Putting Credit Factor Investing into Practice

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KEY FINDINGS

- The authors analyze common corporate bond factors and show the pitfalls when implementing these factors in real-world portfolios.
- In order to identify bonds that are investable for institutional investors, they construct a tradability flag based on past transactions.
- The authors show how long-only factor investors can achieve outperformance loading on corporate bond factors while limiting deviation from the benchmark in key risk characteristics.

ABSTRACT

Implementing established corporate bond factors in real-world portfolios poses many challenges for investors. First, the investment universe is reduced by non-tradable assets. In this article, the authors avoid investing into these bonds by constructing a tradability measure based on past transaction data. A realistic strategy to implement should target bonds that are being traded in the market. Second, factor performance is typically measured against a benchmark. To allow for a fair comparison, the authors limit the deviation between the portfolio and the benchmark in key dimensions. Consequently, not only bonds with the best signals can be included in the portfolio. Overall, this reduced universe, along with other restrictions and higher transaction costs than on the equity side, leads to a substantial performance decrease. Nevertheless, the authors show that factor investing in credit is still a successful strategy if it is approached with realistic expectations and common pitfalls are avoided. Their enhanced approach translates signals into usable trading strategies, outperforming the benchmark with an information ratio of 1.1 (1.4) for investment grade (high yield).

Previous literature on factor investing has produced several promising credit factors for investors to exploit. When implementing these strategies in live portfolios, a substantial portion of the reported outperformance is typically lost. We present evidence that the main culprits causing this effect are investor constraints (which most investors are bound to) and poor tradability of a major portion of the bond universe. Our results show how researchers can control for these effects and still earn a positive significant outperformance for investment-grade (IG) and high-yield (HY) corporate bond factors, even if it is smaller than previously reported in the literature.

The interest surrounding factor investing for corporate bonds has gained momentum in recent years, not only in academia but also in the industry. While factor investing within the equity market is widely established and has been implemented by various players within the industry, the optimal implementation of corporate bond factor strategies remains nebulous, especially for benchmark investors. Thus, it is pivotal to determine how to translate corporate bond factors into actual portfolios, analyze their performance before and after transaction costs, and identify the constraints often used by fixed income investors. For this reason, research on the practical implementation of factor investing within corporate bonds has gained traction recently (e.g., Polbennikov, Desclée, and Dubois 2021).

Previous research on equity markets has uncovered hundreds of factors; this has led recent studies to question the out-of-sample performance of such factors (for instance, Harvey, Liu, and Zhu 2016 list 313 factors published in top journals). Data mining, overcrowded factors (see Arnott et al. 2019), and transaction costs are often cited as reasons for poor factor performance (Novy-Marx and Velikov 2016). Restricting the company universe to investable, liquid companies—and thereby creating a smaller space to invest in—greatly diminishes factor returns even further. For example, Hou, Xue, and Zhang (2020) show that, after accounting for microcaps through New York Stock Exchange breakpoints and value-weighted returns, 65% of the 452 previously published anomalies do not generate significant risk premia at the 5% level. This suggests that restricting the investment universe or reducing the weight of illiquid or non-tradable assets either through constraints or strict exclusions could have detrimental effects on the risk premia of credit factors too.

Factor investing within corporate bond markets has a much shorter history and criticism of data mining on the equity side has led researchers to emphasize economic reasoning when finding new factors. Given the relative novelty of credit factor investing, however, researchers have not yet analyzed the performance of factor investing strategies under realistic constraints like the ones most fixed income investors are bound to (for fixed income investors, see Israel, Palhares, and Richardson 2018; for equity-related studies, see Chow, Kose, and Li 2016 and Leung et al. 2021). With corporate bonds, realistic portfolio construction is eminently important because the cross section of corporate bonds has a much greater dispersion of beta and risk than equity markets (see Israel, Palhares, and Richardson 2018). Thus, neglecting these constraints during the portfolio construction process leads to portfolios risk characteristics that are far removed from any realistic benchmark.

Constraints that most institutional fixed income investors face and are often mentioned in the literature include constraints on the no-shorting of assets, full investment, and an upper bound on the maximum weight of single assets within the portfolio. However, these are not the only constraints fixed income investors face. Often-neglected constraints include 1) turnover constraints to prevent excessive trading with every optimization, 2) risk constraints (duration and spread) that ensure similar portfolio risks as the benchmark, 3) constraints on excessive bets on individual issuers to prevent idiosyncratic risks stemming from a single issuer, and 4) exclusion of sheer untradable bonds from the investment universe. Similar to the micro-cap exclusion in equities, these constraints often result in a smaller investable fraction of the total universe, compared with the equity side. The effect of such constraints on the implementability and performance of previously researched credit factors has not been thoroughly discussed in the literature.

We bridge this gap in the literature by analyzing the performance of credit factors after taking into account realistic constraints faced by fixed income investors. We construct a multifactor signal from prominent credit factors and examine its performance after incrementally adding investor constraints. For a representative (balanced) investor, the base-case outperformance in investment grade (high yield) of 5.8% (12.6%) is reduced by 1.6% (2.6%) after the maximum turnover constraint, 1.6% (4.2%) after the duration-times-spread (DTS) constraint, 0.6% (1.4%) after the issuer constraint, and 0.6% (1.1%) after the tradability constraint, leaving the investor with a final outperformance of 1.4% (3.3%). While the outperformance is heavily influenced by the constraints, the information ratio of the same investor only decreases marginally from 1.0 (1.5) before constraints to 0.9 (1.2) after constraints for IG (HY). Changing the multifactor signal from a balanced to a more ambitious factor mix results in an improved information ratio of 1.1 (1.4). To construct the multifactor signal, we use recent studies' most prominent corporate bond factors in the IG and HY spaces, which, in our opinion, are 1) *value*, 2) *equity momentum* (i.e., momentum), 3) *carry*, 4) *quality*, and 5) *size*. We combine these single factors into a multifactor signal and discuss common pitfalls when combining factors.

When constructing these factor portfolios, we propose a novel methodology to combat a weakness of the value factor in the extant literature. While momentum, size, quality, and carry vary only slightly across studies, there are several definitions of value. The most common definition of value posits that it is the residual in the regression of the option-adjusted spread (OAS) on various balance sheet and market data items. However, there is no consensus regarding the choice of independent variables. To alleviate possible data mining concerns by choosing particular variables, we propose a variable selection through a least absolute shrinkage and selection operator (LASSO) approach. We find that rating dummies and market data are the best features when explaining credit spreads, while balance sheet information falls behind in this regard.

Several studies—by Houweling and van Zundert (2017), Israel, Palhares, and Richardson (2018), as well as Polbennikov, Desclée, and Dubois (2021)—are closely related to our own. To the best of our knowledge, we are the first to include a tradability flag based on data from the Trade Reporting and Compliance Engine (TRACE) as a constraint when constructing portfolios. We further extend the study of Houweling and van Zundert (2017) by also analyzing the carry factor and constructing optimized portfolios under realistic investor constraints. We confirm the results of Israel, Palhares, and Richardson (2018) on the merits of the tested credit factors under more realistic conditions: We include a tradability constraint that is a common but necessary factor to consider when constructing corporate bond portfolios. Polbennikov, Desclée, and Dubois (2021) test the performance of the momentum and value factors in credit under realistic transaction costs, tracking the risk of a benchmark after identifying illiquid securities based on Barclays bond analytics data. We test a wider variety of credit factors, use a different turnover constraint, add a constraint to avoid overweighting single issuers, and use a tradability flag.

It should be noted that there is currently no consensus on what constitutes a "good" factor model for the credit market. For instance, Bai, Bali, and Wen (2019) suggest a model that includes downside risk, credit rating, market beta, and a liquidity proxy. Kelly, Palhares, and Pruitt (2020) treat factors as unobservable and argue for a conditional instrumented principal components (IPCA) factor model for bond returns with time-varying betas. Our goal is not to argue in favor of one factor model or another, nor to propose a perfect factor model that explains the cross section of corporate bond returns. Instead, we aim to determine whether investors are systematically able to capture the risk premium of the factors we analyzed, even after including transaction costs. As Feng, Giglio, and Xiu (2020) state: "The risk premium of a factor tells us whether investors are willing to pay to hedge a certain risk factor, but it does not tell us whether that factor is useful in pricing the cross section of returns." Thus, here we are interested in the risk premium, rather than the price of risk (see Cochrane 2009; and Feng, Giglio, and Xiu 2020).

EXHIBIT 1
Summary Statistics

	Investment Grade						High Yield					
	Min	1st Q	Median	Mean	3rd Q	Max	Min	1st Q	Median	Mean	3rd Q	Max
Bonds	2,361	2,796	4,101	4,476	6,261	7,054	755	895	1,210	1,216	1,559	1,716
Financials	351	699	849	941	1,206	1,583	27	40	82	88	136	163
Corporates	1,749	2,352	3,256	3,535	4,880	5,877	709	857	1,124	1,128	1,418	1,576
Face Value (USD billions)	1,067	1,216	2,284	2,686	4,388	5,219	200	271	450	543	897	1,011
Market Value (USD billions)	1,364	1,697	3,407	3,495	5,235	6,337	191	356	616	670	1,023	1,270
Avg OAS (market value weighted, basis points)	81	104	132	154	165	610	205	317	398	450	512	1,607
Avg TTM (market value weighted, years)	9	9.6	9.8	9.9	10	12.1	5.9	6.6	6.9	7.2	7.9	9.2
Avg Rating Score (market value weighted)	6.2	6.6	7	6.9	7.1	7.5	12.9	13.1	13.2	13.2	13.3	13.5
Avg Excess Return (market value weighted, %)	–10.4	–0.3	0.2	0.2	0.6	4.8	–12.8	–0.6	0.5	0.5	1.6	10.3
Tradable Universe (%)	33.5	44.3	51.2	50.1	55.6	65.5	40.2	52.6	57.8	59.3	67.5	76.8

NOTES: Summary statistics for the investment-grade (G0BC) and high-yield (HW00) index for all senior USD bonds in Financial, Utility, and Industrials from September 2002 through June 2021. The counts/calculations are performed by date. Based on that, the respective statistic is calculated. Rating Score is the transformed rating; a score of 1 = AAA, 2 = AA+, and so on. For convenience, 7 = A– and 14 = B+.

DATA

We use monthly constituent data of the Intercontinental Exchange (ICE) global investment-grade (G0BC) and high-yield (HW00) indices, for the period spanning from September 2002 to June 2021 and—due to reliable liquidity data from TRACE being available for USD bonds—filter for all bonds denominated in USD. For every month-end, ICE provides characteristics like credit spread (OAS), credit rating, time to maturity (TTM), modified duration (MDur), total return, excess return over US Treasuries, and sector. We also keep only those bond observations for which the sector is Financial, Utility, or Industrial. Conversely, we remove "Cash," "Quasi & Foreign Government" (no corporate debt), and "Covered"/"Securitized" due to their different risk structures, compared with unsecured debt. This cleaning leaves 99.9% of the data untouched. We also remove subordinated debt from the sample, as most investors see senior and subordinated debt as different investment universes. For the HY universe, we keep only bonds with a BB or B rating. The reason for the exclusion of CCC–C rated bonds is twofold. On the one hand, many investors explicitly exclude these rating categories in their investment guidelines. On the other hand, the price of these bonds can jump sharply depending on whether a restructuring or refinancing is successful. We want to avoid that an investment into a single bond has a high influence on the overall performance of the strategy.[1] If a bond defaults, it is priced at the expected recovery rate provided by ICE. Thus, we have no survivorship bias in this study. Summary statistics for the sample are reported in Exhibit 1.

In the final sample, we focus only on bonds that can be linked to a listed company, as certain credit factors require equity or equity-related information for their construction. In order to maintain comparability, we also remove from the benchmark bonds of non-listed companies. Thus, the resulting credit portfolios, as well as the benchmark we use, do not contain non-listed companies. This has the advantage of ensuring that we invest in exactly the desired fraction (e.g., the top quintile) of all investable companies in the sample. In addition, the return of the benchmark is not biased by

[1] We also performed our analysis leaving CCC–C rated bonds in the benchmark. The results remained the same.

bonds without matching stock.[2] In September 2002, the IG (HY) universe consists of around 2,700 (700) bonds with an amount outstanding of around \$1.1 (\$0.2) trillion, going up to around 7,100 (1,700) bonds with \$5.2 (\$1.0) trillion outstanding in the last years. The OAS was highest during the financial crisis period, followed by the recent COVID-19 pandemic period and the past dot-com bubble.

ICE has provided data for G0BC since December 1996 and for HW00 since December 1997. Corporate bond liquidity data in the form of trade dissemination via TRACE began in July 2002 for relatively liquid bonds only and began in the beginning of 2006 for almost all over-the-counter secondary market transactions (see for example Financial Industry Regulatory Authority 2019). Because cross-sectional coverage of the TRACE data appears to increase heavily from July to September 2002, we commence our analysis from September 2002. We clean TRACE data based on the filter provided by Dick-Nielsen (2009). For every bond, we count the total number of institutional trades per month. A trade is considered as institutional if the trade volume is at least \$100,000. If the number of trades is at least 10, we flag the bond as tradable, otherwise not. As visible in Exhibit 1 in the row "Tradable Universe," in the worst case, only 34% (40%) of the bonds are still investable in the IG (HY) universe.

We focus on credit excess returns over duration-matched treasuries, rather than total returns, based on the assumption that investors in the corporate bond market primarily want to harvest risk premia that are mainly driven by the default premium, independent of the term risk.

FACTOR DEFINITIONS

The five most common factors within systematic credit investing are value, (equity) momentum, carry, quality,[3] and size. For value and momentum, an extensive collection of academic literature supports these premia. The results for carry, quality, and size are not as clear-cut, but there is enough empirical support for inspecting these factors.

Value

We define the value signal of a corporate bond as the difference between the OAS and the estimated fair spread. If the market spread is larger than the estimated fair spread, the market price is lower than the estimated fair price and the corporate bond is undervalued, and vice versa. The idea dates back to L'Hoir and Boulhabel (2010).

The final signal is, thus, formed as follows:

$$\text{Value}_i = \text{OAS}_i - \widehat{\text{OAS}}_i.$$

An estimate for the fair spread is typically generated from regressing the OAS at time t on several variables (features). Subtracting from the actual OAS, the model-estimated fair spread yields the value forecast for the next period. Exhibit 2 summarizes the most prominent studies and their chosen variables for the value factor. The choice of a particular regression model is carefully outlined in every single

[2] If bonds of non-listed companies are included in the benchmark, the results are slightly better than what is reported in this study.

[3] Other studies also use the term "Low Risk" instead of "Quality" and include bond-specific factors (mainly duration) in addition to the familiar company-specific variables that are also represented in our quality factor. Because we want to use the entire universe and do not want one of our factors to already subdivide the universe, however, we use "Quality."

EXHIBIT 2

Features used for the Value Factor by Study

Paper	Features
L'Hoir and Boulhabel (2010)	Sector, Seniority, Return on assets, Equity volatility
Houweling and van Zundert (2017)	Rating, Modified duration, Spread change absolute (3 months)
Israel, Palhares, and Richardson (2018)	Modified duration, Rating, Excess return volatility (12 months)
Lair, Peeters, and Skibinski (2018)	Modified duration, Size, Volatility, Industry, Rating
Ben Slimane et al. (2018)	Time to maturity, Face value, Callable, Hybrid, Sector, Rating, Region
Bektic et al. (2019)	Book-to-price ratio
Doctor (2019)	Time to maturity, Distance to default
Henke et al. (2020)	Equity volatility, Market capitalization, Debt/enterprise value, EBITDA/total assets, Rating, Modified duration, Spread change absolute (3 months)
Polbennikov, Desclée, and Dubois (2021)	Rating, Sector, Maturity, Debt/assets, Debt/EBITDA, EBIT/interest

study. Viewed in its completeness, however, it is hard to argue why certain variables are included or excluded across different studies. In this study, we are mainly interested in the practical implementation of the factors. Nevertheless, we want to avoid raising the question of whether any specific additional feature could have a major impact on the results. Therefore, instead of a manual feature selection, we use a wide set of features and perform an adaptive LASSO regression instead of a simple linear regression with a restricted pre-determined set of features.[4]

The variables under consideration are listed in Exhibit A1 in the Appendix and are a mixture of variables that 1) are considered in the literature as potential variables explaining the spread of corporate bonds or 2) could be useful based on our own judgment and theoretical considerations.

For example, we not only add the absolute spread change (three-month) as in Houweling and van Zundert's (2017) study, but we also include the one-month up to six-month absolute and relative spread change. We also include an interaction term of modified duration and rating. We do this to account for the peculiarity of the HY market that the modified duration does not always have to be exogenous. Not all companies in the HY sector can choose which maturities they issue. High-risk companies have a hard time generating enough investor interest for a longer maturity bond; thus, they often opt for issuance of shorter maturities. Therefore, the modified duration already contains information about the creditworthiness, which we try to account for via the interaction term of modified duration and rating.

In Exhibit 3, we report the relative feature importance for all of our features averaged over time. We group our variables into four categories for an easier overview (Balance Sheet Data, Market Data, Rating, Sector). The most important variables to explain the spread of IG bonds are mainly rating dummies, followed by market data, such as the excess return volatility, the spread change and sector dummies. Balance sheet variables do not play an important role, as this information is already captured by bond ratings. In the HY universe, we also see a rating dummy as the most important variable, but market data are the dominating bucket overall. Sector dummies and balance sheet data play only a minor role. This behavior is expected, as an increase in risk (and, therefore, a higher volatility) can be better explained by faster variables (in our case, the market variables). The low influence of balance sheet variables is a result of the fact that rating agencies who also use balance sheet information and balance sheet data are often updated no more than once a quarter.

[4] For more details on the technical implementation of the adaptive LASSO for estimating the fair OAS, see the Appendix.

EXHIBIT 3

Feature Importance for the LASSO

NOTES: Calculations are performed first by date and then averaged over all dates. Results are shown for IG (left) and HY (right).

Equity Momentum

Momentum strategies are trend-following strategies. This means that an investor hopes to generate profits by investing in past winners and avoiding past losers. In theory, rational pricing should guarantee that news is equally incorporated in the stock and bond prices of the same company. Gebhardt, Hvidkjaer, and Swaminathan (2005) show that there exists a momentum spillover in IG from the equity to the corporate bond market—firms earning higher equity returns in the past tend to earn higher corporate bond returns in the future. While they argue that both stock and corporate bond prices underreact to company news, equities adjust to the news faster than corporate bonds. Further, equity momentum is able to predict future downgrades. Haesen, Houweling, and van Zundert (2017) show that this effect also persists in HY and argue for the use of a residual instead of an absolute momentum metric.

We follow Polbennikov and Desclée (2017), who show that equity momentum strategies can be improved by using a combined signal of one-, three-, and six-month momentum factors. A straightforward definition of an M-month momentum factor is to divide the return index at date t (RI_t) by the return index M months ago (RI_{t-M}). Because momentum factors suffer strongly from microstructural noise, however, we follow Kaufmann and Messow (2020) and define the M-month momentum factor as a daily average around the respective dates:

$$MOM_{\mathrm{Mx0}} = \frac{\frac{1}{11}\sum_{i=0}^{10} \mathrm{RI}_{t-i}}{\frac{1}{11}\sum_{i=-5}^{5} \mathrm{RI}_{(t-M)-i}}$$

Hence, MOM_{3x0} would be the average return of the last 11 days divided by the average return over days t – 71 to t – 61 (for months with 22 business days). We combine the momentum signals MOM_{1x0}, MOM_{3x0}, and MOM_{6x0} by averaging the individual signals. A special case is the one-month momentum factor, where we use only 7 instead of 11 days to average the RI due to the short time horizon of the original signal.

Carry

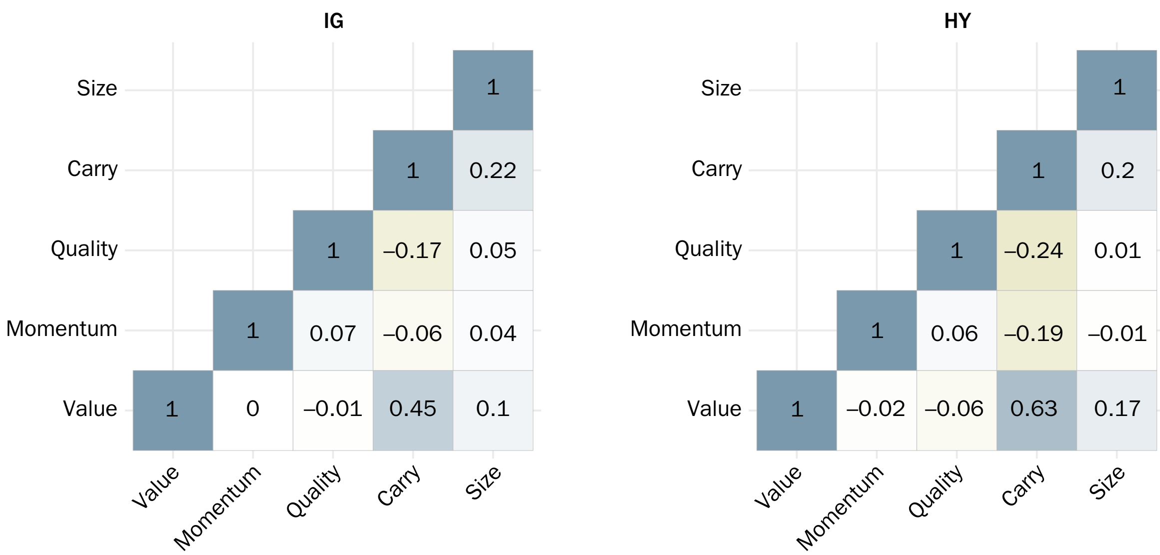
Koijen et al. (2018) define "an asset's 'carry' as its future return, assuming that prices stay the same." Carry is a model-free characteristic, and its concept can potentially be applied in many different asset classes, including corporate bonds. Similar to Israel, Palhares, and Richardson (2018), we use the most straightforward measure of carry: the OAS. As carry directly harvests market risk, this factor should show extreme results in both risk-on and crisis periods. However, as most investors want the asset manager to stay within a pre-defined risk range, the following question arises: How well does a pure risk signal translate into a real portfolio? Thus, we analyze the usefulness of carry in multifactor signals in the section Portfolio Performance.

Quality

A fundamental principle in finance is that greater risk should bring greater rewards in the long run, albeit with short-term uncertainty. However, not all risks are rewarded equally. For investors who can leverage their risk exposure, assets with a higher-quality exposure can offer greater risk-adjusted returns. However, there is no single definition of the quality factor in the market. For us, a quality factor for corporate bonds should be focused on fundamental variables, as defined by Henke et al. (2020). In total, 14 balance sheet variables are used to identify high-quality companies. In this case, the term "high quality" refers to companies that have good profitability, liquidity, and operating efficiency. The chosen variables are a refined version of Piotroski's F-Score (Piotroski 2000), mainly focusing on bank-specific variables as a refinement. We integrate these variables, as the quality of banks is typically not well captured by standard measures. First, for each of the 14 variables, we rank the assets in the cross section and center their distribution around zero. Then we calculate a weighted average of all available balance sheet items, filling missing variables with a zero. Bank-specific variables get a higher weight, in order to adequately mirror the

EXHIBIT 4

Correlation Matrix of All Factors under Consideration



NOTE: Calculations are performed first by date and then averaged over all dates from September 2002 through June 2021.

importance of industry-specific ratios. A list of all variables used can be found in Exhibit A3 in the Appendix.

Size

The effect of firm size on stock returns is well documented in the literature. In general, small firms tend to have higher risk-adjusted returns, compared with large firms with similar fundamental characteristics. Regarding corporate bonds, there are different opinions. Houweling and van Zundert (2017) show that there is also a size premium in the corporate bond market, whereas Polbennikov (2018) comes to the opposite conclusions. We define size as the sum of the market value of all bonds outstanding of one specific issuer in a specific month. There are also other definitions of size that are more complex; for example, Lair, Peeters, and Skibinski (2018) make use of a combination of the market capitalization of the underlying stock and total debt outstanding. As this alternative definition of size does not significantly change the results, we stick to the simplest definition. The factor premium of size is also often described as a liquidity premium. This assumes that issuers with low amounts outstanding are typically small companies, and that debt of those companies is less traded. In the Portfolio Performance section, we analyze how a tradability constraint affects a signal including this factor.

Multifactor

Whether a multifactor framework is suitable depends highly on the correlation structure of the underlying factors. We analyze pairwise correlations between the factors. As shown in Exhibit 4, almost all correlations are close to zero. The only exception is carry, as more exposed correlation levels are observable here. The highest rank correlation can be observed between value and carry with 45% (63%) for IG (HY), but the slightly negative correlation of carry and momentum is also striking. Overall, the correlation results suggest that a multifactor framework would be appropriate to exploit the attractive correlation structure between the factors. Due to the low correlations, the multifactor portfolio can differ substantially from the single-factor asset selection. Because a multifactor portfolio maximizes the overall factor exposure, preference is given to assets that have high factor exposure to multiple individual factors. This way, a multifactor portfolio can profit from interaction effects.

This raises the question on how to mix the single factors. Most papers weight all single factors equally (e.g., Houweling and van Zundert 2017; Doctor 2019). Some papers weight on a risk or a risk–return basis (e.g., Henke et al. 2020). We follow the majority of the literature for the first part of the study. We construct a multifactor signal by first ranking all individual factor signals by date and then calculating the average of the ranks.

In practice, the choice of single-factor signals to create a multifactor signal depends primarily on investor preferences. Do they want some additional risk? If so, carry might be a good choice. Do they want to avoid drawdowns in crisis periods? In that case, quality might be a good choice. Later, we create additional multifactor signals based on stylized investor preferences and show the consequences of including or excluding certain factors.

Instead of mixing the factors and using the aggregated signals for portfolio construction, it is also possible to mix the portfolios of the individual factors. As explained in more detail in Henke et al. (2020), however, using the aggregate signal works better for corporate bonds; therefore, we use aggregated signals when referring to multifactor.

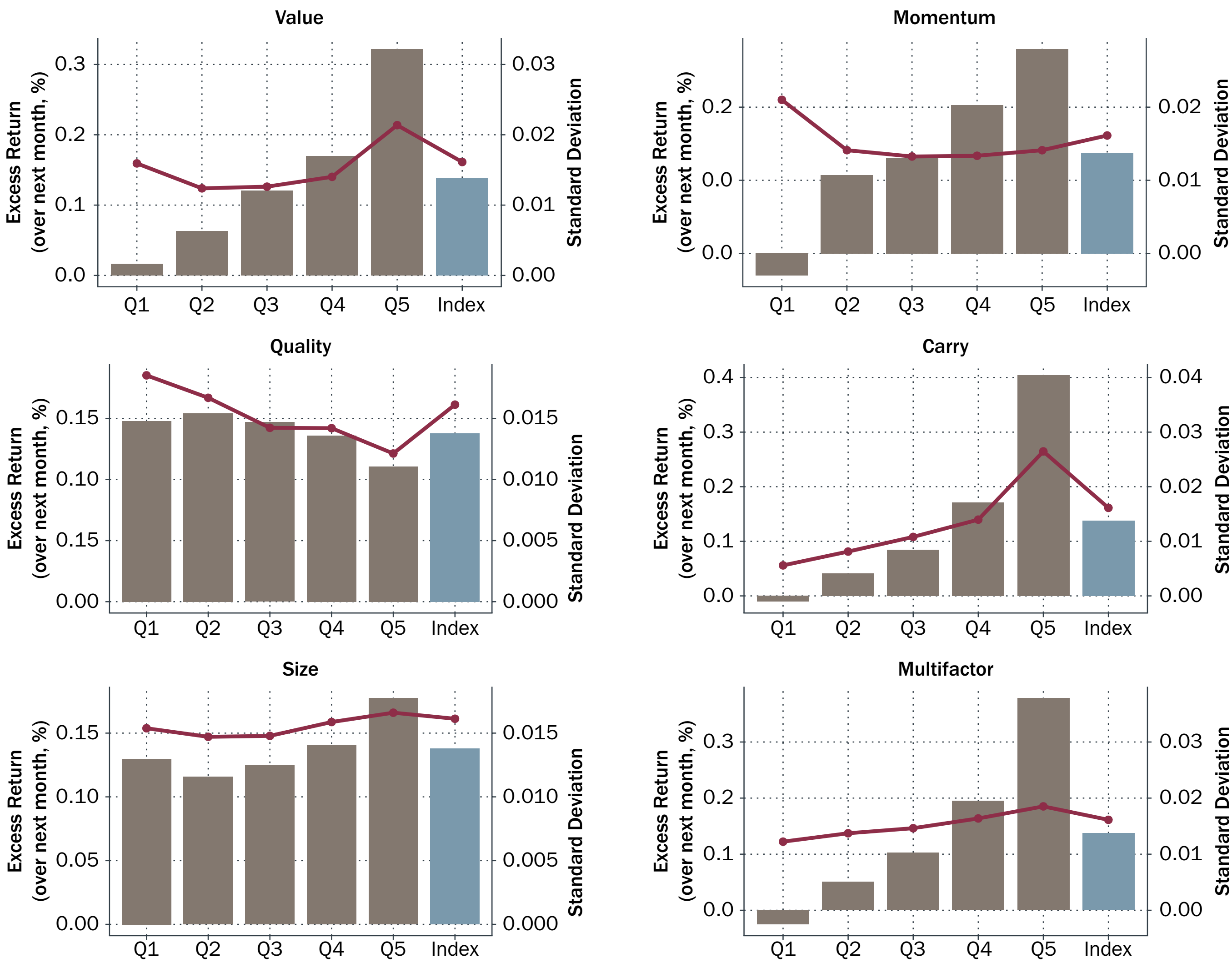
Factor Characteristics

In order to get a first impression of the risk premia related to the aforementioned factors, we rank the bonds based on their factor exposure and then average the (credit excess) returns of the following month per quintile. The resulting quintile plots are shown in Exhibit 5 for IG and Exhibit 6 for HY. The results show that carry, value, momentum, and multifactor have a monotonic positive relationship between future excess returns and higher factor loadings in both universes. However, for value and carry, higher factor exposure implies a substantial risk increase. In contrast, momentum is the only factor where risk decreases while return increases with increasing factor exposure. Conversely, quality does not show a clear relationship between factor exposure and returns. Nevertheless, the volatility of the returns is monotonously decreasing. Similarly, size also does not show a stable behavior; however, the highest quintile outperforms the overall index. As for value and carry, this additional return comes with additional risk.

We also report the average DTS, TTM, and rating score of the complete index and the quintile with the highest exposure of our considered factors in Exhibit 7. By doing so, we check whether the risk profile of the factors significantly differs from the index. The exhibit shows that value and carry can build up a higher DTS exposure compared with the reference index. This excess exposure is quite high for value, with 5.6 (9.0) in IG (HY), whereas for carry it is 10.5 (13.6). This is highly problematic for investors. The risk attributes of the Q5 portfolio differ from the benchmark to such an extent that typical investment guidelines are no longer met. Outperformance is mainly achieved by increasing risk and not by asset-picking characteristics of the factor. In contrast, quality and momentum have a lower average DTS that is comparable with the index. Multifactor stands in-between; although it has a lower risk profile than value and carry, it still increases the risk of the portfolio. However, multifactor returns are almost as high as those of carry in IG, and may even be the highest returns in HY. This is the first indicator that the performance of multifactor is not solely based on a risk increase.

EXHIBIT 5

Average Quintile Returns of Proposed Factors in IG



NOTES: Q1 (Q5) is the quintile with the lowest (highest) factor exposure. Calculations are performed first by date and then averaged over all dates. Bars show the excess return, and lines show the associated volatility.

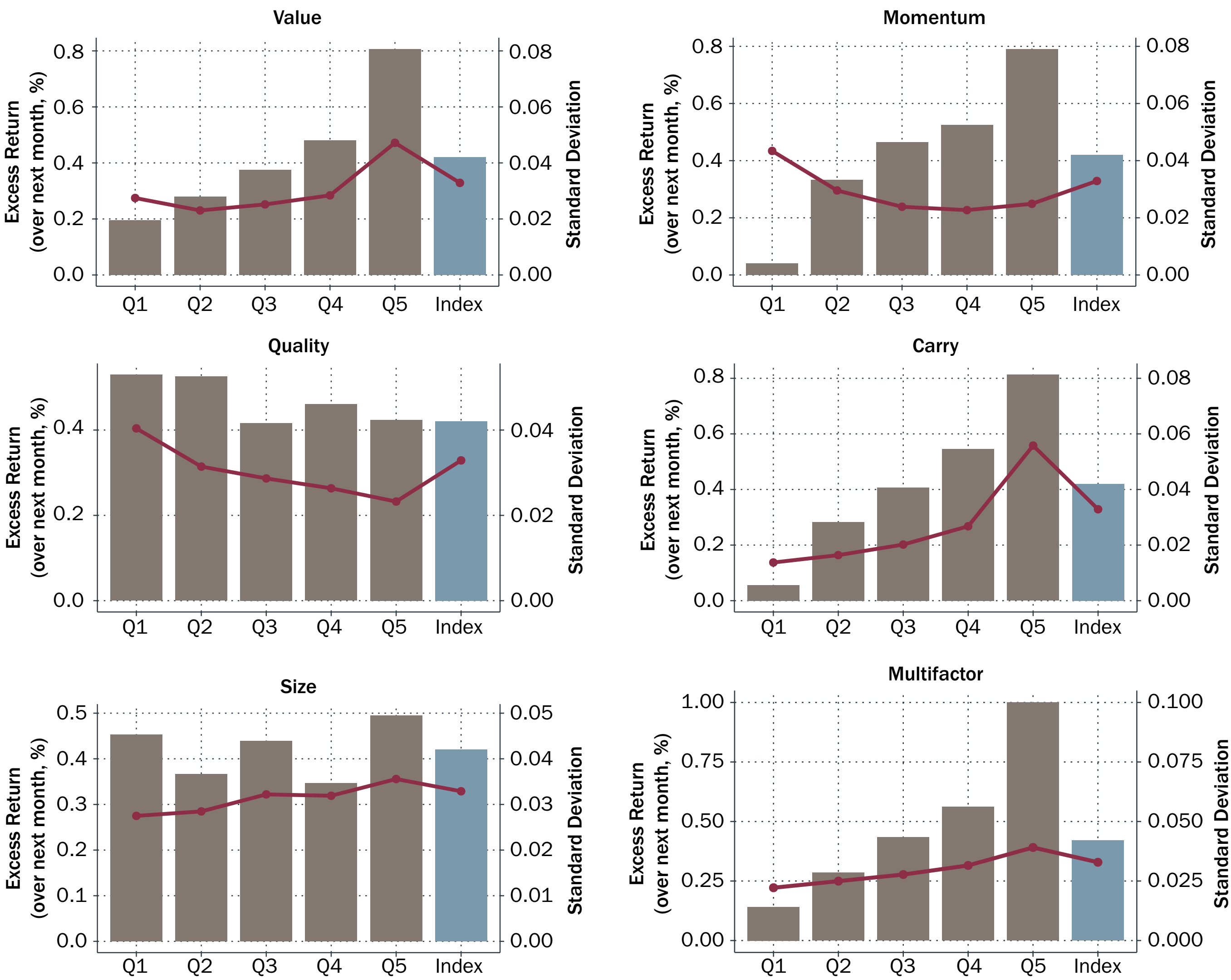
PORTFOLIO PERFORMANCE

Unconstrained Long-Only Benchmark Investor with Transaction Costs

After setting up the individual signals, we investigate the performance with and without transaction costs of portfolios formed based on these factors. This analysis ignores the interaction of the different risk profiles of the factors discussed earlier; however, it allows for a comparison with the existing literature as well as with the constrained portfolios in the next section. We invest in a specific factor by creating a portfolio based on the quintile with the highest factor exposure. These portfolios are rebalanced every month and every asset gets the same weight within the portfolio. We measure the performance against an equally weighted benchmark. Please note that we limit ourselves to long-only portfolios, as it is not possible to implement corporate bond long–short portfolios for institutional investors.

We report return statistics before and after costs. As an estimate of transaction costs, we rely on the results of Chen, Lesmond, and Wei (2007), who report corporate

EXHIBIT 6
Average Quintile Returns of Proposed Factors in HY



NOTES: Q1 (Q5) is the quintile with the lowest (highest) factor exposure. Calculations are performed first by date and then averaged over all dates. Bars show the excess return, and lines show the associated volatility.

bond bid–ask spreads based on maturity and rating. Half of the bid–ask spread is used as one-way transaction costs (buy and sell). The complete table of all bid–ask spreads used can be found in Exhibit A2 in the Appendix.

By looking at Exhibit 8 and taking the alpha and the information ratio into account, we can see that momentum is the best-performing single-factor strategy before transaction costs, with an alpha of 1.7% (4.8%) and an information ratio of 1.6 (1.9) in IG (HY). Taking transaction costs into account, multifactor is the best performing factor with an alpha of 1.8% (5.4%) and an information ratio of 1.0 (1.4). Surprisingly, we observe a high maximum drawdown for quality. This is because the drawdown is measured relative to the benchmark and quality shows a constant underperformance in the risk-on phases, which also results in a maximum drawdown of –13.5% (–14.2%); however, it can still unfold its cushioning effect in crisis periods. Overall, these simple back tests show that it is worthwhile to combine the individual factors into a multifactor signal.

EXHIBIT 7

Factor Portfolio Characteristics

	Investment Grade				High Yield			
	Excess Return	DTS	TTM	Rating Score	Excess Return	DTS	TTM	Rating Score
Complete Index								
	0.14	10.90	10.0	7.2	0.42	19.98	7.3	13.2
Q5 Portfolio								
Value	0.29	16.46	11.8	7.9	0.81	28.98	7.4	13.8
Momentum	0.28	10.93	10.2	7.5	0.79	18.30	7.3	13.3
Quality	0.11	9.40	11.1	6.5	0.42	17.04	7.7	12.9
Carry	0.40	21.42	14.1	8.8	0.84	33.53	7.0	14.4
Size	0.18	11.52	8.6	7.9	0.50	20.21	6.0	13.8
Multifactor	0.36	15.63	11.6	8.4	1.02	24.43	6.8	13.9

NOTES: Monthly averages of the excess return (over the next month, %), DTS (modified duration in years times spread, %), TTM (years), Rating Score for the complete index, and the Q5 portfolios from September 2002 through June 2021. Calculations are performed first by date and then averaged over all dates. Rating Score is the transformed rating, a score of 1 = AAA, 2 = AA+, and so on. For convenience, 7 = A– and 14 = B+.

EXHIBIT 8

Factor Portfolio Performance with and without Transaction Costs, High Yield and Investment Grade

	Investment Grade							High Yield						
	Without TC			With TC				Without TC			With TC			
Factor	Alpha	IR	DD	Alpha	IR	DD	TO	Alpha	IR	DD	Alpha	IR	DD	TO
Value	2.1	1.0	–7.4	1.0	0.5	–11.0	623	4.4	1.0	–12.8	2.5	0.6	–15.7	725
Momentum	1.7	1.6	–1.6	–0.2	–0.1	–10.5	1031	4.8	1.9	–2.6	2.0	0.8	–5.8	1018
Quality	–0.3	–0.2	–10.4	–0.6	–0.4	–13.5	205	0.2	0.1	–11.3	–0.4	–0.1	–14.2	326
Carry	3.0	0.7	–12.5	2.5	0.5	–14.0	308	4.0	0.5	–28.5	3.0	0.3	–29.8	426
Size	0.5	0.3	–7.0	0.4	0.2	–7.1	113	0.9	0.4	–6.6	0.7	0.3	–6.8	192
Multifactor	2.8	1.5	–6.4	1.8	1.0	–6.8	554	7.2	1.8	–7.2	5.4	1.4	–9.0	662

NOTES: Performance statistics of all proposed factors against an equally weighted benchmark from September 2002 through June 2021. Alpha is the return of the portfolio minus the return of the benchmark and is annualized in %; IR is the information ratio; DD is the maximum drawdown in %; TO is the annualized two-sided turnover in %. Results are reported without and with transaction costs (TC).

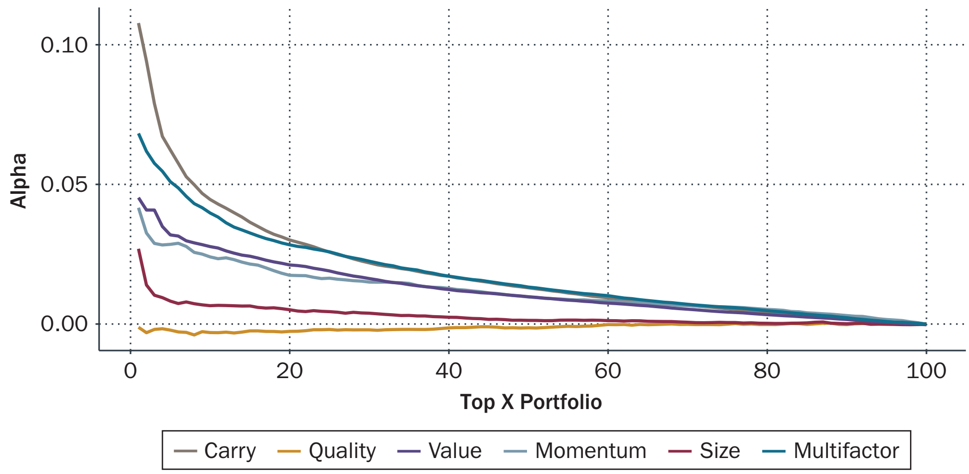
Previous studies show further portfolio construction techniques, for instance, minimum holding periods of 12 months (see Houweling and van Zundert 2017) or Bender–Wang tilted portfolios (see Bender and Wang 2015). These additional heuristic back tests serve as a tool to make the results more realistic. However, these approaches remain simple approximations, compared with our holistic optimization, presented in the next section. Therefore, we refrain from alternative forms of representation here and refer to the later discussion.

Factor Performance in Concentrated Portfolios

We check whether the performance of our factors is robust to specific portfolio formation rules by analyzing the alpha behavior with increasing factor exposure. This is of particular importance for our next results, as a typical investor, in practice, invests into a smaller subset of the entire bond universe, depending on the strictness of their investment constraints. While we show an exemplary set of constraints, other

EXHIBIT 9

Portfolio Alphas against an Equally Weighted Benchmark in IG



NOTE: The x-axis shows the portfolio formation rule; for example, 20 means that the best 20% of the respective signals were used to create the portfolio.

investors might face stricter or looser constraints depending on their investment guidelines. With alternating constraints, the size of the investable corporate bond universe as a fraction of the entire corporate bond universe changes and with it potentially the attractiveness of factor investing strategies. Hence, we answer the following question: What outperformance can we expect if we go toward the extreme of investing only in a couple of bonds with the very best factor values? We analyze this for each of the six factors in our study. For each factor we start with the extreme case and invest only in the bonds that are within the top 1% and then go up in 1% steps until we invest in all bonds that have a signal for the respective factor (best 100%). The alpha is measured against an equally weighted benchmark without transaction costs, so that the top 20% portfolio is identical to Exhibit 8.

The results are shown in Exhibit 9 for IG and Exhibit 10 for HY. In the case of size and carry, the best 100% match the benchmark exactly. For the other factors, we see small deviations from the benchmark, as not every bond has a signal every month. The graph shows that carry, value, momentum, and multifactor show a steady and mostly monotonic increase as the factor exposure goes up (except for the highly concentrated top 1% portfolio). Quality tends downward; however, the loss in performance is small because the risk is severely reduced by investing only in the safest companies. Size shows a relatively steady increase from the top 40% to the top 1% portfolio; however, for the portfolios ranging from 40%–100% there is almost no performance effect. In summary, the results for IG and HY are similar and show that concentrated portfolios are also associated with higher returns. We conclude that marginal variations in the strictness of investor constraints should not have a substantial effect on the expected outperformance of the factor investing strategies presented here.

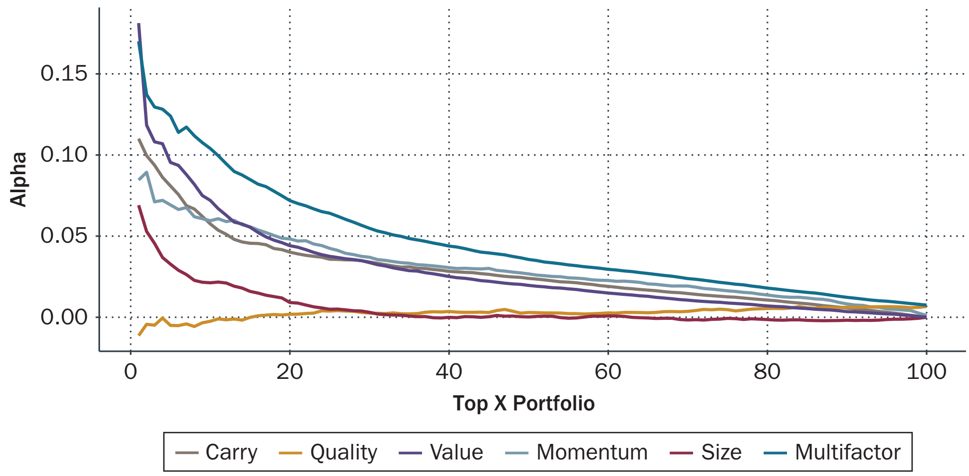
Constrained Long-Only Benchmark Investor with Transaction Costs

In this section, we would like to address the question of whether the aforementioned factors can contribute to a real-world investment strategy.

First, an obvious difference to a theoretical analysis is that results without transaction costs can be misleading, particularly in the corporate bond space. Momentum might be an amazing factor, in theory, but with a turnover of more than

EXHIBIT 10

Portfolio Alphas against Equally Weighted Benchmark in HY



NOTE: The x-axis shows the portfolio formation rule; for example, 20 means that the best 20% of the respective signals were used to create the portfolio.

1,000%, it loses most of its outperformance if transaction costs are included. Therefore, in this section, we focus solely on results including transaction costs.

Second, in an academic framework, factor outperformance is typically measured against an equally weighted benchmark in the corporate bond space. In reality, all benchmarks are market value weighted. Thus, we measure all strategies in this section against a market-value-weighted benchmark.

Third, asset managers cannot construct portfolios without any restrictions. Investors want not only to measure the asset managers' success against a market-value-weighted benchmark but also to ensure that the risk profile of the portfolio does not differ too much from that benchmark. Investment guidelines ensure that the asset manager meets the investors' requirements. Those restrictions are typically quite complex, which means that a simple heuristic is not sufficient anymore to construct the portfolio. Therefore, we optimize all strategies numerically in this section. We focus on rules that a "standard" investor may be interested in. Special restrictions, such as ESG rules or sector allocations, are not investigated.

The last large deviation to the top quintile portfolios is the acknowledgement that just because a bond is issued and quoted, it is not certain that this bond is also tradable. By including a tradability constraint in our analysis, we shed light on the question of whether certain factor premia just exist in theory and may never be harvested in practice owing to the poor tradability of the bonds it selects.

We focus solely on multifactor signals. However, as we discussed in the Multifactor subsection, the individual factors included vary across studies and depend on which factors are analyzed. Furthermore, there is no uniform solution for the weighting scheme of the individual factors. Therefore, we construct four multifactor signals that reflect the risk–return expectations of certain investor groups.

In this section, after defining the investors, then we set up the optimization problem. Next, we show the impact of real-life constraints by activating constraints step-by-step and subsequently conducting a performance drill down. Lastly, we discuss the effects of different multifactor choices.

Investor styles. To the best of our knowledge, there is no golden rule on how factor weights should be determined in a multifactor context. Therefore, we weight all factors equally; however, we want to explore whether different factor mixes lead to different risk–return profiles.

For this purpose, we define four different multifactor signals that map to different types of investors observable in the market. Our four investor types are as follows:

- *Classic*: Uses the most prominent factors from the previous decades (value and momentum).
- *Ambitious*: Increases performance by buying riskier assets on average (value, momentum, and carry).
- *Cautious*: Reduces the risk of drawdowns by investing in high-quality assets (value, momentum, and quality).
- *Balanced*: Harvests as many factor premia as possible (value, momentum, carry, quality, and size).

Note that the factor mix of the "balanced" investor is identical to the definition of multifactor from the previous analysis in the previous subsection Factor Characteristics.

Optimization problem. The main objective of institutional investors is to outperform the benchmark (alpha) and at the same time this outperformance should be continuous (low tracking error). Therefore, all the investor types require well-balanced portfolios that have the following restrictions:

- Long-only positions
- Fully invested
- Diversified in terms of the number of holdings and the number of issuers; thus, it does not contain concentrated bets
- Keep turnover at a reasonable level to avoid high transaction costs
- Match average exposures to certain risk measures (e.g., DTS) relative to the benchmark

Taking all these restrictions into account, the following optimization problem arises.

For every t, maximize

$$\sum_{i=1}^{I} w_{i,t} s_{i,t}$$

subject to

$$w_{i,t} \geq 0 \quad \forall i \qquad \text{(no shorting constraint)}$$

$$\sum_{i=1}^{I} w_{i,t} = 1 \qquad \text{(fully invested constraint)}$$

$$w_{i,t} \leq 5\% \quad \forall i \qquad \text{(max. weight constraint)}$$

$$\sum_{i=1}^{I} |w_{i,t} - w_{i,t-1}| - \sum_{i=1}^{I} |b_{i,t} - b_{i,t-1}| \leq 20\% \qquad \text{(two-sided turnover constraint)}$$

$$0.9 \sum_{i=1}^{I} b_{i,t} \mathrm{DTS}_{i,t} \leq \sum_{i=1}^{I} w_{i,t} \mathrm{DTS}_{i,t} \leq 1.1 \sum_{i=1}^{I} b_{i,t} \mathrm{DTS}_{i,t} \qquad \text{(DTS constraint)}$$

$$\left| \sum_{i \in D_{j,t}} b_{i,t} - \sum_{i \in D_{j,t}} w_{i,t} \right| \leq 2\% \quad \forall j \qquad \text{(issuer constraint)}$$

$$\sum_{i \in D_{j,t}} w_{i,t} \leq 20 \sum_{i \in D_{j,t}} b_{i,t} \quad \forall j \qquad \text{(no outsized bets in small issuers constraint)}$$

$$|w_{i,t} - w_{i,t-1}| \leq l_{i,t} \quad \forall i, \qquad \text{(tradability constraint)}$$

where I is the number of assets in the optimization, $w_{i,t}$ is the weight of asset i in the portfolio at time t, $b_{i,t}$ is the weight of asset i in the benchmark at time t, $s_{i,t}$ is the signal of asset i at time t, $DTS_{i,t}$ is the duration times the spread of bond i at time t; and $l_{i,t}$ is 0 if bond i is not liquid and 1 otherwise. $D_{j,t}$ is the set of all bonds i that are issued by company j and outstanding in our universe at time t.

This optimization problem is solved every month t. The investible universe comprises all bonds in the index. Bonds within the portfolio at t – 1 that are no longer in the benchmark at time t are forced-sold at the last observed price. If the optimization problem cannot be solved, we relax the turnover constraint by 10% and try the optimization again. This happens, for instance, for the IG universe in January 2005 because the benchmark guidelines changed at the end of 2004.

The equal weighting of the factors for the cautious and the ambitious investors seems questionable in the light of these restrictions. For example, it appears that the cautious/ambitious investors will constantly have an active DTS exposure of ±10%. However, we will see later that this is not the case. Furthermore, a high carry relative to quality exposure ensures that the factor effects also have an impact on the portfolio weights.

Performance of the classic investor under real-world constraints. Next, we want to analyze the impact of the different constraints on portfolio characteristics and performance. We run five different optimizations for the Classic investor and add restrictions step-by-step (e.g., "+ turnover constraint" indicates that we add this constraint to the base case).

1. *Base*: Here, we use only the first three of the aforementioned restrictions. This lets the optimizer invest 5% in the 20 bonds with the best signal.
2. *+turnover constraint*: This increases the number of holdings slightly while factor loadings remain very high. The turnover constraint is relative to the benchmark because we want to ensure that signals can reach the portfolio at all times, even when we see heavy changes within the benchmark—for example, during the COVID-19 pandemic, with several downgrades and shifts in the HY benchmark weights in April 2020 (two-sided benchmark turnover: 24%), or after the burst of the dot-com bubble in December 2003 (31%).
3. *+DTS constraint*: We ensure that the portfolio is within DTS range of the benchmark (±10%). This is still a highly concentrated portfolio, but bonds cannot be selected purely by signal anymore.
4. *+Issuer constraints*: We ensure that no outsized bets are placed on small issuers and that the weight deviation from the benchmark always stays within a reasonable interval. We take the minimum of 20x issuer benchmark weight and 2% as the highest absolute deviation from the issuer benchmark weight. This ensures that an issuer with weight 0.05% in the benchmark can only have a weight of 1% in the portfolio, whereas an issuer with 3% benchmark weight is bounded between 1% and 5% in the portfolio. This increases the number of holdings in the portfolio by a factor of 4.6 (3.3) in the IG (HY) universe. Therefore, the tracking error goes down and the IR goes up.
5. *+Tradability constraint*: We treat bonds as tradable when they have at least 10 institutional trades in a given month. This constraint overrules the issuer constraints; thus, if we violate an issuer constraint due to market price changes (which cause an increase in the relative weight), the bond is not touched. Due to the very high amount of illiquid bonds this restriction is crucial.

Exhibit 11 shows the key statistics of the optimized portfolios. We can see that the alpha drops from 5.8% in the base case to 1.4% if we include all constraints for the IG universe. While the maximum drawdown is almost twice as high in the base

EXHIBIT 11
Optimized Portfolio Performance

	Investment Grade					High Yield				
Restrictions	Alpha	IR	Holdings	TO	DD	Alpha	IR	Holdings	TO	DD
Base	5.8	1.0	20	1,516	–11.5	12.6	1.5	20	1,395	–19.3
+TO	4.2	1.0	25	299	–18.0	10.0	1.5	23	350	–9.2
+DTS	2.6	1.1	26	300	–10.1	5.8	1.2	25	351	–7.6
+Issuer	2.0	1.4	120	300	–4.8	4.4	1.4	82	350	–8.3
+Tradability	1.4	0.9	95	300	–6.5	3.3	1.2	65	349	–5.2

NOTES: Performance statistics of all simulations against a market-value-weighted benchmark. Alpha is annualized in %; IR is the information ratio; DD is the maximum drawdown in %; TO is the two-sided turnover in %. All values are shown net of transaction costs.

case for HY, compared with IG, we end up with a slightly higher maximum drawdown for IG when including tradability constraints.

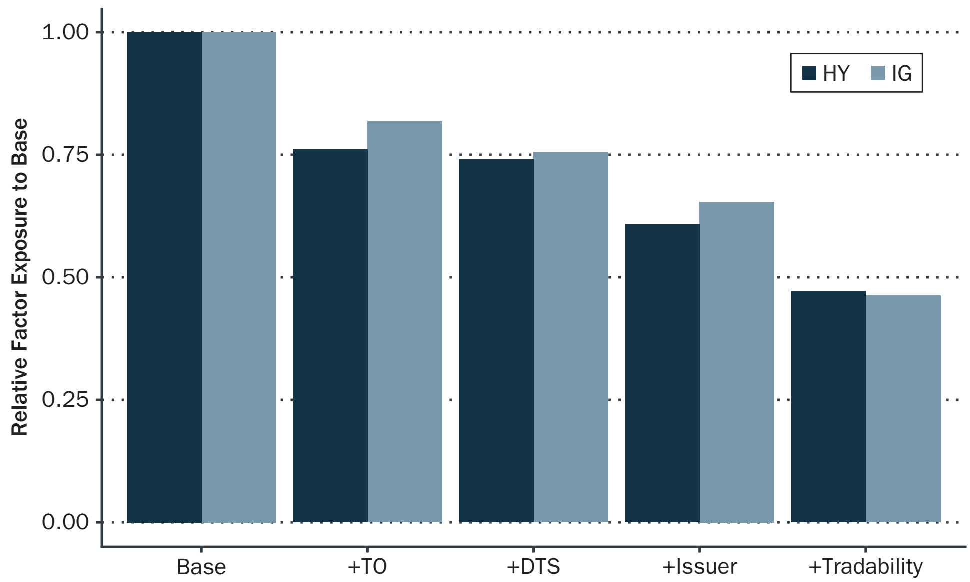
For HY, the outperformance against the market-weighted benchmark drops from 12.6% to 3.3%. When the alpha decreases, the tracking error does so, too. Therefore, the information ratio is almost stable. The average number of holdings is highest for the optimization without tradability constraints. That shows that in particular small issuers (whose benchmark weight is smaller than 0.1%, which means the overweight in the portfolio is smaller than 2%) are illiquid and, therefore, excluded from the portfolio. The turnover shows only marginal differences across all strategies except for the Base strategy, which is expected owing to the high turnovers of value and momentum in the previous section (see Exhibit 8). It also shows that tracking the HY benchmark alone creates significant turnover, as 240% is the maximum additional turnover per year. For IG, we see again the expected behavior in the portfolio outperformance—every additional restriction is costly. However, as for HY, the restrictions also lower default risks and concentration risks, resulting in a more stable information ratio.

An interesting contrast arises by analyzing the maximum drawdown. Lowering the risk by enforcing more holdings also reduces the drawdown. However, adding the tradability constraint increases the drawdown again from 4.8% to 6.5%. The tradability constraint can have two effects on performance. First, it is not possible to sell certain bonds that are already in the portfolio and have a bad signal. If these bonds have a below-average return in the future, the performance of the portfolio is reduced, and consequently, the drawdown increases. Conversely, it is also possible that bonds cannot be bought, even if they have a good signal. If these bonds generate a below-average return in the future, the tradability constraint has a protection effect. Within the IG universe, we can see that the former effect is more pronounced. In the HY universe, the opposite holds true, and the drawdown decreases from 8.3% to 5.2%.

Exhibit 12 shows the average relative factor loadings of the portfolios for the IG and HY universes. First, we map the classic multifactor signal to a standard normal distribution by date and then calculate a weighted average based on the portfolio weights over this mapped signal for each date. The average over time is the absolute factor loading. Subsequently, we divided this absolute factor loading by the absolute factor loading of the Base strategy. Imposing the turnover restriction leads to a 25 percentage point reduction in factor exposure. This reduction stems from the fact that the optimizer can only buy the two bonds with the best signal (which are not in the portfolio) and sell the two bonds with the lowest signal. All other bonds remain in the portfolio. Imposing the DTS restriction does not cost further factor exposure, which shows that the signal is not tilted in high/low DTS bonds but has enough bonds with high signals available that match the benchmark. The issuer constraint

EXHIBIT 12

Average Factor Loadings of the Multifactor Signal for the Classic Investor Relative to Base



increases the minimum number of holdings from 20 to at least 50, thereby lowering the factor exposure, by definition. Making illiquid bonds unavailable forces the optimizer to potentially hold bonds with sell signals and to pass on bonds with buy signals if they are flagged as illiquid. This lowers the factor exposure by more than 50% in comparison to the Base case.

This means that roughly half of the theoretical signal can be transferred into a realistic portfolio. While average factor exposure is higher for IG in the first four scenarios, the average factor exposure is slightly lower for IG, compared with HY, if the tradability constraint is imposed. This is in line with our prior findings, as the tradability constraint is more binding in IG than in HY. As only 50% (59%) of the bonds in the index are liquid, on average, with a low of only 34% (40%) during the financial crisis, this is a promising result.

Performance of different investor styles. In this section, we compare the different investor styles outlined earlier, using our fully constrained optimization framework. Exhibits 13 and 14 show the cumulative returns of all strategies for IG and HY, respectively. We can see that all investors outperform the benchmark. Ambitious and balanced investors obtain the highest return, as they are the only investors who actively consider carry (and size) in their mix. The cautious investor has the smallest outperformance, which shows that a risk-reducing factor such as quality affects performance in the long run.

Next, we compare the risks and performances of the four strategies in Exhibit 15 for IG and Exhibit 16 for HY. Here, we show the alpha versus the tracking error and the return versus the volatility of the different strategies. In the HY space, the classic, ambitious, and balanced investors have information ratios higher than 1.0, while only the cautious investor has an information ratio slightly below 1.0. The best results can be achieved by the ambitious type investor with an information ratio of 1.1 in IG and 1.4 in HY. Because adding quality reduces the volatility, the Sharpe ratio is comparable for all investors, ranging from 0.7 to 0.8.

Exhibit 17 shows the alpha of the different strategies, compared with the maximum drawdown relative to the benchmark. The cautious investor has no drawdown in the financial crisis but suffers (compared with the benchmark) from the rebound

EXHIBIT 13

Cumulative Log Excess Returns of the Respective Strategies and the Market-Value-Weighted Benchmark in IG, September 2002–June 2021

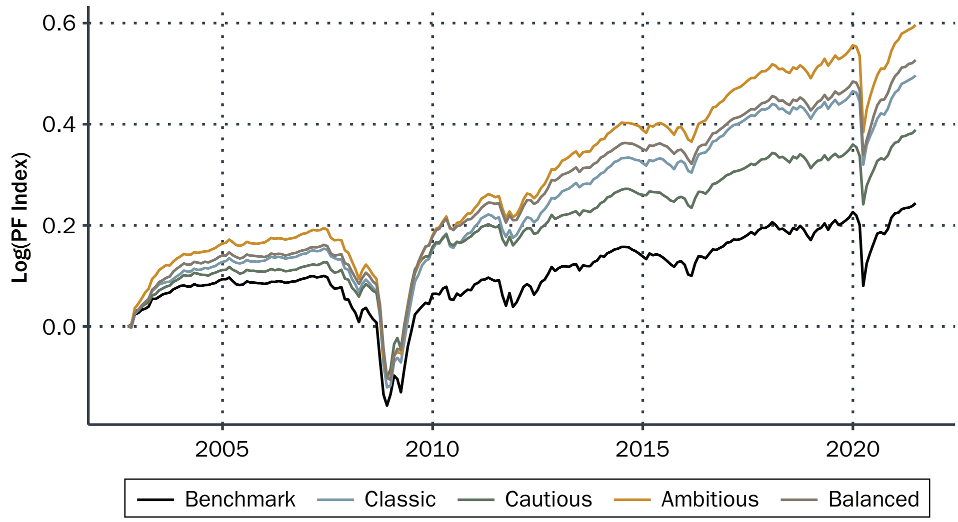
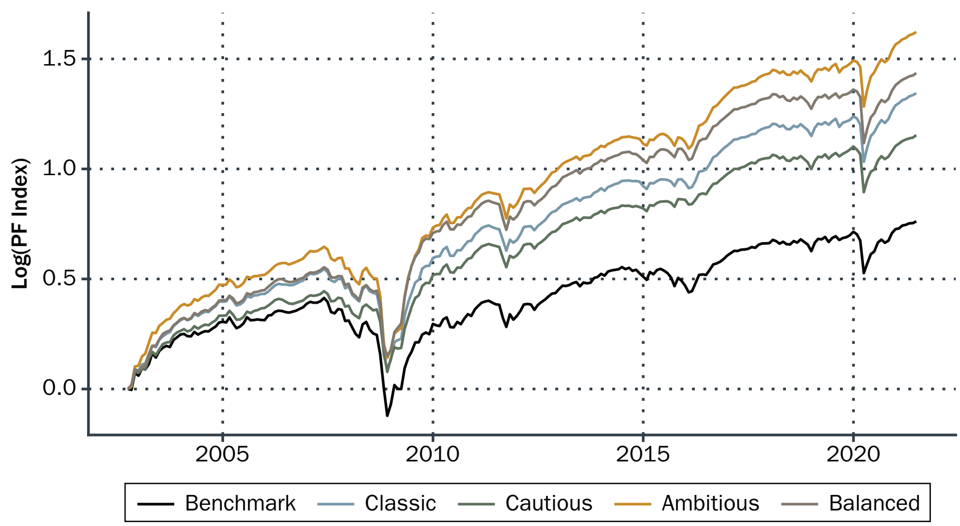


EXHIBIT 14

Cumulative Log Excess Returns of the Respective Strategies and the Market-Value-Weighted Benchmark in HY, September 2002–June 2021

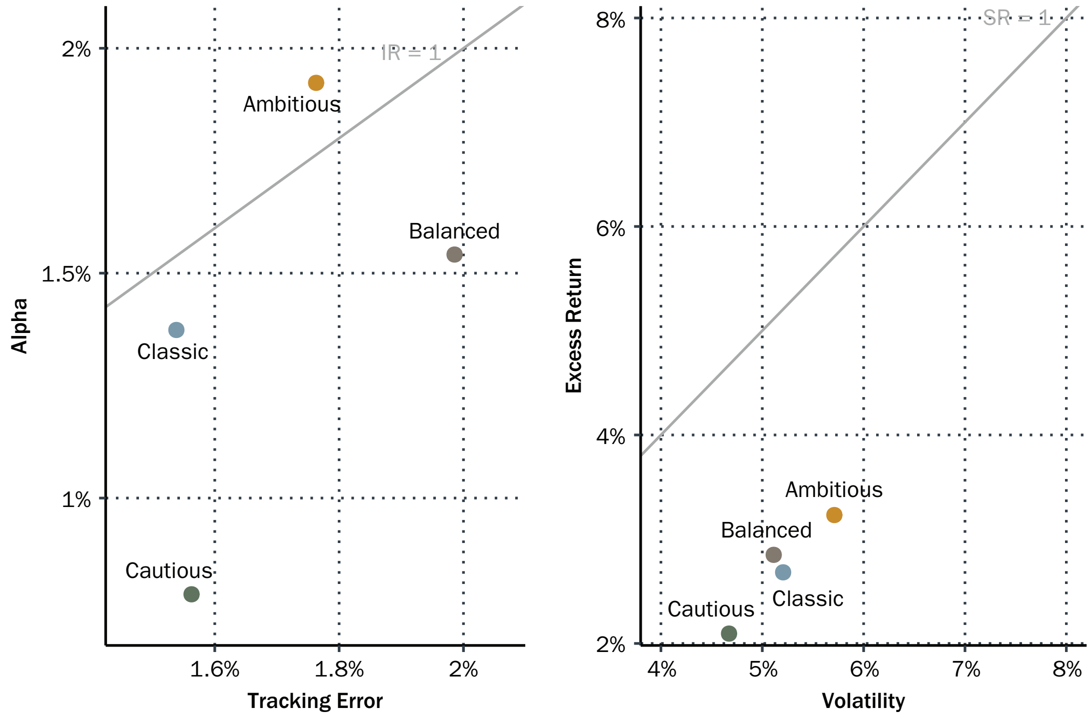


phase after the energy crisis in 2016. The classic and ambitious investors have the strongest drawdown during the financial crisis, while the balanced investor loses most during the recent COVID-19 pandemic. Based on Exhibit 17, the ambitious investor shows the highest outperformance but also the highest drawdowns, whereas the classic investor has the most attractive risk–return profile, based on the alpha and drawdown.

Note that the different investors suffer from different levels of drawdown during the biggest crises, namely, the 2008/09 Global Financial Crisis (GFC) and the 2020's COVID-19 pandemic. This result is highlighted in Exhibit 18, where the absolute performance of the benchmark and the portfolio performance of the different investors is shown. For IG, it is noticeable that all styles show an underperformance during

EXHIBIT 15

Alpha vs. Tracking Error and Return vs. Volatility Plots for the Respective Strategies in IG, September 2002–June 2021



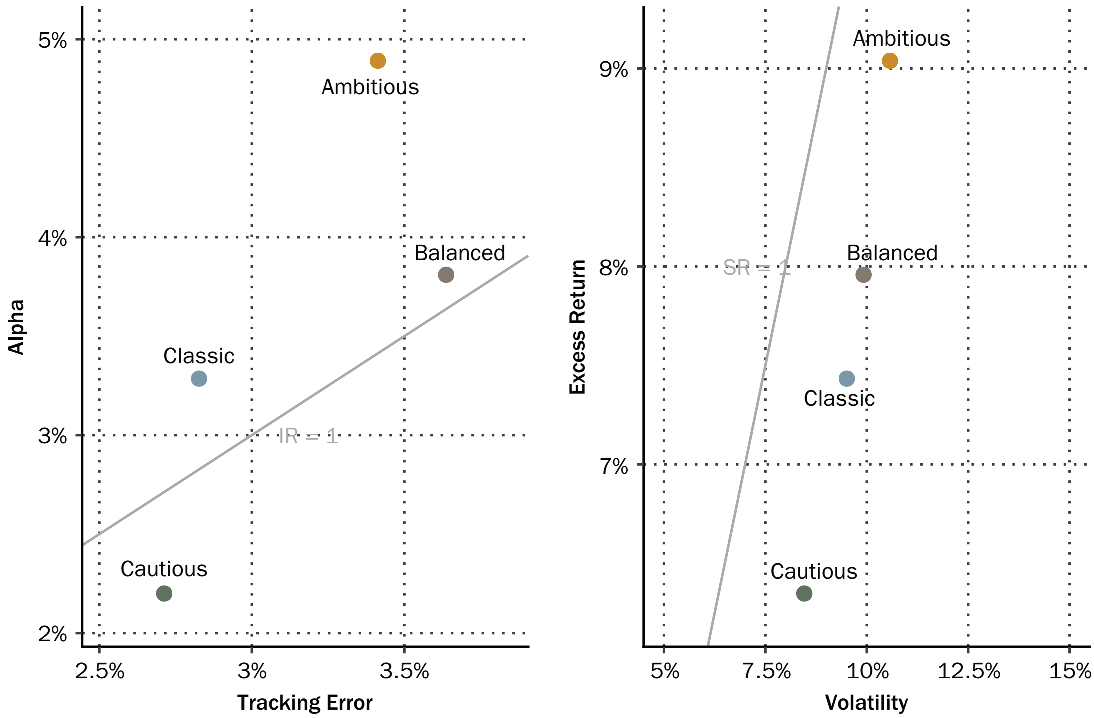
NOTE: Strategies above the line on the left-hand plot have an information ratio (IR) greater than 1, and strategies above the line on the right-hand plot have a Sharpe ratio (SR) greater than 1.

the GFC. For the COVID-19 pandemic, the situation is different. The cautious investor achieves a relative outperformance, whereas the ambitious investor underperforms. In HY, the picture is reversed. During the GFC, all investors have a lower drawdown, compared with the benchmark, with the cautious investor performing the best. However, during the COVID-19 pandemic, all investors underperform. These drawdowns mainly occur because the signal changes faster during the crises, making the turnover constraint more binding. In addition, tradability deteriorates simultaneously.

Finally, we analyze some key portfolio characteristics in Exhibit 19. We measure the active DTS, MDur, and OAS position of the strategies relative to the benchmark. Rating score and TTM of the portfolios are calculated as the absolute difference to the benchmark. The classic investor exhibits only mild active positions. This shows that a steady outperformance can be achieved without increasing risk. Conversely, the ambitious investor shows a strong active position toward risk—on average, the spread is 33% higher than the benchmark OAS. The strategy holds the DTS restriction by reducing the active duration position of the portfolio. However, even this investor, who has a high amount of carry in the multifactor mix does not hit the DTS constraint at all times. The cautious investor shows the opposite positions. This is expected, as companies with a relatively good quality score can issue bonds with longer maturities and have lower spreads. However, the quality effect, compared with the carry effect, is less pronounced for the ambitious investor. The balanced investor is in between those two extremes, but tends more toward the ambitious investor, as the two risk-on factors carry and size, outweigh quality.

EXHIBIT 16

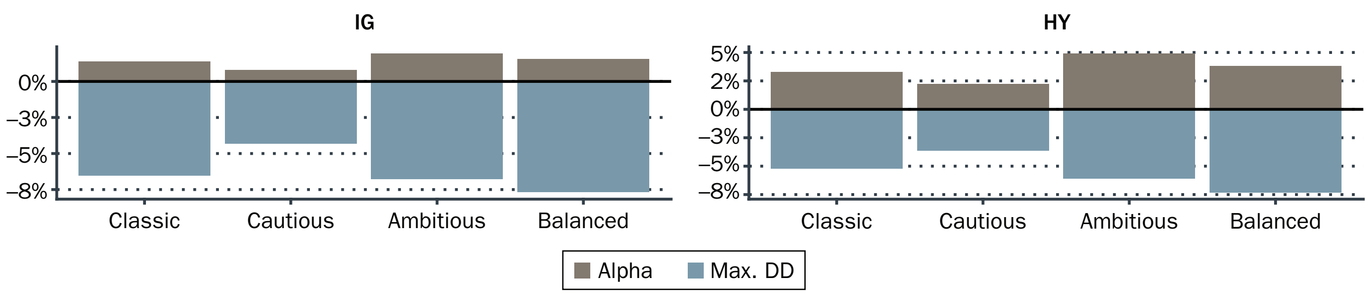
Alpha vs. Tracking Error and Return vs. Volatility Plots for the Respective Strategies in HY, September 2002–June 2021



NOTE: Strategies above the line on the left-hand plot have an information ratio (IR) greater than 1, and strategies above the line on the right-hand plot have a Sharpe ratio (SR) greater than 1.

EXHIBIT 17

Alpha vs. Maximum Drawdown for the Respective Strategies



With constant outperformance and attractive risk–return characteristics, all investor styles are valid options for real portfolio strategies.

CONCLUSION

In this study, we examine the effect of common institutional investor constraints on the performance of the most well-known corporate bond factor strategies. After sequentially adding constraints and observing their effect on the backtest performance

EXHIBIT 18

Absolute Portfolio Performance in Comparison to the Benchmark during the Global Financial Crisis (GFC) from September to November 2008 and the COVID-19 Pandemic (COVID-19) in March 2020

	IG		HY	
Portfolio	**GFC**	**Covid-19**	**GFC**	**Covid-19**
Index	–8.7%	–11.3%	–24.2%	–13.7%
Classic	–13.1%	–11.7%	–23.4%	–15.6%
Cautious	–12.1%	–9.1%	–20.4%	–15.9%
Ambitious	–12.8%	–14.0%	–24.5%	–16.5%
Balanced	–13.5%	–12.0%	–21.2%	–18.9%

and factor exposures, we obtain a glimpse of what investors can expect from corporate bond factor investing if they are bound to similar constraints. These constraints include the most important restrictions that a portfolio manager faces: index tracking, DTS, turnover, issuer constraint, and tradability.

We map different signal mixes to different types of investors. Even under the most binding restrictions, we still measure a factor exposure of 50% and obtain an IR of 1.1 (1.4) in IG (HY) for the period between September 2002 and June 2021. We model different factor investor styles with different multifactor signals based on their risk appetite. The results remain robust no matter which investor style is considered. Our results are in line with those of previous studies: Although investor constraints have a negative effect on factor performance, investors can still harvest significant risk premia in the long run. However, unlike previous studies, the present study adds a tradability constraint that removes illiquid (thereby untradable) bonds from the universe.

Thus, this study provides valuable insights into which portfolios can actually be implemented. However, further steps are needed to fully reflect reality. For instance, we assume that we can calculate the signal for a bond and execute the bond on the same day, which is too ambitious. Follow-up research could also include a wider set of corporate bond factors (for instance IPCA) besides the mainstream factors mentioned in this study. Nevertheless, our results show that at this stage, it is possible to implement factor investing strategies for corporate bonds under realistic conditions and achieve appealing outperformance. As novel factors are discovered in the future, a constrained institutional investor can use our framework to gain a better understanding of their factor mix's performance before an actual implementation in live portfolios.

EXHIBIT 19

Portfolio Characteristics of the Different Investor Styles Relative to the Market-Weighted Benchmark

	Investment Grade					High Yield				
	Relative (in %)			Absolute		Relative (in %)			Absolute	
	DTS	**MDur**	**Oas**	**Score**	**TTM**	**DTS**	**MDur**	**Oas**	**Score**	**TTM**
Deviation to Benchmark										
Classic	9.4	–16.2	28.8	0.7	–1.3	4.4	–16.6	18.2	–0.4	–0.6
Ambitious	9.9	–23.8	52.0	1.4	–2.4	8.0	–26.5	36.7	–0.2	–1.6
Cautious	6.3	–3.9	5.1	0.1	0.1	1.1	–7.3	0.6	–1.0	0.7
Balanced	9.8	–15.7	36.8	1.5	–1.8	5.4	–22.6	26.8	–0.4	–1.7
Reference Value for Comparison										
Benchmark	10.5	6.3	154.6	6.8	9.9	19.0	4.3	448.2	13.1	7.2

NOTES: The first five rows show portfolio characteristics of the different investor styles relative to the market-weighted benchmark. The last row shows the absolute portfolio characteristics of the benchmark as a reference.

APPENDIX

FEATURES FOR THE LASSO

The features for the LASSO estimation can be found in Exhibit A1.

TECHNICAL IMPLEMENTATION: ADAPTIVE LASSO

Based on the features in Exhibit A1, we run an adaptive LASSO for choosing which features to include in the final model that estimates the fair OLS. The LASSO was introduced by Tibshirani (1996) in order to improve ordinary least squares estimates by shrinking the estimated coefficients and setting the coefficients of the least important independent variables to zero. It thus solves two problems: Allowing better interpretability by removing useless variables and reducing model variance by shrinking the rest of the coefficients.

An alternative to this would be performing subset selection and a ridge regression separately. The downside of this alternative is that iteratively selecting a subset of the independent variables and testing all combinations for their predictive power in OLS regressions can become computationally infeasible if the number of variables gets very large (as discussed in Zou 2006) and can suffer from high model variance—small changes in the data can lead to a significantly different variable selection (see Tibshirani 1996). Hence, the LASSO is generally preferred.

Zou (2006) modifies the LASSO allowing for different penalization weights of each individual predictor. The author shows that other than the original LASSO, the adaptive LASSO can satisfy the oracle property of an estimator. As an initialization weight for the feature specific penalization, the β of an OLS regression is often chosen. However, Zou (2006) argues that, in the case of high collinearity in the explanatory variables, the estimated β of a ridge regression is more stable. Because our variables exhibit a reasonable level of collinearity, we choose the estimated coefficients of a ridge regression as an initialization of the individual feature weighting.

Thus, our procedure looks as follows:

- Every month t run a ridge regression and store the penalized βs.

$$\hat{\beta}_{ridge,t} = \underset{\beta_t}{\operatorname{argmin}} \left\{ \sum_{i=1}^{I} (OAS_{i,t} - \beta_{0,t} - \sum_{j=1}^{p} \beta_{j,t} x_{i,j,t})^2 + \lambda_{ridge} \sum_{j=1}^{p} \beta_{j,t}^2 \right\},$$

  where I is the number of bonds and p is the number of features.

- Every month run a LASSO regression with adaptive weights. The weighting vector is the inverse of the individual $\hat{\beta}_{ridge,t}$ estimates from the step before such that variables with a high β from the ridge regression are penalized less.

$$\hat{\beta}_{lasso,t} = \underset{\beta_t}{\operatorname{argmin}} \left\{ \sum_{i=1}^{I} (OAS_{i,t} - \beta_{0,t} - \sum_{j=1}^{p} \beta_{j,t} x_{i,j,t})^2 + \lambda_{lasso} \sum_{j=1}^{p} w_{j,t} |\beta_{j,t}| \right\}$$

$$\text{with} \quad w_{j,t} = \frac{1}{\hat{\beta}_{ridge,j,t}}$$

We use five-fold cross validation to estimate the hyperparameters λ_{ridge} and λ_{lasso}. Our algorithm for determining which fold an observation falls into takes into account both the time series dependencies and the cross-sectional dependencies.[5]

[5] More detailed information about the functionality of the algorithm can be requested from the authors.

EXHIBIT A1
LASSO Feature Selection

Feature	Description
Spread Change Absolute 1 month – Spread Change Absolute 6 months	Spread change on an absolute basis for one month up to six months
Spread Change Relative 1 month – Spread Change Relative 6 month	Spread change on a relative basis for one month up to six months
Excess Return Volatility 12 month	Excess return volatility of the last 12 months
Gross Operating Margin	The ratio of (revenues minus cost of goods sold) to revenues
Return on Assets	Return on assets
FCF/NOA	Free cash flow to net operating assets
Net Tier 1 Ratio	Tier 1 capital to risk-weighted assets
LLR/NPL	Reserves for loan losses to non-performing loans
Long Term Debt	Long-term debt
Cash to Total Assets	Cash to total assets
Growth FCF/NOA	Relative change in free cashflow to net operating assets
External Financing	Ratio of change in external capital to total assets
Short Term Debt to EV	Short-term debt to enterprise value
EBITDA/Total Debt	EBITDA to total debt
Short Term Debt/Total Assets	Short-term debt to total assets
Short Term Debt/Total Debt	Short-term debt to total debt
Earnings Yield	IBES analyst estimate of the 12-month EPS divided by stock price
Earnings Variability	Deviation of the earnings yield from its 24-month moving average by its rolling standard deviation
Retained Earnings to Total Assets	Retained earnings to total assets
Analyst Recommendation	Average of IBES analyst recommendations
Debt to Assets	Debt to assets
Return on Equity	Return on equity
FCF/Debt	Free cashflow to debt
FCF/Interest Expenses	Free cashflow to interest expenses
Texas Ratio	The ratio of total non-performing assets to the sum of tangible common equity and loan loss reserves.
Book to Price	Book to price
Equity Volatility	Calculated as the mean of the 10-, 30-, 60-, and 90-day historical volatilities
Distance to Default	Naivedistance to default based on Bharath and Shumway (2008)
Equity Momentum 1x0 – Equity Momentum 12x0	1-month equity momentum – 12-month equity momentum
Equity Market Capitalization	Equity market capitalization
Modified Duration	Modified duration
Rating	Rating (AAA1-3, AA1-3, A1-3, BBB1-3, BB1-3, B1-3)
Sector	Sector classification

TRANSACTION COSTS

The transaction costs used for the back test can be found in Exhibit A2.

EXHIBIT A2

Bid–Ask Spread in Basis Points

	Bond Rating						
TTM	AAA	AA	A	BBB	BB	B	CCC-D
1–7	24.51	26.02	25.82	31.01	54.26	58.76	77.00
7–15	49.52	36.57	38.20	44.22	54.65	60.44	180.35
>15	51.65	52.68	54.76	58.62	73.56	82.47	86.75

NOTES: The bid–ask spread in basis points is as reported in Chen et al. (2007). We use 50% of the bid–ask spread as one-way transaction costs (buy and sell). Note that the analysis by Chen et al. (2007) is based on S&P rating, while we use the bond rating reported by ICE. The category >15 is reported as 15–40 in the original study.

QUALITY VARIABLES

The variables used to build the quality composite can be found in Exhibit A3.

EXHIBIT A3

Quality Variables Used to Build the Quality Composite

Variable	Description
Gross Margin	The ratio of (revenues minus cost of goods sold) to revenues; it reveals the portion of money left over from revenues after accounting for direct production costs
Return on Assets	The ratio of (net income before extraordinary items and after preferred dividends) to total assets, expressed as a percentage
Free Cashflow/Net Operating Assets	Free cash flow/net operating assets is the ratio of free cashflow to net operating assets
Return on Equity	The ratio of (net income before extraordinary items and after preferred dividends) to common equity, expressed as a percentage
Texas Ratio	The ratio of total non-performing assets to the sum of tangible common equity and loan loss reserves, expressed as a percentage
Net Core Capital Ratio	The ratio of “performing assets” such as tier 1 capital to risk-weighted assets, expressed as a percentage
Reserve Coverage	The ratio of reserves for loan losses to non-performing loans, expressed as a percentage
Loan-to-Deposit Ratio	The ratio of total loans to total deposits, expressed as a percentage
Operating Cashflow/Total Debt	The ratio of net cash flow from operating activities to total debt
Operating Cashflow/Interest Expenses	The ratio of net cashflow from operating activities to interest expenses on debt; it measures how many times a company could pay its current interest payment from operating cash flow
Cash/Total Assets	The ratio of cash to total assets
Long-Term Debt/Total Assets	The ratio of total debt, adjusted for cash and short-term investments, to total assets
Growth in Free Cashflow/ Net Operating Assets	The relative change in free cashflow/net operating assets over a look-back period
External Financing	The ratio of change in external capital measured over a look-back period to total assets, expressed with a negative sign; high ratios indicate overinvestment and aggressive accounting

SOURCE: See Henke et al. (2020).

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