63	0.31	1.99	3.16	16.01

Note: The table shows the average sector exposure and the resulting variance and returns from exposure to each sector for the short-only value-weighted value factor. We report the sector contributions for the overall factor and for its two components. Data are monthly from July 1963 to December 2020 (690 months).

average of 0.59% per month with a *t*-value of 2.75. Panels B and C decompose this premium. The sector component generates 0.20% of the premium (*t*-value of 2.72) and the within component generates 0.39% (*t*-value of 2.57). Notice that the 0.20% contribution of the sector component is exactly equal to the 0.20% contribution of the sector component in Table 4. The return from the within component, however, is 0.39% and is smaller than the 0.61% of the within component of the long leg.[11]

We next study the volatility of the components. The variance of the sector component of the long value factor (Table 4) is 1.53 and that of the sector component of the short value factor (Table 5) is 3.59. The large variance of the sector bet of the short leg therefore cannot be properly diversified by the variance of the long leg in the long–short portfolio. The variance asymmetry is reflected in the large variance of 3.20 (Table 3) for the sector component of the long–short value factor. At the same time, the variance asymmetry between the within components is much smaller: The within component of long value has a variance of 17.74 (Table 4) and the within component of short value has a similar variance of 16.01 (Table 5).

To summarize, the market-wide predictive power of a characteristic can arise because it predicts the cross-section of sectors or because it predicts the cross-section of the elements within each sector. The results we present in this section show that the across BM is better at predicting the outperforming *sectors*, and the within BM is better at predicting the underperforming *stocks* within each sector.

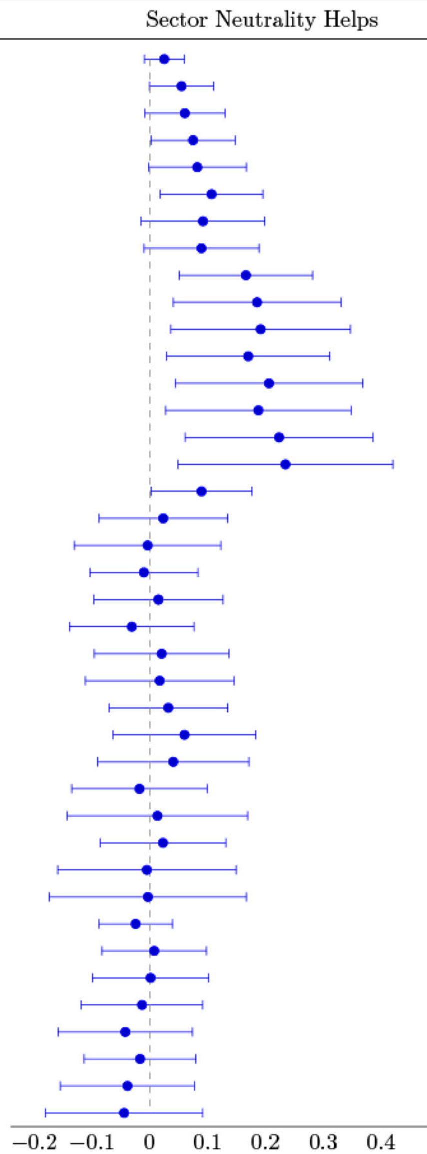
Sensitivity to the Choice of Sector Classification.

The previous results were based on the 12 industry sector classifications of Fama and French. This section tests the sensitivity of the inferences to the choice of sector classification. In the interest of brevity and to conserve space, we present the results for the value-weighted portfolios most often used in practice: size, value, profitability, investment, and momentum. We follow Ledoit and Wolf (2008) and use time-series bootstraps to obtain confidence intervals for differences in Sharpe ratios.

Figure 5 shows differences between the Sharpe ratios of sector-neutral and standard factors constructed using the value-weighted long–short methodology. The figure shows that most factors constructed using this method benefit from sector neutrality regardless of the sector classification. The largest improvement of 0.42 units in annualized Sharpe ratio occurs for the value factor that hedges out exposure to 49 industries.[12]

Figure 6 shows the changes in Sharpe ratios from removing sector bets for the value-weighted long-

Figure 5. The Impact of Industry Classification on Changes in Sharpe Ratios of Long–Short Factors



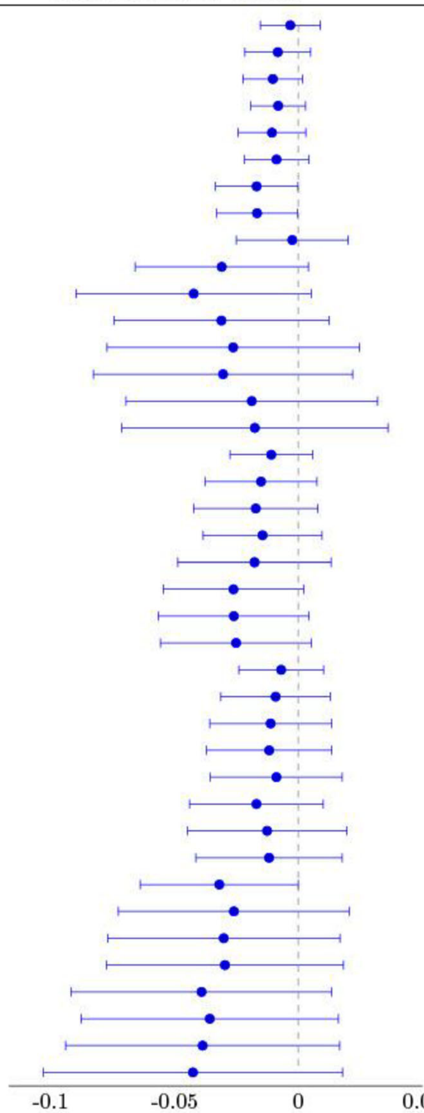
Factor	$SR^N - SR$	95% CI
Size-05	0.03	(−0.01 to +0.06)
Size-10	0.06	(+0.00 to +0.11)
Size-12	0.06	(+0.00 to +0.13)
Size-17	0.08	(+0.01 to +0.15)
Size-30	0.08	(+0.00 to +0.17)
Size-38	0.11	(+0.03 to +0.20)
Size-48	0.09	(+0.00 to +0.20)
Size-49	0.09	(−0.01 to +0.19)
Value-05	0.17	(+0.06 to +0.28)
Value-10	0.19	(+0.05 to +0.33)
Value-12	0.19	(+0.04 to +0.35)
Value-17	0.17	(+0.04 to +0.31)
Value-30	0.21	(+0.05 to +0.37)
Value-38	0.19	(+0.03 to +0.35)
Value-48	0.22	(+0.06 to +0.39)
Value-49	0.23	(+0.06 to +0.42)
Profitability-05	0.09	(+0.01 to +0.18)
Profitability-10	0.02	(−0.09 to +0.13)
Profitability-12	0.00	(−0.11 to +0.12)
Profitability-17	−0.01	(−0.11 to +0.08)
Profitability-30	0.02	(−0.09 to +0.13)
Profitability-38	−0.03	(−0.14 to +0.08)
Profitability-48	0.02	(−0.10 to +0.14)
Profitability-49	0.02	(−0.11 to +0.15)
Investment-05	0.03	(−0.07 to +0.13)
Investment-10	0.06	(−0.07 to +0.18)
Investment-12	0.04	(−0.09 to +0.17)
Investment-17	−0.02	(−0.13 to +0.10)
Investment-30	0.01	(−0.14 to +0.17)
Investment-38	0.02	(−0.11 to +0.13)
Investment-48	0.00	(−0.17 to +0.15)
Investment-49	0.00	(−0.16 to +0.17)
Momentum-05	−0.02	(−0.09 to +0.04)
Momentum-10	0.01	(−0.08 to +0.10)
Momentum-12	0.00	(−0.08 to +0.10)
Momentum-17	−0.01	(−0.10 to +0.09)
Momentum-30	−0.04	(−0.13 to +0.07)
Momentum-38	−0.02	(−0.10 to +0.08)
Momentum-48	−0.04	(−0.14 to +0.08)
Momentum-49	−0.04	(−0.16 to +0.09)

Note: The figure shows the changes in Sharpe ratios as a result of neutralizing sector exposures of value-weighted long–short factor portfolios. For each factor, we compute the difference between the Sharpe ratio of its industry-neutral version, SR^N, and its standard version. We use all eight industry portfolios of Fama and French: 5, 10, 12, 17, 30, 38, 48, and 49. Value 12, for example, refers to the difference between the Sharpe ratio of the sector-neutral value factor and the original value factor using the 12 industry classifications of Fama and French. We compute the confidence interval for this difference in Sharpe ratios by bootstrapping the data by time.

only factors. Once again, we find that the choice of sector classification is generally inconsequential. The Sharpe ratios of long-only factors are reduced if the sector component is neglected regardless of the classification. Comparing Figures 5 and 6, we conclude that the key determinant for whether sector neutrality is beneficial is the choice of long–short versus long-only. The former group is more likely to benefit, and the latter group is more likely to deteriorate.[13]

Spanning Regressions. The preceding tests focus on the benefit (or lack thereof) of sector neutrality for the individual factor investor. Whether our main finding—that the long–short factor generally

Figure 6. The Impact of Industry Classification on Changes in Sharpe Ratios of Long-Only Factors



Factor	$SR^N - SR$	95% CI
Size-05	0.00	(−0.02 to +0.01)
Size-10	−0.01	(−0.02 to +0.01)
Size-12	−0.01	(−0.02 to +0.00)
Size-17	−0.01	(−0.02 to +0.00)
Size-30	−0.01	(−0.02 to +0.00)
Size-38	−0.01	(−0.02 to +0.00)
Size-48	−0.02	(−0.03 to +0.00)
Size-49	−0.02	(−0.03 to +0.00)
Value-05	0.00	(−0.02 to +0.02)
Value-10	−0.03	(−0.07 to +0.00)
Value-12	−0.04	(−0.09 to +0.01)
Value-17	−0.03	(−0.08 to +0.01)
Value-30	−0.03	(−0.07 to +0.02)
Value-38	−0.03	(−0.08 to +0.02)
Value-48	−0.02	(−0.07 to +0.03)
Value-49	−0.02	(−0.07 to +0.04)
Profitability-05	−0.01	(−0.03 to +0.01)
Profitability-10	−0.02	(−0.04 to +0.01)
Profitability-12	−0.02	(−0.04 to +0.01)
Profitability-17	−0.01	(−0.04 to +0.01)
Profitability-30	−0.02	(−0.05 to +0.01)
Profitability-38	−0.03	(−0.05 to +0.00)
Profitability-48	−0.03	(−0.06 to +0.00)
Profitability-49	−0.03	(−0.05 to +0.01)
Investment-05	−0.01	(−0.02 to +0.01)
Investment-10	−0.01	(−0.03 to +0.01)
Investment-12	−0.01	(−0.04 to +0.01)
Investment-17	−0.01	(−0.03 to +0.01)
Investment-30	−0.01	(−0.04 to +0.02)
Investment-38	−0.02	(−0.05 to +0.01)
Investment-48	−0.01	(−0.04 to +0.02)
Investment-49	−0.01	(−0.04 to +0.02)
Momentum-05	−0.03	(−0.06 to +0.00)
Momentum-10	−0.03	(−0.07 to +0.02)
Momentum-12	−0.03	(−0.08 to +0.02)
Momentum-17	−0.03	(−0.07 to +0.02)
Momentum-30	−0.04	(−0.09 to +0.01)
Momentum-38	−0.04	(−0.08 to +0.02)
Momentum-48	−0.04	(−0.09 to +0.02)
Momentum-49	−0.04	(−0.10 to +0.02)

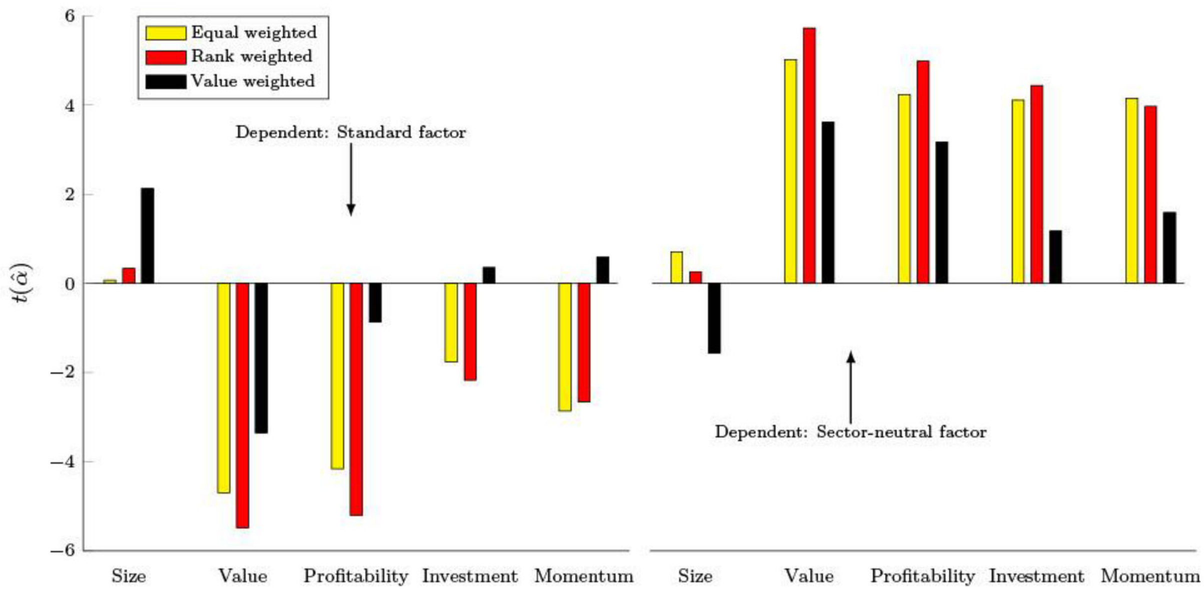
Note: The figure shows the changes in the Sharpe ratios of sector-neutral value-weighted long-only factors for the eight industry portfolios of Fama and French: 5, 10, 12, 17, 30, 38, 48, and 49. All else remains as in Figure 5.

benefits from sector neutrality, whereas the long-only factor does not—continues to hold for the multi-factor investor is an empirical question. For example, in the previous sections, we show that long-only standard factors earn a higher Sharpe ratio than their sector-neutral counterparts. Individual Sharpe ratios may not convert to a higher Sharpe ratio for the multi-factor portfolio if the improved factors are more correlated. We use time-series spanning regressions of the following form to test whether changes in individual factor efficiency translate into similar changes in multi-factor efficiency:

$$r = \alpha + \beta_m MKTRF + \beta_s SMB + \beta_h HML + \beta_r RMW + \beta_c CMA + \beta_u UMD + e.$$

The first group of tests regresses each standard long–short factor on the market and five

Figure 7. Long–Short Factor Intercepts in Multivariate Regressions



Note: The figure shows the *t*-values of intercepts in factor model regressions with standard factors (bars on the left) or sector-neutral factors (bars on the right) as the dependent variable. Each standard (sector-neutral) factor is regressed on all the sector-neutral (standard) factors.

sector-neutral long–short factors. The second group of tests regresses each long–short sector-neutral factor on the market and five long–short standard factors. The intercept of each regression reveals the value of each lefthand-side portfolio in the presence of the righthand-side assets.

Figure 7 shows that the intercepts of most long–short standard factors are negative. By contrast, the intercepts of long–short sector-neutral factors are mostly positive and those of value and profitability are highly significant. We conclude that the long–short multi-factor investor can expand the mean-variance frontier by trading sector-neutral factors.

We next run spanning tests for long-only factors. Our long-only regressions are constrained to produce nonnegative coefficients for the righthand-side assets because a negative coefficient implies that spanning the lefthand-side asset requires a short position in the righthand-side asset, which is not possible in a long-only portfolio. Figure 8 shows that all 15 versions of long-only standard factors earn positive intercepts. In contrast, 8 out of 15 intercepts of sector-neutral factors are negative. All sector-neutral versions of the size and profitability factors as well as the value-weighted value and momentum factors earn negative alphas. For the investment factor, the standard and sector-neutral versions earn similar alphas.

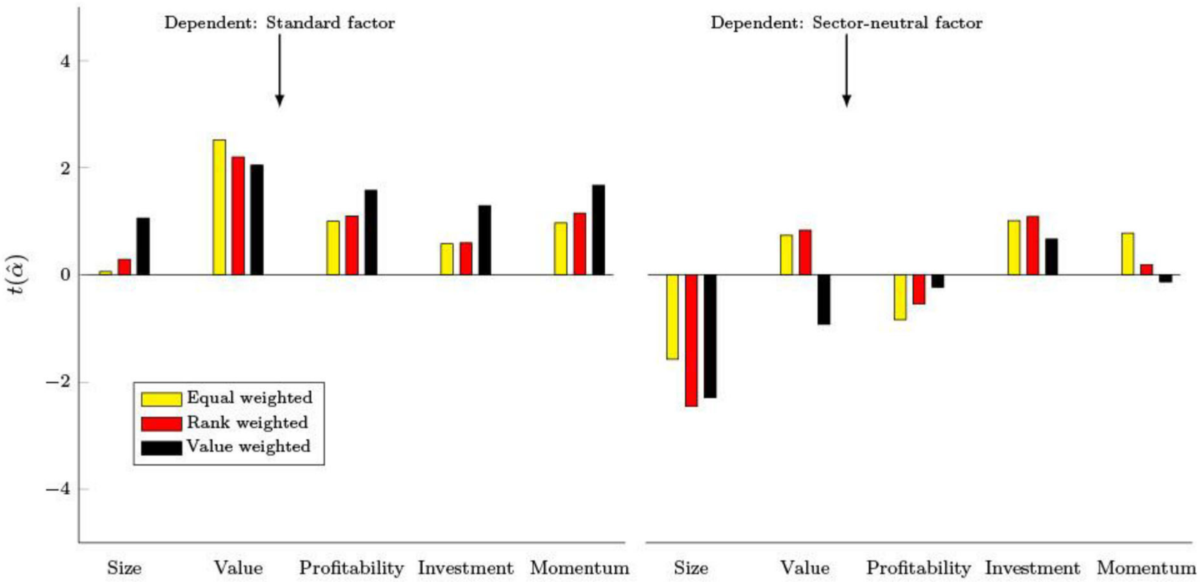
The results from spanning regressions on long-only portfolios support the hypothesis that long-only standard factors are more mean-variance efficient than their sector-neutral counterparts in a multivariate sense.

To summarize, standard long-only factors earn higher Sharpe ratios and are more multivariate mean-variance–efficient than long-only sector-neutral factors. The individual or multi-factor long-only investor should not pursue sector neutralization, because they gain the most by investing in as-is factors.

Conclusion

Investors pursuing factor strategies face numerous choices—and the choices do not end after they determine the set of factors. For example, should the factors be sector neutralized? If the investor pursues sector neutralization, which sector classification is

Figure 8. Long-Only Factor Intercepts in Multivariate Regressions



Note: The figure shows the *t*-values of intercepts in factor model regressions with standard factors (bars on the left) or sector-neutral factors (bars on the right) as the dependent variable. Each standard (sector-neutral) factor is regressed on the market and all the sector-neutral (standard) factors.

optimal? Is the sector-neutrality decision contingent on the particular factor? Are the choices potentially different for the long-only investor compared to the long–short investor? Our paper provides insights on these four questions.

While previous research has provided some evidence in favor of sector neutrality for certain factors, we present a simple framework with two sources of predictability: across sector and within sector. The question of whether to use both sources of predictability or to just focus on the within sector (i.e., sector neutralization) is related to the static two risky-asset mean-variance problem. We derive the condition whereby it is likely optimal to sector neutralize. The condition relies on the Sharpe ratios of the individual sources of predictability as well as the correlation of the two sources.

We show in bootstrap simulations that our analytical framework does a good job of matching the data. While others have argued for the benefits of sector neutralization mostly in long–short setups, our framework reveals the drivers of those results. Our model also predicts that it is unlikely sector neutralization is beneficial for the long-only investor, and the empirical results are consistent with this prediction.

Although our analytical model does not predict the number of sectors an investor should use, our empirical results suggest this choice is generally inconsequential. The main variable that determines whether sector neutrality remains is the long–short versus the long-only construction methodology.

Our analysis has three caveats. First, our empirical results based on the mean-variance framework are ex post. That is, sector neutralization of long–short (long-only) factors is generally beneficial (detrimental) based on an ex post historical analysis. Indeed, some previous research also comes to this conclusion. The importance of our paper is that we show the "why" behind this finding. Although the empirical analysis is ex post, our framework based on the Sharpe ratios of the factor within-industry and across-industry predictability as well as the correlation can be used on an ex ante basis. It is reasonable to expect that both Sharpe ratios and correlations can change through time. Our method gives investors engaged in active portfolio management a metric to forecast the sign of expected contribution of sector neutralization in factor portfolios.

The second caveat is the mean-variance framework itself. While commonplace in investment management, the choice of whether to neutralize assumes that investors only care about mean and variance. It is well known, however, that investors prefer positively skewed returns and that most factor returns are not normally distributed. For example, suppose the sector component has positive skew. An investor might think twice about expunging sector exposures—even if our mean-variance framework suggests neutralization.

Finally, we exclusively focus on sector exposures while other sources such as region or country exposures may also impact factor performance. The analytical and empirical properties of portfolios with a larger number of components are distinct from the two-component problem studied in this paper.

Editor's Note

Submitted 2 March 2022

Accepted 27 March 2023 by William N. Goetzmann

Notes

1. Appendix A shows the derivation of (3).

2. Empirically, the across and within components covary positively except for the long–short value-weighted size factor. The mean return to the within component is positive without exception. The mean return to the sector component is positive for all but the three versions of the size factor. Sector neutrality is always beneficial when the mean return to the sector component is negative ($\mu_a < 0$). Starting with the return to the factor, $w_a\mu_a + (1 - w_a)\mu_w$, the investor can earn a higher return, $w_a 0 + (1 - w_a)\mu_w$, by substituting the sector component with cash. The (minimum) variance of the first portfolio, when the two components are uncorrelated, is $w_a^2\sigma_a^2 + (1 - w_a)^2\sigma_w^2$, which is larger than the variance of the portfolio that substitutes the sector component with cash, ($(1 - w_a)^2\sigma_w^2$). When the sector component earns a positive premium, the denominator in (3) is positive because means and correlations are positive. The sign of the numerator determines the sign of the identity,
$$\begin{aligned} optimal\ weight(a) \\ \leq 0 \Longleftrightarrow \mu_a\sigma_w^2 - \mu_w COV(r_w, r_a) \leq & \quad 0 \\ \mu_a\sigma_w^2 \leq & \quad \mu_w\rho\sigma_w\sigma_a \\ SR_a/SR_w \leq & \quad \rho. \end{aligned}$$
In retrospect, we know the values for SR and ρ from the data, but in practice an investor should use prospective measures of SR and ρ. This difference, however, does not alter the thrust of the analysis we present here: The real-time investor should form a sector-neutral factor if the ratio of *expected* Sharpe ratios is less than the *expected* correlation between the two portfolios.

3. We emphasize that our analysis is restricted to mean-variance efficiency. An investor who considers higher moments (see, e.g., Harvey and Siddique 2000, 2022) should not use (4) for decision making.

4. We thank an anonymous referee for raising this point.

5. Appendix B presents the factor-by-factor return decompositions for equal- and rank-weighted portfolios based on the 12 industry classifications of Fama and French. We examine the robustness of results by running the decomposition using the 5, 10, 12, 17, 30, 38, 48, 49 Fama and French industry classifications in the section "Sensitivity to the Choice of Sector Classification."

6. Appendix C shows that the gain from sector neutrality is even larger for equal- and rank-weighted long–short factors.

7. We conduct the Jobson and Korkie (1981) test to determine whether the difference in Sharpe ratios between the standard and sector-neutral long-only factors are statistically different from zero. For example, the standard bottom-up factor has an annualized Sharpe ratio of 0.694 (mean of 0.98% and *t*-statistics of 5.26), while the neutral version has a Sharpe ratio of 0.659 (mean of 0.82% and *t*-statistics of 4.99). Although the difference in annualized Sharpe ratios (0.694 – 0.659) is only 0.035, it has a Jobson-Korkie *z*-statistic of 2.22, implying a p-value of 2.67%. The high correlation (0.98) between the two factors is key to this surprising result. Due to this very high correlation, the test has an extremely high power, enabling us to reject the small difference with high confidence.

8. Our focus in this paper is on the total impact of the across component on factor portfolios. However, as depicted in Figure 3, sector exposures encompass both a static component (such as the overall positive exposure to the financials sector) and a time-varying component. For instance, our estimate of 0.01 (with a *t*-statistic of 0.09) for the across component of the value factor reflects the combined impact of both components. Determining the specific contribution of each component of sector exposures to the overall effect is an interesting topic for future research.

9. We compute variance contributions by computing $1_{1\times12}\Sigma_{12\times12}$. That is, each sector's contribution to the portfolio's variance is the sum of the elements of the associated column of the 12×12 covariance matrix of 12 sector returns. For example, if durables is the second sector, then the sum of the elements in the second column gives the variance contribution of durables to the portfolio.

10. The average exposure to some sectors is negative. How can a long value factor have negative exposure to certain sectors? Note that we compute sector exposures by finding $\frac{1}{S \times N} \sum_s \sum_n \left(C_s - \overline{C}\right)$. Suppose the average BM in the entire cross-section is 1. Also assume that we want to form the value factor using four stocks in a sector and that these stocks have BMs of 3, 2, –2, and –3. The mean BM of this sector is 0. The long value factor invests in the first two stocks only; it allocates $(3-1)/2 = 1$ to the first stock and $(2-1)/2 = 0.5$ to the second. Next, we decompose these weights into within and across components. The within strategy sorts based on the difference with the sector mean rather than with the cross-sectional mean, so it allocates $(3-0)/2 = 1.5$ to the first stock and $(2-0)/2 = 1$ to the second. This means that in a long-only construction, the within component of sectors whose BMs are smaller than the average BM will be positive, while the sector exposures of the sector component will be negative. This example explains the negative exposures in Panel B of Table 4.

11. We present the sector-level decomposition of returns to the long–short, long-only, and short-only constructions of the size, profitability, investment, and momentum factors in Online Supplemental Material.

12. Unlike most of the other factors, the long–short momentum degrades from sector neutrality. This finding is consistent with previous studies such as Moskowitz and Grinblatt (1999) who find that trading momentum in the cross-section of industries is highly profitable.

13. We conduct a historical simulation for changes in Sharpe ratios as a result of neutralizing sector exposures at the intersection of all portfolio construction methodologies in Appendix D.

References

Asness, Cliff S., Andrea Frazzini, and Lasse H. Pedersen. 2014. “Low-Risk Investing without Industry Bets.” *Financial Analysts Journal* 70 (4): 24–41. doi:10.2469/faj.v70.n4.1.

Asness, Cliff S., R. Burt Porter, and Ross L. Stevens. 2000. “Predicting Stock Returns Using Industry-Relative Firm Characteristics.” Available at SSRN: https://ssrn.com/abstract=213872.

Baker, Malcolm, Brendan Bradley, and Ryan Taliaferro. 2014. “The Low-Risk Anomaly: A Decomposition into Micro and Macro Effects.” *Financial Analysts Journal* 70 (2): 43–58. doi:10.2469/faj.v70.n2.2.

Banz, Rolf W. 1981. “The Relationship between Return and Market Value of Common Stocks.” *Journal of Financial Economics* 9 (1): 3–18. doi:10.1016/0304-405X(81)90018-0.

Basu, Sanjoy. 1983. “The Relationship between Earnings’ Yield, Market Value and Return for NYSE Common Stocks: Further Evidence.” *Journal of Financial Economics* 12 (1): 129–56. doi:10.1016/0304-405X(83)90031-4.

Bender, Jennifer, Rehan Mohamed, and Xiaole Sun. 2019. “Country and Sector Bets: Should They Be Neutralized in Global Factor Portfolios?” *Journal of Beta Investment Strategies* 10 (1): 60–74.

Blitz, David, and Matthias X. Hanauer. 2020. “Resurrecting the Value Premium.” *Journal of Portfolio Management* 47 (2): 63–81. doi:10.3905/jpm.2020.1.188.

Ehsani, Sina, Michael Hunstad, and Manan Mehta. 2020. “Compensated and Uncompensated Risks in Global Factor Investing.” Available at SSRN: https://ssrn.com/abstract=3631222.

Fama, Eugene F., and Kenneth R. French. 1993. “Common Risk Factors in the Returns on Stocks and Bonds.” *Journal of Financial Economics* 33 (1): 3–56. doi:10.1016/0304-405X(93)90023-5.

Fama, Eugene F., and Kenneth R. French. 2015. “A Five-Factor Asset Pricing Model.” *Journal of Financial Economics* 116 (1): 1–22. doi:10.1016/j.jfineco.2014.10.010.

Harvey, Campbell R., and Akhtar Siddique. 2000. “Conditional Skewness in Asset Pricing Tests.” *Journal of Finance* 55 (3): 1263–95. doi:10.1111/0022-1082.00247.

Harvey, Campbell R, and Akhtar Siddique. 2022. Conditional Skewness in Asset Pricing: 25 Years of Out-of-Sample Evidence.” Available at SSRN: https://ssrn.com/abstract=4085027.

Ingersoll, Jonathan E. 1987. *Theory of Financial Decision Making*. Lanham, MD: Rowman & Littlefield Publishers, Inc.

Israel, Ronen, Kristoffer Laursen, and Scott Richardson. 2020. “Is (Systematic) Value Investing Dead?” *Journal of Portfolio Management Quantitative Special Issue 2021* 47 (2): 38–62.

Jegadeesh, Narasimhan, and Sheridan Titman. 1993. “Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency.” *Journal of Finance* 48 (1): 65–91. doi:10.1111/j.1540-6261.1993.tb04702.x.

Jobson, J. Dave, and Bob M. Korkie. 1981. “Performance Hypothesis Testing with the Sharpe and Treynor Measures.” *Journal of Finance* 36 (4): 889–908. doi:10.1111/j.1540-6261.1981.tb04891.x.

Kessler, Stephan, Bernd Scherer, and Jan Philipp Harries. 2019. “Value by Design?” *Journal of Portfolio Management* 46 (2): 25–43. doi:10.3905/jpm.2019.1.122.

Ledoit, Oliver, and Michael Wolf. 2008. “Robust Performance Hypothesis Testing with the Sharpe Ratio.” *Journal of Empirical Finance* 15 (5): 850–9. doi:10.1016/j.jempfin.2008.03.002.

Moskowitz, Tobias J., and Mark Grinblatt. 1999. “Do Industries Explain Momentum?” *Journal of Finance* 54 (4): 1249–90. doi:10.1111/0022-1082.00146.

Novy-Marx, Robert. 2013. “The Other Side of Value: The Gross Profitability Premium.” *Journal of Financial Economics* 108 (1): 1–28. doi:10.1016/j.jfineco.2013.01.003.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein. 1985. “Persuasive Evidence of Market Inefficiency.” *Journal of Portfolio Management* 11 (3): 9–16. doi:10.3905/jpm.1985.409007.

Appendix A. Two Risky-Asset Problem

Denote the vector of means to the within and across component by $\mu = \begin{bmatrix} \mu_w \\ \mu_a \end{bmatrix}$ and the covariance matrix by $\Sigma = \begin{bmatrix} \sigma_w^2 & \rho\sigma_a\sigma_w \\ \rho\sigma_a\sigma_w & \sigma_a^2 \end{bmatrix}$. We find $\Sigma^{-1}\mu = \begin{bmatrix} \dfrac{\mu_a\rho\sigma_w - \mu_w\sigma_a}{\sigma_w^2\sigma_a(\rho^2-1)} \\ \dfrac{\mu_w\rho\sigma_a - \mu_a\sigma_w}{\sigma_a^2\sigma_w(\rho^2-1)} \end{bmatrix}$

and $1'\Sigma^{-1}\mu = \frac{\mu_w\sigma_a^2 - \rho(\mu_w\sigma_w\sigma_a + \mu_a\sigma_w\sigma_a) + \mu_a\sigma_w^2}{\sigma_w^2\sigma_a^2(1-\rho^2)} = \frac{\mu_w\sigma_a^2 + \mu_a\sigma_w^2 - \text{cov}(w,a)(\mu_w+\mu_a)}{\sigma_w^2\sigma_a^2(1-\rho^2)}$.

The optimal weights for the within, *w*, and across, *a*, components become

$$\frac{\Sigma^{-1}\mu}{1'\Sigma^{-1}\mu} = \begin{bmatrix} w_w \\ w_a \end{bmatrix} = \begin{bmatrix} \dfrac{\mu_a\rho\sigma_w - \mu_w\sigma_a}{\sigma_w^2\sigma_a(\rho^2-1)} \times \dfrac{\sigma_w^2\sigma_a^2(1-\rho^2)}{\mu_w\sigma_a^2 + \mu_a\sigma_w^2 - \text{cov}(w,a)(\mu_w+\mu_a)} \\ \dfrac{\mu_w\rho\sigma_a - \mu_a\sigma_w}{\sigma_a^2\sigma_w(\rho^2-1)} \times \dfrac{\sigma_w^2\sigma_a^2(1-\rho^2)}{\mu_w\sigma_a^2 + \mu_a\sigma_w^2 - \text{cov}(w,a)(\mu_w+\mu_a)} \end{bmatrix} = \begin{bmatrix} \dfrac{\mu_w\sigma_a^2 - \mu_a\text{cov}(w,a)}{\mu_w\sigma_a^2 + \mu_a\sigma_w^2 - \text{cov}(w,a)(\mu_w+\mu_a)} \\ \dfrac{\mu_a\sigma_w^2 - \mu_w\text{cov}(w,a)}{\mu_w\sigma_a^2 + \mu_a\sigma_w^2 - \text{cov}(w,a)(\mu_w+\mu_a)} \end{bmatrix},$$

which is the solution we use in (3).

Appendix B. Sector Neutrality Can Be Beneficial Even When the Optimal Sector Allocation Is Positive

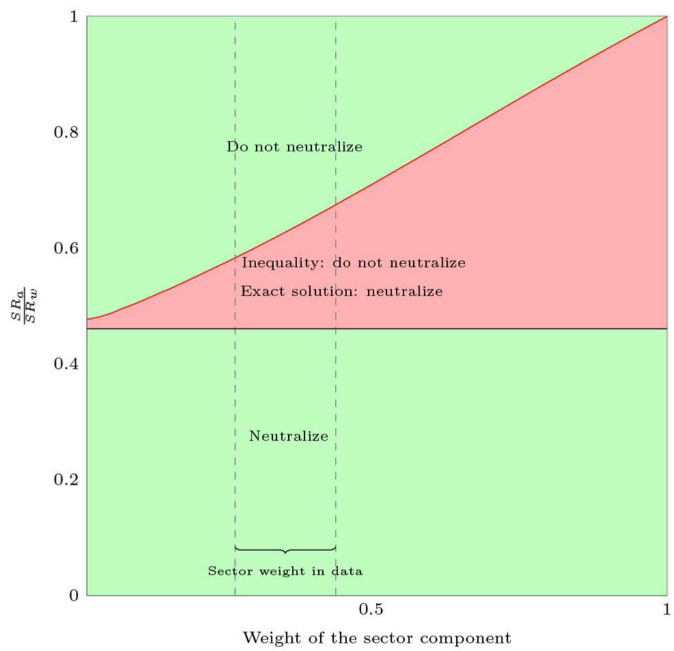
This appendix studies the condition under which the inequality expressed in (4) recommends not pursuing sector neutralization when neutralization is the better decision. Suppose that the optimal weight to the sector component of a factor is 5%. Also assume that the factor has far more sector exposure, for example, 50%. This investor may benefit from pursuing sector neutrality despite the positive optimal allocation. The inequality in (4) is the sufficient condition for pursuing sector neutrality, but neutrality may be beneficial even when the inequality does not hold. Empirically, this divergence only occurs in long–short factors, because they have a large exposure to the sector component.

How much sector exposure do empirical factors have? We compute *implied* sector exposures as follows. Our factor decomposition gives equal weights to the within and across components, $r_{factor} = r_{within} + r_{across}$. We denote the ratio of the standard deviation of the sector to the within component by k. The volatility of the sector component scaled by k equals the volatility of the within component. Rewriting the equation gives $r_{within} + k\ (r_{across}/k)$, where r_{within} and r_{across}/k have equal volatilities. Rescaling to produce an overall exposure of a unit gives $r_{within}/(1+k) + k/(1+k)\ (r_{across}/k)$; $k/(1+k)$ is our proxy for the factor's implied sector exposure. Mean absolute sector exposure of long–short factors is 0.36 and varies between 0.27 (5 industry portfolios) and 0.43 (49 industry portfolios). Mean sector exposure of long-only factors is 0.16 and varies between 0.09 (5 industry portfolios) and 0.21 (49 industry portfolios).

The small sector exposures of long-only portfolios reveal that the condition in (4)—both when it holds and when it does not—is an accurate decision-making criterion for the long-only investor. The inequality, however, may underestimate the benefits of neutrality for the long–short investor who neutralizes using a classification with many sectors.

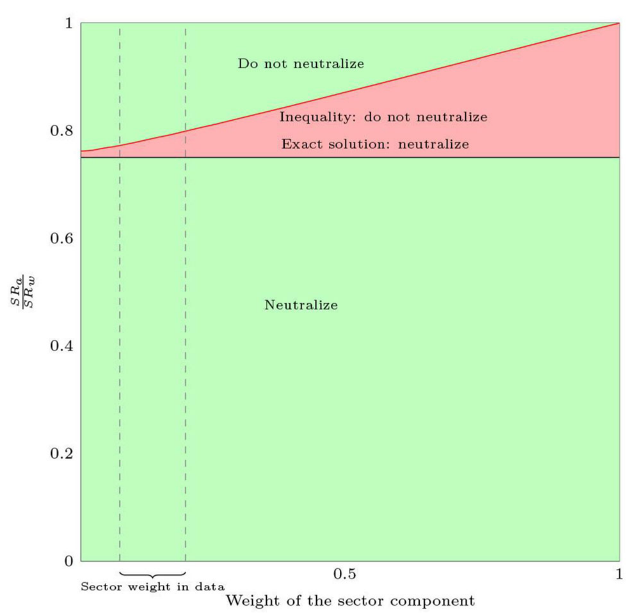
Figure B1 illustrates how often the inequality and the exact solution make different recommendations in long–short factors. We plot the graph assuming that the correlation coefficient between the two components is 0.46 (0.46 is the average of correlation coefficients between the components in Panel A of Table 1). The areas in green indicate where the two approaches

Figure B1. The Inequality Versus the Exact Solution for Long–Short Portfolios



Note: The figure shows the areas where the inequality and the exact solution make similar (green) or different (red) recommendations. We plot the graph by varying the weight of the sector component between 0 and 1 and the ratio of Sharpe ratios between 0 and 1. The area between the dashed lines indicates the range of exposures to the sector component of empirical long–short factors.

Figure B2. The Inequality Versus the Exact Solution for Long-Only Portfolios



Note: The figure shows the areas where the inequality and the exact solution make similar (green) or different (red) recommendations. We plot the graph by varying the weight of the sector component between 0 and 1 and the ratio of Sharpe ratios between 0.5 and 1. The area between the dashed lines displays the range of exposure to the sector component of empirical long-only factors.

are in harmony, and the area in red indicates where the inequality suggests investing in the standard factor and the exact solution recommends neutralization. The two approaches tend to disagree more often as the allocation to the sector component increases. Empirically, exposure to the sector component of various long–short factors falls between the dashed lines. Conditional on the optimal allocation to the sector component being positive (the inequality prescribes "do not neutralize"), there is roughly a one-in-three chance that neutralization remains beneficial.

Figure B2 is the same as Figure B1 when the correlation between the sector and within components is 0.75 (the average correlation between the components of the long-only factor). The figure shows that the area where the inequality and exact solution make different recommendations (red area between the dashed lines) is small in long-only factors. Therefore, the simple inequality gives an accurate assessment of the optimal decision in long-only factors.

Appendix C. Return Decompositions for Equal- and Rank-Weighted Factor Portfolios

Table C1 reports the return decompositions using (10) for equal- and rank-weighted factor portfolios.

Table C1. Equal-Weighted and Rank-Weighted Factor Returns

	Long–short factors				Long-only factors		
	Factor	Across	Within		Factor	Across	Within
Panel A: Equal weighted							
Size	0.23	−0.06	0.28	Size	0.92	0.08	0.84
	(1.72)	(−2.23)	(2.29)		(3.58)	(3.38)	(3.57)
Value	0.41	0.02	0.38	Value	1.01	0.19	0.82
	(3.65)	(0.38)	(6.24)		(5.03)	(4.65)	(4.82)
Profitability	0.15	0.04	0.11	Profitability	0.88	0.10	0.77
	(1.71)	(1.16)	(1.79)		(4.09)	(3.95)	(4.04)
Investment	0.40	0.02	0.38	Investment	1.00	0.07	0.93
	(5.96)	(0.93)	(7.34)		(4.64)	(3.46)	(4.62)
Momentum	0.58	0.14	0.44	Momentum	1.05	0.16	0.89
	(4.14)	(2.80)	(4.36)		(4.68)	(3.95)	(4.60)
Multi-factor	0.35	0.03	0.32	Multi-factor	0.97	0.12	0.85
(EW)	(7.96)	(1.60)	(10.84)	(EW)	(4.14)	(5.15)	(3.93)
Multi-factor	0.71	0.10	0.60	Multi-factor	1.16	0.14	1.02
(bottom-up)	(6.68)	(2.34)	(8.76)	(bottom-up)	(5.88)	(5.52)	(5.75)
Panel B: Rank weighted							
Size	0.19	−0.05	0.25	Size	0.88	0.09	0.80
	(1.33)	(−1.94)	(1.82)		(3.23)	(3.27)	(3.19)
Value	0.52	0.02	0.50	Value	1.06	0.20	0.86
	(3.90)	(0.25)	(6.52)		(5.08)	(4.55)	(4.90)
Profitability	0.20	0.03	0.17	Profitability	0.89	0.11	0.78
	(1.71)	(0.71)	(2.04)		(4.04)	(3.91)	(3.98)
Investment	0.56	0.04	0.52	Investment	1.04	0.07	0.97
	(6.80)	(1.56)	(7.96)		(4.49)	(3.47)	(4.46)
Momentum	0.72	0.18	0.55	Momentum	1.11	0.18	0.93
	(4.23)	(3.07)	(4.29)		(4.49)	(3.99)	(4.38)
Multi-factor	0.44	0.04	0.40	Multi-factor	1.00	0.13	0.87
(EW)	(8.10)	(1.75)	(11.10)	(EW)	(4.36)	(5.01)	(4.24)
Multi-factor	0.94	0.13	0.80	Multi-factor	1.24	0.17	1.07
(bottom-up)	(5.46)	(2.79)	(9.14)	(bottom-up)	(6.10)	(5.53)	(5.97)

The table shows mean returns and *t*-values to factor returns and their within and across components using the decomposition of (10) for equal- and rank-weighted portfolios. The rest of the table is similar to Table 2.

Appendix D. Estimating Likelihoods Using Sample Moments and Historical Simulation

The inequality in (1) that relates the ratio of Sharpe ratios to the correlation between the two components determines whether an investor should take sector bets. We examine three ways to compute weights and eight ways to define sectors for each of the five factors (size, value, profitability, investment, and momentum), for a total of $3 \times 8 \times 5 = 120$ different long–short or long-only factors. Table D1 shows the average moments of the two parameters of (1) across these variations.

Table D1 shows that the mean correlation between the within and across components of long–short factors is 0.465, which implies an investor should avoid the across component if they believe the Sharpe ratio of the across component is less than half of the Sharpe ratio of the within component. The across component meets this low Sharpe ratio bar by earning a monthly Sharpe ratio of 0.032, which is less than 20% of that of the within component.

Unsurprisingly, because all long portfolios have significant exposure to the market factor, the correlation between the components of long-only factors is substantially higher at 0.794. Because of this high correlation, the bar for the sector component is much higher: its Sharpe ratio should be at least 79% of the within component. It turns out that the across component of long factors meets this high bar by earning a monthly Sharpe ratio of 0.149, which is more than 90% of the Sharpe ratio of the within component (note that the bar was 79%). It is also important to note that these two moments—Sharpe ratio and correlation—are much less volatile in long portfolios. Correlations and Sharpe ratios of long portfolios fall in a narrow range because of the large exposure of long portfolios to the market; exposure to the market makes long portfolios very similar.

The moments in Table D1 estimate the likelihood that the factor portfolio benefits from neutralizing its sector bets. We must have $\rho \times SR_{within} > SR_{across}$ for the across component to be redundant. If the correlation parameter and Sharpe ratios of the within component do not covary, the product on the left side of the inequality will have a mean of $0.47 \times 0.16 = 0.08$ with a standard deviation of $\sqrt{0.26^2 \times 0.08^2 + 0.26^2 \times 0.15^2 + 0.07^2 \times 0.47^2} = 0.05$.

According to Table D1, the parameter on the right side of the inequality, SR_{across}, has a distribution of $N(0.03, 0.07^2)$. The probability that a variable drawn from a normal distribution $N(0.08, 0.05^2)$ is less than another *independent* variable drawn from $N(0.03, 0.07^2)$ is 29%. That is, we expect a long–short factor to benefit from adding sector bets only about 29% of the time. This is an approximation because in data the right and left sides of the inequality are positively correlated. A similar back-of-the-envelope calculation using the moments of the long-only portfolios estimates a 78% probability that adding sector bets increases the Sharpe ratio.

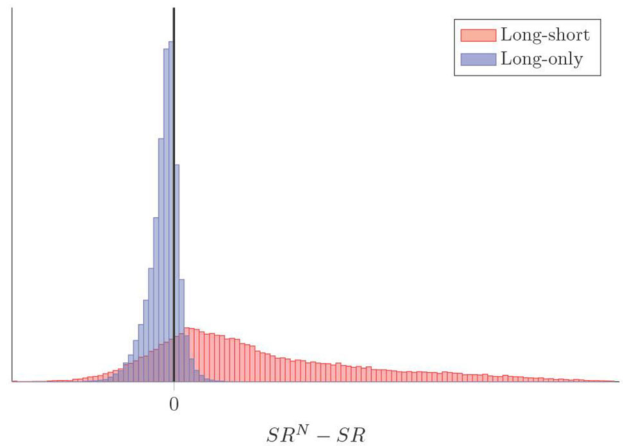
We now turn to historical data to estimate these likelihoods and compare them with their analytical counterparts. We use the same $3 \times 8 \times 5 = 120$ long–short or long-only sector-neutral factors to estimate the likelihoods. For each type we form long–short or long-only standard factors and their sector-neutral versions. We bootstrap the time series of the factors 1,000 times and compute the difference in the Sharpe ratio of the standard factor and its sector-neutral version. This procedure provides us with 120,000 differences in Sharpe ratios for the

Table D1. Moments of Data

	Long–short			Long-only		
	rho	SR_{within}	SR_{across}	*rho*	SR_{within}	SR_{across}
Mean	0.465	0.154	0.032	0.794	0.158	0.149
SD	0.261	0.078	0.069	0.102	0.020	0.017

Note: The table shows the mean and standard deviation (SD) for the determinative moments of data for the inequality in (4). The mean and standard deviation are obtained using the data for long–short or long-only factor portfolios. SR_{within} is the Sharpe ratio of the within component, SR_{across} is the Sharpe ratio of the across component, and *rho* is the correlation coefficient between the two components.

Figure D1. Historical Simulation



Note: The figure shows the distribution of changes in the Sharpe ratios of factors as a result of removing sector bets from historical data. SR^N is the Sharpe ratio of the factor constructed using only the within signal (i.e., sector-neutralized factor), and SR is the Sharpe ratio of the standard factor that sorts on the original signal, which consists of both across and within components. The factors are size, value, profitability, investment, and momentum (×5). We construct equal-, rank-, and value-weighted factors (×3). We construct sector-neutral factors using eight definitions of sector classification based on the Fama and French industry classification (×8). This procedure generates $3 \times 5 = 15$ factors and $3 \times 5 \times 8 = 120$ sector-neutral factors. We form both long-only and long–short versions of the factors. The figure shows the distribution of differences between the Sharpe ratios of each sector-neutral factor and its original version. The distribution is obtained by bootstrapping the data by month.

long–short factor and 120,000 differences in Sharpe ratios for the long-only factor.

Figure D1 shows the distributions associated with this historical simulation. The larger standard deviations of the moments of the long–short factors are reflected in the wider distribution of the long–short outcome. This means that the long–short investor is more likely to gain or lose a substantial amount by hedging out sector bets. The total likelihood of the investor to lose, as reflected by the density mass of the red distribution that lies to the left of zero, is 20%; our back-of-the-envelope estimate for this probability was 29%.

The blue distribution in Figure D1 shows differences in Sharpe ratios—as a result of removing sector bets—for the long-only portfolio. The distribution is narrow and peaked, consistent with the low volatility of the moments of long-only portfolios. The density mass on the negative side is 78%, which is precisely equal to its back-of-the-envelope predicted probability of 78%.