Corporate Greenness and Bond Yield Spreads

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Corporate Greenness and Bond Yield Spreads

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Abstract

We examine the cross-sectional relationship between corporate greenness and bond spreads using a comprehensive dataset of U.S. corporate bonds over the period 2008–2021. Portfolio sorts based on firms' environmental scores (ENV), our proxy for corporate greenness, reveal a negative relationship between ENV and bond spreads, which persists after controlling for an extensive set of firm and bond characteristics in Fama–MacBeth and panel regressions. Our results are robust to propensity score matching, which accounts for selection on observable characteristics, and to a two-step orthogonalization procedure, which isolates the component of ENV orthogonal to these characteristics. Finally, we find strong evidence for cash flow uncertainty and downside risk as potential economic channels underlying the ENV-spread relationship, consistent with a pecuniary interpretation. The persistence of this relationship beyond observable financial characteristics is also consistent with a potential role for non-pecuniary investor preferences.

JEL Classification: C51; C52; G11; G12

Keywords: Corporate Greenness, Sustainable Investing, Climate Finance, Empirical Asset Pricing, Corporate Bonds

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1 Introduction

The profound impact of climate change on human life and financial markets is now widely acknowledged. The 2015 Paris Agreement underscored the urgent need for decisive policy action to mitigate climate change, heightening global awareness of physical risks, such as extreme weather events, as well as regulatory risks associated with the transition toward a low-carbon economy. These developments have, in turn, spurred increased demand for sustainable investments.[1] In this context, corporate greenness has attracted growing attention from regulators, practitioners, and academic researchers.

The existing literature on the impact of firms' environmental performance on financial outcomes has focused predominantly on equity markets (e.g., Engle et al., 2020; Bolton and Kacperczyk, 2021, 2023; Ardia et al., 2023; Faccini et al., 2023; Ginglinger and Moreau, 2023; Sautner et al., 2023; Aswani et al., 2024), with evidence broadly consistent with risk-based asset pricing theories according to which greater exposure to climate risk is associated with a higher cost of equity and higher expected returns. Despite this growing body of evidence, comparatively less attention has been devoted to the impact of corporate greenness on corporate bond markets.

To fill this gap, we examine whether corporate greenness, as measured by firms' environmental scores (ENV), is priced in the cross-section of corporate bond spreads, and if so, what economic mechanisms underlie this relationship. This question is motivated by a growing body of evidence suggesting that environmental performance is associated with credit risk and borrowing costs (Seltzer et al., 2022; Huang et al., 2022; Feng et al., 2024; Altavilla et al., 2024) and by the theoretical framework of Pástor et al. (2021), which formalizes the relationship between investor preferences for green assets and their equilibrium pricing. More broadly, it is of direct relevance to the theory and practice of corporate bond pricing, as credit spreads reflect

[1]Bloomberg Intelligence predicts that ESG assets could surpass $40 trillion by 2030, representing more than a quarter of a projected $140 trillion in global assets under management. A 2024 Morgan Stanley survey found that 54% of individual investors intended to expand their allocations to sustainable investments over the following year, with more than 70% believing that robust ESG practices contribute to higher returns (https://www.morganstanley.com/content/dam/msdotcom/en/assets/pdfs/MSInstituteforSustainableInvesting-SustainableSignals-Individuals-2024.pdf).

investors' assessment of default risk (Longstaff et al., 2005), liquidity risk (Chen et al., 2007; Helwege et al., 2014), and broader macroeconomic conditions (Bali et al., 2021). In addressing this question, we contribute to the literature in several ways. We provide novel evidence that corporate greenness is priced in the cross-section of bond spreads, with a one standard deviation increase in ENV scores associated with a reduction in bond spreads of approximately 6.3–8.5 basis points, highlighting the financial materiality of corporate greenness for default risk pricing and the cost of debt, with direct implications for credit risk modelling and bond valuation. We further examine potential economic channels underlying this relationship, finding strong support for a cash flow uncertainty channel and a downside risk channel.

Our research also speaks to the broader debate on the *value* versus *values* motivations behind ESG investing (Starks, 2023), that is, whether investors are driven by pecuniary motives related to the financial materiality of environmental risks or by non-pecuniary motives reflecting their personal values and preferences for environmental sustainability.[2] Both motivations predict a negative relationship between corporate greenness and bond spreads, and formally testing the distinction between them is inherently difficult. The corporate bond market offers a natural laboratory for this purpose. Unlike equity, bond payoffs are fixed by contract. In this setting, any pricing of greenness that operates through default risk is consistent with a pecuniary mechanism, whereas pricing that persists beyond what can be attributed to default risk is more likely to reflect non-pecuniary investor preferences. This makes the corporate bond market a cleaner setting than equity markets for detecting values-driven investment motives. Our analysis sheds new light on this debate by examining the potential roles of pecuniary and non-pecuniary motives in corporate bond pricing.

We focus on the U.S. corporate bond market for several reasons. As the largest and most liquid corporate bond market globally, it provides an ideal setting for examining the pricing of corporate greenness. Moreover, the U.S. operated under a comparatively lighter sustainability-

[2] A *value investor* seeks superior risk-adjusted returns by incorporating ESG criteria into their investment process. In contrast, a *values investor* is primarily motivated by the intention to generate positive social impact, typically avoiding companies whose activities are environmentally harmful or ethically questionable.

related disclosure framework than the EU during the latter part of our sample period. For example, the Federal Reserve's corporate bond purchases in 2020 did not incorporate an explicit environmental tilt.[3] These features suggest that our estimates may provide a conservative benchmark relative to more heavily regulated markets. Although our analysis focuses on the U.S. market, the mechanisms we examine are not U.S.-specific and should, in principle, operate across international bond markets. Whether these associations are stronger in more heavily regulated markets remains an empirical question. Given the integration of global capital markets, the pricing of corporate greenness in the world's largest bond market may have broader implications for the cross-border cost of debt and the international allocation of capital.[4]

We begin by establishing the theoretical motivation underpinning our research hypotheses using the framework of Pástor et al. (2022), from which we derive testable predictions about the relationship between ENV and bond spreads. We then test these hypotheses empirically using a large cross-section of U.S. corporate bonds from the TRACE database over the period 2008–2021, matched with environmental scores (ENV) from LSEG Workspace (formerly Asset4). Portfolio sorts reveal a negative and statistically significant cross-sectional relationship between ENV and bond spreads that remains robust after controlling for key systematic bond risk factors, including market, credit, downside, and liquidity risk. The documented negative relationship is further supported by Fama-MacBeth and panel regressions that control for a comprehensive set of firm- and bond-level characteristics, indicating that the pricing of corporate greenness cannot be fully explained by systematic risk factors or these observable characteristics. The results are generally consistent when carbon intensity is used as an alternative emissions-based proxy for corporate greenness.[5]

[3]Unlike the U.S., the EU introduced mandatory sustainability-related disclosures for certain large companies through the Non-Financial Reporting Directive (NFRD), with the first reports published in 2018 for the 2017 financial year. The Sustainable Finance Disclosure Regulation (SFDR), which began applying in March 2021, introduced additional disclosure requirements for financial market participants and advisers. Subsequent developments include the Corporate Sustainability Reporting Directive (CSRD), and the ECB's introduction of a climate-based tilt to corporate bond purchases in October 2022 (European Central Bank, 2022).

[4]We regard the role of institutional and regulatory heterogeneity in shaping the pricing of environmental performance across countries as an important direction for future research.

[5]Since greater carbon intensity signals lower environmental performance, its association with bond spreads

We further examine the financial characteristics of ENV-sorted portfolios and find that greener firms tend to exhibit greater profitability, lower leverage, higher market-to-book ratios, greater distance to default, and lower asset and cash flow volatility, while their bonds tend to be more liquid. These results suggest that greenness is systematically associated with stronger financial fundamentals, lower credit risk, and greater bond liquidity. While informative about the dimensions along which green and brown firms differ, these findings raise an important concern. Specifically, lower bond spreads among greener firms may partly reflect differences in observable firm and bond characteristics that are associated with both corporate greenness and bond spreads. To investigate this possibility, we employ two complementary approaches. First, we use propensity score matching to improve comparability between high- and low-ENV firms on observable characteristics. Second, we implement a two-step orthogonalization procedure to isolate the component of ENV scores that is orthogonal to these observable characteristics.

We then explore the economic mechanisms underlying the relationship between ENV and bond spreads by examining three potential channels: a cash flow uncertainty channel, a downside risk channel, and an illiquidity channel. We find strong empirical support for the first two, consistent with a pecuniary interpretation of the ENV-bond spread relationship. Taken together, our findings are consistent with a role for pecuniary motives, reflected in cash flow uncertainty and downside risk, in the pricing of corporate greenness. The persistence of the relationship between ENV and bond spreads after accounting for observable financial characteristics is further consistent with a potential role for non-pecuniary investor preferences alongside these pecuniary mechanisms.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 develops the theoretical framework and research hypotheses. Section 4 describes the data and variable construction. Section 5 presents and discusses the main empirical results. Section 6 reports additional analyses and robustness checks. Finally, Section 7 concludes.

is positive, i.e. the opposite of the negative ENV-spread relationship documented in our main analysis.

2 Related Literature

Our research contributes to several strands of literature. The first examines the relationship between firms' environmental performance and financial outcomes and has focused predominantly on equity markets (e.g., Engle et al., 2020; Bolton and Kacperczyk, 2021, 2023; Ardia et al., 2023; Faccini et al., 2023; Ginglinger and Moreau, 2023; Sautner et al., 2023; Aswani et al., 2024), with evidence broadly consistent with risk-based asset pricing theories, according to which greater exposure to climate risk is associated with a higher cost of equity and higher expected returns. The pricing of greenness in corporate bond markets has received comparatively less attention. Our study relates most directly to Huynh and Xia (2021) and Seltzer et al. (2022), both of which highlight the growing importance of environmental factors in fixed-income markets. We differ from Seltzer et al. (2022), who examine the interaction between climate and regulatory risks, by adopting a broader asset pricing perspective that focuses on the cross-sectional pricing of corporate greenness in bond spreads and explicitly examines the potential economic channels and investor motivations underlying this relationship. Our approach also differs from Huynh and Xia (2021) in three key respects. First, we focus on bond spreads rather than returns, allowing for a more direct interpretation of the compensation investors require for bearing credit risk. Second, we measure corporate greenness using firm-level ENV scores rather than bond sensitivities to a climate-news index, thereby capturing issuer-level environmental characteristics rather than news-based variation in climate betas. Third, while Huynh and Xia (2021) focus on climate risk, our analysis considers corporate greenness more broadly, reflecting multiple dimensions of firms' environmental performance. To the best of our knowledge, we are among the first to provide evidence on the potential role of non-pecuniary investor preferences in the pricing of greenness in corporate bond markets.

Our research also contributes to the literature on the relationship between environmental performance and firms' cost of debt and external financing. A growing literature documents that better environmental performance is associated with lower borrowing costs (Jung et al., 2018; Palea and Drogo, 2020; Apergis et al., 2022; Ali et al., 2023; Francis et al., 2025), reduced leverage (Ginglinger and Moreau, 2023), lower bankruptcy risk (Feng et al., 2024), and greater financial flexibility (Zhang et al., 2024; Wellalage and Kumar, 2021; Sautner et al., 2025; Li et al., 2025). Relatedly, Oikonomou et al. (2014) show that broader corporate social performance is associated with firms' cost of debt and credit ratings. While this literature documents a relationship between environmental performance and the cost of debt, it has focused predominantly on bank loans and credit ratings, with comparatively less attention to corporate bond markets. This distinction is important because bond spreads provide a market-based measure of required compensation for risk and, therefore, offer a natural setting for examining whether corporate greenness is reflected in bond spreads. Furthermore, the economic channels underlying the relationship between corporate greenness and bond spreads, and the relative role of pecuniary versus non-pecuniary investor motives, remain under-explored. Our study addresses these gaps by providing direct evidence that ENV scores are negatively associated with corporate bond spreads in the cross-section. We further provide evidence consistent with a role for cash flow uncertainty and downside risk as potential channels underlying this relationship, and examine the roles of pecuniary and non-pecuniary motives in the ENV-spread relationship.

Finally, our research relates to the growing literature on green bond markets and the pricing of environmental attributes in fixed-income securities. Pinto and Ribeiro (2026) document that green and sustainability bonds exhibited significantly lower spreads than comparable conventional bonds during the COVID-19 period, but find no significant spread advantage outside of this period. Contractor et al. (2023) find that green bonds display greater resilience to macroeconomic shocks and economic uncertainty, using a matched sample of green and conventional bonds issued by the same firms. Overall, this evidence suggests that the relative pricing and resilience of green bonds may vary with market conditions and become more pronounced during periods of heightened uncertainty. Importantly, Fornari et al. (2026) show that green bond pricing is two-tiered, with investors rewarding both the green label and the environmental score of the issuer. The greenium increases significantly when the issuer's ENV score is in the top tercile of the cross-sectional distribution. This evidence is closely related to ours because it shows that issuer-level environmental performance, in addition to the green label itself, is associated with yield differentials. Relatedly, Guesmi et al. (2025) find that firms with greater climate risk exposure are more likely to issue green bonds, primarily to hedge against physical and regulatory risks. They also show that although green bond issuance is associated with higher ESG scores, it is not accompanied by lower CO_2 emissions, underscoring the importance of distinguishing between green bond issuance and underlying environmental outcomes.

Our study complements this literature in two ways. First, by examining a broad cross-section of corporate bonds rather than labelled green bonds alone, we document a systematic relationship between issuer-level ENV scores and bond spreads across the corporate bond market. Second, by examining potential economic channels and the possible roles of pecuniary and non-pecuniary investor motives, we provide evidence on the mechanisms that may contribute to the pricing of corporate greenness in corporate bond markets, a dimension that remains comparatively under-explored in the green bond literature.

3 Hypothesis Development

3.1 Theoretical Motivation: Corporate Greenness and Bond Pricing

In this section, we describe the theoretical background underpinning our research hypotheses. To build intuition, consider a one-period, zero-coupon defaultable corporate bond with a promised face value F at maturity (i.e., at $t = 1$) and a realized payoff that is uncertain due to default risk. Specifically,

$$\widetilde{F} = \begin{cases} F, & \text{with probability } 1 - q, \\ R\,F, & \text{with probability } q, \end{cases} \tag{1}$$

where q denotes the *probability of default*, with $0 \leqslant q \leqslant 1$, and R is the fraction of face value recovered in the event of default, with $0 \leqslant R < 1$.

The *conditional expected bond payoff* at time 0 is therefore

$$\begin{aligned} \mathrm{E}_0(\widetilde{F}) &= (1-q)F + qRF \\ &= [1-(1-R)q]F \\ &\equiv (1-\lambda)F, \end{aligned} \tag{2}$$

where $\lambda = (1-R)q$ is the *expected default loss rate*, equal to the probability of default multiplied by the loss given default. The bond price at time 0 is the discounted expectation of the bond's payoff (see Cochrane, 2009). If $\widetilde{m}$ is the *stochastic discount factor*, then from a bond buyer's perspective, the *price of the bond* at time 0 (P_0) is given by

$$\begin{aligned} P_0 &= \mathrm{E}_0\left(\widetilde{m}\widetilde{F}\right) \\ &= \mathrm{E}_0\left(\widetilde{m}\right)\mathrm{E}_0\left(\widetilde{F}\right) + \mathrm{Cov}_0\left(\widetilde{m}, \widetilde{F}\right). \end{aligned} \tag{3}$$

Dividing both sides of Eq. (3) by P_0 and using the standard relation between the stochastic discount factor and the *gross risk-free rate of return* (R_f), namely $\mathrm{E}_0(\widetilde{m}) = 1/R_f$,[6] we can re-write Eq. (3) as

$$1 = \frac{\mathrm{E}_0(\widetilde{F}/P_0)}{R_f} + \mathrm{Cov}_0\left(\widetilde{m}, \frac{\widetilde{F}}{P_0}\right). \tag{4}$$

Combining Eq. (2) with Eq. (4) and defining the bond's *promised gross return* as $Y_0 = F/P_0$ and its *realized gross return* as $\widetilde{Y} = \widetilde{F}/P_0$, we obtain

$$\begin{aligned} Y_0 &= \frac{F}{P_0} \\ &= \frac{R_f}{1-\lambda}\left[1 - \mathrm{Cov}_0\left(\widetilde{m}, \widetilde{Y}\right)\right]. \end{aligned} \tag{5}$$

[6]For a risk-free asset with gross return R_f, the stochastic discount factor pricing condition implies $1 = \mathrm{E}_0(\widetilde{m}R_f)$. Since R_f is known at time 0, it follows that $R_f = 1/\mathrm{E}_0(\widetilde{m})$. See also Cochrane (2009).

Taking natural logarithms in Eq. (5) gives

$$\log(Y_0) = \log(R_f) + \log\left[1 - \mathrm{Cov}_0\left(\widetilde{m}, \widetilde{Y}\right)\right] - \log(1-\lambda). \tag{6}$$

where Y_0 is the bond's promised gross return, while $\widetilde{Y}$ is its realized gross return.[7]

Using the first-order approximations $-\log(1-\lambda) \approx \lambda$ and $\log(1-x) \approx -x$ for sufficiently small λ and x, Eq. (6) can be written approximately as

$$\begin{aligned} y_0 \approx & \underbrace{r_f}_{\text{risk-free rate}} + \underbrace{\lambda}_{\text{expected default loss rate}} \\ & + \underbrace{\mathrm{Cov}_0(-\widetilde{m}, \widetilde{Y})}_{\text{risk-adjustment}} \end{aligned} \tag{7}$$

where $y_0 = \log(Y_0)$ and $r_f = \log(R_f)$. The term λ captures the expected loss associated with default, while $\mathrm{Cov}_0(-\widetilde{m}, \widetilde{Y})$ captures the risk adjustment associated with the covariance between the bond's realized return and the stochastic discount factor. As we show below, the covariance term reflects not only compensation for systematic risk but also investors' non-pecuniary preferences through the stochastic discount factor. Therefore, within this stylized framework, the bond's yield in excess of the risk-free rate (*bond spread*) is approximately determined by expected default losses and compensation for systematic risk. If the bond's realized return does not covary with the stochastic discount factor, the risk-adjustment term vanishes and the bond spread reflects only expected default losses.

Including Non-Pecuniary Preferences for Greenness

The covariance term, $\mathrm{Cov}_0(-\widetilde{m}, \widetilde{Y})$, in Eq. (7) allows bond pricing to reflect systematic risk and investor preferences beyond expected default losses. In this context, Pástor et al. (2022, Section 2, p. 406) provide evidence that greenness may be reflected in bond prices

[7] Specifically, to derive Eq. (5), we start from $1 = \mathrm{E}_0(\widetilde{F}/P_0)/R_f + \mathrm{Cov}_0(\widetilde{m}, \widetilde{F}/P_0)$ and using Eq. (2), $\mathrm{E}_0(\widetilde{F}) = (1-\lambda)F$, we obtain $1 = (1-\lambda)Y_0/R_f + \mathrm{Cov}_0(\widetilde{m}, \widetilde{Y})$. Solving for Y_0 yields $Y_0 = \frac{R_f}{1-\lambda}[1 - \mathrm{Cov}_0(\widetilde{m}, \widetilde{Y})]$.

even when contractual cash flows and credit risk are closely matched. The authors analyze German twin bonds, i.e., green bonds issued by the German government that are structurally identical to their non-green counterparts, sharing the same coupon rate, payment dates, and maturity. These twin bonds provide identical cash flow streams and exhibit similar credit risk, yet they differ primarily in their green designation, providing a particularly informative setting for examining the pricing of environmental attributes. The authors document a yield differential between green and non-green bonds, commonly referred to as the *greenium*. Their findings are consistent with environmental attributes carrying pricing implications beyond differences in expected default losses.

To isolate the preference-based component of $\mathrm{Cov}_0(-\widetilde{m}, \widetilde{Y})$ in Eq. (7), we draw on Pástor et al. (2021, Corollary 2). In their model, a stock's CAPM alpha is given by $-(\bar{d}/a)g_n$, reflecting investors' preferences for greenness. Motivated by this result, and abstracting from other systematic risk components, we parameterize the covariance term for a representative bond (dropping the firm subscript n for notational simplicity) as

$$\mathrm{Cov}_0(-\widetilde{m}, \widetilde{Y}) = -\left(\frac{\bar{d}}{a}\right) g, \tag{8}$$

where $\bar{d}$ captures the aggregate investor preference for greenness,[8] $a > 0$ denotes the common coefficient of relative risk aversion across investors, and g denotes the individual firm's green characteristic. Pástor et al. (2021) develop a theoretical framework for the pricing of sustainability in equity markets and argue that investors may derive non-pecuniary benefits from holding green assets. Although their framework is developed for equities, its underlying preference-based mechanism is not specific to that asset class. If investors derive non-pecuniary benefits from holding securities issued by greener firms, such preferences may also affect the equilibrium prices and required returns of corporate bonds. We therefore extend this intuition

[8]Specifically, if $d_i \geqslant 0$ denotes agent i's ESG taste, $\bar{d} = \int_i \omega_i d_i \, di$ is the wealth-weighted mean of ESG tastes across agents (see Pástor et al., 2021, Eq. (5)), where $\omega_i = W_{0i}/W_0$ denotes agent i's share of aggregate initial wealth ($W_0 = \int_i W_{0i} \, di$ denotes aggregate initial wealth) and the integral is taken over the continuum of investors i.

to corporate bonds, assuming that investors value environmental attributes across asset classes.

Substituting the preference-based specification into Eq. (7), the bond spread, defined as the bond yield in excess of the risk-free rate, can be expressed as

$$SPR \equiv y_0 - r_f \approx \lambda - \frac{\bar{d}}{a} g. \tag{9}$$

In what follows, we present the model's implications regarding the relationship between a firm's greenness (as measured by its ENV score) and its bond spread. Within the preference-based component of the model, a governs the extent to which investor preferences for greenness impact bond spreads. For given $\bar{d}$ and g, a larger a reduces the magnitude of this component. The variable g denotes the firm's green characteristic. Firms with $g > 0$ generate positive environmental externalities (green firms), whereas firms with $g < 0$ generate negative environmental externalities (brown firms). Here we assume that firms' environmental characteristics are observable via ESG rating agencies. Importantly, the relationship between corporate greenness (g) and bond spreads is not uniform, as it depends on the prevailing aggregate investor preference toward greenness, represented by $\bar{d}$. A larger positive $\bar{d}$ reflects a stronger aggregate investor preference for green attributes in the bond market, implying a stronger negative relationship between greenness and bond spreads.

Therefore, when aggregate investor preferences favor greenness (i.e., $\bar{d} > 0$), the model predicts lower bond spreads for greener firms relative to their brown counterparts, ceteris paribus. The strength of investor preferences for greenness, however, may vary and may be weak or absent. A related perspective is provided by the Friedman doctrine,[9] which asserts that a firm's only responsibility is to maximize shareholder value. If investors subscribe to this view and have weak or no preferences for greenness, the aggregate preference parameter $\bar{d}$ may be small or zero. When $\bar{d} = 0$, the preference-based component of the bond spread vanishes.

[9] See Milton Friedman, "The Social Responsibility of Business Is to Increase Its Profits," *The New York Times Magazine*, September 13, 1970. Available at: https://www.nytimes.com/1970/09/13/archives/a-friedman-doctrine-the-social-responsibility-of-business-is-to.html.

3.2 Hypotheses

We investigate the cross-sectional relationship between corporate greenness and corporate bond spreads, motivated by two considerations. First, corporate bond spreads are closely linked to firms' credit risk, making them a natural setting for examining whether corporate greenness is associated with default risk. Unlike equity prices, which reflect both growth expectations and risk, bond spreads are more directly connected to firms' creditworthiness, providing a cleaner setting in which to study the relation between corporate greenness and bond spreads. Second, we argue that it is more appropriate to use bond spreads than bond returns because the latter incorporate both expected and unexpected components (Elton, 1999). While expected returns reflect compensation for risk, realized bond returns also incorporate unanticipated price changes arising from market volatility, liquidity shocks, and other short-term factors that may obscure the underlying relationship of interest.

This perspective is consistent with the structural credit risk framework of Merton (1974), which links bond yields to the firm's asset value and default probability. Within this framework, firm characteristics associated with the likelihood of default may also be reflected in bond spreads. Corporate greenness may be related to default risk through a mechanism linked to cash-flow stability and regulatory exposure, while the preference-based mechanism developed in the preceding section provides a complementary explanation for why greenness may be reflected in bond spreads.

We thus start by formulating the following hypothesis:

H1: Corporate greenness is priced in the cross-section of corporate bond spreads.

H1 follows from the two mechanisms discussed above. Corporate greenness may be associated with bond spreads through (i) a default-risk mechanism, if greener firms differ systematically in their expected default losses, and (ii) through a preference-based mechanism, captured by $-(\bar{d}/a)g$ in Eq. (9), if investors derive non-pecuniary utility from greenness. Corporate greenness may therefore be priced in bond spreads through either pecuniary or non-pecuniary mechanisms. Whether either generates a systematic cross-sectional relationship is an open empirical question.

We further develop a hypothesis regarding the sign of the relationship between corporate greenness and bond spreads. Both mechanisms discussed above point toward a negative relationship. First, if greater corporate greenness is associated with lower expected default losses, greener firms should exhibit lower bond spreads. Second, when aggregate investor preferences favor greenness (i.e., $\bar{d} > 0$), the preference-based term in Eq. (9), $-(\bar{d}/a)g$, also implies lower bond spreads for greener firms. Given these considerations, we formulate our second hypothesis:

H2: Corporate greenness is negatively associated with corporate bond spreads.

We test H1 and H2 within a standard empirical asset pricing framework, employing portfolio sorts, Fama–MacBeth, and panel regressions. Our primary analysis uses firms' ENV scores to measure corporate greenness, while we also assess the robustness of our results using alternative measures, including broader ESG scores and carbon intensity. Further details are provided in Sections 5 and 6.

4 Data and Variable Construction

We measure corporate greenness using firms' environmental scores (ENV) from Refinitiv. Rather than capturing a single environmental dimension, the ENV score integrates multiple themes, including emissions, biodiversity, resource efficiency, and environmental innovation, making it a comprehensive and widely used measure of corporate greenness. Its use is consistent with a growing body of empirical research that employs Refinitiv environmental scores in related settings (e.g. Alessi et al., 2021; Seltzer et al., 2022). Refinitiv provides one of the most extensive ESG databases available, covering more than 90% of global market capitalization across over 70 countries.[10] The scores are constructed from publicly available sources, including annual

[10]See LSEG, *Environmental, Social and Governance Scores from LSEG* (October 2024), `https://www.lseg.com/content/dam/data-analytics/en_us/documents/methodology/lseg-esg-scores-methodology.pdf`,

reports, CSR reports, stock exchange filings, and news sources, supporting the transparency and verifiability of the underlying data. They are reported annually, in line with firms' ESG disclosure cycles.

The ENV score is constructed by Refinitiv in three steps: (i) category-level scores are computed from underlying data points, (ii) a materiality matrix is applied to weight each category according to its industry relevance, and (iii) the category scores are aggregated into a final composite score. The score captures several dimensions of corporate greenness, including emissions, resource use, environmental product innovation, and biodiversity. Importantly, it is benchmarked against sector peers, making it a sector-adjusted measure of relative rather than absolute corporate greenness.

The ENV score ranges from 0 to 100, with higher values indicating stronger environmental performance. Our sample spans the period from 2008 to 2021. Figure 1 plots the annual median Refinitiv ENV score over the sample period. The median ENV score remains broadly stable at approximately 40 throughout most of the period before rising in the final years to reach 53.01 in 2021. The shaded interquartile range spans approximately 20 to 70, indicating substantial and persistent cross-sectional variation in greenness across firms.

[Insert Figure 1 about here]

We also collect data on corporate bond yields from the Enhanced TRACE database, accessed via WRDS. Enhanced TRACE provides detailed transaction-level information on intraday corporate bond trading. To clean the transaction data, we closely follow the methodology of Dick-Nielsen (2014). Specifically, we implement the following filters: (i) we remove trades with cancellations or corrections reported within the same reporting date, (ii) we remove reversal reports (i.e., cancellations reported on a later date than the date on which the original transaction took place) and delete the corresponding original trades, and (iii) we delete agency and

and WRDS, *Advance your Research with Refinitiv Datastream and ESG*, https://wrds-www.wharton.upenn.edu/pages/data-announcements/advance-your-research-with-refinitiv-datastream-and-esg/.

inter-dealer transactions when the principal transaction has the same price as the agency transaction, thereby avoiding potential double counting. We also remove trades with an odd number of days to settlement, as suggested by Dick-Nielsen (2014). We further remove "When-Issue" trades, namely trades that are not in the secondary market, as well as trades under special circumstances or with non-standard settlement, commissioned trades, and automatic-give-up trades. Finally, we remove observations with negative bond yields and winsorize bond yields at the 5th and 95th percentiles (the results remain robust when winsorizing at the 1st and 99th percentiles).

After cleaning the bond data, we retain each bond's last observed yield on each trading day and use the yield from the last trading day of the month in our main analysis. When a firm has multiple bonds outstanding in a given month, we compute the simple average across its available bond yields to obtain a single firm-month bond yield observation. We then compute the bond spread as the difference between this firm-month bond yield and the yield on the three-month U.S. Treasury bill in the same month. Thus, the unit of observation in our empirical analysis is the firm-month. For the construction of certain variables, such as bond illiquidity, we use daily bond-level data to exploit the available within-month information.

We merge the Refinitiv and TRACE datasets using issuer CUSIP identifiers. Since bond spreads are measured monthly while ENV scores are reported annually, we match each firm-month observation with the ENV score from the preceding calendar year.[11] After applying our data filters, the final sample consists of 820 unique firms and 56,132 firm-month observations. Summary statistics for the full sample are presented in Table 1. The average annualized bond spread is 3.188%, while the mean ENV score is 44.198. ENV scores exhibit substantial cross-sectional variation, indicating considerable heterogeneity in corporate greenness across firms. Refinitiv's ESG coverage expanded considerably over the sample period, with the number of covered firms rising from approximately 100 in the early years to around 500 by the end of the

[11] Specifically, for each month in a given year y we use the latest available annual ENV score as of December of year $y-1$.

sample, as illustrated in Figure 2.[12] To assess whether our results are sensitive to the more limited firm coverage in the early sample period, we conduct sub-period robustness tests in Section 6 and find that the main results remain robust.

[Insert Table 1 about here]

[Insert Figure 2 about here]

Table 2 presents annual summary statistics for monthly corporate bond spreads. Average spreads exhibit a pronounced downward trend over the sample period, interrupted by temporary spikes during the 2008–2009 financial crisis and the 2020 COVID-19 pandemic. The number of observations increases from 1,646 in 2008 to 5,805 in 2021, reflecting the broader availability of ESG data over time. This expansion coincides with the rapid growth in green bond issuance documented by Flammer (2021).

[Insert Table 2 about here]

We also collect a range of firm and bond characteristics to serve as control variables in our subsequent estimations. Specifically, these include net sales over total assets (Sales), operating cash flow over total assets (CF), leverage (Lev), cash holdings (Cash), net operating income scaled by net sales (Inc), return on assets (ROA), firm size (Size), the market-to-book ratio (MB), distance to default (DD), asset volatility (AV), cash flow volatility (CFVol), income volatility (IncVol), and the bond's coupon rate (CPN), time to maturity (TTM), illiquidity (Illiq) and downside beta (DSBeta). Credit ratings represent an important control variable in bond spread regressions, as they provide information about a firm's creditworthiness. Due to data availability constraints, however, credit rating data are not included in our analysis.

[12] Although firm coverage is more limited in the early part of the sample, the number of firms remains adequate for portfolio sorting throughout the entire sample period.

Instead, we employ Merton's distance to default (DD), which captures related information and has been shown to be a strong predictor of credit ratings (see, e.g., Doumpos et al., 2015).

Definitions and detailed descriptions of all control variables are provided in Table A1 of the online appendix. The controls Sales, Cash, CF, Lev, Inc, ROA, Size, MB, DD, and AV follow the same calendar-year alignment as the ENV score (i.e., annual observations from year $y-1$ are assigned to all monthly observations in year y). The bond-related controls CPN, TTM, Illiq, and DSBeta, as well as CFVol and IncVol, are lagged by one month. The distance-to-default (DD) and asset volatility (AV) measures are derived using the KMV model, which builds on the structural framework of Merton (1974). DSBeta captures a bond's sensitivity to downside market movements, measured following Ang et al. (2006). For brevity, all technical details are provided in the online appendix, with the distance-to-default (DD) calculation outlined in Equation A4.

5 Empirical Results

This section presents the empirical findings on the relationship between corporate greenness and corporate bond spreads. We begin with univariate portfolio sorts, a non-parametric approach that imposes no assumptions on the functional form of the relationship between ENV and bond spreads. We then employ Fama–MacBeth (Fama and MacBeth, 1973) and panel regressions to control for firm- and bond-level characteristics. Next, we examine the financial characteristics of ENV-sorted portfolios to shed light on the firm-level dimensions along which green and brown firms differ. Finally, we examine potential economic channels underlying the relationship between ENV and bond spreads, focusing on cash flow uncertainty, downside risk, and bond illiquidity.

5.1 Univariate Portfolio Sorts on ENV

We begin our analysis with univariate portfolio sorts based on firms' ENV scores. At the end of each month, we sort firms according to the latest available one-year-lagged ENV score and form three portfolios based on the tertiles of the cross-sectional ENV score distribution: a Low portfolio comprising firms with an ENV score in the bottom tertile (brown firms), a High portfolio comprising firms with an ENV score in the top tertile (green firms), and a Medium portfolio comprising the remaining firms.[13] Using the firm-month bond spreads constructed in Section 4, we compute the equal-weighted average bond spread for each portfolio. Since Refinitiv reports ENV scores as of December of each year, but the underlying disclosures may not become publicly available until later, the one-year lag reduces the risk of using information that was unavailable to investors at the time of portfolio formation. This procedure generates portfolios of approximately equal size, averaging approximately 110 firms per portfolio.

Table 3 presents the results from the univariate portfolio sorts described above. The High–Low spread differential, defined as the average spread of the High ENV portfolio minus that of the Low ENV portfolio, is −1.037% and is statistically significant at the 1% level (Newey–West t-statistic = −14.825). We also observe a monotonic decline in average bond spreads across the ENV-sorted portfolios. In particular, the average bond spread (i.e., average bond yield in excess of the risk–free rate) is 4.058% for the Low ENV portfolio and 3.021% for the High ENV portfolio. These results provide evidence that corporate greenness is negatively priced in the cross-section of corporate bond spreads, with higher ENV scores associated with lower spreads.

[Insert Table 3 about here]

To assess whether the relationship between ENV and bond spreads is explained by exposure to systematic bond risk factors, we report in Columns (5) and (6) of Table 3 the intercept (α) from regressions of the High–Low spread differential on the adjusted four-factor bond model

[13] In Section 6, we evaluate the robustness of our results when portfolios are formed using quintiles rather than tertiles.

($BBWadj$) proposed by Bai et al. (2018) and subsequently corrected by Dickerson et al. (2023). The time-series regressions are specified as

$$SPR_t^{High-Low} = \alpha_x^{BBWadj} + \beta_{MKT,x} MKT_{t-\ell} + \beta_{DRF,x} DRF_{t-\ell} + \beta_{CRF,x} CRF_{t-\ell} + \beta_{LRF,x} LRF_{t-\ell} + \epsilon_{t,x}, \tag{10}$$

where $SPR_t^{High-Low}$ is the High–Low spread differential in month t, computed as the difference between the equal-weighted average firm-month bond spreads of the High and Low ENV portfolios. The contemporaneous specification uses $\ell = 0$ and $x = C$ and is reported in Column (5), while the specification with lagged risk factors corresponds to $\ell = 1$ and $x = L$ and is reported in Column (6). The intercept α_x^{BBWadj} captures the factor-adjusted High–Low spread differential, with α_C^{BBWadj} corresponding to contemporaneous factor values and α_L^{BBWadj} corresponding to one-month-lagged factor values. MKT is the bond market factor, DRF is the downside risk factor, CRF is the credit risk factor, and LRF is the bond liquidity factor. The $BBWadj$ factor data were obtained from https://openbondassetpricing.com/data/. Details on the construction of the four bond factors are provided in Section 3.1 (p. 4) of Dickerson et al. (2023).

The results reported in Column (5) of Table 3 indicate that the time series regression intercept, α_C^{BBWadj}, is -0.990%, closely aligned with the average unadjusted High–Low spread differential of -1.037% reported in Column (4). α_C^{BBWadj} is statistically significant at the 1% level (Newey–West t-statistic $= -16.149$). Column (6), which presents estimates based on lagged bond risk factors, yields similar findings (i.e., α_L^{BBWadj} is -0.999% and remains statistically significant at the 1% level, Newey–West t-statistic $= -15.923$). Among the bond risk factors, the liquidity risk factor (LRF) has the largest absolute t-statistic among the factor loadings in both the contemporaneous and lagged specifications, consistent with the well-documented role of liquidity in corporate bond pricing (Chen et al., 2007). The negative coefficient on LRF (Newey–West t-statistic $= -3.152$) indicates that the High–Low spread differential has a negative loading on the aggregate liquidity risk factor.

In summary, the univariate portfolio sorts provide evidence of a negative and statistically significant cross-sectional relationship between corporate greenness and bond spreads, with greener firms exhibiting significantly lower average spreads. The High–Low spread differential remains negative and statistically significant after adjustment for the systematic bond risk factors included in the *BBWadj* model, indicating that this relationship is not fully explained by exposure to these factors.[14]

5.2 Fama-MacBeth and Panel Regressions

The portfolio sorts document a negative relationship between ENV scores and bond spreads. To examine whether this relationship persists after accounting for observable firm and bond-related characteristics, we next estimate Fama–MacBeth regressions that explicitly control for these characteristics:

$$SPR_{i,t} = \alpha_t + \beta_t ENV_{i,t-1} + \sum_{j=1}^{K} \gamma_{j,t} Z_{i,j,t-1} + \epsilon_{i,t}, \tag{11}$$

where $SPR_{i,t}$ is the bond spread of firm i in month t, $ENV_{i,t-1}$ denotes the latest one-year-lagged ENV score available for firm i at the end of month $t-1$, as described in Section 4, and $Z_{i,j,t-1}$ is the value of control variable j for firm i as of the end of month $t-1$. The firm-level control variables Sales, Cash, CF, Lev, Inc, ROA, Size, MB, DD, and AV follow the same calendar-year alignment as the ENV score, while the remaining controls (CPN, TTM, Illiq, DSBeta, CFVol, and IncVol) are lagged by one month.

Table 4 reports the time series average slope estimates and corresponding Newey–West (NW) t-statistics (in parentheses) from the Fama–MacBeth regressions. In Column (1), which does not include control variables, the coefficient on ENV (multiplied by 100) is -1.465 and statistically significant at the 1% level (NW t-stat. $= -15.168$), consistent with the portfolio sorting results

[14] Our baseline analysis is based on equal-weighted tertile portfolios. To assess the robustness of these findings, Table A3 of the online appendix explores alternative portfolio construction methods, including volume-weighted portfolios and quintile-based sorting. These robustness checks are discussed further in Section 6.

reported in Table 3. Column (2) introduces firm- and bond-specific control variables. While the average slope estimate on ENV remains negative and statistically significant at the 1% level, its magnitude is attenuated, suggesting that firm and bond-related characteristics partially account for the ENV-bond spread relationship without fully explaining it. We additionally control for financing uncertainty using cash-flow volatility (CFVol) and income volatility (IncVol), as greater uncertainty may be associated with a reduced ability to service debt obligations and, consequently, higher bond spreads (He et al., 2025). As reported in Column (3), the coefficient on ENV remains negative and statistically significant at the 1% level.

Prior studies also document that firms' downside risk is associated with higher borrowing costs (Baltussen et al., 2012; Gemmill and Keswani, 2011). To this end, in Column (4), we augment the baseline specification of Column (1) with firms' downside risk (DSBeta), measured following Ang et al. (2006), and find that the negative relationship between ENV and bond spreads persists after controlling for downside risk. Finally, Column (5) incorporates all control variables simultaneously. The coefficient on ENV remains negative and statistically significant at the 1% level ($\beta_{ENV} = -0.291$, NW t-stat. $= -6.254$). In terms of economic magnitude, a one standard deviation increase in the ENV score (SD = 29.085) is associated with a reduction in bond spreads of approximately 8.5 basis points (i.e., $-0.291/100 \times 29.085 = -0.085$, bond spreads are expressed in %) in the full specification reported in Column (5).

Several control variables are statistically significant and have economically intuitive signs. For instance, leverage (Lev) is positively associated with bond spreads, while profitability (ROA) enters with a negative coefficient, consistent with more profitable firms exhibiting lower credit risk. Likewise, greater distance to default (DD) is associated with lower bond spreads, consistent with its role as a proxy for credit quality. The attenuation of the ENV coefficient following the inclusion of controls suggests that firm and bond-related characteristics partially account for the relationship between ENV and bond yield spreads, although they do not fully explain it. Among the volatility and downside-risk measures, IncVol is positively and significantly associated with bond spreads across specifications, while both CFVol and downside risk (DSBeta) lose statistical significance in the full specification. We examine these relationships in greater detail in the channel analysis that follows. Overall, the Fama–MacBeth results provide further evidence that corporate greenness is priced in the cross-section of corporate bond spreads, with the negative relationship between ENV and bond spreads persisting after controlling for a broad set of observable firm and bond-related characteristics.

[Insert Table 4 about here]

The Fama–MacBeth regressions presented in Table 4 provide evidence of a cross-sectional relationship between corporate greenness and bond spreads. We complement this analysis with panel regressions using the pooled firm-month observations. The panel specification allows us to account for unobserved industry and time heterogeneity through fixed effects and provides a complementary inference framework for examining the relationship between corporate greenness and bond spreads. The panel regression is specified as follows:

$$SPR_{i,t} = \alpha + \beta \, ENV_{i,t-1} + \sum_{j=1}^{K} \gamma_j \, Z_{i,j,t-1} + \eta_s + \tau_t + u_{i,t}, \tag{12}$$

where $SPR_{i,t}$ is the bond spread of firm i in month t, $ENV_{i,t-1}$ denotes the latest one-year-lagged ENV score available for firm i at the end of month $t-1$, as described in Section 4, and $Z_{i,j,t-1}$ is the value of control variable j for firm i as of the end of month $t-1$. The firm-level control variables Sales, Cash, CF, Lev, Inc, ROA, Size, MB, DD, and AV follow the same calendar-year alignment as the ENV score. The term η_s denotes industry fixed effects, with s indexing the industry to which firm i belongs, τ_t denotes time (month) fixed effects, and $u_{i,t}$ is the error term. Industry and time fixed effects are included as indicated in Table 5. Standard errors are two-way clustered by firm and year.

[Insert Table 5 about here]

We first examine baseline models that control only for unobserved heterogeneity, including fixed effects individually and jointly to assess whether the relationship between greenness and bond spreads is accounted for by unobserved time or industry heterogeneity. Columns (1) and (3) control for time and industry fixed effects, respectively, while Column (5) incorporates both. The slope estimates of ENV across these models are uniformly negative and statistically significant at the 1% level with similar magnitudes, indicating that the negative relationship between corporate greenness and bond spreads is not fully explained by unobserved time or industry heterogeneity. Consistent with the Fama–MacBeth results, the inclusion of control variables in Columns (2), (4), and (6) attenuates the magnitude of the ENV coefficient. The ENV coefficient remains negative across all three specifications, although its statistical significance somewhat weakens when the controls are added. In terms of economic magnitude, a one standard deviation increase in the ENV score (SD = 29.085) is associated with a reduction in bond spreads of approximately 6.3 basis points ($-0.217/100 \times 29.085 = -0.063$, bond spreads are expressed in %) based on the full model specification of Column (6).

The COVID–19 pandemic represented an extraordinary macroeconomic shock that was accompanied by a sharp increase in bond spreads in 2020, consistent with the broader evidence on pandemic-period credit market disruptions (O'Hara and Zhou, 2021). This raises a legitimate concern that the relationship between ENV and bond spreads documented in our main analysis may be driven (at least partly) by the pandemic period. Specifically, if brown firms were disproportionately exposed to operational or financial stress during the 2020–2021 pandemic, the full-sample ENV coefficient may overstate the strength of the relationship in normal market conditions. To assess the potential influence of this unusual period, we re-estimate our main specifications restricting the analysis to the pre-pandemic period (i.e., 2008–2019). The pre-pandemic results are reported in Columns (6)–(7) of Table 4 and Column (7) of Table 5. In both tables, Column (7) presents the full-specification estimates for the pre-pandemic period. The negative and statistically significant relationship between corporate greenness and bond spreads persists in the pre-pandemic sub-sample, with coefficient estimates similar in magnitude to those reported in the corresponding full-sample specifications. Taken together, these findings suggest that the cross-sectional pricing of corporate greenness is not specific to the extraordinary market conditions of 2020–2021.

While t-statistics in Table 4 are systematically larger than those in Table 5, potentially reflecting differences in how the two estimators account for dependence across observations (Petersen, 2009), the coefficient estimates across both approaches are closely aligned, providing broadly consistent evidence across the two estimation frameworks.

5.3 Exploring Potential Drivers

5.3.1 Double Portfolio Sorts

The preceding analysis documents a robust cross-sectional relationship between corporate greenness and bond spreads. We complement this evidence with double portfolio sorts, which allow us to examine whether the relationship between greenness and bond spreads persists after conditioning on a second characteristic. Like the univariate sorts, this approach is non-parametric and imposes no functional form assumptions on the relationship of ENV with bond spreads. Specifically, at the end of each month, firms are independently sorted into tertiles based on their ENV scores and a selected conditioning characteristic, yielding nine portfolios from the intersection of the two sorts. ENV scores and conditioning characteristics follow the timing conventions described in Section 4. For consistency with the preceding analysis, the conditioning variables are those employed in the Fama–MacBeth and panel regressions, namely Cash, CF, Lev, Inc, ROA, Sales, Size, MB, CPN, TTM, DD, AV, Illiq, CFVol, IncVol, and DSBeta. If the High–Low ENV spread differential becomes statistically insignificant after conditioning on a given characteristic, this would be consistent with that characteristic accounting for the ENV-spread relationship. Conversely, a negative and statistically significant High–Low differential across the tertiles of the conditioning characteristic would indicate that the cross-sectional relationship between ENV and bond yield spreads persists after conditioning on that characteristic.

Table 6 presents the results of the double portfolio sorts, with each panel corresponding to a different conditioning characteristic. The final column of each panel reports the mean High–Low ENV spread differential within each tertile of the conditioning characteristic and is shaded for ease of reference. To conserve space, we do not report the corresponding High–Low spread differentials for the conditioning characteristic (across the ENV tertiles). Newey–West t-statistics based on four lags are reported in parentheses. Overall, the results show that the High–Low ENV spread differential remains negative and statistically significant within each tertile of every conditioning characteristic. Moreover, the monotonic decline in bond spreads from the Low to the High ENV portfolio is preserved within each tertile of the conditioning characteristic. These findings provide further evidence that corporate greenness is priced in the cross-section of corporate bond spreads and that this pricing pattern is not subsumed by any single characteristic considered in the double sorts.

We now highlight some of the most pronounced High–Low spread differentials. Turning first to bond characteristics, the High–Low ENV differential is −1.268% in the Low time-to-maturity (TTM) portfolio compared with −0.817% in the High TTM portfolio, while the corresponding differential is −1.055% in the Low Illiq portfolio compared with −0.840% in the High Illiq portfolio. These results indicate that the negative relationship between ENV and bond spreads tends to be stronger for more liquid bonds with shorter time to maturity. The larger differential among more liquid bonds is less consistent with bond illiquidity being a primary explanation for the relationship between ENV and bond spreads.

The High–Low ENV differential is also more pronounced across several characteristics associated with weaker financial fundamentals, consistent with the broader literature linking firm financial condition to asset pricing (Chan and Chen, 1991; Fama and French, 1992). Specifically, the average High–Low spread differential is −1.130% in the Low DD portfolio (compared with −0.584% in the High DD portfolio), −1.051% in the High Lev portfolio (compared with −0.854% in the Low Lev portfolio), −1.017% in the Low ROA portfolio (compared with −0.822% in the High ROA portfolio), and −0.963% in the Low MB portfolio (compared with −0.797% in the High MB portfolio). These patterns suggest that the ENV-spread differential tends to be more pronounced among firms with weaker financial fundamentals. A notable exception is asset volatility, for which the differential is larger in the Low AV portfolio (-1.198%) than in the High AV portfolio (-0.811%). Because lower asset volatility is not indicative of weaker financial condition, this pattern does not conform to a simple financial-distress interpretation.

Finally, turning to measures of cash-flow and income uncertainty, the High–Low ENV spread differential is more pronounced when uncertainty is higher, with values of -1.223% in the High CFVol portfolio versus -0.795% in the Low CFVol portfolio, and -1.007% in the High IncVol portfolio versus -0.718% in the Low IncVol portfolio. These patterns indicate that the High–Low ENV spread differential is more pronounced among firms with greater cash-flow and income uncertainty and provide preliminary evidence consistent with the cash-flow uncertainty channel examined formally in the subsequent channel analysis.

In summary, the relationship between corporate greenness and bond spreads tends to be more pronounced among firms with weaker financial fundamentals and greater cash flow uncertainty, and for shorter-maturity and more liquid bonds. More broadly, these findings indicate that the cross-sectional pricing of corporate greenness varies systematically with firm and bond characteristics, with particularly pronounced ENV-spread differentials among firms exhibiting weaker financial fundamentals or greater cash flow uncertainty.

[Insert Table 6 about here]

5.3.2 Corporate Greenness and Firm Characteristics

We next examine how firm and bond characteristics vary systematically across ENV-sorted portfolios. Following the sorting procedure described in Section 5.1, we assign firms to tertile portfolios based on their ENV scores and compute the time-series average of each characteristic within each portfolio. The resulting High–Low differences reveal the dimensions along which green and brown firms differ, raising important questions about whether the relationship between ENV and bond spreads partly reflects underlying differences in firm financial characteristics, which we explore further below and in Section 5.4.

The results are reported in Table 7. Greener firms exhibit higher operating cash flow (CF), income (Inc), and profitability (ROA). For instance, firms in the top ENV tertile have an average ROA of 5.2%, compared to 2.9% for firms in the bottom ENV tertile, a difference statistically significant at the 1% level. Greener firms also tend to exhibit lower leverage (Lev) and higher market-to-book ratios (MB). Following Chan and Chen (1991), who interpret low market-to-book ratios as a proxy for financial distress,[15] the higher market-to-book ratios observed among greener firms are consistent with these firms being relatively less distressed. This interpretation is reinforced by their greater average distance-to-default (DD) relative to brown firms. Brown firms also tend to exhibit higher asset volatility (AV) and greater illiquidity (Illiq), with all High–Low differences being statistically significant at the 1% level. Overall, these findings are consistent with a growing body of literature documenting that corporate greenness is associated with lower borrowing costs (Javadi and Masum, 2021; Huang et al., 2022; Altavilla et al., 2024), and with emerging evidence on the role of climate-related risks in shaping firms' capital structure decisions (Ginglinger and Moreau, 2023).

[Insert Table 7 about here.]

The results suggest that part of the difference in bond spreads between green and brown firms documented in earlier sections is associated with differences in firm fundamentals and bond-related characteristics. However, as shown in our preceding analyses, these factors do not fully account for the relationship between corporate greenness and bond spreads. The persistence of the ENV-spread relationship provides further evidence that corporate greenness represents a distinct, priced characteristic in the cross-section of corporate bond spreads, beyond these observable characteristics.

[15] Additional evidence on the role of the distress premium in the cross-section of stock returns is provided by Fama and French (1992) and Fama and French (1996).

An important concern arising from these results is that the observed relationship between ENV and bond spreads may partly reflect firms' underlying financial strength. Specifically, the results in Table 7 indicate that greener firms tend to exhibit higher profitability, lower leverage, higher market-to-book ratios, and other characteristics typically associated with lower credit risk. This raises the possibility that lower bond spreads among greener firms may partly reflect these financial characteristics rather than greenness itself, since such characteristics may be associated with both corporate greenness and bond spreads.

To further examine whether the relationship between ENV and bond spreads persists after removing variation in ENV associated with observable characteristics, we implement a two-step orthogonalization procedure following Godfrey et al. (2024):

$$\text{(S1) } ENV_{i,t} = \alpha_1 + \sum_{j=1}^{K} \gamma_j^{(1)} Z_{i,j,t-1} + \eta_s^{(1)} + \tau_t^{(1)} + \widetilde{ENV}_{i,t}, \tag{13}$$

$$\text{(S2) } SPR_{i,t} = \alpha_2 + \beta \widetilde{ENV}_{i,t-1} + \sum_{j=1}^{K} \gamma_j^{(2)} Z_{i,j,t-1} + \eta_s^{(2)} + \tau_t^{(2)} + u_{i,t}. \tag{14}$$

where $SPR_{i,t}$ is the bond spread of firm i in month t, $ENV_{i,t}$ denotes the ENV score from the preceding calendar year assigned to firm i in month t, and $Z_{i,j,t-1}$ denotes the lagged value of control variable j for firm i, η_s and τ_t represent industry and time (month) fixed effects, respectively, with s indexing the industry to which firm i belongs, and $u_{i,t}$ is the error term in the second-step (S2) regression. The superscripts (1) and (2) distinguish the coefficients and fixed effects in the two steps.

The step-1 (S1) residual, $\widetilde{ENV}$, captures the component of ENV that is orthogonal to the observable characteristics included in the first-step regression. Using this residual, the second-step (S2) regression examines whether the negative association between ENV and bond spreads persists after accounting for the component of ENV associated with these observable characteristics. Moreover, the residual may contain variation in ENV that is informative about the *non-pecuniary* dimension of corporate greenness. Accordingly, a negative and statistically significant coefficient on $\widetilde{ENV}$ would be consistent with a potential role for non-pecuniary investor preferences in the ENV-spread relationship. Importantly, however, the orthogonalization procedure does not rule out the possibility that the residual captures omitted financial or risk-related characteristics.

[Insert Table 8 about here.]

Table 8 reports the results of the two-step orthogonalization procedure. Column (1) reports the first-step (S1) results. Firm-level ENV exhibits a significant relationship with several prior observable characteristics, with signs broadly consistent with the patterns documented in Table 7. Column (2) reports the second-step (S2) results, where bond spreads are regressed on the orthogonalized ENV measure. The coefficient on the orthogonalized ENV measure is negative and statistically significant at the 5% level. This indicates that the negative association between corporate greenness and bond spreads persists when using the component of ENV that is orthogonal to the observable characteristics included in S1. The result is consistent with a potential role for non-pecuniary investor preferences in the ENV-spread relationship, but does not isolate such preferences from omitted financial or risk-related characteristics.

5.4 Propensity Score Matching Based on Firms' ENV Scores

The evidence presented thus far documents a robust negative association between corporate greenness and bond spreads. However, firms' greenness may itself be associated with underlying financial characteristics that are also related to lower credit risk. It is therefore possible that the observed relationship between ENV and bond spreads partly reflects differences in firm financial strength, such as profitability, rather than greenness itself. To further account for differences in observable firm and bond-related characteristics, we implement a propensity score matching (PSM) procedure to improve comparability between firms with relatively high and low ENV scores on the observable characteristics used in our main analysis.

Specifically, we define the treatment group as firm-month observations with an above-median ENV score based on the lagged ENV measure used in our main analysis, with the remaining observations forming the control group. Propensity scores are estimated each month using a logistic regression that includes the full set of control variables from our baseline regressions, with the aim of improving balance across the full set of observable firm and bond-related characteristics used in the main analysis. Treated observations are then matched to control observations using nearest-neighbour matching within each month, without replacement, to obtain one-to-one matched pairs.

After constructing the matched sample, we estimate monthly Fama–MacBeth cross-sectional regressions of bond spreads on a binary *Treated* indicator, which takes the value of one for observations in the treated group and zero otherwise. Column (1) of Table 9 includes only the *Treated* indicator, while Column (2) augments the specification with the full set of control variables. The coefficient on *Treated* is -0.568 in Column (1) and -0.148 in the full specification in Column (2), and is statistically significant at the 1% level in both specifications. In the full specification (Column (2)), the estimated coefficient indicates that treated firm-month observations are associated with bond spreads approximately 14.8 basis points lower than those of matched control observations, conditional on the included controls. The result provides further evidence that the negative relationship between ENV and bond spreads persists in a sample in which high- and low-ENV firms have been matched to improve comparability on observable firm and bond-related characteristics.

[Insert Table 9 here]

5.5 Channel Analysis

Having established that corporate greenness is priced in the cross-section of corporate bond spreads, with higher ENV scores associated with lower spreads, we now examine potential economic mechanisms underlying this relationship. We test three potential channels that may help explain the relationship between corporate greenness and bond spreads. The first channel is related to cash flow uncertainty. The literature has shown that brown firms tend to face higher borrowing costs than their greener counterparts (Ginglinger and Moreau, 2023; Altavilla et al., 2024; Demetriades and Politsidis, 2025), a disparity that may partly reflect differences in cash flow stability across green and brown firms. Greener firms may exhibit lower cash flow volatility, which may in turn be associated with lower default risk and lower credit risk premia (Safiullah et al., 2021).

The second channel is the downside risk channel. Prior studies have found that firms with stronger ESG performance tend to exhibit lower systematic and downside risk (Albuquerque et al., 2019). ENV scores may therefore be negatively associated with downside risk exposure, which is itself expected to be positively associated with the compensation required by bond investors and, consequently, with bond spreads. The third channel is the illiquidity channel. Green bond market participation has grown considerably in recent years (Flammer, 2021; Tolliver et al., 2020), reflecting broader growth in investor demand for environmentally sustainable fixed-income assets (Zerbib, 2019). Although our study does not focus specifically on the green bond market, such demand may extend more broadly, such that bonds issued by firms with higher ENV scores may attract greater interest from green and ESG-oriented investors and therefore exhibit greater liquidity. Greater liquidity is generally associated with a lower liquidity premium in bond spreads (Chen et al., 2007), providing a potential additional explanation for the negative relationship between ENV and bond spreads.

We conduct this analysis in two steps. In the first step, we examine whether the proposed channel variable is associated with firms' ENV scores. In the second step, we examine the relationship between ENV, the channel variable, and bond spreads by including the channel variable in the bond-spread regression. We interpret the results as providing evidence consistent with a potential channel when two patterns are observed. First, ENV is associated with the proposed channel variable in the expected direction. Second, the channel variable is associated with bond spreads in the expected direction when included alongside ENV. If the ENV coefficient remains significant after the channel variable is included, this would indicate that the proposed channel does not fully account for the ENV-spread relationship. All independent variables are lagged to reduce concerns about contemporaneous reverse causality, and we include control variables relevant to each channel variable (see the notes to Table 10 for details).

The results are reported in Table 10. Columns (1) and (2) show that ENV is negatively associated with cash flow volatility, with the relationship being statistically significant in Column (1) and weaker after including additional controls in Column (2). Column (3) shows that the negative relationship between ENV and bond spreads persists after controlling for cash flow volatility. However, the coefficient on cash flow volatility in the bond-spread regression is positive but statistically insignificant, hence the evidence for cash flow uncertainty as a channel is suggestive rather than conclusive. This evidence is broadly consistent with Safiullah et al. (2021), who document an association between carbon emissions, cash flow uncertainty, and credit ratings.

Columns (4)–(6) report results for the downside risk channel. ENV is negatively and statistically significantly associated with downside risk exposure, while downside risk is positively and significantly associated with bond spreads in Column (6). The negative relationship between ENV and bond spreads also persists after controlling for downside risk. These results provide robust evidence for a potential role of downside risk in the ENV-spread relationship, consistent with evidence that downside risk is priced in credit spreads (Gemmill and Keswani, 2011; Baltussen et al., 2012).

Finally, Columns (7)–(9) report results for the illiquidity channel, where we find only partial support. Illiquidity is positively and significantly associated with bond spreads in Column (9), consistent with the expected pricing of liquidity risk. However, while ENV is negatively associated with illiquidity in Column (7), this relationship loses statistical significance once additional controls are included in Column (8). Thus, the evidence for illiquidity as a channel is more limited. Collectively, these results provide the strongest support for a potential role of downside risk in the ENV-spread relationship. The evidence for cash flow uncertainty is suggestive but weaker, while the evidence for illiquidity is more limited.

[Insert Table 10 here]

6 Additional Results

6.1 Does ESG Matter?

In our baseline analysis, corporate greenness is proxied by firms' ENV scores. While the environmental (E) dimension of ESG is particularly relevant in the context of climate change, it is worthwhile to examine whether the broader ESG score, which incorporates environmental, social (S), and governance (G) dimensions, is also associated with the cross-section of corporate bond spreads. To investigate this, we replicate the portfolio sorting exercise from Section 5.1, replacing firms' ENV scores with their ESG scores.

The results, presented in Table A2, reveal a negative and highly significant cross-sectional relationship between ESG scores and bond spreads. Specifically, the average High-Low spread differential is -1.081% and statistically significant at the 1% level (Newey-West t-stat. $= -15.75$). Importantly, controlling for contemporaneous (Column 5) or lagged (Column 6) bond market factors, as identified by Dickerson et al. (2023), leaves the negative High-Low spread differential largely unchanged. Consistent with our portfolio sorting results, the findings from both the Fama-MacBeth and panel regression analyses (unreported to save space, available upon request from the authors) also corroborate a negative and statistically significant relationship between ESG scores and bond spreads.

6.2 Alternative Sorting and Weighting Schemes

A natural question is whether our results are sensitive to (i) the portfolio weighting scheme and (ii) the sorting procedure used to construct the ENV portfolios. To assess the robustness of our findings, we consider two alternative specifications. First, we apply trading-volume weighting instead of the equal-weighting scheme used in the baseline analysis. The results under this alternative weighting scheme, reported in Panel A of Table A3, are consistent with the baseline findings, with a negative and statistically significant High–Low spread differential of similar magnitude to that reported in Table 3. Specifically, the High–Low spread differential is -0.968% (Newey–West t-statistic $= -13.377$). The factor-adjusted differentials also remain negative and statistically significant at the 1% level, with estimates of -0.916% (Newey–West t-statistic $= -14.456$) and -0.926% (Newey–West t-statistic $= -14.569$) using contemporaneous and lagged bond risk factors, respectively.

Second, we examine whether our results depend on the choice of portfolio breakpoints by replicating the analysis using quintile portfolios instead of tertiles. Firms are sorted into quintiles based on their ENV scores, and we compute the average bond spread within each portfolio and the High–Low spread differential between the top and bottom ENV quintiles. The results in Panel B of Table A3 continue to indicate a negative and statistically significant cross-sectional relationship between corporate greenness and bond spreads. Average bond spreads decline monotonically from the bottom to the top ENV quintile, while the High–Low spread differential remains negative (-1.095%) and statistically significant at the 1% level (Newey–West t-statistic $= -16.52$). Importantly, the negative High–Low spread differential persists after controlling for the systematic bond risk factors included in our baseline factor model, with factor-adjusted estimates of -1.053% (Newey–West t-statistic $= -17.632$) and -1.068% (Newey–West t-statistic $= -18.016$) using contemporaneous and lagged factors, respectively, both statistically significant at the 1% level. Overall, these findings provide further evidence that the main results are robust to alternative portfolio weighting and sorting schemes.

6.3 Alternative Measure of Corporate Greenness: Emission Intensity

In the main analysis, we use the Refinitiv ENV score as our primary measure of corporate greenness and document a negative association between corporate greenness and bond spreads. We also verify that this relationship holds when the broader ESG score from the same data provider is used (Section 6.1). We further assess the robustness of our findings using carbon intensity, obtained from Trucost/S&P Global, as an alternative emissions-based proxy that is inversely related to corporate greenness. Following Aswani et al. (2024), we define carbon intensity as CO_2 emissions scaled by total sales. Because higher carbon intensity reflects lower corporate greenness, we expect a positive association between carbon intensity and bond spreads, consistent with our main hypothesis.

The results are reported in Tables A4–A6 of the appendix, and are broadly consistent with our main findings. Table A4 reports the portfolio sort results, Table A5 reports the Fama–MacBeth regression results, and Table A6 reports the panel regression results. The portfolio sorts show positive and statistically significant High–Low spread differentials for aggregate carbon intensity and for each emissions scope. Following standard classification conventions, carbon emissions are decomposed into Scope 1 (direct emissions from firm operations), Scope 2 (indirect emissions from purchased energy), and Scope 3 (all other indirect emissions across the value chain). Importantly, the positive High–Low differentials remain statistically significant at the 1% level after adjustment for the systematic bond risk factors, using either contemporaneous or lagged factor values. The regression results provide the strongest and most consistent evidence for Scope 1 carbon intensity, which is positively and significantly associated with bond spreads in both the Fama–MacBeth and panel regressions, while the evidence for aggregate, Scope 2, and Scope 3 intensity is less consistent. Specifically, aggregate carbon intensity is positively associated with bond spreads at the 10% significance level in the Fama–MacBeth regressions but is not statistically significant in the panel regressions, while Scope 2 and Scope

3 intensity show no significant association in either specification. Overall, the results obtained using carbon intensity are broadly consistent with our main findings, with the portfolio sorts consistently indicating higher bond spreads among more carbon-intensive firms and the regression evidence being concentrated in Scope 1 intensity.

6.4 Subsample Analysis

A growing body of evidence suggests that the Paris Agreement marked an important shift in how financial markets assess climate-related risks. Monasterolo and De Angelis (2020) document that, following the Agreement's entry into force, stock markets adjusted their risk perceptions, with lower systematic risk for low-carbon indices and a reallocation of capital toward greener assets. Similarly, Tolliver et al. (2020) document a significant increase in green bond issuance directed toward renewable energy projects following the Paris Agreement. Motivated by this evidence, we examine whether the documented relationship between ENV and bond spreads differs between the pre- and post-Paris Agreement periods, using 2016, the year in which the Agreement officially entered into force, as the breakpoint.

Table A7 in the online appendix reports the results for the pre- (2008–2015) and post-Paris Agreement (2016–2021) sub-periods. Corporate greenness is negatively and significantly associated with bond spreads in both sub-periods, indicating that the negative relationship between ENV and bond spreads is present both before and after the Paris Agreement. Specifically, the ENV coefficient (multiplied by 100) is -0.308 in the pre-Paris period (Newey–West t-statistic $=$ -3.854) and -0.269 in the post-Paris period (Newey–West t-statistic $= -10.250$). Although the post-Paris estimate exhibits stronger statistical significance, its magnitude is slightly smaller, and the results do not establish a significant difference between the two periods. Overall, the findings indicate that the negative relationship between ENV and bond spreads is present in both sub-periods.

6.5 Evidence across Sectors

Is the negative relationship between corporate greenness and bond spreads driven by specific sectors? To address this question, we replicate the univariate portfolio sorting exercise from Section 5.1 separately for each sector using the Refinitiv Eikon sector classification. The results, presented in Table A8 of the online appendix, provide evidence on the relationship between firms' ENV scores and bond spreads within each sector. The High–Low ENV spread differential is negative in ten of the eleven sectors considered and is statistically significant in each case. While the magnitude of the differential varies across sectors and is particularly pronounced in sectors such as Energy, the overall pattern is broadly consistent across sectors. Real Estate represents the only exception, with a positive High–Low spread differential. Overall, these findings suggest that the negative relationship between corporate greenness and bond spreads is broadly present across sectors rather than being driven by a particular sector.

7 Conclusion

In this paper, we examine the cross-sectional relationship between corporate greenness and bond spreads using a comprehensive dataset of U.S. corporate bonds over the period 2008–2021. Our empirical analysis draws on portfolio sorts, Fama–MacBeth regressions, and panel regressions that control for a broad range of firm and bond-related characteristics. We provide evidence of a negative cross-sectional association between corporate greenness and bond spreads. A one standard deviation increase in ENV scores is associated with approximately 6.3–8.5 basis points lower spreads across our full regression specifications. We further document that greener firms tend to exhibit stronger financial fundamentals, including greater profitability, lower leverage, greater distance to default, and lower cash flow volatility. These characteristics appear to play a partial explanatory role in the ENV-spread relationship, but do not fully account for it. We also examine cash flow uncertainty, downside risk, and bond illiquidity as potential economic channels underlying the ENV-spread relationship. The evidence is strongest for cash flow uncertainty and downside risk, while support for the bond illiquidity channel is limited.

A key concern is whether the relationship between corporate greenness and bond spreads reflects underlying firm financial strength rather than greenness itself. To investigate this concern, we implement two complementary approaches. First, propensity score matching improves comparability between high- and low-ENV firms on observable characteristics and indicates that bond spreads remain significantly lower for greener firms in the matched sample. Second, a two-step orthogonalization procedure isolates the component of ENV scores orthogonal to observable characteristics. The documented relationship between ENV and bond spreads persists under both approaches, suggesting that it is not fully accounted for by selection on observable characteristics or by the association between ENV and lagged observable characteristics. Collectively, these findings are consistent with a role for pecuniary mechanisms, particularly cash flow uncertainty and downside risk, alongside a potential role for non-pecuniary investor preferences in the pricing of corporate greenness. Finally, our results are robust to alternative portfolio construction and weighting methods and across sub-periods. The findings are also broadly consistent when carbon intensity is used as an alternative measure of corporate greenness.

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Table 1. Descriptive Statistics for Bond Spreads and ENV Scores

This table presents summary statistics for bond spreads (in %) and ENV scores over the period 2008–2021. Reported statistics include the mean, 25^{th} percentile, median (50^{th} percentile), 75^{th} percentile, maximum value (Max.), minimum value (Min.), standard deviation (St. Dev.), skewness, and kurtosis. Percentile statistics are computed separately for each variable and therefore describe the distribution of each variable independently, rather than the joint relationship between bond yield spreads and ENV scores. The final two rows report the number of unique firms and firm-month observations.

	Bond Spread (%)	ENV Score
Mean	3.188	44.198
25^{th} Percentile	1.846	18.568
50^{th} Percentile	2.768	45.410
75^{th} Percentile	4.108	70.215
Max.	13.058	98.546
Min.	0.142	0.000
St. Dev.	1.914	29.085
Skewness	1.447	-0.039
Kurtosis	6.223	1.716
# Firms	820	820
# Firm–month obs.	56,132	56,132

Table 2. Per Year Summary Statistics for Bond Spreads

This table reports annual summary statistics for monthly U.S. corporate bond spreads over the period January 2008 to December 2021. Reported statistics include the mean, standard deviation (St. Dev.), skewness, and kurtosis for each year. The mean and standard deviation are annualized, and bond spreads are expressed in percentage terms. The final column reports the number of firm-month observations in each year.

Year	Mean	St. Dev.	Skewness	Kurtosis	# Obs
2008	4.926	2.452	1.007	3.404	1,646
2009	6.188	2.722	0.956	3.382	2,382
2010	4.418	1.642	0.198	2.097	2,633
2011	4.129	1.669	0.392	2.362	2,968
2012	3.334	1.593	0.626	2.633	3,216
2013	3.306	1.305	0.286	2.317	3,417
2014	3.221	1.204	0.418	2.560	3,495
2015	3.565	1.461	0.933	3.361	3,818
2016	3.523	1.691	1.098	3.620	4,568
2017	2.715	1.128	0.738	2.792	5,026
2018	2.532	1.030	0.871	3.039	5,447
2019	1.642	1.282	1.301	4.128	5,689
2020	3.024	2.545	1.651	5.034	6,022
2021	2.454	1.134	1.108	3.719	5,805

Table 3. Portfolio Sorting on Firms' ENV Scores

This table presents results from univariate portfolio sorts on firms' ENV scores. At the end of each month, firms are sorted into three portfolios based on tertiles of the cross-sectional distribution of the latest available one-year-lagged ENV score. The Low portfolio contains firms in the bottom tertile, the Med portfolio contains firms in the middle tertile, and the High portfolio contains firms in the top tertile. For firms with multiple bonds outstanding in a given month, bond spreads are averaged across the available bonds to obtain a firm-level bond spread. For each portfolio, we report the time-series average of the equal-weighted firm-level bond spreads, defined as the bond yield in excess of the risk-free rate. The High–Low column shows the mean spread differential between the High and Low portfolios. The final two columns display intercept estimates from time-series regressions of the High–Low spread on contemporaneous ($\alpha_C^{BBW adj}$) and one-month-lagged ($\alpha_L^{BBW adj}$) values of the bond risk factors of Dickerson et al. (2023). All portfolio means (Port. Mean) and alpha (α) estimates are annualized and expressed in percentage terms. The final two rows report the R^2 for the factor regressions, where applicable, and the number of monthly observations. Newey–West t-statistics based on four lags are reported in parentheses. The sample spans January 2008 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
	Low	Med	High	High–Low	$\alpha_C^{BBW_{adj}}$	$\alpha_L^{BBW_{adj}}$
Port. Mean / α	4.058	3.439	3.021	-1.037	-0.990	-0.999
	(17.550)	(17.215)	(15.414)	(-14.825)	(-16.149)	(-15.923)
MKT_t					-7.497	
					(-2.395)	
DRF_t					5.549	
					(1.861)	
CRF_t					1.377	
					(0.870)	
LRF_t					-14.195	
					(-3.152)	
MKT_{t-1}						-7.445
						(-1.832)
DRF_{t-1}						5.512
						(1.708)
CRF_{t-1}						2.406
						(1.516)
LRF_{t-1}						-12.928
						(-2.906)
R^2	-	-	-	-	0.131	0.108
# Months	168	168	168	168	168	167

Table 4. Fama–MacBeth Regression Results

This table presents results from monthly Fama–MacBeth cross-sectional regressions of bond spreads on lagged ENV scores and a set of lagged control variables. Column (1) reports estimates from a univariate specification with ENV as the only explanatory variable. Column (2) adds firm and bond-related control variables, while Column (3) further includes proxies for financing uncertainty (CFVol and IncVol). Column (4) augments the univariate specification in Column (1) with firms' downside risk (DSBeta), and Column (5) reports the full specification incorporating all control variables simultaneously. Columns (6) and (7) replicate the specifications in Columns (4) and (5), respectively, excluding observations from the COVID-19 period (2020–2021). Reported coefficient estimates for ENV are multiplied by 100. Newey–West t-statistics based on four lags are reported in parentheses. The final two rows report the number of firm-month observations and the time-series average R^2 (Avg. R^2), respectively. The sample spans January 2008 to December 2021.

	Full Sample					Excl. COVID	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ENV × 100	-1.465	-0.362	-0.313	-1.141	-0.291	-1.381	-0.307
	(-15.168)	(-8.486)	(-7.410)	(-16.434)	(-6.254)	(-17.443)	(-5.834)
Sales		-0.123	-0.047		-0.024		-0.037
		(-3.141)	(-1.218)		(-0.702)		(-0.973)
Cash		0.027	0.056		-0.029		0.034
		(0.114)	(0.199)		(-0.104)		(0.105)
CF		-0.426	-1.038		-1.036		-1.346
		(-1.119)	(-3.006)		(-3.276)		(-4.181)
Lev		0.823	0.804		0.792		0.765
		(8.448)	(7.510)		(7.209)		(6.178)
Inc		-0.542	-0.830		-0.686		-0.859
		(-1.951)	(-2.765)		(-2.085)		(-2.327)
ROA		-3.581	-2.798		-2.585		-2.125
		(-7.221)	(-6.039)		(-6.118)		(-5.893)
Size		-0.236	-0.244		-0.211		-0.210
		(-16.476)	(-13.348)		(-16.327)		(-14.625)
MB		-0.012	-0.009		-0.006		-0.005
		(-1.769)	(-1.134)		(-0.843)		(-0.544)
DD		-0.030	-0.029		-0.028		-0.028
		(-7.014)	(-6.141)		(-7.337)		(-6.350)
AV		0.959	0.900		0.815		0.830
		(7.613)	(7.277)		(8.261)		(7.488)
CPN		0.430	0.427		0.362		0.361
		(14.198)	(14.477)		(13.870)		(12.058)
TTM		0.081	0.084		0.089		0.095
		(11.105)	(11.926)		(12.675)		(12.825)
Illiq		41.970	41.452		41.868		34.775
		(7.812)	(7.936)		(8.235)		(8.514)
CFVol			-2.948		-1.938		-1.803
			(-2.388)		(-1.679)		(-1.386)
IncVol			0.770		0.789		0.771
			(6.373)		(6.370)		(5.981)
DSBeta				0.567	0.007		-0.016
				(3.031)	(0.175)		(-0.469)
Intercept	4.145	6.166	6.249	3.215	5.625	4.224	5.739
	(18.362)	(13.880)	(11.157)	(12.708)	(14.102)	(16.692)	(12.707)
Firm-Month Obs.	56,132	41,402	39,944	43,951	32,253	44,305	25,988
Avg. R^2	0.076	0.656	0.675	0.161	0.690	0.074	0.695

Table 5. Panel Regression Results

This table presents results from panel regressions of bond spreads on lagged ENV scores and a set of control variables. The regression specification, variable definitions, and lag conventions are described in Eq. (12), Section 5.2. Columns (1)–(2) include time (month) fixed effects only, Columns (3)–(4) include industry fixed effects only, and Columns (5)–(6) include both time and industry fixed effects. Columns (1), (3), and (5) include ENV as the only explanatory variable, while Columns (2), (4), and (6) additionally include the full set of control variables. Column (7) replicates the specification of Column (6), excluding observations from the COVID-19 period (2020–2021). Standard errors are two-way clustered by firm and year, and t-statistics are reported in parentheses. Reported coefficient estimates for ENV are multiplied by 100. The full sample spans January 2008 to December 2021.

	Full Sample						Excl. COVID
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ENV × 100	-1.458	-0.276	-1.481	-0.551	-1.351	-0.217	-0.255
	(-6.381)	(-2.430)	(-5.959)	(-3.672)	(-6.179)	(-1.829)	(-2.118)
Sales		0.083		0.100		0.091	0.023
		(1.066)		(1.147)		(1.127)	(0.298)
Cash		-0.343		0.250		-0.336	-0.436
		(-0.916)		(0.547)		(-0.949)	(-1.113)
CF		-0.075		0.741		-0.378	-0.878
		(-0.105)		(1.182)		(-0.620)	(-1.599)
Lev		0.872		0.506		0.976	0.935
		(3.393)		(1.596)		(3.587)	(3.493)
Inc		0.528		0.693		0.801	0.138
		(1.224)		(1.227)		(1.664)	(0.320)
ROA		-4.813		-6.163		-5.091	-4.070
		(-4.063)		(-5.739)		(-4.067)	(-3.634)
Size		-0.214		-0.159		-0.246	-0.217
		(-6.570)		(-2.941)		(-6.142)	(-6.288)
MB		-0.015		-0.019		-0.014	-0.010
		(-1.249)		(-1.671)		(-1.109)	(-0.699)
DD		-0.019		-0.007		-0.018	-0.015
		(-4.643)		(-1.838)		(-4.444)	(-4.724)
AV		0.681		0.160		0.619	0.807
		(2.605)		(0.360)		(2.437)	(3.078)
CPN		0.350		0.484		0.342	0.342
		(8.122)		(7.226)		(7.880)	(7.004)
TTM		0.079		0.072		0.079	0.089
		(6.029)		(6.085)		(5.959)	(6.907)
Illiq		37.256		66.014		37.052	25.103
		(2.589)		(4.884)		(2.573)	(3.239)
CFVol		-0.093		2.451		-1.535	-0.240
		(-0.037)		(0.852)		(-0.582)	(-0.092)
IncVol		0.958		0.626		0.932	0.756
		(2.853)		(1.850)		(3.142)	(2.894)
DSBeta		0.085		0.067		0.091	0.045
		(1.182)		(0.839)		(1.356)	(0.968)
Intercept	3.832	5.334	3.842	3.466	3.785	6.060	5.505
	(34.039)	(7.080)	(12.187)	(2.510)	(35.631)	(6.696)	(6.705)
Time FE	Yes	Yes	No	No	Yes	Yes	Yes
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes
Firm-Month Obs.	56,132	32,251	56,132	32,253	56,132	32,251	25,986
R^2	0.367	0.690	0.102	0.551	0.416	0.693	0.728

Table 6: Double Portfolio Sorts

This table reports results from independent double portfolio sorts based on firms' ENV scores and the conditioning characteristic specified in each panel. At the end of each month, firms are independently sorted into tertiles based on the cross-sectional distributions of ENV and the conditioning characteristic, yielding nine portfolios from the intersections of the two sets of tertiles. Rows correspond to tertiles of the conditioning characteristic, while columns correspond to ENV tertiles. Each cell reports the time-series average bond spread for the corresponding portfolio. The final column reports the time-series average High–Low ENV spread differential within each tertile of the conditioning characteristic, computed as the difference between the average firm-level bond spreads of the High and Low ENV portfolios. Portfolio means and High–Low spread differentials are expressed in percentage terms. Newey–West t-statistics based on four lags are reported in parentheses. The sample spans January 2008 to December 2021.

Sales	ENV				
		Low	Med	High	High-Low
	Low	4.164	3.456	2.978	-1.186
		(16.030)	(13.157)	(14.566)	(-13.144)
	Med	3.845	3.385	3.104	-0.741
		(19.691)	(18.560)	(14.446)	(-10.733)
	High	4.098	3.448	2.956	-1.141
		(18.014)	(19.498)	(16.881)	(-12.045)

Cash	ENV				
		Low	Med	High	High-Low
	Low	4.215	3.547	2.960	-1.255
		(18.551)	(16.182)	(15.409)	(-13.097)
	Med	3.955	3.287	3.023	-0.932
		(19.817)	(19.802)	(17.016)	(-11.495)
	High	3.912	3.470	3.114	-0.798
		(16.193)	(15.863)	(14.150)	(-13.568)

CF	ENV				
		Low	Med	High	High-Low
	Low	4.238	3.936	3.350	-0.888
		(16.238)	(14.949)	(14.224)	(-12.238)
	Med	3.952	3.349	3.120	-0.832
		(17.494)	(17.674)	(15.311)	(-10.197)
	High	3.846	3.101	2.688	-1.158
		(19.670)	(18.177)	(16.744)	(-17.303)

Lev	ENV				
		Low	Med	High	High-Low
	Low	3.798	3.188	2.944	-0.854
		(17.718)	(16.769)	(17.127)	(-12.413)
	Med	3.993	3.376	3.001	-0.992
		(17.796)	(18.567)	(14.879)	(-11.115)
	High	4.279	3.784	3.227	-1.051
		(21.074)	(19.844)	(14.597)	(-10.029)

Inc	ENV				
		Low	Med	High	High-Low
	Low	4.642	4.111	3.675	-0.966
		(19.471)	(19.634)	(14.597)	(-10.801)
	Med	3.650	3.173	2.874	-0.776
		(16.402)	(17.203)	(15.440)	(-13.498)
	High	3.644	3.003	2.670	-0.975
		(15.448)	(14.156)	(16.149)	(-11.246)

ROA	ENV				
		Low	Med	High	High-Low
	Low	4.504	4.172	3.487	-1.017
		(17.357)	(15.715)	(13.675)	(-12.364)
	Med	3.807	3.234	3.022	-0.785
		(17.496)	(18.086)	(15.773)	(-10.842)
	High	3.519	2.993	2.697	-0.822
		(16.736)	(16.947)	(16.312)	(-12.758)

Size	ENV				
		Low	Med	High	High-Low
	Low	4.301	3.774	3.644	-0.657
		(20.147)	(20.133)	(14.785)	(-6.943)
	Med	3.784	3.409	3.049	-0.735
		(15.559)	(16.900)	(15.928)	(-9.356)
	High	3.616	3.105	2.817	-0.799
		(13.221)	(14.086)	(15.125)	(-7.682)

MB	ENV				
		Low	Med	High	High-Low
	Low	4.470	3.917	3.507	-0.963
		(17.145)	(16.853)	(14.672)	(-11.818)
	Med	3.690	3.232	2.979	-0.711
		(15.587)	(16.697)	(15.727)	(-9.743)
	High	3.503	3.058	2.706	-0.797
		(16.784)	(17.979)	(15.338)	(-14.044)

DD	ENV				
		Low	Med	High	High-Low
	Low	4.889	4.500	3.759	-1.130
		(17.385)	(16.905)	(16.451)	(-11.640)
	Med	3.657	3.344	3.089	-0.568
		(15.941)	(15.755)	(14.379)	(-14.349)
	High	3.099	2.688	2.515	-0.584
		(16.924)	(16.669)	(15.705)	(-11.095)

AV	ENV				
		Low	Med	High	High-Low
	Low	4.045	3.184	2.847	-1.198
		(19.122)	(16.127)	(15.272)	(-12.792)
	Med	3.403	3.013	2.798	-0.605
		(15.159)	(15.425)	(14.528)	(-11.488)
	High	4.504	4.034	3.693	-0.811
		(17.265)	(17.727)	(16.567)	(-9.188)

CPN	ENV				
		Low	Med	High	High-Low
	Low	2.976	2.508	2.341	-0.635
		(14.877)	(13.955)	(14.629)	(-7.973)
	Med	3.730	3.281	3.124	-0.606
		(14.068)	(15.463)	(15.181)	(-8.217)
	High	4.935	4.462	4.009	-0.927
		(19.376)	(20.423)	(17.880)	(-10.274)

TTM	ENV				
		Low	Med	High	High-Low
	Low	3.733	2.944	2.465	-1.268
		(15.390)	(14.357)	(13.041)	(-14.277)
	Med	4.323	3.637	3.040	-1.284
		(16.856)	(17.391)	(14.646)	(-16.668)
	High	4.163	3.712	3.346	-0.817
		(19.105)	(17.901)	(16.313)	(-14.461)

Illiq	ENV				
		Low	Med	High	High-Low
	Low	3.626	2.930	2.571	-1.055
		(15.737)	(15.817)	(14.727)	(-13.308)
	Med	3.774	3.189	2.825	-0.949
		(16.044)	(16.657)	(15.762)	(-13.282)
	High	4.587	4.223	3.748	-0.840
		(18.509)	(17.517)	(16.706)	(-11.568)

CFVol	ENV				
		Low	Med	High	High-Low
	Low	3.714	3.293	2.919	-0.795
		(15.831)	(14.330)	(16.478)	(-7.869)
	Med	4.078	3.325	3.111	-0.967
		(19.366)	(18.715)	(14.557)	(-11.657)
	High	4.249	3.634	3.025	-1.223
		(17.096)	(18.405)	(15.132)	(-15.463)

IncVol	ENV				
		Low	Med	High	High-Low
	Low	3.621	3.100	2.903	-0.718
		(18.302)	(17.613)	(16.090)	(-12.964)
	Med	3.774	3.191	2.812	-0.963
		(16.173)	(17.086)	(13.511)	(-16.111)
	High	4.463	4.042	3.456	-1.007
		(17.779)	(15.669)	(16.708)	(-10.633)

DSBeta	ENV				
		Low	Med	High	High-Low
	Low	3.543	3.015	2.533	-0.919
		(15.747)	(15.162)	(17.568)	(-10.476)
	Med	3.569	2.972	2.712	-0.857
		(16.734)	(19.590)	(16.390)	(-11.826)
	High	4.205	3.743	3.384	-0.795
		(19.042)	(18.182)	(16.753)	(-11.319)

Table 7. Characteristics of ENV-Sorted Portfolios

This table presents characteristics of portfolios formed by sorting firms on their ENV scores. At the end of each month, firms are sorted into three portfolios based on tertiles of the cross-sectional distribution of the latest ENV score available at the end of the previous month. The Low portfolio contains firms in the bottom tertile, the Med portfolio contains firms in the middle tertile, and the High portfolio contains firms in the top tertile. For each characteristic reported in the rows, the table presents its average value within each ENV portfolio. For example, the Sales row reports average firm sales across the Low, Med, and High ENV portfolios. The final column reports the time-series average High–Low differential in each characteristic between the High and Low ENV portfolios. Newey–West t-statistics based on four lags are reported in parentheses. The sample spans January 2008 to December 2021.

	(1) Low	(2) Med	(3) High	(4) High-Low
Sales	0.603	0.733	0.709	0.106
				(14.315)
Cash	0.070	0.070	0.072	0.003
				(2.785)
CF	0.079	0.091	0.096	0.016
				(13.436)
Lev	0.529	0.498	0.495	-0.034
				(-8.420)
Inc	0.073	0.080	0.097	0.024
				(7.027)
ROA	0.029	0.044	0.052	0.023
				(15.246)
Size	22.982	23.594	24.283	1.301
				(52.395)
MB	2.596	2.984	3.583	0.987
				(11.211)
DD	18.250	23.312	24.240	5.990
				(16.707)
AV	0.327	0.317	0.267	-0.060
				(-11.301)
CPN	5.280	5.026	4.758	-0.523
				(-14.234)
TTM	9.328	10.616	11.627	2.300
				(12.583)
Illiq	0.699	0.598	0.590	-0.109
				(-4.858)
CFVol	0.016	0.015	0.014	-0.002
				(-11.195)
IncVol	0.154	0.098	0.089	-0.066
				(-19.823)
DSBeta	1.060	0.979	0.874	-0.190
				(-13.387)

Table 8. Two-Step Orthogonalization of ENV Scores

This table presents results from the two-step orthogonalization procedure of Godfrey et al. (2024):

$$(S1)\ ENV_{i,t} = \alpha_1 + \sum_{j=1}^{K} \gamma_j^{(1)} Z_{i,j,t-1} + \eta_s^{(1)} + \tau_t^{(1)} + \widetilde{ENV}_{i,t},$$

$$(S2)\ SPR_{i,t} = \alpha_2 + \beta \widetilde{ENV}_{i,t-1} + \sum_{j=1}^{K} \gamma_j^{(2)} Z_{i,j,t-1} + \eta_s^{(2)} + \tau_t^{(2)} + u_{i,t}.$$

where $SPR_{i,t}$ denotes the bond spread of firm i in month t, $ENV_{i,t}$ denotes its environmental score at time t, and $Z_{i,j,t-1}$ denotes the value of control variable j for firm i selected according to the lag conventions described in Section 4. η_s denotes industry fixed effects, with s indexing the industry to which firm i belongs, and τ_t denotes time (month) fixed effects. Superscripts (1) and (2) distinguish the coefficients and fixed effects in the two steps. $\widetilde{ENV}_{i,t}$ is the residual from Step 1 and captures the component of ENV orthogonal to the observable characteristics included in the first-step regression. Step 2 examines whether the ENV-spread relationship persists when this orthogonalized component of ENV is used. Columns (1) and (2) report the results from Steps 1 and 2, respectively. Standard errors are two-way clustered by firm and year, and t-statistics are reported in parentheses.

	(1) (S1) y = ENV	(2) (S2) y = SPR
$\widetilde{ENV}$		-0.221
		(-2.148)
Sales	-0.013	0.070
	(-0.495)	(0.889)
Cash	0.481	-0.459
	(2.526)	(-1.392)
CF	0.308	-0.513
	(1.466)	(-0.643)
Lev	-0.090	1.098
	(-0.940)	(4.095)
Inc	-0.301	0.765
	(-1.959)	(1.615)
ROA	0.638	-4.754
	(2.071)	(-3.477)
Size	0.142	-0.280
	(12.174)	(-8.763)
MB	0.006	-0.014
	(1.472)	(-1.159)
DD	0.001	-0.016
	(1.825)	(-4.559)
AV	-0.036	0.557
	(-0.497)	(1.885)
CPN	0.004	0.304
	(0.469)	(8.246)
TTM	0.004	0.081
	(2.427)	(5.921)
Illiq	1.589	60.447
	(1.917)	(2.972)
CFVol	0.927	-3.752
	(0.875)	(-1.351)
IncVol	-0.043	1.007
	(-0.646)	(2.956)
DSBeta	-0.022	0.113
	(-1.385)	(1.540)
Intercept	-2.926	6.684
	(-10.225)	(8.488)
Time FE	Yes	Yes
Industry FE	Yes	Yes
Firm-Month Obs.	25,207	24,027
R^2	0.417	0.714

Table 9. Propensity Score Matching Results

This table reports the results of propensity score matching (PSM) analyses examining the relationship between ENV and corporate bond spreads. Firm-month observations with an above-median value of the lagged ENV measure used in the main analysis are classified as the treated group, while all remaining observations constitute the control group. Propensity scores are estimated via a monthly logistic regression using all control variables from the main Fama-MacBeth regressions. Within each month, treated observations are matched to control observations using nearest-neighbor matching based on the estimated propensity scores to obtain one-to-one matched pairs. The table presents Fama-MacBeth regression results where the dependent variable is the corporate bond spread and Treated is an indicator variable equal to one for observations in the treated group and zero otherwise. Newey and West (1987) t-statistics with four lags are reported in parentheses. The sample spans January 2008 to December 2021.

	(1)	(2)
Treated	-0.568	-0.148
	(-14.054)	(-8.072)
Sales		-0.015
		(-0.386)
Cash		-0.152
		(-0.509)
CF		-1.331
		(-3.820)
Lev		0.834
		(6.659)
Inc		-0.250
		(-0.803)
ROA		-3.490
		(-8.512)
Size		-0.267
		(-15.900)
MB		-0.005
		(-0.570)
DD		-0.031
		(-6.853)
AV		0.864
		(7.243)
CPN		0.373
		(12.536)
TTM		0.090
		(11.874)
Illiq		40.546
		(8.206)
CFVol		-1.606
		(-1.311)
IncVol		0.737
		(5.590)
DSBeta		0.007
		(0.175)
Intercept	3.569	6.760
	(19.797)	(13.479)
Firm-Month Obs.	28,983	28,983
Avg. R^2	0.046	0.692

Table 10. Economic Channels

This table reports the results from exploring potential economic channels underlying the relationship between corporate greenness and bond spreads. For each channel, we report three specifications. The first two regress the channel variable on lagged ENV, first without and then with additional control variables. The third regresses bond spreads jointly on lagged ENV and the channel variable, together with the relevant controls. Columns (1)–(3) report results for the cash flow uncertainty channel, Columns (4)–(6) for the downside risk channel, and Columns (7)–(9) for the bond illiquidity channel. All specifications include industry and time fixed effects. Standard errors are two-way clustered by firm and year, and t-statistics are reported in parentheses. The sample spans January 2008 to December 2021.

	Cash Flow Uncertainty (CFVol) Channel			Downside Risk (DSBeta) Channel			Illiquidity (Illiq) Channel		
	(1) y=CFVol	(2) y=CFVol	(3) y=SPR	(4) y=DSBeta	(5) y=DSBeta	(6) y=SPR	(7) y=Illiq	(8) y=Illiq	(9) y=SPR
ENV × 100	-0.004	-0.003	-0.922	-0.190	-0.267	-0.854	-0.001	-0.001	-0.902
	(-2.815)	(-1.782)	(-7.610)	(-2.882)	(-3.875)	(-7.630)	(-2.369)	(-1.266)	(-8.589)
CFVol			2.817						
			(1.102)						
DSBeta						0.276			
						(2.806)			
Illiq									50.296
									(2.814)
Sales		0.002	-0.060		-0.064	0.008		0.000	-0.085
		(1.180)	(-0.695)		(-1.830)	(0.092)		(0.985)	(-1.134)
Cash		0.039	0.790		0.781	0.974		0.003	0.915
		(5.224)	(1.905)		(2.498)	(2.296)		(1.633)	(2.258)
Lev		0.008	1.208		0.527	0.973		0.001	1.219
		(2.077)	(3.533)		(3.748)	(3.343)		(0.818)	(3.946)
Inc		-0.002	0.121		-0.127	0.287		-0.000	0.219
		(-0.302)	(0.233)		(-0.497)	(0.525)		(-0.049)	(0.477)
ROA		0.004	-6.717		-0.822	-6.103		-0.012	-6.143
		(0.262)	(-5.132)		(-1.399)	(-4.785)		(-3.174)	(-4.893)
MB		0.000	-0.033		-0.032	-0.024		-0.000	-0.030
		(1.455)	(-2.300)		(-4.987)	(-1.935)		(-1.285)	(-2.283)
CPN			0.488			0.426		0.000	0.470
			(10.622)			(10.110)		(3.617)	(9.879)
TTM			0.065			0.073		0.000	0.055
			(4.093)			(5.086)		(2.112)	(3.411)
Intercept	0.016	0.008	0.308	1.055	0.954	0.151	0.006	0.002	0.240
	(20.626)	(3.701)	(1.630)	(30.312)	(12.355)	(0.702)	(18.226)	(2.314)	(1.296)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Month Obs.	41,881	31,755	40,967	35,167	26,761	33,542	42,659	32,373	41,941
R^2	0.113	0.196	0.628	0.213	0.321	0.636	0.275	0.283	0.645

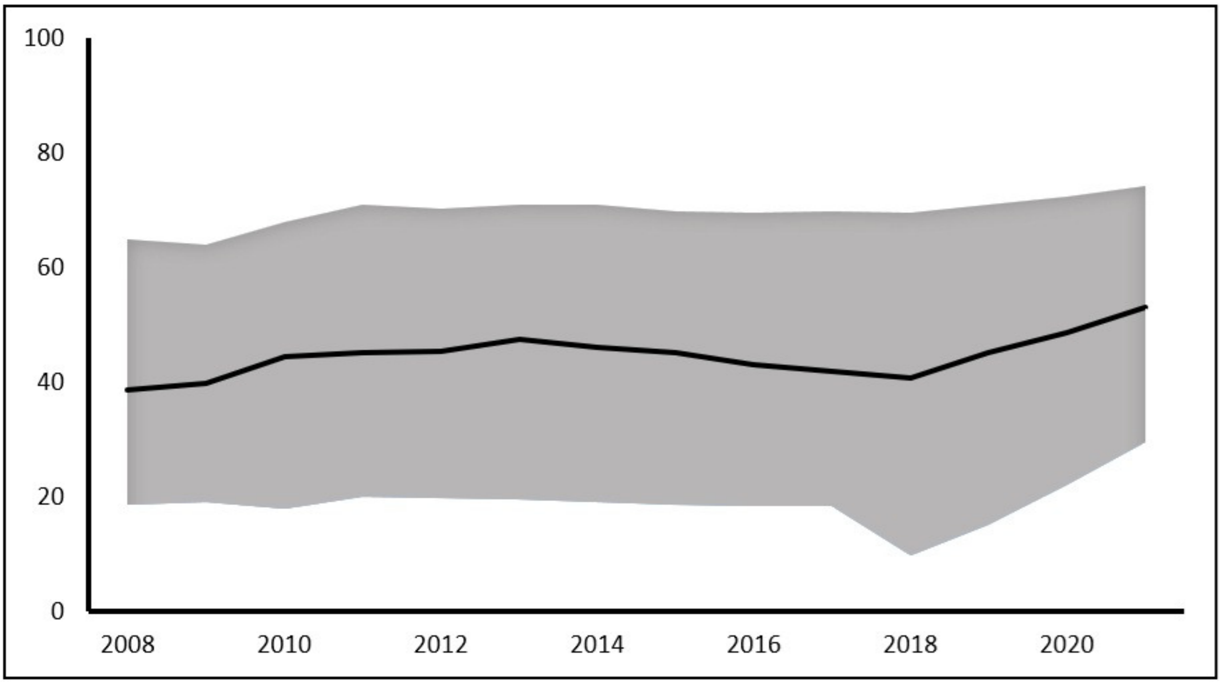

Figure 1: Median Refinitiv ENV Score

This figure plots the median ENV score for each year from 2008 to 2021, with the shaded area representing the interquartile range (25th–75th percentiles).

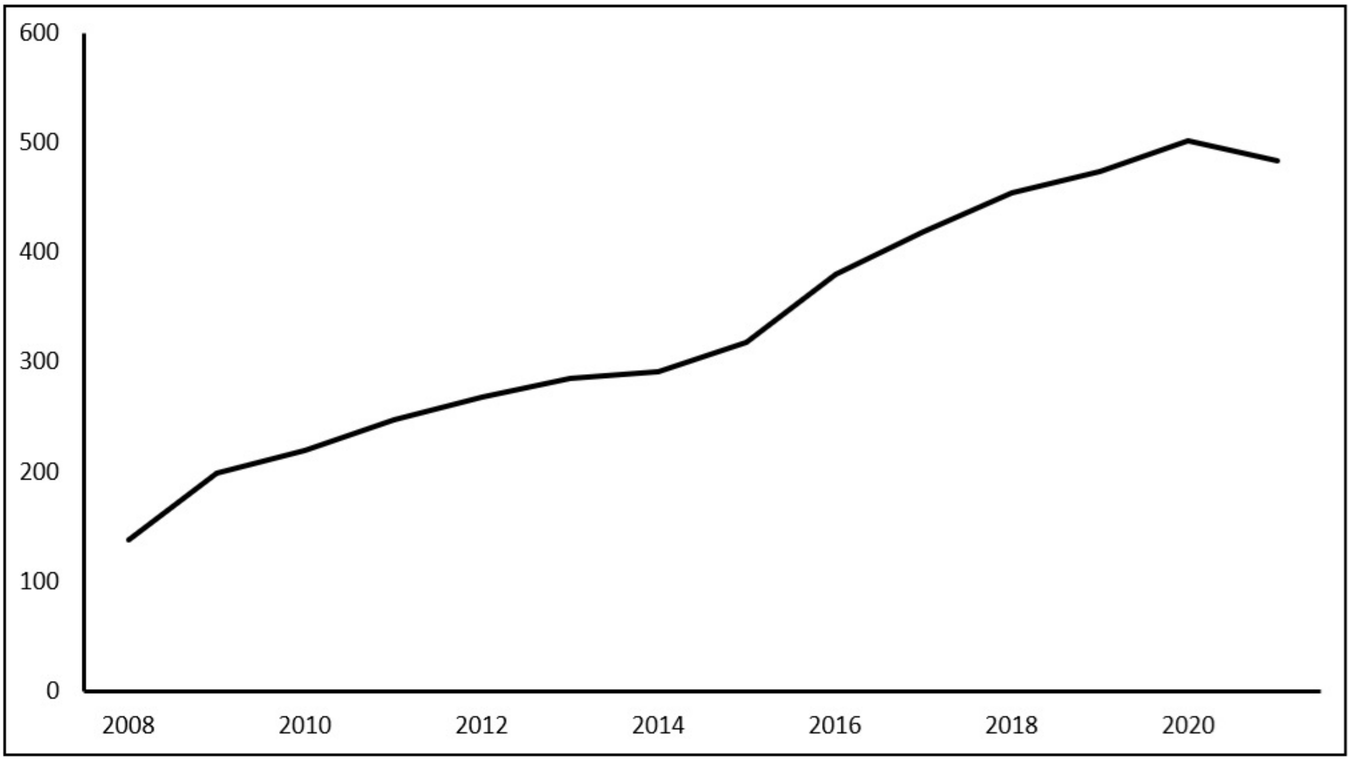

Figure 2: Number of Unique Firms

This figure plots the number of unique firms in the sample for each year from 2008 to 2021.