Integrating and mixing in credit (and equities?)

Introduction

This article expands on BSIC's previous work on systematic credit by investigating further the use and implementation of factors in the investment-grade corporate bond market. The article starts by discussing the definition of factors used in the analysis and presents two different approaches to the construction and selection of portfolios. Rather than simply focusing on a single strategy, this article aims to illustrate the different ways in which either strategy can be structured by giving a basic framework, as presented in the literature. A further objective of this article, which has not been explored in a great deal of literature, stems from the definition of our factors in the previous article. Some of the factors (e.g. equity momentum in credit) come directly from equity data, which were used to explain credit returns. Here, we aim to see if going in the opposite direction yields positive results, and we explore whether credit factors can be used to explain equity returns. This would provide useful information to agents operating in the credit markets, as hedging factor exposures through equity trading would result in a cheaper hedge than through credit.

The problem of data cleaning is largely similar to what we faced in the first article. However, in this case, we only focus on the IG universe in order to have a better link to equity returns. We obtained the data from the CRSP dataset and merged to the WRDS and Open Bond Asset Pricing datasets through the PERMNO, with a sample covering the period from 09-2002 to 09-2022. In this article, we do not go through the segmentation of the group of peers, as we aim to only utilize information contained in the cross-section of the credit market.

Factor construction

As mentioned, the definition of factors in this article seek to exploit only information provided by the bond market and therefore we will not include factors influenced by entity-level data. The reason for this is that part of our objective is to verify whether bond market information can be used to drive equity investing decisions.

The factors we that define come from Houweling and Van Zundert (2016). To compute the signals, we defined a metric that represents each factor and then we computed the z-scores for each date.

The Size signal is computed based on the total public debt outstanding for the issuing company. The idea of defining the factor at the company level, instead of the size of individual bonds, is to use the company size as a proxy for default risk, similar to the logic behind the relative effect in equity markets. This factor captures a potential premium arising from the fact that smaller issuers tend to face greater challenges such as higher default risks and limited access to capital markets. Moreover, the Size factor indirectly captures an illiquidity premium, as bonds issued by smaller firms typically trade less frequently.

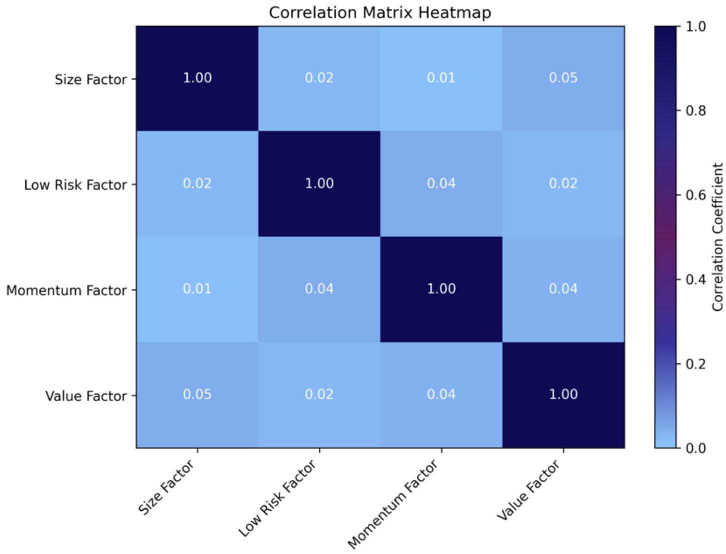
The Low-Risk factor identifies bonds with shorter maturities and high credit ratings, reflecting their lower risk profile. It builds on the observation that low-risk bonds can outperform on a risk-adjusted basis. This signal is computed for each bond on the sum of the time to maturity and the rating expressed as a number that goes from 1 for AAA rated bonds to 21 for the lowest rated bonds.

The Value factor seeks to exploit pricing inefficiencies in the bond market, focusing on the difference between a bond's actual credit spread and its modelled "fair" spread. Bonds whose spreads are significantly higher than the modelled value are considered undervalued, while those with lower spreads are viewed as overvalued. This factor highlights opportunities in mean reversion, demonstrating that undervalued bonds tend to correct and deliver superior returns, whereas overpriced bonds underperform. The fair spread is computed using a cross-sectional regression model that incorporates credit rating dummies, time to maturity, and recent spread changes. Particularly:

$$c_{s_i} = \alpha + \sum_{r=1}^{21} \beta_r \cdot \mathbf{I}_{\mathbf{ir}} + \gamma \cdot \mathrm{tmt}_i + \delta \cdot \Delta c_{s_{6m_i}} + \epsilon_i$$

Where $\mathbb{I}_{ir}$ is equal to 1 if the bond i has rating r and 0 otherwise. The signal is then computed on the percentage difference between the actual spread and the fitted fair spread.

The Momentum factor captures the persistence of bond performance, a phenomenon observed across financial markets. This factor leverages behavioural anomalies such as underreaction to information and herding behaviour, where investors drive persistence in returns. For bonds, Momentum is defined as the past six-months return, excluding the most recent month to avoid short-term reversals. Excess returns are calculated relative to duration-matched Treasuries to isolate bond-specific performance.



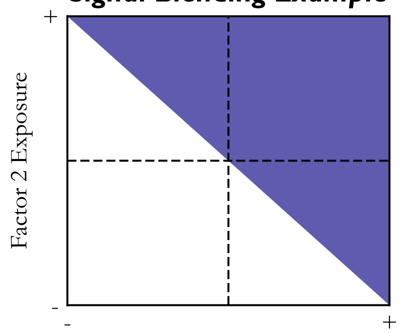
Finally, we plot the correlation matrix to provide insights into the relationships between the different factors. Overall, the weak correlations (always below 0.05) across the factors imply that they capture distinct aspects of the dataset, which is advantageous in applications such as multi-factor investment models. This independence reduces the risk of multicollinearity and ensures that the factors contribute unique information. The results validate the appropriateness of the selected factors for diverse and independent analyses.

Portfolio versus signal blending

As previously first part of this article will focus on the comparison of two of the main approaches used for factor investing: portfolio blending (also defined as mixing) and signal blending (also defined as integrating). These approaches are widely discussed in the literature: Ghayur et al. (2018) provides a detailed methodology on how to construct long-only multifactor portfolios in equities, and Blonk and Messow (2024) extends the application of mixing and integrating to the credit market. Before presenting their conclusion, we borrow their simple and intuitive graphical representation of the case with 2 uncorrelated (orthogonal) factors to better understand which securities are included in each of the two cases.

The main concept behind the procedures is to select, at each point in time, the bonds which exceed a given threshold (quantile) in the cross-sectional ranking of the bonds at that date, based on a characteristic that will vary from factor to factor. In order to have comparable values across factors, the scores in the cross-section are standardized to be z-scores so that in the case of signal blending they can be meaningfully combined into a composite signal. The procedure starts from an equal weight universe of securities and the threshold for inclusion is changed to match the desired level of factor exposures. The first figure below shows how the securities to hold in a low-exposure portfolio are selected. A combined score is assigned to every security as the sum of the 2 z-scores and the shaded area is where the selected securities will lie. The average exposure with a threshold of 50% as in this figure will be of around 0.5 and each security will be held at twice the weight it had in the initial equally-weighted universe.

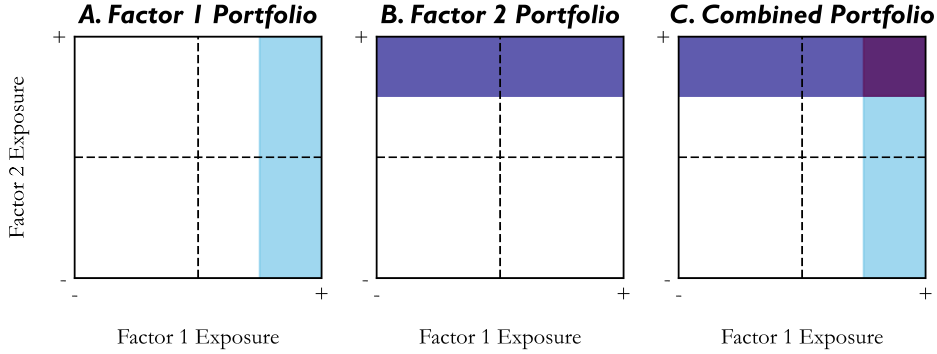
Signal Blending Example



Source: BSIC

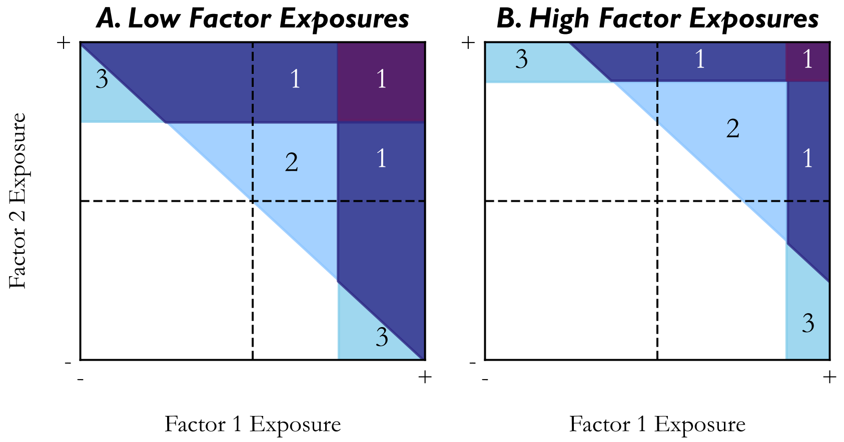
In the case of portfolio blending, single factor portfolios are constructed by selecting the top 25% of the securities along each factor ranking and the portfolios are combined. The securities in the light blue and purple areas will still be held at 2 times their original weights and the securities in the intersection will have 4 times their original weight.

Portfolio Blending Example



Source: BSIC

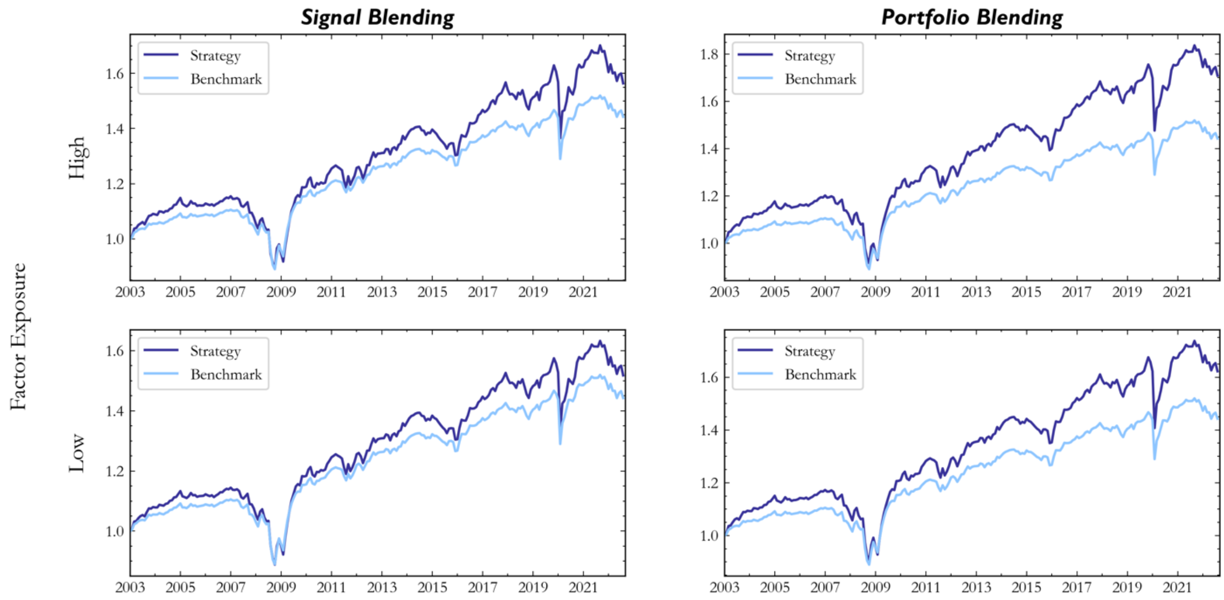
The last chart below is indicative to understand what the trade-offs are, and which bonds are excluded/included in the portfolios when we change the thresholds. In particular, we can see how in the low-exposure case the area of the intersection (marked as area 1 and purplish) is larger than in the high-exposure case. It is important to note that in the portfolio blending case, these securities are held at 4 times their initial weight and therefore the portfolio will be more overweight the best securities. The conclusion is that the portfolio blending approach is expected to provide higher information ratios in the low-exposure portfolios while the signal blend is expected to perform better in the high factor exposure case. Another important fact used by advocates of the portfolio blend is that performance attribution becomes easier where we deal with traded factor portfolios.



Source: BSIC

Performance comparison

In the following section we examine the performance of the long-only strategies based on the rules explained above, in particular we compare the results obtained with portfolio (mixing) and signal (integrating) blending. In particular, our analysis will consist of two steps: the first one is to analyse the performances by isolating the credit returns, i.e. by hedging interest rate risk. This is obtained by computing the difference in returns between the bonds and a basket of duration-matched treasuries, as explained by Van Binsbergen et al. (2021) and provided by Open Bond Asset Pricing. The reason for this is that our factors should capture the risk premia contained in the credit part of the yields rather than rates.

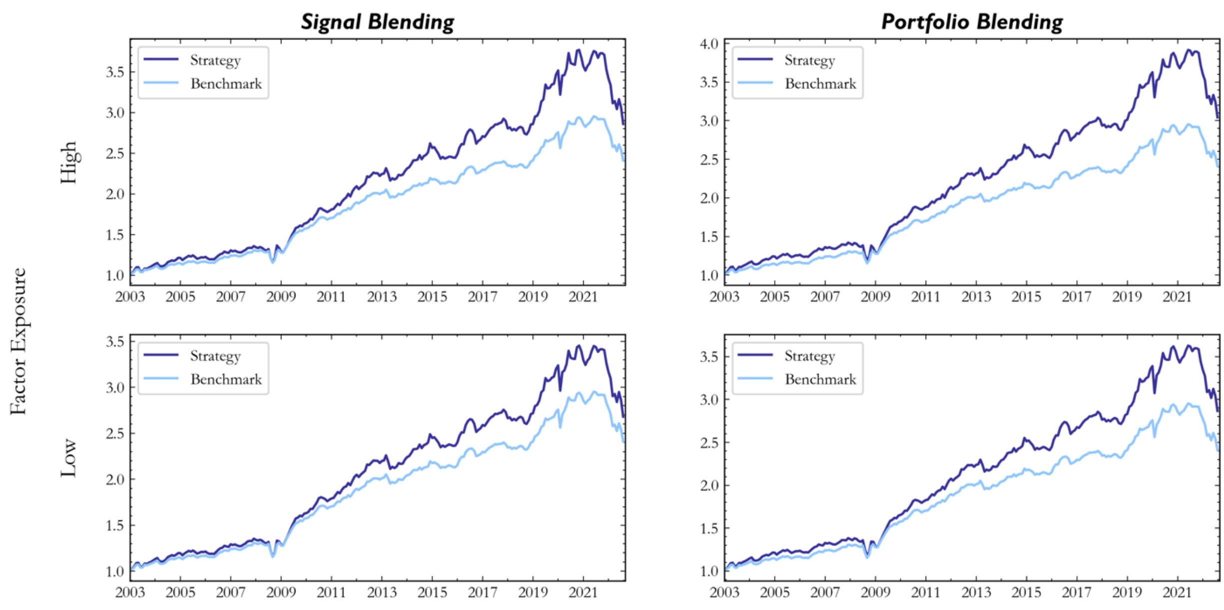


Source: BSIC

The thresholds used to include bonds at each date based on the portfolio blending sorts are based on the literature. We assign thresholds of 50% and 75% for low and high exposures in the signal blending case, which will ensure that we include 50% and 25% of the securities, respectively.

To exclude the same volume in the 4-dimentional space created by the 4 factors (they have very low correlations), we have to set the thresholds to 0.84 (the fourth root of 0.5) and 0.93 (the fourth root of 0.75) for the portfolio blending case, rather than building exposure-matched portfolios. We see that all strategies outperform the equally weighted benchmark, and that portfolio blending tends to outperform signal blending given the more restrictive inclusion parameters.

The following chart represents the performance using total returns of the bonds rather than the performance obtained by hedging interest rate exposure. We will use these strategies to evaluate performance metrics such as the Sharpe ratio.



Source: BSIC

We report in the following the Sharpe ratio of every strategy with the risk-free rate taken from the Fama-French website for the period 2002-2022.

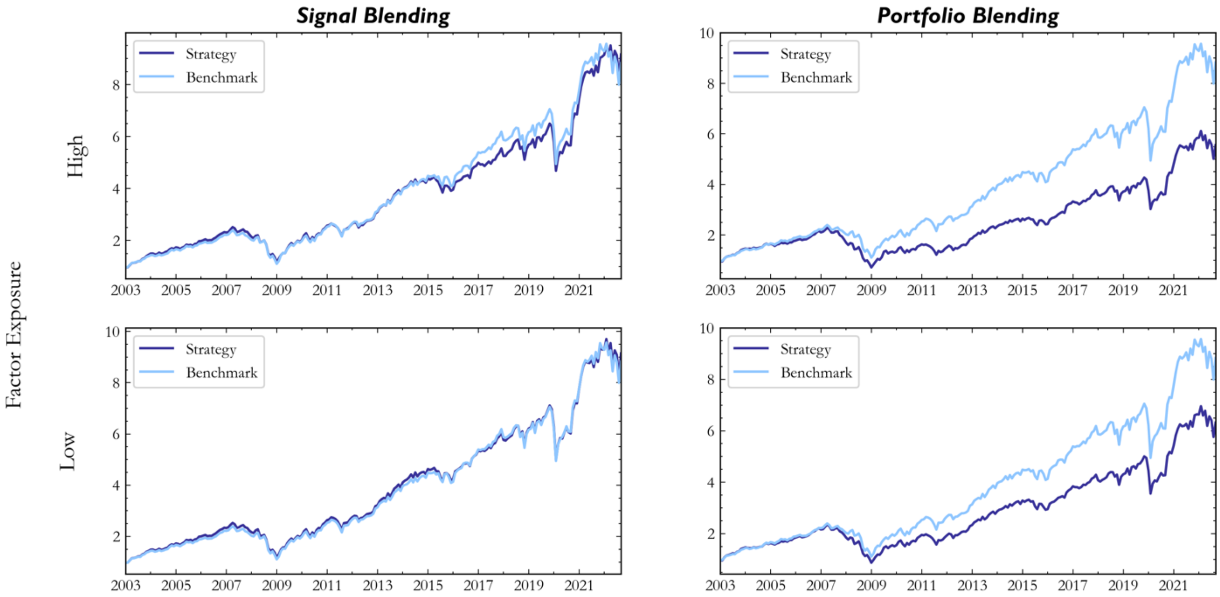
	Signal Blending		Portfolio Blending	
	High	Low	High	Low
Sharpe Ratio	0.5248	0.5316	0.5894	0.5833

Source: BSIC

As can be seen, the strategies do not obtain stellar performances, particularly after taking into account transaction costs. The strategies are simply an implementation of cross-sectional factor exposures and are not aimed at being directly implementable strategies. Instead we have used them to show the different methods available to construct a multi-factor strategy, which may be further improved by implementing a more sophisticated weighting mechanisms rather than equal weights, which done in our previous analysis.

Can we trade equities?

Our final question was whether we could use the information contained in the cross-section of corporate bonds to trade equities. We computed, at each date, entity-level factor exposures, obtained as a market capitalization weighted sum of the single bond's factor exposures. This was done to obtain a single score for each factor for every Permno at each date. Once that was obtained the portfolios were constructed following the same rules we used in credit based on exposures and mixing versus integrating.



Source: BSIC

The above chart clearly shows how the credit factor strategies underperform or are very close to the equal-weighted benchmark. This confirms the findings from Keshavarz and Sirmans (2024) that equity returns can be used to forecast bond returns while the opposite is not true. This implies that the equity market is the first and faster to respond to information in the markets, this would justify the inclusion of equity momentum as a factor in credit and not of credit momentum as a factor in equity. To conclude, we report the results from the regression of the equity strategies on the Fama-French factors to see whether the information contained in the sorts based on credit information is already contained in typical equity factors.

	Portfolio Blending		Signal Blending	
	Low	High	Low	High
Mkt-RF	1.007***	1.056***	0.958***	0.940***
SMB	-0.114***	-0.133***	0.083***	0.076**
HML	0.420***	0.552***	0.268***	0.294***
RMW	-0.129***	-0.288***	0.047	-0.008
CMA	0.109*	0.052	0.125***	0.201***
const	0.000	-0.000	0.001*	0.001*

Source: BSIC

As we see, the equity strategies excess returns are largely priced by the typical equity factors, implying that the information contained in the credit factors is largely redundant to what is contained in equity factors.

Conclusion

As already mentioned, this article does not provide a framework to construct a direct implementation of the strategies, because a more sophisticated way to consider transaction costs and dynamic rebalancing would be required, as was studied in our previous article on systematic credit. This article provides an overview of how information contained only in the corporate bond market can be used to construct factors and how securities can be selected based on either their combined factor exposures or the single factor exposures. Further research could be dedicated to extending the factors to contain information from the CDS market as was done in [3] or to implement more sophisticated rebalancing techniques to explore the real-world implementation of these strategies. Furthermore, we conclude that the inclusion of information contained in the equity markets can indeed help when constructing credit portfolios and this can be subject of future research. In conclusion, the outperformance relative to equal weights is robust to transaction costs as the equal-weight portfolio would imply trading the whole cross-section at each date.

References

[1] Blonk J. and Messow P., "How to construct a long-only multifactor credit portfolio?", 2024

[2] Ghayur K. et al., "Constructing Long-Only Multifactor Strategies: Portfolio Blending vs. Signal Blending", 2018

[3] Houweling P. and Van Zundert J., "Factor Investing in the Corporate Bond Market", 2017

[4] Keshavarz J. and Sirmans S., "How Similar Are the Factor Structures of Equity and Credit Markets?", 2024

[5] Van Binsbergen J. et al., "Duration-Based Valuation of Corporate Bonds", 2021

TAGS:

Credit, Trading, Factors, Fixed Income, Quant

