Factor Investing in Credit*

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2020-01-14

Abstract

This paper investigates the application of factor investing in corporate bonds. Our results show that proficiency in the drivers of risk and return, the factors, should be used for bottom-up corporate bond selection. We analyze five different factors (Value, Equity Momentum, Carry, Quality, Size) and their combinations within the USD investment grade (IG) and high yield (HY) markets. These factors have positive risk-adjusted returns and explain a significant portion of the cross-sectional variation in corporate bond excess returns. We find evidence that factor combinations are superior to single factors in risk-adjusted terms. Multifactor as a signal blending strategy is particularly suitable for active approaches targeting high alpha, while portfolio blending is better aligned with more passive strategies, targeting low turnover and low tracking error.

1 Introduction

Factor-based or style investing has an increasingly large footprint in equity portfolios, with applications in active, passive, and smart beta strategies. Broadly speaking, factor-based investing is a function of historical data that can explain the cross-section of subsequent asset returns, discriminating between the assets that will tend to outperform their peers and the ones that will tend to underperform. The preferred method for establishing the validity of factors has been to sort stocks into portfolios based on simple rules. However, factor-based investing is still in its infancy for corporate bonds, where buy-and-hold strategies still comprise a significant part of the overall investment strategies in this asset class. Given widespread evidence in many asset classes, and the similarity in fundamental analysis, it should come as no surprise that this is equally applicable to corporate bond as well as equity portfolios. However, prices of corporate bonds are not independent from equity prices, nor are they simply a mirror image. So factor investing in corporate bonds can lean on equity factor investing but needs to be challenged and enhanced in particular areas. Therefore, an analysis of corporate bond returns requires more than a simple extension from equity returns.

The corporate bond market is massive. As of 30th June 2019 the ICE BofAML Global Corporate Index consists of 14,269 constituents with a market value of €10 trillion, and ICE BofAML Global High Yield Index consists of 3,138 constituents with a market value of €1.8 trillion. The purpose of this paper is to give insight about a sytemic investing approach within the corporate bond market, similar to that which Quoniam has successfully applied now for 14 years.

We find that style investing in corporate bonds could have offered an abnormal premium throughout the last 20 years, if exploited correctly. Even though we focus purely on implementable long-only portfolios, our single factor strategies (Value, Momentum, Size, Carry, and Quality) and multifactor approaches yield yearly alphas up to 1.24% and IRs up to 1.39 under realistic portfolio construction rules and considering transaction costs for IG. Overall, these results confirm our hypothesis that Multifactor strategies in IG credit, rooted in Value and Momentum, lead to abnormal returns beyond typical equity and bond risk premia.

Our approach works for HY, with an alpha up to 4.07% and IR of 1.04 under the same realistic portfolio construction rules and considering transaction costs, but there are some striking

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differences to IG, too. First of all, factors that are based on the OAS - namely Carry and Value - work less effectively in HY because the universe is much more heterogenous due to additional complexity, e.g. bond-specific covenants. This additional complexity cannot be fully captured within a simple framework for Value as proposed in this paper, but can still be exploited if modelled correctly. Secondly, Quality as a factor doesn't positively enhance performance in IG but is beneficial in HY.

The remainder of this paper is organized as follows. The next section reviews the literature on factor investing in corporate bonds. Section 3 describes the data used. In Section 4, we describe our methodology for calculating various bond factors. Combining those factors into a multifactor signal is discussed in Section 5. Section 6 presents the empirical results while Section 7 concludes.

2 Literature Review

Factor Investing in the equity space goes back to at least Fama and French (1992), who demonstrate that value stocks have higher expected returns than growth stocks, and Jegadeesh and Titman (1993) who show the presence of a momentum factor. Consequently, numerous papers on hundreds of different factors were published (see Harvey, Liu, and Zhu 2016 for a critical assessment), and factor strategies are now employed in managing hundreds of billions of dollars or their equivalent.

Although the application to corporate bonds is a natural extension of the factor investing idea, the studies on fixed income assets are both recent and limited. Consequently, for corporate credit the factors discussed in the literature are concentrated. In the paragraphs below we summarize the literature dealing with the most common factors for corporate bonds. These include Value, Equity Momentum, Carry, Quality/Low Risk, Bond Momentum and Size. The last part of the literature section focuses on studies answering the question of how to combine different factors into a multifactor approach.

The Value premium is a widely investigated premium in equity markets (Basu 1977; Fama and French 1992, 1993, 1995; Lakonishok, Shleifer, and Vishny 1994). Based on the value premium cheap stocks outperform expensive stocks. Value investors buy relatively cheap securities to achieve higher returns on a risk-adjusted basis. Asness, Moskowitz, and Pedersen (2013) find consistent value premium across different markets and asset classes. Ben Graham and Warren Buffett are the most famous value investors worldwide, and provide anecdotal evidence for value investing in the equity market. Whereas Value for equities usually relates the stock price to a measure of fundamental value, thus providing an indication of the valuation of the company, for corporate bonds a value measure usually relates the corporate bond spread to a model spread in order to assess the relative valuation of the bond. In order to arrive at a value measure for a corporate bond it is necessary to specify a fair value model for it.

There have been a few attempts to come up with a value measure for bonds. Correia, Richardson, and Tuna (2012) in their seminal paper investigate various value approaches and find that different approaches can explain a considerable amount of variance in the cross-section of corporate bond returns. In particular, they find that the distance-to-default measure from Bharath and Shumway (2008), a valuation model with several accounting- and market-based variables (Beaver, Correia, and McNichols 2012) and the commercial Moody's KMV model all rate high on this measure. Moreover, the authors find mean reversion in the differences between market spreads and theoretical spreads - indicating that the investigated value measures all contribute to the prediction of credit spread returns.

Another approach to build a value factor dates back to Houweling and Zundert (2017) who regress credit spreads on rating dummies, time-to-maturity, and short-term credit spread changes. Their value factor considerably outperforms a market portfolio. Other ideas include relating the credit spread to additional variables that theoretically determine credit spreads such as equity volatility (see Campbell and Taksler 2003).

The conclusion, however, is that there is no general agreement as to how to measure value. While the measures used in the literature all outperform their respective benchmarks, their exact performance heavily depends on their exact definitions. This justifies further research and allows for possible better formulations of value measures.

The second factor we cover is Equity Momentum. Momentum strategies are a well-known and well-documented stylized fact in the academic literature. Starting with equity momentum on equity returns, Jegadeesh and Titman (1993) were the first to describe a successful momentum strategy. Carhart (1997) shows that most of mutual fund persistence is attributable to exposure to momentum. Again Jegadeesh and Titman (2001) analyze different explanations for the profitability of momentum strategies and argue that behavioral explanations - in contrast to risk-based explanations - are drivers for abnormal momentum returns.

Momentum in the fixed income universe is not as clear-cut as for equities. Jostova et al. (2013) show for an USD IG universe that there is no significant momentum return, but report momentum in HY returns. Barth, Scholz, and Stegmeier (2017) conduct the same exercise for EUR-denominated bonds, and confirm the result that there is no momentum effect in investment grade, but it can be observed in the HY universe.

Cross-asset momentum strategies (bond momentum on equity returns and equity momentum on bond returns) are also well-documented. Bittlingmayer and Moser (2014) and Dor and Xu (2015) report significant returns in equities by using corporate bond momentum as a factor. The best researched cross-asset momentum strategy is equity momentum for corporate bonds. Gebhardt, Hvidkjaer, and Swaminathan (2005) are the first to show that there are spillover effects from the equity market to the corporate bond market, and that this strategy can be successfully deployed. They argue that both stock and bond prices under-react to company news. However, such news is better reflected in equity prices than in bond prices, and equity prices adjust to this under-reaction much faster than bond prices. In addition, equity momentum is able to predict future downgrades.

Polbennikov and Desclée (2017) confirm these findings and show that equity momentum strategies can be improved by using a combined signal of one, three and six months momentum factors. Moreover, the equity momentum factor has low correlation to their inhouse value factor, making it an attractive candidate for a multifactor strategy. There is an ongoing debate in the academic literature as to whether equity momentum strategies in the corporate bond universe are mainly driven by illiquidty. Lin, Wang, and Wu (2013) argue that the profitability of the equity momentum strategy is just an artifact and mainly attributable to the (il)liquidity premium. In contrast, Gebhardt, Hvidkjaer, and Swaminathan (2005) as well as Polbennikov and Desclée (2017) show that their results are robust to liquidity concerns. Overall, there is compelling evidence for a spillover effect from equity momentum to bond returns. Promising results for equity momentum in EUR-denominated bonds have already been provided by Kaufmann and Messow (2019).

Our third factor is Carry. While Carry is a concept that is very well known and frequently adopted among practitioners, there has only recently been a discussion on Carry as a factor. The most important paper in the field of carry investing is Koijen et al. (2018), who analyze Carry in various asset classes, including corporate bonds. They define the carry of an asset "as its futures return assuming that prices stay the same." This means that Carry is a deterministic and model-free characteristic. The idea of Carry is that assets with higher yields tend to outperform assets with lower yields. Normally these higher yields come with higher risks: a positive return should therefore be expected as a compensation for taking these additional risks. In their paper, Koijen et al. (2018) find that a carry factor has - on average - positive returns, with Sharpe Ratios between 0.4 and 0.5. Therefore, there is some evidence for carry being present as a factor in corporate bonds.

Next, we survey the evidence on the quality factor. This factor is generally approached in two different ways. First, a traditional quality factor draws heavily on balance sheet- or income statement-related factors (for an overview concerning such factors in the literature, see Hsu, Kalesnik, and Kose 2019). There is little evidence on a premium with such a classical quality factor for investment grade corporate bonds. Bender and Samanta (2017) show that a quality factor can reduce overall risk and enhance risk-adjusted returns in a balanced equity-bond portfolio.

The second definition of Quality in the literature can also be described as a low-risk factor. Ilmanen et al. (2004) demonstrate that short-dated credit risk consistently outperforms longer-dated spread exposure on a risk-adjusted basis. Similarly, Leote de Carvalho et al. (2014) find that the low-risk quintile consistently outperforms on a risk-adjusted basis for various segments of the fixed income market, using different measures of risk such as yield, yield elasticity, duration, DTS, and spread.

Related to the short spread duration definition of low risk, Frazzini and Pedersen (2014) find that better rated bonds outperform bond portfolios with lower average ratings on a risk-adjusted basis. Houweling and Zundert (2017) use a combination of these two low-risk factor definitions to construct a quality measure.

In sum, whilst evidence for a quality factor similar to those applied in equity portfolio management is scarce, there is some evidence of a low-risk anomaly and a related low-risk factor in corporate bonds.

Other factors found in the literature are bond momentum and size. However, there is at best weak evidence for the presence of those factors in investment grade corporate bonds.

In their seminal study, Jostova et al. (2013) find bond momentum in corporate bonds, but analyze that this is driven exclusively by non-investment grade bonds. In their paper, a long-short bond momentum portfolio of investment grade bonds does not exhibit significant excess returns. Bali, Subrahmanyam, and Wen (2019) even find reversal in corporate bonds, indicating that a bond momentum strategy would exhibit negative expected returns.

Within equity factor investing the size effect is well-documented in the academic literature (e.g. Fama and French 1993; Asness et al. 2018). But within corporate credit it is not clear-cut as to whether size offers a significant abnormal return premium on a risk-adjusted basis. On the one hand Polbennikov's (2018) analysis does not support the existence of a size factor in the USD IG & HY markets, something which is also supported by Alquist, Israel, and Moskowitz (2018). Houweling and Zundert (2017) on the other hand find evidence for a size factor that could be systematically exploited in the same way that equity investors do. The size effect is incorporated in the multi-factor approach of Houweling and Zundert (2017). They define size as a bond's index weight of a credit benchmark and show that there is a risk premium associated with small cap bonds. On the other hand, when using market capitalization of the equity as the size factor Alquist, Israel, and Moskowitz (2018) find that there is no size effect among investment grade bonds. This result is consistent with Palhares and Richardson (2018), who do not find risk-adjusted outperformance of less liquid bonds in the corporate bond market.

Finally, after having determined a couple of single factors priced in the corporate bond market, every researcher has to answer the question as to how to combine these factors in a portfolio. Bender and Wang (2016) analyze an integrated bottom-up approach that combines signal at the factor level with a mixed top-down approach that combines individual factor portfolios. They show - theoretically as well as empirically - that the bottom-up approach yields superior results, since a top-down approach ignores interaction effects of factors at the security level. Using long-only portfolios Clarke, Silva, and Thorley (2016) confirm that the integrated approach captures roughly twice as much of the factor exposure as the mixed approach. On the other hand, after controlling for factor interaction effects by building exposure-matched portfolios, Ghayur, Heaney, and Platt (2018) obtain mixed results with respect to the superiority of one of the two approaches. More recently, Blitz and Vidojevic (2019) confirm that without considering interaction effects, a top-down factor mix yields inferior results to the integrated approach.

The literature on constructing a multifactor portfolio, therefore, shows that when using simple combinations of factors an integrated approach seems to be superior. For a mixed approach to realistically compete, a correction for interaction is required that may be difficult to achieve in practice.

Overall, there already exist empirical studies analyzing the corporate bond factors covered in this paper. Mostly, we can support the literature with our subsequent analysis.

3 Data

We use monthly constituent data of the Intercontinental Exchange (ICE), the Global Corp IG Index (G0BC, referred to as IG), and the Global HY Index (HW00, referred to as HY), between January 2000 and December 2018, and filter for all bonds denominated in USD. For every month-end, ICE provides characteristics like credit spread (Option adjusted Spread, OAS), credit rating, time to maturity (TTM), total return, excess return over US treasuries, and sector. We keep only those bond observations for which the sector is "Financial", "Utility" or "Industrials".[1]

In 2000, the IG universe had an amount outstanding of below €1 trillion going up to around €5 trillion in 2018. At the same time, the number of bonds increased from ~3000 to ~7300. The average rating of these bonds has dropped over the period by one notch from A- to BBB+. Also, the average TTM has dropped from ~10 years in 2000 to ~8 years in 2018. The HY universe starts with ~€200 billion outstanding in 2000 and has been at ~€900 billion since 2015. The number of bonds increased from ~600 to ~2,000 today, with an average rating of B+. As in IG, the TTM dropped from ~8 to below 6 years.

In the final sample we focus only on bonds which can be mapped to a listed company, since most factors depend on equity or equity-related information. This means that our portfolio contains not only bonds of listed companies, but also the benchmark. This has two advantages:

1. We ensure that we invest exactly in the desired proportion (e.g. the top quintile) of all companies in the sample
2. The return of the benchmark is not biased by bonds without mapping equity return

For companies with more than one bond outstanding, we follow Haesen, Houweling, and Zundert (2017) and compute the market-value-weighted return over all its outstanding bonds to represent the bond return for that company. All other characteristics, such as OAS or duration, are also computed as market-value-weighted average over all outstanding bonds of a specific company. Summary statistics for both samples, IG and HY, are reported in Table 1.

4 Single Factors

The five most common factors within systematic credit investing are Value, (Equity) Momentum, Carry, Quality and Size. For Value and Momentum there is extensive collection of academic and empiric literature supporting these premia. For Carry, Quality and Size, results are not as clear-cut as for the other two premia but there is enough empirical support for inspecting these factors.

[1] Removed are "CASH", "Quasi & Foreign Government" (no corporate debt) and "Covered" / "Securitized" (due to their different risk structure compared to 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.

Table 1: Summary statistics for the indices G0BC (Investment Grade) and HW00 (High Yield) for all USD bonds in 'Financial', 'Utility' and 'Industrials' which can be mapped to a listed company from 2000-2018. First, the individual bonds are aggregated by company (market-value-weighted), then the single statistics were computed by date and aggregated over time (equally weighted). 10% and 90% are the respective quantiles.

	Investment Grade				High Yield			
	Avg	Median	10%	90%	Avg	Median	10%	90%
Bonds	3941	3152	2606	6311	1205	1082	695	1697
Companies	741	630	585	987	509	429	293	730
Financials	167	152	97	248	33	25	17	58
Corporates	574	523	447	740	476	405	275	677
Face Value (bn)	2225	1555	1123	4440	487	339	244	973
Market Value (bn)	2361	1579	1196	4754	475	326	191	932
Avg Rating Score	7.6	7.7	7.3	8	14.2	14.2	14	14.4
Avg OAS (bp)	187	171	101	252	795	633	354	1632
Avg TTM (years)	8.8	8.7	8.1	9.5	6.6	6.5	5.8	7.5
Avg Excess Return (%)	0.1	0.15	-0.93	0.9	0.27	0.3	-2.33	3.08

4.1 Value

We define the absolute 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.
In order to calculate the fair spread, the following equation is used:

$$\begin{aligned}\text{OAS}_{it} = {} & {}_{0} + {}_{1}\text{Volatility30D}_{it} + {}_{2}\log(\text{MCap})_{it} \\ & + {}_{3}\frac{\text{Debt}}{\text{Enterprise Value}}_{it} + {}_{4}\frac{\text{Ebitda}}{\text{Total Assets}}_{it} \\ & + \sum_{k=1}^{21}\Big({}_{5,k}\text{Rating}_{it,k} + {}_{6}\text{Mdur}_{it} + {}_{7}\Delta\text{OAS3m}_{it} + \epsilon_{it}.\end{aligned}$$

OAS_{it} is the market value weighted average OAS of all corporate bonds issued by the same ultimate parent company i at the end of each month t. The selection of independent variables is based on prior literature regarding determinants of corporate bond spreads. Merton's (1974) structural model shows that asset volatility (historical volatility of the ultimate parent companies' stocks is used as proxy for asset volatility) and leverage ratio (Debt / Enterprise Value) are very important spread determinants. We also include profitability (Ebitda / Total Assets) and size (natural logarithm of the market capitalization) of the ultimate parent companies. Two bond characteristics, rating score and modified duration, are included. They are calculated as average value of all bonds issued by the same ultimate parent companies. Therefore, the rating is transformed into a rating score from 1 (AAA) to 21 (D) before averaging, and rounded to whole digits before entering the model as a dummy variable (1 if company i has rating k and 0 otherwise).

Instead of using the deviation of the prediction and the OAS directly (which is the residual ϵ_{it}) as a factor, we calculate a relative value signal:

$$\text{Value}_{it} = \ln \left(\frac{\widehat{\text{OAS}}_{it}}{\text{OAS}_{it}} \right) - 1,$$

where $\widehat{\text{OAS}}_{it}$ is the prediction of the regression model above. We do so, in order to account for the fact that simple absolute value models typically suffer from a high correlation with the OAS and thus just increase the risk instead of investing in real value.

4.2 Equity Momentum

We use a 3-month equity momentum to forecast future bond returns. The most simple definition of a 3-month momentum factor is to divide the return index at date t (RI_t) by the return index 3 months ago (RI_{t-3}). However, since momentum factors suffer strongly from microstructural noise we define the return index as an average of the daily return index around the respective dates,

$$\text{Momentum}_{it} = \frac{\frac{1}{11}\sum_{i=0}^{10} \text{RI}_{i(t-i)}}{\frac{1}{11}\sum_{i=-5}^{5} \text{RI}_{(t-3)-i}}.$$

For a detailed analysis of equity momentum in corporate bonds we refer to Kaufmann and Messow (2019).

4.3 Carry

We make use of the OAS as our measure of carry. As Israel, Palhares, and Richardson (2018) note, OAS will only represent an unbiased carry estimate if the credit curve is flat, which is almost never the case. Thus, by using OAS as a carry measure while having an upward (downward) sloping credit curve, we underestimate (overestimate) Carry. One could fix this problem by using issuer specific credit curves. But this approach would add too much complexity and hence model risk for our exercise.

There are also alternative definitions of Carry. Instead of using the OAS, Lair, Peeters, and Skibinski (2018) use a risk-adjusted OAS as their carry factor. But as one sets OAS in proportion to a risk measure the nature of the carry factor is lost, making it work almost like another value factor - something which is also reflected by the correlation of 62% postulated by Lair, Peeters, and Skibinski (2018).

4.4 Quality

We focus solely on fundamental variables to form a quality measure on company level. In total, 14 balance sheet variables are used to identify high-quality companies. High quality in this case means companies which 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, the 14 variables are ranked, and then a weighted average of all available balance sheet items is calculated. Bank-specific variables get a higher weight, in order to adequately mirror the importance of industry-specific ratios. A list of all variables used can be found in the Appendix.

Note that our definition of Quality does not include any security-based risk measures which select bonds that are defensive based on their remaining maturity or spread segment (so called Low Risk, see Leote de Carvalho et al. 2014; also Ilmanen et al. 2004). Theoretically, a combination of fundamental and risk-based quality is possible, but mixes two different things – factor definition and product feature. In our view, quality as a factor is a company attribute, independent of any security-specific measures such as duration or spread cohort. The combination of the two quality measures does not allow for a clear identification of where the risk premium comes from. Is there a risk premium associated with the investment in high-quality companies, or does it originate from the investment into assets with short maturity?

Consequently, our rationale for not including risk-based Low Risk as a factor is twofold. First, a Low Risk factor is bond-specific, and since we evaluate the issuer and not particular bonds, we cannot form a Low Risk factor within our framework. Second, institutional investors formulate their needs in terms of relative or total return strategies ex-ante. A Low Risk factor selecting defensive duration and/or spread securities stands in clear contradiction to many established strategies (e.g. long duration relative): for this reason we consider Low Risk purely in a product context, not as a factor, in our alpha model.

4.5 Size

Following the most promising definition from academic papers (see Literature Review), we simply define Size as the sum of the market value of all bonds outstanding of one specific issuer in a specific month. We therefore focus on the size relative to peer issuers, which means that an issuer with the same market value of all bonds outstanding could be qualified as 'large' in past years and as 'small' nowadays. There are also more complex definitions for Size as for example Lair, Peeters, and Skibinski (2018) make use of a combination of 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 most simple definition.

4.6 Factor Characteristics

If the factors under consideration reward (risk) premia then we would expect that more exposure to the given factor results in a higher return (ceteris paribus). The easiest way to analyze whether higher exposure to the factor results in higher future returns is by ranking the companies based on their factor exposure and then average the (credit excess) return of the following month per quintile - as shown in Figure 1 for IG and in Figure 2 for HY. We also report the average OAS, TTM, and rating score of the complete index and the quintile with the highest exposure of each single factor. By doing so, we check whether the risk profile of the factors under consideration significantly differs from the index.

Looking at the return behavior for IG in Figure 1, all factors behave as expected. For Value, we find that there is a monotonous increase of average excess return from Q1 to Q5, which means that undervalued companies perform better than overvalued companies. For Momentum, one can observe a smooth increase in return from the low- to the high-exposure buckets. It is remarkable that the companies with the lowest returns and highest risk can be isolated by using Momentum as the sorting criterium. Momentum is the only standalone factor that offers attractive returns without being accompanied by the cost of higher risk. Higher Quality exposure does not come with a higher return, but with less risk - a behavior that is in line with expectations. Higher Carry exposure results in higher returns and higher risk. The highest Carry exposure (Q5) delivers notably higher returns than (Q4), but also much higher risk. Size behaves somewhat like a low-risk version of Carry, whereby higher exposure is still associated with higher returns and higher risk, but less extreme.

Results for HY in Figure 2 are comparable to IG for Value, Momentum, and Size. Value offers the same monotonic pattern as in IG, but is unable to distinguish an underperformer as well as in IG. Momentum shows the same risk/return profile as in IG, which makes the factor results independent of the investment universe. Size offers again a high return in Q5, but at the cost of higher risk.

Carry and Quality show major differences to IG. While Carry is offering higher returns at higher levels of risk in IG, an investment in the assets with the highest spreads in HY leads only to a

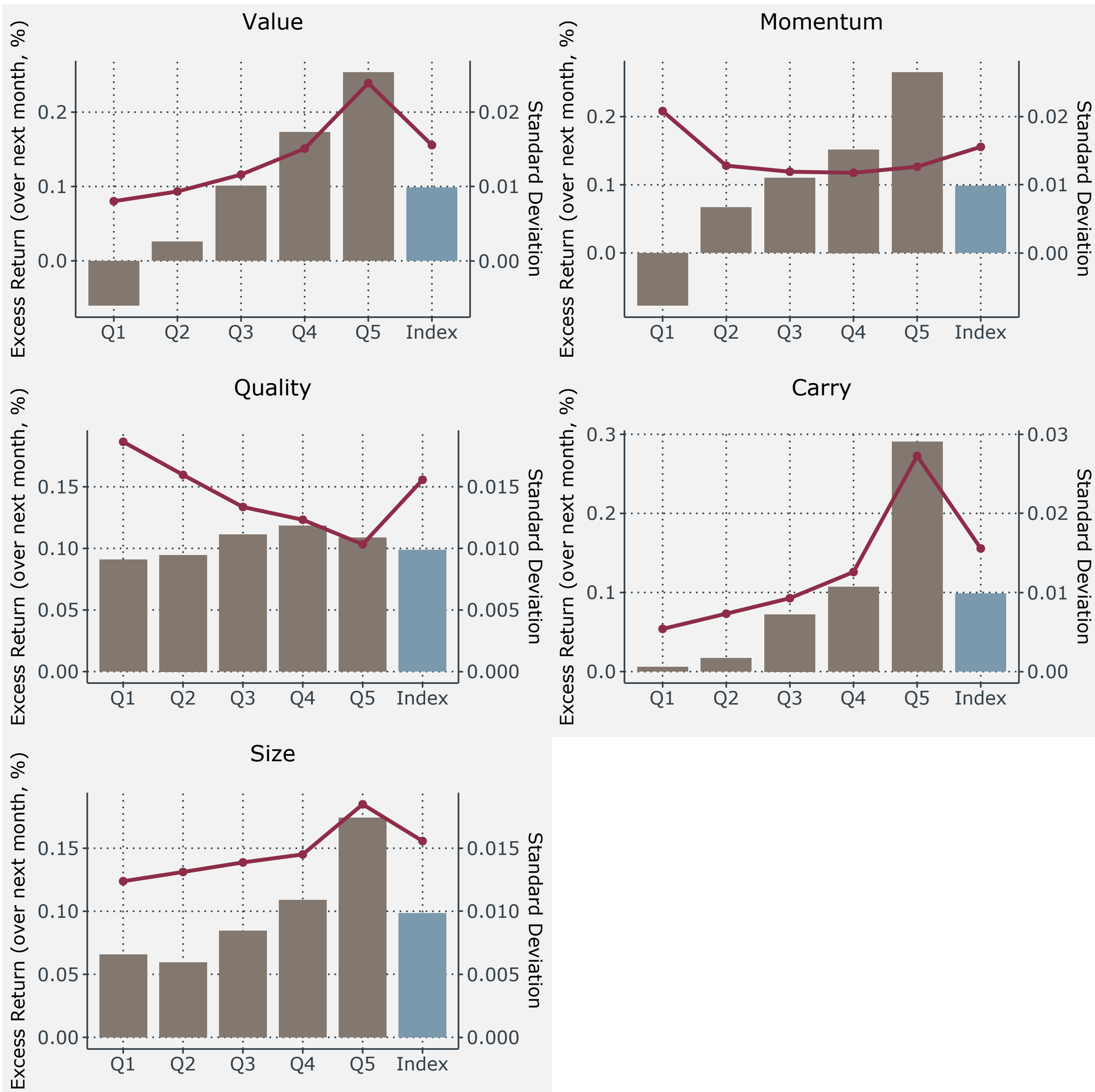

Figure 1: Average quintile returns of proposed factors for IG. Q1 (Q5) is the quintile with the lowest (highest) factor exposure. Calculations are performed firstly by date, and then averaged over all dates.

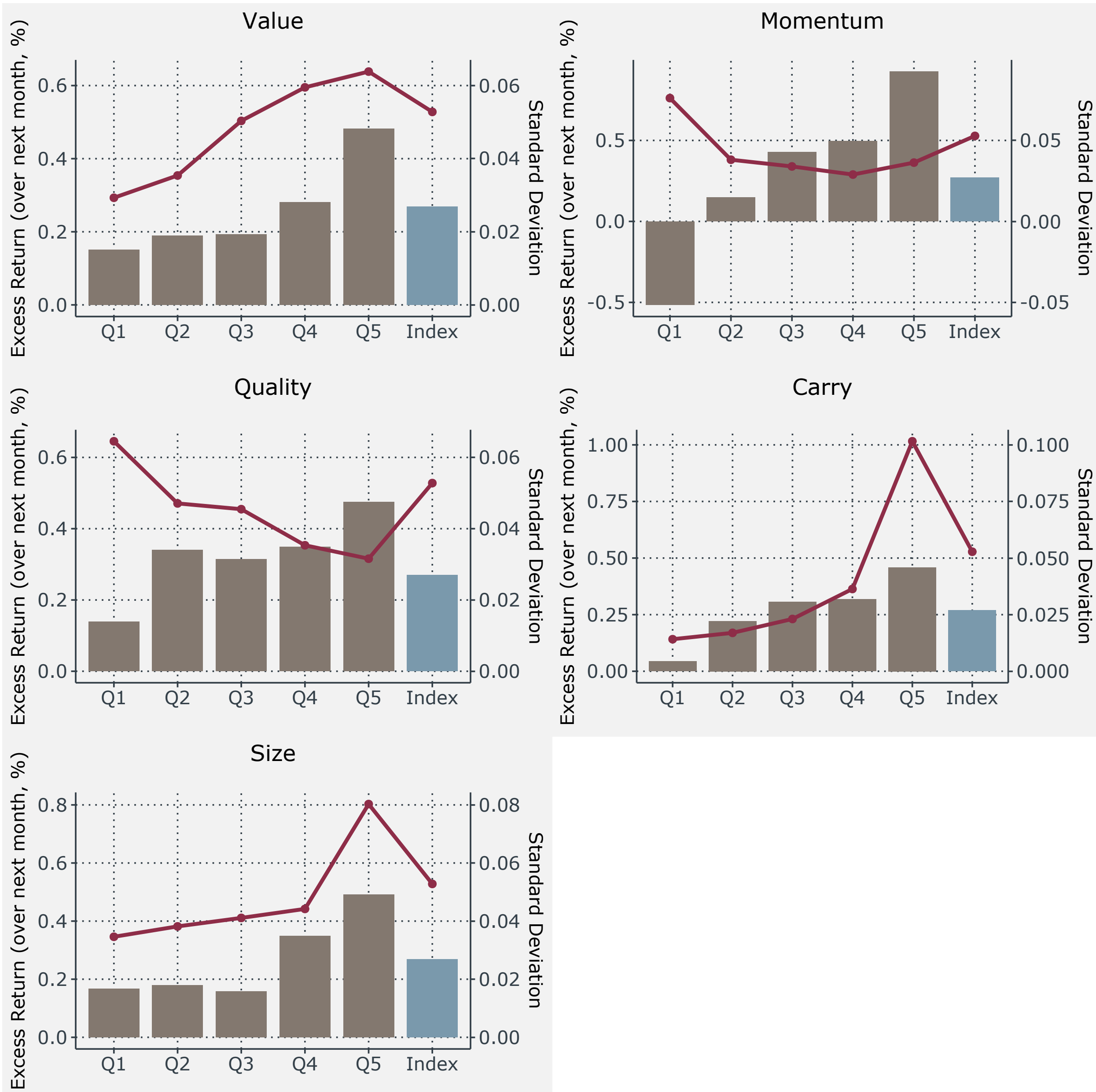

Figure 2: Average quintile returns of proposed factors for HY. Q1 (Q5) is the quintile with the lowest (highest) factor exposure. Calculations are performed firstly by date, and then averaged over all dates.

Table 2: Monthly averages of the Excess Return (over the next month, %), OAS (bp), TTM (years) and Rating Score for the complete index and the Q5 portfolios for the respective universes (IG and HY) from 2000-2018. Calculations are performed first by date, and then averaged over all dates. Rating Score is the transformed rating, a score of 1 means 'AAA', 2 means 'AA+' and so on. For convenience: 7 is 'A-', 14 is 'B+'.

	Investment Grade				High Yield			
	Excess Return	OAS	TTM	Rating Score	Excess Return	OAS	TTM	Rating Score
Complete Index								
	0.10	187	8.8	7.6	0.27	795	6.6	14.2
Q5 Portfolio								
Value	0.25	265	9.1	7.4	0.48	1069	7.1	14.0
Momentum	0.26	192	8.9	7.9	0.92	619	6.5	14.2
Quality	0.11	148	9.0	6.8	0.47	470	7.0	13.2
Carry	0.29	343	9.2	9.1	0.46	2133	5.5	16.5
Size	0.17	230	7.4	8.2	0.49	1554	5.9	15.1

small extra return given the large extra risk. On the other hand the quintile with the highest Quality exposure offers high returns on a relative basis with the same kind of risk reduction as in IG.

In Table 2 different descriptive statistics (excess return over the next month, OAS, TTM, and rating score) are depicted for the complete sample and the top quintile portfolios of IG and HY between 2000 and 2018. On the one hand, it can be seen that the statistics of the Q5 portfolios of factors associated with a true risk premia (Value, Carry, Size) show a somewhat different behavior in comparison to the complete indices. On average, they have higher OAS and a worse rating score. On the other hand, the Q5 Momentum portfolio has almost the same characteristics as the complete index, and the Quality portfolio - as expected - has lower OAS and better rating scores.

5 Multifactor

There are two competing techniques of constructing multifactor portfolios based on single factors - portfolio blending and signal blending. In the portfolio blending approach the individual factor portfolios are first constructed and then combined to create a blended multifactor portfolio. As an alternative, the signal blending approach combines single factors into a composite signal which is then used to create a portfolio.

If the single factors are highly correlated, both multifactor approaches lead to similar results. In this case a multifactor strategy of any kind is not beneficial as a similar result can be obtained by just using one individual factor. The true power of multifactor strategies stems from low or even negatively correlated single factors which possess beneficial individual attributes. We show in Figure 3 that all correlations between single factors are mild, with the exception of Value and Carry (52% IG / 23% HY). Thus, the proposed single factors show a correlation pattern which is favorable for multifactor approaches.

For a given portfolio construction method, blending leads to a more diversified portfolio since more assets with smaller weights are in the portfolio. While the outperformance is just an average of the outperformance of the single portfolios, the tracking error can be reduced. In contrast, a multifactor portfolio based on signal blending does not invest in assets which perform poorly in any single factor. If the underlying single factors show outperformance, this can be increased due to interaction effects. Therefore only signal blending has high factor exposure guaranteed for all single factors, and only signal blending can achieve an outperformance in terms of alpha against the single factors. Reduced tracking error, something

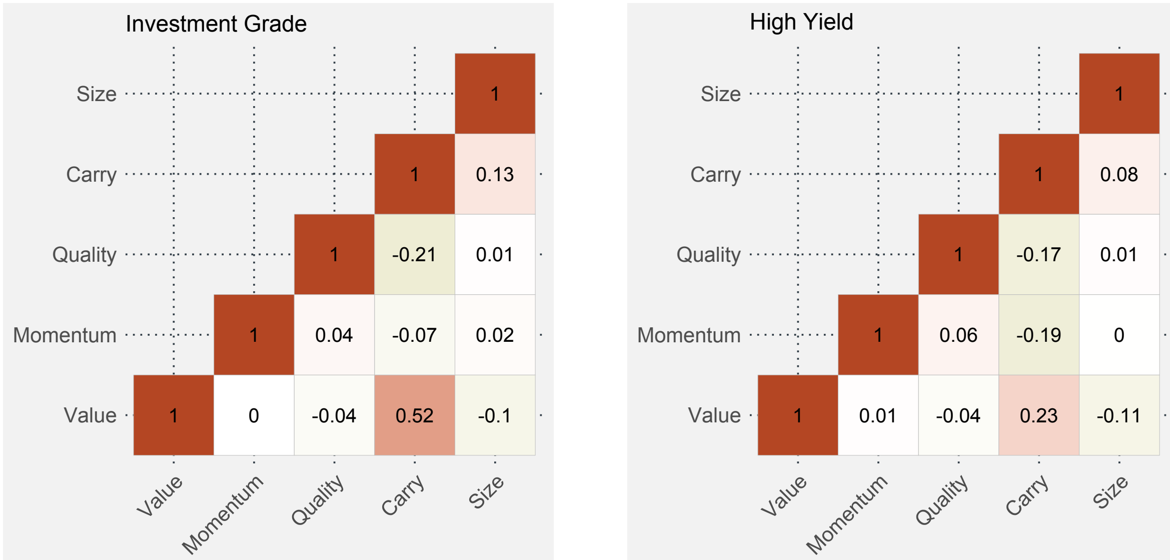

Figure 3: Correlation matrix of individual factor signals for IG (left) and HY (right). Calculations are performed firstly by date, and then averaged over all dates.

that occurs naturally with portfolio blending, can be achieved by the portfolio construction method if preferred. Therefore, Quoniam focuses on signal blending, which is referred to as Multifactor in the following.

Figure 4 shows the differences of the techniques for two uncorrelated factors. One can see that by portfolio blending the final portfolio does possess exposures to underlying assets with a low exposure in Factor 1 and 2. By signal blending, one invests in the underlying assets with the overall highest factor exposures - avoiding the assets with a low exposure in one of the factors.

The remaining question is how the individual factors should be weighted into one multifactor signal. Typically, equal-weighting or risk-weighting (e.g. volatility contribution) is used in the literature. As investors are interested in an attractive mix of return (here measured as alpha) and risk (here measured as tracking error), we rank single factors based on their information ratio (IR). Since a strong single-factor performance contributes to a better multifactor performance, the exposures of the single factors within our multifactor framework are weighted based on their standalone IR. For every asset i and every date t the single-factor exposures are combined into a multifactor signal (bottom-up):

$$\text{Multifactor}_{it} = \frac{\sum_{\text{Factor}=1}^{5} \text{IR}_{\text{Factor}} * \text{Factor}_{it}}{\sum_{\text{Factor}=1}^{5} \text{IR}_{\text{Factor}}}, \ \text{Factor} \in (\text{Value}, \text{Momentum}, \text{Carry}, \text{Quality}, \text{Size})$$

Note that these IR-based weights depend on the portfolio construction technique. As the single factors come at different scales, we standardize first by date before building the multifactor signal.

For comparison, we also blend the single portfolios (top-down) instead of the signals based on the individual IR. The result is not an individual factor, but solely an averaging of portfolio weights. In the following tables, this is referred to as Portfolio Blending.

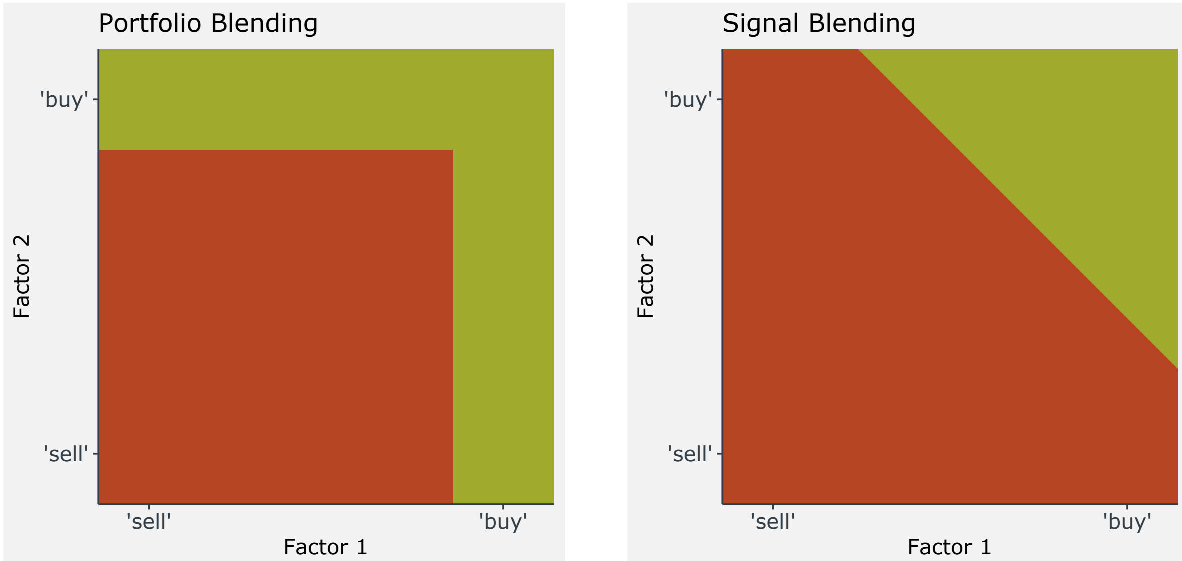

Figure 4: Comparison of the two multifactor construction rules - illustrative example for two uncorrelated factors. The blue area shows where the respective strategy is invested.

6 Results

We split our analysis in two different parts. Within Backtests we form portfolios based on two different portfolio formation rules and analyze the performance with and without transactions costs of the factors discussed above. In CAPM / FF regressions we analyse whether the factors mentioned earn a significant premia that is not explained by typical risk premia in the bond and equity market.

6.1 Backtests

In Section 4.6 we showed that the proposed factors offer an attractive return behavior, and the question emerges of how to make use of these stylized facts.

The easiest way of investing in a specific factor is by forming a portfolio based on the quintile with the highest factor exposure (Q5), and holding these companies up to a point where the portfolio is rebalanced. Within this paper we analyze two different holding periods. Firstly, a one-month holding period, which normally results in the highest returns since exposure to the factor is the highest, but also in higher turnovers. Additionally, we analyze a 12-month holding period, originated by Jegadeesh and Titman (1993), which leads to more realistic turnovers. Both portfolio construction techniques are long-only, since long-short portfolios are unrealistic to implement in the corporate bond market. The portfolio, as well as the benchmark, is equally weighted.

We report return statistics before and after costs. As an estimate of transaction costs we make use of Chen, Lesmond, and Wei's (2007) study, who report corporate bond bid-ask spreads based on maturity and rating. The average bid-ask spread ranges from 25bp (AAA-rated bonds with short maturity) to 180bp (CCC and lower rated bonds with medium maturity). 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 the Appendix.

The LHS of Table 3 reports the results for the portfolios with one-month rebalancing and 12-month rebalancing before and after transaction costs for IG. Looking at the results for

Table 3: Performance statistics of all proposed factors. Alpha is annualized in %, IR is the information ratio, TO is the two-sided turnover in %. Results are reported without (w/o) and with (w/) transaction costs (TC).

	Investment Grade					High Yield				
	w/o TC		w/ TC			w/o TC		w/ TC		
Strategy	Alpha	IR	Alpha	IR	TO	Alpha	IR	Alpha	IR	TO
Q5 portfolio, one-month rebalancing										
Value	1.81	0.88	0.81	0.39	545	2.30	0.53	-0.21	-0.05	813
Momentum	2.04	2.08	-0.08	-0.08	1116	8.48	2.37	4.97	1.38	1069
Quality	0.15	0.13	-0.23	-0.20	221	2.78	0.61	2.02	0.44	287
Carry	2.19	0.65	1.66	0.49	280	0.76	0.07	-0.07	-0.01	262
Size	0.93	0.69	0.76	0.56	112	2.55	0.53	1.95	0.40	206
Multifactor	3.00	2.31	1.27	0.97	896	9.13	2.43	5.90	1.56	976
Portfolio Blending	1.60	2.29	0.21	0.30	740	5.97	2.48	3.56	1.48	758
Q5 portfolio, 12-month holding period										
Value	0.59	0.38	0.42	0.26	113	1.25	0.41	0.92	0.30	144
Momentum	0.64	1.39	0.34	0.75	172	2.33	0.97	1.87	0.77	183
Quality	0.08	0.08	-0.04	-0.04	79	1.91	0.48	1.67	0.42	123
Carry	1.24	0.42	1.08	0.37	96	2.52	0.29	2.23	0.25	107
Size	0.81	0.63	0.71	0.55	73	4.07	1.04	3.85	0.98	98
Multifactor	1.19	1.39	0.94	1.09	150	4.86	1.48	4.49	1.36	144
Portfolio Blending	0.65	1.65	0.51	1.29	91	2.68	1.48	2.45	1.35	107

one-month rebalancing without transaction costs, we see results which are consistent with the ones as reported before in Section 4.6. Within IG all factors except for Quality offer positive abnormal returns. The best results for single-factor strategies are achieved for Momentum, with an IR of 2.08. Results change if transaction costs are considered, as the IR of the Momentum strategy drops to -0.08 due to the high turnover of 1116% (two-sided). For Value, Carry and Size, returns are still positive after transaction costs, especially for Carry and Size, as these factors have a much lower turnover than Value and Momentum. Multifactor clearly outperforms the single-factor strategies, and also Portfolio Blending, with an IR of 0.97. The high turnover exhibited by portfolios with one-month rebalancing has led us to consider additional tests where the factors are analyzed under more realistic conditions, i.e. imposing limits on turnover (see the lower section of the Table 3, Highest Quintile). After extending the holding period to 12 months the turnover has fallen to much more acceptable levels (in a range between 73% and 172%), and portfolios have become more diversified - as reflected in the lower tracking error. The reduction in alpha in all but momentum and quality factors - as well as their combinations - has not been completely compensated by lower tracking error. Consequently, the strategies exhibit on average a lower IR than their counterparts with one-month rebalancing. The only special case is Size, as results for the one-month and 12-month holding periods are almost identical. This is due to the low turnover of the one-month strategy of Size, resulting in near-identical behavior for both strategies. Momentum is the best-performing strategy before (after) transaction costs with an IR of 1.39 (0.75), with Size being the second-best factor with an IR of 0.63 (0.55), Carry the third-best factor with an IR of 0.42 (0.37) and Value with 0.38 (0.26). Both factor mixing strategies clearly outperform the single-factor strategies, but for different reasons. The alpha of Multifactor is almost double the alpha of portfolio blending, indicating that portfolio blending yields much lower TE.

The RHS of Table 3 reports the results for the portfolios with one-month rebalancing and 12-month rebalancing, before and after transaction costs for HY. Most of the results carry over from IG to HY but there are some striking differences to IG. First of all, factors that are based on the OAS - namely Carry and Value - work less well in HY because the universe is significantly more heterogenous due to additional complexity, e.g. bond-specific covenants. This additional complexity cannot be fully captured within a simple framework, as our Value or Carry factor indicated by showing negative alphas after transaction costs. Secondly, Quality as a factor doesn't add any benefit within IG, but is beneficial in HY. Thirdly, while Momentum was by far the best strategy within IG before TC, all performance was lost by incorporating transaction costs. Even though turnover within HY is still the highest for Momentum, it is the best-performing single factor after transaction costs for one-month rebalancing and second-best (after Size) for 12-month rebalancing. As for IG, both mixing strategies perform better than the single factors. Portfolio blending and Multifactor have almost the same IR, but as in IG, Multifactor's alpha is almost double that of portfolio blending. The results support the thesis that Multifactor is particularly suitable for investors searching for high alpha strategies, while portfolio blending fits better for index tracking approaches with a low TE.

The superiority of the mixed strategies is illustrated in Figures 5 and 6, where TE and alpha for all single-factor strategies, Multifactor and Portfolio Blending are shown. The top left quadrant is the most attractive one as it has the highest alpha and additionally the lowest TE. It can be seen that Multifactor and Portfolio Blending are more attractive than the single-factor strategies, but Multifactor is also more appealing than portfolio blending since Multifactor is associated with higher alphas.

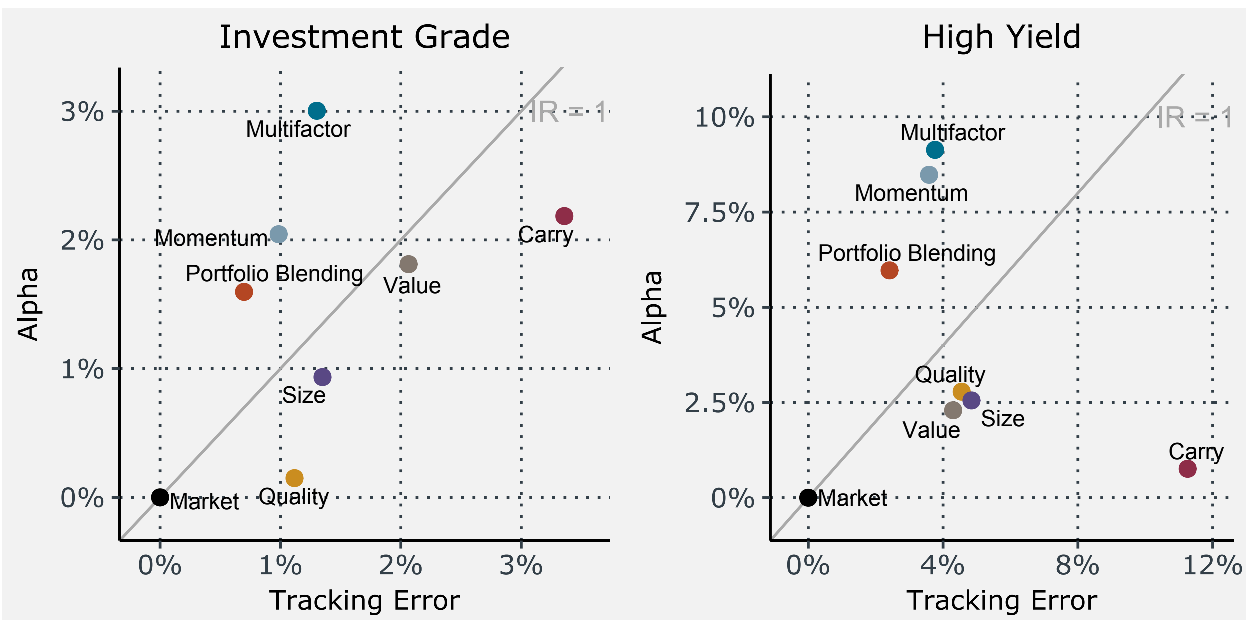

Figure 5: Alpha vs. Tracking Error plot per factor portfolio for one-month rebalancing without transaction costs.

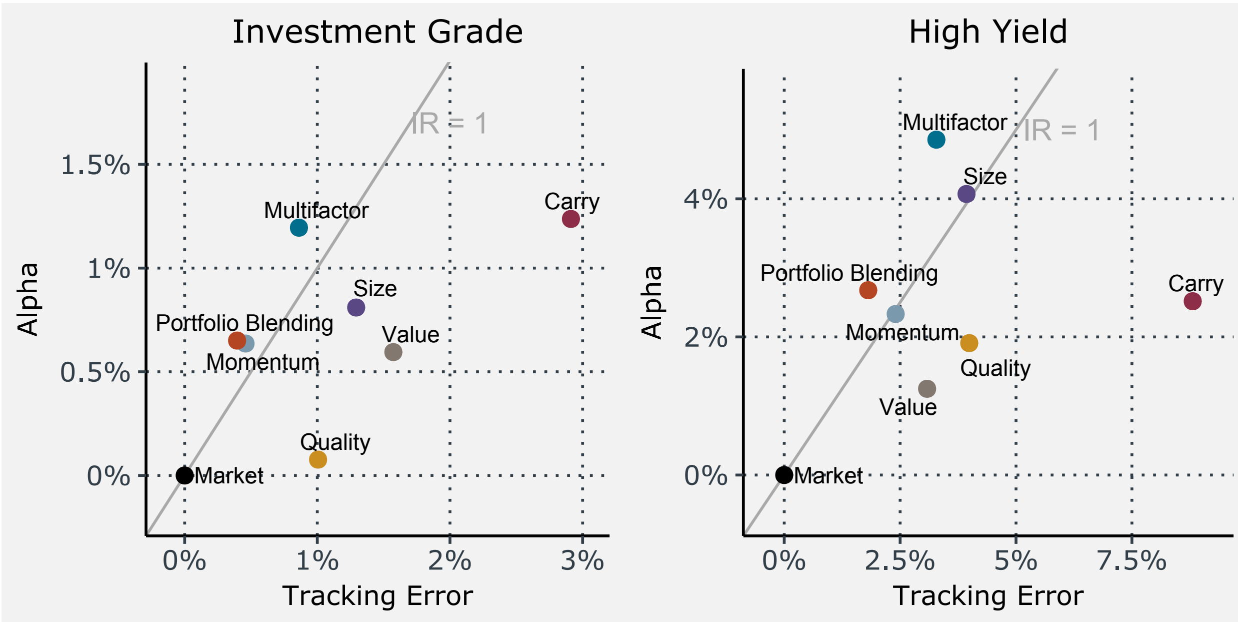

Figure 6: Alpha vs. Tracking Error plot per factor portfolio for 12-month rebalancing without transaction costs.

6.2 CAPM / Fama-French regressions

We next test the hypothesis that the portfolio excess returns cannot be explained by loadings on traditional sources of market risk premia as well as exposures to well-known equity factors. As this exercise is more of a theoretical question, we make use of the portfolios with the highest factor exposures (one-month rebalancing). The first regression (CAPM) is used to calculate the predicted rate of return given the market exposure of the portfolio under consideration. It compares the relationship between systematic risk and expected return.The latter regression (FF) examines whether stocks and bonds with a certain characteristic both earn their expected return due to a common exposure. For example, do cheap stocks (high book-to-market) and cheap bonds (high spread in relation to default risk) earn high average returns due to a common, shared exposure - or are there two distinct expected return sources?

We run the following regressions:

$$\begin{aligned} \text{CAPM} : r_t &= \; + \; \text{FIMRF}_t + \epsilon_t \\ \text{FF} : r_t &= \; + \; {}_1\text{FIMRF}_t + \; {}_2\text{TSY}_t + \; {}_3\text{HML}_t + \; {}_4\text{SMB}_t \\ &\quad + \; {}_5\text{MOM}_t + \; {}_6\text{CMA}_t + \; {}_7\text{RMW}_t + \; {}_8\text{EQMRF}_t + \epsilon_t \end{aligned}$$

The dependent variable is the return of the respective factor portfolio. FIMRF is the market-value-weighted credit excess return of the investment grade universe respective high yield universe. For FF the additional factors are the 10y USD treasury (TSY), the equity value

Table 4: Alpha (annualized, %) and t-value for the CAPM and Fama-French regressions.

	Investment Grade		High Yield	
Strategy	Alpha	t-value	Alpha	t-value
CAPM regression				
Value	2.25	3.76	2.63	2.31
Momentum	2.54	5.01	8.95	5.28
Quality	0.78	2.34	3.61	3.94
Carry	2.32	2.79	1.70	0.59
Size	1.57	2.14	3.90	2.44
Multifactor	3.42	4.98	9.55	5.68
Portfolio Blending	2.11	4.41	6.57	4.81
Fama-French regression				
Value	1.75	2.21	2.06	1.64
Momentum	2.12	4.22	7.95	5.80
Quality	0.57	1.74	2.79	3.32
Carry	1.57	1.78	0.67	0.26
Size	1.31	1.78	4.01	2.62
Multifactor	2.94	4.51	8.26	5.91
Portfolio Blending	1.73	3.87	5.79	4.97

premium (HML: HIGH - LOW), the equity size premium (SMB: SMALL - BIG), the equity momentum premium for the equity market (MOM), the equity investment premium (CMA: CONSERVATIVE - AGGRESSIVE), the equity profitability premium (RMW: ROBUST - WEAK), and the equity market premium (EQMRF). We download these equity factors from the website of Kenneth French.

In Table 4 we report annualized alphas (the estimated intercept of the respective regression) and t-statistics (indicating whether the intercept is statistically different from 0). T-statistics are corrected for auto-correlation and heteroskedasticity (Newey-West). It can be seen that for both regressions and all strategies in IG, all alphas are significantly different from zero, except FF regression for Quality, Carry and Size, with estimates ranging from 0.6% to 3.4% and t-values from 1.7% to 5% for a one-month rebalanced portfolio. For HY, alphas range from 0.7% to 9.5% and t-values from 0.3% to 5.9% resulting in significant estimates for Value, Momentum, Quality, Size, Multifactor and Portfolio Blending.

As pointed out by Harvey, Liu, and Zhu (2016), due to extensive data mining explaining the cross-section of expected returns there should be caution when establishing significance. They propose a t-statistic of greater than 3.0 instead of usual cut-offs. Applying this more conservative hurdle, Momentum, Value (CAPM) and Multifactor remain signifcant in IG and Momentum, Quality, Multifactor and Portfolio Blending remain significant in HY.

Overall, these results confirm our hypothesis that there are certain factors in corporate bonds that lead to abnormal returns beyond typical equity and bond risk premia.

7 Conclusion

We find evidence for several factor premia within the corporate bond market. Within IG, Value, Momentum, Carry and Size offer excess returns. For HY, the general results also hold but with some remarkable differences to IG. Quality as a factor doesn't add any benefit within IG but is beneficial in HY. But most notably, Carry and Value - which have a fundamental anchor in terms of OAS - work less well in HY. This is due to certain bond-specific characteristics, e.g. Covenants, lead to a heterogenous universe. This additional complexity cannot be fully captured within a simple Value or Carry framework used within this paper. But this additional complexity also leaves room for an active manager - such as Quoniam - to implement more sophisticated Value and Carry models for HY corporate bonds.

By mixing single factors using signal or portfolio blending, results are enhanced significantly. Overall, signal blending works better than portfolio blending (especially with a much higher alpha) as signal blending results in the highest factor exposures. Under the most strict portfolio formation rules with a 12-month rebalancing - and considering transaction costs - the signal blending strategy still offers an alpha of 0.94% (4.49%) for IG (HY) and IR of 1.09 (1.36) for IG (HY).

Being in line with studies for the equity market, our results suggest that investors in the corporate bond market should strongly consider using systematic strategies in the form of an integrated Multifactor approach instead of relying on external managers to implement factor exposures. For the last 14 years, Quoniam's Fixed Income strategies have accordingly been based on a Multifactor model with a realised IR of 1.2, combining a wide variety of factors from the areas of Risk, Value, Quality, and Sentiment. In addition to the attractive risk/return profile, this approach offers renewed control over factor exposures.

8 Appendix

8.1 Quality variables

The variables used to build the Quality composite can be found in Table 5.

8.2 Transaction costs

The transaction costs used for the backtest can be found in Table 6.

References

Alquist, Ron, Ronen Israel, and Tobias Moskowitz. 2018. "Fact, Fiction, and the Size Effect." *Journal of Portfolio Management* 45 (1): 34–61.

Asness, Clifford, Andrea Frazzini, Ronen Israel, Tobias Moskowitz, and Lasse Heje Pedersen. 2018. "Size Matters, If You Control Your Junk." *Journal of Financial Economics* 129 (3): 479–509.

Asness, Clifford, Tobias Moskowitz, and Lasse Heje Pedersen. 2013. "Value and Momentum Everywhere." *Journal of Finance* 68 (3): 929–85.

Bali, Turan, Avanidhar Subrahmanyam, and Quan Wen. 2019. "Long-Term Reversals in the Corporate Bond Market." *Working Paper*.

Barth, Florian, Hendrik Scholz, and Matthias Stegmeier. 2017. "Momentum in the European Corporate Bond Market: The Role of Bond-Specific Returns." *The Journal of Fixed Income* 27 (3): 54–70.

Basu, S. 1977. "Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis." *Journal of Finance* 32 (3): 663–82.

Beaver, William, Maria Correia, and Maureen McNichols. 2012. "Do Differences in Financial Reporting Attributes Impair the Predictive Ability of Financial Ratios for Bankruptcy?" *Review of Accounting Studies* 17 (4): 969–1010.

Bender, Jennifer, and Ritirupa Samanta. 2017. "Quality Assurance: Demystifying the Quality Factor in Equities and Bonds." *Journal of Portfolio Management* 43 (5): 88–98.

Bender, Jennifer, and Taie Wang. 2016. "Can the Whole Be More Than the Sum of the Parts? Bottom-up Versus Top-down Multifactor Portfolio Construction." *Journal of Portfolio Management* 42 (5): 39–50.

Bharath, Sreedhar, and Tyler Shumway. 2008. "Forecasting Default with the Merton Distance to Default Model." *The Review of Financial Studies* 21 (3): 1339–69.

Bittlingmayer, George, and Shane M Moser. 2014. "What Does the Corporate Bond Market Know?" *Financial Review* 49 (1): 1–19.

Blitz, David, and Milan Vidojevic. 2019. "The Characteristics of Factor Investing." *Journal of Portfolio Management* 45 (3): 69–86.

Campbell, John, and Glen Taksler. 2003. "Equity Volatility and Corporate Bond Yields." *Journal of Finance* 58 (6): 2321–49.

Carhart, Mark M. 1997. "On Persistence in Mutual Fund Performance." *The Journal of Finance* 52 (1): 57–82.

Chen, Long, David Lesmond, and Jason Wei. 2007. "Corporate Yield Spreads and Bond Liquidity." *The Journal of Finance* 62 (1): 119–49.

Clarke, Roger, Harindra de Silva, and Steven Thorley. 2016. "Fundamentals of Efficient Factor Investing." *Financial Analysts Journal* 72 (6): 9–26.

Correia, Maria, Scott Richardson, and Irem Tuna. 2012. "Value Investing in the Corporate Bond Market." *Review of Accounting Studies* 17 (3): 572–609.

Dor, Arik Ben, and Zhe Xu. 2015. "Should Equity Investors Care About Corporate Bond Prices? Using Bond Prices to Construct Equity Momentum Strategies." *Journal of Portfolio Management* 41 (4): 35.

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

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

———. 1995. "Size and Book-to-Market Factors in Earnings and Returns." *Journal of Finance* 50 (1): 131–55.

Frazzini, Andrea, and Lasse Pedersen. 2014. "Betting Against Beta." *Journal of Financial Economics* 111 (1): 1–25.

Gebhardt, William R, Soeren Hvidkjaer, and Bhaskaran Swaminathan. 2005. "Stock and Bond Market Interaction: Does Momentum Spill over?" *Journal of Financial Economics* 75 (3): 651–90.

Ghayur, Khalid, Ronan Heaney, and Stephen Platt. 2018. "Constructing Long-Only Multi-Factor Strategies: Portfolio Blending Versus Signal Blending." *Financial Analysts Journal* 74 (3): 70–85.

Haesen, Daniel, Patrick Houweling, and Jeroen van Zundert. 2017. "Momentum Spillover from Stocks to Corporate Bonds." *Journal of Banking & Finance* 79 (1): 28–41.

Harvey, Campbell, Yan Liu, and Heqing Zhu. 2016."... and the Cross-Section of Expected Returns." *Review of Financial Studies* 29 (1): 5–68.

Houweling, Patrick, and Jeroen van Zundert. 2017. "Factor Investing in the Corporate Bond Market." *Financial Analysts Journal*.

Hsu, Jason, Vitali Kalesnik, and Engin Kose. 2019. "What Is Quality?" *Financial Analysts Journal* 75 (2): 44–61.

Ilmanen, Antti, Rory Byrne, Heinz Gunasekera, and Robert Minikin. 2004. "Which Risks Have Been Best Rewarded?" *Journal of Portfolio Management* 30 (2): 53–57.

Israel, Ronen, Diogo Palhares, and Scott Richardson. 2018. "Common Factors in Corporate Bond Returns." *Journal of Investment Management* 16 (2): 17–46.

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

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

Jostova, Gergana, Stanislava Nikolova, Alexander Philipov, and Christof W Stahel. 2013. "Momentum in Corporate Bond Returns." *The Review of Financial Studies* 26 (7): 1649–93.

Kaufmann, Hendrik, and Philip Messow. 2019. "Equity Momentum in European Credits." *Working Paper*.

Koijen, Ralph, Tobias Moskowitz, Lasse Heje Pedersen, and Evert Vrugt. 2018. "Carry." *Journal of Financial Economics* 127 (2): 197–225.

Lair, Thibault, Bas Peeters, and Marco Skibinski. 2018. "Factor Investing in Corporate Bonds." *NN Investment Partners*.

Lakonishok, Josef, Andrei Shleifer, and Robert Vishny. 1994. "Contrarian Investment, Extrapolation, and Risk." *Journal of Finance* 49 (5): 1541–78.

Leote de Carvalho, Raul, Patrick Dugnolle, Xiao Lu, and Pierre Moulin. 2014. "Low-Risk Anomalies in Global Fixed Income: Evidence from Major Broad Markets." *Journal of Fixed Income* 23 (4): 51–70.

Lin, Hai, Junbo Wang, and Chunchi Wu. 2013. "Liquidity Risk and Momentum Spillover from Stocks to Bonds." *The Journal of Fixed Income*, 5–42.

Merton, Robert C. 1974. "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates." *Journal of Finance* 29 (2): 449–70.

Palhares, Diogo, and Scott Richardson. 2018. "(Il)liquidity Premium in Credit Markets: A Myth?" *Journal of Fixed Income* 28 (3): 5–23.

Piotroski, Joseph. 2000. "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers." *Journal of Accounting Research* 38: 1–41.

Polbennikov, Simon. 2018. "Issuer Size Premium in Credit Markets." *Barclays Research*.

Polbennikov, Simon, and Albert Desclée. 2017. "Equity Momentum in Credit (Emc) Scorecard." *Barclays Research*.

Table 5: Quality variables variables used to build the Quality composite.

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

Table 6: Bid-ask spread in basis points 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 paper.

TTM	Bond Rating						
	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