Primary Corporate Bond Markets and Social Responsibility *

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ABSTRACT

We document a robust, negative relation between corporate environmental and social (ES) performance and corporate bond issue spreads, even after controlling for ratings and other firm characteristics. Consistent with our theoretical model, this relation is due to bonds rated BBB or below, with spread-reductions of up to 98 basis points. These effects are predominantly related to product and employee scores. We do not find time trends for the ES-spread relation but document strong supply effects, as the share of issuers with good ES ratings has increased substantially. Finally, we provide evidence for a negative ES-credit-risk link.

JEL Classifications: G11, G12

Keywords: Corporate environmental and social responsibility, primary corporate bond markets, credit risk.

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1 Introduction

The increasing importance of corporate objectives beyond narrowly defined profit maximization has arguably been one of the most fundamental trends in financial markets over recent years. In particular environmental, social and governance objectives, denoted as ESG, are now explicitly recognized by a large number of asset managers and institutional investors and by a fast growing number of CEOs (see Matos (2020) for an overview). At the center of the debate surrounding these developments is the question, how such broader objectives affect financial asset prices and in particular risk premia. Especially for equity markets, there is by now a large academic literature that analyzes the connection between ESG objectives and returns. As first shown in Heinkel et al. (2001), high ESG stocks should be valued more highly and come with lower expected risk premia when a subset of investors has ESG preferences. However, Pastor et al. (2021) and Pedersen et al. (2021) show that this result may not always hold in settings, where some investors do not fully account for the relation between ESG scores and the distribution of future corporate cash flows or where investors' ESG preferences are changing stochastically over time. Essentially, unanticipated increases in ESG preferences or unanticipated improvements of future cash-flow distributions of high ESG firms may lead to further appreciation of such stocks, thus providing higher returns to investors already following an ESG strategy.

Empirically, the effects of ESG investor preferences on equity risk premia are therefore difficult to document, since expected risk premia are not directly observable. By contrast, bond markets have the potential to provide a much cleaner setting to measure these relations. In particular primary bond markets represent a setting, in which expected risk premia may be quantified via observed spreads over a riskless reference rate. Primary markets have the additional advantage that offering prices are usually intermediated by investment banks, which should ensure that corporate bonds can be issued at a fair spread which is less likely to be influenced by temporary market (il)liquidity levels, compared to secondary bond markets (see Collin-Dufresne et al. (2001), or Chen et al. (2007)). At the issue stage, bonds generally also have a recent credit risk rating, which effectively controls for many issuer and bond characteristics. Furthermore, corporate bonds are frequently issued by repeat issuers, so that time-series of issuer ES ratings are available and can be analyzed. Thus, this market represents a good laboratory to study the joint time-series of ESG pricing effects and the dynamics of issuing firms' ESG-characteristics.

This paper presents the first comprehensive analysis of the effects of different ESG dimensions on corporate bond issue spreads and the supply-side consequences. We hereby follow the literature and focus on the first two ESG components, i.e. E and S. To guide our empirical analysis, we first develop a simple theoretical framework that identifies the three possible channels, via which ES may affect issue spreads: ES-scores may contain information about (i) expected cash flows generated by the bonds, (ii) the risk of these cash flows and (iii) about extra demand from investors with ES preferences. Firms in the model may also invest resources to improve their ES-score so that the supply of good-ES bonds is endogenously determined in equilibrium. We show that bonds issued by firms with good ES performance are priced above those issued by firms with poor ES performance and that the resulting yield spread increases in absolute value if good ES-scores signal a larger reduction in expected default losses or in the riskiness of payments to bondholders, and as more investors exhibit ES preferences. The latter effect is mitigated since such a shift in investor preferences also generates an increase in the relative supply of bonds with good ES ratings. Furthermore, we find that the price premia of good ES bonds rise with the average cost of ES-improving investments.

Using a large sample of U.S. issues from 2002 to 2020, we test these model predictions and thereby address several main questions. First, are E and S scores correlated with corporate bond spreads in the primary market, when controlling for bond ratings and other firm characteristics? Second, are there differences in the importance of ES-scores for issue spreads across the various E and S dimensions, rating classes and industries? These cross-sectional tests map nicely into our theoretical framework by capturing, for example, variation in investor preferences for certain ES-dimensions (e.g., the environmental dimension having captured most of the attention in the public debate), in firms' credit riskiness (e.g., rating classes capturing variation in credit risk) and in adjustment costs to improve in a specific ES-score (e.g., firms in the mining industry may find it particularly costly to improve their environmental score). Third, is there time-variation in the relative supply of bonds issued by firms with good ES-scores in response to shifting investor preferences, as our model suggests, and what is the interaction between bond supply dynamics and the pricing effects of E and S in primary bond markets?

We document several key results. Most importantly, we find a robust, negative relation between ES ratings and issue spreads in primary corporate bond markets. Thus, these markets reward firms for good ES-performance, even when controlling for bond ratings and various firm characteristics, such as net book leverage, size, profitability, tangibility, dividend status, experience as a bond issuer, and industry and time fixed effects.

However, the relation between ES and issue spreads is much more nuanced than this general finding may lead us to suspect. First of all, this overall finding masks interesting differences across the various dimensions of characteristics which are aggregated in firms' ES-scores. When using the individual, more granular sub-scores, we find that the negative association between aggregate ES-sores and issue spreads is largely due to product-related dimensions of ES-scores. This seems intuitive, since these dimensions are most closely related to corporate value creation and should directly affect the valuation of corporate bonds via the cash-flow channels featured in our model. Other dimensions such as environment, community, or human rights, which get more attention in the media and by policy makers, do not seem to matter for the pricing of corporate bonds when the full sample of issuers is considered.

The theoretical framework that guides our empirical analysis suggests that the negative relation between ES-scores and spreads should be more pronounced for low-rated bonds. The underlying rationale is that "arbitrage" activities that offset potential ES-induced price differences between bonds are less risky and therefore easier to implement for highly-rated bonds. Empirically, we find support for this prediction, as the negative relation between a good aggregate ES-score and issue spreads is only significant for bonds rated BBB or below and for those that do not have a rating. While we find no significant relation for A-rated bonds, the coefficient of the aggregate ES-score is even significantly positive for highly rated issuers, i.e. AAA or AA. This last finding suggests that good ES-performance might even be punished by the market through higher spreads, potentially because it is seen as a signal of agency frictions. When we split the aggregate score into its components, we find across the board, with the exception of A-rated bonds, that the product and employment related subscores drive the negative association.

Given that the effects of ES ratings on spreads are predominantly due to lower-quality issuers, this suggests that the spread-reducing effects may be risk-induced, i.e. good ES-performance may be considered to signal lower credit risk, even when controlling for credit ratings. This interpretation is consistent with predictions from the theory model, as equilibrium bond price differences increase with the variances in bond cash flows. The model, however, also highlights that if bond payoffs are less correlated among lower rated bonds, pure demand effects due to investors' preferences for sustainable investments are also consistent with this empirical result. To further disentangle these two explanations, we study the relation between ES-scores and credit risk. We find that for high-yield bonds good ES-performance at the time of issuance is significantly associated with lower credit risk, measured either via subsequent probabilities of defaults or via subsequent rating downgrades. Instead, for investment-grade bonds the relation between ES-scores and subsequent credit risk is ambiguous or even increasing. These findings suggest that the risk-based channel represents a main mechanism through which ES-scores affect spreads.

We corroborate the above findings with complementary evidence. When analyzing the cross-section of industries, we find that ES-scores reduce bond spreads for industry group

AgriForeFishMineCons (including agriculture, forestry, fishing, and mining) and for manufacturing firms. Most importantly, the environment-related score shows a significantly negative and economically substantial impact on spreads for firms in industry group AgriForeFishMineCons which pools industries that are particularly exposed to environmental risks. While the environmental score does not play a role in explaining bond spreads and credit risk in the full sample, it is reassuring to observe that it matters in those industries that should be materially exposed to environmental risks and that, most likely, face substantial costs to improve their environmental scores.

Finally, we also study the time-series dynamics of the relation between ES-performance and spreads by estimating a rolling-window version of our empirical model. As mentioned above, the topic of sustainable investing has received growing attention during our sample period. If investor preferences and the resulting demand effects play an important role in determining spread differences between bonds with high versus low ES-scores and if the proportion of bonds issued by firms with good ES-scores is kept constant, then we should find the regression coefficients on ES-scores to rise over time, both in terms of their economic magnitude (i.e., to become more negative) as well as their statistical significance. Once we allow the proportion of bonds issued by firms with good ES-scores to adjust endogenously, the impact of increasing investor preferences on the dynamics of the regression coefficients should be mitigated.

The empirical time-series results confirm these theoretical predictions and suggest a significant role of investor preferences on capital allocation via corporate bond markets. While regression coefficients of spreads on ES ratings do not show strong time trends, the supply of corporate bonds from issuers with good ES ratings has generally increased substantially over time. Importantly, we also document that this supply-side response in primary corporate bond markets is predominantly driven by repeat issuers. The product-related sub-score represents a notable exception, as it retains negative and large spread regression coefficients through time and shows hardly any supply response. This suggests that either the costs of improving this particular score are very large, or that investor preferences along this dimension have not changed much.

Our paper is related to a large literature that analyzes the relation between securities' risk premia and their ESG ratings. Most of these contributions focus on equity markets, however (for a recent literature survey see, for example, Matos (2020)). Substantially less work exists on the interaction between ESG and corporate debt pricing.[1]

[1] There is a first paper by Bauer and Hann (2010) that explores the effects of environmental scores on bond issue spreads, using the KLD STATS database. But their sample only covers S&P 500 firms until 2001 and stops in 2006. They find that environmental concerns are related to larger spreads whereas firms' proactive environmental practices imply lower spreads.

In a recent paper, Seltzer et al. (2020) show that climate regulatory risks affect corporate bond risks, which manifests itself via lower credit ratings and higher spreads. Exploiting differences in the stringency of environmental regulation across U.S. states and arguably exogenous events such as the signing of the Paris Agreement and the subsequent U.S. withdrawal under President Trump, they provide evidence for causal effects. In contrast to Seltzer et al. (2020), we focus on the bond pricing effects of investor preferences along a broad set of E and S dimensions, study the cross-sectional variation in the effects across bond ratings and industries, and assess the impact of supply-side adjustments. We also provide novel evidence that corporate E and S performances may reflect credit risk differences not fully captured by ratings and other firm characteristics.

Amiraslani et al. (2021) also study a subset of ES-dimensions, namely corporate social capital. Their main finding is that corporate social capital only matters for bond characteristics (i.e., spreads, principal raised, maturities) during the 2008-2009 financial crisis. While their main focus is on secondary markets, they also report some findings for primary markets. During the crisis, firms with high social capital seem to be able to raise debt through bonds at lower spreads, with larger principal amounts, better credit ratings and longer maturities. In contrast to their study, we focus on primary markets, using a comprehensive sample that also includes the most recent COVID-induced recession, and we consider both environmental and social dimensions of ESG. Also, we update E and S scores all the way through 2018, i.e. the last year for which data are available, whereas Amiraslani et al. (2021) use firms' SRI scores from 2006. Our results differ substantially since we find that aggregate as well as individual ES-scores matter in the primary markets not only during crises or recessions but also during normal times. In addition, Amiraslani et al. (2021) focus only on the aggregate SRI score, while some of our main results pertain to the differences between the effects of the various dimensions of E and S on bond prices.[2]

Yang (2020) provides an interesting analysis of the link between ESG scores and credit ratings, since rating agencies announced in late 2015 (Moody's and S&P) that they would take ESG dimensions more explicitly into consideration when determining ratings. Exploiting the fact that Fitch only adopted similar strategies in 2017, the paper finds that this announcement by the rating agencies seems to have improved the information content of ratings changes, since rating downgrades by Moody's and S&P were associated with stronger

[2]Several other papers look at ESG-related questions in corporate bond markets. Schneider (2011) studies bond prices in secondary markets for bonds from two particularly polluting industries, namely the pulp and paper and chemical industries. Menz (2010) and Stellner et al. (2015) focus on secondary markets for European corporate bonds. Baker et al. (2021) analyze the pricing of U.S. green bonds and Barth et al. (2020) study the impact of ESG on credit spreads in CDS markets. Our paper differs from these studies by providing a theory-guided analysis of both aggregate and granular ES-subscores for a comprehensive cross-section of bond issues and by studying time variation of the results and issuers' supply responses.

stock price reactions than downgrades by Fitch. However, when studying negative news about ESG issues of individual firms, the paper finds no evidence that ratings adjust or respond to such negative news. Our results suggest that ratings do not fully subsume all the effects of ESG scores on credit spreads.

Goss and Roberts (2011) analyze a risk mitigation and an overinvestment channel, via which ESG may affect debt prices. Empirically they study bank loans and find that social responsibility concerns result in an increase in loan costs. They also provide some evidence for the ESG overinvestment channel in the case of low-quality borrowers that make discretionary CSR investments. Chava (2014) estimates the effect of ESG on firms' overall cost of capital. He finds that "bad" firms face a higher cost of equity, based on analysts' earnings forecasts, as well as a higher cost of debt, measured via loan data.[3]

In contrast to the contributions discussed above, we present a theoretically motivated, comprehensive study of the interaction between ES ratings and primary corporate bond markets. It is based on a large number of issuers and on a sufficiently long sample period so that both the cross-sectional effects of ES ratings as well as their dynamics and firms' supply-side responses can be analyzed.

The rest of the paper is organized as follows. Section 2 provides a simple theoretical framework that helps us derive predictions to guide our empirical analysis . Section 3 summarizes the data and empirical methodology while Section 4 describes the results. Finally, Section 5 concludes.

2 Bond IPO Pricing and ES-scores

In this section we derive a simple equilibrium model of a primary market for corporate bonds where firms differ in their ES performance and some investors have non-pecuniary preferences for holding bonds issued by firms with good ES ratings. A distinguishing feature of the model is that firms are allowed to react to investor preferences and can improve their ES performance, as in Heinkel et al. (2001). We then use the propositions derived from the model to guide and focus our subsequent empirical strategy.

2.1 Production technologies and bond cash flows

Consider an economy where firms use different production technologies. Green firms produce with green technologies and polluting firms utilize polluting ones. The total number of

[3]Gao et al. (2020) use the staggered state-level adoption of constituency statues as quasi-natural experiments to examine the causal effect of stakeholder orientation on loan spreads. Their results suggest that stakeholder orientation could reduce borrowing cost through the governance channel.

firms is fixed and given by $N = N_G + N_P$ where N_G is the number of green firms and N_P the number of polluting firms. By making an investment K_i, firm i can switch from a polluting technology to a green technology. As it will be shown below, the choice of switching technology characterizes endogenous bond supply, N_G and N_P, in equilibrium.

For simplicity, we assume that each firm issues one zero-coupon corporate bond with a face value normalized to one.[4] We will refer to bonds issued by a green firm as a G-bond and a bond issued by a polluting firm as a P-bond. Thus, there is a total supply of N_G G-bonds and N_P P-Bonds. It will be convenient to aggregate all G-bonds and all P-bonds into two distinct bond portfolios, referred to as portfolios G and P, respectively. We can then define $CF_G = 1 - \tilde{\epsilon}_G$ as the end-of-period cash flow per unit of face value from holding portfolio G, where $\tilde{\epsilon}_G \sim N(\bar{\epsilon}_G, \sigma_G^2)$. $\bar{\epsilon}_G$ represents the expected default loss of portfolio G, per unit of face value. Similarly, $CF_P = 1 - \tilde{\epsilon}_P$ represents the end-of-period cash flow per unit of face value from holding bond portfolio P, where $\tilde{\epsilon}_P \sim N(\bar{\epsilon}_P, \sigma_P^2)$. The covariance between the two bond portfolios' cash flows is denoted by σ_{GP}. The assumption of normally distributed cash flows is not crucial for our results below and is only made to obtain particularly simple expressions.[5]

Denote by $\delta = \bar{\epsilon}_P - \bar{\epsilon}_G$ the difference in the expected default losses between the two bond portfolios. δ, if positive, captures bond investors' (expected) pecuniary benefits of corporate ES investment.

2.2 Bond investors and their portfolio choice

We consider two types of bond investors: green investors (g) are pollution averse and only buy bonds issued by firms with green technology (G-Bonds). Neutral investors (n), on the other hand, may buy bonds issued by all firms. The total mass of investors is $I = I_g + I_n$, where I_g (I_n) is the mass of green (neutral) investors.

Assume CARA preferences (with risk tolerance parameter τ) and that the riskless asset is at perfectly elastic supply at a rate of zero. Both groups of investors choose the optimal

[4]Thus, we do not require firms to raise a fixed amount of capital via the bond issue. Imposing this, would complicate the analysis without generating qualitatively different results. Essentially, we assume that debt financing is optimal, but that the maximum amount of debt that a firm can issue is given by the normalized debt face value of one.

[5]Note that we are only concerned with the payoffs of bond portfolios, for which the assumption of normally distributed returns is less problematic. Also, one may interpret the one-period cash flow in a multi-period world, where the bond payoffs at the end of the first period are affected by both credit risk and interest rate risk, making the normal distribution assumption even less critical. In addition, $\bar{\epsilon}$ and σ_ϵ can always be calibrated to make payoffs larger than the bonds' face values negligible.

portfolio weights to maximize their utility as follows

$$\max_{x_{nG},x_{nP}} U_n = x_{nG}(1-\bar{\epsilon}_G - P_G) + x_{nP}(1-\bar{\epsilon}_P - P_P) \\ - \frac{1}{2\tau}\left(x_{nG}^2\sigma_G^2 + x_{nP}^2\sigma_P^2 + 2x_{nG}x_{nP}\sigma_{GP}\right);$$

and

$$\max_{x_{gG}} U_g = x_{gG}(1-\bar{\epsilon}_G - P_G) - \frac{1}{2\tau}x_{gG}^2\sigma_G^2.$$

With a slight abuse of notation, we now denote the optimal portfolio weights by x_{nG}, x_{nP}, and x_{gG}. The first order conditions are

$$P_G = 1-\bar{\epsilon}_G - \frac{1}{\tau}\left(x_{nG}\sigma_G^2 + x_{nP}\sigma_{GP}\right); \tag{1}$$

$$P_P = 1-\bar{\epsilon}_P - \frac{1}{\tau}\left(x_{nP}\sigma_P^2 + x_{nG}\sigma_{GP}\right); \tag{2}$$

and

$$P_G = 1-\bar{\epsilon}_G - \frac{1}{\tau}x_{gG}\sigma_G^2. \tag{3}$$

2.3 Firms and their ES investment choice

All firms are endowed with polluting production technologies, but they can switch to the green technology by investing in environmentally and/or socially beneficial projects. Firms differ in how costly it is for them to improve their ES performance. K denotes a firm's cost of ES investment, where the firm subscript is suppressed for simplicity. The investment cost is distributed on the interval $\mathcal{K} = [\underline{K}, \overline{K}]$ according to a measure μ with continuous distribution function F.[6]

Since prices at which G-Bonds can be sold at the primary market, P_G, will differ from those of P-Bonds, P_P, some firms may have an incentive to undertake costly ES investments. Given that the investment decision is a binary choice, we conjecture (and will verify later) that there exists one and only one endogenously determined cutoff K^c such that the corporate ES investment choice, INV, follows a threshold policy given by

$$INV = \mathbf{1}(K \leq K^c). \tag{4}$$

where $\mathbf{1}(.)$ is an indicator function equal to one if the condition in the parenthesis holds and zero otherwise.

[6]Note that μ is not a probability measure.

Intuitively, firms with low investment costs are endowed with a positive-NPV ES project. They turn green ($INV = 1$) and issue G-Bonds. By contrast, other firms face high investment costs and thus do not wish to invest in ES improvements. They remain brown ($INV = 0$) and issue P-Bonds.

2.4 Aggregation and equilibrium

The difference in equilibrium bond prices is determined by the **marginal firm** with $K = K^c \in \mathcal{K}$, that is,

$$P_G - P_P = K^c. \tag{5}$$

Note that the marginal firm has a zero-NPV project and to break the tie, we assume it pays K^c and turns green.[7]

The total mass of firms, N, is given by

$$N = \mu(\mathcal{K}) = \int_{\underline{K}}^{\overline{K}} dF(K) = F(\overline{K}) - F(\underline{K}) = F(\overline{K})$$

where the last equality follows from $F(\underline{K}) = 0$. Since each firm issues one bond, N is also the total supply of bonds. Furthermore, the supply of G-Bonds is equal to the mass of green firms for which $INV = 1$ or equivalently, $K \leq K^c$. Therefore,

$$N_G = \mu(K \leq K^c) = \int_{\underline{K}}^{K^c} dF(K) = F(K^c) \tag{6}$$

and the supply of P-Bonds is given by $N_P = N - N_G$.

Finally, market clearing requires

$$I_n x_{nG} + I_g x_{gG} = N_G; \tag{7}$$

and

$$I_n x_{nP} = N_P. \tag{8}$$

In summary, equilibrium is defined by (i) bond investors choosing optimal bond portfolio weights according to equations (1)-(3); (ii) firms making optimal ES investment decisions according to equation (4) which, in aggregation, determine bond prices (equation (5)) and the endogenous supply of G-Bonds (equation (6)), and (iii) corporate bond markets clearing (equation (7) and (8) hold). Solving these equations simultaneously allows us to derive seven

[7]This assumption is not crucial because we have a continuum of firms and thus the marginal firm belongs to a set of measure zero.

equilibrium quantities: P_G, P_P, N_G, K^c, x_{nG}, x_{nP}, and x_{gG}.

2.5 Main results and empirical predictions

This section states the model's main results and discusses its predictions. All proofs are provided in Appendix B. The first proposition derives the equilibrium bond prices and yields.

Proposition 1 *For given supply of corporate bonds N_G and N_P, prices are given by*

$$P_G = 1 - \bar{\epsilon}_G - \frac{1}{\tau I}\left[N_G\sigma_G^2 + N_P\sigma_{GP}\right]; \tag{9}$$

and

$$P_P = 1 - \bar{\epsilon}_P - \frac{1}{\tau I}\left[N_P\sigma_P^2 + N_G\sigma_{GP} + N_P\frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right]. \tag{10}$$

where $\phi = \sigma_G^2\sigma_P^2 - \sigma_{GP}^2 = \sigma_G^2\sigma_P^2\left(1-\rho_{GP}^2\right)$ and ρ_{GP} is the correlation of the two bond portfolios' cash flows. Yield spreads are given by

$$S_G = \frac{1}{P_G} - 1 = \frac{1}{1 - \bar{\epsilon}_G - \frac{1}{\tau I}\left[N_G\sigma_G^2 + N_P\sigma_{GP}\right]} - 1; \tag{11}$$

and

$$S_P = \frac{1}{P_P} - 1 = \frac{1}{1 - \bar{\epsilon}_P - \frac{1}{\tau I}\left[N_G\sigma_{GP} + N_P\sigma_P^2 + N_P\frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right]} - 1. \tag{12}$$

Equations (9) and (10) reveal that bond IPO prices are negatively related to their expected default per unit of face value, represented by $\bar{\epsilon}_P$ and $\bar{\epsilon}_G$, and to their riskiness, which is captured by the terms in the square brackets and is pre-multiplied by investors' aggregate risk tolerance, $\frac{1}{\tau I}$. The average price of the polluting bonds, P_P, has an extra risk term in the squared brackets, when compared to P_G. It is due to the lack of risk sharing with green investors (see the last term in the squared bracket of equation (10)). It goes to infinity, if all investors become green, i.e. if I_n goes to zero.

Equations (9) and (10) also imply that the difference between equilibrium bond prices is given by

$$P_G - P_P = \delta + \frac{1}{\tau I}\left(N_P\sigma_P^2 - N_G\sigma_G^2 + (N_G - N_P)\sigma_{GP} + N_P\frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right). \tag{13}$$

It is important to recognize that N_G and N_P are endogenous and thus depend on K^c.

In the cross-section of firms, the NPV of corporate ES investment is a function of K (a firm's own investment cost) and K^c (that of the marginal firm). Precisely,

$$NPV(K, K^c) = \delta + \underbrace{\frac{1}{\tau I}\left(N_G(K^c)(\sigma_{GP} - \sigma_G^2) + N_P(K^c)\left(\sigma_P^2 - \sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right)\right)}_{\text{depends on } K^c \text{ through } N_G \text{ and } N_P} - \underbrace{K}_{\text{its own cost}}. \tag{14}$$

For the marginal firm, $K = K^c$ and thus the NPV of the marginal firm's ES investment becomes $NPV(K^c, K^c)$. Likewise, for an arbitary cutoff value K^0, we can define a function $y(K^0)$ as

$$y(K^0) = NPV(K^0, K^0). \tag{15}$$

Assumption 1 *The model parameters satisfy both*

$$y(\underline{K}) = NPV(\underline{K}, \underline{K}) > 0$$

and

$$y(\overline{K}) = NPV(\overline{K}, \overline{K}) < 0.$$

The assumption states that (i) the firm with the lowest investment cost $\underline{K}$ would have a strictly positive NPV project if it were the marginal firm and (ii) the other firm with the highest investment cost $\overline{K}$ would have a strictly negative NPV project if it were the marginal firm. As a consequence, neither firm can be the marginal firm. We next derive the equilibrium cutoff value for the ES investment.

In equilibrium the difference between bond prices must be equal to K^c for the marginal firm, i.e., $y(K^c) = 0$. We formally state this result in Proposition 2 below.

Proposition 2 *The cutoff value of the ES investment, K^c, is the unique solution satisfying $\underline{K} < K^c < \overline{K}$ and*

$$y(K^c) = \delta + \frac{1}{\tau I}\left(N_G(K^c)(\sigma_{GP} - \sigma_G^2) + N_P(K^c)\left(\sigma_P^2 - \sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right)\right) - K^c = 0 \tag{16}$$

where $N_G(K^c) = F(K^c)$ and $N_P(K^c) = N - F(K^c)$.

Moreover, the endogenous supply of G-Bonds is given by

$$N_G = F(K^c) = \frac{N\left(\sigma_P^2 - \sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right) - (K^c - \delta)\tau I}{\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}}. \tag{17}$$

Equation (17) has an intuitive interpretation. First, N_G increases with δ because it is the reduction (or increase, if it is negative) in the expected default losses offered by G-Bonds.

Second, G- and P-Bonds differ in the riskiness of their cash flows, which is captured by the variance and covariance terms. Third, P-Bonds do not offer any risk-sharing benefit because green investors do not hold them. Such difference is reflected by $\frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}$.[8]

Finally, Assumption 1 and Proposition 2 together imply that we have an interior equilibrium, in which some firms invest to become green and others do not. That is, G- and P-Bonds co-exist in equilibrium.

2.5.1 Sources of bond yield differences

Equation (13) illustrates that price differences may occur due to three channels. The first mechanism is driven by differences between expected default losses. The second channel is related to differences between the riskiness of bond payoffs. If $\sigma_P^2 - \sigma_G^2$ increases, risk-averse investors will ask for higher risk premia to buy P-Bonds. Both these mechanisms are related to credit risk. The third channel, in contrast, is driven by green investors' preference for G-Bonds. Intuitively, the fraction of investors with a preference for green bonds, i.e. as the ratio I_g/I_n increases, affects the relative pricing of G-Bonds compared to P-Bonds.

To identify the effect of each of these channels on the price and yield differences between the two bond portfolios, it is crucial to account for the endogeneity of the ES ratings of bond issuers. As parameters change, firms may respond by investing to improve their ES ratings, which in our model corresponds to switching to a green technology. This supply response will affect price differences and, thus, the impact of the different channels discussed above. The following proposition summarizes the results.

Proposition 3 *Let* $\iota \equiv \frac{I_g}{I_n} = \frac{I_g}{I-I_g}$ *and assume* $\sigma_P > \frac{\sigma_G \rho_{GP}}{2\left(1+\iota(1-\rho_{GP}^2)\right)}$.[9] *First, fixing* N_G *and* N_P*,*

1. $\dfrac{\partial(P_G - P_P)}{\partial\delta} = 1,$

2. $\dfrac{\partial(P_G - P_P)}{\partial\sigma_P} = \dfrac{N_G\sigma_G\rho_{GP} + N_P(2\sigma_P - \sigma_G\rho_{GP} + 2\iota\sigma_P(1-\rho_{GP}^2))}{\tau I} > 0,$

3. $\dfrac{\partial(P_G - P_P)}{\partial\iota} = \dfrac{N_P\frac{\phi}{\sigma_G^2}}{\tau I} > 0.$

Second, when bond supply becomes endogenous, i.e., $N_G = F(K^c)$ *and* $K^c = P_G - P_P$*,*

1. $\dfrac{\partial K^c}{\partial\delta} = \dfrac{\tau I}{\tau I + F'(K^c)\left(\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \iota\frac{\phi}{\sigma_G^2}\right)} > 0,$

[8] See Section 2.5.1 for a thorough analysis of different channels underlying bond price differences.

[9] This assumption is mild. E.g., $\sigma_P > \frac{1}{2}\sigma_G$ is a sufficient, but not necessary, condition for the assumption to hold. Also, this assumption is only required for the riskiness of bond payoffs channel.

2. $$\frac{\partial K^c}{\partial \sigma_P} = \frac{F(K^c)\sigma_G\rho_{GP} + (N - F(K^c))(2\sigma_P - \sigma_G\rho_{GP} + 2\iota\sigma_P(1-\rho_{GP}^2))}{\tau I + F'(K^c)\left(\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \iota\frac{\phi}{\sigma_G^2}\right)} > 0,$$

3. $$\frac{\partial K^c}{\partial \iota} = \frac{(N - F(K^c))\frac{\phi}{\sigma_G^2}}{\tau I + F'(K^c)\left(\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \iota\frac{\phi}{\sigma_G^2}\right)} > 0.$$

Third, since $N_G = F(K^c)$ increases with K^c, the partial derivatives of N_G with respect to δ, σ_P, and ι are also positive.

Since K^c is equal to the difference between bond prices, it is also monotonically related to spread differences.[10] Consequently, the first part of Proposition 3 implies that an increase in either P-Bonds' credit risk (the first two channels) or an increase in investor demand for G-Bonds (the third channel) all decrease spread differences, $S_G - S_P$ (i.e., spread differences become less positive or more negative).

Comparing the first part of Proposition 3 to the second one can see that endogenizing firms' ES investment decisions and thus the supply of G- and P-Bonds, attenuates the effects of the credit risk and investor demand channels. Indeed, partial derivatives in the second part of Proposition 3 can be mapped one-to-one to those in the first part except that the denominators in the second part all have an additional term, $F'\left(\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \iota\frac{\phi}{\sigma_G^2}\right)$, which is positive. That is, despite of being deflated by larger denominators, the second part of the proposition shows that predictions on price and spread differences still hold even when the supply of G-Bonds is endogenous.

2.5.2 Comparative statics analyses

This section explores how bond yield differences across issuers with different ES ratings are affected by the riskiness of bond returns and by the technologies that are available to firms to adopt socially and environmentally more attractive business models. These comparative statics will guide the empirical analyses and the interpretations of the results.[11]

Proposition 4 *If investment costs K shift for all firms by Δ_K, K^c and the equilibrium bond price differences become larger (smaller) when $\Delta_K > 0$ ($\Delta_K < 0$).*

[10] Precisely,

$$S_G - S_P = \frac{1}{P_G} - \frac{1}{P_P} = \frac{P_P - P_G}{P_P P_G} = \frac{-K^c}{P_P P_G}.$$

[11] Testing these comparative statics results empirically assumes that bond markets are not fully integrated across ratings and across industries with different distribution functions for the investment cost K.

Proposition 4 predicts that K^c is larger and, thus, spread differences are more negative in industries and/or for ES-dimensions (e.g., environmental concerns versus human rights issues) for which larger investments are required to switch to an environmentally or socially more attractive business model.

Proposition 5 *Let $K^c > \delta > 0$. K^c increases with the variances of bond cash flows, σ_G^2 and σ_P^2. In the limit, K^c converges to δ as the variances approach zero.*

Proposition 5 implies that the spread differences are less negative and converge towards δ as bond cash flows become less volatile. Furthermore, it is plausible to expect that $\delta = \bar{\epsilon}_P - \bar{\epsilon}_G$ is smaller (that is, closer to zero) for bonds with less risky cash flows. Such risk-related bond characteristics are usually reflected in bond credit ratings. Thus, a testable model prediction is that the effect of ES-performance on spread differences is less negative (i.e., closer to zero) for bonds with higher ratings.

3 Data Description and Empirical Methodology

3.1 Data Sources and Variable Definitions

Our analysis covers the period from 2002 through 2020. We obtain information on new bond issues by non-financial, non-utility, publicly listed firms from the Mergent FISD database.[12] For each bond issue, we collect information on its principal amount (in \$M), yield spread (over the treasury benchmark; bond issues with missing spread information are excluded), maturity, rating, and industry group. For each bond issuer, we also extract all past issuance activities covered in the Mergent FISD database since 1984. Using these data, we calculate the total number of past issues to proxy issuer-level experience with primary bond markets. We use the available industry classifications to control for industry fixed effects throughout all regressions, except for situations in which we focus on individual industries to begin with. To make sure that we have a sufficient number of bond issues within each industry group, we pool individual industries into five groups using bond issuers' main industry classification (that is, SIC code) reported in the Mergent FISD database. We explain how we define these industry groups in Table A1 in the Appendix.

[12] In an earlier version of this paper, we used bond issues from SDC as our main sample. We decided to switch to Mergent in order to exploit its information on defaults and rating downgrades. Both, the Mergent and SDC database have good coverage of the bond universe but do not perfectly overlap. Unfortunately, there is also not a unique identifier that one could use to merge the two databases (some identifiers are available but suffer from missing and repetitive values). Importantly, however, our results are similar and consistent across the two databases.

We use two primary sources to obtain issuer-/firm-level data. First, the MSCI ESG KLD database provides ESG scores covering seven categories: Community, Diversity, Employee Relations, Environment, Product, Human Rights, and Corporate Governance. Each category includes individual indicators (zero-one-dummies) representing strengths or concerns regarding a firm's performance with respect to a specific ESG-dimension. Following Albuquerque et al. (2020), we use the first six categories to construct our ES-score. Table A2 provides further details regarding individual sub-categories included within each ES-dimension. Following the literature on sustainability, we do not consider the seventh category that focuses on corporate governance. To aggregate the individual indicator variables across ES-dimensions, we first sum the total number of strengths across the six categories and do the same for the total number of concerns. We then scale the aggregate number of strengths (concerns) for each firm-year by the cross-sectional maximum, that is, the maximum number of strengthens (concerns) across all firms in that year. In the final step, we subtract the scaled number of concerns from the scaled number of strengths to get an ES-score for each firm-year.

Second, we use Compustat balance sheet variables to construct key firm characteristics that are likely to be related to bond spreads. Those variables include net book leverage (total debt less cash and short term investments to total assets ratio), size (logarithm of net sales), profitability (operating income before depreciation to total assets ratio), tangibility (net PPE to total assets ratio), and dividend payer (a dummy equals one if the issuer has paid a dividend at least once in the four quarters prior to the issue and zero otherwise). Table A1 in the Appendix provides a detailed description for each variable used in the empirical analysis.

3.2 Empirical Methodology and Link to Theory

To estimate the effect of corporate ES-performance on primary market bond spreads, we use a panel regression model similar to that in Halling et al. (2020). The exact specification is as follows:

$$Spread_{i,t+1} = \alpha + \mathbf{X}_{i,t}\beta + \gamma ES_{i,t} + u_i + v_{t+1} + e_{i,t+1} \tag{18}$$

where bond issues are indexed by i and years by t, ES is a measure of corporate ES performance (either the aggregate ES-score or one of the six individual ES-scores), $\mathbf{X}$ is a vector of control variables including the issuer-level characteristics discussed in the previous section. We also control for industry and year fixed effects (that is, u_i and v_{t+1}, respectively) in all regressions except for the industry groups analyses (Table 3), where we only control for year fixed effects.

In Section 4.3, where we study the association between ES-scores and credit risk we extend the above specification to logit models, which use dummy variables to capture credit events as dependent variables. In those models, we only control for industry fixed effects.

The empirically estimated effect of ES on corporate bond spreads is given by γ in equation (18), and corresponds to the partial derivative:

$$\gamma = \frac{\partial Spread}{\partial ES}.$$

To link this empirical setup to the discrete firm types in the theoretical model, ES-scores can be interpreted as affecting the likelihood with which firms are able to place their bonds as G-bonds, i.e. to make them eligible for the bond portfolios of green investors. The discrete counterpart in the model, where two types of bond-issuing firms are modelled, is therefore

$$\gamma = \frac{S_G - S_P}{ES_G - ES_P}$$

where ES_G and ES_P represent the average ES-scores of issuers of G- and P-bonds.

To relate firm and investor characteristics to potential spread differences across ES ratings, recall that the theoretical model implies that K^c, the cost at which a P-firm is indifferent between investing to become a G-firm and remaining a P-firm, is an important variable that not only reflects the difference in bond prices, and thus our empirical proxy, γ, but also the fraction of G-Bonds issued as $N_G = F(K^c)$.

When relating the empirical estimates for γ to the model, we recall that the model propositions are derived under Assumption 1, which imposes parameter restrictions such that G- and P-Bonds co-exist. In practice, this assumption may not hold, i.e. it may be the case that (nearly) all P-firms adjust their production technology along a certain ES-dimension, so as to make their bonds acceptable to both neutral and green investors. In this case, our theory implies (i) an insignificant γ along this specific ES-score and (ii) a large fraction of firms with good scores compared to other ES-dimensions, for which we find significant effects on bond prices.

An alternative reason why the theoretical model may be consistent with an empirically insignificant coefficient γ could be negligible diversification costs of G-investors. If P-bonds and G-bonds are almost perfect substitutes, then neutral investors can costlessly arbitrage between these portfolios of bonds, thereby ensuring insignificant spread differences between bonds issued by firms with different ES ratings along this dimension (see also Berk and van Binsbergen (2021) for a similar argument in equity markets). As a consequence, P-firms would not invest to improve along that ES-dimension and we should not find a significant γ. Finally, the analyzed ES-score may simply be irrelevant or immaterial for investor preferences. In this case, we would not predict any spread differences, as this case can be interpreted as the number of green investors being zero.

Note that in none of the three "irrelevance" cases discussed above would we expect a clear time-trend in average ES-scores. By contrast, in the scenarios discussed earlier, in which there is an interior K^c, shifting investor preferences induce more firms to invest and adjust their ES-scores over time, leading to increasing trends in average ES-scores. More specifically, Proposition 3 predicts that the spread between G-bonds and P-bonds should widen when the fraction of investors with preferences for G-bonds, I_g/I, increases. This effect, however, might be attenuated by the endogenous supply of G-bonds. Thus, in the empirical analysis, we would expect γ to become more negative over time, as investor preferences for sustainable investments are becoming more wide-spread, as long as the proportion of issuers with high ES-scores does not increase too much.

The discussion also suggests that bond spread differences as well as average ES-scores should vary across ES-dimensions and industries, see Proposition 4, and that such variations are informative about the underlying economic mechanisms. Specifically, we would expect that environmental scores are more costly for firms to improve than other ES-dimensions (e.g., community-related aspects), in particular for firms in industries (e.g., mining) whose business activities are inherently linked to potential ecological damages and are considered to be important contributors to environmental risks (i.e, the cost of switching, K, should be particularly high for these firms). Furthermore, we would expect more bond investors to have the desire to avoid issuers with poor environmental ES ratings in industries with potentially large environmental impacts, i.e. I_g should be high as well. Thus, Proposition 4 implies cross-industry variation in the environmental ES-score's impact on bond-spreads.

Finally, our theoretical model has implications for the cross-sectional heterogeneity of ES-related spread differences across rating groups. To see this, we first observe that for bonds in the highest rating classes, expected losses and the variances of these losses should be small, since these bonds should be almost risk-free. According to Proposition 5, price differences between G- and P-bonds should therefore be small for bonds in the highest rating classes compared to those in lower rating classes.

4 Empirical Findings

The main goal of our paper is to study the relation between ES-performance of issuing firms and bond spreads in primary markets. Before we address this question, we briefly describe our sample and present some simple, univariate tests.

4.1 Summary Statistics

Table 1, Panel A, provides summary statistics for the entire sample, which covers the period 2002 to 2020. Our sample consists of a total of 5,227 bond issues. For the average bond issue, the spread is equal to 212 bps, the principal amounts to USD 748 million, and the maturity is slightly shorter than 12 years. Only around 2.2% of all bond issues receive a rating of AAA, while more than 38% have a rating of BBB and, thus, are at-risk of being downgraded from investment grade. The average issuing firm has issued 19 bonds during the sample period, has 31% tangible assets, and a net book leverage of 22%. Around 80% of the sample firms pay dividends.

We also split the sample into "good" and "bad" firms based on the aggregate ES-score. More precisely, the ES-good dummy is set to one (zero) if the ES-score is greater than or equal to zero (is less than zero), which means that ES-good firms have more strengths than weaknesses. Slightly more than 60% of the sample observations come from ES-good firms. Those bond issues are larger (significant difference of USD 112 million) and pay lower spreads (significant difference of 59 bps). They have a maturity that is, on average, identical to the one of issues from ES-bad firms, which is somewhat surprising if one considers ES-related risks as being predominantly long-term risks. As a consequence, one would expect that ES-good firms, keeping all other firm and bond characteristics constant and ignoring other determinants of optimal maturity choice, are less exposed to those risks and, thus, have an advantage in raising longer-term funds. It seems, however, that ES-good firms do not exploit this advantage. In terms of firm characteristics, ES-good firms are larger, have lower net book leverage and fewer tangible assets; they are also more profitable, pay dividends more frequently and have slightly more experience with primary bond markets (i.e., more issues in our sample). All of these differences are statistically significant.

Panel B of Table 1 provides some perspective on the interaction between ES-scores and industries in our sample of primary bond issues. We pool firms into 5 industry groups. The large majority of observations comes from the Manufacturing industry, followed by Trade-related industries and the Services industry. For each group, we report ES-scores as well as scores of individual ES dimensions. Similarly, we report the fraction of ES-good firms for the aggregate score and individual dimensions.

The fraction of ES-good firms is largest, amounting to 73%, among industry group Services and smallest, with only 46%, among group AgriForeFishMineCons. Some individual values stand out. For example, 100% of firms in the Services industry are ENV-good (i.e., have an ENV-score — a score with respect to the environmental dimension — that is above zero). On the other end, only 54% of sample firms in industry group Trade show good performance (i.e., having a score above zero) with respect to employee relations. The

TransCommEGSSvc group of industries contains the smallest fraction of good firms within the ES-dimensions community and product-related. Finally, the AgriForeFishMineCons-Industry holds the bottom spot for the environmental as well as the diversity dimension. These pronounced differences in average ES-performance across industries highlight that it is important to control for industry effects in our empirical analysis. As a consequence all regression models include industry fixed effects.

Finally, Panel C of Table 1 shows a correlation matrix of ES-scores as well as spreads, principals and maturities of issued bonds. As one would expect, individual ES-scores are positively related to each other but the magnitudes of the correlations are small. The highest correlation, amounting to 0.30, is observed between the environmental score and the employee relations score. On the other end, the human rights score shows correlations below 0.1 with all other ES-dimensions. The correlation table also suggests a predominantly negative correlation between ES-scores and spreads and a mostly positive association between ES-scores and principal amounts. Whether these simple, univariate results also hold up in a comprehensive multivariate framework will be discussed in the next section.

4.2 ES-Scores and Bond Spreads

We now estimate the panel models described in Section 3.2. As discussed before, the base case model without ES-related variables represents a comprehensive set of potential drivers of bond spreads, including year fixed effects, industry fixed effects (we use the 5 groups of industries as discussed above) and rating fixed effects[13] together with continuous issuer characteristics.

Table 2 shows the corresponding results. Before focusing on the impact of ES-scores, we briefly describe the explanatory power of the models and the coefficients estimated for the base case variables. The model works well in terms of explanatory power with r-squares of around 60%. Furthermore, coefficients estimated for rating dummies as well as for firm characteristics are plausible across all specifications and are frequently estimated to be significant. In general, net book leverage increases spreads while size, profitability, being a dividend payer and having experience with the bond market all decrease spreads. Coefficients obtained for rating dummies are also consistent with the interpretation that better-rated bonds are less risky and pay significantly lower spreads, as one would expect.

We now focus on the main object of our empirical analysis, namely the relation between

[13] We create dummies for AAA, AA, A and BBB rated bonds; high-yield issues are captured by the constant. Results are robust to the inclusion of an even finer grid of rating fixed effects that capture each individual credit rating notch (see Table A3 in the Appendix for details). The motivation to focus on the coarser grid in the main results is that this set of fixed effects can be used consistently across all subsequent sub-sample results as well.

ES-scores and the pricing of corporate bonds in the primary market. Overall, we find that good ES-performance is related to a statistically significant reduction in spreads. The coefficient of -18.8 implies that for the issuer with the best ES-score in a given year (i.e., an ES-Score equal to one) there is, on average, a reduction of bond spreads by around 19 bps. While this may appear to be a moderate effect in economic terms, we will see later that these aggregate, full sample estimates hide substantial variation of ES effects across industries, rating classes, or different dimensions of ES-scores.

When considering the individual ES-dimensions in columns 2, 4, 6 and 8 in Table 2, we find that the significantly negative coefficient of the aggregate ES-score is driven to a large extent by the product-related category. The observation that this dimension of ES matters for bond spreads accords well with economic intuition, given that it captures aspects of product quality and safety, customer treatment, etc. and, thus, is very closely related to the core of any corporate activity. The only two other individual dimensions that receive negative coefficients that pass or are close to passing the 10% significance threshold, but that are substantially smaller in absolute magnitude, are the scores related to employee relations and diversity. Again, these dimensions represent aspects of ES that appear intuitive in affecting spreads, as employees and human capital, more broadly speaking, are core value drivers for almost all firms.

The remaining ES-dimensions such as the environmental, community and human rights score do not seem to explain variation in corporate spreads. One interpretation of these non-results is that these ES-dimensions are neither related to the credit risk of firms nor relevant for ESG-oriented investors. As discussed above and motivated by our theoretical framework, there is, however, an alternative interpretation, namely that the supply of good firms (i.e., firms for which strengths exceed concerns) has increased over time, thereby largely offsetting the demand-driven spread effects of ES performance. We will explore this channel in more detail in Section 4.2.3.

One limitation of our ES data is that the latest scores are from 2018. As we do not want to lose the most recent bond issuance observations, we forward fill the ES data from 2018 until 2020, assuming that variation in firms' ES-performance is small over a short period such as two years. To check whether this approach has any noticeable effect on our results, columns (3) and (4) in Table 2 show coefficient estimates when we rerun the panel regressions for a sample period that ends in 2019[14]. We see that the main results as discussed before are robust to estimating the models for this slightly shorter sample period.

[14]As we lag all explanatory variables including ES-related information by one year, we can include bond issuance data up to the end of 2019 in those regressions.

4.2.1 Non-crisis and crisis periods

In a next step, we study the dynamics of the link between ES-performance and corporate bond spreads by separately estimating the regression models during "normal" and "crisis" times where crisis times include the Global Financial Crisis (GFC) and the COVID-19 pandemic. As discussed earlier, the literature (see, for example, Albuquerque et al. (2020) and Matos (2020)) studying sustainability and equity returns suggests that sustainable firms are more resilient and earn higher returns during crises. Similarly, Amiraslani et al. (2021) find that social trust only matters for bond prices in secondary markets during the GFC. In contrast to this evidence, we find that the ES effects in primary bond markets are not restricted to crisis times but instead are largely due to observations during normal times.

During normal times, the aggregate ES-score receives a significantly negative coefficient that is slightly smaller than the one estimated from the full sample (see column (5) in Table 2). When considering the individual dimensions of ES, we find that only the product-related ES-score drives the spread decreasing effect of sustainability during normal times. In stark contrast, during crisis periods we neither find any impact for the aggregate ES-score on spreads nor for the product-related sub-score (see columns (7) and (8) in Table 2). We find, however, substantial variation in coefficients across the remaining individual ES-dimensions: good employee-related scores are highly rewarded in crises periods via large drops in spreads (the coefficient estimates are more than ten times as large as during normal times) while good scores in community and environment lead to significant and very substantial increases in spreads. These results challenge some of the conventional wisdom which suggests that sustainable firms do better during crises. In our case, this does not seem to be the case, when sustainability is measured by the community or the environmental score. It is important to note, however, that the number of observations during recessions is small (especially, at the issuer-level at which ESG information varies). Thus, these somewhat controversial results have to be interpreted with caution.

The result that ES-induced effects on bond spreads are weaker during crises periods is somewhat surprising. One potential reason could be that only firms for which ES-dimensions are less relevant tend to issue bonds during recessions. Our theoretical framework suggests that firms with low credit risk represent an example of such firms (see Section 2 for details). Empirically, ratings are comprehensive measures of credit risk. Thus, we evaluate whether average ratings of bond-issuing firms vary systematically across the business cycle and find that they do. While the fraction of investment-grade bonds is 75% during normal times, it increases to almost 86% during recessions. In particular, the share of bonds with an A (Aa) rating increases substantially during recessions, from 27.1% (6.6%) during normal times to 35.5% (11.2%) during crises periods. Thus, one potential explanation for the different and reduced effect of ES-scores on spreads during recessions is that firms with low credit risk, whose valuation is expected to be less affected by ES-dimensions according to our model, represent a disproportionally large share of the sample during these periods. We will revisit the link between credit risk and the importance of ES-scores for bond spreads in Section 4.3.

4.2.2 Results by Industry Group

The next set of empirical results investigates the variation across different industries. It is well-known that ES-scores vary substantially across industries and that firms in certain industries are more affected by some ES-dimensions than firms in other industries due to the specific nature of a given industry. In our theoretical model we capture these effects through variation in the cost that a P-firm (i.e., a firm with bad ES-performance) must incur to become a G-firm (i.e., a firm with good ES-performance, see proposition 4).

Our discussion of the summary statistics has already pointed out strong industry effects. We have therefore controlled for industry fixed effects across all regressions discussed up to now. To better understand this cross-industry variation, we now split the sample of bond issues into the five sub-samples based on groups of industries introduced before (see the Appendix for a detailed definition).

Table 3 shows the corresponding results. We find pronounced differences in the relation between ES-scores and spreads across industries. In the case of industry group AgriForeFishMineCons (including agriculture, forestry, fishing, mining, and construction) and the Manufacturing industry (Panel A) we find significantly negative coefficients of the aggregate ES-score. This finding is consistent with the idea that firms in those two industry groups are particularly exposed to ES-related risks (for example, mining, paper and pulp, chemical industry are often considered to be "brown" industries). As a consequence, ES-scores become more informative and relevant for bond spreads. For industry groups TransCommEGSSvc and Services (Panel B), in contrast, we do not find any significant effects of the aggregate ES-score on spreads while for industry group Trade (Panel B) we document a significantly positive coefficient.

Importantly, we find that the ENV-score is significantly negatively related to spreads for firms in industry group AgriForeFishMineCons. Given that this group of industries contains predominantly industries that are ex-ante exposed to environmental risks, this result seems plausible and reassuring. Furthermore, the absolute magnitude of the estimated effect is large with a coefficient of -78.8 suggesting that for firms in these industries having a good environmental score reduces spreads, on average, by a non-trivial amount. In most other industry groups, however, the environment-related score does not significantly affect spreads, potentially because environment-related risks do not represent large enough risks for firms in those industries.

When interpreted in light of the theoretical framework, these findings also suggest that adjustment costs of firms with low ENV-scores to improve their scores vary across industries. Specifically, such firms in industry AgriForeFishMineCons must face substantial costs if they prefer to issue bonds at spread premiums of up to 80 basis points compared to firms in the same industry but with better ENV-scores. On the other hand, it seems plausible that firms in agriculture, forestry, fishing, mining and construction find it particularly costly to improve their ENV-score given the nature of their business.

Finally, in the context of this analysis we also find several positive coefficients for individual ES-dimensions suggesting that some activities that result in good ES-scores are not appreciated by bond investors for firms in certain industries. Instead, the significantly positive coefficients suggest that investors require an additional premium from these firms to buy their bonds. In our theoretical framework, the parameter δ captures the difference in the expected default losses. Whereas it seems sensible to focus on the case in which the expected default losses are lower for G-Bonds than P-bonds (that is, δ is positive), agency costs could manifest themselves via high ES-scores and thus imply a negative δ, consistent with the observed positive coefficients. Again, these results reinforce that industry characteristics matter for ES-related analyses and that the link between ES-performance (at the aggregate and the individual score level) and spreads is multi-faceted and nuanced.

4.2.3 Time-Series Dynamics of the Relevance of ES-scores

The final set of empirical results in this section studies the dynamics of the relation between ES-scores (aggregate and individual) and spreads in more detail. Intuitively, we would expect pronounced time-series effects, showing an increasing importance of ES ratings in recent years, given the increase in overall awareness, in media attention, in ES-related regulation, and in the share of institutional capital being invested according to ES principles.

In the model, a growing fraction of investors with preferences for sustainable investments leads to increasing differences (more negative) in spreads between bonds issued by high ES firms (G-firms) and low ES firms (P-firms). It also shows, however, that this effect is reduced by the endogenous increase in the supply of G-bonds in equilibrium. To study this empirically, we estimate the panel regression described in Equation (18) including rating, industry and year fixed effects using 5-year rolling estimation windows. Then we plot the coefficient of the ES-score from each of those regressions in Figure 1 for the aggregate ES-score and in Figure 2 for individual ES-scores. In addition, we also calculate the fraction of bond issuers, again across 5-year rolling windows, with corresponding positive ES-scores, as we interpret such firms as “good”or G-firms in the notion of our theoretical model.

For the aggregate ES-score (Figure 1), we find that the coefficient estimate (solid line) is consistently negative, with the exception of 2015. We do not observe, however, any negative trend over time that would reflect the increase in investor preferences for ESG. However, the supply of firms with a positive aggregate ES-score has increased noticeably over time, from below 40% in 2009 to almost 80% in 2020. As explained in the theoretical section, such an increase in the supply of "good"firms will attenuate any impact that the observed increase in investor preference for sustainable investments would otherwise have on the coefficient estimate.

Focusing on the different dimensions of ES-scores (Figure 2), we observe consistently negative coefficient estimates for the product-related score, which has been found to be strongly negatively related to corporate spreads in the earlier analysis. Only during the most recent years, the coefficient estimates are close to zero implying a reduced impact of this ES-dimension. Interestingly, however, we do not observe a pronounced increase in the supply of firms with positive product-related ES-scores. While this fraction is around 60% in the beginning of the sample period, it reaches slightly above 70% towards the end, which represents the lowest level among all individual sub-scores at the end of the sample period. Given the large spreads that are associated with the product-related ES-score according to our analysis, this result suggests either that improving these scores is particularly costly for firms, or that investments in product-related performance is largely driven by shareholder value maximization, and not by green investors' preferences.

Another important sub-score according to our analysis focuses on employment-related aspects. The time-series results show that during early years (until 2012) the associated coefficient estimate is basically zero while the fraction of firms with a positive score is close to 50%. After 2012, however, the supply of issuing firms with a positive EMP-score increases strongly, reaching 80% until the end of the sample period. Despite this, we observe that the coefficient estimate decreases over the more recent period, reaching an estimate of roughly -20 bps at the end of the sample period. Overall, these patterns suggest that there was a structural break in the importance of the employment-related ES-dimension for credit spreads around 2012. One possible interpretation of this break is that investor preferences for firms that consider their employees as important stakeholders have become more important over time.

The patterns for the ENV-score look somewhat similar, but both the decreasing trend of the coefficient estimates as well as the increase in the supply of "green"firms start earlier and are somewhat weaker than those of the EMP-score. Towards the end of the sample, however, more than 90% of the bond issuing firms have a positive ENV-score while the discount in spreads, for being an environmentally-friendly firm, is estimated to be around 10 bps. Together these patterns indicate a pronounced impact of "greener" investor preferences over time on primary bond markets.

The remaining three sub scores – diversity, community and human rights – show weaker and more ambiguous patterns. In all three cases, the fraction of firms with positive scores is high throughout the entire sample period. At the same time, their effects on spreads are small (i.e., coefficient estimates are not significantly different from zero). Thus, an incremental increase or decrease in a given score does not have a noticeable effect on spreads, which may not be surprising, given that 80% to 90% of firms have positive scores throughout the sample period. In the context of our theoretical model, this situation would be consistent with an equilibrium in which almost all firms have made the investment to become Good-firms with respect to that ES-dimension.

As a next step, we investigate the documented increases in the supply of issuing firms with positive ES-scores in more detail. There are two potential channels. First, issuers that have issued bonds before might improve their ES-score in order to benefit from the discount in spreads, as modelled and discussed in detail in our theoretical framework. Second, a new set of firms, with on average better ES-scores, that have previously not used the primary bond markets might start issuing bonds. Distinguishing between this intensive and extensive margin is important, because one specific challenge in the area of sustainable finance is to document that the reallocation of capital, represented by the documented differences in spreads, actually has an impact on the ES-characteristics of the firms.

A first piece of relevant empirical evidence is that only 10% of our sample of bond issues are issued by firms that come to the bond market for the very first time. This is a simple reflection of the well-documented fact that the process of bond issuance incurs substantial fixed costs including, for example, costs due to a lack of reputation for first-time issuers, as well as costs to establish a network of investment banks and institutional investors. Thus, most of the supply dynamics we observe will naturally be related to repeat issuers adjusting their ES-characteristics.

This, however, still leaves open the question how prevalent and economically relevant these adjustments are. To study this in more detail, we calculate for each repeat issuer the simple change in aggregate ES-score and individual sub-scores. Figure 3 shows the distribution of those changes by reporting the median together with the 10th and 90th-percentile using a 5-year rolling window.

Across all three sub-graphs, the figure shows that the median change in the aggregate ES-score as well as in the individual sub-scores is zero. Thus, it does not seem to be the case that the majority of repeat bond issuers consistently improves its ES-scores. The 90th-percentile, however, implies that some firms improve their scores quite considerably between subsequent issuances of bonds. For example, in the case of the aggregate ES-score the 90th-percentile corresponds to increases between 0.1 and 0.2 (note that scores are normalized between -1 and +1) consistently since 2011. In the case of the employment-related scores, we observe periods in which the improvements at the 90th-percentile are even larger.

Focusing on the 10th-percentile, the change in ES-scores is frequently close to or equal to zero but with some noticeable exceptions. For the employment-related sub-scores some firms show sizable drops in their scores early in our sample period while for the environmental dimension we observe some bond-issuing firms with deteriorating ENV-scores towards the end of the sample period. In general, however, the positive effects of the 90th-percentile outweigh the negative effects of the 10th-percentile and due to this asymmetry the overall supply of good ES-score firms has increased over time, as discussed before.

Overall, the time-series results accord well with an increase in investor preferences for sustainable investment. The supply of corporate bonds from issuers with good ES ratings has generally increased and comes to a large extent from repeat issuers. For those ES-scores for which we document the strongest supply effects (i.e. aggregate ES-score, EMP-score, and ENV-score), the spread coefficients show little downward-trend, consistent with the prediction in Proposition 3. Finally, while the product-related score retains a negative and large spread regression coefficient, we do not find a supply response. This suggests that either the cost of improving these scores are very large, or that investments along this dimension are not driven by shifting investor preferences, but may instead be determined in a standard shareholder value maximizing paradigm. In summary, corporate bond markets suggest a significant role of investor preferences for capital reallocation.

4.3 ES-Scores and Credit Risk

After having analyzed the link between ES-scores and spreads in detail, we now shed light on the underlying mechanisms. As discussed in Section 2, one such mechanism is related to risk: firms with good ES-scores could be less risky than firms with low ES-scores. This risk-based mechanism should matter more for issuers that are already closer to the default boundary and, thus, have lower credit ratings. As a consequence, we expect that the negative link between ES-scores and spreads will be stronger for bonds with low ratings if the explanation for the difference is risk-related.

An alternative mechanism could be the higher demand for bonds with high ES-scores. If a subset of investors excludes bonds with low ES ratings from their portfolios, then bonds with high ES ratings are faced with relatively higher demand. The latter ones can be bought by both investors, i.e. by those with "green" preferences as well as by investors without such preferences, whereas bonds with low ES ratings can only be bought by the latter type of investors. In this case, we expect spreads of high-ES issues to be lower. However, as discussed above, this demand-based mechanism should also matter more for issuers with lower ratings and thus, more default risk. As shown in Section 2, investors without green preferences can "arbitrage" between bonds with high and low ES-scores. In other words, they can reduce or even short-sell the more expensive high-ES bonds and load up on issues with low ES ratings, without incurring large diversification costs. Demand effects from investors with green preferences are therefore likely to be limited for these highly rated bonds. By contrast, for low ratings, exploiting any price differences between bonds with high and low ES-scores is risky, since there will be some idiosyncratic default risk. Both our proposed channels are therefore related to the bonds' credit risk.

In a first step we therefore study the relation between ratings and ES-scores in more detail. While we controlled for different rating groups in the full sample results discussed in the previous section, we now split the sample into the following four sub-samples based on the available rating information: (i) issues with AAA and AA ratings, (ii) issues with A ratings, (iii) issues with BBB ratings, and finally (iv) high-yield issues and issues without rating information. This approach allows us to study the interaction between ES-scores and credit ratings.

Table 4 shows the corresponding results. Most importantly, the aggregate ES-score is significantly negatively related to bond spreads only for low rated bonds — i.e., BBB-rated as well as HY and unrated bonds. For these issues, coefficients on the ES-score are substantially larger than in the full sample results. For example, in the most risky group of high-yield and unrated bonds, the coefficient of the aggregate ES-score is estimated to equal -98.4 while, in comparison, the same coefficient has been estimated to be -18.8 in the full sample results. Even for BBB-rated bonds, the coefficient is much larger in absolute terms at -39.4. Thus, for risky bonds with low ratings, being a sustainable firm with a good ES-score results in an economically substantial reduction of bond spreads.

When analyzing the individual ES-dimensions, we find that, as before, the results are driven by the product-related ES-dimension. However, in both cases — BBB-rated bonds and HY/unrated bonds — the employee-related dimension also contributes significantly, both statistically and economically, to spread reductions. In the case of high-yield and unrated bonds, for example, the employee-related effect is even larger than the one coming from product-related ES-dimensions with a coefficient estimate of -64.4. For this sub-sample of bonds, we also find negative and sizable coefficient estimates for the environmental score and the community score, albeit not statistically significant in the case of the environmental score.

Focusing on the results for single-A rated bonds in more detail, we find that the aggregate ES-score does not matter at all. When analyzing the individual ES-dimensions, all coefficient estimates are insignificant and small in absolute magnitude with the only exceptions being the scores associated with the community (diversity) dimension, for which we find a significant, spread-increasing (spread-decreasing) effect. Finally, in the case of top-rated bond issues (i.e., AA and AAA) we find a significantly positive, but economically relatively small coefficient of the aggregate ES-score. When considering the sub-scores, we find significantly negative effects of the product-related and employment-related scores and significantly positive ones of the environment-related and diversity-related scores.

Overall, our analysis shows patterns across rating sub-samples that match the predictions of the theoretical framework well, especially regarding the variation in the importance of the aggregate and individual ES-scores across rating sub-samples. As discussed above, these findings are consistent with the two proposed channels, via which an effect of ES on spreads may take place. If better ES-scores indicate lower risk, not fully captured in ratings or firm fundamentals, the effects should be stronger in lower rated firms. If ES-scores affect spreads via demand effects, then these should also be stronger for lower rated bonds, since for these it is riskier to exploit spread differences.

To further disentangle these two alternative explanations, we study the link between ES-scores and credit events, rating downgrades as well as defaults. For this purpose, we define a default dummy, *def*, that equals one if the issuer files for bankruptcy during a three- or five-year horizon; and zero otherwise. Similarly, we define a downgrade dummy, *dng*, that equals one if a given bond's rating (from any rating agency) is downgraded during a three-year horizon; and zero otherwise. We then use logit models to predict those credit events using the same firm characteristics as in the spread regressions as control variables in addition to ES-related scores and industry fixed effects. However, we neither include rating dummies nor calendar year fixed effects, as they would absorb almost all of the variation in the sample.

Table 5 summarizes the corresponding coefficient estimates if we use the default dummy as the dependent variable. Because default happens at the firm level, we run these regressions at the issuer level. Given that the test setup also requires that we observe issuers either for at least 3 or 5 years, sample sizes are relatively small. Further more, the number of defaults that we actually see in the data is small (e.g., we only have 28 defaults at the 3-year horizon). When comparing these results with the earlier spread results, it is also important to highlight that all issuers that eventually went into default issued bonds with HY ratings.

Despite those data challenges, the results of the logit regressions support our earlier results for spreads, as we find that the aggregate ES-score reduces default risk significantly, both for the 3-year and the 5-year horizon. Similarly, results for ES sub-scores are, broadly speaking, consistent with the earlier spread regressions. Employment and diversity related scores that are associated with lower spreads for the sample of high-yield bonds in Table 4 show up with negative coefficients in the default prediction models. At the 3-year horizon, the environmental and the community scores also reduce default risk while scoring high with respect to human rights increases it. The only notable exception is documented for product scores: while firms with good product scores experience lower spreads, we do not find a corresponding effect on default risk.

As discussed before, the sample that we use in the default prediction analysis is small. To overcome this issue, we extend the credit event notion and analyze rating downgrades. Those downgrade events happen much more frequently than defaults (thus, we focus only on the 3-year horizon in the analysis) and we observe them at the bond level. As a consequence, sample sizes are substantially larger in this case. Table 6 presents the coefficient estimates of the corresponding logit models. For the full sample, the aggregate ES-score receives a positive but insignificant coefficient estimate. At the individual ES-score level, the product and community scores show significantly negative coefficients while the diversity and human rights scores get positive and significant coefficients. Except for the product score, those results appear to be inconsistent with the earlier spread results at first sight.

To better understand these patterns, we investigate whether selection effects of bonds with certain ratings play a role and split the sample into investment grade and high yield bonds. Given that almost 75% of the full rating downgrade sample consists of IG bonds, it is not surprising that the results look very similar to the ones for the full sample. However, an important difference is that the aggregate ES-score now becomes significant, indicating a higher risk of being downgraded for IG bonds with good aggregate ES-scores. Albeit not a perfect match, this result might explain to some extent the positive impact of the aggregate ES-score on the spreads of AAA and AA-rated bonds shown in Table 4.

In the case of HY bonds, the results look very differently. In this case, the aggregate ES-score obtains a negative and very significant coefficient estimate. When analyzing the individual scores, we find that the employment, community and the environmental score have significantly negative coefficients in the logit regression and, thus, all reduce the risk of rating downgrades. Importantly, these results are all consistent with the spread regressions discussed above and summarized in Table 4.

Overall, the picture emerges that for highest quality bond issues the impact of good ES ratings might be detrimental (i.e., lead to increased spreads and probabilities of downgrades), or at best ambiguous. In the case of relatively risky high-yield bonds, the evidence suggests that good ES performance reduces both credit risk as well as spreads — and the evidence of the spread regressions suggests that ratings do not perfectly capture this reduction in credit risk. Given that the results of the credit risk prediction models, broadly speaking, match the results from the spread regressions, we interpret the evidence to point towards the risk-based mechanism playing an important role linking ES-scores and corporate bond spreads.

5 Conclusion

This paper provides a comprehensive analysis of the interactions between firms' ES-scores and the spreads at which they can issue corporate bonds in the primary markets. In contrast to equity markets, this allows us to directly measure the premia charged by the market for expected default losses and for risk. We first develop a simple theoretical framework, which identifies three possible channels, through which such a relation can arise: ES-scores may provide information about (i) expected cash flows generated by the bonds, (ii) the risk of these cash flows and (iii) about extra demand from investors with ES preferences.

For the full sample we document an economically small, but statistically strong negative relation between ES-scores and issue spreads, even when controlling for ratings, a range of firm characteristics as well as industry and time dummies. However, our results show that the link between ES and bond spreads is much more nuanced than what one would suspect based on this general result. In particular, aggregate ES-scores are constructed from a number of individual scores on different ES-dimensions. We find that, again for the full sample, the negative relation between ES and issue spreads is only driven by the product dimension and, to a lesser extent, by employee-related dimensions. That is, high scores on characteristics such as product quality or product safety are priced in the bond IPO markets, but there is no evidence that this is also true for dimensions such as the environment, community or human rights.

Consistent with our theoretical model, we document that the interactions between ES and issue spreads vary with bond ratings. In particular, the aggregate ES-score has a significantly negative coefficient only for bonds rated BBB or below, and is in turn driven by good product and employee scores. By contrast, the aggregate ES-score is insignificant or even positively-related to spreads for issuers rated AAA to A. This is also true for almost all individual ES-scores, with the exception of employee and product related dimensions, which significantly reduce spreads also for highly rated issuers.

We also find strong differences across industries. Aggregate ES-scores reduce issue spreads only for firms in agriculture, forestry, fishing, and mining, and for manufacturing firms. For these industries, even the environment-related score, which in most of our analysis does not play a prominent role, has an economically and statistically significant negative effect on issue spreads. This is not the case for any of the other industries. For some of these other industries, such as the Transportation and Communication or the Trade sector, the coefficients of some ES-dimensions even flip signs. For example, the community dimensions of ES actually exhibit a statistically significant positive coefficient.

We also document variation of the ES-issue-spread relation over the business cycle. ES aggregate scores only have a significantly negative effect on issue spreads during expansions, somewhat contradicting conventional wisdom that ES effects are stronger in recessions or crises. In our analysis, the effect of aggregate ES-scores is insignificant during recessions. However, individual dimensions of ES still matter during recessions. In particular, high employee related scores are associated with strong negative effects on issue spreads. By contrast, other dimensions of ES, such as community and environment are all significantly positively related to spreads during recessions.

Finally, preference-based explanations for spread differences between high and low ES issuers predict increasingly stronger negative associations between ES and issue spreads towards the end of the sample period, since an increasing number of investors and portfolio managers adopt ES strategies. These effects, however, are potentially mitigated by supply-side responses, since our theoretical framework predicts that bond issuing firms should make investments to improve their ES-scores in response to the shifts in investor preferences. Our empirical results are consistent with these predictions and show pronounced supply-side responses for some of the ES-dimensions. These results are predominantly driven by repeat issuers, suggesting that firms that regularly tap the primary bond markets to raise capital have responded more to investor pressure and have improved their ES-scores during the sample period.

Overall, it appears that, in addition to preference-based demand for bonds from high ES issuers, ES-contained information about bonds' expected cash flows and their riskiness is responsible for the relation between ES-scores and issue spreads. This interpretation is also supported by our analysis of the link between ES-scores and credit risk, which finds that good ES-performance results in a significant reduction in credit risk for risky, high-yield bonds.

We believe that the primary market for corporate bonds offers great potential to improve our understanding of the interactions between corporate social responsibility strategies, investor preferences and asset prices. One avenue is to analyze the link between ES-related issue spread differences and their subsequent risk-return characteristics in the secondary markets. We intend to do this in future work.

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Appendix A

Our main data sources are Mergent FISD, MSCI ESG KLD, and Compustat. In this appendix, Table A1 presents the definitions of the variables used in the empirical analysis. In particular, we use bond issuers' one-digit SIC code to form five major industry groups. Table A2 lists the six dimensions of the MSCI ESG scores, which are Environment (env), Community (com), Diversity (div), Employee Relations (emp), Human Rights (hum), and Product (pro). For each of the six dimensions, we also report their subcategories and group these subcategories according to strengths and concerns.

We construct our environmental and social scores as follows. Using the environmental dimension as an example, we calculate the total number of environmental strengths for each firm-year and scale this total number by the maximum total number of strengths achieved in this year. We calculate and scale the total number of environmental concerns the same way. We then subtract the (scaled) total number of concerns from that of strengths, the resulted difference is our env_score for this particular firm-year. We do the same for the other five dimensions. For the aggregate environmental and social score (es_score), we first aggregate across all six dimensions for the total number of strengths and that concerns, scale them by the respective cross-sectional maximum, and finally take the difference.

We also define es dummies for each of the six individual ES-scores and the aggregate ES-score. Precisely, an es dummy is set to one (zero) if the ES-score is greater than or equal to zero (is less than zero).

Table A1 Variable definitions

Variables	Definition
Bond issue variables	
Spread	Offering spread over benchmark (bp)
Principal	Principal amount ($M)
Maturity	Maturity (Year)
Coupon	Coupon rate (Percent)
AAA	A rating dummy variable equals one if the issue is rated AAA; and zero otherwise[1]
AA	A rating dummy variable equals one if the issue is rated AA (incl. AA+, AA-); and zero otherwise[1]
A	A rating dummy variable equals one if the issue is rated A (incl. A+, A-); and zero otherwise[1]
BBB	A rating dummy variable equals one if the issue is rated BBB (incl. BBB+, BBB-); and zero otherwise[1]
HY	A rating dummy variable equals one if the issue is rated below investment grade; and zero otherwise[1]
NR	A dummy variable equals one if the issue is not rated; and zero otherwise[1]
Rating downgrade and default dummies	
dng	A dummy variable equals one if the issue is downgraded over a three-year horizon; and zero otherwise
def	A dummy variable equals one if the issuer files bankruptcy over a three- (or five-) year horizon; and zero otherwise
Issuer characteristics	
es_score	An aggregate environmental and social responsibllity score constructed using the below six individual scores (more on this in Appendix A2)
env_score	Total environmental strengths less total environmental concerns
com_score	Total community strengths less total community concerns
div_score	Total diversity strengths less total diversity concerns
emp_score	Total employee relations strengths less total employee relations concerns
hum_score	Total human rights strengths less total human rights concerns
pro_score	Total product strengths less total product concerns
Net book leverage	The total debt less cash and short term investments to total assets (book value) ratio
Size	The natural logarithm of net sales (in 2002 USD)
Profitability	The operating income before depreciation to total assets (book value) ratio
Tangibility	The net PPE to total assets (book value) ratio
Dividend payer	A dummy variable equals one if payout is greater than zero; and zero otherwise
Total no. of past issues	Total number of past bond issues since 1984
Industry groups	
AgriForeFishMineCons	Agriculture, Forestry, and Fishing (sic1 = 0); Mining and Construction (sic1 = 1)
Manufacturing	Manufacturing (sic1 = 2 or 3)
TransCommEGSSvc	Transportation, Communications, Electric-Gas-Sanitory Services (sic1 = 4, excl. utilities)
Trade	Wholesale and Retail Trade (sic1 = 5)
Services	Services (sic1 = 7 or 8)
Sample periods	
COVID19	March 15, 2020 through June 15, 2020
GFC	August 2008 through March 2009
REC	Either COVID19 or GFC period
Normal Period	All but REC period

[1] We use S&P rating as our primary source and supplement it with Moody's rating. When neither is available, we take Fitch's rating as the last resort.

Table A2 MSCI KLD environmental and social variables

Strengths		Concerns	
Environment (env)			
A	Environmental Opportunities–Clean Tech	A	Hazardous Waste
B	Pollution & Waste–Toxic Emissions and Waste	B	Regulatory Compliance
C	Pollution & Waste– Packaging Materials and Waste	C	Ozone Depleting Chemicals
D	Climate Change–Carbon Emissions	D	Toxic Emissions and Waste
F	Property, Plant, and Equipment	E	Agricultural Chemicals
G	Environmental Management Systems	F	Energy and Climate Change
H	Natural Capital–Water Stress	G	Impact of Products & Services
I	Natural Capital–Biodiversity & Land Use	H	Biodiversity & Land Use
J	Natural Capital–Raw Material Sourcing	I	Operational Waste (Non-Hazardous)
K	Climate Change–Financing Environment Impact	J	Supply Chain Management
L	Environmental Opportunities–Opportunities in Green Building	K	Water Stress
M	Environmental Opportunities–Opportunities in Renewable Engery	X	Other Concerns
N	Pollution & Waste–Electronic Waste		
O	Climate Change–Engergy Efficiency		
P	Climate Change–Product Carbon Footprint		
Q	Climate Change–Climate Change Vulnerability		
X	Other Strengths		
Community (com)			
A	Generous Giving	A	Investment Controversies
B	Innovative Giving	B	Impact on Community
C	Support for Housing	D	Tax Disputes
D	Support for Education	X	Other Concerns
F	Non-US Charitable Giving		
G	Volunteer Programs		
H	Community Engagement		
X	Other Strengths		
Diversity (div)			
A	CEO	A	Discrimination & Workforce Diversity
B	Representation	B	Representation
C	Board of Directors–Gender	C	Board Diversity–Gender
D	Work/Life Benefits	D	Borad Diversity–Minorities
E	Women & Minority Contracting	X	Other Concerns
F	Employment of the Disabled		
G	Gay & Lesbian Policies		
H	Employment of Underrepresented Groups		
X	Other Strengths		

Strengths		Concerns	
Employee Relations (emp)			
A	Union Relations	A	Collective Bargaining & Unions
B	No-layoff Policy	B	Health & Safety
C	Cash Profit Sharing	C	Workforce Reductions
D	Employee Involvement	D	Retirement Benefits Concern
F	Retirement Benefits Strength	F	Supply Chain Labor Standards
G	Employee Health & Safety	G	Child Labor
H	Supply Chain Labor Standards	H	Labor Management Relations
I	Compensation & Benefits	X	Other Concerns
J	Employee Relations		
K	Professional Development		
L	Human Capital Development		
M	Labor Management		
N	Controversial Sourcing		
X	Other Strengths		
Human Rights (hum)			
A	Positive Record in S.Africa	A	South Africa
D	Indigenous People Relations	B	Northern Ireland
G	Labor Rights	C	Support for Controversial Regimes
X	Human Rights Policies & Initiatives	D	Mexico
		F	Labor Rights Concern
		G	Indigenous People Relations
		H	Operations in Sudan
		J	Freedom of Expression & Censorship
		K	Huan Rights Violations
		X	Other Concerns
Product (pro)			
A	Product Quality & Safety	A	Product Quality & Safety
B	R&D, Innovation	D	Marketing & Advertising
C	Socal Opportunities	E	Anticompetitive Practices
D	Access to Finance	F	Customer Relations
E	Access to Communications	G	Privacy & Data Security
F	Opportunities in Nutrition and Health	X	Other Concerns
G	Product Safety–Chemical Safety		
H	Product Safety–Financial Product Safety		
I	Product Safety–Privacy and Data Security		
J	Product Satefy–Responsible Investment		
K	Product Safety–Insuring Health and Demographic Risk		
X	Other Strengths		

Table A3 Bond Spreads and ES-Scores - Controlling for the Most Granular Credit Rating Dummies

This table presents regression results using the offering spread of our sample bonds as the dependent variable. This table estimates the same set of regression models as those in Table 2 except that its models control for each individual credit rating notch. Definitions of variables are discussed in Section 3 and summarized in the appendix. *p*-values are placed in the parentheses underneath the estimated coefficients.

VARIABLES	(1) ES-score All Years Spread	(2) Individual scores All Years Spread	(3) ES-score 2002-2019 Spread	(4) Individual scores 2002-2019 Spread	(5) ES-score Normal Period Spread	(6) Individual scores Normal Period Spread	(7) ES-score REC Spread	(8) Individual scores REC Spread
Net book leverage	4.655	4.278	-0.424	0.346	2.932	3.479	-35.993	-48.526
	(0.553)	(0.588)	(0.957)	(0.965)	(0.685)	(0.632)	(0.293)	(0.159)
Size	-7.467	-7.750	-10.809	-11.173	-14.485	-14.719	26.864	29.614
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Profitability	-107.079	-109.267	-111.142	-114.502	-110.675	-113.199	-110.481	-101.565
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.272)	(0.318)
Tangiblity	25.577	25.106	14.664	15.145	9.240	8.511	109.443	103.042
	(0.000)	(0.000)	(0.033)	(0.031)	(0.149)	(0.192)	(0.000)	(0.001)
Dividend payer (dummy)	-7.703	-7.916	-12.683	-13.284	-14.338	-14.743	46.344	46.179
	(0.059)	(0.053)	(0.002)	(0.001)	(0.000)	(0.000)	(0.016)	(0.016)
Total no. of past issues	-0.126	-0.101	-0.148	-0.130	-0.048	-0.033	0.022	0.089
	(0.151)	(0.257)	(0.117)	(0.176)	(0.579)	(0.712)	(0.935)	(0.746)
env_score		-3.699		-6.665		-5.544		65.955
		(0.542)		(0.262)		(0.324)		(0.005)
com_score		6.587		1.593		1.220		47.681
		(0.136)		(0.722)		(0.766)		(0.008)
div_score		-5.098		-3.048		-3.944		-23.236
		(0.214)		(0.473)		(0.311)		(0.098)
emp_score		-4.260		-0.551		0.544		-35.518
		(0.444)		(0.922)		(0.918)		(0.063)
hum_score		13.200		8.345		11.998		16.476
		(0.046)		(0.206)		(0.051)		(0.547)
pro_score		-18.008		-22.651		-20.160		-1.584
		(0.001)		(0.000)		(0.000)		(0.936)
es_score	-12.656		-18.597		-13.504		17.292	
	(0.061)		(0.007)		(0.037)		(0.431)	
COVID19							-206.498	-219.574
							(0.000)	(0.000)
Constant	293.340	294.365	234.607	234.244	270.037	270.957	86.235	59.784
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.319)	(0.491)
All credit rating dummies	Y	Y	Y	Y	Y	Y	Y	Y
Industry and Year Fes	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,181	5,181	4,631	4,631	4,564	4,564	617	617
R-squared adjusted	0.660	0.661	0.691	0.691	0.715	0.716	0.600	0.611

Appendix B

Proof for Proposition 1

From equation (8), we can immediately derive

$$x_{nP} = \frac{N_P}{I_n}.$$

Using the above right-hand side expression to eliminate x_{nP} in equations (1) and comparing the resulted expression with equation (3) yields

$$x_{gG} = x_{nG} + \frac{\sigma_{GP}}{\sigma_G^2}\frac{N_P}{I_n}. \tag{B.1}$$

Combing equations (B.1) with (7), we can show

$$x_{nG} = \frac{1}{I}\left(N_G - N_P \frac{I_g}{I_n}\frac{\sigma_{GP}}{\sigma_G^2}\right);$$

and

$$x_{gG} = \frac{1}{I}\left(N_G + N_P \frac{\sigma_{GP}}{\sigma_G^2}\right).$$

Plugging the solved optimal portfolio weights into the first order conditions (1)-(3), we can derive the bond prices as follows

$$P_G = 1 - \bar{\epsilon}_G - \frac{1}{\tau I}\left[N_G\sigma_G^2 + N_P\sigma_{GP}\right];$$

and

$$P_P = 1 - \bar{\epsilon}_P - \frac{1}{\tau I}\left[N_G\sigma_{GP} + N_P\sigma_P^2 + N_P\frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right].$$

where $\phi = \sigma_G^2\sigma_P^2 - \sigma_{GP}^2 = \sigma_G^2\sigma_P^2\,(1 - \rho_{GP}^2)$.

The bond yield spreads results follow from (i) all bonds have face value of one and are pure discount bonds and (ii) the riskless rate of return is normalized to zero.

Proof for Proposition 2

Using equation (16) to solve for N_G (and then N_P) yields

$$N_G = \frac{N\left(\sigma_P^2 - \sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right) - (K^c - \delta)\tau I}{\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}},$$

and

$$N_P = N - N_G = \frac{N\left(\sigma_G^2 - \sigma_{GP}\right) + (K^c - \delta)\tau I}{\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}}.$$

The endogenous cutoff value of the investment cost K^c is the solution to the fixed point problem

$$F(K^c) = N_G = \frac{N\left(\sigma_P^2 - \sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right) - (K^c - \delta)\tau I}{\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}}.$$

To show existence and uniqueness, we note that

$$y(K^0) = \delta + \frac{1}{\tau I}\left(N\left(\sigma_P^2 - \sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right) - F(K^0)\left(\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \frac{I_g}{I_n}\frac{\phi}{\sigma_G^2}\right)\right) - K^0$$

is decreasing in K^0 because (i) $\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} = \sigma_G^2 + \sigma_P^2 - 2\rho_{GP}\sigma_G\sigma_P = (\sigma_G - \sigma_P)^2 + 2(1 - \rho_{GP})\sigma_G\sigma_P > 0$, (ii) $F > 0$, and (iii) $\tau I > 0$. Monotonicity and Assumption 1 then imply that K^c is the unique solution satisfying $y(K^c) = 0$ and $\underline{K} < K^c < \overline{K}$.

Proof for Proposition 3

For the first part of the proposition, we treat N_G and N_P as fixed parameters. Partially differentiating $P_G - P_P$, given by equation (13), with respect to δ, σ_P, or ι yields the expressions provided in the proposition.

For the second part of the proposition, to emphasize that K^c is determined in the equilibrium and thus is a function of model parameters, we can rewrite equation (16) as

$$y(K^c(\mathbf{p}), \mathbf{p}) = \delta + \frac{1}{\tau I}\left(N\left(\sigma_P^2 - \sigma_{GP} + \iota\frac{\phi}{\sigma_G^2}\right) - F(K^c(\mathbf{p}))\left(\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \iota\frac{\phi}{\sigma_G^2}\right)\right) - K^c(\mathbf{p}) = 0 \tag{B.2}$$

where $\mathbf{p}$ is a set of exogenous parameters.

(i) To focus on the effect of δ, we consider

$$y(K^c(\delta), \delta) = 0$$

where we keep all other parameters fixed.

Since the above equality holds for all δ, its first derivative with respect to δ must also be equal to zero. That is,

$$F'(K^c)\frac{\partial K^c}{\partial \delta}\left(\sigma_G^2 + \sigma_P^2 - 2\sigma_{GP} + \iota\frac{\phi}{\sigma_G^2}\right) + \frac{\partial K^c}{\partial \delta}\tau I - \tau I = 0.$$

Rearranging the terms yields

$$\frac{\partial K^c}{\partial \delta}\left[F'(K^c)\left(\sigma_G^2+\sigma_P^2-2\sigma_{GP}+\iota\frac{\phi}{\sigma_G^2}\right)+\tau I\right]=\tau I. \tag{B.3}$$

The right-hand side of equation (B.3) is positive. On its left-hand side, the sum of the terms inside the square parentheses is positive since (a) $\sigma_G^2+\sigma_P^2-2\sigma_{GP}=\sigma_G^2+\sigma_P^2-2\rho_{GP}\sigma_G\sigma_P=(\sigma_G-\sigma_P)^2+2(1-\rho_{GP})\sigma_G\sigma_P>0$, (b) $F'>0$, and (c) $\tau I>0$. As a consequence,

$$\frac{\partial K^c}{\partial \delta}>0. \tag{B.4}$$

(ii) Focusing on σ_P, differentiating both sides of

$$y(K^c(\sigma_P),\sigma_P)=0$$

with respect to σ_P, and simplifying yields

$$\frac{\partial K^c}{\partial \sigma_P}\left[F'(K^c)\left(\sigma_G^2+\sigma_P^2-2\sigma_{GP}+\iota\frac{\phi}{\sigma_G^2}\right)+\tau I\right]=(N-F(K^c))\left(2\sigma_P-\sigma_G\rho_{GP}+2\iota\sigma_P(1-\rho_{GP}^2)\right)+F(K^c)\sigma_G \tag{B.5}$$

where we carefully take into account that both $\sigma_{GP}=\sigma_G\sigma_P\rho_{GP}$ and $\frac{\phi}{\sigma_G^2}=\sigma_P^2(1-\rho_{GP}^2)$ depend on σ_P.

On the left-hand side of equation (B.5), the sum of the terms inside the square parentheses is positive (see part (i) of this proof). Its right-hand side is also positive because (a) $N>N_G=F(K^c)$ and (b) $2\sigma_P-\sigma_G\rho_{GP}+2\iota\sigma_P(1-\rho_{GP}^2)>0$ (a condition we assume to hold), and (c) $F(K^c)\sigma_G\rho_{GP}>0$ as long as $\rho_{GP}>0$. Thus,

$$\frac{\partial K^c}{\partial \sigma_P}>0. \tag{B.6}$$

(iii) To analyze the effect of investor demand, we can perform a comparative statics analysis on ι. Differentiating both sides of

$$y(K^c(\iota),\iota)=0$$

with respect to ι yields

$$F'(K^c)\frac{\partial K^c}{\partial \iota}\left(\sigma_G^2+\sigma_P^2-2\sigma_{GP}+\iota\frac{\phi}{\sigma_G^2}\right)+F(K^c)\frac{\phi}{\sigma_G^2}+\frac{\partial K^c}{\partial \iota}\tau I-N\frac{\phi}{\sigma_G^2}=0.$$

Rearranging the terms yields

$$\frac{\partial K^c}{\partial \iota}\left[F'(K^c)\left(\sigma_G^2+\sigma_P^2-2\sigma_{GP}+\iota\frac{\phi}{\sigma_G^2}\right)+\tau I\right]=(N-F(K^c))\frac{\phi}{\sigma_G^2}. \tag{B.7}$$

On the left-hand side of equation (B.7), the sum of the terms inside the square parentheses is positive (see part (i) of this proof). Its right-hand side is also positive because $N > N_G = F(K^c)$. As a consequence,

$$\frac{\partial K^c}{\partial \iota}>0. \tag{B.8}$$

Finally, using equation (6) we can immediately show

$$\frac{\partial N_G}{\partial q}=F'(K^c)\frac{\partial K^c}{\partial q}>0,\ \text{for } q=\delta,\sigma_P,\text{or } \iota, \tag{B.9}$$

because $F'(K^c)$ is a density function and thus is always positive.

Proof for Proposition 5

First, note that

$$\frac{\phi}{\sigma_G^2}=\frac{\sigma_G^2\sigma_P^2-\sigma_{GP}^2}{\sigma_G^2}=\sigma_P^2(1-\rho_{GP}^2).$$

To fix ideas, we parameterize the variances as $\xi^2\sigma_G^2$ and $\xi^2\sigma_P^2$ where $\xi \geq 0$ is a scaling parameter.[15] For ease of exposition, we define

$$A \equiv \xi^2\sigma_G^2+\xi^2\sigma_P^2-2\rho_{GP}\xi^2\sigma_G^2\sigma_P^2+\iota\xi^2\sigma_P^2(1-\rho_{GP}^2)=a\xi^2$$

where $a \equiv \sigma_G^2+\sigma_P^2-2\rho_{GP}\sigma_G\sigma_P+\iota\sigma_P^2(1-\rho_{GP}^2)$ and

$$B \equiv \xi^2\sigma_P^2-\rho_{GP}\xi^2\sigma_G\sigma_P+\iota\xi^2\sigma_P^2(1-\rho_{GP}^2)=b\xi^2$$

where $b \equiv \sigma_P^2-\rho_{GP}\sigma_G\sigma_P+\iota\sigma_P^2(1-\rho_{GP}^2)$.

Using the defined variables to simplify equation (B.2) yields

$$F(K^c)a\xi^2+(K^c-\delta)\tau I-Nb\xi^2=0. \tag{B.10}$$

This equilibrium condition implies that K^c depends on ξ^2. Differentiating it with respect to

[15] Our analysis so far has dealt with a special case in which $\xi = 1$.

ξ^2 and rearranging the terms yields

$$\frac{\partial K^c}{\partial \xi^2}\left(F'(K^c)a\xi^2+\tau I\right)=Nb-F(K^c)a=\frac{K^c-\delta}{\xi^2}\tau I.$$

where the last equality follows from equation (B.10). Since $K^c>\delta$, we conclude that K^c increases with ξ^2.

Finally, equation (B.10) also implies that K^c converges to δ as ξ^2 is approaching to zero.

Proof for Proposition 4

For simplicity, we parameterize the investment cost as

$$\hat{K}=K+\Delta_K$$

where K is distributed according to the distribution function F with finite support $[\underline{K},\overline{K}]$.

We can then define another distribution function G such that

$$G(K^c)=\mu(\hat{K}<K^c)=\mu(K+\Delta_K<K^c)=\mu(K<K^c-\Delta K)=F(K^c-\Delta K).$$

The newly defined G function preserves the order of the firms in terms of their costs of ES investment, as is given by the original distribution function F. The mere difference between the two distributions is the level of the investment cost, which is captured by Δ_K.

Using the terms defined in the proof of Proposition 5 and noting that $\hat{K}$ is distributed according to G, we can rewrite equation (B.2) as

$$G(K^c)a+(K^c-\delta)\tau I-Nb=0.$$

Substituting $F(K^c-\Delta_K)$ into to the above equation for $G(K^c)$ yields

$$F(K^c-\Delta_K)a+(K^c-\delta)\tau I-Nb=0.$$

Differentiating it with respect to Δ_K and simplifying yields

$$\frac{\partial K^c}{\partial \Delta_K}\left(F'(K^c-\Delta_K)a+\tau I\right)=F'(K^c-\Delta_K)a.$$

Since F' is a density function and $a>0$, it follows immediately that K^c increases with Δ_K.

Table 1 Bond issues

This table has three panels. Panel A reports the summary statistics for ES-scores, bond issue-level characteristics and issuer-level (that is, firm-level) characteristics. All ES-scores and issuer-level variables are lagged by one year. Panel B splits our sample into five industry groups and provides summary statistics for ES-scores and dummies across these five industry groups. Panel C is a correlation matrix for bond issue characteristics and ES-scores. Variable definitions are summarized in the appendix. ****, **, or * next to the differences in Panel A (the correlation coefficients in Panel C) indicate that the differences (the correlation coefficients) are significantly different from zero at the 1%, 5%, and 10% level.*

Panel A

	(1)	(2)	(3)	(4)	(5)	(6)	
	All		es_good = 1		es_good = 0		
VARIABLES	mean	N	mean	N	mean	N	(3) - (5)
es_score	0.075	5,227	0.211	3,328	-0.164	1,899	
env_score	0.141	5,227	0.241	3,328	-0.033	1,899	
com_score	0.031	5,227	0.104	3,328	-0.099	1,899	
div_score	0.115	5,227	0.249	3,328	-0.118	1,899	
emp_score	0.044	5,227	0.153	3,328	-0.146	1,899	
hum_score	0.005	5,227	0.026	3,328	-0.030	1,899	
pro_score	-0.046	5,227	0.024	3,328	-0.168	1,899	
Spread	212.340	5,227	190.964	3,328	249.803	1,899	-58.839***
Principal	747.604	5,227	788.265	3,328	676.346	1,899	111.919***
Maturity	11.561	5,227	11.584	3,328	11.523	1,899	0.061
Coupon	4.514	5,224	4.088	3,326	5.260	1,898	-1.172***
AAA	0.022	5,227	0.026	3,328	0.014	1,899	0.012***
AA	0.071	5,227	0.066	3,328	0.080	1,899	-0.014*
A	0.279	5,227	0.302	3,328	0.237	1,899	0.065***
BBB	0.385	5,227	0.397	3,328	0.364	1,899	0.033**
Net book leverage	0.215	5,227	0.205	3,328	0.234	1,899	-0.029***
Size	9.070	5,227	9.118	3,328	8.985	1,899	0.133***
Profitability	0.155	5,227	0.159	3,328	0.147	1,899	0.012***
Tangibility	0.308	5,227	0.268	3,328	0.378	1,899	-0.110***
Dividend payer	0.796	5,227	0.818	3,328	0.758	1,899	0.060***
Total no. of past issues	18.841	5,227	19.246	3,328	18.131	1,899	1.115*

Panel B

	AgriForeFishMineCons			Manufacturing			TransCommEGSSvc			Trade			Services		
VARIABLES	mean	p50	N	mean	p50	N	mean	p50	N	mean	p50	N	mean	p50	N
env_score	-0.052	0.000	508	0.192	0.167	2,781	0.075	0.000	594	0.126	0.000	687	0.154	0.000	657
com_score	0.012	0.000	508	0.052	0.000	2,781	-0.095	0.000	594	0.038	0.000	687	0.060	0.000	657
div_score	-0.123	0.000	508	0.191	0.000	2,781	0.049	0.000	594	0.022	0.000	687	0.137	0.000	657
emp_score	-0.018	0.000	508	0.085	0.000	2,781	-0.011	0.000	594	-0.081	0.000	687	0.105	0.000	657
hum_score	0.154	0.000	508	-0.009	0.000	2,781	-0.020	0.000	594	-0.031	0.000	687	0.013	0.000	657
pro_score	-0.027	0.000	508	-0.025	0.000	2,781	-0.118	0.000	594	-0.107	0.000	687	-0.018	0.000	657
es_score	-0.044	-0.036	508	0.115	0.096	2,781	0.003	0.000	594	0.007	0.000	687	0.131	0.077	657
env_good	0.677	1.000	508	0.858	1.000	2,781	0.818	1.000	594	0.902	1.000	687	1.000	1.000	657
com_good	0.799	1.000	508	0.890	1.000	2,781	0.731	1.000	594	0.917	1.000	687	0.982	1.000	657
div_good	0.642	1.000	508	0.869	1.000	2,781	0.793	1.000	594	0.686	1.000	687	0.845	1.000	657
emp_good	0.756	1.000	508	0.729	1.000	2,781	0.594	1.000	594	0.544	1.000	687	0.845	1.000	657
hum_good	0.947	1.000	508	0.921	1.000	2,781	0.956	1.000	594	0.888	1.000	687	0.953	1.000	657
pro_good	0.886	1.000	508	0.707	1.000	2,781	0.626	1.000	594	0.645	1.000	687	0.734	1.000	657
es_good	0.457	0.000	508	0.693	1.000	2,781	0.502	1.000	594	0.574	1.000	687	0.726	1.000	657

Panel C

	Spread	Principal	Maturity	es_score	env_score	com_score	div_score	emp_score	hum_score	pro_score
Spread	1									
Principal	-0.095***	1								
Maturity	-0.085***	0.080***	1							
es_score	-0.218***	0.100***	0.020	1						
env_score	-0.235***	0.126***	0.041**	0.673***	1					
com_score	-0.079***	0.019	-0.012	0.376***	0.213***	1				
div_score	-0.215***	0.135***	0.043**	0.508***	0.265***	0.168***	1			
emp_score	-0.146***	0.090***	0.017	0.681***	0.297***	0.113***	0.205***	1		
hum_score	0.060***	0.019	-0.003	0.156***	0.042**	0.070***	0.035*	0.036**	1	
pro_score	0.002	-0.066***	-0.056***	0.448***	0.161***	0.120***	0.066***	0.154***	0.054***	1

Table 2 Bond Spreads and ES-Scores

This table presents regression results using the offering spread of our sample bonds as the dependent variable. Definitions of variables are discussed in Section 3 and summarized in the appendix. p-values are placed in the parentheses underneath the estimated coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	ES-score	Individual scores	ES-score	Individual scores	ES-score	Individual scores	ES-score	Individual scores
	All Years	All Years	2002-2019	2002-2019	Normal Period	Normal Period	REC	REC
VARIABLES	Spread	Spread	Spread	Spread	Spread	Spread	Spread	Spread
Net book leverage	44.213	43.225	40.662	41.001	43.518	43.548	54.034	37.557
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.132)	(0.302)
Size	-17.606	-17.801	-20.195	-20.619	-23.973	-24.267	9.864	12.790
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.243)	(0.137)
Profitability	-216.167	-217.228	-206.882	-208.688	-206.883	-208.197	-279.577	-251.909
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.019)
Tangiblity	31.290	31.195	17.061	18.166	11.398	11.299	172.306	160.161
	(0.000)	(0.000)	(0.020)	(0.015)	(0.098)	(0.108)	(0.000)	(0.000)
Dividend payer (dummy)	-28.387	-28.804	-31.528	-32.446	-32.872	-33.571	11.255	11.344
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.597)	(0.591)
Total no. of past issues	-0.207	-0.193	-0.267	-0.259	-0.163	-0.158	-0.161	-0.093
	(0.023)	(0.036)	(0.006)	(0.009)	(0.074)	(0.087)	(0.593)	(0.759)
AAA	-206.320	-210.390	-193.933	-197.490	-185.067	-188.409	-318.225	-351.036
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
AA	-235.518	-238.886	-224.971	-227.421	-214.941	-216.828	-354.319	-394.169
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A	-224.532	-224.710	-221.377	-221.782	-215.899	-216.117	-274.438	-291.762
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BBB	-187.798	-187.293	-187.075	-186.504	-187.519	-186.889	-179.239	-184.655
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
env_score		0.192		-4.888		-2.658		66.435
		(0.976)		(0.437)		(0.658)		(0.012)
com_score		5.971		1.091		1.013		45.696
		(0.204)		(0.819)		(0.819)		(0.024)
div_score		-7.003		-2.876		-4.036		-24.286
		(0.108)		(0.526)		(0.337)		(0.121)
emp_score		-9.722		-6.084		-4.698		-57.460
		(0.098)		(0.307)		(0.405)		(0.006)
hum_score		11.036		5.485		9.387		26.611
		(0.119)		(0.438)		(0.159)		(0.390)
pro_score		-20.501		-24.432		-22.055		-17.625
		(0.000)		(0.000)		(0.000)		(0.420)
es_score	-18.824		-24.841		-18.547		-6.877	
	(0.007)		(0.001)		(0.006)		(0.773)	
COVID19							-198.824	-210.048
							(0.000)	(0.000)
Constant	493.910	495.080	540.257	541.128	614.460	616.192	581.681	580.506
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry and Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	5,227	5,227	4,662	4,662	4,595	4,595	632	632
R-squared adjusted	0.607	0.608	0.640	0.641	0.662	0.662	0.460	0.474

Table 3 Bond Spreads and ES-Scores: industry groups

This table presents regression results for five industry groups of bond issuers. The first two (next three) industry groups are replaced in Panel A (B). Definitions of variables are discussed in Section 3 and summarized in the appendix. p-values are placed in the parentheses underneath the estimated coefficients.

Panel A				
	(1)	(2)	(3)	(4)
	ES-score	Individual scores	ES-score	Individual scores
	AgriForeFishMineCons	AgriForeFishMineCons	Manufacturing	Manufacturing
VARIABLES	Spread	Spread	Spread	Spread
Net book leverage	173.623	174.717	15.168	15.829
	(0.000)	(0.000)	(0.155)	(0.143)
Size	-47.342	-52.681	-14.840	-14.719
	(0.000)	(0.000)	(0.000)	(0.000)
Profitability	-124.888	-110.288	-187.657	-196.808
	(0.017)	(0.034)	(0.000)	(0.000)
Tangiblity	-44.353	-56.393	90.579	93.111
	(0.025)	(0.007)	(0.000)	(0.000)
Dividend payer (dummy)	-19.263	-20.141	-27.243	-28.342
	(0.213)	(0.191)	(0.000)	(0.000)
Total no. of past issues	0.565	0.530	-0.088	-0.097
	(0.363)	(0.399)	(0.551)	(0.515)
AAA			-224.609	-226.348
			(0.000)	(0.000)
AA			-226.564	-227.583
			(0.000)	(0.000)
A	-168.577	-173.097	-216.793	-217.106
	(0.000)	(0.000)	(0.000)	(0.000)
BBB	-141.367	-138.432	-169.244	-168.840
	(0.000)	(0.000)	(0.000)	(0.000)
env_score		-78.812		11.032
		(0.004)		(0.147)
com_score		-21.323		-5.360
		(0.154)		(0.372)
div_score		-2.154		-10.956
		(0.921)		(0.054)
emp_score		-0.776		-14.125
		(0.981)		(0.052)
hum_score		32.958		-1.624
		(0.139)		(0.862)
pro_score		-125.911		-31.274
		(0.008)		(0.000)
es_score	-90.483		-31.112	
	(0.037)		(0.000)	
Constant	631.799	676.445	455.854	452.349
	(0.000)	(0.000)	(0.000)	(0.000)
Year FEs	Y	Y	Y	Y
Observations	508	508	2,781	2,781
R-squared adjusted	0.641	0.651	0.575	0.577

Panel B

VARIABLES	(5) ES-score TransCommEGSSvc Spread	(6) Individual scores TransCommEGSSvc Spread	(7) ES-score Trade Spread	(8) Individual scores Trade Spread	(9) ES-score Services Spread	(10) Individual scores Services Spread
Net book leverage	33.505	41.996	34.310	32.136	58.431	62.400
	(0.336)	(0.230)	(0.134)	(0.174)	(0.020)	(0.015)
Size	-23.082	-26.078	-15.675	-17.540	-14.431	-13.790
	(0.000)	(0.000)	(0.004)	(0.002)	(0.009)	(0.018)
Profitability	-339.675	-336.296	-178.824	-166.880	-207.930	-160.163
	(0.010)	(0.011)	(0.008)	(0.014)	(0.006)	(0.040)
Tangiblity	-39.106	-18.179	54.179	48.384	38.007	27.222
	(0.059)	(0.447)	(0.025)	(0.048)	(0.115)	(0.261)
Dividend payer (dummy)	-5.858	-2.329	-28.411	-25.596	-49.504	-48.580
	(0.741)	(0.898)	(0.009)	(0.021)	(0.000)	(0.000)
Total no. of past issues	-0.223	-0.153	-0.593	-0.413	0.712	0.577
	(0.189)	(0.380)	(0.065)	(0.229)	(0.065)	(0.139)
AAA					-189.926	-205.780
					(0.000)	(0.000)
AA	-307.647	-295.962	-242.676	-240.912	-295.418	-305.933
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
A	-239.781	-237.177	-251.664	-248.265	-221.559	-241.700
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
BBB	-225.704	-224.593	-206.358	-203.228	-182.021	-184.742
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
env_score		-3.616		-5.147		64.723
		(0.884)		(0.824)		(0.024)
com_score		29.974		35.083		-49.728
		(0.030)		(0.049)		(0.033)
div_score		-20.107		14.011		-28.948
		(0.140)		(0.256)		(0.063)
emp_score		-42.752		-5.751		0.003
		(0.055)		(0.727)		(1.000)
hum_score		-31.093		23.572		-32.550
		(0.412)		(0.260)		(0.315)
pro_score		4.731		15.609		-7.780
		(0.849)		(0.374)		(0.717)
es_score	-31.904		50.807		-20.759	
	(0.233)		(0.026)		(0.454)	
Constant	654.162	665.289	509.340	524.534	470.148	471.588
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year FEs	Y	Y	Y	Y	Y	Y
Observations	594	594	687	687	657	657
R-squared adjusted	0.600	0.603	0.601	0.601	0.625	0.630

Table 4 Bond Spreads and ES-Scores: rating groups

This table presents regression results for four bond credit rating groups. Definitions of variables are discussed in Section 3 and summarized in the appendix. p-values are placed in the parentheses underneath the estimated coefficients.

VARIABLES	(1) ES-score AAA & AA Spread	(2) Individual scores AAA & AA Spread	(3) ES-score A Spread	(4) Individual scores A Spread	(5) ES-score BBB Spread	(6) Individual scores BBB Spread	(7) ES-score HY & NR Spread	(8) Individual scores HY & NR Spread
Net book leverage	-5.872	-15.546	15.477	15.289	-25.783	-26.817	74.067	82.588
	(0.737)	(0.368)	(0.085)	(0.095)	(0.029)	(0.026)	(0.001)	(0.000)
Size	2.898	0.477	-2.538	-2.659	-3.349	-4.609	-31.592	-33.426
	(0.620)	(0.934)	(0.224)	(0.211)	(0.177)	(0.072)	(0.000)	(0.000)
Profitability	-108.115	-162.345	-15.314	-22.112	-128.820	-121.751	-294.368	-273.995
	(0.009)	(0.000)	(0.467)	(0.299)	(0.000)	(0.001)	(0.000)	(0.000)
Tangiblity	20.834	20.789	-12.004	-12.201	14.181	21.867	58.837	45.673
	(0.098)	(0.164)	(0.243)	(0.238)	(0.155)	(0.033)	(0.002)	(0.017)
Dividend payer (dummy)	47.273	47.848	-8.618	-7.448	-1.477	-4.764	-40.685	-41.591
	(0.000)	(0.000)	(0.163)	(0.229)	(0.800)	(0.419)	(0.000)	(0.000)
Total no. of past issues	-0.252	-0.405	-0.186	-0.154	-0.030	0.005	-0.233	-0.159
	(0.035)	(0.001)	(0.078)	(0.148)	(0.842)	(0.974)	(0.338)	(0.516)
env_score		43.139		-2.470		-5.256		-22.146
		(0.000)		(0.662)		(0.573)		(0.345)
com_score		-0.283		8.166		8.801		-38.805
		(0.969)		(0.042)		(0.165)		(0.040)
div_score		29.548		-12.125		0.144		-5.391
		(0.000)		(0.003)		(0.981)		(0.704)
emp_score		-36.065		4.857		-14.672		-64.385
		(0.000)		(0.369)		(0.066)		(0.007)
hum_score		-1.579		6.532		9.096		98.941
		(0.836)		(0.316)		(0.393)		(0.000)
pro_score		-16.388		-1.543		-35.671		-47.094
		(0.008)		(0.769)		(0.000)		(0.081)
es_score	21.000		0.217		-39.420		-98.354	
	(0.011)		(0.972)		(0.000)		(0.001)	
Constant	-3.978	50.871	110.540	113.955	162.422	170.824	728.140	740.106
	(0.953)	(0.458)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry and Year FEs	Y	Y	Y	Y	Y	Y	Y	Y
Observations	482	482	1,457	1,457	2,013	2,013	1,275	1,275
R-squared adjusted	0.468	0.499	0.449	0.453	0.354	0.357	0.370	0.378

Table 5 Defaults and ES-Scores

This table presents the results from logit regressions that use a default dummy (defined either over a three-year horizon or five-year horizon) as the dependent variable. Definitions of variables are discussed in Section 3 and summarized in the appendix. p-values are placed in the parentheses underneath the estimated coefficients.

VARIABLES	(1) ES-score Three-year Horizon def	(2) Individual scores Three-year Horizon def	(3) ES-score Five-year Horizon def	(4) Individual scores Five-year Horizon def
Net book leverage	3.907	4.252	3.299	4.017
	(0.002)	(0.003)	(0.003)	(0.001)
Size	-0.388	-0.534	-0.307	-0.362
	(0.087)	(0.050)	(0.152)	(0.116)
Profitability	-4.624	-5.097	-3.069	-3.485
	(0.113)	(0.129)	(0.238)	(0.215)
Tangiblity	-0.883	-2.235	-1.055	-1.909
	(0.413)	(0.075)	(0.404)	(0.181)
Dividend payer (dummy)	0.398	0.791	0.215	0.272
	(0.443)	(0.182)	(0.643)	(0.591)
Total no. of past issues	-0.106	-0.105	-0.049	-0.033
	(0.011)	(0.025)	(0.132)	(0.332)
env_score		-3.540		-1.271
		(0.023)		(0.320)
com_score		-2.553		-0.784
		(0.031)		(0.447)
div_score		-3.245		-3.249
		(0.001)		(0.001)
emp_score		-2.513		-1.688
		(0.083)		(0.229)
hum_score		4.788		2.499
		(0.004)		(0.087)
pro_score		-0.157		-0.500
		(0.907)		(0.670)
es_score	-6.268		-4.778	
	(0.001)		(0.003)	
Constant	-0.350	1.125	0.252	0.958
	(0.860)	(0.624)	(0.888)	(0.634)
Industry FEs	Y	Y	Y	Y
Observations	317	317	176	176
pseudo R squared	0.350	0.450	0.291	0.361

Table 6 Rating Downgrades and ES-Scores

This table presents the results from logit regressions that use a credit rating downgrade dummy (defined over a three-year horizon) as the dependent variable. Definitions of variables are discussed in Section 3 and summarized in the appendix. p-values are placed in the parentheses underneath the estimated coefficients.

	(1)	(2)	(3)	(4)	(5)	(6)
	ES-score	Individual scores	ES-score	Individual scores	ES-score	Individual scores
	All	All	IG	IG	HY	HY
VARIABLES	dng	dng	dng	dng	dng	dng
Net book leverage	0.505	0.532	0.689	0.694	-0.323	-0.234
	(0.005)	(0.003)	(0.002)	(0.002)	(0.369)	(0.520)
Size	0.059	0.021	0.067	0.025	0.100	0.044
	(0.093)	(0.574)	(0.159)	(0.617)	(0.143)	(0.542)
Profitability	-1.256	-1.156	-0.650	-0.524	-2.900	-2.912
	(0.006)	(0.011)	(0.264)	(0.376)	(0.001)	(0.001)
Tangiblity	0.338	0.256	-0.130	-0.221	1.006	1.002
	(0.039)	(0.129)	(0.554)	(0.330)	(0.001)	(0.001)
Dividend payer (dummy)	0.070	0.047	0.166	0.147	0.038	0.018
	(0.450)	(0.613)	(0.210)	(0.273)	(0.797)	(0.906)
Total no. of past issues	-0.008	-0.008	-0.009	-0.010	-0.005	-0.004
	(0.004)	(0.004)	(0.004)	(0.002)	(0.322)	(0.458)
env_score		-0.168		-0.032		-1.087
		(0.209)		(0.832)		(0.003)
com_score		-0.398		-0.378		-0.896
		(0.000)		(0.002)		(0.005)
div_score		0.485		0.617		0.239
		(0.000)		(0.000)		(0.308)
emp_score		-0.076		-0.014		-0.783
		(0.557)		(0.922)		(0.025)
hum_score		0.481		0.448		0.375
		(0.002)		(0.008)		(0.386)
pro_score		-0.287		-0.237		-0.315
		(0.024)		(0.083)		(0.451)
es_score	0.053		0.297		-1.583	
	(0.730)		(0.080)		(0.001)	
Constant	-1.249	-0.965	-1.313	-0.976	-1.151	-0.870
	(0.000)	(0.005)	(0.005)	(0.042)	(0.052)	(0.156)
Industry FEs	Y	Y	Y	Y	Y	Y
Observations	3,935	3,935	2,921	2,921	928	928
pseudo R squared	0.010	0.020	0.014	0.024	0.032	0.048

Figure 1: **The impact of the aggregate ES-Score on spreads and the fraction of firms with a positive ES-score over time**
This figure shows 5-year rolling window estimates of the coefficient of the aggregate ES-score in the panel models of bond spreads (solid line). It also shows the fraction of firms for which the aggregate ES-score is positive, calculated also over a 5-year rolling window (dashed line). Definitions of variables are provided in Section 3 and summarized in the Appendix.

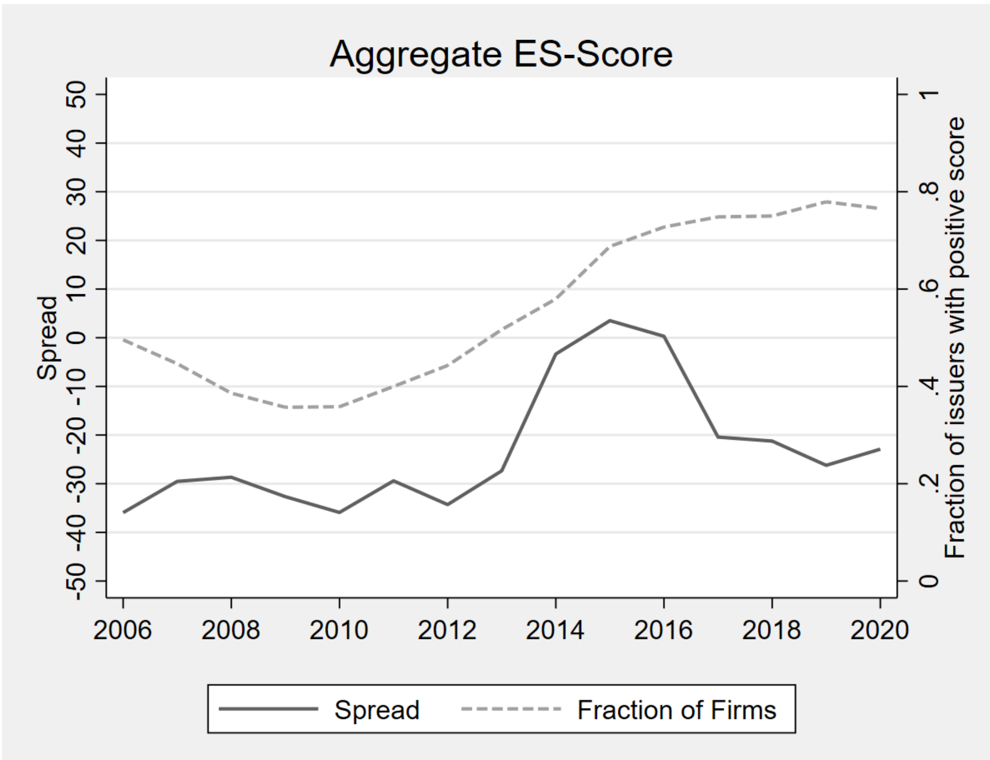

Figure 2: **The impact of individual ES-Scores on spreads and the fraction of firms with positive individual ES-scores over time**
This figure shows 5-year rolling window estimates of the coefficients of individual ES-score in the panel models of bond spreads (solid line). It also shows the fraction of firms for which the corresponding individual ES-scores are positive, calculated also over a 5-year rolling window (dashed line). Definitions of variables are provided in Section 3 and summarized in the Appendix.

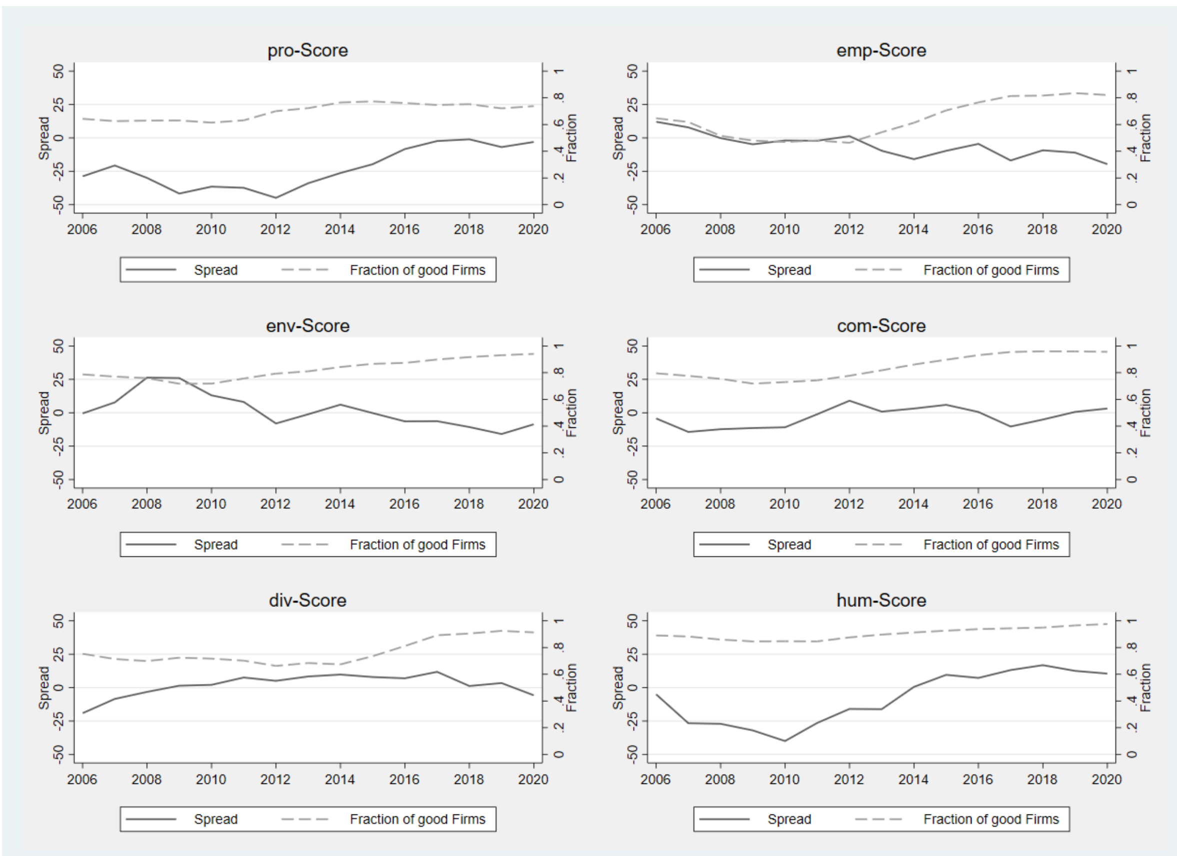

Figure 3: **Time-series dynamics of average changes in ES-Scores for repeat bond issuers.**

The figure shows the median, 10th and 90th percentile of the cross-sectional distribution of simple changes of the aggregate ES-score as well as selected sub-scores for repeat bond issuers. I.e., for every repeat issuer we calculate the difference in the corresponding ES-Score compared to the last time the same issuer issued a bond that is included in our sample. All estimates are calculated over 5-year rolling windows. Definitions of variables are provided in Section 3 and summarized in the Appendix.