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RESEARCH INSIGHTS

14 APRIL 2023

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Excess Returns in Corporate Bonds: A Case Study in Alpha Factor-Based Investment Strategies

Abstract

This article presents a case study for implementing an active corporate bond investment strategy based on Moody's Analytics' Alpha Factor framework. The Alpha Factor framework is based on a bond pricing model that yields Fair Value Spreads (FVS) – i.e., bond spreads consistent with measured risk factors. The primary inputs into the model are the Expected Default Frequency (EDF™) credit risk measure, Loss Given Default (LGD) and other market risk parameters. We demonstrate that portfolios of bonds selected based on their Alpha Factors – the ratio of their option-adjusted spreads to FVS – outperform market-value weighted benchmark indexes.

A Framework for Discovering Bond Investing Alpha

The current market climate has reawakened the need for active credit investment strategies. Rising interest rates, macroeconomic uncertainty, lower levels of liquitidy, and constrained credit availability have led to higher expected losses from increasing defaults and have impacted valuations for more default-remote debt securities. In this article we present a case study for implementing an active corporate bond investment strategy based on Moody's Analytics' Alpha Factor framework. We demonstrate that a portfolio of bonds selected based on their Alpha Factors outperforms a market-weighted index.[1]

A corporate bond's spread reflects both issuer and issue-specific risk factors, including default probability (PD), loss-given default (LGD), duration risk, liquidity risk, etc. Credit risk is a major determinant of a corporate bond's spread over a comparable duration risk free bond, especially for bonds with below-investment-grade ratings. Although markets attempt to efficiently price securities, temporary deviations from valuations implied by fundamental factors can and have occurred, especially during systemic shocks or events affecting a whole industry sector. Price deviations can also occur at the bond/issuer level as well (such as for small bond issues). Significant devations of a bond's spot market spread from the spread implied by fundamental risk factors suggests mispricing that has the potential to be systematically exploited as an investment strategy. The Alpha Factor framework was designed to identify potentially mispriced securities that yield higher risk-adjusted returns.

Figure 1 provides a succint overview of Moody's Analytics' Alpha Factor framework. We derive a bond pricing model[2] linking bond spreads with the bond duration-matched EDF measure (PD), LGD, market risk parameters (denoted by M), and issuer size by discounting expected cash flows of the bond in a risk-neutral pricing framework. One of the primary inputs into the model is the bond issuer's Expected Default Frequency (EDF), which assesses its probability of default by analyzing its balance sheet liabilities in conjunction with an estimate of its asset value inferred from its equity (stock) market valuation. The EDF effectively measures forward-looking credit risk to the extent that the stock market provides a forward-looking view of a company's future cash flows' ability to service a its debt liabilities.

The model is then calibrated on a sample of liquid bonds by estimating sector- and rating-level (investment grade, non-investment grade) LGDs and market parameters so that modeled spreads on average match market option-adjusted spreads.[3] The resulting FVS is the modeled bond spread that is consistent with the expected loss (informed by the EDF measure), the bonds' terms, and market risk factors. Fair Values spreads are updated daily.

Figure 1 Fair Value Spread and Alpha Factor Overview

$$FVS = (PD \times LGD) + M + Size$$

$$\text{Alpha Factor (AF)} = OAS / FVS$$

OAS > FVS => "Cheap," undervalued given risk factors
OAS < FVS => "Rich," overvalued given risk factors

The Alpha Factor (AF) is defined as the ratio of a bond's OAS and FVS. The ratio shows whether the bond is overvalued or undervalued given its risk factors. On average, FVS match market-observed OAS closely. However, at the individual bond issue level market OAS can deviate from FVS for non-trivial periods of time. Differences between OAS and FVS should not be persistent; any market mispricing should be bid away in an efficient market. That implies that market spreads should converge to FVS over time, generating superior risk-adjusted returns. Therefore, strategies that invest in undervalued bonds should outperform an appropriate exposure weighted and duration matched benchmark. Similarly, more undervalued bonds should

[1] This study ia a proof of concept designed to test if the Alpha Factor framework can identify mispriced securities. We demonstrate it potentially, but in practice fund managers may not achieve the same results in market all conditions.

[2] For complete details of the bond pricing model please refer to Liu, Peter, Zhuang, Zhong, Dwyer, Douglas, Edwards, James, Choi, Yukung, Malone, Samuel. 2022. "Moody's Analytics EDF-Based Bond Valuation Model Version 2.0." Moody's Analytics. Available at https://www.moodysanalytics.com/articles/pa/2022/edf_based_bond_valuation_model

[3] Note that bonds with option-like features are excluded from our data set.

earn higher expected returns, in line with their greater exposure to the value risk factor. In the following case study, we use the Alpha Factor to build and evaluate the performance of a systematic investment strategy.

Designing and Testing an Alpha Factor-Based Investment Strategy

The investment strategy we demonstrate is based on dividing the set of investable bonds into quintiles based on their Alpha Factors. That is, we rank order bonds by their Alpha Factors, divide them into five equally sized groups, and calculate the total returns on the best 20% (i.e., the quintile with the highest Alpha Factors), the worst 20% (lowest Alpha Factors), and compare it to a market value-weighted benchmark. We find that the top quintile (best 20% AF) groupings outperform their respective benchmarks on average and in most years, while the benchmark indices (representing the broad markets) in turn do better than the worst 20% AF groups. The strategy is backtested to 2007.

We show how the Alpha Factor helps generate cumulative excess returns for corporate bond portfolios across geographic markets: the United States, Europe, and Asia-Pacific (APAC) between 2007 and 2022. To construct a strategy portfolio, we begin with the universe of bonds in several categories. For the United States, we look at the U.S. investment-grade and U.S. high-yield markets. In Europe, we focus only on Euro investment-grade bonds from issuers in Austria, Belgium, Switzerland, Germany, Spain, France, United Kingdom, Italy, Netherlands, Portugal, Slovakia, US, Serbia, and European Union. In APAC, we divide results into two groups: an index of USD-denominated bonds issued by corporations domiciled in Australia, Hong Kong, China, Singapore, Korea, Thailand, India, Indonesia, Philippines, Malaysia, Taiwan, and Macao (denoted APAC ex-Japan), and JPY-denominated Japanese corporate bonds. For APAC ex-Japan index, we include both investment-grade and high-yield bonds, whereas for Japan, we only include investment-grade bonds.

Alpha Factor strategy bond portfolios are assembled as follows:

1. For a given country/region, divide the eligible bonds into five fixed duration buckets. Within each bucket, divide the bonds into broad sectors, namely financial institutions vs. industrials and utilities. For high yield bond portfolios, we do not divide into sectors.
2. Within each duration/sector bucket, rank the bonds by their Alpha Factors.
3. Select the bonds in the top 20% and bottom 20% of each duration/sector bucket's rank order by bond count.
4. On a monthly basis, calculate the market value-weighted total returns of the top and bottom 20% buckets, as well as for all the bonds in each duration/sector bucket.
5. Combine the duration/sector bucket results on a market value-weighted basis.

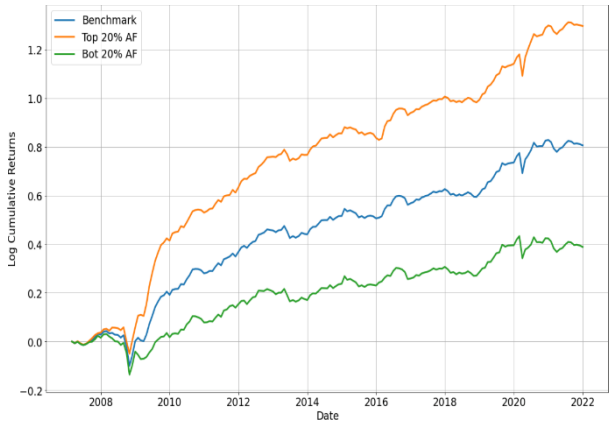
The bucketing step (step 1) mitigates potential bias in OAS values arising from varying bond durations or differences between corporate and financial issuers. Since the Best 20% and Worst 20% groups are subsets of the indices, we do not calculate transaction costs. For the sake of simplicity, each selected bond is weighted equally in the final portfolio. The portfolios are rebalanced monthly, "buying" bond issues with top 20% AFs and "selling" out the ones no longer in the top 20% AF. We compare both Top 20 and Bottom 20 portfolios' performance relative to a benchmark index where we equally weigh bonds without considering their Alpha Factors.

Figure 2 shows the cumulative monthly returns of the Top Quintile AF and Bottom Quintile AF portfolios. The blue line shows the cumulative returns of the Top Quintile AF portfolio; the green line shows the returns of the benchmark index; and the orange line shows the cumulative returns of the Bottom Quintile AF portfolio. The Top Quintile AF strategy outperforms its benchmark in the back-tests in each of the geographic markets studied since 2009, where the Bottom Quintile AF underperforms against its benchmark.

The graphs reveal three notable results. The first and most obvious is that the margin of outperformance of the Top Quintile AF strategy grows over time relative to the benchmark index. This is true for all the geographic bond portfolios we studied. The second notable result is that the outperformance of the Top Quintile AF is much stronger after the Global Financial Crisis than before it. We observe this result for US investment grade, US high yield, and Europe investment grade. This may simply reflect the fact that, just prior to the GFC, credit spreads were historically compressed across the ratings scale, with little differentiation for default risk. The third notable feature is that during the GFC, the AF based investment strategy for US investment grade preserved the portfolio performance rank ordering: in other words, the Top Quintile AF strategy still experienced a sharp draw-down, but it not as severe as for the market benchmark. Taken together, these three features of the portfolio performance data demonstrate the effectiveness of active asset selection using Alpha Factors.

Figure 2 Performance of Alpha Factor strategy portfolios against benchmark indexes

US Investment Grade



Year	Top 20% AF Returns	Benchmark Returns	Bottom 20% AF Returns
2008	0.086451	0.029716	-0.016434
2009	0.397836	0.206376	0.042099
2010	0.508034	0.292070	0.101903
2012	0.727166	0.462677	0.227032
2014	0.820714	0.520846	0.257290
2016	0.902535	0.572784	0.280163
2018	0.955049	0.611179	0.305587
2020	1.248079	0.827726	0.444713
2021	1.246601	0.806237	0.410379

US High Yield

Year	Top 20% AF Returns	Benchmark Returns	Bottom 20% AF Returns
2008	-0.250001	-0.331307	-0.327393
2009	0.360596	0.086895	-0.081891
2010	0.506626	0.216851	0.016036
2012	0.710729	0.394111	0.144588
2014	0.836552	0.475705	0.174711
2016	1.068876	0.580417	0.210850
2018	1.151468	0.640838	0.235917
2020	1.515678	0.859871	0.305396
2021	1.572959	0.923318	0.344466

APAC[4] ex-Japan (All Ratings)

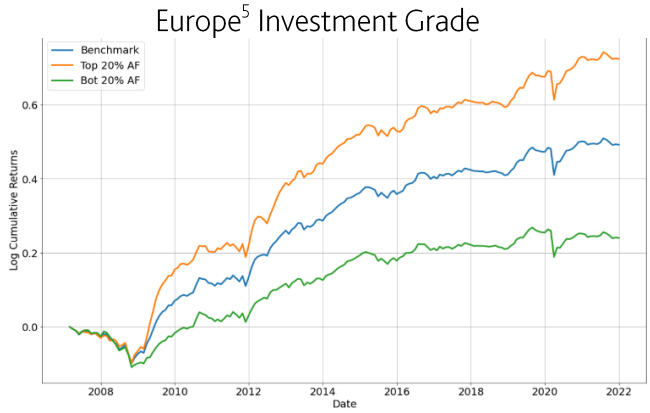
Year	Top 20% AF Returns	Benchmark Returns	Bottom 20% AF Returns
2013	0.008377	0.004765	0.013546
2014	0.085152	0.072568	0.061193
2015	0.116139	0.110402	0.097200
2016	0.172428	0.165222	0.145896
2017	0.235983	0.213455	0.181150
2018	0.237987	0.208303	0.180865
2019	0.364482	0.314475	0.276103
2020	0.483762	0.387411	0.297976
2021	0.493143	0.382140	0.288680

Japan Investment Grade

Year	Top 20% AF Returns	Benchmark Returns	Bottom 20% AF Returns
2016	0.024233	0.014357	0.007388
2017	0.045836	0.026667	0.020076
2018	0.065009	0.03703	0.026224
2019	0.070058	0.039924	0.028971
2020	0.071548	0.043614	0.028022
2021	0.086172	0.05185	0.033734

[4] APAC includes Hong Kong, China, Singapore, Korea, Thailand, India, Indonesia, Philippines, Malaysia, Taiwan and Macao.

Europe[5] Investment Grade



Year	Top 20% AF Returns	Benchmark Returns	Bottom 20% AF Returns
2008	-0.05523	-0.06525	-0.09457
2009	0.146119	0.070141	-0.01514
2010	0.193328	0.115944	0.024067
2012	0.36983	0.253219	0.115677
2014	0.4972	0.352697	0.190394
2016	0.561211	0.396295	0.209206
2018	0.574113	0.401941	0.209252
2020	0.707227	0.492957	0.251475
2021	0.701455	0.484108	0.239776

To demonstrate that the superior performance of the Top Quintile AF portfolios is achieved by asset selection and not from excessive risk taking, we compare some of their risk characteristics to the market-weighted index. Table 1 presents the mean LGDs, OAS, durations, ratings and EDF for the Top Quintile AF portfolio and each index. We can see from the mean values that the risk profiles of the Top Quintile AF portfolio and the index are quite similar. The mean EDF for the outperforming portfolio per category also shows the lower level of credit risk.

Table 1 Mean LGDs, spreads, durations, ratings and EDF for the Top Quintile AF portfolio and benchmark

	USIG		USHY		EUIG		APAC ex-Japan		Japan	
	Top 20 AF	Index	Top 20 AF	Index	Top 20 AF	Index	Top 20 AF	Index	Top 20 AF	Index
LGD	0.5	0.5	0.5	0.5	0.4	0.5	0.4	0.4	0.3	0.3
OAS	183.3	136.1	587.6	555.3	157.0	104.0	223.2	180.1	63.1	35.9
Duration	6.9	7.2	4.8	4.9	5.6	5.3	5.9	6.0	9.8	12.0
Rating	Baa1	A3	B1	B1	Baa1	A3	Baa1	Baa1	A2	A2
EDF	0.03	0.10	0.04	0.10	0.03	0.04	0.06	0.11	0.10	0.15

For the sector composition, Table 2 presents the mean sector weights for the Top Quintile AF portfolio and the respective indices. Overall, except for a few sectors such as the utilities sector, the sector profile of the selected bonds for the Top Quintile AF portfolio and the index are largely similar.

[5] The Europe Investment-grade portfolio includes Austria, Belgium, Switzerland, Germany, Spain, France, United Kingdom, Italy, Netherlands, Portugal, Slovakia, US, Serbia, and European Union.

Table 2 Mean sector weights for the Top Quintile AF portfolio and Index

	USIG		USHY		EUIG		APAC ex-Japan		Japan	
Sector	Top 20 AF	Index	Top 20 AF	Index	Top 20 AF	Index	Top 20 AF	Index	Top 20 AF	Index
Utilities – Low Risk	27%	15%	18%	6%	18%	9%	14%	6%	13%	8%
Cable TV & Printing/Publishing	15%	7%	17%	13%	8%	10%	15%	6%	16%	6%
Banks and S&Ls	13%	12%	1%	1%	23%	24%	15%	27%	15%	39%
REITS/Finance – High Risk	6%	6%	6%	5%	4%	5%	5%	12%	9%	6%
Finance Co & Broker/Dealers	12%	13%	6%	5%	11%	9%	9%	6%	6%	10%
General Sector	4%	5%	10%	17%	9%	8%	21%	16%	25%	9%
Aerospace & Measuring Equipment	1%	2%	1%	1%	1%	1%	4%	1%	0%	0%
Transportation	1%	3%	2%	3%	1%	2%	5%	2%	6%	1%
Equipment	1%	3%	2%	2%	2%	2%	2%	1%	4%	3%
Consumer Goods & Durables	10%	13%	13%	13%	13%	14%	6%	7%	15%	12%
Medical	2%	5%	6%	5%	4%	3%	5%	1%	6%	2%
High Tech	1%	4%	2%	3%	1%	1%	5%	2%	5%	3%
Materials/Extraction	7%	12%	17%	25%	7%	11%	23%	15%	5%	2%

We examine the performance of some sector specific Alpha Factor strategy portfolios in Figure 3, again comparing the cumulative returns of the Top Quintile AF portfolio with the relevant benchmark indexes. As in Figure 1, the blue line shows the returns of the Top Quintile AF portfolio; the green line shows the returns of the benchmark index; and the orange line shows the returns of the Bottom Quintile AF portfolio.

For the three industry sectors shown, the Top Quintile AF portfolio generally outperforms both the market benchmark and the Bottom Quintile AF portfolio. Further, we can see the superior performance of the Top Quintile AF portfolio during both good and adverse macroeconomic conditions. In a rising market, such as from 2018 to 2020, the Top Quintile AF portfolio generated strong cumulative returns. Following the Covid pandemic shock in 2020, Top Quintile AF portfolios outperformed strongly. This is likely a result of the Alpha Factor's ability to identiry over-sold issues in a market rocked by a systemic event. By choosing the highest AF bonds in the midst of the market downturn, the outperformance in the subsequent periods is all that much higher. While bond markets saw a sharp drop in cumulative returns in 2022, the Top Quintile AF portfolios showed their strength as a defensive play in a down market.

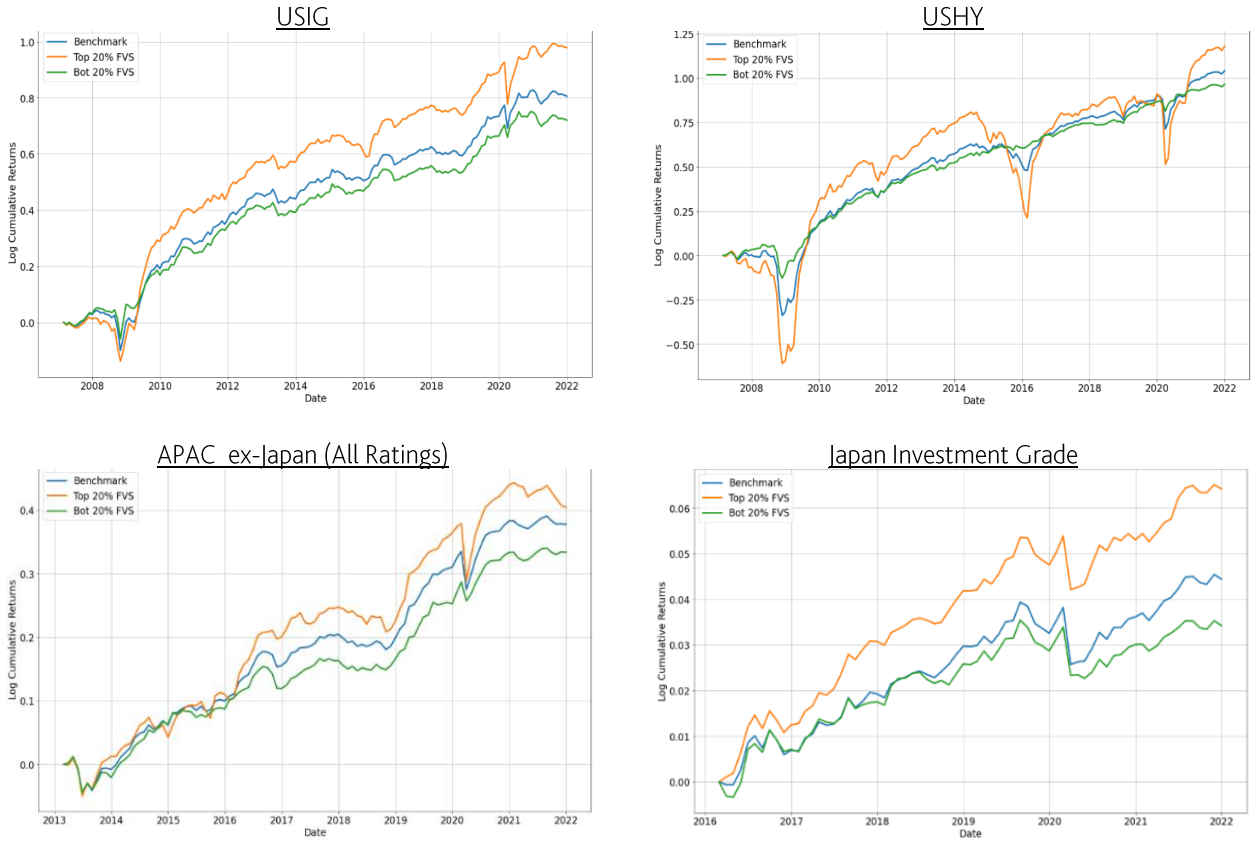
Figure 3 Performance of Alpha Factor strategy portfolios against benchmark index for selected sectors

Euro Investment Grade Medical

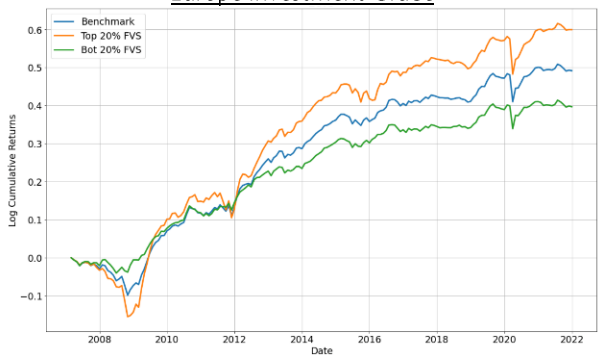
Finally, we demonstrate that FVS alone is not enough to create a better investment strategy. While FVS helps to pin down modeled bond value, the combination of FVS and the observed OAS provides a complete signal of relatively undervalued and overvalued bonds.

Figure 4 presents the cumulative returns of two portfolios from 2018 to 2022. One portfolio has bonds with high FVS and the other portfolio bonds with low FVS as of the end of 2018. The data used in this case are all bonds that are covered by Moody's Analytics. The orange line refers to the returns from the high-FVS portfolio; and the blue line refers to the returns from the low-FVS portfolio.

Figure 4 Time series performance of high-FVS bonds against low-FVS bonds



Europe Investment Grade



While we expect the portfolio with low FVS and accordingly lower credit risk to outperform the one with high FVS, this result is not always consistent as the observed OAS may also be low in the low FVS portfolio i.e., no mispricing opportunity exists. This underscores the point that Alpha Factor should be the key Factor used to build the investment strategy, as the FVS should be compared to a benchmark for mispricing opportunities – the OAS in our case.

Summary

The performance of a corporate bond portfolio hinges on asset selection: achieving the highest spread while controlling for risk, and for high yield portfolios avoiding credit events. While investors attempt to estimate risks and price bonds efficiently, market valuations can deviate from risk fundamentals long enough to provide investable opportunities arising from the mispricing.

In this study, we examined the performance of investment strategies based on Moody's Analytics' Alpha Factor, targeting undervalued bonds with high OAS relative to FVS, and demonstrated their ability to outperform a benchmark index. The strategy generally outperformed in most years we analyzed and was robust across industry sectors and geographies. Importanly, the portfolio outperformance we document was not associated with selecting higher spread bonds due to higher risk; in this case study, the Alpha Factor successfully identified bonds undervalued given their risk factors.