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Factor Investing in the Corporate Bond Market

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We offer empirical evidence that size, low-risk, value, and momentum factor portfolios generate economically meaningful and statistically significant alphas in the corporate bond market. Because the correlations between the single-factor portfolios are low, a combined multi-factor portfolio benefits from diversification among the factors: It has a lower tracking error and a higher information ratio than the individual factors. Our results are robust to transaction costs, alternative factor definitions, alternative portfolio construction settings, and constructing factor portfolios on a subsample of liquid bonds. Finally, allocating to corporate bond factors provides added value beyond allocating to equity factors in a multi-asset context.

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This article examines the performance of size, low-risk, value, and momentum factor portfolios in the corporate bond market. A factor portfolio is constructed by sorting bonds on a specific characteristic: Size contains bonds of small companies, based on the market value of their outstanding bonds; low risk contains short-maturity bonds with a high credit rating; value selects bonds whose credit spread is high relative to a model-implied fair spread; and momentum consists of bonds with high past returns. In addition to these individual factors, in our study we analyzed a multi-factor portfolio that combines the four factors. We found that both single-factor and multi-factor portfolios generate economically meaningful and statistically significant alphas.

Our study belongs to the empirical asset pricing literature[1] documenting that factor portfolios carry a premium beyond the traditional asset class premium, as postulated by the CAPM. Even though this literature has existed for decades, it has focused predominantly on equities. The best-documented factors in the equity literature are low risk (starting with Haugen and Heins 1972), value (Basu 1977), size (Banz 1981), and momentum (Jegadeesh and Titman 1993). For corporate bonds, the evidence is both more limited and more recent. The documented factors are low risk (e.g., Ilmanen, Byrne, Gunasekera, and Minikin 2004; Frazzini and Pedersen 2014) and momentum (e.g., Pospisil and Zhang 2010; Jostova, Nikolova, Philipov, and Stahel 2013). Evidence on other factors is scarce. We are aware of only two papers on value (L'Hoir and Boulhabel 2010; Correia, Richardson, and Tuna 2012) and none on size. The existing studies on factors in the corporate bond market each focus on one particular factor, whereas in our study, we analyzed the size, low-risk, value, and momentum factors using a consistent methodology with a single dataset. Our

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dataset consisted of all bonds in the Barclays U.S. Corporate Investment Grade and High Yield Indexes[2] over January 1994–June 2015.

Our study contributes to the existing literature in three ways. First, we confirm previous work on low risk and momentum, confirm and extend the relatively new evidence on value, and are the first to provide evidence on size. We show that all factors have significant alphas, in both the CAPM—correcting factor returns for their beta to the corporate bond market—and the Fama–French–Carhart framework, additionally correcting for betas to equity and bond common risk factors. Our study's second contribution is that we went beyond previous work by combining factors in a multi-factor portfolio. We found that factors have relatively low pairwise correlations, and thus, the multi-factor portfolio, compared with single-factor portfolios, substantially reduces tracking error and improves the information ratio versus the corporate bond market index. The annualized Fama–French–Carhart alpha of a long-only multi-factor portfolio is 0.84% (3.65%) for investment grade (high yield), which is sizable given the corporate bond market premium of 0.50% (2.33%). We found that breakeven transaction costs are well above actual transaction costs of corporate bonds reported in various studies, so the after-cost alphas remain substantial. These findings are robust to a variety of sensitivity checks, including alternative factor definitions, alternative portfolio construction choices, and evaluating factor portfolios on a subset of liquid bonds. Our study's final contribution is the application of factor investing in both the equity market and the corporate bond market. We show that the corporate bond factors provide added value beyond their counterparts in the equity market: By applying factor investing not only in the equity market but also in the corporate bond market, investors can increase the alpha of their multi-asset portfolio by more than 1% a year.

Our findings have strong implications for strategic asset allocation decisions. Most investors focus on traditional asset classes when determining their strategic investment portfolio. For example, by including stocks, government bonds, and corporate bonds, they aim to earn the equity, term, and default premiums. Implementation of the actual investment portfolio is typically delegated to external managers. However, the results of our study, in line with results of similar studies on equity markets, suggest that investors should strategically and explicitly allocate to factors in the corporate bond market instead of relying on external managers to implement factor exposures. A seminal study on this topic is Ang, Goetzmann, and Schaefer (2009), who were asked by the Norwegian Government Pension Fund to analyze the fund's performance. They found that a large part of the fund's outperformance versus its strategic benchmark could be explained by factor exposures that were implicitly present in the investment portfolios. Therefore, they recommended making the fund's exposure to factors a "top-down decision rather than emerging as a byproduct of bottom-up active management" (Ang et al. 2009, p. 20). Blitz (2012) argued that investing in factors should be a strategic decision because of the long-term investment horizon required to harvest the premiums. Bender, Briand, Nielsen, and Stefek (2010) and Ilmanen and Kizer (2012) also made the case for strategic allocations to factors, stressing the diversification benefits. Ang (2014) devoted an entire book to factor investing.

Two studies related to ours are Israel, Palhares, and Richardson (2016) and Bektic, Wenzler, Wegener, Schiereck, and Spielmann (2016). Like our study, these studies examine single-factor and multi-factor portfolios in the corporate bond market. Our study differs from Israel et al. (2016) in three important aspects. First, we used more-realistic assumptions, such as a holding period of 12 months (instead of 1 month), we studied long-only portfolios (instead of long–short portfolios), and we did not use leverage. Second, in our study we conducted a variety of sensitivity analyses, including alternative factor definitions, to verify the robustness of our results. Finally, we performed a multi-asset analysis to investigate the value added by corporate bond factor investing beyond equity factor investing. The key difference between Bektic et al. (2016) and our study is that they used equity definitions for each factor, whereas we focused on bond-specific factor definitions. In one of our robustness checks, we show that although factor portfolios constructed using the equity definitions do generate a premium

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in the corporate bond market, they do not work as well as the bond-specific definitions, with the exception of momentum.

Data and Methodology

In this section, we describe our data and data sources as well as the methodology we used in our study.

Data. We used monthly constituent data of the Barclays U.S. Corporate Investment Grade Index and the Barclays U.S. Corporate High Yield Index over January 1994–June 2015. For each bond in each month, Barclays provides various characteristics, including its market value, time to maturity, credit rating, credit spread, and return. The dataset is free of survivorship bias: Whenever a company defaults, the returns of its bonds are based on their final traded price, reflecting the market's expected recovery rate.

To calculate the monthly return of the factor portfolios, we used the excess return of each corporate bond versus duration-matched Treasuries. These excess returns (also provided by Barclays) accurately remove the term premium. The term premium is driven by changes in risk-free interest rates and can be efficiently harvested by investing in government bonds. The main purpose of investing in corporate bonds is to earn, in addition to the term premium, the default premium, which is driven by changes in credit spreads. By using excess returns versus Treasuries, we could focus on the credit spread component.

Because we evaluated factor portfolios using excess returns versus Treasuries, we also obtained excess returns for the investment-grade and high-yield market indexes from Barclays. Barclays calculates the index return each month as the market value–weighted average excess return over all index constituents in that month. We used the index returns to calculate the outperformances and alphas of the factor portfolios. Note that this index return is basically the standard benchmark return for active portfolio managers but is calculated using excess returns instead of total returns. In practice, portfolio managers are benchmarked using total returns. Portfolio managers could come close to replicating the excess return outperformance by using Treasury bond futures to hedge the interest rate exposure of the portfolio to that of the benchmark.

Our dataset contained over 1.3 million bond-month observations, of which about 900,000 were for investment grade and about 400,000 for high yield. The average number of monthly observations was 3,520 for investment grade and 1,473 for high yield. **Table 1** provides further summary statistics of our dataset by showing the mean and various percentiles of the bond characteristics. We first calculated all statistics cross-sectionally per month and then averaged them over time. Comparing investment-grade bonds with high-yield bonds, we observed that the former tend to have lower excess returns over Treasuries and longer times to maturity and are issued by larger companies.

Methodology. For each factor in each month, we constructed an equally weighted top (bottom) portfolio of the 10% of corporate bonds with the highest (lowest) exposure to that factor. For our study, we framed our key results in two ways. First, we analyzed long–short portfolios over a one-month investment horizon. This analysis served to identify the factors' potential to generate alpha in the corporate bond market by overweighting or underweighting bonds. Shorting corporate bonds, however, is difficult and costly, so including the short side inflates potential benefits beyond those achievable in practice (for a discussion of long–short factor portfolios in the equity market, see Huij, Lansdorp, Blitz, and van Vliet 2014). For our second set of results, we thus analyzed long-only portfolios over a 12-month horizon using the overlapping portfolio methodology of Jegadeesh and Titman (1993). This holding period is realistic and prevents extreme turnover. In addition to the single-factor portfolios, we analyzed a multi-factor portfolio, invested 25% in each of the four single-factor portfolios. In Appendix A (available online at www.cfapubs.org/doi/suppl/10.2469/faj.v73.n2.1), we describe the robustness checks of our results when (1) the factor portfolios contain 20% of the bonds (instead of 10%) and (2) the bonds in the portfolio

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Table 1. Summary Statistics of Dataset, January 1994–June 2015

	Investment Grade						High Yield					
	Mean	5%	25%	50%	75%	95%	Mean	5%	25%	50%	75%	95%
Annualized excess return (%)	0.58	–1.75	–0.40	0.08	0.56	1.86	2.46	–5.78	–1.02	0.33	1.68	5.92
Time to maturity (years)	10.89	1.63	3.92	7.21	16.13	28.93	7.74	2.45	4.98	6.76	8.44	18.61
Credit rating	6.69	3.45	5.56	7.04	8.80	10.00	14.30	11.00	12.93	14.67	16.09	18.22
Credit spread (bps)	148	59	94	127	173	294	481	214	322	441	677	1,541
Market value of company ($ billions)	13.83	0.44	1.70	4.43	9.49	19.32	3.27	0.14	0.30	0.77	2.10	8.48
Number of observations	3,520						1,473					

Notes: This table shows summary statistics for all constituents of the Barclays U.S. Corporate Investment Grade and High Yield Indexes. The annualized excess return is the monthly return of the bond over duration-matched Treasuries, multiplied by 12. The time to maturity is the number of years until the bond expires. Credit rating is the middle credit rating of the rating agencies S&P, Moody's, and Fitch (worse rating in case of two ratings) whereby the credit ratings are converted to a numeric scale as follows: AAA = 1, AA+ = 2, AA = 3, and so on. The credit spread is the option-adjusted yield of the bond in excess of the yield of the duration-matched government bond. The market value of company is the sum of the market values of all bonds of the company in the corporate bond index. The number of observations is the average number of bonds per month. For every characteristic, the mean and five percentiles (5%, 25%, 50%, 75%, 95%) are reported. Each statistic is first calculated cross-sectionally per month and then averaged over time.

are market value weighted (instead of equally weighted).

We created the factor portfolios separately for investment grade and high yield because these market segments are treated as two separate asset classes by financial market participants, including (1) asset owners (making separate allocations to investment grade and high yield), (2) both passive and active asset managers (offering separate investment products for investment grade and high yield), (3) index providers (offering separate indexes for investment grade and high yield), and (4) regulators (often prohibiting certain groups of institutional investors from holding high-yield bonds). Evidence on the division of the corporate bond market into investment-grade and high-yield segments is provided by Ambastha, Ben Dor, Dynkin, Hyman, and Konstantinovsky (2010) and Chen, Lookman, Schürhoff, and Seppi (2014). Chen et al. (2014) mentioned that a large stream of extant theoretical literature shows that labels (in this case, ratings of corporate bonds) can lead to market segmentation and asset class effects by influencing investors' willingness to hold the security and can thus affect security prices. Chen et al. (2014) offered empirical evidence that credit ratings do indeed segment the market into two parts: investment grade and high yield. Therefore, it was crucial for us to create and evaluate the factor portfolios separately in the investment-grade and high-yield market segments.

We calculated outperformances and alphas of factor portfolios versus their own market segment. To calculate the CAPM alpha, we ran the following regression:

$$R_t = \alpha + \beta \mathrm{DEF}_t + \varepsilon_t, \tag{1}$$

where R_t is the return on a factor portfolio and DEF_t is the corporate bond market premium, which is the

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investment-grade index excess return for investment-grade factor portfolios and the high-yield index excess return for high-yield factor portfolios. The intercept of Equation 1 is the CAPM alpha. We also evaluated the factor portfolios against the Fama and French (1993) five-factor model supplemented with the Carhart (1997) equity momentum factor:

$$R_t = \alpha + \beta_1 \mathrm{RMRF}_t + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{MOM}_t + \beta_5 \mathrm{TERM}_t + \beta_6 \mathrm{DEF}_t + \varepsilon_t, \quad (2)$$

where RMRF_t is the equity market premium, SMB_t is the equity size premium, HML_t is the equity value premium, MOM_t is the equity momentum premium, and TERM_t is the default-free interest rate term premium. The intercept of Equation 2 is referred to as the Fama–French–Carhart alpha. We downloaded the four equity factors from the website of Kenneth French.[3] We constructed the term factor as the total return of the Barclays U.S. Treasury: 7–10 Year Index minus the one-month T-bill rate (from the same website).[4]

Defining Factors in the Corporate Bond Market

In the next step in our study, we defined our size, low-risk, value, and momentum factors. For each factor definition, we purposely used only bond characteristics, such as rating, maturity, and credit spread, and we did not use accounting data (e.g., leverage or profitability) or equity market information (e.g., equity returns or equity volatility). This choice allowed us to include all bonds in our analyses, not just bonds issued by companies with publicly listed equity. Our definitions facilitate the actual implementation of factors in investment portfolios. We acknowledge that accounting and equity market information, or the use of more-sophisticated methods, could improve the results. Applying bond-only definitions, however, we can demonstrate that factor investing already works by using readily available data and methods. In Appendix A (available online at www.cfapubs.org/doi/suppl/10.2469/faj.v73.n2.1), we examine the sensitivity of our results by testing alternative definitions.

Size. To define the size factor in the corporate bond market, we used the total index weight of each company, defined as the sum of the market value weights of all its bonds in the index in that month. We thus looked at a company's total public debt instead of the size of individual bonds because most explanations for the size effect in equity markets concern company size (e.g., incomplete information about small companies) or consider size a proxy for (default) risk (for a literature overview, see van Dijk 2011). Moreover, because smaller companies tend to issue smaller bonds[5] and smaller bonds are less liquid than larger bonds (Sarig and Warga 1989), our size definition picks up a potential illiquidity premium as well. To the best of our knowledge, we are the first to document a size effect at the company level in the corporate bond market.

To construct size decile portfolios, we ranked all bonds on their issuer's size each month, with the top (bottom) portfolio containing the bonds of the 10% smallest (largest) companies.

Low Risk. Previous studies have shown that bonds with lower risk earn higher risk-adjusted returns. Most of these studies have used maturity and/or rating as risk measures. The short-maturity effect has been documented by Ilmanen et al. (2004) and Derwall, Huij, and de Zwart (2009); the high-rating effect has been observed by, among others, Kozhemiakin (2007) and Frazzini and Pedersen (2014). Blitz, Falkenstein, and van Vliet (2014) have provided an overview of possible explanations for the existence of a low-volatility effect in equity markets. In their overview, most explanations concern behavioral biases or rational behavior vis-à-vis incentive structures or constraints and are thus equally applicable to corporate bond markets and equity markets.

We followed Ilmanen (2011) by using both maturity and rating to construct our low-risk factor portfolios. For the low-risk top portfolio, we selected high-rated, short-dated bonds, with the bottom portfolio consisting of low-rated, long-dated bonds. For the investment-grade top portfolio, we first selected all bonds rated AAA to A–, thus excluding the most risky bonds (rated BBB+, BBB, or BBB–). From these bonds, we selected all bonds shorter than M years each month so that the portfolio contained 10% of the total number of bonds in the index; this

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maturity threshold M thus fluctuated over time. We used this approach to allow a fair comparison with the other factor portfolios, which also contained 10% of the bonds by definition. For high yield, we followed the same procedure, selecting bonds rated BB+ to B– in the first step. We found that the maturity threshold equals 3.1 (3.6) years for investment grade (high yield), on average.

For the bottom portfolio, we selected for investment grade (high yield) the longest 10% of all bonds rated below AA– (BB–). We found that the maturity threshold for the bottom portfolio equals 26.4 (11.6) years for investment grade (high yield), on average.

Value. The value effect in equity markets has been well documented since the 1970s, starting with Basu (1977). It can be summarized as mean reversion in valuations: Cheap stocks outperform and expensive stocks underperform. To determine whether a stock is cheap or expensive, the market value of a company is compared with a fundamental measure, such as earnings or the equity book value. To our knowledge, L'Hoir and Boulhabel (2010) and Correia et al. (2012) are the only studies that examine value investing in the corporate bond market. In those studies, the value concept is translated from equities to corporate bonds by comparing the market's required compensation for the bond's riskiness (i.e., the credit spread) with fundamental risk measures. In other words, a bond is cheap if it offers an ample reward for the risk that investors bear in buying the bond. Both studies consider a variety of risk measures, including leverage, profitability, equity volatility, and the distance-to-default measure of Merton (1974). The methodology we used in our study is in the spirit of L'Hoir and Boulhabel (2010) and Correia et al. (2012), but we restricted ourselves to risk measures that can be derived from the bond market only: maturity, rating, and the three-month change in the bond's credit spread. The last risk measure was motivated by Norden and Weber (2004) and Norden (2014), who showed that, on average, credit spreads already increase three months before a rating downgrade. Therefore, the spread change is a useful risk indicator beyond rating or maturity.

To construct value factor portfolios each month, we first ran a cross-sectional regression of credit spreads on rating dummies (AAA, AA+, AA, ..., C), time to maturity, and three-month spread change:

$$S_i = \alpha + \Sigma_{r=1}^{21}\beta_r I_{ir} + \gamma M_i + \delta \Delta S_i + \varepsilon_i, \tag{3}$$

where

S_i = the credit spread of bond i

I_{ir} = 1 if bond i has rating r and 0 otherwise

M_i = the maturity

ΔS_i = the three-month change in the credit spread

Following Correia et al. (2012), we calculated the percentage difference between the actual credit spread and the fitted ("fair") credit spread for each bond. Finally, we ranked all bonds on this percentage difference from high to low and selected the first (last) 10% of bonds for the top (bottom) value portfolio.

Momentum. Research on momentum began with the seminal study on equity markets by Jegadeesh and Titman (1993). The results of studies on corporate bond momentum are mixed. Investment-grade bond returns exhibit either reversal (Khang and King 2004; Gebhardt, Hvidkjaer, and Swaminathan 2005) or insignificant momentum effects (Jostova et al. 2013). But in the high-yield market, momentum strategies have been shown to generate profits (see Pospisil and Zhang 2010; Jostova et al. 2013).

We followed Jostova et al. (2013) by defining momentum as the past-six-month return using a one-month implementation lag. We used the excess return versus duration-matched Treasuries for consistency with our return measure for evaluating factor portfolios. We selected the 10% of bonds with the highest (lowest) past returns for the top (bottom) momentum portfolio.

The Benefits of Allocating to Factors

In this section, we present our main result—namely, that factor portfolios in the corporate bond market earn alpha beyond the corporate bond market premium and beyond common

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equity and bond risk premiums. We also highlight the tension between evaluating factors in an absolute versus relative risk context and the importance of a long investment horizon. In addition, we show the diversification benefits of combining the factors into a multi-factor portfolio, which, compared with single-factor portfolios, substantially reduces tracking error and improves the information ratio vis-à-vis the corporate bond market. Finally, by calculating breakeven transaction costs and comparing them with actual transaction costs, we show that single-factor and multi-factor portfolios deliver positive after-cost alphas.

Long–Short Factor Portfolios. We present our empirical analysis by first showing performance statistics for long–short factor portfolios, which go long in the top-decile portfolio and short in the bottom-decile portfolio (**Table 2**). Panels A and B report both the annualized CAPM alphas and the Fama–French–Carhart alphas. A comparison of these panels shows that both alphas are actually quite similar. For investment grade, the alphas range from around 1.2% for size and low risk to 2.5%–3.0% for value. For low risk and value, the alphas are statistically significant, with *t*-statistics well above 2 for low risk and above 3 for value. For size, the *t*-values are around 1.6. The absence of a momentum effect for

Table 2. Performance Statistics and Correlations of Long–Short Factor Portfolios, January 1994–June 2015

	Investment Grade				High Yield			
	Size	Low Risk	Value	Momentum	Size	Low Risk	Value	Momentum
A. CAPM statistics								
Alpha	1.15%	1.27%*	2.56%**	–1.38%	3.28%	2.02%*	5.14%**	8.49%**
t-Value	1.63	2.49	3.14	–0.77	1.21	2.04	2.70	2.80
Beta	–0.27	–1.28	0.98	–1.04	0.19	–0.76	0.60	–1.07
Adjusted R^2	0.17	0.81	0.65	0.29	0.03	0.66	0.40	0.38
B. Fama–French–Carhart statistics								
Alpha	1.22%	1.18%*	3.01%**	–3.46%	4.84%	1.19%	5.33%**	7.84%*
t-Value	1.56	2.39	3.24	–1.68	1.77	1.18	2.82	2.28
Adjusted R^2	0.23	0.82	0.67	0.38	0.09	0.70	0.43	0.40
C. CAPM alpha correlations								
Size		–17%	41%	18%		–19%	51%	–19%
Low risk			10%	–17%			–18%	10%
Value				–14%				–36%
Momentum								

Notes: This table shows performance statistics of the size, low-risk, value, and momentum factors for US investment-grade and US high-yield corporate bonds. Each month, a factor portfolio takes equally weighted long positions in the top 10% (short positions in the bottom 10%) of the bonds: for size, the issuers with the smallest (largest) market value of debt in the index; for value, the bonds with the highest (lowest) percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, the bonds with the highest (lowest) past-six-month return, implemented with a one-month lag; for low risk, the short-maturity bonds in AAA/AA/A (long-maturity bonds in A/BBB) for investment grade and the short-maturity bonds in BB/B (long-maturity bonds in B/CCC/CC/C) for high yield. Panel A shows the CAPM alpha and CAPM beta with respect to the corporate bond market (DEF). Panel B reports the Fama–French–Carhart alpha (RMRF, SMB, HML, MOM, TERM, DEF). Panel C shows pairwise correlations between the CAPM alphas of the factors. Alphas are annualized. Corporate bond returns are measured as excess returns versus duration-matched Treasuries. Statistical significance is determined through two-sided tests of whether the mean returns and alphas are different from zero (*t*-tests with Newey–West standard errors).

*Significant at the 5% level.

**Significant at the 1% level.

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investment grade is consistent with prior literature (see, e.g., Jostova et al. 2013).

For high yield, the CAPM alphas and the Fama–French–Carhart alphas of value and momentum are highly significant, with *t*-values between 2 and 3. The alphas are around 5% for value and 8% for momentum. For low risk, the CAPM alpha of 2.0% is statistically significant, whereas the Fama–French–Carhart alpha of 1.2% is not. As was the case for investment grade, the alphas for size are strongly positive but insignificant.

Reflecting our investigation of diversification opportunities between the factors, Panel C shows pairwise correlations between the CAPM alphas. Most of the correlations tend to be below 20%, except the correlations between value and size. The lowest correlations are between value and momentum. The results imply that there are diversification benefits to be gained by combining multiple factors into one portfolio. We next consider this implication in a long-only context.

Long-Only Single-Factor Portfolios. We have discussed the more theoretical long–short portfolios evaluated on a one-month investment horizon. We now turn our attention to the more realistic long-only portfolios on a 12-month horizon. **Table 3** reports the performance statistics for the long-only factor portfolios as well as for the corporate bond market. Panel A shows that for our sample period, the investment-grade (high-yield) corporate bond market generated 0.50% (2.33%) a year in excess of duration-matched Treasury bonds. For both investment grade and high yield, we see substantial outperformances for size (1.12% and 5.50%, respectively), low risk (0.41% and 1.45%), value (1.30% and 4.26%), and momentum (0.30% and 2.04%) versus the corporate bond market (Panel B). The magnitude of these factor premiums is substantial: Investors could have tripled their long-term average excess returns by investing in factors compared with passively investing in the corporate bond market index.

We calculate risk-adjusted returns in three ways. First, in Panel A of Table 3, we measure returns relative to total volatility using the Sharpe ratio measure. For investment grade (high yield), the Sharpe ratios of the factor portfolios are all higher than the market's Sharpe ratio of 0.12 (0.23). Except for investment-grade momentum, these differences are statistically significant. Second, in Panel C, we calculate annualized CAPM alphas, correcting factor returns for their systematic exposure to the corporate bond market. We find that all CAPM alphas are positive, large, and statistically significant, except for investment-grade momentum and value. For investment grade, the alphas range from 0.35% to 1.24%, and for high yield, from 2.15% to 5.68%. These alphas are sizable compared with the average corporate bond market returns of 0.50% and 2.33% for investment grade and high yield, respectively. Third, we calculate annualized Fama–French–Carhart alphas, which are quite similar in magnitude to the CAPM alphas. Again, most alphas are statistically significant, except for investment-grade size and momentum. We conclude that factor portfolios generate superior risk-adjusted returns, measuring risk as volatility (Panel A), beta to the corporate bond market (Panel C), or betas to equity and bond common risk factors (Panel D).

Nonetheless, investing in factor portfolios could be considered risky in a *relative* sense, as evidenced by the substantial tracking errors (volatility of outperformance) reported in Panel B of Table 3.[6] For investment grade, the tracking errors range from 1.84% to 3.07%, which are fairly large compared with the market's excess return volatility of 4.32%. For high yield, the tracking errors range from 3.86% to 7.95%, which are again substantial compared with the high-yield market's excess return volatility of 10.04%. Thus, the information ratios of single-factor portfolios are not high, especially for low risk, with information ratios of only 0.14 and 0.29 for investment grade and high yield, respectively, but the low-risk portfolio does have high Sharpe ratios of 0.41 and 0.56. This finding highlights the importance of a long-term investment horizon for factor investing because over shorter horizons, factor portfolios may underperform the market index owing to their large tracking errors. The relatively low information ratios also make clear that single-factor portfolios are unattractive to portfolio managers of delegated

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Table 3. Performance Statistics of Long-Only Factor Portfolios, January 1994–June 2015

	Investment Grade						High Yield					
	Market	Size	Low Risk	Value	Momentum	Multi-factor	Market	Size	Low Risk	Value	Momentum	Multi-factor
A. Return statistics												
Mean	0.50%	1.61%	0.91%	1.79%	0.80%	1.28%	2.33%	7.83%	3.78%	6.58%	4.37%	5.64%
Volatility	4.32%	3.82%	2.24%	6.76%	4.32%	3.98%	10.04%	12.20%	6.69%	13.37%	10.29%	10.04%
Sharpe ratio	0.12	0.42*	0.41*	0.27*	0.19	0.32**	0.23	0.64**	0.56**	0.49**	0.42*	0.56**
t-Value		2.57	2.14	2.02	0.76	3.44		2.72	3.32	3.02	2.33	3.88
B. Outperformance statistics												
Outperformance		1.12%*	0.41%	1.30%	0.30%	0.78%**		5.50%*	1.45%	4.26%*	2.04%*	3.31%**
Tracking error		2.29%	2.85%	3.07%	1.84%	1.18%		7.95%	5.02%	5.66%	3.86%	3.88%
Information ratio		0.49	0.14	0.42	0.16	0.66		0.69	0.29	0.75	0.53	0.85
t-Value		2.15	0.60	1.35	0.72	2.79		2.24	1.16	2.28	2.20	3.04
C. Alpha statistics												
CAPM		1.24%*	0.70%**	1.06%	0.35%	0.84%**		5.68%*	2.39%**	3.72%*	2.15%*	3.49%**
t-Value		2.08	3.12	1.87	0.81	2.71		2.36	3.43	2.49	2.24	3.12
Fama–French–Carhart		1.13%	0.78%**	1.32%*	0.15%	0.84%**		6.36%**	2.28%**	3.62%**	2.36%**	3.65%**
t-Value		1.76	3.68	2.01	0.35	2.64		2.78	3.61	2.64	2.88	3.61
D. Turnover and breakeven transaction costs												
Turnover	31%	63%	78%	80%	103%	81%	55%	86%	92%	96%	118%	98%
Breakeven costs		1.97%	0.90%	1.33%	0.34%	1.04%		6.60%	2.60%	3.88%	1.82%	3.56%

Notes: This table reports performance statistics of the corporate bond market and the size, low-risk, value, and momentum factors for US investment-grade and US high-yield corporate bonds. The return in month *t* is calculated as the average of the portfolios constructed from month *t* − 11 to *t*. Each month, a factor portfolio takes equally weighted long positions in 10% of the bonds: for size, the issuers with the smallest market value of debt in the index; for value, the bonds with the highest percentage deviation between their market spread and the fitted spread from a regression on rating dummies, maturity, and three-month spread change; for momentum, the bonds with the highest past-six-month return, implemented with a one-month lag; for low risk, the short-maturity bonds in AAA/AA/A (BB/B) for investment grade (high yield). The multi-factor portfolio is an equally weighted combination of size, low risk, value, and momentum. Panel A reports the return statistics, and Panel B, the outperformance statistics. Panel C shows the CAPM alpha (DEF) and the Fama–French–Carhart alpha (RMRF, SMB, HML, MOM, TERM, DEF). Panel D shows the turnover and breakeven transaction costs implied by the CAPM alpha and turnover. Mean, volatility, outperformance, tracking error, and alpha are annualized. Corporate bond returns are measured as excess returns versus duration-matched Treasuries. Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is different from the Sharpe ratio of the corporate bond market (Panel A; test of Jobson and Korkie 1981), (2) the outperformance is different from zero (Panel B; *t*-test), and (3) the alphas are different from zero (Panel C; *t*-test). The *t*-tests are calculated with Newey–West standard errors.

*Significant at the 5% level.

**Significant at the 1% level.

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investment portfolios that are benchmarked to the market index.

Long-Only Multi-factor Portfolios. The correlations in Table 2 indicate that combining multiple factors into a single portfolio can generate substantial diversification benefits. We constructed a multi-factor long-only portfolio with equal allocations to each of the single-factor portfolios.[7] Table 3 shows that for both investment grade and high yield, the multi-factor portfolio has a lower tracking error than each of the single-factor portfolios. Even so, the alphas and Sharpe ratios are among the highest. Because of the lower tracking error and the still substantial outperformance, the information ratio of the multi-factor portfolio is higher than that of every single-factor portfolio. The investment-grade (high-yield) multi-factor portfolio has a Sharpe ratio of 0.32 (0.56), which is more than twice as high as the corporate bond market's Sharpe ratio of 0.12 (0.23), and an information ratio of 0.66 (0.85). The annual CAPM (Fama–French–Carhart) alphas for investment grade and high yield are 0.84% (0.84%) and 3.49% (3.65%), respectively.

Note that one can easily improve the multi-factor portfolio—for example, by allocating more to size and low risk, which have the highest standalone Sharpe ratios, or by allocating more to size and value, which have the highest returns and alphas, or by omitting momentum from the investment-grade multi-factor portfolio. One should be careful, however, not to cherry-pick the results. A multi-factor approach, which balances the individual factors, is a robust method for harvesting the various premiums offered in the corporate bond market.

Breakeven Transaction Costs. These results show that allocating to factors leads to higher risk-adjusted returns. But these analyses do not consider transaction costs. Therefore, we must calculate breakeven transaction costs for both single-factor and multi-factor portfolios. We define the breakeven transaction costs of a portfolio as the costs that would lower its CAPM alpha to zero.

To calculate the breakeven transaction costs, we first calculate the turnover of each portfolio. Recall that we used the overlapping portfolio approach of Jegadeesh and Titman (1993) with a 12-month holding period, which implies that the weight of each bond in a factor portfolio is equal to the average weight across the 12 portfolios constructed from month t – 11 to t. The single-counted turnover from month t to month t + 1 is subsequently determined as the sum of all weight increments across the portfolio constituents. We likewise calculate the turnover for the investment-grade and high-yield market indexes. Panel D of Table 3 reports the results. Note that the 31% (55%) annualized turnover of the investment-grade (high-yield) index indicates that tracking the market comes at a cost. The index turnover comes from new bonds entering the index (because of bond issuance or rating migrations between investment grade and high yield) and from bonds leaving the index (because of redemptions, calls, and migrations, or no longer satisfying the index inclusion rules—e.g., a maturity shorter than one year). The four single-factor portfolios have higher turnover than the market, with size being on the lower end (small companies tend to remain small) and momentum on the high end, with more than 100% turnover. One might expect the low-risk portfolio to also have low turnover (because ratings tend to be fairly sticky). But because the low-risk portfolio contains only short-dated bonds, it must regularly reinvest redemptions from maturing bonds. The turnover of the multi-factor portfolio is equal to the average turnover of the single-factor portfolios.

Next, we calculate the breakeven transaction costs of each portfolio as its gross alpha divided by its turnover (Panel D of Table 3). For investment grade, we see that the low-risk, value, and multi-factor portfolios can sustain transaction costs of around 1% to generate positive after-cost alphas. The breakeven transaction costs for size are the highest (around 2%) because it has the highest gross alpha and the lowest turnover. The opposite holds for momentum, which has the lowest before-cost alpha and the highest turnover, resulting in breakeven transaction costs of only 0.34%. We see similar patterns for high yield, with size having the highest breakeven transaction costs at 6.60% and momentum the lowest at 1.82%. The breakeven transaction costs for the low-risk, value, and multi-factor portfolios are in between.

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To put these figures into perspective, we can compare them with actual bid–ask spreads and transaction costs of corporate bonds. Chen, Lesmond, and Wei (2007, Table I) reported that the average bid–ask spread over 1995–2003 is 41 (81) bps for investment grade (high yield). Using data over 2004–2009, Feldhütter (2012, Table 1) estimated average transaction costs of 42 bps for trade sizes of at least US$100,000 and just 18 bps for trade sizes of at least US$1,000,000—without distinguishing between investment grade and high yield. Harris (2015, Table 1) analyzed a 2014–15 dataset, estimating bid–ask spreads to be 30 (51) bps for investment grade (high yield). Finally, Mizrach (2015, Figure 13) analyzed data over 2003–2015 and estimated a 30 bp average bid–ask spread across all ratings.

All these transaction costs and bid–ask spreads are well below the breakeven transaction costs reported in Panel D of Table 3, except for investment-grade momentum. We thus conclude that even after transaction costs, single-factor and multi-factor portfolios generate positive CAPM alphas.

Robustness Checks. We conducted extensive robustness checks for all these documented results. In particular, we checked whether our findings are robust to alternative definitions of the factors, the portfolio weighting, and portfolio size. We also verified that performance is robust across subperiods, ratings, maturity segments, and sectors. Finally, we checked that our results are robust to liquidity effects by creating factor portfolios on a liquid subset of our data sample (see Appendix A, www.cfapubs.org/doi/suppl/10.2469/faj.v73.n2.1, for more details).

Strategic Allocation to Factors in a Multi-Asset Context

Asset owners hold in their portfolios not only corporate bonds but also other assets, such as government bonds and equities. In this section, we show that allocating to corporate bond factors leads to better performance, even if investors already apply factor investing to their equity investments.

Data. For the equity factors size, value, and momentum, we can use the top-decile portfolio returns from Kenneth French's website.[8] For size, we take the equally weighted portfolio consisting of the 10% of stocks with the lowest equity market value ("Lo 10"). For value, we take the equally weighted portfolio containing the 10% of stocks with the highest equity book-to-market ratio ("Hi 10"). For momentum, we take the equally weighted portfolio containing the 10% of stocks with the highest past-12-month returns, skipping the most recent month ("High"). The construction methodology for these portfolios is quite similar to the methodology we used in our study. Unfortunately, Kenneth French's website does not provide a series for the equity low-risk factor. Therefore, we use the returns of the MSCI Minimum Volatility Index, obtained via Bloomberg (ticker: M00IMV$T). For all four equity factor series, we subtract the one-month T-bill rate ("RF"; from Kenneth French's website). The RMRF factor is used to reflect the equity market premium. We construct the government bond market premium (term) as the total return of the Barclays U.S. Treasury: 7–10 Year Index minus the one-month T-bill rate.

So far, we have used excess returns over Treasuries to analyze the corporate bond market and factor premiums. To compare them with equity and government bond premiums, which are measured in excess of the risk-free rate, we add the term premium to our corporate bond series. This addition implies that the corporate bond total returns thus constructed have the same interest rate return as the term factor; thus, interest duration differences do not affect our results.

Analyses. Panel A of **Table 4** shows the performance statistics of the market portfolios for equities, government bonds, and investment-grade and high-yield corporate bonds. As Treasury yields have declined substantially over the sample period, government bonds have generated a large 3.50% annualized excess return over the risk-free rate, with a Sharpe ratio of 0.55. This occurrence has also led to high Sharpe ratios of 0.61 and 0.64 for the investment-grade and high-yield market portfolios. Note that these Sharpe ratios are higher than the 0.12 and 0.23 reported in Table 3 because the return series in Table 4 also benefit from the term premium. The equity market Sharpe

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Table 4. Performance Statistics of Government Bond, Corporate Bond, and Equity Market and Factor Portfolios, January 1994–June 2015

		Corporate Bonds		
	Government Bonds	Investment Grade	High Yield	Equities
A. Market				
Mean	3.50%	3.99%	5.82%	7.54%
Volatility	6.34%	6.51%	9.10%	15.30%
Sharpe ratio	0.55	0.61	0.64	0.49
B. Multi-factor portfolio				
Mean		4.78%	9.14%	12.85%
Volatility		6.21%	9.14%	17.87%
Sharpe ratio		0.77**	1.00**	0.72
t-Value		3.84	3.77	1.93
C. Outperformance statistics				
Outperformance		0.78%**	3.31%**	5.31%*
Tracking error		1.18%	3.88%	9.21%
Information ratio		0.66	0.85	0.58
t-Value		2.79	3.04	2.22
D. Outperformance correlations				
Investment grade			0.23	0.17
High yield				0.35
Equities				

Notes: This table reports the performance statistics for equities, government bonds, and US investment-grade and US high-yield corporate bonds. The government bond index is the Barclays U.S. Treasury: 7–10 Year Index. Panel A shows the mean, volatility, and Sharpe ratio of the excess return over the one-month T-bill rate for the market portfolios. Panel B shows the same statistics for the multi-factor portfolios in equities and investment-grade and high-yield corporate bonds. Panel C reports the outperformance statistics, and Panel D, the correlations between the outperformances. Mean, volatility, outperformance, and tracking error are annualized. Statistical significance is determined through two-sided tests of whether the Sharpe ratio is different from the Sharpe ratio of the market (Panel B; test of Jobson and Korkie 1981) and whether the outperformance is different from zero (Panel C; *t*-test with Newey–West standard errors).

*Significant at the 5% level.

ratio of 0.49 is the lowest among the four asset classes.

Panel B of Table 4 shows the same statistics for the multi-factor portfolios in equities and investment-grade and high-yield corporate bonds. All three multi-factor portfolios have higher returns and Sharpe ratios than their own market portfolios. The Sharpe ratios range from 0.72 (equities) to 1.00 (high yield). Panel C shows that the multi-factor portfolios also did relatively well, significantly outperforming their market indexes with information ratios between 0.58 and 0.85. Panel D of Table 4 reports the correlations of the outperformance of the multi-factor portfolios with investment grade, high yield, and equities.[9] We see modestly positive correlations, between 0.17 and 0.35, suggesting that the outperformance of the corporate bond multi-factor portfolios diversifies with the outperformance of the equity multi-factor portfolio. Thus, factor investing in the corporate bond market captures different though somewhat similar effects compared with factor investing in the equity market.

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To further analyze the value added by factor investing in a multi-asset context, we construct four portfolios. The first portfolio, "Traditional," consists of an equal allocation of 25% to each asset class.[10] The second portfolio, "Equity Factor Investing," allocates the 25% equities to the equity multi-factor portfolio instead of to the equity market. The third portfolio, "Corporate Bond Factor Investing," replaces the investment-grade and high-yield allocations of the Traditional portfolio with their respective multi-factor portfolios. The fourth portfolio, "Equity + Corporate Bond Factor Investing," allocates to both the equity and the corporate bond multi-factor portfolios.

Panel A of **Table 5** reports the return statistics of the four portfolios. Clearly, investing in either equity or corporate bond factors leads to higher Sharpe ratios: 0.91 and 0.96 versus 0.78 for the Traditional portfolio. But investing in factors in both the equity and the corporate bond markets leads to an even higher Sharpe ratio of 1.07. Panel B shows that investing in not only the equity multi-factor portfolio but also the corporate bond multi-factor portfolios improves the outperformance from 1.33% to 2.35% and the information ratio from 0.58 to 0.81. Panel C reports the four-factor alpha relative to the four market portfolios. The alphas of the three portfolios that include at least one multi-factor portfolio are large and highly significant. The Equity + Corporate Bond Factor Investing portfolio has an alpha of 2.53% versus 1.26% for Equity Factor Investing. This finding shows that the

Table 5. Performance Statistics of Multi-Asset Portfolios, January 1994–June 2015

	Traditional	Equity Factor Investing	Corporate Bond Factor Investing	Equity + Corporate Bond Factor Investing
A. Return statistics				
Mean	5.21%	6.54%	6.24%	7.57%
Volatility	6.69%	7.16%	6.48%	7.09%
Sharpe ratio	0.78	0.91	0.96**	1.07**
t-Value		1.86	4.65	3.07
B. Outperformance statistics				
Outperformance	0.00%	1.33%*	1.02%**	2.35%**
Tracking error	0.00%	2.30%	1.17%	2.91%
Information ratio		0.58	0.88	0.81
t-Value		2.22	3.13	2.91
C. Alpha statistics				
Alpha		1.26%*	1.27%**	2.53%**
t-Value		2.09	4.10	3.18

Notes: This table reports performance statistics of four multi-asset portfolios consisting of government bonds, corporate bonds, and equities. All portfolios are constructed like the portfolios shown in Table 4. The "Traditional" portfolio invests 25% in equities, 25% in government bonds, 25% in investment-grade corporate bonds, and 25% in high-yield corporate bonds. The "Equity Factor Investing" portfolio applies factor investing only in the equity market. The "Corporate Bond Factor Investing" portfolio applies factor investing only in the corporate bond market. The "Equity + Corporate Bond Factor Investing" portfolio applies factor investing in both the equity and the corporate bond markets. Panel A reports the statistics of the excess return over the one-month T-bill rate, and Panel B, the outperformance statistics. Panel C shows the alpha of a regression of the portfolio return on the four market returns (Table 4, Panel A). Mean, volatility, outperformance, tracking error, and alpha are annualized. Statistical significance is determined through two-sided tests of whether (1) the Sharpe ratio is larger than the Sharpe ratio of the Traditional portfolio (Panel A; test of Jobson and Korkie 1981), (2) the outperformance is different from zero (Panel B; *t*-test), and (3) the alpha is different from zero (Panel C; *t*-test). The *t*-tests are calculated with Newey–West standard errors.

*Significant at the 5% level.

**Significant at the 1% level.

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corporate bond factors add over 1% alpha a year for investors compared with their equity counterparts.

Conclusion

In this article, we have provided empirical evidence that explicitly allocating to the four well-known factors size, low risk, value, and momentum delivers economically meaningful and statistically significant risk-adjusted returns in the corporate bond market. We used monthly constituent data of the Barclays U.S. Corporate Investment Grade Index and the Barclays U.S. Corporate High Yield Index over January 1994–June 2015, measuring corporate bond returns in excess of duration-matched Treasury bonds. We found that both single-factor and multi-factor portfolios exhibit higher Sharpe ratios than the corporate bond market and significant alphas. The investment-grade long-only multi-factor portfolio has a Sharpe ratio of 0.32, versus 0.12 for the market. For high yield, the Sharpe ratio also more than doubles, from 0.23 to 0.56. The annual Fama–French–Carhart alphas are 0.84% and 3.65% for investment grade and high yield, respectively; these alphas are statistically significant and are large compared with the investment-grade (high-yield) market returns over the period of 0.50% (2.33%). We found that breakeven transaction costs are well above actual transaction costs of corporate bonds reported in various studies, and thus after-cost alphas remain substantial. These findings are robust to a variety of sensitivity checks, including alternative factor definitions, alternative portfolio construction choices, and the evaluation of factor portfolios on a subset of liquid bonds. Finally, we found that the corporate bond factors add value above equity factors. Investors already applying factor investing in the equity market can add more than 1% alpha and 0.1 Sharpe ratio by allocating *also* to factors in the corporate bond market.

We see several advantages to investing in a multi-factor portfolio over selecting a single factor. First, diversifying across factors protects against the possible underperformance of one or more factors for prolonged periods (for a more detailed exposition of the diversification benefits of allocating to factors, see Bender et al. 2010; Ilmanen and Kizer 2012). Second, the tracking errors of individual factors to the market are relatively large, but given the modest correlations between the factors' outperformances, the tracking error of the multi-factor portfolio is well below the average of the tracking errors of the individual factors. Third, the magnitude of the premiums realized in the past may not be predictive of the future. So, the best-performing factor in the past might not be the winning factor in the future.

What about the implementation of factors in actual investment portfolios? Traditionally, investors delegate the implementation of their investment portfolios to contracted external managers. But these investment managers, benchmarked to the market index, might be unwilling to implement certain factors because of the factors' large tracking errors or limited information ratios. The low-risk factor, for example, does not yield a high information ratio. Therefore, the traditional paradigm of delegated and benchmarked asset management leads at best to implicit and time-varying exposures to factors and at worst to no exposures at all.

In an absolute-risk framework, evaluated by the Sharpe ratio instead of the information ratio, allocating to factors does offer clear benefits. Factor investing is thus a strategic choice: In the short run, the tracking error versus the market may be large, but in the longer run, higher risk-adjusted returns beckon. Investors should thus seek managers who explicitly and consistently implement factor exposures in their investment strategy.

At the moment, investors have few investment vehicles available to harvest factor premiums in the corporate bond market.[11] In equity markets, value, small-capitalization, and low-volatility funds are numerous. With the increasing popularity of the factor-investing concept, we expect the corporate bond market to follow suit.

Editor's Note

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Notes

1. Note that the fixed-income return attribution literature (e.g., Kahn 1991) also uses the term *factors*. This stream of literature is concerned with an *ex post* decomposition of a manager's outperformance into various drivers, or "factors," such as currency, duration, yield curve, and credit. The remaining outperformance is often called "issuer selection" or "managerial skill." This managerial skill is precisely what *our* factors (size, low risk, value, and momentum) try to replicate in a rules-based manner.

2. All the Barclays indexes cited in this article were renamed Bloomberg Barclays indexes after we completed our study.

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

4. We used the Barclays U.S. Treasury: 7–10 Year Index because it best matches the average maturity of the corporate bonds. For investment grade (high yield), the average maturity in our sample is about 10.9 (7.7) years. We could have used a Barclays index containing all maturities, such as the Barclays U.S. Treasury Index. But our results would not change materially; the return correlation of the Barclays U.S. Treasury: 7–10 Year Index with the Barclays U.S. Treasury Index is 98.6%.

5. For investment grade (high yield), the average size of bonds issued by the 10% largest companies is about 3.4 (4.5) times larger than the average size of bonds issued by the 10% smallest companies.

6. Recall that in practice, portfolio managers could come close to this excess return tracking error by using Treasury futures to hedge duration differences between their portfolio and the corporate bond market index.

7. Alternatively, one could conduct a portfolio optimization aimed at maximizing the Sharpe ratio. Blitz (2012) demonstrated that, compared with single-factor portfolios, a portfolio with equal allocations to each factor already captures most of the improvements of a multi-factor portfolio.

8. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

9. We also computed correlations for individual factors and found modestly positive correlations. This finding shows that corporate bond factors capture different though somewhat similar effects compared with their equity counterparts.

10. The allocation chosen is arbitrary and serves only to illustrate.

11. The exceptions are various funds that invest exclusively in short-dated corporate bonds, thus offering partial exposure to the low-risk factor.

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