Foundations of ESG Investing in Corporate Bonds
How ESG Affected Corporate Credit Risk and Performance
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Contents

Executive Summary ................................................................. 3
ESG Introduction .................................................................. 4
Data and Methodology .......................................................... 9
  Analysis Outline ................................................................. 9
ESG and Traditional Corporate-Bond Metrics ...................... 12
  How ESG Correlates with Credit Ratings .............................. 12
  The Price of ESG in Terms of Spreads ................................. 13
ESG Economic-Transmission Channels into Credit Risk ...... 17
  Cash-Flow Channel ............................................................. 17
  Systematic-Risk Channel ..................................................... 21
  Idiosyncratic-Risk Channel .................................................. 26
  Effectiveness of ESG Across Issuer Universes .................... 29
Performance of ESG .............................................................. 30
  Average Performance of ESG and Its Pillars ...................... 30
  Did ESG Add Value over Traditional Credit Factors? ............ 32
Conclusion ............................................................................ 35
Appendix ................................................................................ 38
  Appendix A1: Merton Model Framework ............................ 38
  Appendix A2: Cross-Sectional Regression Model ............... 41
  Appendix A3: Average Fundamental Statistics Tables .......... 44
  Appendix A5: Corporate-Bond Universe and ESG Profile ...... 47
ESG Profile ......................................................................... 48
Executive Summary

This paper extends our research on how ESG has affected equity investing to corporate bonds. Unlike with equities — where MSCI’s previous research shows that MSCI ESG Ratings had positive effects on stocks’ risk and return characteristics — we found that a corporate bondholder’s main ESG focus could be mitigating downside risk, rather than capturing upside. In this paper, we also examined whether ESG added value beyond credit ratings — a significant point of interest for bondholders. In short, we found that ESG complemented credit ratings.

This research aims to provide insights for institutional investors looking to incorporate ESG factors into the fixed-income investment process and build on the existing body of ESG literature in equities. We summarized the economic rationale and related empirical evidence in three so-called transmission channels (i.e., economic arguments): cash flow, systematic risk and idiosyncratic risk. This framework linked the observed stock performance and risk characteristics to companies’ fundamental properties.

In our empirical analysis, we found that ESG was in general more financially relevant in high-yield (HY) than in investment-grade (IG) bonds and more relevant in IG bonds with longer than shorter maturities. We could explain this dependency with the sensitivity of default risk (Merton model) with respect to ESG-related transmission channels: The predicted default risk of the Merton model is more sensitive with respect to changes in its input parameters in HY than in IG, and it is more sensitive for long maturities than for short maturities, particularly in IG.

We also looked at financial risk and performance characteristics of ESG score terciles, reflecting high, medium and low ESG ratings. We found that, over the broader universe, the upper tercile had improved risk characteristics (ESG was a defensive strategy) and even showed better risk-adjusted returns than the lower tercile. Within the three pillars, the social (S) pillar showed the strongest performance in returns, while the environmental (E) pillar showed the strongest differentiation in terms of risk across terciles, over the broader universe. However, the aggregate ESG rating showed more risk reduction than the individual pillars did, which suggested a holistic approach to ESG over a single-pillar approach.

In sum, our analysis suggests ESG ratings can add financial value when used in addition to credit ratings to assess credit risks and build corporate-bond portfolios.
ESG Introduction

Environmental, social, and governance (ESG) investing is a very broad field with many different investment approaches addressing various investment objectives across asset classes. While there are many studies relating to ESG in equities, the risk assessment of ESG considerations within fixed income may be equally if not more important. Bonds have limited upside, but in a negative scenario, investors can potentially lose all their invested capital. At a top level, we can break down ESG investing into three main areas that each has its own investment objective (Exhibit 1): first, ESG incorporation, in which the key objective is to improve the risk-return characteristics of a portfolio; second, values-based investing, in which investors seek to align their portfolio with their norms and beliefs; and third, impact investing, in which investors want to use their capital to trigger change for social or environmental purposes — for example, to accelerate the decarbonization of the economy. In this paper, we focus on the first investment objective — ESG as a means to achieve financial objectives in portfolio management in the context of corporate bonds.

Exhibit 1: Main Categories of ESG Investing

An increasing number of studies from both academia and the asset-management industry have investigated the financial benefits of ESG investing. For example, Friede, Busch and Bassen (2015) conducted a meta-analysis of over 2,000 such studies; since then, numerous new studies have emerged. These studies differ significantly based on which ESG methodologies were used (e.g., different ESG
scores and whether there were industry exclusions), as well as which financial metrics were used to assess the performance impact of ESG. With vast differences in the conceptualization and construction of both the independent and dependent variables in these studies, it is not surprising that there is no clear consensus across the universe of research contributions on the question of ESG and performance.

It is interesting to note that most of the research contribution in this field has focused on equity markets, despite the fact that asset owners, who typically diversify their investments across asset classes, also have significant exposure to fixed income.

However, there are some research contributions on ESG in fixed income worth mentioning: Desclee et al. (2016) used MSCI ESG Ratings and individual E, S and G pillar scores within the Bloomberg Barclays Global Aggregate Index universe and analyzed the financial risk and performance of the Bloomberg Barclays MSCI Sustainability Indexes, which are based on MSCI ESG Ratings. They showed that higher-ESG-rated corporate bonds had lower systematic risk, lower spreads and therefore higher valuations while controlling for common corporate-bond factors. They also observed that issuers with high G-pillar scores showed lower frequencies of credit-rating downgrades.

Clubb, Takahashi and Tiburzio (2016) used Bloomberg ESG scores on corporate credit within the Russell 1000 Index for their study from 2005 to 2016. They found a consistent negative correlation between ESG scores and individual E, S and G scores with option-adjusted spread (OAS) and variability in OAS, while controlling for issuers’ interest coverage ratio, debt to equity, return on assets, debt/EBITDA and current ratio. This negative correlation was found to be strongest during turbulent market phases. Similar to Desclee et al. (2016), they found that higher-ESG-rated companies showed lower levels of risk, especially in volatile markets. The authors explained these results by suggesting that ESG is a broad proxy for management quality and good corporate governance by market participants.

Bahra and Thukral (2020) analyzed the financial relevance of MSCI ESG scores and individual pillar scores in the corporate-bond market. They found that correlations among the three pillar scores were very low — which mirrored the finding in Giese, Lee and Nagy (2020) — and that there were no significant correlations between MSCI ESG scores and credit ratings. Their main finding was that MSCI ESG Ratings were additive to credit ratings in their financial relevance: MSCI ESG Ratings can be used to reduce risks (e.g., volatility and drawdowns) and, in some cases, improve risk-adjusted returns. They explained their finding with the fact that the contingent liabilities related to ESG issues are not necessarily factored into credit-rating assessments.
To show that the economic rationale is financially relevant for equity investments, Giese et al. (2019a) emphasized the need to test ESG ratings within an economic model that allows for an assessment of causality. The authors identified three so-called economic-transmission channels to explain how ESG characteristics may influence the performance of corporate equity:

- **Cash-flow channel**: High-ESG-rated companies are more competitive and can generate abnormal returns, leading to higher profitability and dividend payments.

- **Idiosyncratic-risk channel**: High-ESG-rated companies are better at managing company-specific business and operational risks and therefore have a lower probability of suffering incidents that can impact their share price. Consequently, their stock prices display lower idiosyncratic tail risks.

- **Systematic-risk channel**: High-ESG-rated companies tend to have lower exposure to systematic-risk factors. Therefore, their expected cost of capital is lower, leading to higher valuations in a discounted-cash-flow (DCF) model framework.

In this paper, we build on this previous research to understand how much these economic-transmission channels for equity investments may also influence corporate bonds’ financial risk and performance characteristics.

Economically, the impact of these channels can be explained by looking at credit risk through the lens of the well-known Merton model (Merton 1974), which describes holding equities as a long call option on a company’s assets and holding bonds as a short put option on the company’s assets. The company’s debt level defines the strike level, and the assets minus the debt level define the distance to default.

Exhibit 2 explains how the transmission channels observed in equities may influence corporate bonds’ credit risk through differences in the probability distribution of a company’s assets within the Merton model:

- **Cash-flow channel**: Better profitability shifts the asset-value probability distribution to the right (A → B), leading to a greater distance to default.

- **Lower level of systematic risk** means less volatile asset value.

- **Lower level of idiosyncratic risk** means less downside skew in the asset-value distribution.
Exhibit 2: Hypothetical Impact of ESG Within Merton Credit-Risk Model

![Diagram showing the hypothetical impact of ESG within the Merton credit-risk model.]

While the Merton model has been shown to be overly simplistic for accurately quantifying the credit-default risk in practice (Bharath and Shumway 2008), we can use it to derive a qualitative understanding of how these transmission channels may conceptually impact default risks and spreads. Appendix A1 develops the transmission channels within a Merton model in more detail and derives some theoretical results that are important for understanding the empirical results in this paper: While these transmission channels were found to work consistently across the equity universe (the MSCI World Index in Giese et al. 2019a and MSCI ACWI Investable Market Index in Giese et al. 2020), we cannot assume the same holds in corporate bonds.

To start with, in equities, these transmission channels may in theory improve results on the upside (performance) and downside (risk protection), since economically speaking equity investors hold an in-the-money call option. By contrast, since a bond is effectively a short put option, improvements on the upside are limited (especially for IG bonds) and in theory we may expect stronger results in terms of downside protection. In addition, based on the assessment in Appendix A1, we expect the effectiveness of the transmission channels to depend on both an issuer’s credit quality and the bond’s maturity. The lower the credit quality and/or the longer the duration, the stronger the theoretical impact of the transmission channels should be. In the following, we will empirically test these hypothetical observations.

While the aforementioned research contributions in corporate-credit markets found a positive correlation between ESG characteristics and lower levels of OAS and lower levels of risk, they did not explicitly explore the economic rationale for the observed
effects. Moreover, they developed neither economic arguments nor empirical evidence for causal relationships between ESG characteristics and financial risk and performance.

In this paper, we will assess three fundamental questions:

• How far can the aforementioned economic-transmission channels be supported by empirical evidence in the corporate-credit market?

• To what extent can these transmission channels provide evidence for correlation or causal relationships?

• How far can MSCI ESG Ratings provide similar or different financial value compared with credit ratings?

The third question is important for practitioners who wish to understand whether ESG ratings can add financial value when used in addition to credit ratings in portfolio construction.

In this paper, we first explain the data that forms the basis of our analysis and its general characteristics. We then offer an overview of the methods used to validate the transmission channels. In the main body, we present our empirical findings. Finally, in the performance section, we show the risk and return properties of ESG portfolios over the full sample set.
Data and Methodology

The empirical analysis in this paper is based on a corporate-bond universe defined by the following indexes:

- MSCI USD Investment Grade (USD IG) Corporate Bond Index
- MSCI USD High Yield (USD HY) Corporate Bond Index
- MSCI EUR Investment Grade (EUR IG) Corporate Bond Index
- MSCI EUR High Yield (EUR HY) Corporate Bond Index

Collectively, these indexes include global developed-market IG and HY fixed-coupon corporate-bond issues rated by S&P/Moody’s and issued in USD or EUR, with certain exclusions applied based on predefined criteria such as size, maturity and credit ratings (refer to MSCI Fixed Income Indexes for details). To facilitate better comparison among the four indexes, we restrict the analysis universe to only those issuers with available ESG scores within each index and refer to this restricted universe as simply the “analysis universe.” In most of the analysis, we also include a composite universe defined as the combination of the four individual universes. Appendix A5 shows the profile of these indexes across various metrics.

Analysis Outline

To analyze the relationship between ESG scores and financial variables, we first divided the analysis universe into terciles based on industry-adjusted ESG scores, with each tercile containing equal numbers of issuers and each issuer represented by its market-value-weighted corporate bonds. To disentangle the impact of duration and ESG, one may consider creating duration-neutral terciles. However, we found that the differences in duration among the terciles were minimal; for that reason, creating duration-neutral terciles would have added complexity for little benefit (see Exhibit 3 for the composite universe and Appendix A3 for each sub-universe).
Foundations of ESG Investing in Corporate Bonds

Exhibit 3: Average Statistics Across ESG Terciles for Composite Universe

<table>
<thead>
<tr>
<th>ESG Terciles</th>
<th>Number of Issuers</th>
<th>ESG Score</th>
<th>OAS (bps)</th>
<th>Effective Duration</th>
<th>Spread Duration</th>
<th>MSCI Average Credit Rating</th>
</tr>
</thead>
<tbody>
<tr>
<td>T1 (Low)</td>
<td>478</td>
<td>2.4</td>
<td>409</td>
<td>4.5</td>
<td>4.6</td>
<td>11.3</td>
</tr>
<tr>
<td>T2</td>
<td>478</td>
<td>4.8</td>
<td>289</td>
<td>4.8</td>
<td>4.8</td>
<td>9.9</td>
</tr>
<tr>
<td>T3 (High)</td>
<td>478</td>
<td>7.5</td>
<td>183</td>
<td>5.0</td>
<td>5.0</td>
<td>8.0</td>
</tr>
<tr>
<td>Universe</td>
<td>1434</td>
<td>4.9</td>
<td>294</td>
<td>4.8</td>
<td>4.8</td>
<td>9.7</td>
</tr>
</tbody>
</table>

Mean of equal-weighted-average monthly samples over January 2014 to June 2020. Sample universe restricted to issuers with available ESG scores. The MSCI Average Credit Rating is the average rating of S&P and Moody's with lower credit rating number representing higher credit quality.

With respect to our analysis universe, we first analyze how ESG related to traditional corporate-bond metrics. We investigate (1) the correlations of ESG and individual pillar scores with credit ratings and (2) the price of ESG and its individual pillars based on option-adjusted spreads.

In the main body, we will assess the aforementioned transmission channels by examining how ESG score terciles were linked to financial variables that are part of the expected economic transmission, as summarized in Exhibit 4. For each transmission channel, we chose financial variables that are commonly used in financial literature and may support each transmission channel’s economic argument. A key finding from the theoretical analysis of transmission channels within the Merton model (Appendix A1) is that we expect the sensitivity of financial variables with respect to these economic-transmission channels to be a function of a bond’s credit quality and maturity. In other words, one can expect varying degrees of outcome depending on the market segment along these two dimensions (e.g., IG vs. HY and long-dated vs. short-dated debt).

With reference to Exhibit 4, the analysis of the cash-flow channels is based on standardized cross-sectional exposure to fundamental metrics such as net profit margin, return on equity and interest coverage ratio, all metrics sourced from Refinitiv. The entire
analysis of risk and return is based on “excess returns” — i.e., the residual return of a corporate bond after offsetting the return of duration-matched respective Treasurys/German Bunds. The idiosyncratic- and systematic-risk channels rely on a simplified excess-return risk model based on a cross-sectional regression accounting for both traditional (e.g., duration-times-spread (DTS) sector exposure) and credit style factors (e.g., quality, value, size, carry, risk and liquidity, all scaled by spread duration). Appendix A2 offers further details on the model used to calculate the systematic and idiosyncratic risks, as well as the method to compute the residual returns. It is important to note that the idiosyncratic risk of ESG portfolios that we obtained from this model is by design, after accounting for credit ratings (quality), among other factors.

Exhibit 4: Overview of ESG Tercile Analysis to Validate Transmission Channels

The chart illustrates the hypothetical financial impact of ESG (left) characteristics on credit related financial variables (right). Credit risk sensitivities (middle) explain the strength of this hypothetical relationship. Source: MSCI ESG Research

The study period for the analysis is January 2014 to June 2020, which was chosen to obtain enough ESG coverage of the underlying index to draw meaningful conclusions. All analysis was conducted at the issuer level and based on month-end data sampling.

For the excess return and risk performance, we analyzed the performance of the tercile portfolios computed at the end of each month over the subsequent month. Hence, we also include the terciles’ July 2020 performance computed based on scores at the end of June 2020.

The average fundamental statistics like number of issuers, ESG score, credit spread, duration and credit rating for various ESG terciles across all universes are detailed in Appendix A3.
ESG and Traditional Corporate-Bond Metrics

ESG ratings can help assess companies’ exposure to and management of environmental, social and governance risks that can have a potential impact on companies’ valuation. How does ESG in corporate bonds relate to traditional credit-rating analysis? What is the correlation between ESG ratings and individual pillar scores with credit ratings? How much overlap is there among the two ratings? How is ESG priced in the market? These are some of the questions we address in this section.

How ESG Correlates with Credit Ratings

To establish a relationship between ESG and credit ratings, we calculated cross-sectional correlations between various ESG metrics and the credit rating of the issuer for each respective universe. In Exhibit 5 we plot the sample mean of those monthly cross-sectional correlations with credit ratings for sector-adjusted pillar scores — namely, the environmental score (E score), social score (S score), governance score (G score), as well as the industry-adjusted ESG score that underlies the ESG Rating (ESG score) for the four issuer universes and the composite universe. Across the correlation matrix, we observe the strongest positive correlation between the ESG score and credit rating in the composite universe (at +0.37), followed by the E score (at +0.29). Correlations of S and G pillars within the composite universe have been notably weaker. It is interesting to note that within the four sub-universes, correlations were generally much lower, which means the observed correlations in the combined universe are mainly due to correlations across the sub-universes: HY issuers tend to have both lower MSCI ESG Ratings (see Exhibit A5 (c)) and lower credit ratings.

Exhibit 5: Correlation Between ESG Rating Measures and Credit Ratings

<table>
<thead>
<tr>
<th></th>
<th>Composite</th>
<th>USD IG</th>
<th>USD HY</th>
<th>EUR IG</th>
<th>EUR HY</th>
</tr>
</thead>
<tbody>
<tr>
<td>E score</td>
<td>0.29</td>
<td>0.11</td>
<td>0.10</td>
<td>-0.01</td>
<td>0.05</td>
</tr>
<tr>
<td>S score</td>
<td>0.15</td>
<td>0.04</td>
<td>0.04</td>
<td>0.01</td>
<td>0.10</td>
</tr>
<tr>
<td>G score</td>
<td>0.11</td>
<td>-0.05</td>
<td>0.09</td>
<td>-0.13</td>
<td>0.09</td>
</tr>
<tr>
<td>ESG score</td>
<td>0.37</td>
<td>0.23</td>
<td>0.09</td>
<td>0.00</td>
<td>0.13</td>
</tr>
</tbody>
</table>
Mean of month-end cross-sectional correlations (Spearman) of each ESG metric with credit rating over the period from January 2014 to June 2020 across universes.

Nonetheless, the question remains to what extent MSCI ESG Ratings may provide additional explanatory power for credit risk not fully captured by credit ratings, which we will assess in the main body of this paper, by controlling our financial analysis for credit quality to assess the residual effect from ESG.

The Price of ESG in Terms of Spreads

The OAS reflects the market price of credit risk, encapsulating the probability of default, loss given default and other considerations such as liquidity and risk aversion. Typically, bonds with lower credit ratings have wider OAS. How does OAS relate to the ESG rating of issuers?

Based on the Merton model (Exhibit 2) we would expect that, if the aforementioned transmission channels affect issuers’ credit risk, this should show up in OAS. However, as outlined in Appendix A1 we would expect the potential financial relevance of ESG in explaining credit risk to be a nonlinear function of both credit quality and maturity. As shown in Exhibit 6, we expect ESG to have a greater impact on HY than on IG; and within IG, we expect the impact to be greater on longer-dated bonds than on shorter-dated bonds. The maturity impact on HY depends on the distance to default — i.e., the closer to default, the impact on shorter-dated maturities is greater, but further from default the impact transitions to a greater impact on longer-dated maturities.
Exhibit 6: Illustrative Spread Sensitivity of Merton Model

Geometrical average of the Merton model’s risk sensitivities (Equations 5 and 6 in Appendix A1) and the location of HY and IG in EUR and USD on the sensitivity surface.

To validate these economic arguments, we will look at the average credit spreads of the lowest- (tercile 1) and highest-ESG-rated (tercile 3) issuers (based on industry-adjusted ESG scores), relative to their respective universes, as well as across E, S and G pillars. In addition, we will look at OAS differences across ESG score terciles for different maturities.

To start with, Exhibit 7a plots the average OAS across universes for ESG and individual E, S and G terciles, and Exhibit 7b shows the ESG spread, OAS spread (including relative OAS spread) and spread-duration spread, between high- and low-ESG-score terciles across the universes. In our setup we found that the differences in spread durations between the terciles were negligible across universes and hence we did not explicitly control for duration.
Exhibit 7a: Active OAS per ESG Terciles

- Average active OAS: ESG terciles
- Average active OAS: Environmental terciles
- Average active OAS: Social terciles
- Average active OAS: Governance terciles

Mean of month-end equal-weighted average OAS of the lowest (T1) and highest (T3) ESG score terciles, relative to their respective analysis universes, over the period from January 2014 to June 2020.

Exhibit 7b: Average ESG and OAS Spread Between High- and Low-ESG Terciles

<table>
<thead>
<tr>
<th></th>
<th>Composite</th>
<th>USD IG</th>
<th>USD HY</th>
<th>EUR IG</th>
<th>EUR HY</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) ESG score spread</td>
<td>5.1</td>
<td>5.0</td>
<td>4.2</td>
<td>4.8</td>
<td>5.0</td>
</tr>
<tr>
<td>(2) OAS spread, bps</td>
<td>-226</td>
<td>-33</td>
<td>-119</td>
<td>-15</td>
<td>-83</td>
</tr>
<tr>
<td>(3) OAS relative spread, %</td>
<td>-73.5</td>
<td>-24.2</td>
<td>-22.5</td>
<td>-13.9</td>
<td>-17.7</td>
</tr>
<tr>
<td>(4) Spread Duration spread</td>
<td>0.5</td>
<td>-0.3</td>
<td>-0.0</td>
<td>0.1</td>
<td>0.4</td>
</tr>
<tr>
<td>Ratio</td>
<td>(2) / (1)</td>
<td>44.3</td>
<td>6.6</td>
<td>28.3</td>
<td>3.1</td>
</tr>
<tr>
<td>Ratio</td>
<td>(3) / (1)</td>
<td>14.4</td>
<td>4.8</td>
<td>5.4</td>
<td>2.9</td>
</tr>
</tbody>
</table>

Mean of month-end equal-weighted averages, over the period from January 2014 to June 2020. (1), (2) and (4) are average spreads calculated as [ T3 (high) – T1 (low) ]
(3) is average relative spread calculated as [ T3 (high) – T1 (low) ] / Universe

Across all universes, exposure to high historical average MSCI ESG Ratings correlated with tighter OAS relative to low-ESG-rated securities. This trend continues across all individual pillars and markets. Interestingly, Exhibit 7a shows that the
overall ESG score generally resulted in more pronounced OAS-tercile differences across all issuer universes than the individual pillar scores — i.e., the total ESG score was the best identifier for differences of credit risk. This finding mirrors the findings in Giese et al. (2020) that, for equities (the MSCI World Index universe from end of 2006 to end of 2019), the total ESG score was a better descriptor for stock-specific drawdown risk than the individual pillar scores.

Exhibit 7b shows that the OAS spread between the high- and low-ESG-score terciles, per unit of ESG-score spread, is higher for HY than for IG, across both USD and EUR and for both absolute as well as relative OAS spreads (last two rows of the table). Overall, this confirms our conjecture that ESG was more relevant for differentiating risks in HY than in IG.

The second step is to validate the dependency of results on the time to maturity. Exhibit 8 compares OAS tercile differences per unit of ESG-score spreads, using the absolute (T3-T1) OAS spread\(^1\) for shorter-dated (less than five years to maturity) and longer-dated (more than five years to maturity) bonds across the universes. As noted above, we found that the differences in spread durations between the terciles were negligible across universes and hence did not explicitly control for duration. We found that OAS-spread compression per unit of ESG-score spread was higher for longer-dated bonds for EUR IG universe and was higher for shorter-dated bonds in both the USD HY and EUR HY universes. For the USD IG universe we found the spread compression was not materially different between the longer- and shorter-dated bonds.

Exhibit 8: Average ESG and OAS Spreads Across Time-to-Maturity Buckets

<table>
<thead>
<tr>
<th></th>
<th>USD IG</th>
<th></th>
<th>USD HY</th>
<th></th>
<th>EUR IG</th>
<th></th>
<th>EUR HY</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Short</td>
<td>Long</td>
<td>Short</td>
<td>Long</td>
<td>Short</td>
<td>Long</td>
<td>Short</td>
<td>Long</td>
</tr>
<tr>
<td>(1) ESG score spread</td>
<td>5.1</td>
<td>5.0</td>
<td>4.3</td>
<td>4.2</td>
<td>4.8</td>
<td>4.8</td>
<td>4.9</td>
<td>5.1</td>
</tr>
<tr>
<td>(2) OAS spread, bps</td>
<td>-28</td>
<td>-27</td>
<td>-156</td>
<td>-91</td>
<td>-14</td>
<td>-16</td>
<td>-92</td>
<td>-86</td>
</tr>
<tr>
<td>(3) Spread Duration spread</td>
<td>-0.1</td>
<td>0.2</td>
<td>-0.1</td>
<td>-0.2</td>
<td>0.0</td>
<td>0.1</td>
<td>0.2</td>
<td>0.4</td>
</tr>
<tr>
<td>Ratio</td>
<td>(2) / (1)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>5.5</td>
<td>5.4</td>
<td>36.3</td>
<td>21.7</td>
<td>2.9</td>
<td>3.3</td>
<td>18.8</td>
<td>16.9</td>
</tr>
</tbody>
</table>

Mean of month-end equal-weighted averages, over the period from January 2014 to June 2020. (1), (2) and (3) are average spreads calculated as \([T3 \text{ (high)} - T1 \text{ (low)}]\). Short/Long constitute bonds with <5/>5 years remaining time to maturity.

\(^1\) We exclude relative spreads from our maturity analysis as the option-adjusted spreads for short-dated bonds in IG were too small and consequently led to unreliable ratios.
Overall, our findings are broadly in-line with theoretical findings from the Merton model (Appendix A1 and Exhibit 6) that the spreads depended on credit quality (HY versus IG) and time to maturity in a nonlinear fashion.

**ESG Economic-Transmission Channels into Credit Risk**

We now investigate and validate the three transmission channels to explain how ESG characteristics may influence corporate-credit risk and performance.

**Cash-Flow Channel**

The cash-flow channel in equities showed that high-ESG-rated companies showed better return on equity (ROE), higher earnings and more stable earnings compared to low-ESG-rated companies. In this section, we will test the cash-flow transmission channel for corporate bonds along the following hypothesis:

1. Companies with a strong ESG profile are more competitive than their peers. For instance, this competitive advantage may arise from more efficient use of resources, better development of human capital or better innovation management. In addition, high-ESG-rated companies are typically better at developing long-term business and incentive plans for senior management.

2. High-ESG-rated companies use their competitive advantage to generate operational efficiencies and abnormal returns, which ultimately lead to higher profitability.

3. Higher profitability should result in higher cash-flow generation to cover debt-servicing expenses.

4. Ultimately this could lead to a greater distance to default or better credit quality.

In the context of the Merton model, the hypothesis is that better profitability shifts the asset probability distribution to the right, making the short put representing the bond deeper out-of-the money (Exhibit 2). In other words, higher profitability leads to a greater distance to default, and hence tighter OAS (all other factors remaining equal). In our cash-flow analysis, we looked at all fundamental metrics on a sector-neutral basis to make a fairer comparison versus peers.
We test the above transmission channel step by step:

**Step 1: Were companies with high ESG ratings more competitive?** We use companies’ net profit margins as an indicator of competitiveness. Exhibit 9 shows the active net-margin exposure on a sector-neutral basis for ESG terciles. We observe that companies with higher ESG ratings showed a strong competitive advantage in terms of profit margins compared to lower-rated companies, which is in-line with the intuition of the cash-flow transmission channel.

Exhibit 9: Relative Competitiveness of ESG Terciles (Active Net-Margin Exposure)

Step 2: Were companies with high ESG ratings more profitable? Exhibit 10 looks at the ROE exposure of ESG terciles on a sector-neutral basis: We observe that across all universes, high-ESG-rated companies showed higher levels of ROE compared to low-rated companies.
Exhibit 10: Profitability of ESG Terciles (Active ROE Exposure)

Step 3: Did companies with High ESG Ratings Have stronger interest coverage ratios? The final question in the cash-flow channel is whether higher profitability of high-ESG-rated companies translated into stronger interest coverage ratios, as measured by their cash-flow from operations (CFO) to interest expense ratio, which we analyze in Exhibit 11. We observed that higher-ESG-rated companies had on average higher interest coverage ratio exposure, on a sector neutral basis, than low rated companies across all universes.

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2 We exclude financial companies when looking at interest coverage ratios due to the nature of their business model.
Step 4: Have companies with high ESG ratings shown greater distance to default?

Ultimately, we are interested in whether high-ESG-rated companies — through the economic arguments of better competitiveness, better profitability and better interest-rate coverage — have ultimately shown a wider distance to default in the logic of the Merton model. In Exhibit 12, we proxy distance to default (which is hard to observe) by credit quality. Credit quality is defined as the market-value-weighted average credit rating aggregated from the issuers’ bonds in the respective universes.
Mean of month-end equal-weighted average sector-neutral exposures to companies’ credit quality (as defined by its average credit rating) relative to their respective analysis universes, over the period from January 2014 to June 2020.

We found data supporting the assertion that high-ESG-rated issuers (tercile 3) had a higher exposure to quality, which reflects lower default risks (assuming recovery values are fixed) within their respective universes, especially when compared to lowest-ESG-rated issuers (tercile 1), as can be seen in Exhibit 12. Although the relative profile of tercile 3 versus tercile 1 is consistent across IG and HY in both USD and EUR, the difference is most pronounced at the composite level.

It is important to mention that, in our fundamental analysis of the cash-flow channel, we focused on profitability-related variables — i.e., net margins, ROE and interest coverage — that potentially support the academic argument that ESG characteristics may have a positive impact on distance to default since they are financial measures that typically enter standard credit-rating models. Therefore, we haven’t controlled for credit quality in this analysis, since controlling for credit quality would lead to a circular regression. In other words, the cash-flow-channel analysis above provided a fundamental explanation for why ESG ratings and credit ratings showed some degree of positive correlation in our introductory analysis, particularly in the composite universe, and weaker correlations at the IG and HY levels, given these credit segments already conditioned on credit quality. In summary, good ESG characteristics were associated with financial properties such as better interest coverage ratio, better ROE and better profit margins, all of which support better credit ratings.

Systematic-Risk Channel

We now assess the systematic-risk channel for each of the USD and EUR IG and HY individual universes as well as for the composite universe (restricted to issuers with available ESG scores), for the sample period January 2014 to June 2020. All risk and factor calculations were performed using a cross-sectional regression model detailed in Appendix A2.

Valuation Channel

For equities, Eccles, Ioannou and Serafeim (2011); El Ghoul et al. (2011); and Gregory et al. (2014) argued that a strong ESG profile leads to higher valuations through the following transmission process:

1. Companies with a strong ESG profile are less vulnerable to systematic market shocks and therefore show lower systematic risk. For instance, energy- or commodity-efficient companies are less vulnerable to changes in energy or commodity prices than less efficient companies, and therefore their share price tends to show less systematic market risk with respect to these risk factors.
2. In capital-asset-pricing models (cf. Ruefli 1999), the beta of a company has two important functions: Beta measures the systematic-risk exposure of companies (i.e., lower beta means less systematic risk), and it translates the equity risk premium into the required rate of return for the individual company. Therefore, lower systematic risk means that a company’s equity has a lower value for beta, and therefore investors require a lower rate of return. Ultimately, this translates into a lower cost of capital for a company. This argument can be extended to multi-factor models, where the systematic-risk exposure of a company is measured by several factor loadings instead of one beta.

3. Finally, a lower cost of capital leads directly to the last step of the transmission mechanism: In a DCF model framework, a company with lower cost of capital, ceteris paribus, would have a higher valuation.

We will assess to what extent a similar transmission channel can be established for corporate credit as follows:

We will empirically validate each step in the chain:

**Step 1: Lower systematic risk.** As in the analogous analysis for equities (Giese et al. 2019a), we use the systematic volatility as a measure for systematic risk. Exhibit 13 compares the average systematic volatility of ESG-rating-score terciles across universes. We found issuers with high ESG ratings (tercile 3) had shown less systematic volatility than those with low ESG ratings (tercile 1), and the impact was more pronounced in HY compared to IG in the respective currency market. Overall, this result is in-line with the hypothesis that companies with high ESG exposure have lower systematic risk.
Exhibit 13: Systematic Volatility of ESG Terciles

Average annualized equal-weighted systematic risk (from the cross-sectional regression model detailed in Appendix A2) of the lowest (T1) and highest (T3) ESG-score terciles, over the period from January 2014 to June 2020.

To analyze the impact on the maturity dimension, in Exhibit 14 we plot the systematic risk spread between the highest- and lowest-ESG-rated issuers, across the two time-to-maturity buckets: short (less than five years to maturity) and long (more than five years to maturity). We observed a stronger risk reduction at the longer end of the maturity segment in both the USD and EUR IG universes. In the HY universe, we observed higher risk reduction at the shorter end of the spectrum for EUR HY but marginally lower risk reduction at the shorter maturity for USD HY.

Exhibit 14: Systematic-Volatility Spread of ESG Terciles Across Maturities

Average equal-weighted systematic-risk spread between the highest (T3) and lowest (T1) ESG-score terciles, (T3-T1), across the two time-to-maturity buckets: short (<5 years to maturity) and long (>5 years to maturity).
years to maturity), over the period from January 2014 to June 2020. Systematic risk calculated from cross-sectional regression model as detailed in Appendix A2.

**Step 2: Lower cost of capital.** The link between companies’ ESG characteristics and cost of capital has been widely researched by both academics and industry practitioners. For instance, El Ghoul et al. (2011) show that higher-ESG-rated companies had lower costs of capital according to four different measures while controlling for common factor exposures. More specifically for equities, Lodh (2020) showed that companies with high ESG ratings showed lower cost of equity capital than low-rated companies in both developed and emerging markets and across all 11 Global Industry Classification Standard (GICS®) sectors. In the corporate-bond space, cost of debt capital can be measured as the average credit spread of an issuer’s outstanding bonds, which we used in Exhibit 15 to compare the cost of debt capital of high- versus low-ESG-rated terciles. For all universes we observed that the lowest-ESG-rated companies had higher average credit spreads, which is in-line with the intuition that high-ESG-rated companies have lower average cost of debt capital.

**Exhibit 15: Average Issuer-Specific Credit Spreads of ESG Terciles**

![Graph showing average issuer-specific credit spreads of ESG terciles](image)

Mean of month-end equal-weighted average OAS of the highest (T3) and lowest (T1) ESG-score terciles, over the period from January 2014 to June 2020.

**Do Credit Ratings Fully Reflect ESG Risks in the Cost of Capital?**

To assess whether credit ratings fully reflect ESG risks in the cost of capital, we measured the carry exposure of the lower and upper ESG terciles, where the carry exposure reflects differences in the OAS intra-credit-rating buckets (Exhibit 16). We found that after adjusting for credit quality, the higher-ESG-rated issuers still had

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3 GICS is the global industry classification standard jointly developed by MSCI and Standard and Poor’s.
lower spreads compared to the lower-ESG-rated issuers, suggesting that ESG risks may not have been fully reflected in credit ratings.

Exhibit 16: Average Active Carry Exposure of ESG Terciles

Mean of month-end equal-weighted average carry exposures relative to their respective analysis universes, over the period from January 2014 to June 2020. Carry exposure for an issuer is defined as log OAS standardized within the same credit-rating peer universe.

Step 3: Higher valuation. Ultimately, we expect lower costs of capital to result in higher valuations for the debt, given a lower discount factor. Exhibit 17 plots the average sector-neutral value exposures of ESG terciles, relative to their respective universes. The higher value exposure for an issuer means that the issuer is relatively cheaper compared to its intrinsic value (see Exhibit A2 for the complete of the value factor). The exhibit shows that higher ESG ratings (T3) coincided with lower value exposures — i.e., they have higher valuations in terms of market spread (OAS) being wider than the fair-value spread.
Overall, in our analysis we found that the higher ESG-rated corporate bonds had lower systematic risk, lower spreads (within credit ratings) and therefore higher valuations. The results are in line with the analogous analysis for equities (Giese et al. 2019a).

**Idiosyncratic-Risk Channel**

The last issuer-specific transmission channel relates how well high-ESG-rated companies manage their business and operational risks beyond what is explained by credit ratings. Their bond prices (excess returns) typically have shown lower idiosyncratic tail risk, as outlined as follows:

1. Companies with strong ESG characteristics typically have above-average risk-control and compliance standards across the company and within their supply-chain management.
2. Because of better risk-control standards, high-ESG-rated companies suffer less frequently from severe incidents such as fraud, embezzlement, corruption or litigation cases (cf. Hong and Kacperczyk 2009) that can seriously impact the value of the company and therefore the company’s stock price. Hoepner, Rezec and Siegl (2017) call this an “insurance-like protection of firm value against negative events.”

3. Less frequent risk incidents ultimately lead to less stock-specific downside or tail risk in the company’s stock price.

In the following we adapt this approach in the context of corporate bonds using the aforementioned Merton model: Risks that materialize as severe corporate events that hit the share price can potentially have a severe impact on a company’s asset-price volatility and/or distance to default.

Once again, we would like to empirically verify these three steps in the transmission channel:

**Step 1: Better risk management.** To what extent high-ESG-rated issuers have better risk management is not directly observable in the market. However, the assessment of companies’ risk management capabilities with respect to potential financially relevant risks is the core principle of the MSCI ESG Rating model. We use steps 2 and 3 of the transmission channel to validate the extent to which the ESG rating has been successful at identifying idiosyncratic risks.

**Step 2: Lower likelihood of severe incidents.** To assess the ability of issuers’ risk management functions to successfully mitigate severe incidents that can lead to a deterioration in credit quality, we first looked at the magnitude of large, adverse residual excess returns (i.e., after adjusting for common factors, including quality, as measured by credit ratings). More precisely, we measured the value-at-risk of 12-month forward residual returns at the 10% level, of each ESG-rating tercile in the respective universe (see Exhibit 18’s left plot). On average, issuers in the lower ESG tercile had a higher value-at-risk than issuers in the upper tercile across each universe. Second, we measured the percentage of issuers, in the bottom decile of forward 12-month residual returns, that fell in each ESG-rating tercile. We found that, across each universe and with the exception of EUR IG, the percentage of issuers below the lowest residual-return decile were most often found in the lower-ESG-rating tercile (see Exhibit 18’s right plot).
Exhibit 18: Value-at-Risk and Percentage of Issuers in the Tail by ESG Profile

Mean tail return is calculated as the 10th percentile of forward 12-month residual returns, and likelihood of tail event is calculated as fraction of issuers in the lowest decile of forward 12-month residual returns, for the lowest (T1) and highest (T3) ESG-score terciles, for each of the respective analysis universes, over the period from January 2014 to June 2020. Residual returns are returns from the cross-sectional regression model that are left unexplained by all model factors (including credit-quality factor) as detailed in Appendix A2.

Step 3: Lower idiosyncratic risks. To illustrate how ESG characteristics are linked to idiosyncratic risks, Exhibit 19 compares the average residual volatility of issuers in the top and bottom ESG terciles for each market. This metric measures the volatility of excess returns that is not explained by the common factors, such as credit ratings or DTS sector exposures. We note that the differences in spread duration of each tercile within the same universe are small, and so we can rule out differences in the idiosyncratic risk stemming from biases in spread duration. We find lower levels of idiosyncratic risk for high-ESG-rated issuers compared to lower-ESG-rated issuers in the HY universe, while there are muted differences in IG. The muted difference between tercile 1 and tercile 3 within IG could be partly due to the lower levels of idiosyncratic risks in general.
Did ESG Identify Tail Risks Not Fully Captured by Credit Ratings?

We observed that companies with good ESG characteristics showed a lower likelihood of suffering from issuer-specific risks than companies with low ESG Ratings, after accounting for common factors including credit ratings. Therefore, this provides evidence for ESG ratings to add a degree of information that can potentially help investors to manage or mitigate risks in their bond portfolios.

Effectiveness of ESG Across Issuer Universes

To sum up, we were able to empirically verify the three transmission channels we identified in equities (Giese et al. 2019b), but using credit-related financial variables as target variables. However, some of the insights obtained are very specific to fixed income: The first transmission channel explains how ESG characteristics are associated with financial variables that typically directly enter credit-risk analysis and therefore explains why and how ESG ratings are positively correlated with credit ratings. It also shows why ESG ratings may be used within traditional credit-risk analysis. The second and third channels account for credit-related factors, thus presenting evidence that ESG characteristics provide additional explanatory power for credit risk, even for investors who already use credit ratings. Finally, we showed that the impact of ESG on systematic risk varies between (1) IG and HY bonds and (2) shorter- and longer-dated maturities in a nonlinear manner.
Performance of ESG in Corporate Bonds

The analysis of the transmission channels in the previous sections illustrated the relationships between companies’ ESG characteristics and their fundamental risk characteristics. The logical question is how far these fundamental differences may have influenced the actual performance of bonds.

Therefore, we evaluate the risk and return of industry-adjusted ESG score terciles by considering the subsequent month’s performance of the terciles computed at the end of each month, over the sample period from January 2014 to July 2020. We calculated excess returns of the various terciles across universes by subtracting the average duration-matched respective Treasury/German Bund returns of the tercile from the average total return of the tercile. We consider total returns calculated using MSCI’s methodology for fixed-income indexes before adjusting for any transaction-related costs.

Average Performance of ESG and Its Pillars

We first analyze the excess return and excess risk of the ESG-score terciles across various universes. With reference to Exhibit 20, there are several key observations based on the analysis (see also Appendix A4 for detailed tabular results). First, a significant improvement in ESG scores had been realized with reduced excess risk and, in some cases, higher excess returns. For example, for the composite universe, the highest-ESG-rated tercile (T3) showed higher excess return as well as lower excess risk than both the lowest tercile (T1) and the universe. Second, we observe that tercile 3 clearly showed a lower level of excess risk compared to tercile 1 across all issuer universes. This finding is in-line with the risk-reducing effect we found in the idiosyncratic- and systematic-risk channels described above. Finally, performance differences were much stronger in HY than in IG, which is in-line with our observation above that the transmission channels were more effective in HY.
Exhibit 20: Excess Return and Excess Risk of ESG Terciles

Average equal-weighted excess return and risk of the lowest (T1) and highest (T3) ESG-score terciles and their corresponding universes, over the period from January 2014 to July 2020. Excess returns calculated by subtracting the duration-matched respective Treasury/German Bund returns from the total returns (prior to transaction costs). Excess risk is volatility of the excess returns.

Exhibit 21 extends this performance and risk assessment to the analogous tercile analysis based on the individual E-, S- and G-pillar scores for the composite universe. It is quite interesting to note that, among the three pillars, the S-pillar score showed the strongest (T3 - T1) difference in performance, while the E pillar showed the highest reduction in both risk and maximum drawdown.
Exhibit 21: Performance of Individual E, S and G Pillars Compared to Total ESG

Average equal-weighted excess return, excess risk, risk-adjusted excess return and maximum drawdown spread between the highest (T3) and lowest (T1) rated E-, S- and G-pillar score and industry-adjusted ESG score terciles for the composite universe, over the period from January 2014 to July 2020. Excess returns calculated by subtracting the duration-matched respective Treasury/German Bund returns from the total returns (prior to transaction costs). Excess risk is volatility of the excess returns.

One more finding in Exhibit 21 is worth mentioning: The aggregate MSCI ESG Rating score showed stronger results in terms of reducing risks than the three individual pillar scores, which means that the aggregation of E, S and G risks, using industry-specific weights, into a combined ESG score added financial value, which is similar to the findings for equities in Giese et al 2020.

Did ESG Add Value over Traditional Credit Factors?

We recognize that excess returns may include returns stemming from a credit-rating bias, and perhaps other factor biases inherent in ESG portfolios. Therefore, in addition to excess returns, we show high-level performance results for residual returns. The residual returns are simply excess returns minus common factor returns from the credit model (see Appendix A2).
Exhibit 22 plots the residual return and risk spread (T3 - T1) for each universe. This gives us more transparency on the impact of ESG ratings after accounting for common style factors, such as credit ratings. We found that the upper-ESG-rating tercile outperformed the lower tercile in each universe, except for EUR HY. In terms of risk, the upper-ESG-rating tercile realized lower volatility than the lower tercile across all universes, and this risk reduction was more pronounced among USD IG bonds.

Exhibit 22: Residual-Return Spread and Residual-Risk Spread of ESG Terciles

Similarly, Exhibit 23 shows the residual-return and -risk performance of the highest (T3) tercile relative to the lowest tercile (T1) across the three individual pillars and ESG-score terciles, for the composite universe. We found that the aggregate ESG-rating score showed a marginally lower risk spread than the three individual pillar scores, which again emphasized the value added by the combined ESG score even after adjusting for common factors such as credit ratings. We also note that the G pillar showed the weakest results after adjusting for all the common factors, which could be because governance-related risks were better understood by market participants and may therefore have been priced in by the market (through some common factor) — in contrast to social and environmental risks, which may be relatively less exposed by traditional credit analysis.
Exhibit 23: Residual-Return Spread and Residual-Risk Spread of ESG Terciles

Average equal-weighted residual return and risk spread between the highest- (T3) and lowest-rated (T1) E-, S- and G-pillar scores and industry-adjusted ESG score terciles for the composite universe, over the period from January 2014 to July 2020. Residual returns are returns from the cross-sectional regression model that are left unexplained by all the model factors (including credit quality factor) as detailed in Appendix A2.

Overall, we found that MSCI ESG ratings provided additional information relevant to the identification of risk that has not been fully captured in credit ratings.
Conclusion

We analyzed the effectiveness of three transmission channels identified in previous research (the cash-flow channel, systematic-risk channel and idiosyncratic-risk channel) in developed-market corporate bonds (USD and EUR and IG and HY). Based on a conceptual analysis using the Merton credit-risk model, we expected these transmission channels to be potentially most effective in terms of downside protection and to show more financially significant results in HY than in IG. Across all the empirical tests conducted in this paper, these two economic arguments were in-line with the empirical results.

Our analysis of the cash-flow channel showed that high-ESG-rated issuers showed stronger financials (better profit margins, higher ROE and higher interest-rate coverage) than low-rated issuers, which ultimately led to better credit quality. This transmission channel provides an explanation for the observed positive correlation between ESG ratings and credit ratings.

The analysis of risks showed that high-ESG-rated issuers showed lower levels of systematic and idiosyncratic risks after controlling for traditional DTS factors and style factors, including credit quality, which means there was a residual effect in explaining credit risk not yet captured by credit ratings. The reduction in systematic risk was higher in HY than in IG; and within IG, the impact was greater among longer-dated bonds than shorter-dated bonds.

Our performance analysis showed that investing in high-ESG-rated issuers did not result in underperformance. In fact, the risk-adjusted returns were slightly better than in the overall universe.

All in all, in our analysis we found that ESG-related risks were not fully captured in credit ratings, which means ESG ratings provided extra information to investors. We also observed that the aggregate MSCI ESG Rating showed stronger results in terms of reducing risks than the individual pillars, which means that aggregating E, S and G risk into a combined ESG rating added financial value.
References


Banking & Finance, Number 13-010, School of Management, University of St Andrews.


Appendix

Appendix A1: Merton Model Framework

We are using a standard Merton model for credit risk to measure the probability of default (PD). Therefore, we model companies’ value of assets (A) and liabilities (L). The price of the bond B can be approximated by a short put option on the company’s assets:

\[ B = A \cdot N(-d_1) - L \cdot e^{-rT} \cdot N(-d_2) \]  

(1)

Where \( N(\cdot) \) denotes the cumulative standard normal distribution, \( r \) = risk free rate, \( T \) = time to maturity and

\[ d_1 = \frac{\ln\left(\frac{A}{L}\right) + (r + 1/2\sigma_A^2)T}{\sigma_A \sqrt{T}} \]  

and

\[ d_2 = d_1 - \sigma_A \sqrt{T} \]  

\( \sigma_A \) = asset price volatility

In this model setup, the default probability is given by

\[ PD = N(-d_2) \]  

(2)

The asset volatility \( \sigma_A \) is not directly measurable, but it can be derived from the observable stock price volatility \( \sigma_E \), since in the Merton model the stock is the long call option on the company’s assets and therefore we have (with \( N(d_1) \) denoting the Delta of the long call):

\[ \sigma_E = \frac{A}{E} N(d_1) \sigma_A \]  

(3)

Which can be used to replace the asset volatility by the observable equity volatility \( \sigma_E \). Relation (3) also provides the economic rationale for analyzing the transmission channels through the Merton model: Giese et al 2019a observed that high-ESG-rated companies show lower systematic and lower residual stock-price volatility (idiosyncratic and systematic risk channels), which through equation (3) affects the unobservable asset volatility in a similar way. In addition, the authors found better and more stable earnings for high-ESG-rated companies (cash-flow channel), which we can model in the Merton framework as an increase in the distance to default defined as A/L.

This raises the question of how sensitive default probabilities and spreads may (hypothetically) be with respect to differences in ESG related distance to default A/L and stock specific and systematic risks, modelled through the asset price volatility \( \sigma_A \).

Therefore, we need to derive the sensitivity of the default probability (2) with respect to changes in the asset value (=changes in distance to default) and asset volatility:

\[ \frac{\partial PD}{\partial A} = -\frac{n(d_2)}{A \sigma_A \sqrt{T}} \]  

(4)
\[
\frac{\partial PD}{\partial \sigma_A} = -n(d_2) \left( \sqrt{T} - \frac{d_2}{\sigma_A} \right)
\]

Where \( n() = N'(\cdot) \). Exhibit A1 shows how sensitive the probability of default (PD) in the Merton model is to changes in asset volatility on an absolute basis and relative basis for different levels of distance to default = \( A/L \).

These PD-sensitivities can be translated into sensitivities of the spread \( s \) via the approximation:

\[ s = PD \times LGD \] (loss given default)

Which we will use to illustrate spread sensitivities in this paper (assuming constant LGD in our illustrations).

**Exhibit A1: Stylized Spread Sensitivities in the Merton Model**

Spread sensitivity with respect to changes in distance to default
The essential observation from Exhibit A1 is that the amount of impact the aforementioned transmission channels can have strongly depends on an issuer’s distance to default and the bond’s maturity. For instance, for short-dated bonds with high distance to default even a strong improvement of risks through ESG would hardly impact the bond price and its spread, since the spread sensitivity in Exhibit A1 is low. By contrast, a long-dated bond with low distance to default may be affected significantly by the economic-transmission channels. In brief, we expect clear differences between HY and IG bonds as well as short-dated versus long-dated bonds in our economic analysis of transmission channels.
Appendix A2: Cross-Sectional Regression Model

In order to calculate the systematic and idiosyncratic risks of various ESG portfolios described in the paper we used a cross-sectional regression model wherein we try to explain the weekly excess local price returns of the security using beginning-of-the-week traditional DTS factor exposures and a set of customized style factor exposures. The regression equation used is as follows:

\[ ER_{lt} = \sum_{k=1}^{11} (DTS_{lt-1}^k \cdot f_{lt}^k) + \sum_{s=1}^{m} (SpDur_{lt-1}^s \cdot Z_{lt-1}^s \cdot f_{lt}^s) + s_{lt}; \ i \epsilon (1, n_t) \]

Where:

- \( ER_{lt} \) = Local currency price return – Dur-matched respective Treasury/German Bund return
- \( DTS_{lt-1}^k \) = Security DTS, if security \( \epsilon \) k\textsuperscript{th} ICS sector 0, otherwise
- Security DTS = \( \left\{ \begin{array}{ll} \text{SpDur} \times 30/10000, & \text{OAS(bps) } \leq 30 \\ \text{SpDur} \times \text{OAS(bps)}/10000, & 30 < \text{OAS(bps)} < 2500 \\ \text{SpDur} \times 2500/10000, & \text{OAS(bps)} \geq 2500 \end{array} \right. \)
- \( f_{lt}^k \) = DTS factor return for k\textsuperscript{th} GICS sector
- \( Z_{lt-1}^s \) = Security standardized exposure to s\textsuperscript{th} style factor
  \[ Z = \frac{x - \mu}{\sigma} \]
  - \( x \) = security exposure to s\textsuperscript{th} style factor
  - \( \mu \) = regression weighted average of \( x \)
  - \( \sigma \) = equal weighted standard deviation of \( x \)
- \( f_{lt}^s \) = Factor return for s\textsuperscript{th} style factor
- \( s_{lt} \) = Security residual return
- \( n_t \) = Number of securities in regression universe
- \( m \) = number of style factors

We ran five different weekly weighted-least-squares (WLS) regressions with square root of security market value as regression weights — one each for four individual universes and one for the composite universe. In each regression model we used the same set of six style factors that are standardized within different universes, while some are orthogonalized to DTS factor. The Exhibit A2 below details the various style factors used in the regression models.
Exhibit A2: Style Factors Used in Regression Model

<table>
<thead>
<tr>
<th>Style factor</th>
<th>Definition</th>
<th>Standardized w.r.t.</th>
<th>Orthogonalized w.r.t.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Liquidity</td>
<td>Bid-ask Spread</td>
<td>Index</td>
<td>DTS</td>
</tr>
<tr>
<td>Low size</td>
<td>Log Issuer Outstanding Debt</td>
<td>Index</td>
<td>-</td>
</tr>
<tr>
<td>Carry</td>
<td>Log OAS</td>
<td>Index X Credit rating</td>
<td>DTS</td>
</tr>
<tr>
<td>Low risk</td>
<td>Spread duration (SpDur)</td>
<td>Index X Credit rating</td>
<td>DTS</td>
</tr>
<tr>
<td>Quality</td>
<td>Credit rating</td>
<td>Index X GICS sector</td>
<td>-</td>
</tr>
<tr>
<td>Value</td>
<td>Residual from regression of OAS on log(SpDur), Credit ratings and Size; OLS regression across DTS quintiles</td>
<td>Index X GICS sector</td>
<td>-</td>
</tr>
</tbody>
</table>

* Wherever the style factor is orthogonalized, it is re-standardized as per the table.

Risk Calculation

Using the regression equation defined above, we predict the systematic and idiosyncratic risk of various portfolios as

\[ Systematic \ risk = \sqrt{W.B.F.B^T.W^T} \]

\[ Idiosyncratic \ risk = \sqrt{W.S.W^T} \]

Where:

- \( W \) = security weight matrix (1xn)
- \( B \) = security exposure matrix (nxb); \( b=17, 11 \) DTS factors + 6 style factors
- \( F \) = factor return covariance matrix (bxb)
- \( S \) = security residual return variance diagonal matrix (nxn)

To get equal-weighted risk predictions, we equal weight the universe at issuer level with securities within each issuer weighted pro rata based on its market value. The security exposures we use are as of date of regression, as opposed to beginning-of-the-week values used in the regression equation, in order to get predicted risk.

The factor-return covariance matrix \( F \) is estimated from the history of weekly factor returns estimated from the regression model. The return history is exponentially weighted, using a longer two-year half-life for correlations and a shorter 13-week half-life for volatilities, in order to strike a good balance between responsiveness and robustness of the covariance matrix. An expanding window of factor returns is used,
with at least two years of data available for each factor. Similarly, the security residual return variance diagonal matrix ($S$) is estimated from the exponentially weighted expanding window history of weekly estimated security residual returns using a 13-week half-life.
### Exhibit A3: Average Statistics Across ESG Terciles

<table>
<thead>
<tr>
<th>Universe</th>
<th>ESG terciles</th>
<th>Number of issuers</th>
<th>ESG score</th>
<th>OAS (bps)</th>
<th>Effective duration</th>
<th>Spread duration</th>
<th>MSCI Average Credit Rating</th>
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</thead>
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Mean equal-weighted-average of monthly samples over January 2014 to June 2020. Sample universe restricted to issuers with available ESG scores. The MSCI Average Credit Rating is the average rating of S&P and Moody’s, with lower credit rating number representing higher credit quality.
## Exhibit A4 (a): Average Excess Performance Across ESG

<table>
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<tr>
<th>ESG terciles</th>
<th>Universe</th>
<th>Tercile</th>
<th>Excess return (%)</th>
<th>Excess risk (%)</th>
<th>Risk adj. excess return</th>
<th>Active excess return (%)</th>
<th>Active excess risk (%)</th>
<th>Risk adj. active excess return</th>
<th>Correlation</th>
<th>Beta</th>
<th>ESG score</th>
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</thead>
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*Equal-weighted average excess performance for low- and high-ESG-score terciles, over January 2014 to July 2020. Return and risk numbers are annualized. Beta is measured with regard to the universe.*
Exhibit A4 (b): Average Excess Performance Across E, S and G Terciles

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<th>Excess return (%)</th>
<th>Excess risk (%)</th>
<th>Risk adj. excess return</th>
<th>Risk adj. active excess return</th>
<th>Active excess return (%)</th>
<th>Active excess risk (%)</th>
<th>Risk adj. active excess return</th>
<th>Risk adj. active excess return</th>
<th>Correlation</th>
<th>Beta</th>
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<td>7.81</td>
<td>0.33</td>
<td>0.40</td>
<td>1.66</td>
<td>0.24</td>
<td>0.98</td>
<td>0.96</td>
<td>6.03</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Equal-weighted average excess performance for low and high E, S and G pillar score terciles, over January 2014 to July 2020. Return and risk numbers are annualized. Beta is measured with regard to the universe.
Appendix A5: Corporate-Bond Universe and ESG Profile

Exhibit A5 (a): Profile of MSCI USD and EUR, IG and HY Corporate-Bond Indexes

Sample period: January 2014 to June 2020.

Exhibit A5 (a) shows the profile of the individual indexes used in the paper’s analysis, across various metrics. We found that the EUR HY segment was clearly smaller in terms of both number of bonds and issuers compared to the USD IG, USD HY and EUR IG markets. Spreads were generally higher in the USD market in both IG and HY bonds compared to their respective EUR counterparts. For both currencies the average effective duration in the IG market was significantly higher than in the high yield market.

In terms of country exposure, Exhibit A5 (b) gives a snapshot of the top 5 country allocations as of 30th June 2020. Within the USD market, dollar weight allocation to US exceeded 80%. Within the EUR market, US also had a meaningful presence in EUR IG (18.2%) and EUR HY (13.7%). The rest of the EUR market is dominated by European countries.

Exhibit A5 (b): Country-Weight Allocation of Corporate-Bond Indexes
Rank | USD UG | USD HY | EUR IG | EUR HY
--- | --- | --- | --- | ---
Top 5 | Country | Weight | Country | Weight | Country | Weight | Country | Weight
1 | US | 82.8% | US | 83.8% | FR | 22.0% | IT | 16.1%
2 | GB | 5.0% | CA | 4.4% | US | 18.2% | US | 13.7%
3 | CA | 2.5% | NL | 2.8% | NL | 15.3% | FR | 12.7%
4 | NL | 2.4% | GB | 2.7% | GB | 9.5% | NL | 11.5%
5 | JP | 2.1% | IE | 1.2% | DE | 7.7% | LU | 11.2%

Top-5 domicile countries by market value weight across indexes, as of June 30, 2020.

**ESG Profile**

This paper uses MSCI ESG Ratings throughout to analyze how an ESG overlay impacted different segments of the corporate-bond portfolios. MSCI ESG Research LLC provides both an industry-adjusted ESG score and individual (absolute) E, S and G pillar scores, all scored on a 0-10 scale, where 0 is worst and 10 is best (refer to MSCI ESG Ratings Methodology for details). Exhibit A5 (c) shows the ESG score for each of the corporate-bond indexes along with its availability or coverage within each index.

**Exhibit A5 (c): ESG Rating Score and Coverage Across Indexes**

Sample period is January 2014 to June 2020.

Over the sample period, we observe two clear trends. First, IG corporate bonds had a higher ESG score than HY bonds vis-à-vis their respective currencies; and second, EUR IG (HY) corporate bonds had notably higher ESG scores than USD IG (HY). The latter observation is in-line with the findings in Giese et al. (2019b) that average MSCI ESG Ratings for equities were higher in developed Europe than in North America.

The ESG score coverage varies across the four indexes, with USD IG having the largest coverage (~95% recently) and EUR HY having the smallest coverage (~70%...
recently). In order to facilitate better comparison among the four indexes, we restricted the analysis universe to only those issuers with available ESG scores within each index and refer to this restricted universe as simply “analysis universe.”

In most of our analysis, we also include a composite universe defined as the combination of the four individual universes. Exhibit A5 (d) shows the number of issuers and total market capitalization in USD for each of the analysis universes.

Exhibit A5 (d): Coverage and Size of the Analysis Universes

Sample period is January 2014 to June 2020.

MSCI ESG Ratings are derived from industry-adjusted ESG scores. So, in order to make better comparisons, we normalized the individual E, S and G absolute pillar scores within GICS sectors at the composite-universe level. Throughout the paper the individual pillar scores refer to this sector-adjusted scores, unless specified otherwise.

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4 The evolution in coverage has had a notable impact on the ESG scores, particularly the EUR HY index. In EUR HY, as more unlisted companies were added to ESG coverage, the ESG score showed a steady decline over the sample period.
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