Funding the Fittest? Pricing Climate Transition Risk in the Corporate Bond Market*

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Abstract

We study whether climate transition risk affects the cost of debt and how corporate bond investors value green innovation. Using confidential bond holdings and global firm data, we find a positive transition risk premium. This premium is significantly lower for emission-intensive firms engaging in green innovation, suggesting investors perceive green innovations to carry option value. Institutional investors, particularly mutual funds, exhibit higher demand for bonds issued by transitioning firms. Our findings suggest that risk pricing is the channel through which environmental performance influences yield spreads, highlighting the role of risk-bearing investors to channel capital to firms central to the transition.

Keywords — Climate Transition Risk, Green Innovation, Bond Markets, Non-Bank Financial Intermediation, Institutional Investors.

JEL codes — G12, G23, Q51.

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I. Introduction

The transition to net-zero emissions involves significant uncertainties, particularly as delays in climate action increase the risk of a disorderly transition. This exposes firms, and especially those with high emissions, to regulatory, technological, and legal challenges that may affect their financial performance, creating a downside risk for investors. Forward-looking investors play a critical role in shaping the transition by adjusting their capital allocations in response, thereby affecting firm's access to and cost of external finance. While sustainable investing has gained increasing prominence since the Paris Agreement, reallocating capital toward already low-emitting firms may be counterproductive, as the marginal climate impact of investing in already green firms is limited (Hartzmark and Shue, 2023). At the same time, emission-intensive firms may play a critical role in developing and advancing green technologies (Cohen et al., 2023). This raises the question whether investors are channeling capital toward the firms most central to the green transition – those that are currently emission-intensive but actively invest in greener technologies.

This paper examines how corporate bond investors price climate transition risk and whether they recognize firm-level efforts to innovate in green technologies. We explore (i) whether corporate bond investors value green innovation in the presence of climate transition risk and (ii) which types of investors have a higher demand for bonds issued by emission-intensive yet green-innovative firms (which we refer to as "transitioning firms"). While previous research has examined the role of equity markets in stimulating green innovation more broadly (De Haas and Popov, 2023), we focus on whether corporate bond investors value green innovation in the presence of climate transition risk. Unlike equity investors, who can benefit from upside potential, bond investors are primarily concerned with downside risks that threaten a firm's ability to meet its debt obligations. Given that climate risks are fundamentally downside risks, it can have mixed effects on equity prices, whereas it yields clear predictions for bond prices (Ilhan et al., 2021; Hoepner et al., 2024). Therefore, corporate debt markets provide a key setting to understand how climate transition risk is priced and how investors respond to firms' efforts to mitigate their climate transition risk exposure. Moreover, corporate bond markets play a central role in firm financing globally (Gourio, 2013), and emission-intensive firms in particular often depend heavily on bond issuance to fund their operations (Papoutsi et al., 2022).

We document three main findings. First, we show that corporate bond investors price climate transition risk, evidenced by higher bond spreads for emission-intensive firms. We then demonstrate that this transition premium is smaller for firms investing in green technologies. We measure green innovation as the share of green patents over total patents. The lower premium for these firms suggests that investors perceive green innovation to carry option value. That is, firms investing in green technologies signal that they are technologically prepared to adapt a low-carbon economy. Second, we show that European institutional investors, in particular mutual funds, exhibit a higher demand for bonds issued by transitioning firms. We confirm that these findings are not driven by an increase in the supply of bonds by these firms. Third, we find that our results are consistent with rational risk pricing. More precisely, our effects are concentrated in firms with weak cash flow prospects and near-maturity bonds where default risk is most salient and option value matters most. Taken together, these findings highlight the importance of investors with greater risk-bearing capacity in supporting the green transition by providing lower-cost financing to firms that, while currently emission-intensive, actively invest in greener technologies.

We obtain these findings by combining confidential, security-level bond holdings data from the European Central Bank (ECB) with global firm-level data on corporate carbon emissions and (green) patents. This novel linkage allows us to identify the investors that hold each bond within our sample and to measure investor demand for specific issuers conditional on their environmental performance. This unique combination enables direct identification of how climate transition risk is priced and how it is allocated across investor types (see e.g., Acharya et al., 2024; Khwaja and Mian, 2008). Our data on bond holdings is sourced from the ECB Securities Holdings Statistics Sectoral, which provides detailed security-level information on aggregate portfolio holdings by financial and non-financial investors across all European countries for bonds issued worldwide. We obtain data on greenhouse gas emissions from Trucost and define and measure a firm's environmental performance as its firm-level emissions relative to a firm's revenue (emission intensity). This measure is particularly informative for bond investors as the financial impact of climate-related costs depends on a firm's ability to absorb those costs. While reducing future emissions is central to the green transition, conventional emissions data – which capture firms' past and present carbon emissions – provides a limited view of firms' forward-looking efforts to transition to greener technologies.[1] We therefore incorporate a measures of green innovation alongside carbon emissions in our bond pricing analysis to assess how investors value firms' efforts to transition to greener technologies. We enhance our dataset with patent-level data from Orbis Intellectual Property and identify patents classified as green patents under the Climate Change Mitigation and Adaptation category of the Cooperative Patent Classification (CPC) (Haščič and Migotto, 2015). Our dataset includes nearly 20 million patents, of which approximately 1-2 percent are green patents. To account for differences in firms' overall patenting activity, we measure green innovation as the share of green patents relative to a firm's total patents (Bolton et al., 2023; Cohen et al., 2023; Li et al., 2024).

We adopt a corporate perspective and focus on within-firm variation over time to measure the effect of changes in a firm's emission intensity and green patent ratio on its costs of debt. To this end, we control for a rich set of firm and bond characteristics, as well as firm fixed effects and industry-time fixed effects. This allows us to account for unobserved, persistent firm characteristics and industry-wide time varying shocks, thereby isolating the impact of changes in firms' environmental performance on bond pricing. Our regression analysis covers the period from 2016-Q1 to 2021-Q4. We provide evidence of a positive carbon premium that rises with a firms' emission intensity. Importantly, we find that the cost of debt is lower for emission-intensive firms that make an efforts to transition to greener technologies,

[1] For instance, Cohen et al. (2023) find that brown firms are often key innovators in green technologies. These firms tend to develop a significantly higher amount of green patents, which are also more often technologically successful.

compared to their non-green innovative peers. Quantitatively, a one standard deviation increase in the green patent ratio reduces the carbon premium by 3.7 basis points, or by approximately 15 percent.

We conduct several robustness tests to further confirm our main finding. We first consider alternative measures of green innovation. Our findings remain robust when employing a stricter classification of green patents, focusing on green technologies aimed at reducing greenhouse gas emissions in energy generation, transmission, or distribution (Acemoglu et al., 2023). The magnitude of the effect becomes significantly stronger when we restrict the analysis to "blockbuster" green patents. These are breakthrough innovations that are among the top five percent most cited patents within their respective technology class. Overall, we observe that the combined impact of emission intensity and green patenting becomes more pronounced as green patents are technologically more relevant, measured by their forward citations (Kogan et al., 2017). We further verify that our measure is uncorrelated with firms' environmental scores (E-Scores), and that our results are not driven by general investment, R&D expenditures, or overall patenting activity. This confirms that it is specifically green innovation that provides value to investors.

While our sample includes firms worldwide, a substantial share of European investors' holdings is concentrated in European issuers. As the Corporate Sector Purchase Programme (CSPP) of the ECB has significantly eased financing conditions in the euro area corporate debt market since June 2016, we verify that our results are not driven by the purchases of corporate sector bonds by the Eurosystem We account for bond eligibility and actual purchases made by the ECB. While bonds eligible for purchase under CSPP exhibited lower yield spreads in general, we show that it did not disproportionately lower the cost of debt for emission-intensive companies that also innovate in the green space. Additionally, and in the light of some evidence that banks are reducing lending to emission-intensive firms due to climate risks (e.g., Ivanov et al., 2024; Degryse et al., 2023), we also ensure that our results are not driven by a disproportionate expansion in bond supply of these transitioning firms.

We examine whether the joint effect of a firm's emission intensity and green innovation on bond yield spreads is driven by a differential impact of environmental performance through conventional bond characteristics, such as credit risk, liquidity, and maturity. While we do not find such a differential effect when interacting our measures of environmental performance with credit ratings, we show that the pricing effects are concentrated among firms with weaker cash flow prospects. This supports a default risk channel, whereby investors price climate transition risk more strongly when firms are financially fragile (Seltzer et al., 2022; Carbone et al., 2021), while green innovation alleviates this vulnerability. Moreover, we find that the results are stronger for near-maturity bonds. Conceptually, these findings align closely with the mechanism documented by Choi et al. (2019), who show that flow-motivated investors are reluctant to roll over bonds of firms with weak cash flow prospects, and respond more strongly to cash-flow news when bonds are closer to maturity.

We investigate which European investors are inclined to incorporate climate transition risk into their investment decisions. That is, we explore which investor types are more likely to demand bonds issued by emission-intensive firms that engage in green innovation. To elicit investor demand, we follow the methodology of Khwaja and Mian (2008) and Acharya et al. (2024), which allows us to explicitly control for bond supply. More precisely, we compare the demand of different investor types for bonds issued by firms with a similar exposure to climate transition risk, while controlling for potential differential portfolio choices of investors types over time and for all other potential time-varying firm characteristics (including bond supply) that might interact with the portfolio choice. Our results demonstrate that European institutional investors, and mutual funds in particular, exhibit a higher demand for bonds issued by transitioning firms.[2] This suggests that mutual funds are more willing to finance emission-intensive firms that are actively investing in green technologies.[3]

Given the substantial increase in flows to European sustainable funds during our sample period, these findings raise the question whether the demand from mutual funds primarily reflects a green preference of those funds, or whether it is consistent with risk-based pricing. To evaluate the role of exposure to climate risk more specifically, we construct a market-based measure of a firm's climate risk exposure. We estimate a firm's exposure to aggregate climate risk and examine whether the effect of environmental performance on bond yield spreads is more pronounced for firms with a higher climate risk exposure. We use innovations in the Climate Change News Index, developed by Engle et al. (2020), as a proxy for aggregate climate risk. This index measures the unexpected component of climate change-related news intensity in newspapers, allowing us to capture exogenous changes in climate-related concerns. We introduce stock-level data to obtain worldwide firm-level stock returns from the ECB Centralised Securities Database (CSDB). We estimate each firm's stock return sensitivity to aggregate climate risk, which we refer to as the firm's "Climate Beta". Our findings indicate that the carbon premium is higher for firms that have a higher exposure to aggregate climate risk, as measured by their Climate Beta. At the same time, the reduction in the carbon premium due to green innovation is higher for firms with a higher exposure to climate risks. Intuitively, this means that investors place greater value on efforts to transition to greener technologies made by firms that are more vulnerable to climate risk.

Finally, we explore why investors value green innovation efforts undertaken by emission-intensive firms. While we do not find any evidence that green innovation reduces corporate carbon emissions over a one, two or three year horizon – which is qualitatively in line with the findings of (Bolton et al., 2023) –, the ownership of green patents may signal a firm's technological capabilities, indicating that firms possess technologies relevant to the green transition (Hege et al., 2024). We show that this conveys positive option value to corporate bond investors, as green technologies enhance the firm's resilience and readiness for the green transition, thereby reducing its perceived downside risk. To test the option-value hypothesis, we exploit the carbon policy surprises from Känzig (2023), which measures unexpected euro changes in the EU ETS carbon price. This series captures new information that directly alters firms' expected

[2] Given that many foreign investors access European markets via mutual funds domiciled in Luxembourg and Ireland (Beck et al., 2024), we examine whether the effect differs across mutual fund locations. We shows that the effect holds for all European mutual funds, irrespective of whether they are located in these "off-shore financial centers" or elsewhere.

[3] We assess whether the holdings of European investors influence the extent to which environmental performance is reflected in bond yield spreads (Crosignani et al., 2020). Consistent with our demand estimation, our findings show that the yield spread reduction associated with green innovation is more pronounced if European institutional investors, and particularly mutual funds, hold a larger share of the bond.

regulatory costs, allowing us to identify the value investors assign to technological preparedness for future climate policy changes.

Focusing on firms domiciled in Europe that fall under the EU ETS, we find that the carbon premium is higher when carbon policy surprises are larger. This is intuitive, as larger carbon policy surprises imply larger environmental compliance costs, thus translating in higher bond yield spreads. Consistent with the option-value hypothesis, we further show that investors reward green innovation more strongly following unexpected policy changes. This suggests that investors price green innovation not as a guarantee of lower future emissions, but as a signal of reduced technological uncertainty for emission-intensive firms in the process of transitioning to greener technologies.

A. *Related literature*

This paper relates to two broad strands of literature. First, our paper contributes to the literature on the pricing of climate transition risk in financial markets. This literature has focused predominately on stock markets (e.g., Bolton and Kacperczyk, 2021; Pástor et al., 2021; Hsu et al., 2023; Pástor et al., 2022; Ardia et al., 2023; Bauer et al., 2022; Aswani et al., 2024; Zhang, 2025; Boermans and Galema, 2025; Eskildsen et al., 2024) and bank lending (e.g., Delis et al., 2024; Kacperczyk and Peydró, 2022; D'Arcangelo et al., 2023; Altavilla et al., 2023; Ivanov et al., 2024; Giannetti et al., 2023; Sastry et al., 2024). Bolton and Kacperczyk (2021) find evidence of a positive carbon premium in the cross-section of U.S. stock returns and Bolton and Kacperczyk (2023) show that this premium is observed in global stock markets. Hsu et al. (2023) consider the asset pricing implications of industrial pollutants, rather than just CO_2-related emissions, and show that environmental policy uncertainty affects the pricing of cross-sectional stocks returns. Aswani et al. (2024) and Zhang (2025) suggest that the association between corporate emissions and stock returns disappears when using emission intensity rather than unscaled emission levels. Boermans and Galema (2025) confirm this result for European stock, but find a carbon premium for non-European stocks. Pástor et al. (2022) and Ardia et al. (2023) empirically test whether green firms outperform brown firms when concerns about climate change increase unexpectedly (Pástor et al., 2021). Bauer et al. (2022) find more generally and for a range of methodologies that green stocks provide higher returns than brown stocks for much of the past decade. Eskildsen et al. (2024) conduct a replication study and propose a new measure of environmental performance, combining information on firms' emission intensities and their Environmental, Social and Governance (ESG) scores. They find evidence of a small, yet significant carbon premium, which is higher in greener countries and rises over time. Li et al. (2024) further develop a text-based measure of transition risk and show that firms facing high transition risk have been valued at a discount in recent years.

Using syndicated loan data, Delis et al. (2024), and D'Arcangelo et al. (2023) show that that the cost of debt is higher for brown firms, especially in countries where climate- policy risk is high. Ivanov et al. (2024) show that high emission firms face shorter loan maturities, lower access to permanent forms of bank financing, and higher interest rates. Also Kacperczyk and Peydró (2022) find that high emission firms receive less credit from banks committed to sustainable lending practices. Using administrative credit registry data from Europe, Altavilla et al. (2023) provide evidence that loan spreads are higher for emission-intensive firms, and lower for those that set emission reduction targets. This effect is particularly driven by banks that publicly commit to environmentally responsible lending practices. However, Sastry et al. (2024) highlight the limits of voluntary commitments for decarbonization, finding that net zero banks neither reduce credit supply to sectors targeted for decarbonization, nor reduce financed emissions through engagement. Also Giannetti et al. (2023) show that banks that emphasize climate change in their disclosures do not adhere to more environmentally friendly lending practices, as these banks continue their relationships with existing brown borrowers, especially with those that exhibit financial underperformance.

Some research has also been conducted on the pricing of climate transition risk in the corporate bond market (e.g., Duan et al., 2023; Seltzer et al., 2022; Fabisik et al., 2023; Broeders et al., 2025).[4] Duan et al. (2023), who focus on bonds issued by U.S. companies and traded on the U.S. public market, find that bonds of carbon-intensive firms earn significantly lower returns due to investor underreaction to the predictability of emission intensity for firm's financial performance. In contrast, and exploiting the Paris Agreement as a shock to climate regulation, Seltzer et al. (2022) provide evidence that climate regulatory risks affect yield spreads and ratings of bonds issued by U.S. companies. Broeders et al. (2025) also find evidence of a carbon premium for bonds issued by high emission firms in the euro area. Finally, Fabisik et al. (2023) study the effect of changes in firms' ESG ratings on the cost of debt of U.S. firms, showing that downgraded ESG-rated firms face higher loan spreads in the secondary corporate loan market.

We make two contributions to this literature. First, we consider the forward-looking efforts firms undertake to transition to greener technologies in our bond pricing analysis, linking this explicitly to firms' current environmental footprints. We show that the "carbon premium" is smaller for emission-intensive companies that engage in green innovation, indicating that investors value firm's efforts to transition to greener technologies. Second, our detailed bond holdings data allows us to identify investor demand for bonds of firms based on their environmental profiles, while controlling for bond supply.[5] We show that institutional investors, and among those, mutual funds, exhibit a higher demand for bonds issued by transitioning firms, and that this demand is consistent with rational risk pricing rather than green preferences.

Our paper also relates to the literature on green innovation and financial performance.[6] Hege et al. (2024), Leippold and Yu (2023) and Battiston et al. (2023) focus on the association between green innovation and stock returns. Hege et al. (2024) show that equity markets respond positively to the

[4]While we focus on the corporate bond market as a whole and do not focus on corporate green bonds exclusively, our paper somewhat relates to studies in this literature (e.g., ElBannan and Löffler, 2024; Flammer, 2021; Zerbib, 2019; Baker et al., 2022).

[5]Seltzer et al. (2022) show that, after the Paris Agreement, mutual funds increased their ownership share of bonds issued by emission-intensive firms. Our bond-level approach focuses on investor demand, controlling for potential differential portfolio choices of investors in different holder areas and sectors over time and for all other potential time-varying firm characteristics that might interact with the portfolio choice (Acharya et al., 2024). We further show that mutual funds hold more bonds of transitioning firms, i.e., those emission-intensive firms that actively engage in green innovation.

[6]Our paper relates to the literature on the real effect of climate risk pricing and the effects of green innovation on corporate environmental performance (see e.g., Bolton et al., 2023; Dugoua and Gerarden, 2025; Hartzmark and Shue, 2023; Leippold and Yu, 2023).

granting of climate patents, with firms experiencing higher stock returns, lower costs of capital, and increased holdings by environmentally-focused investors. Leippold and Yu (2023) develop a text-based green innovation using earnings-call reports and show that firms actively discuss their green innovation efforts during these calls. They show that stocks of firms with higher green innovation exhibit lower expected returns. Battiston et al. (2023) find that the adoption of sustainable technologies is associated with better future financial and operating performance in the long run. Our paper also relates to De Haas and Popov (2023) and Accetturo et al. (2024), who examine how the structure of financial markets and supply of external financing shape the green transition. De Haas and Popov (2023) show that in countries where stock markets are more developed relative to bank lending, emission-intensive sectors engage more in green innovation. Accetturo et al. (2024) document a large positive elasticity of green investments to credit supply. Our paper contributes to this literature by focusing on corporate bond markets, the primary source of external financing for many emission-intensive firms, and by showing that debt investors recognize the option value that green innovation provides, specifically when it is undertaken by emission-intensive firms. This also speaks to the debate in Hartzmark and Shue (2023), who show that allocating capital away from brown firms and toward green firms may be counterproductive as it makes brown firms more brown without making green firms more green. Our results suggest that rather than reallocating capital away from brown firms, investors with risk-bearing capacity target financing to transitioning firms and can thereby support the transition to a low carbon economy.

II. Data

We construct a comprehensive dataset by compiling data from various sources. Our sample covers the period from 2016-Q1 up until 2021-Q4. The data is reported at quarterly frequency at the security-by-security level for bonds issued worldwide. We use confidential data on security-level portfolio holdings from the ECB Securities Holdings Statistics Sectoral (SHS-S, hereafter referred to as SHS). This data is complemented with the ECB Centralised Securities Database (CSDB), which provides various issuer- and bond characteristics at the security level. We use Trucost Environmental for data on corporate carbon emissions and collect (green) patent information from Orbis Intellectual Property (IP). Corporate fundamentals and bond characteristics are obtained from Refinitiv. Table 1 provides summary statistics.[7]

A. Security-level portfolio holdings

The Securities Holdings Statistics provides detailed information on aggregate security-level portfolio holdings by financial and non-financial holders from all 20 euro area countries, as well as six other European Union countries not part of the euro area. SHS is operated by the European System of Central

[7]The European firms in our sample are significantly larger than most European firms. We verify that other firm characteristics, such as leverage, cash-ratio and the profitability ratio, are comparable to those of the segment of (very) large European firms in Amadeus. The European firms in our sample account for 1-1.5 billion ton of CO_2 emissions annually, which constitutes approximately 60 percent of the overall emissions in the European Union as reported by Trucost over our sample period.

Table 1: Summary statistics

This table provides summary statistics for our sample, based on 38,954 observations reported at quarterly frequency and the security-by-security level. Emission intensity is defined as scope 1 and scope 2 CO2 emissions relative to the firm's revenue and is measured in CO2e/USDm. Emission intensity is scaled by a factor 1/100 and winsorized at the 2.5 percent level. Absolute emissions is defined as scope 1 and 2 emissions, which is measured in CO2e and is reported in natural logarithms. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total and is scaled by a factor 100. Yield to maturity is winsorized at the 99th percentile. Fixed coupon is a dummy which is equal to 1 if a bond has a fixed coupon. EUR respectively USD are dummy variables, which are equal to 1 if a bond is denominated in euros respectively dollars. Green bond is a dummy which is equal to 1 if a bond has a green bond label. The profitability-ratio is defined as net income dividend by total assets (ROA). Leverage is defined as total debt divided by total assets. The cash- and investment ratio are defined as cash and capital expenditures divided by total assets, respectively. All ratio's are reported in percentages.

	Mean	Median	SD	P10	P90
Environmental Variables					
Emission Intensity	2.792	0.494	4.914	0.117	8.958
Absolute Emissions (in log)	14.669	14.236	2.106	12.242	17.431
Green Patent Ratio (%)	0.736	0.098	2.131	0.007	1.676
Bond Characteristics					
Yield to Maturity (%)	2.119	1.785	2.255	-0.007	4.373
Spread (%)	1.558	1.044	2.002	0.315	3.249
Bond Holding Value (in m EUR)	202.093	55.801	304.004	2.957	631.012
Amount Outstanding (in m EUR)	658.135	500	539.540	107.004	1293.103
Fixed Coupon	0.901	1	0.299	1	1
EUR	0.348	0	0.476	0	1
USD	0.503	1	0.500	0	1
Green Bond	0.013	0	0.112	0	0
Corporate Fundamentals					
Revenue (in bn EUR)	57.260	29.117	83.832	4.903	148
Total Assets (in bn EUR)	91.135	53.262	93.703	8.806	277
Total Debt (in bn EUR)	28.910	16.601	32.022	2.377	67.456
Profitability-Ratio (%)	5.031	4.039	5.828	-0.284	11.953
Leverage-Ratio (%)	32.440	30.629	12.946	17.942	50.675
Cash-Ratio (%)	5.503	3.325	8.162	0.323	9.557
Investment-Ratio (%)	12.522	7.400	14.529	1.160	33.469

Banks (ESCB) and data is reported directly to national central banks and shared with the ECB. The data is reported quarterly at the security-by-security level for bonds issued globally. In each period, we observe the bond holdings value held by a specific holder, which is identified at the country-sector level for each period. Investors are classified into 8 distinct investor sectors. Specifically, we observe the bond holdings of banks, insurance companies, pension funds, mutual funds (including money market funds and other investment funds), other financial institutions (including securitizations vehicles), non-financial corporations, governments and households (including non-profit institutions serving households). The SHS data thus allows us to observe how much of each unique security each investor sector in a given European country holds. The magnitude of holdings (as measured by total bond holdings at market value) within our sample encompasses 1 trillion euro in 2016-Q1 and rises to 1.46 trillion euro (in 2021-Q4), which covers approximately 58 percent of all security holdings reported by euro area investors for stock-listed, non-financial corporate issuers worldwide.[8]

The CSDB complements the European holdings data with various issuer - and bond characteristics at the security level. The CSDB provides data on the issuer name and the country of issuance. It provides us with a time series of the yield to maturity and the amount of the debt that is outstanding in a given quarter for a given bond. The yield to maturity is reported at the end of the quarter and winsorized at the 99th percentile.[9] Since we are interested in estimating risk premia, we determine the return in excess of the risk-free rate by subtracting the maturity-matched eurozone central government bond par yield curve spot rate from the yield to maturity.[10,11] We also source end-of-quarter data on bond credit ratings from the CSDB as reported to the ECB by ratings agencies Fitch, Moody's, and S&P.[12] We further obtain information on other bond specific characteristics, such as the coupon rate, the currency in which the bond is denominated, and the residual maturity of the bonds.[13] Moreover, the CSDB contains information on the sustainability labels of bonds, including green bond certifications. Within our sample of 3,349 bonds, only 2.2 percent carry a green bond label.[14]

B. *Corporate environmental performance*

We collect information on corporate carbon emissions from Trucost Environmental, which provides firm-level data on carbon and other greenhouse gas emissions annually. Trucost's global coverage significantly expands after 2016, coinciding with the Paris Agreement, which raised climate change awareness and emphasized the importance of measuring and reporting environmental data (Bolton and Kacperczyk, 2021). As the data is published with a considerable publication lag, our analysis focuses on the period from 2016-Q1 until 2021-Q4. Trucost provides data on absolute carbon emissions (measured in tons of CO_2e) and emission intensities - a company's emissions relative to its revenue - measured in tons of CO_2 emissions per million dollars of revenue (CO_2e/USDm). A distinction is made between three sources of emissions. Scope 1 emissions cover emissions from the use of fossil fuels in the companies' production (direct emissions). Scope 2 emissions cover indirect emissions, which stem from the purchase

[8]In line with the SHS practitioner's guide of Boermans (2025), short-positions, non-active securities, and investments in tax havens are excluded. Small positions, highly implausible prices, and debt types as warrants and equity like debt are excluded as well.

[9]Since bonds are frequently observed for multiple periods, we assess the time series properties of bond yields by estimating an autoregressive model in Appendix A, which confirms that bond yields are stationary. We also plot the evolution of the mean and median bond yields over time in Figure A1 in Appendix A.

[10]We verify the robustness of our main results when matching based on bond duration in Table D1 in Appendix D (van Binsbergen et al., 2025).

[11]The percentage of bonds within our sample which are denominated in euros is 34.8 percent. Since a large amount of bonds within our sample is denominated in US dollars (50.3 percent), we use Treasury Rates when determining the spread for US dollar-denominated bonds. Bonds denominated in other currencies are benchmarked against the euro area rates.

[12]Rating data is only available for 16,997 observations, which constitutes 43 percent of our main sample. Bond credit ratings range from 1 to 22. A bond rating of 1 corresponds to an AAA-rating, while a bond rating of 22 corresponds to a D-rating. Within our main sample, the average credit rating is 7.350 (standard deviation of 2.530), which corresponds to an upper medium-grade (A-) bond. We take the average of ratings across the three rating providers and group credit ratings into 7 rating classes, where bonds with an AAA rating fall in category 1 and bonds with a C/D rating fall in category 6.

[13]To take into account a bond's residual maturity in our analysis, we construct a dummy variable which indicates whether the residual maturity of the bond is longer than 10 years. Within our sample, the average maturity of a bond is approximately 9.2 years.

[14]The summary statistics report a lower share of green bonds (1.3 percent) as they are calculated at the security–time level, whereas the 2.2 percent figure refers to the share of unique bonds within our sample.

and consumption of heat, steam and electricity by a company. Scope 3 emissions cover indirect emissions, which are the result of activities from assets not owned or controlled by the company, but that arise along its value chain. These emissions are more challenging to measure and are less frequently reported, often requiring estimates from data providers. Due to the lack of methodological clarity in estimating Scope 3 emissions, the data are often noisy and inconsistent compared to Scope 1 and 2 emissions (Klaaßen and Stoll, 2021). Therefore, we exclude Scope 3 emissions from our analysis.

We construct a measure of a company's environmental performance by jointly considering Scope 1 and Scope 2 emissions. Firms with higher emissions are subject to greater regulatory and operational costs as they adjust to stricter environmental policies. While absolute emissions are important for assessing a firm's total environmental impact, emission intensity, which measures these costs relative to a company's revenue, may be more informative for bond investors. This is because the financial impact of climate-related costs depends on a firm's financial ability to absorb those costs. A firm with high absolute emissions but strong revenue generation may be better positioned to absorb climate-related costs than a firm with lower emissions but also less output. We therefore measure the emissions of a company (denoted by f) relative to its revenue in the same period (denoted by t):[15]

$$\text{Emission Intensity}_{f,t} = \frac{\text{Scope } 1_{f,t} + \text{Scope } 2_{f,t}}{Revenue_{f,t}}$$

where emission intensity is reported in tons of CO_2e/USDm. We scale 'Emission Intensity' by a factor 1/100 for exposition, and winsorize it at the 2.5 percent level to reduce the impact of outliers (Bolton and Kacperczyk, 2021).[16] We plot the evolution of mean (median) emission intensity at the firm-year level in Figure A2 in Appendix A, which shows that, on average, emission intensity falls by 5 percent annually over our sample period.[17] In our analysis, we also explore whether this decline is partly explained by green innovation of emission-intensive firms.

C. (Green) patent information

To measure green innovation, we rely on patent data, a well-established proxy for innovation (e.g., Nagaoka et al., 2010). Patents provide a direct and observable measure of directed technological progress, capturing both the scale and, unlike R&D data, the nature of innovation. Investors can also observe firms' green innovation activities through patent disclosures and related announcements. For example, Kogan et al. (2017) show that investors extract information about firms' innovative activities from public filings and statements, while Leippold and Yu (2023) develop a text-based measure of green innovation from earnings-call transcripts and show that firms actively discuss such efforts. This enables corporate bond

[15]We verify the robustness of our main results by considering absolute emissions instead of emission intensity in Table D8 in Appendix D.

[16]Our measure is similar to the ECB Climate Indicators for the financial sector's carbon intensity and the financed emissions when measuring carbon emissions in absolute terms, (see European Central Bank, 2024) and used in others studies (e.g., Boermans and Galema, 2025; Aswani et al., 2024; Andersson et al., 2016).

[17]We also assess the time series properties of our emission intensity variable (see Appendix A). Our estimates show considerable persistence. Once controlling for time- and firm specific effects, however, there is no evidence of a unit root.

Table 2: Patent filings over the sample period

This table reports the number of patent filed over our sample period. Patents^{all} represents the number of patents filed by all companies in our sample. Patents^{green} refers to the number of patents (green, brown, and other) filed by companies which have at least one green patent. Green patents indicates the number of green patents filed by companies within our sample

Variable	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Patents^{all}	641,047	650,080	648,820	627,067	565,062	476,300
Patents^{green}	558,027	568,524	567,110	548,989	494,080	416,317
Green Patents	7,661	8,235	8,695	8,714	6,717	9,804

investors to assess whether emission-intensive firms are making progress toward greener technologies.

We obtain data on (green) patents from Orbis IP, which provides comprehensive patent information for public and private companies filed with various patent offices globally, including the European Patent Office (EPO), the US Patent Office (USPTO), and the Japanese Patent Office (JPO). We match the security identifiers in our primary sample with their corresponding identifiers in Orbis (Bureau Van Dijk-ID numbers) to track all patent filings registered by a given company within our sample. We identify a total of 19.4 million patent filings associated with 1,240 unique companies, which is approximately 84 percent of all firms on which we obtain information in SHS, Trucost and Refinitiv.[18] We obtain information on the patent publication number, the priority - and application date, the identity of the current owners, the description of the patent, the classification according to its CPC-code, and the forward citations of each patent. Patents are assigned to each of their respective owners, and we use the priority date, which is the first filing date of a patent application, to assign each patent to the appropriate year.[19]

Since we are interested in green innovation, we utilize Cooperative Patent Classification (CPC) codes to identify companies' green patents. We follow Haščič and Migotto (2015) and consider patents in the class on Climate Change Mitigation and Adaptation (with CPC-code Y02) as green patents.[20] This process results in about 240,000 green patent filings by 400 unique companies. Hence, green patents represent 1.2 percent of the total number of patent filings within our dataset and, among the companies in our sample engaged in patenting, 32 percent also file green patents. However, these companies are collectively responsible for 90 percent of all patent filings, amounting to 17.5 million patent filings out of

[18]Following Hémous et al. (2025), we include applications and not-granted patents. Certain patent offices may only formally grant a patent if the applicant requests an examination of the invention. However, this may only be requested once their legal rights are challenged.

[19]The priority date is used to determine the novelty of the invention and is crucial for patent procedures, since it marks the date from which legal rights associated with the patent can be claimed. For statistical purposes, the priority date is considered the closest approximation to the date of invention (Haščič and Migotto, 2015). If the priority date is not available, we substitute it with the application date. Generally, we verify that our main results are qualitatively and quantitatively similar when using the application date (rather than the priority date) to assign the invention to a given year.

[20]The Y02 consists of 8 subclasses, i.e., technologies for adaptation to climate change (Y02A); climate change mitigation technologies related to buildings (Y02B); capture, storage, sequestration or disposal of greenhouse gases (Y02C); climate change mitigation technologies in ICT (Y02D); reduction of greenhouse gasses related to energy generation, transmission or distribution (Y02E); climate change mitigation technologies in the production or processing of goods (Y02P); climate change mitigation technologies related to transportation (Y02T); climate change mitigation technologies related to wastewater treatment or waste management (Y02W). We first consider all patents within the Y02 class as green patents, and verify the robustness of our results against adopting a stricter classification of green patents. Within the stricter classification, we only consider patents in the Y02E10 (renewable electricity), Y02E30 (nuclear energy) or Y02E50 (biofuels and fuel from waste) subclass as green patents.

Table 3: Distribution of observations across sectors

The table shows the distribution of observations across GIC sectors. Observations are reported at the quarterly frequency and firm-level. We also report the mean of emission intensity, the green patent ratio (%) and the number of green patents held by each sector.

GIC Sector	Observations	Emission Intensity	Green Patent Ratio	#Green Patents
Basic Materials	905	7.036	1.078	42.446
Consumer Cyclicals	610	0.638	1.142	2,443.757
Consumer Non-Cyclicals	438	1.574	1.010	349.393
Energy	444	4.684	2.727	49.782
Healthcare	483	0.324	0.182	91.166
Industrials	1,060	0.983	1.226	214.147
Real Estate	55	0.912	0.371	3.182
Technology	960	0.468	0.462	886.841
Utilities	557	10.948	4.586	257.576
Total	5,513	3.143	1.403	538.786

the total 19.4 million filings. This suggests a strong correlation between patenting and green patenting in general. We therefore construct a relative measure of green innovation, the green patent ratio, which measures the number of patents related to green technologies relative to the total number of patents held by a specific company (Bolton et al., 2023; Cohen et al., 2023; Li et al., 2024):

$$\text{Green Patent Ratio}_{f,t} = \frac{\#\text{Green Patents}_{f,t}}{\#\text{Patents}_{f,t}}$$

We scale the green patent ratio by a factor 100 for exposition. We focus on companies that have at least one green patent in our main sample.[21] The ultimate sample consists of 3,349 unique bonds, issued by 361 unique companies from 38 countries worldwide, which gives us 38,954 observations. We compare the summary statistics of firms with green patents (as reported in Table 1) to those of firms with any patent.[22] Compared to firms that have filed any patent, firms that patent in green technologies (and which patent relatively more in general) tend to be larger in terms of their revenue and assets.

D. Corporate Fundamentals

We collect information on corporate fundamentals via Refinitiv, which is also available at quarterly frequency.[23] We also obtain information on firm's sector - and industry classification based on the Global Industry Classification Standard (GICS) and exclude all financial corporations from our analysis. Table 3 summarizes the mean emission intensity, mean green patent ratio and mean amount of green patents across sectors. A more detailed classification based on GIC Industries is provided in Appendix B, with 49 distinct industries. There is large variation in the green patent ratio across sectors. The green patent

[21] We verify the robustness of our main findings in a sample which includes all companies for which patent information is available, effectively taking into account the extensive margin by incorporating firms with a green patent ratio of zero. The results are shown in Table D7 in Appendix D.

[22] This sample consists of 8,255 unique bonds, issued by 1,175 unique firms from 52 countries worldwide, resulting in 90,807 observations. The summary statistics for this sample are reported in Table D6 in Appendix D.

[23] There are a few firms for which data is missing in a given quarter, which we fill with the most recent firm-observation.

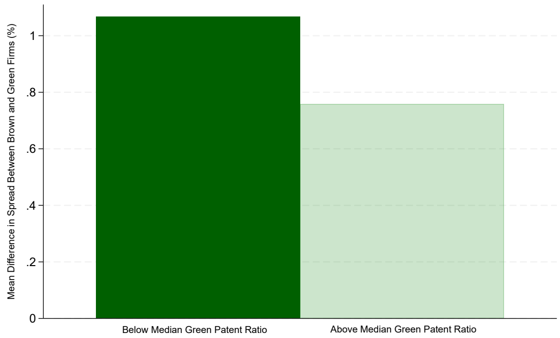

Figure 1: Descriptive evidence

This figure shows the mean difference in observed bond yield spreads (in percentage points) between bonds issued by high- and low-emission-intensive firms. The mean difference is reported separately for firms with a below-median green patent ratio (left bar) and those with an above-median green patent ratio (right bar).

ratio is highest in the utilities sector, which also has the highest emission intensity on average. Table 3 also shows the importance of considering the ratio of green patents to the overall number of patent filings. For example, the utilities sector has the highest green patent ratio, but the number of green patents is relatively moderate compared to other sectors. We also provide an overview of the issuer-countries within our sample in Appendix B. Approximately 23.2 percent of the distinct firms in our sample are established in the United States, and 35.5 percent in the European Union.

III. Empirical Analysis

As a primer to our analysis, Figure 1 provides descriptive evidence on how bond market investors price firms' environmental performance. Specifically, the figure plots the difference in average bond yield spreads (in the raw data) between firms in the top ("brown firms") and bottom ("green firms") quintiles of the emission intensity distribution. Within the emission intensity quintiles, we further distinguish firms based on whether they have a high (i.e., above-median) or low (i.e., below-median) green patent ratio. The left bar in Figure 1 shows the spread differential between brown and green firms with low green innovation, and the right bar shows the spread differential between brown and green firms with high green innovation. Figure 1 suggests that there is a carbon premium, that is, the yield spread differential between brown and green firms is positive. The figure also suggests that the carbon premium is substantially smaller for firms with higher levels of green innovation. Therefore, investors may be more willing to finance emission-intensive firms which undertake efforts to transition to greener technologies, reflecting the potential role of green innovation in mitigating the costs of climate transition risks.

To formally assess whether the cost of debt is lower for emission-intensive firms that transition towards greener technologies, we next examine this relationship in a regression framework. The key element in the regression model is that we interact emission intensity with the firm's green patent ratio.

A. *Emission intensity, green innovation and to cost of debt*

We observe each bond i, issued by a company f, in industry g, held by holder j (located in holder-country c and sector s) in year-quarter t. We estimate the following regression for the bond yield spread, measured in percentage points, at the bond-period level:

$$\begin{aligned}\text{Spread}_{i,t} = {} & \beta_1 \text{Emission Intensity}_{f,t-1} + \beta_2 \text{Green Patent Ratio}_{f,t-1} + \beta_3 \text{Emission Intensity}_{f,t-1} \\ & \cdot \text{Green Patent Ratio}_{f,t-1} + \delta' X_{f,t-1} + \gamma' Z_{i,t-1} + FE + \varepsilon_{i,t} \qquad (1)\end{aligned}$$

where

$$FE = \begin{cases} \eta_f + \alpha_t & \text{(i)} \\ \eta_f + \mu_{g,t} & \text{(ii)} \end{cases}$$

and where we take the lagged value of emission intensity (Zhang, 2025), the green patent ratio and the interaction of the two. The vector of one-period lagged corporate (f) fundamentals ($X_{f,t-1}$) includes the (i) profitability ratio, defined as net income over total assets; (ii) leverage ratio, defined as total debt over total assets; (iii) cash-ratio, defined as cash over total assets; and (vi) investment ratio, defined as capital expenditures over total assets. We also include a vector of lagged bond (i) characteristics, $Z_{i,t-1}$, which includes the outstanding amount (in logarithms), a dummy which indicates if the bond has a fixed coupon, a dummy which indicates whether the bond is denominated in euro and a dummy which indicates whether the bond has a green bond label. We further verify the robustness of our main results against controlling for the bond rating, liquidity (measured by the bid-ask spread) and the bonds' maturity.[24] We estimate Equation (1) using two different sets of Fixed Effects (FE). We first use (i) firm fixed effects (η_f) and time fixed effects (α_t). This allows us to control for unobserved, persistent firm characteristics and aggregate time trends.[25] To further strengthen the identification, we estimate the relation with (ii) industry-time fixed effects ($\mu_{g,t}$) and firm fixed effects. This allows us to absorb industry-wide time varying shocks, which is crucial as 70 percent of firms operate in tradable industries (see Table B1 in Appendix B). We include analytical weights based on the total number of bonds outstanding of each firm in a given period in each specification.[26,27] We cluster standard errors at the more detailed GICS industry-level (see Table B2 in Appendix B), allowing the idiosyncratic error term $\epsilon_{i,t}$ to be correlated within industry clusters.

Table 4 presents the estimation results of Equation (1). Panel A shows the results using firm and time fixed effects, while Panel B displays the results using firm and industry-time fixed effects. The first

[24] Since we take a corporate perspective, bond factors are absent as control variables in yield spread regressions. For related approaches that analyze determinants of corporate bond spreads (see e.g., Bauer et al., 2021; Huang and Petkevich, 2016; Helwege et al., 2014; Dick-Nielsen et al., 2012).

[25] Remark that the industry dimension is nested in the firm dimension, f.

[26] Companies have on average 22.6 bonds outstanding in a given time period, and the highest number of bonds outstanding for a given company in a given period is equal to 77.

[27] The results are robust against the exclusion of sampling weights.

Table 4: Effect of Emission Intensity and Green Patenting on Yield Spreads

*This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. '$EI \times GPR$' is the interaction of emission intensity and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.128**		0.128**	0.145***	0.145***
	(0.056)		(0.056)	(0.053)	(0.053)
Green Patent Ratio$_{f,t-1}$		0.202	0.198	0.489***	0.490***
		(0.127)	(0.128)	(0.114)	(0.116)
EI$_{f,t-1}$×GPR$_{f,t-1}$				-0.023***	-0.023***
				(0.007)	(0.007)
Green Bond$_{i,t-1}$					-0.474**
					(0.188)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	39,014	39,014	39,014	39,014	39,014
R-squared	0.456	0.452	0.456	0.457	0.458

(b) Firm and Industry-Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.149*		0.148*	0.192***	0.193***
	(0.076)		(0.076)	(0.061)	(0.060)
Green Patent Ratio$_{f,t-1}$		0.126	0.112	0.565***	0.568***
		(0.110)	(0.107)	(0.108)	(0.108)
EI$_{f,t-1}$×GPR$_{f,t-1}$				-0.032***	-0.032***
				(0.007)	(0.007)
Green Bond$_{i,t-1}$					-0.471**
					(0.200)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Observations	38,954	38,954	38,954	38,954	38,954
R-squared	0.538	0.535	0.538	0.539	0.540

Column of each panel shows the baseline regression where emission intensity is the sole explanatory variable. This specification estimates the "carbon premium", i.e., the extent to which bond yield spreads rise with a firm's emission intensity. We find evidence of a positive carbon premium, indicating that the cost of debt is higher for more emission-intensive firms. We show in Appendix C that this result is broadly consistent across specifications, showing that the positive association is neither driven by time trends in yield spreads, nor unobserved firm heterogeneity, nor by industry-specific shocks that may influence the relationship between bond yield spreads and firm's emission intensity. In our most stringent specification with firm fixed effects and industry-time fixed effects, a one standard deviation increase in emission intensity raises bond yield spreads by 24.5 basis points.[28] This estimate, which is qualitatively and quantitatively in line with the findings of Eskildsen et al. (2024), highlights a statistically significant and economically meaningful carbon premium.

Green patents provide a signal of the technological effort firm's are undertaking to transition to cleaner technologies and investors can also observe firms' green innovation activities through patent disclosures and related announcements.[29] This enables corporate bond investors to assess whether emission-intensive firms are making progress toward greener technologies, which motivates our use of the green patent ratio as a measure of green innovation (Li et al., 2024; Bolton et al., 2023; Cohen et al., 2023). Column 2 of Table 4 includes the green patent ratio as an explanatory variable, while Column 3 adds both emission intensity and the green patent ratio. In neither case is the green patent ratio individually significant. This hints towards the interpretation that the interaction term with emission intensity, as introduced in Column 4, is the key driver of our descriptive findings. The results in Column 4 confirm this, displaying a statistically significant and negative interaction effect of the green patent ratio and emission intensity (labeled '$EI \times GPR$'). Quantitatively, a one-standard deviation increase in the green patent ratio reduces bond yield spreads by 3.7 basis points for a company with a mean emission intensity. This constitutes a reduction in the carbon premium of approximately 15 percent, indicating that the cost of debt is lower for emission-intensive companies that make an effort to transition to greener technologies.[30] The coefficient on the green patent ratio becomes statistically significant and positive once the interaction term is included. This level effect reflects the impact of green patenting for a firm with zero emissions. Thus, this indicates that among already-green firms, additional green patents do not lower the cost of debt and may instead increase it, potentially reflecting higher costs associated with undertaking innovation activities. What investors value is green innovation where it mitigates risk, that is, for emission-intensive firms – as captured by the interaction term.

We further examine the dynamic evolution of the interaction between emission intensity and the green patent ratio over time, by allowing the coefficient of the interaction term to vary by year. Figure D1 in Appendix D plots these coefficients, along with the 90 percent confidence interval, using 2016 as reference

[28] This estimate is based on within-firm variation, which is 25.7 percent of the overall variation.

[29] For example, Kogan et al. (2017) show that investors extract information about firms' innovative activities from public filings and statements, while Leippold and Yu (2023) develop a text-based measure of green innovation from earnings-call transcripts and show that firms actively discuss such efforts.

[30] This estimate again exploits the within-firm variation, which is 19.6 percent of the overall variation.

period – which is the year in which the Paris agreement was concluded. The interaction effect becomes significant from 2017 onward and remains stable in terms of size thereafter.

Over our sample period, there has been a rise in green financing products, such as green bonds (Flammer, 2021). Prior research (e.g., Zerbib, 2019) shows that green bonds typically trade at a yield discount, commonly referred to as the "greenium". To ensure that our findings are not driven by the presence of green bonds in our sample, we explicitly distinguish the carbon premium – the positive risk premium for exposure to climate transition risk – and the greenium – the yield discount associated green bonds. We do this by controlling for whether a bond is green-labeled. [31] When including this green bond indicator in Column 5, our results remain consistent in both magnitude and statistical significance, confirming that the effects we identify are not confounded by the green bond yield discount.[32]

A.1 Alternative yield measures

In Appendix D, we explore several alternative yield measures. We begin with the duration-matched yield spread, which accounts for differences in bonds' sensitivity to interest rate changes (van Binsbergen et al., 2025).[33] The results, shown in Table D1 in Appendix D, confirm that the interaction between emission intensity and green patenting remains statistically significant and negative, with a coefficient stable in magnitude to that in our baseline specification. We also examine expected yields, defined as yields adjusted for expected default losses, which we compute for bonds with available credit ratings.[34] The results using expected yields, which are presented in Table D2 in Appendix D, provide similar insights. We also confirm our findings when using yield spreads adjusted for expected default losses (Table D3), as well as when using the raw yield to maturity (Table D4).

A.2 Alternative measures of green innovation

Our baseline results indicate that investors recognize and price the efforts emission-intensive companies make to transition towards greener technologies, as measured by their relative engagement in green innovation. To assess the robustness of this finding, we examine whether our main results hold when using several alternative measures of green innovation.

[31]The results in Column 5 indicate that bonds that qualify as green bond are associated with a large and highly significant yield discount. This coefficient cannot be interpreted as estimate of the greenium within our sample, as the greenium is usually estimated by determining the average difference in yield spreads between green bonds and the most similar conventional bonds (e.g., Zerbib, 2019).

[32]Our results are qualitatively and quantitatively similar when we exclude all green bonds from our sample.

[33]For the duration matching, we focus on bonds with a fixed coupon and those denominated in euros and US dollars. We calculate the Macaulay duration using the present value of the bond's cash flows, which includes both coupon payments and the principal payment at maturity. The bond's duration is computed as the time-weighted average of the present value of cash flows, adjusted by the bond's yield and maturity. For bonds denominated in US dollars, the coupon payments and principal (which are originally denominated in euros) are adjusted by the exchange rate to account for currency differences. This ensures a consistent comparison across currencies. The average duration in our sample is 5.5 years.

[34]We use the method of Campello et al. (2008) and Eskildsen et al. (2024), determining the expected bond yield by subtracting the expected default loss from the yield to maturity, where the expected default loss is computed as the probability of loss times one minus the expected recovery rate. Following Campello et al. (2008), we determine the probability of default as the average default rate over the past three years for bonds with the same rating. Following Eskildsen et al. (2024) we use the annual default rates for our seven rating categories provided by S&P Global Ratings (2023) and use recovery rates estimates from Altman et al. (2000).

Table 5: Alternative Measures of Green Innovation

*This table reports the OLS estimation results of Equation (1), estimated with firm and industry-time fixed effects and using various measures of green innovation. The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. '$EI \times GPR$' is the interaction of emission intensity and the green patent ratio. The citations ratio is defined as the total number of citations obtained on the green patents issued in a given year by the firm, relative to the total number of total patents owned by the firm on an annual basis. $'EI \times Citations'$ is the interaction of emission intensity and the citations ratio. $'EI \times GPR \times E - Score'$' is the interaction of emission intensity, the green patent ratio and the firm's $E - score$. We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio, as well as bond characteristics, i.e., the outstanding amount, a dummy for fixed coupon bonds, a dummy for euro denominated bonds, and a dummy for green bonds. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

	Bond Yield Spreads$_{i,t}$				
	Classification	Blockbusters	Citations	E-Scores	Green Innovator
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.209***	0.155**	0.177**	0.265**	0.283***
	(0.067)	(0.076)	(0.068)	(0.117)	(0.015)
Green Patent Ratio$_{f,t-1}$	0.788***	3.118*		0.413***	
	(0.130)	(1.734)		(0.077)	
EI$_{f,t-1}\times$ Green Patent Ratio$_{f,t-1}$	-0.053***	-0.161*		-0.040**	
	(0.017)	(0.091)		(0.018)	
Citations Ratio$_{f,t-1}$			0.152***		
			(0.051)		
EI$_{f,t-1}\times$ Citations$_{f,t-1}$			-0.008***		
			(0.003)		
E-Score$_{f,t-1}$				0.009*	
				(0.004)	
EI$_{f,t-1}\times$ Green Patent Ratio$_{f,t-1}\times$ E-Score$_{f,t-1}$				0.001	
				(0.001)	
Green Innovator$_{f,t-1}$					0.276**
					(0.128)
EI$_{f,t-1}\times$ Green Innovator$_{f,t-1}$					-0.233***
					(0.017)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Double Interactions ESG	-	-	-	Yes	-
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Observations	19,195	37,105	37,105	35,264	38,954
R-squared	0.547	0.544	0.544	0.570	0.541

We first consider a more stringent classification of green patents, recognizing that the YO2 class in patent classification includes a broad range of technologies related to climate change mitigation and adaptation. Specifically, we focus on the Y02E subclass of the CPC, which consists of green patents aimed to reduce carbon emissions related to energy generation, transmission or distribution. We follow Acemoglu et al. (2023) who only consider a subset of innovations in the technological subclass Y02E of the CPC as green innovations.[35] Around 14 percent of green patents fall under this stricter classification, and they are held by 178 unique companies. The results in Column 1 of Table 5 indicate that the combined effect of emission intensity and green patenting remains stable in terms of magnitude and significance. This indicates that the negative association between green innovation and corporate bond yield spreads for emission-intensive firms remains, even when focusing narrowly on innovations specifically aimed at reducing carbon emissions.

We next examine "blockbuster" green patents, a subset of green patents that are distinguished by their high technological impact, as measured by forward citation. Specifically, we define blockbuster patents as those whose number of forward citations places them in the top 95th percentile within their respective 6-digit CPC subclass (Cohen et al., 2023). Within our sample, 150 unique firms hold at least one blockbuster green patent and approximately 5 percent of all green patents fall into the blockbuster category. When we focus on blockbuster green patents in our relative measure of green innovation, the results become significantly larger in magnitude, as shown in Column 2 of Table 5. This suggests that the effect of green innovation on bond yield spreads is more pronounced when focusing on patents with greater technological significance.

To further assess the technological relevance of green innovation, we also examine the number of forward citations received by green patents, a standard proxy for a patent's technological impact and influence. Forward citations reflect how frequently a given patent is cited by subsequent patents, thereby capturing its contribution to technological progress Kogan et al. (2017). In our sample, a green patent on average receives 3.5 forward citations. We normalize the forward citations by the total number of patents. This measure, which we refer to as the citations-ratio, captures how impactful the green patents of a firm are relative to the its overall patent portfolio. We interact the citations-ratio with emission intensity, to capture whether the "quality" of a firm's green patents affects the relation between its emission intensity and bond yield spreads. As reported in Column 3 of Table 5, the interaction term is negative and statistically significant, indicating that the effect of green innovation is stronger when green patents are of higher technological relevance.

ESG scores have become increasingly popular in guiding sustainable investment decisions, with mutual funds investing according to ESG ratings experiencing substantial inflows (Hartzmark and Sussman, 2019) and a growing share of investors relying on these scores in portfolio allocation. To ensure that our measure of environmental performance captures information beyond what is already reflected in environmental scores, we augment our dataset with E-scores which we obtain via Refinitiv. We include

[35] Following Acemoglu et al. (2023), we only consider patents which are in the Y02E10 (renewable electricity), Y02E30 (nuclear energy) or Y02E50 (biofuels and fuel from waste) subclass as green patents.

the firm's E-Score together with its interactions with emission intensity and the green patent ratio in Table 5 Column 4 to assess whether our measures of environmental performance is orthogonal to E-scores. We include the firm's E-Scores as well as its interactions with emission intensity and the green patent ratio in Column 4. The results show that the interaction with E-scores is statistically insignificant, while our main interaction remains stable in magnitude and significance to the baseline. This suggests that the recognition of green innovation among emission-intensive firms is not merely a reflection of their ESG rating, but captures an additional dimension of firm-level transition efforts.

To better capture how green innovation affects the cost of debt for emission-intensive firms, we construct an indicator for whether a firm qualifies as a "green innovator", defined as having an above-median green patent ratio. This specification offers a clearer comparison between green innovative and non-innovative firms and illustrates how green innovation influences the pricing of transition risk.[36] The results, reported in Column 5 of Table 5, indicate that the carbon premium is substantially lower for emission-intensive green innovators. At the mean level of emission intensity, being a green innovator reduces yield spreads by 37.4 basis points. This confirms that it is specifically the interaction of green innovation with the firm's current emission intensity that investors value when pricing transition risk.

Our results primarily focus on the intensive margin of green innovation, as we limit our sample to firms that have at least one green patent. We extend the analysis to include all companies for which patent information is available, including those with no green patents. This expands our sample to 1,175 unique firms and 90,729 observations, for which we provide summary statistics in Table D6 in Appendix D. Including the extensive margin allows us to test whether our results hold when accounting for variation in both the presence and the intensity of green innovation, thereby capturing the broader relationship between green innovation efforts and bond pricing across the full distribution of patenting activity. The results, presented in Table D7 in Appendix D, show that the combined effect of emission intensity and green patenting remains statistically significant when including the extensive margin.

A.3 Alternative emission measures

There is an ongoing debate in the literature regarding whether emission intensity or absolute emissions provides a more accurate measure of a firm's environmental impact (e.g., Aswani et al., 2024; Zhang, 2025; Bolton and Kacperczyk, 2024). Emission intensity, which scales emissions by firm size, is often used to account for the growth of emissions with firm revenues. However, absolute emissions, which measure the total quantity of emissions, may better capture the overall environmental footprint of a firm, especially when considering large emitters. While emission intensity is particularly relevant in the bond context, as it captures a firm's environmental risk relative to its financial capacity, we assess the robustness of our findings by considering absolute emissions as an alternative measure. The results, reported in Table D8 in Appendix D, show that the combined effect of absolute emissions and green patenting remains statistically significant at the 1 percent level, with the effect being substantially larger in magnitude

[36] We report the results of the baseline regression with standardized variables in Appendix D. We standardize variables using the sample standard deviation, while using the within-firm standard deviation to determine the effect size.

when using absolute Scope 1 and 2 emissions. This confirms the robustness of our findings, regardless of whether emissions are measured in intensity or absolute terms.

A.4 Alternative explanations

General Investment, R&D and Patenting We rule out the possibility that our results are driven by other alternative explanations. We first consider general investment or innovation activities. We control for the total number of patents a firm holds (in logarithms) and its interaction with emission intensity, as reported in Column 1 of Table D9. The results show that the effect of the interaction between emission intensity and the green patent ratio remains consistent in both magnitude and significance after accounting for the total number of patents owned by the firm. This indicates that our effect is not driven by overall patenting activity. In Column 2 of Table D9, we include an interaction between emission intensity and the investment ratio, one of our control variables. This interaction term is statistically insignificant, suggesting that general investments do not drive our results either. In Column 3, we additionally control for a firm's R&D expenditures, measured relative to its revenue, along with the interaction between emission intensity and R&D expenditures. Firms in our sample spend substantial amounts on R&D, with an average expenditure of approximately 2.6 billion euros (and a median of 0.3 billion euros). Our main interaction of interest remains significant, implying that green innovation by emission-intensive firms adds value which is not captured by general R&D efforts. Taken together, these results highlight the distinct importance of green innovation efforts by emission-intensive firms, as neither general patenting, investments, nor R&D expenditures can fully account for the documented effect.

Corporate Sector Purchase Programme In Column 4 and Column 5 of Table D9, we rule out that the Corporate Sector Purchase Programme (CSPP) of the ECB, which commenced in 2016, explains our results. The first phase of CSPP ran from June, 2016 to December, 2018, and involved purchases of corporate sector bonds by the Eurosystem. Purchases were restarted on 1 November 2019 and continued until the end of June 2022. Over our sample period, the total amount purchased was 309.7 billion euro, with 77.16 percent of these purchases occurring in the secondary market. While the ECB did not incorporate climate change considerations into corporate bond purchases over the course of our sample period[37], there is some evidence that the easing of financing conditions in the euro area corporate debt market has fostered corporate R&D investments Grimm et al. (2022). We therefore verify that our results are not driven by bond eligibility for purchase under the CSPP, nor by actual purchases made by the ECB. We generate a dummy which indicates whether a given bond in our sample is eligible for purchase under the CSPP, which is the case for 10.2 percent of bonds within our sample.[38] We interact emission intensity and the green patent ratio (both separately and jointly) with the eligibility- and purchase-dummy. The

[37] The ECB announced in July 2022 that it would start incorporating climate change considerations into the Eurosystem's purchases under CSPP. The Eurosystem started to tilt its purchases towards issuers with a better climate performance from October 2022 until July 2023, when the CSPP ended.

[38] To be eligible for purchase under the CSPP, a bond should be (i) IG rated by S&P, Moody's, Fitch or DRBS, (ii) issued by a NFC in the eurozone, (iii) denominated in euros, (iv) have a residual maturity between 6 months and 31 years, and (v) have a yield to maturity that exceeds the ECB deposit facility rate. See https://www.ecb.europa.eu.

results are reported in Column 4 and Column 5, respectively. While eligibility for purchase under CSPP generally reduced bond yield spreads, neither eligibility for purchase nor the actual purchases made drive our main results. The key interaction of emission intensity and green patent ratio for the yield spread regression remains significant, while the interaction of emission intensity, the green patent ratio and the CSPP dummy is insignificant in both cases. This indicates that CSPP is not a mechanism driving our main findings.

Bond Supply There is some evidence that banks have started to incorporate the exposure to climate transition risk in their lending decisions and are reducing lending to emission-intensive firms (e.g., Kacperczyk and Peydró, 2022; Ivanov et al., 2024; Degryse et al., 2023; Altavilla et al., 2023). As lending conditions become more stringent for emission-intensive firms, these firms may rely to an increasing extent on bond markets for their debt financing. A potential concern is thus that yield spreads are higher for emission-intensive firms due to a rise in their bond supply. We examine whether our results are driven by a rise in bond financing by emission-intensive firms relative to other firms by plotting the evolution of the total amount outstanding, splitting the sample based on the emission intensity of the issuing company. Figure D2 in Appendix D shows that the trends are comparable for firms in the higher emission intensity quintile.[39] Hence, we do not find evidence of a disproportionate expansion in bond supply of emission-intensive companies. Rather, by controlling explicitly for bond supply in our analysis in Section C, we show that our pricing effects are demand driven.

Utility Sector We also re-estimate equation (1) excluding utility sector firms in Table D10 in Appendix D. The utilities sector is characterized by being highly emission-intensive, yet it also has a relatively high green patent ratio (see Table 3). Given this sector's environmental performance characteristics, we verify that our results are not driven by firms in this sector in particular. When excluding firms in the utility sector, the combined effect of emission intensity and green patenting remains stable in terms of magnitude, confirming that the effect are not driven by utility sector firms.

A.5 The role of ratings, liquidity and maturity

Bond yield spreads are significantly influenced by the bond's credit risk, liquidity, and maturity. We investigate whether the joint effect of emission intensity and green innovation on bond yield spreads could be explained by these factors, by assessing whether our findings are driven by the joint determination of conventional bond characteristics and firm's environmental performance. We include interactions between our main variables of interest and each of these relevant bond characteristics.

We first consider credit ratings, accounting for the possibility that bond credit ratings and environmental performance may be related (Seltzer et al., 2022; Carbone et al., 2021). We control for

[39] Figure D2 in Appendix D rather shows that the amount outstanding of firms with the lowest emission intensity vastly increased over the sample period. This can partially be explained by the increase in coverage in Trucost of low-emission-intensive firms after the Paris Agreement (2016), as this increases the number of bonds of low-emission-intensive firms that appear in our sample. This observation is in line with previous literature (e.g., Bolton and Kacperczyk, 2021).

Table 6: Ratings, Liquidity and Maturity

*This table reports the OLS estimation results of robustness tests for Equation (1), estimated with firm and industry-time fixed effects. The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in CO_2e/USDm. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. '$EI \times GPR$' is the interaction of emission intensity and the green patent ratio. The rating captures the credit rating bucket, where higher values correspond to higher levels of credit risk. Liquidity is measured using the bid-ask spread. Maturity is a dummy variable equal to 1 if the residual maturity of the bond is longer than 10 years. '$EI \times GPR \times ...'$' is the interaction of emission intensity, the green patent ratio, and credit ratings or liquidity or maturity, respectively. While not reported, we include all pairwise interactions as controls. We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio, as well as bond characteristics, i.e., the outstanding amount, a dummy for fixed coupon bonds, a dummy for euro denominated bonds, and a dummy for green bonds. Standard errors are reported in parentheses and are clustered at the industry-level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

	Bond Yield Spreads$_{i,t}$					
	Ratings	Financially Fragile	Financially Stable	Liquidity	Maturity	All
	(1)	(2)	(3)	(4)	(5)	(6)
Emission Intensity$_{f,t-1}$	0.209**	0.135**	-0.039***	0.228***	0.205***	0.255**
	(0.083)	(0.050)	(0.011)	(0.060)	(0.061)	(0.111)
Green Patent Ratio$_{f,t-1}$	1.206**	0.322***	-0.500**	0.655***	0.579***	1.144**
	(0.539)	(0.091)	(0.209)	(0.112)	(0.114)	(0.556)
EI$_{f,t-1}\times$GPR$_{f,t-1}$	-0.045***	-0.017***	0.006	-0.040***	-0.034***	-0.052***
	(0.014)	(0.005)	(0.007)	(0.008)	(0.008)	(0.018)
Rating$_{i,t-1}$	-0.026					-0.032
	(0.109)					(0.104)
EI$_{f,t-1}\times$GPR$_{f,t-1}\times$Rating$_{i,t-1}$	-0.006					-0.007
	(0.009)					(0.008)
Liquidity$_{i,t-1}$				0.673***		0.337***
				(0.151)		(0.123)
EI$_{f,t-1}\times$GPR$_{f,t-1}\times$Liquidity$_{i,t-1}$				1.260***		0.900***
				(0.176)		(0.179)
Maturity$_{i,t-1}$					0.753***	0.431***
					(0.086)	(0.102)
EI$_{f,t-1}\times$GPR$_{f,t-1}\times$Maturity$_{i,t-1}$					0.009***	-0.005
					(0.002)	(0.008)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Double Interactions	Yes	-	-	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,215	10,258	22,426	36,237	38,954	15,641
R-squared	0.637	0.687	0.380	0.601	0.577	0.694

the interactions between our main variables of interest and the credit rating class. The results are presented in Column 1 of Table 6. The combined effect of emission intensity and green innovation is statistically significant. Moreover, all interactions with bond credit ratings are insignificant. Environmental performance therefore does not differentially affects bond yield spreads based on credit ratings, suggesting that traditional credit risk models do not fully account for the impact of climate risk.

Since we are using firm fixed effects in our regressions, the interactions with ratings rely on time variation in credit ratings within firms. However, ratings tend to be rather static at the firm-level. We therefore split our sample to estimate our model separately for firms that are financially fragile and those that are financially stable. As 43 percent of the bonds in our sample are rated and fewer than 11 percent of rated bonds carry a rating below investment grade, we rely on the balance sheet implied ratings following (Acharya et al., 2024; Altman, 2018). We construct the Altman Z-score as an alternative measure of credit risk.[40] We determine whether a firm is financially fragile or stable based on their Z-score. Firms with Z-scores corresponding to a BBB-rating and above are considered financially stable, whereas those with Z-scores corresponding to a BB-rating and below are classified as financially fragile.

We show the results for financially fragile firms in Column 2 of Table 6 and for those which are financially stable in Column 3. The combined effect of emission intensity and green innovation on yield spreads is concentrated among financially fragile firms. This supports a default risk channel: investors price climate transition risk more strongly when firms have weaker cash flow prospects, while green innovation alleviates this vulnerability. The pattern aligns closely with the mechanism in Choi et al. (2019), who show that mutual funds (whom we later identify as the main investor sector driving our effects) are reluctant to roll over bonds of firms with weak cash flows, thereby amplifying credit risk. In the same spirit, we find that climate transition risk is most salient for firms with higher implied credit risk, making green innovation particularly valuable when cash flow prospects are weak.[41] Note that the coefficient for emission intensity for financially stable firms, while statistically significant, is very small in terms of economic magnitude.

We also assess whether the relationship between a firm's environmental performance and bond yield spreads varies with the bond's liquidity and maturity. We use the bid-ask spread as proxy for a bond's liquidity, which is calculated from daily bid- and ask prices obtained via Refinitiv.[42] As shown in Column 4 of Table 6, the combined effect of emission intensity and the green patent ratio on yield spreads remains statistically significant, and is therefore not driven by a differential bond liquidity. Column 5 presents the results considering the joint relationship between environmental performance and bond maturity. The reduction in bond yield spreads associated with green innovation by emission-intensive firms is smaller

[40]The Altman Z-score is defined as $Z = 3.25 + 6.56 \times \frac{\text{Current Assets}-\text{Current Liabilities}}{\text{Total Assets}} + 3.26 \times \frac{\text{Retained Earnings}}{\text{Total Assets}} + 6.72 \times \frac{\text{EBIT}}{\text{Total Assets}} + 1.05 \times \frac{\text{Book Value of Equity}}{\text{Total Liabilities}}$. For the purpose of constructing the Z-score, we use the relevant income statement and balance sheet items from Orbis.

[41]While Choi et al. (2019) emphasize that mutual funds divest from financially distressed firms, our results align through the gradient: for firms that are financially fragile, marginal improvements in financial viability, such as those stemming from green innovation, are particularly valued by cash-flow motivated investors.

[42]We calculate the bid-ask spread for each bond i as the difference between the ask price and the bid price, relative to the ask price. The daily bid-ask spreads are averaged to determine the bid-ask spread at a quarterly frequency. We express the bid-ask spreads in percentages. The mean bid-ask spread is 0.407, with a standard deviation of 0.445.

for bonds with a longer residual maturity. This suggests that green innovation efforts become particularly relevant to investors as bond rollover approaches. This pattern is again consistent with Choi et al. (2019), who document that flow driven funds respond more strongly to cash-flow news when bonds are closer to maturity.

In summary, the combined effect of emission intensity and the green patent ratio remains highly statistically significant, even after accounting for potential heterogeneity related to bond liquidity. While we find that the pricing effects are concentrated in the segment of firms with weaker cash flow prospects, we do not find a differential effect when interacting our measures of environmental performance with credit ratings. This suggests that, within our sample, variation in credit ratings at the firm-level is too limited to identify rating-based heterogeneity in firms' climate risk exposure.

B. Holdership dynamics

In light of the European Union's broader efforts to promote green transition goals and the public concerns about climate change within Europe compared to other regions, we assess whether European investors also have a higher demand for bonds of emission-intensive firms that engage in green innovation. We compare the demand of different investor types for bonds issued by firms with a similar exposure to climate transition risk. To this end, we collapse our sample to the firm-investor-time (f, j, t) [43] and estimate the following bond demand regression (e.g., Khwaja and Mian, 2008; Acharya et al., 2024):

$$\begin{aligned}\text{Holdings}_{f,j,t} = &\ \beta_1 \text{Emission Intensity}_{f,t-1} + \beta_2 \text{Green Patent Ratio}_{f,t-1} + \beta_3 \mathbb{1}_{\text{Investor Type}=j} \\ &+ \beta_4 \text{Emission Intensity}_{f,t-1} \cdot \text{Green Patent Ratio}_{f,t-1} \cdot \mathbb{1}_{\text{Investor Type}=j} \\ &+ \gamma \text{Amount Outstanding}_{f,t-1} + \lambda_{f,t} + \zeta_{c,s,t} + \nu_{f,j,t} \end{aligned} \tag{2}$$

where we include all pairwise interactions between emission intensity, the green patent ratio, and a variable indicating the type of investor as controls. We expect the parameter of interest, β_4, to be positive for institutional investors, indicating that these investors have a relatively higher demand for bonds issued by emission-intensive firms that engage in green innovation efforts. Institutional investors include insurance companies, pension funds, mutual funds, and other financial institutions, while we consider banks separately. The reference investor sectors, against which we measure the relative demand of institutional investors and banks, comprise other financial institutions, non-financial corporations, governments, and households. We estimate the regression with firm-time $(\lambda_{f,t})$ and holder area-sector-time $(\zeta_{c,s,t})$ fixed effects. Our holder area-sector-time fixed effects control for potential differential portfolio choices of investors in different holder areas and sectors. Our firm-time fixed effects control for all other potential characteristics that might interact with the portfolio choice, including changes in bond supply (Acharya et al., 2024). We cluster standard errors at the industry-level. The results are reported in Panel

[43] Since we observe the trades in bonds among investors in different countries and investor sectors within a given period, this increases our sample by almost fivefold.

Table 7: Bond Demand, Emission Intensity and Green Innovation

*This table reports the OLS estimation results of Equation (2), estimated by with firm-time and holder country-sector-time fixed effects. The dependent variable in all regressions is the bond holdings of a given investor sector in a given firm, measured in natural logarithms. Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. '$EI \times GPR \times \mathbb{1}_j$' is the interaction of emission intensity, the green patent ratio and a variable indicating the type of investor, j. Panel A reports the regressions of bond holding of all European institutional investors on emission intensity, the green patent ratio, a variable indicating the type of institutional investor, and their interaction. Column 2-5 report the regression results for insurance companies, mutual funds, pension funds and banks separately. While not reported, we include all pairwise interactions as controls. In Panel B, we estimate the regressions of bond holding of mutual funds for all funds located in the European Union (1), those located outside of Ireland and Luxembourg (2), and those located in Ireland and Luxembourg (3). We control for the total bond amount outstanding in all regressions. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

(a) Institutional Investors and Banks

Panel A	Holdings$_{f,j,t}$				
	Instit.	Insur.	Mfund.	Pfund.	Bank
	(1)	(2)	(3)	(4)	(5)
EI$_{f,t-1}$×GPR$_{f,t-1}$× $\mathbb{1}_j$	0.010***	0.004	0.005***	0.003	0.006**
	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
Amount Outstanding	Yes	Yes	Yes	Yes	Yes
Firm-Time FEs	Yes	Yes	Yes	Yes	Yes
Holder Area-Sector-Time FEs	Yes	Yes	Yes	Yes	Yes
Observations	183,034	183,034	183,034	183,034	183,034
R-squared	0.659	0.658	0.659	0.658	0.658

(b) Mutual Funds

Panel B	Holdings$_{f,j,t}$		
	Mfund.		
	EU	EU - OFCs	OFCs
	(1)	(2)	(3)
EI$_{f,t-1}$×GPR$_{f,t-1}$×Mfund$_j$	0.005***	0.004**	0.007**
	(0.002)	(0.002)	(0.003)
Amount Outstanding	Yes	Yes	Yes
Firm-Time FEs	Yes	Yes	Yes
Holder Area-Sector-Time FEs	Yes	Yes	Yes
Observations	183,034	153,993	28,310
R-squared	0.659	0.645	0.793

A of Table 7. We first evaluate the combined effect of emission intensity and the green patent ratio on the demand of European institutional investors generally. We interact emission intensity and the green patent ratio (both separately and jointly) with an dummy variable indicating whether the investor is an institutional investor. The results are reported in Column 1 of Panel each type of institutional investor separately in Column 2-4 of Panel A of Table 7. Our findings show that the effect of institutional investors is driven by European mutual funds, who hold 0.9 percent more bonds of firms with an average emission intensity and green patent ratio. This implies that mutual funds, potentially due to their greater risk-bearing capacity, are more responsive to firms' green innovation efforts and help direct capital toward emission-intensive firms that invest in such activities. In contrast, we do not observe a similar pattern for insurance companies or pension funds.

Our European holdings data cover roughly 32 percent of the total bond amount outstanding in our sample (Table E1 in Appendix E), implying that about two-thirds is held by foreign investors. Do foreign investors behave similar to European investors? While we do not directly observe the holdings of foreign investors, it is well-established that many foreign investors access European markets via mutual funds domiciled in Luxembourg and Ireland – the so-called offshore financial centers (OFCs) (Beck et al., 2024). We examine whether the demand of mutual funds differs in the OFCs compared to the rest of Europe. Panel B of Table 7 shows that the effect holds for all European mutual funds, irrespective of whether they are located in OFCs or elsewhere. The effect is quantitatively stronger for mutual funds based in OFCs, suggesting that the demand we identify may not be limited to European investors. While only suggestive, this aligns with survey evidence of Edmans et al. (2024), who find few geographic differences in environmental and social (E&S) views in a global survey of funds marketed around the world.

Finally, in Column 5 of Panel A of Table 7 we assess whether European banks have a differential demand for bonds issued by emission-intensive firms that engage in green innovation. In this case, we also find a positive and statistically significant interaction effect. While this suggests that banks also hold relatively more bonds of emission-intensive firms that engage in green innovation compared to the average investor, banks' holdings are too small at a global level to significantly affect corporate bond yield spreads (see Table E1 in Appendix E).

B.1 Do holdings influence yield spreads in relation to environmental performance?

We assess whether the holdings of European investors influence the extent to which environmental performance is reflected in bond yield spreads. That is, we examine whether the sensitivity of bond yield spreads to firms' environmental performance differs depending on the volume of holdings of a given investors type.[44] To measure the holdings of each respective investor, we follow Crosignani et al. (2020) and construct the "holder share":

$$\text{Holder Share}_{i,j,t} = \frac{\frac{\text{Bond Holdings}_{i,j,t}}{\text{Amount Outstanding}_{i,t}}}{\frac{\sum_i \text{Holdings}_{i,j,t}}{\sum_i \sum_j \text{Holdings}_{i,j,t}}}$$

The numerator measures the holdings of a specific European investor sector j of a given bond i relative to the total amount outstanding (at market values) in a given period t.[45] To take into account the size of the investor sector, we divide the numerator by the total holdings of the investor sector relative to the total holdings in that given period.[46] We interact emission intensity and the green patent ratio with the

[44] While some papers analyzing bond spreads use ownership data, these studies look at equity holdings of bond-issuing firms (e.g., Huang and Petkevich, 2016; Bauer et al., 2021) but not at the direct investors of the particular bond itself.

[45] Since we observe the holdings of all European investors, the remaining holdings correspond to foreign investors.

[46] Consider the following example. Pension fund X and mutual fund Y buy €100 in corporate bonds of emission-intensive firms that innovate in the green space and €100 in corporate bonds of low emission-intensive firms. The total amount

holder share and estimate the following regression at the bond-period level:

$$\begin{aligned}\text{Spread}_{i,t} = {} & \beta_1 \text{Emission Intensity}_{f,t-1} + \beta_2 \text{Green Patent Ratio}_{f,t-1} + \beta_3 \text{Holder Share}_{j,t-1} \\ & + \beta_4 \text{Green Patent Ratio}_{f,t-1} \cdot \text{Emission Intensity}_{f,t-1} \cdot \text{Holder Share}_{j,t-1} \\ & + \delta' X_{f,t-1} + \gamma' Z_{i,t-1} + \mu_{g,t} + \nu_{i,t} \end{aligned} \tag{3}$$

where we include all pairwise interactions between emission intensity, the green patent ratio, and the holder share as controls. The parameter of interest is β_4, which we expect to be negative whenever j concerns an European institutional investor sector or mutual fund. This parameter captures whether holdings of European investors are associated with lower yield spreads for emission-intensive firms that engage in green innovation. We include a vector of corporate fundamentals, $X_{f,t-1}$, and bond characteristics, $Z_{i,t-1}$ as control variables. Since there is limited within-firm variation in the holder shares, and all variation in emission intensity and the green patent ratio is at the firm-level, we include only industry-time fixed effects ($\mu_{g,t}$) in this specification. Standard errors are clustered at the industry-level.

Table E2 in Appendix E reports the results of Equation (3). Our findings show that the yield spread reduction associated with green innovation is more pronounced when European institutional investors hold a larger share of the bond. Consistent with the findings of our demand estimation, we show that this effect is driven by mutual funds.[47]

B.2 Risk or preferences?

Our results show that mutual funds have a relatively higher demand for bonds issued by emission-intensive firms that engage in green innovation. Given the substantial increase in flows to European sustainable funds over our sample period[48], this raises the question whether such demand is primarily driven by green mutual funds. While the SHS data allows us to identify bond holdings at the investor sectoral level, it does not provide sufficient granularity to determine which individual fund holds a given bond. As a result, we are unable to directly attribute observed demand to green mutual funds. To assess whether their higher demand reflects funds' green preferences or rather is consistent with risk pricing, we turn to an alternative approach. Specifically, we determine a firm's exposure to aggregate climate risk and assess

outstanding of bonds of emission-intensive firms that innovate in the green space is €400 and €800 for bonds of low emission-intensive firms. When focusing solely on the numerator of the holder share, the shares held by both pension fund X and mutual fund Y are 0.25 and 0.125, respectively. However, if pension fund X is larger than mutual fund Y, holdings should be weighted by the relative size of the investor's assets to take into account that mutual fund Y has a stronger preferences for environmental performance relative to its size (i.e., mutual fund Y relatively overweights bonds of firms with a better environmental performance in their portfolio relative to their size). By simply looking at holdings, even adjusted for the amount outstanding, the two investors do not seem to value environmental performance differentially (see Crosignani et al., 2020)).

[47] Given that we also find significant results for insurance companies when incorporating each holder share separately, we run a horse-race by including the interactions with all investor types simultaneously. Consistent with our demand estimates, only the interaction between emission intensity, the green patent ratio, and the share of holdings by mutual funds remains statistically significant.

[48] For example, Morningstar reports that European sustainable fund launches and assets under management have risen substantially since 2016. Sustainable fund assets reached nearly 882 euro billion in 2020-Q3, accounting for 9.3 percent of total European fund assets. Net inflows represented approximately 40 percent of all fund flows during this period (Source: Morningstar Direct, September 2020).

whether the effect of environmental performance on bond yield spreads is stronger for firms with a higher exposure to climate risk.

We collect stock prices of all listed firms included in the bond-holdings sample using the Centralised Securities Database (CSDB). This dataset provides quarterly information on market capitalization, along with stock prices reported for each month within the quarter, which we use to compute monthly stock returns.[49] We use the Climate Change News Index developed by Engle et al. (2020) as an aggregate measure of climate risk. The Climate Change News Index tracks the number of news articles mentioning climate change negatively, subtracting the number of times it is mentioned positively on a given day.[50] We follow Engle et al. (2020) and average the daily values of the Climate Change News Index at the monthly level. We then construct the innovations in the climate news index as residuals from an AR(1) model. These innovations capture the unexpected component in the intensity of climate change discussions in newspapers.[51] Based on the assumption that media coverage of climate change tends to rise when climate risk is perceived to be high, this measure allows us to capture exogenous changes in climate-related concerns and use them as a measure of aggregate climate risk.[52] We augment the dataset with annual corporate fundamentals from Orbis, focusing on the variables relevant for explaining stock returns.[53] Finally, we retrieve market betas from Refinitiv, which are estimated based on daily return data. The stock-return sample consists of 85 percent of all firms observed in our bond-holdings sample. The summary statistics of our control variables for the stock regressions are reported in Table E3 in Appendix F.

We observe each stock, issued by a company f, in industry g, in year-month t. We estimate the following regression for the stock returns, measured in percentage points, at the firm-period level:

$$\text{Stock Return}_{f,t} = \beta \text{Aggregate Climate Risk}_{t-1} + \delta' X_{f,t-1} + \theta_g + \alpha_t + \epsilon_{f,t} \tag{4}$$

The vector of control variables includes: the (i) market capitalization (in logarithms); (ii) the return on equity (RoE), defined as net income divided by shareholders' equity; (iii) book-to-market ratio, defined as (book value per share times shares outstanding) divided by (market price per share times shares outstanding); (iv) leverage ratio, defined as total debt over total assets; (v) investment ratio (winsorized at 2.5 percent), defined as the year-over-year growth rate of tangible assets; (vi) property, plant and equipment (PPE), defined as tangible assets (in logarithms); (vii) sales growth, defined as the

[49] To mitigate the impact of outliers, we winsorize the monthly stock returns at the 99th percentile.

[50] We use the Climate Change News Index constructed based on news articles in the New York Times, rather than the Index based on news articles in the Wall Street Journal (which is originally done in Engle et al. (2020)), given that the latter series only covers part of our sample period. The Climate Change News Index is available online via `https://www.biodiversityrisk.org`.

[51] While the index captures articles related to both climate transition and physical climate risks, we argue that our results are not confounded by firms' exposure to physical risk. Since physical climate risk is largely determined by a firm's location, our firm fixed effects absorb any effects arising from physical risk exposure.

[52] Arteaga Garavito et al. (2025) verify in a global sample that news shocks related to climate change typically constitute bad-news.

[53] Following Kalemli-Özcan et al. (2022), we drop firm-year observations for which current assets, total equity, short-term debt, long-term debt, revenue or book value per share have negative values. We also drop the observations for which total debt (defined as short- plus long-term debt) exceeds total assets.

year-over-year growth rate of the firm's revenue; (viii) earnings-per-share (EPS) growth, defined as the annual change in the firm's EPS normalized by the firm's stock price; (ix) the market beta, defined as the CAPM beta calculated over a 12-month period using daily data; and (x) the volatility of the firm's stock, defined as the standard deviation of stock returns based on the past 12 months of monthly returns. We estimate Equation (4) using industry fixed effects (θ_g) and year-quarter fixed effects (α_t). For robustness, we also estimate the relation using year-quarter fixed effects only, and year-quarter- and firm fixed effects. We cluster standard errors at the industry-level. This estimation is closely related to the methodology from Bolton and Kacperczyk (2021), where we use the innovations in the climate news index as a measure of (aggregate) climate risk.

The estimation results of Equation (4), which are estimated at the monthly frequency and stock-level, are presented in Column 1-3 of Table 8. Column 1 reports the results of the stock return regression on the aggregate climate risk measure, while controlling for other fundamental drivers of stock returns and year-quarter fixed effects. In Column 2, we additionally include industry fixed effects, and in Column 3 we include firm fixed effects alongside the year-quarter fixed effects. The coefficient on climate risk is positive and statistically significant across specifications, indicating that, within an industry–quarter (Column 2) and within a firm over time (Column 3), stock returns tend to be higher on average during periods of elevated climate risk. This confirms the relevance of our climate risk measure in explaining stock returns.

We measure a firm's exposure to aggregate climate risk — which we refer to as the Climate Beta — by estimating the sensitivity of its stock returns to innovations in the Climate Change News Index, using a 12-month rolling window based on Equation (4).[54] We incorporate the Climate Betas into our bond-holdings dataset and interact the measure with emission intensity and the green patent ratio, both separately and jointly.[55] These interactions allow us to assess whether the effect of environmental performance on bond yield spreads is stronger for firms with a higher exposure to climate risk. If the interactions load significantly, this suggests that the pricing of environmental performance reflects risk-based considerations. Conversely, insignificant interactions suggest that the observed pricing effects are more likely to reflect investor preferences rather than risk compensation. The results in displayed in Column 4 of Table 8, which are estimated at quarterly frequency and the bond-level, reveal that the interaction of emission intensity and the Climate Beta is positive and statistically significant. This indicates that the carbon premium is higher for firms that have a higher exposure to aggregate climate risk. At the same time, the reduction in the carbon premium due to green innovation is larger for firms with a higher exposure to climate risks, as the interaction of emission intensity, the green patent ratio, and the Climate Beta is negative. Intuitively, for firms that are more vulnerable to climate risk, investors place greater value on efforts to transition, as measured by their green patenting activity.

This evidence points toward risk pricing as the channel through which environmental performance

[54]This measure is spirit related to the Carbon Beta measure of Huij et al. (2022).

[55]We use the end-of-quarter Climate Beta, scaled by a factor of 1/100. While Climate Beta estimates are available for approximately 70 percent of firms in our bond-holdings sample, coverage at the firm-quarter level amounts to 35.4 percent. We report summary statistics for the Climate Beta in Table E4 in Appendix E. The results are robust to using the quarterly average Beta instead of the end-of-quarter Beta's.

Table 8: Climate Beta's, Emission Intensity, and the Green Patent Ratio

This table reports the estimation results of our risk vs preferences test. Column 1-3 reports the OLS estimation results of Equation (4), which is estimated at the monthly frequency and ***firm-level****. We estimate the relationship with year-quarter fixed effects in Column 1, with industry- and year-quarter fixed effects in Column 2 and with firm- and year-quarter fixed effects in Column 3. The dependent variable is the stock return, which is measured in percentages. Aggregate Climate Risk captures the innovations in the Climate Change News Index. We include a set of corporate fundamentals (market capitalization, RoE, book-to-market-ratio, leverage-ratio, investment-ratio, PPE, sales growth, EPS-growth, market beta, and stock volatility). Standard errors are reported in parentheses and are clustered at the industry-level. Column 4 reports the OLS estimation results of Equation (1), estimated at the quarterly frequency and the* ***bond-level****, with firm and industry-time fixed effects. The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). We include Emission intensity, which is measured in CO_2e/USDm, the green patent ratio (%) and their interaction ('EI $\times$ GPR'). Climate Beta is the firm-specific exposure to climate risk. 'EI $\times$ GPR $\times$ ClimateBeta' is the interaction of emission intensity, the green patent ratio and the firm's Climate Beta. We further include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio, as well as bond characteristics, i.e., the outstanding amount, a dummy for fixed coupon bonds, a dummy for euro denominated bonds, and a dummy for green bonds. Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

	Stock Returns$_{f,t}$			Bond Yield Spreads$_{i,t}$
	Aggregate Climate Risk			Climate Beta
	(1)	(2)	(3)	(4)
Aggregate Climate Risk$_{t-1}$	0.304*	0.346**	0.554***	
	(0.169)	(0.168)	(0.179)	
Climate Beta$_{f,t-1}$				-0.832
				(0.658)
EI$_{f,t-1}\times$Climate Beta$_{f,t-1}$				0.233**
				(0.087)
GPR$_{f,t-1}\times$Climate Beta$_{f,t-1}$				0.091
				(0.072)
EI$_{f,t-1}\times$GPR$_{f,t-1}\times$Climate Beta$_{f,t-1}$				-0.053***
				(0.017)
Corporate Fundamentals	Yes	Yes	Yes	Yes
Bond Characteristics	No	No	No	Yes
Firm-FEs	No	No	Yes	Yes
Industry-FEs	No	Yes	No	No
Industry-Time-FEs	No	No	No	Yes
Time-FEs	Yes	Yes	Yes	No
Observations	11,611	11,611	11,611	17,554
R-squared	0.138	0.149	0.182	0.589

influences bond yield spreads. While we do not find any differential effect by credit ratings, this result aligns with our finding that investors price transition risk more strongly when default risk is salient: the effects are concentrated among firms with higher exposure to aggregate climate risk, as captured by the Climate Beta.

C. Green innovation and corporate environmental progress

Our findings indicate that investors recognize the efforts emission-intensive companies make to transition to greener technologies, as these firms experience a significantly lower carbon premium compared to their non-innovative counterparts. To better understand the implications of this finding, we explore whether green innovation is associated with improvements in corporate environmental performance. Following Bolton et al. (2023), we assess whether green patenting is associated with a decline in future emissions. That is, we estimate the impact of green innovation on corporate environmental performance by linking a companies' contemporaneous green innovation activity to its future absolute emissions, at the one-, two- and three-year horizon. The methodology and accompanying results are described in Appendix F.

In summary, our results do not provide a definitive answer as to whether green innovation directly improves environmental performance. This aligns qualitatively with the findings of Bolton et al. (2023), who also do not observe that green innovation leads to emission reductions. This raises the question why investors factor green innovation into the bond pricing relationship. A plausible explanation is that investors expect emission reductions to materialize over a longer time horizon. Hege et al. (2025) offer another explanation: green product innovations reduce carbon emissions along the downstream supply chain, at customer firms. While the innovators themselves may not become greener, these customer firms show a preference for suppliers with green patents, allowing innovators to attract new clients and generate higher revenues. This may explain why bond yield spreads are lower for emission-intensive, green innovating companies even though these companies do not become greener themselves.

A complementary explanation is that the ownership of green patents signals a firm's technological capabilities, indicating that firms possess technologies relevant to the green transition (Hege et al., 2024). We argue that this conveys positive option value to corporate bond investors, as these green technologies enhance the firm's resilience and readiness for the green transition, thereby reducing perceived downside risks. Firms holding green patents are better positioned to respond to stricter future climate policies, enabling them to mitigate potential regulatory costs associated with the green transition. Consistent with this interpretation, we hypothesize that the pricing of environmental performance, and the role of green innovation in this context, should be stronger during periods of unexpected changes in carbon prices, when the option value of green technology becomes higher.

To test the option-value hypothesis, we interact firms' emission intensity and green patent ratio, both separately and jointly, with the carbon policy surprise series from Känzig (2023), which measures unexpected euro changes in the carbon price. This surprise series is constructed from daily changes in carbon futures prices around EU ETS regulatory update events related to the supply of emission allowances, and is orthogonalized with respect to macroeconomic, financial, and oil market news. We focus on this surprise series because it captures new information that directly alter firm's expected regulatory costs. Therefore, it allows us to precisely capture the value investors assign to being prepared for future regulatory changes, i.e., the option value of green technologies. As these shocks pertain to the EU ETS, we restrict the analysis to firms domiciled in the EU that fall under the EU ETS and are thus directly affected by these regulatory surprises.[56] We use the contemporaneous carbon policy shock,

[56]We exclude Luxembourg-domiciled firms, as it is common for companies to be legally domiciled in Luxembourg while their actual operations, and corresponding ETS obligations, are located elsewhere. This can lead to a discrepancy between the company's reported location and its true policy exposure.

Table 9: Carbon Policy Surprises and Environmental Risk Pricing

*This table reports the OLS estimation results of Equation (1), estimated with firm and industry-time fixed effects and using various measures of green innovation. The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). We include Emission intensity, which is measured in $CO_2e/USDm$, the green patent ratio (%) and their interaction ('$EI \times GPR$'). '$EI \times Surprise$', respectively '$GPR \times Surprise$', '$EI \times GPR \times Surprise$' is the interaction of emission intensity, receptively the green patent ratio and the carbon policy surprise series from Känzig (2023). The surprises are absorbed by the time fixed effects. We further include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio, as well as bond characteristics, i.e., the outstanding amount, a dummy for fixed coupon bonds, a dummy for euro denominated bonds, and a dummy for green bonds. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

	Bond Yield Spreads$_{i,t}$	
	Average Surprises (1)	Cumulative Surprise (2)
$\text{EI}_{f,t-1} \times$ Surprise$_t$	0.041***	0.014***
	(0.013)	(0.004)
$\text{GPR}_{f,t-1} \times$ Surprise$_t$	0.044	0.015
	(0.106)	(0.035)
$\text{EI}_{f,t-1} \times \text{GPR}_{f,t-1} \times$ Surprise$_t$	-0.015*	-0.005*
	(0.009)	(0.003)
Corporate Fundamentals	Yes	Yes
Bond Characteristics	Yes	Yes
Firm-FEs	Yes	Yes
Industry-Time-FEs	Yes	Yes
Observations	10,581	10,581
R-squared	0.331	0.331

as these regulatory surprises are realized and publicly observed within the quarter, allowing markets to incorporate their effects into bond prices by quarter-end. We consider both the average carbon policy surprise as well as the cumulative carbon policy surprise over the quarter.

The results using the average carbon policy surprise over the quarter are reported in Column 1 of Table 9. The results consistently show that the carbon premium is higher when carbon policy surprises are larger. This is intuitive, as larger carbon policy surprises imply larger environmental compliance costs, which thus translate in higher bond yield spreads. Consistent with the option-value hypothesis, the findings in Column 1 also show that investors reward green innovation more in response to unexpected policy changes. Specifically, the combined effect of emission intensity and green innovation on bond yield spreads becomes stronger in periods during which carbon policy surprises are larger. This suggests that investors price green innovation, not as a guarantee of lower future emissions, but as a signal of reduced technological uncertainty for emission-intensive firms as they are transitioning to greener technologies. The results using the cumulative carbon policy surprise over the quarter, which are reported in Column 2 of Table 9, confirm these insights.

IV. Conclusion

The urgency to meet the temperature targets set by the Paris Agreement necessitates a shift towards net-zero emissions by 2050. Financial investors may anticipate the associated climate transition risks and could contribute to the green transition by providing cheaper financing for firms making an effort to transition towards greener technologies. We investigate whether European corporate bond investors have taken up this role in the years following the Paris Agreement. Specifically, we study whether corporate bond investors value companies' green innovation efforts in the presence of climate transition risk, and which investors do so. Recognizing that emission metrics are backward-looking, we complement emission intensity with a forward-looking measure, capturing firms' green relative to their overall patent portfolio. We examine whether bond markets price this interaction – penalizing firms for current emissions while rewarding those signaling efforts to transition through green innovation.

Our findings indicate that investors respond not only to current emission levels but also to efforts to reduce them, suggesting that investors perceive green innovation to carry option value. Specifically, we find that the carbon premium is significantly lower for emission-intensive firms that engage in green innovation activities. These results are robust across alternative specifications, including stricter green patent definitions, the use of blockbuster patents, and controls for broader investment and patenting activities. Importantly, the effects are also neither driven by eligibility nor purchases of corporate bonds under the ECB's Corporate Sector Purchase Programme.

We find that our results are consistent with rational risk pricing, as our effects are concentrated among firms with weak cash flow prospects and near-maturity bonds, where default risk is most salient. Moreover, we show that the pricing effects are stronger among firms with a higher exposure to aggregate climate risk - as measured by the Climate Beta.

The results from our demand estimation indicate that institutional investors, and mutual funds in particular, exhibit a higher demand for bonds issued by transitioning firms. Taken together, these findings underscore the importance of investors with greater risk-bearing capacity in supporting the green transition by channeling capital toward firms that, while currently emission-intensive, are actively investing in cleaner technologies, and thus are central to the green transition.

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Appendix A. Time-series properties

A1. Bond yields

We estimate the following second-order autoregressive panel data model:

$$\text{Yield to Maturity}_{i,t} = \rho_1 \text{Yield to Maturity}_{i,t-1} + \rho_2 \text{Yield to Maturity}_{i,t-2} + \varsigma_i + \alpha_t + \epsilon_{i,t}$$

where ς_i are bond fixed effects, and α_t are time fixed effects. We estimate the model by (i) pooled OLS, (ii) fixed effects OLS and (iii) first-differenced GMM. While pooled OLS only controls for time effects, fixed effects OLS and first-difference GMM also control for the bond specific effects. Standard errors are clustered at the bond-level.

Table A1: Testing for autocorrelation in bond yields

*This table shows the estimation results of our second-order autoregressive model for the yield to maturityintensity. We estimate the relation using (i) OLS, (ii) FEs, and (iii) GMM. We estimate the relation with bond and time fixed effects. Standard errors are clustered at the bond-level. ** p<0.05, * p<0.1.*

	OLS	FE	GMM
Yield to Maturity$_{i,t-1}$	0.768**	0.566**	0.559**
	(0.006)	(0.002)	(0.017)
Yield to Maturity$_{i,t-2}$	0.178**	0.115**	0.106**
	(0.006)	(0.002)	(0.007)

Table A1 shows that there is significant autocorrelation in yields, even when including fixed effects as well as when estimating the relationship using GMM. The pooled OLS estimate, which only corrects for aggregate time effects, suggests that bond yields are highly persistent over time. However, the fixed effects OLS and GMM estimates show that there is no reason to assume that bond yields are nonstationary. We therefore continue our estimation in levels, rather than in first-differences.

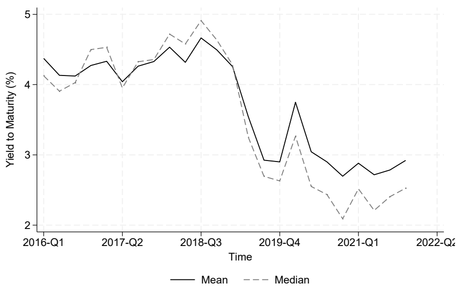

Figure A1: Evolution of bond yields

This figure shows the evolution of the mean and median yield to maturity, reported at the quarterly-frequency and bond-level over the sample period.

A2. Emission intensity

To assess the time series properties of emission intensity, we first collapse our sample to the firm-period level. We again use a second-order autoregressive model:

$$\text{Emission Intensity}_{f,t} = \rho_1 \text{Emission Intensity}_{f,t-1} + \rho_2 \text{Emission Intensity}_{f,t-2} + \eta_f + \alpha_t + \epsilon_{f,t}$$

where η_f are firm fixed effects and α_t are time fixed effects. We estimate the model by the same three methods as before and standard errors are clustered at the firm-level.

Table A2: Testing for autocorrelation in emission intensity yields

*This table shows the estimation results of our second-order autoregressive model for emission intensity. We estimate the relation using (i) OLS, (ii) FEs, and (iii) GMM. We estimate the relation with firm and time fixed effects. Standard errors are clustered at the firm-level. ** p<0.05, * p<0.1.*

	OLS	FE	GMM
Emission Intensity$_{f,t-1}$	0.667**	0.052**	0.081
	(0.101)	(0.022)	(0.311)
Emission Intensity$_{f,t-2}$	0.281**	-0.010	0.429**
	(0.097)	(0.023)	(0.127)

Table A2 displays the results. The pooled OLS estimate, which only corrects for aggregate time effects, suggests that emission intensity is persistent over time. However, the autocorrelation pattern weakens significantly when controlling for firm fixed effects, as is apparent from the fixed effects OLS and GMM estimates. There is no sign that the emission intensity variable is non-stationary as the autoregressive estimates are far from the unit root.

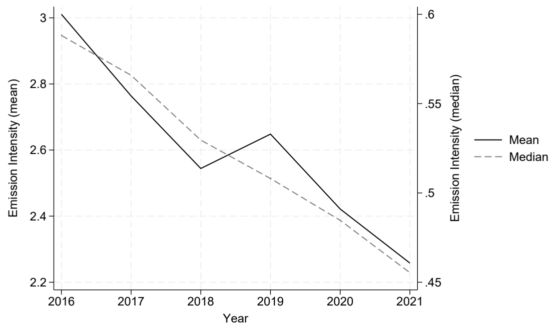

Figure A2: Evolution of emission intensity

This figure shows the evolution of the mean and median emission intensity, reported at the firm-year level over the sample period.

Appendix B. Additional summary statistics

Table B1: Distribution of observations across industries

This table reports the distribution of observations across GICS Industries. Observations are reported at the quarterly frequency and firm-level. We classify industries as tradable, non-tradable and others.

GICS Industry Name	Frequency	Percent	Classification
Aerospace & Defense	236	4.28	Tradable
Air Freight & Logistics	46	0.83	Tradable
Automobile Components	172	3.12	Tradable
Automobiles	213	3.86	Tradable
Beverages	66	1.20	Non-Tradable
Biotechnology	138	2.50	Tradable
Broadline Retail	54	0.98	Non-Tradable
Building Products	72	1.31	Tradable
Chemicals	448	8.13	Tradable
Commercial Services & Supplies	34	0.62	Non-Tradable
Communications Equipment	72	1.31	Tradable
Construction & Engineering	111	2.01	Non-Tradable
Construction Materials	29	0.53	Non-Tradable
Consumer Staples Distribution & Retail	105	1.90	Non-Tradable
Containers & Packaging	46	0.83	Tradable
Diversified Telecommunication Services	180	3.27	Other
Electric Utilities	368	6.68	Non-Tradable
Electrical Equipment	226	4.10	Tradable
Electronic Equipment, Instruments & Components	89	1.61	Tradable
Energy Equipment & Services	15	0.27	Tradable
Food Products	129	2.34	Tradable
Gas Utilities	46	0.83	Non-Tradable
Ground Transportation	46	0.83	Non-Tradable
Health Care Equipment & Supplies	69	1.25	Tradable
Household Durables	71	1.29	Tradable
Household Products	21	0.38	Tradable
IT Services	62	1.12	Tradable
Independent Power and Renewable Electricity Producers	79	1.43	Non-Tradable
Industrial Conglomerates	80	1.45	Tradable
Leisure Products	20	0.36	Tradable
Life Sciences Tools & Services	9	0.16	Tradable
Machinery	271	4.92	Tradable
Marine Transportation	39	0.71	Tradable
Media	46	0.83	Non-Tradable
Metals & Mining	285	5.17	Tradable
Multi-Utilities	87	1.58	Non-Tradable
Oil, Gas & Consumable Fuels	339	6.15	Tradable
Paper & Forest Products	95	1.72	Tradable
Personal Care Products	19	0.34	Tradable
Pharmaceuticals	267	4.84	Tradable
Real Estate Management & Development	30	0.54	Non-Tradable
Semiconductors & Semiconductor Equipment	311	5.64	Tradable
Software	88	1.60	Tradable
Specialized REITs	23	0.42	Non-Tradable
Technology Hardware, Storage & Peripherals	99	1.80	Tradable
Textiles, Apparel & Luxury Goods	23	0.42	Tradable
Tobacco	20	0.36	Tradable
Trading Companies & Distributors	73	1.32	Tradable
Wireless Telecommunication Services	46	0.83	Non-Tradable

Table B2: Emission intensity and green patents across industries (mean)

This table reports the mean emission intensity, green patent ratio (%), and green patents for each GIC industry. Observations are reported at the quarterly frequency and firm-level.

GICS Industry Name	Emission Intensity	Green Patent Ratio	Green Patents
Aerospace & Defense	0.291	0.104	16.458
Air Freight & Logistics	1.466	0.106	3.848
Automobile Components	1.131	0.238	165.512
Automobiles	0.264	2.336	6782.850
Beverages	0.648	0.528	39.636
Biotechnology	0.291	0.235	15.659
Broadline Retail	0.322	0.864	7.796
Building Products	1.029	0.571	74.014
Chemicals	5.643	0.427	61.598
Commercial Services & Supplies	0.365	0.334	127.206
Communications Equipment	0.162	0.024	55.681
Construction & Engineering	0.496	1.428	13.631
Construction Materials	19.940	1.041	9.172
Consumer Staples Distribution & Retail	0.543	0.693	2.762
Containers & Packaging	1.469	0.104	4.500
Diversified Telecommunication Services	0.402	0.669	305.822
Electric Utilities	12.601	5.644	377.690
Electrical Equipment	0.737	2.607	233.611
Electronic Equipment, Instruments & Components	0.812	0.571	455.090
Energy Equipment & Services	1.163	1.146	1.667
Food Products	0.849	2.087	4.682
Gas Utilities	2.667	2.961	49.978
Ground Transportation	1.457	2.735	208.109
Health Care Equipment & Supplies	0.237	0.122	364.015
Household Durables	0.352	1.165	9256.761
Household Products	0.307	0.083	75.381
IT Services	0.130	1.871	156.468
Independent Power & Renewable Electricity Producers	16.167	2.309	24.848
Industrial Conglomerates	5.458	0.795	1836.225
Leisure Products	0.453	1.456	517.500
Life Sciences Tools & Services	0.384	0.038	3.111
Machinery	0.369	1.459	558.096
Marine Transportation	11.007	0.433	1.641
Media	0.120	0.209	3.000
Metals & Mining	9.319	2.752	30.705
Multi-Utilities	1.939	1.869	2.770
Oil, Gas & Consumable Fuels	5.455	1.245	24.749
Paper & Forest Products	3.327	0.352	26.053
Personal Care Products	0.331	0.011	8.000
Pharmaceuticals	0.362	0.175	62.648
Real Estate Management & Development	0.449	0.471	3.967
Semiconductors & Semiconductor Equipment	1.939	1.936	70.473
Software	0.120	0.100	3.886
Specialized REITs	1.565	0.035	2.000
Technology Hardware, Storage & Peripherals	0.182	0.172	623.879
Textiles, Apparel & Luxury Goods	0.078	0.062	22.174
Tobacco	0.387	0.437	114.700
Trading Companies & Distributors	1.026	1.508	129.370
Wireless Telecommunication Services	0.414	0.748	151.978
Total	3.143	1.403	538.786

Table B3: Emission intensity and green patents across industries (median)

This table reports the median emission intensity, green patent ratio (%), and green patents for each GIC industry. Observations are reported at the quarterly frequency and firm-level.

GICS Industry Name	Emission Intensity	Green Patent Ratio	Green Patents
Aerospace & Defense	0.220	0.038	4.000
Air Freight & Logistics	1.352	0.132	5.500
Automobile Components	0.563	0.066	8.000
Automobiles	0.243	0.641	366.000
Beverages	0.477	0.171	19.000
Biotechnology	0.311	0.071	10.000
Broadline Retail	0.285	0.216	3.000
Building Products	0.777	0.072	62.000
Chemicals	4.043	0.046	10.000
Commercial Services & Supplies	0.339	0.022	1.000
Communications Equipment	0.177	0.022	68.000
Construction & Engineering	0.398	0.971	2.000
Construction Materials	19.940	0.051	3.000
Consumer Staples Distribution & Retail	0.515	0.452	2.000
Containers & Packaging	1.424	0.098	4.500
Diversified Telecommunication Services	0.373	0.211	6.000
Electric Utilities	13.960	4.762	10.000
Electrical Equipment	0.466	0.073	11.000
Electronic Equipment, Instruments & Components	0.292	0.323	15.000
Energy Equipment & Services	1.111	0.055	1.000
Food Products	0.630	0.037	2.000
Gas Utilities	3.008	2.604	40.500
Ground Transportation	1.379	2.550	189.500
Health Care Equipment & Supplies	0.131	0.132	7.000
Household Durables	0.349	1.083	5923.000
Household Products	0.309	0.082	75.000
IT Services	0.143	0.090	10.000
Independent Power & Renewable Electricity Producers	19.940	1.639	8.000
Industrial Conglomerates	0.637	0.072	6.000
Leisure Products	0.365	0.749	232.000
Life Sciences Tools & Services	0.284	0.058	2.000
Machinery	0.390	0.031	10.000
Marine Transportation	11.756	0.250	3.000
Media	0.130	0.207	3.000
Metals & Mining	7.456	0.344	8.000
Multi-Utilities	1.399	1.333	1.000
Oil, Gas & Consumable Fuels	4.884	0.344	12.000
Paper & Forest Products	3.074	0.449	35.000
Personal Care Products	0.332	0.011	8.000
Pharmaceuticals	0.242	0.039	25.000
Real Estate Management & Development	0.388	0.814	7.000
Semiconductors & Semiconductor Equipment	0.752	0.046	13.000
Software	0.099	0.019	4.000
Specialized REITs	1.526	0.035	2.000
Technology Hardware, Storage & Peripherals	0.110	0.055	3.000
Textiles, Apparel & Luxury Goods	0.083	0.058	22.000
Tobacco	0.391	0.499	123.000
Trading Companies & Distributors	0.735	1.634	149.000
Wireless Telecommunication Services	0.385	0.848	172.000
Total	0.568	0.153	8.000

Table B4: Distribution of observations across countries

This table reports the distribution of observations across countries. Observations are reported at the quarterly frequency and firm-level.

Country	Frequency	Percent
United Arab Emirates	23	0.42
Austria	58	1.05
Australia	22	0.40
Belgium	94	1.71
Brazil	72	1.31
Canada	135	2.45
Chile	23	0.42
China	167	3.03
Colombia	23	0.42
Czech Republic	23	0.42
Germany	401	7.27
Denmark	23	0.42
Finland	210	3.81
France	383	6.95
Hong Kong	23	0.42
Hungary	23	0.42
India	136	2.47
Italy	160	2.90
Japan	640	11.61
South Korea	220	3.99
Luxembourg	54	0.98
Malaysia	23	0.42
Netherlands	162	2.94
Norway	164	2.97
New Zealand	23	0.42
Philippines	6	0.11
Poland	24	0.44
Russia	87	1.58
Saudi Arabia	7	0.13
Spain	122	2.21
Sweden	218	3.95
Switzerland	194	3.52
Singapore	13	0.24
Thailand	9	0.16
Turkey	50	0.91
Taiwan	39	0.71
United Kingdom	181	3.28
United States	1,278	23.18

Appendix C. Carbon premium regression

Table C1: Effect of Emission Intensity on Yield Spreads

*This results the OLS estimation results for our "Carbon Premium" regression. The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). We exploit three different sets of fixed effects, i.e., time fixed effects (Column 1-3), firm fixed effects and time fixed effect (Column 4-6), and firm fixed effects and industry-time fixed effects (Column 7-9). For each set of fixed effects, the first Column reports the results of a simple regression using emission intensity as explanatory variable, which is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The second Column reports the results when including control variables. We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio, as well as bond characteristics, i.e., the outstanding amount, a dummy which indicates if the bond has a fixed coupon, a dummy which indicates whether the bond is denominated in euro. The third Column additionally controls for whether a bond has a green bond label. Standard errors are reported in parentheses and are clustered at the industry-level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

	Bond Yield Spreads$_{i,t}$								
	Time FEs			Firm + Time FEs			Firm + Industry-Time FEs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Emission Intensity$_{f,t-1}$	0.114***	0.090**	0.090**	0.130**	0.128**	0.129**	0.132*	0.149*	0.150**
	(0.035)	(0.036)	(0.036)	(0.055)	(0.056)	(0.056)	(0.067)	(0.076)	(0.075)
Green Bond$_{i,t-1}$			-0.430**			-0.474**			-0.469**
			(0.175)			(0.194)			(0.204)
Corporate Fundamentals	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Bond Characteristics	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No
Firm-FEs	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	No	No	No	No	No	No	Yes	Yes	Yes
Observations	39,046	39,046	39,046	39,014	39,014	39,014	38,954	38,954	38,954
R-squared	0.159	0.228	0.229	0.442	0.456	0.457	0.523	0.538	0.539

Appendix D. Robustness and additional tests for Equation (1)

D1. Dynamic plot of the main coefficient

Figure D1: Dynamic coefficient plot

This Figure dynamically plots the coefficient for the interaction of emission intensity and the green patent ratio ($EI \times GPR$), along with the 90 percent confidence intervals. The reference period is 2016.

D2. Alternative yield measures

D2.A. Duration-Matched Bond Yield Spreads

Table D1: Effect of Emission Intensity and Green Patenting on Yield Spreads

*This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the duration-matched yield spread (YTM in excess of the duration-matched risk-free rate). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. '$EI \times GPR$' is the interaction of emission intensity and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio, revenue) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.160*		0.160*	0.174**	0.174**
	(0.089)		(0.089)	(0.086)	(0.086)
Green Patent Ratio$_{f,t-1}$		0.077	0.074	0.365**	0.358**
		(0.055)	(0.062)	(0.154)	(0.152)
EI$_{f,t-1}$×GPR$_{f,t-1}$				-0.022**	-0.021**
				(0.009)	(0.009)
Green Bond$_{i,t-1}$					-0.848**
					(0.319)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	30,346	30,346	30,346	30,346	30,346
R-squared	0.379	0.375	0.379	0.380	0.383

(b) Firm and Industry-Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.194*		0.194*	0.228***	0.230***
	(0.100)		(0.101)	(0.084)	(0.082)
Green Patent Ratio$_{f,t-1}$		0.032	0.015	0.444**	0.446**
		(0.019)	(0.031)	(0.216)	(0.210)
EI$_{f,t-1}$ × GPR$_{f,t-1}$				-0.029**	-0.029**
				(0.011)	(0.011)
Green Bond$_{i,t-1}$					-0.844**
					(0.334)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	30,299	30,299	30,299	30,299	30,299
R-squared	0.459	0.456	0.459	0.460	0.463

D2.B. Expected Bond Yields

Table D2: Effect of Emission Intensity and Green Patenting on Yield Spreads

This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the expected yield (YTM corrected for the expected default loss). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. '$EI \times GPR$' is the interaction of emission intensity and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio, revenue) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.191		0.196	0.247*	0.247*
	(0.136)		(0.136)	(0.145)	(0.145)
Green Patent Ratio$_{f,t-1}$		0.268	0.355	0.848**	0.845**
		(0.209)	(0.254)	(0.324)	(0.328)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-0.044*	-0.043*
				(0.023)	(0.023)
Green Bond$_{i,t-1}$					-0.449**
					(0.179)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	16,929	16,929	16,929	16,929	16,929
R-squared	0.533	0.529	0.533	0.534	0.535

(b) Firm and Industry-Time Fixed Effects

	Bond Yields$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.106		0.118	0.235*	0.237*
	(0.117)		(0.121)	(0.137)	(0.135)
Green Patent Ratio$_{f,t-1}$		0.229	0.305	1.032***	1.046***
		(0.189)	(0.244)	(0.367)	(0.371)
EI$_{f,t-1}$ $\times$ GPR$_{f,t-1}$				-0.051**	-0.051**
				(0.022)	(0.022)
Green Bond$_{i,t-1}$					-0.484***
					(0.152)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	16,888	16,888	16,888	16,888	16,888
R-squared	0.703	0.702	0.703	0.704	0.704

D2.C. Expected Yield Spreads

Table D3: Effect of Emission Intensity and Green Patenting on Yield Spreads

*This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the expected yield spread (YTM in excess of the risk-free rate, corrected for the expected default loss). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in CO_2e/USDm. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. 'EI × GPR' is the interaction of emission intensity and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio, revenue) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.196		0.200	0.249	0.249
	(0.141)		(0.142)	(0.149)	(0.149)
Green Patent Ratio$_{f,t-1}$		0.158	0.247	0.723**	0.718**
		(0.143)	(0.182)	(0.310)	(0.311)
EI$_{f,t-1}$×GPR$_{f,t-1}$				-0.042*	-0.041*
				(0.022)	(0.022)
Green Bond$_{i,t-1}$					-0.689***
					(0.213)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	16,929	16,929	16,929	16,929	16,929
R-squared	0.465	0.460	0.466	0.467	0.468

(b) Firm and Industry-Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.108		0.116	0.231	0.234
	(0.129)		(0.133)	(0.142)	(0.140)
Green Patent Ratio$_{f,t-1}$		0.145	0.221	0.931**	0.951**
		(0.135)	(0.187)	(0.367)	(0.353)
EI$_{f,t-1}$ × GPR$_{f,t-1}$				-0.049**	-0.050**
				(0.022)	(0.021)
Green Bond$_{i,t-1}$					-0.710***
					(0.201)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
	16,888	16,888	16,888	16,888	16,888
R-squared	0.696	0.695	0.696	0.698	0.699

D2.D. Yield to Maturity

Table D4: Effect of Emission Intensity and Green Patenting on Yield Spreads

This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the yield to maturity. Emission intensity is defined as scope 1 and scope 2 CO_2 *emissions relative to the firm's revenue and is measured in* $CO_2e/USDm$*. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. 'EI* $\times$ *GPR' is the interaction of emission intensity and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. **** $p < 0.01$*, *** $p < 0.05$*, ** $p < 0.1$*.*

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.119*		0.118*	0.133**	0.134**
	(0.060)		(0.060)	(0.059)	(0.059)
Green Patent Ratio$_{f,t-1}$		0.206	0.203	0.466***	0.466***
		(0.133)	(0.136)	(0.138)	(0.139)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-0.021***	-0.021***
				(0.007)	(0.008)
Green Bond$_{i,t-1}$					-0.245
					(0.174)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	39,016	39,016	39,016	39,016	39,016
R-squared	0.523	0.520	0.523	0.523	0.524

(b) Firm and Industry-Time Fixed Effects

	Bond Yield to Maturity$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.133		0.132	0.174**	0.175**
	(0.082)		(0.081)	(0.071)	(0.070)
Green Patent Ratio$_{f,t-1}$		0.165	0.153	0.594***	0.595***
		(0.123)	(0.122)	(0.152)	(0.154)
EI$_{f,t-1}$ $\times$ GPR$_{f,t-1}$				-0.031***	-0.031***
				(0.010)	(0.010)
Green Bond$_{i,t-1}$					-0.244
					(0.186)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	38,956	38,956	38,956	38,956	38,956
R-squared	0.585	0.583	0.585	0.586	0.586

A. D3. Standardized coefficients

Table D5: Effect of Emission Intensity and Green Patenting on Yield Spreads

*This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total and is measured in %. We standardize emission intensity green patent ratio using their sample mean and standard deviation. 'EI $\times$ GPR' is the interaction of emission intensity and the green patent ratio (which are both standardized). Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.602**		0.601**	0.593**	0.594**
	(0.263)		(0.261)	(0.229)	(0.228)
Green Patent Ratio$_{f,t-1}$		0.481	0.472	1.027***	1.028***
		(0.302)	(0.306)	(0.238)	(0.243)
EI$_{f,t-1}$×GPR$_{f,t-1}$				-0.256***	-0.254***
				(0.074)	(0.075)
Green Bond$_{i,t-1}$					-0.474**
					(0.188)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	39,014	39,014	39,014	39,014	39,014
R-squared	0.456	0.452	0.456	0.457	0.458

(b) Firm and Industry-Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.699*		0.695*	0.781***	0.787***
	(0.356)		(0.355)	(0.262)	(0.256)
Green Patent Ratio$_{f,t-1}$		0.300	0.267	1.154***	1.160***
		(0.261)	(0.255)	(0.218)	(0.217)
EI$_{f,t-1}$×GPR$_{f,t-1}$				-0.355***	-0.355***
				(0.082)	(0.081)
Green Bond$_{i,t-1}$					-0.471**
					(0.200)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Observations	38,954	38,954	38,954	38,954	38,954
R-squared	0.538	0.535	0.538	0.539	0.540

D4. Full sample of patenting firms

Table D6: Summary statistics

This table reports summary statistics for our sample, based on 90,807 observations reported at quarterly frequency and the security-by-security level. Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in CO_2e/USDm. Emission intensity is scaled by a factor 1/100 and winsorized at the 2.5 percent level. Absolute emissions is defined as scope 1 and 2 emissions, which is measured in CO_2e and is reported in natural logarithms. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total and is scaled by a factor 100. Yield to maturity is winsorized at the 99th percentile. Fixed coupon is a dummy which is equal to 1 if a bond has a fixed coupon. EUR respectively USD are dummy variables, which are equal to 1 if a bond is denominated in euros respectively dollars. Green bond is a dummy which is equal to 1 if a bond has a green bond label. The profitability-ratio is defined as net income dividend by total assets (ROA). Leverage is defined as total debt divided by total assets. The cash- and investment ratio are defined as cash and capital expenditures divided by total assets, respectively. All ratio's are reported in percentages.

	Mean	Median	SD	P10	P90
Environmental Variables					
(Scope1 + Scope2) Emission Intensity	2.534	0.457	4.598	0.109	8.399
(Scope1 + Scope2) Absolute Emissions (in log)	13.827	13.870	2.313	10.895	16.962
Green Patent Ratio (%)	0.316	0.001	1.443	0.001	0.356
Bond Characteristics					
Yield to Maturity (%)	2.574	2.237	2.652	0.037	5.218
Spread (%)	2.037	1.351	2.441	0.415	4.280
Bond Holding Value (in m EUR)	170.161	50.522	260.312	1.914	527.817
Amount Outstanding (in m EUR)	580.535	467.290	510.255	88.757	1150
Fixed Coupon	0.915	1	0.279	1	1
EUR	0.334	0	0.472	0	1
USD	0.499	0	0.500	0	1
Green bond	0.015	0	0.123	0	0
Corporate Fundamentals					
Revenue (in bn EUR)	37.485	15.614	63.990	1.654	84.853
Total Assets (in bn EUR)	62.426	28.475	80.191	3.852	171.75
Total Debt (in bn EUR)	21.191	9.611	28.190	1.213	56.846
Profitability-Ratio (%)	4.754	4.166	6.154	-0.587	11.144
Leverage-Ratio (%)	36.070	35.138	14.574	19.218	54.578
Cash-Ratio (%)	6.452	2.988	10.463	0.385	14.379
Investment-Ratio (%)	13.208	6.875	17.711	0.913	34.986

Table D7: Effect of Emission Intensity and Green Patenting on Yield Spreads

*This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. '$EI \times GPR$' is the interaction of emission intensity and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.105*		0.105*	0.112*	0.109*
	(0.059)		(0.059)	(0.061)	(0.062)
Green Patent Ratio$_{f,t-1}$		0.216	0.212	0.465***	0.462***
		(0.135)	(0.136)	(0.143)	(0.147)
EI$_{f,t-1}$×GPR$_{f,t-1}$				-0.020**	-0.020**
				(0.008)	(0.008)
Green Bond$_{i,t-1}$					-0.283***
					(0.090)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	90,885	90,867	90,867	90,867	90,867
R-squared	0.549	0.546	0.549	0.549	0.549

(b) Firm and Industry-Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.114		0.113	0.124	0.123
	(0.079)		(0.079)	(0.080)	(0.080)
Green Patent Ratio$_{f,t-1}$		0.112	0.094	0.353**	0.349**
		(0.095)	(0.094)	(0.153)	(0.156)
EI$_{f,t-1}$×GPR$_{f,t-1}$				-0.019**	-0.018*
				(0.009)	(0.009)
Green Bond$_{i,t-1}$					-0.297***
					(0.082)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Observations	90,807	90,807	90,807	90,807	90,807
R-squared	0.589	0.587	0.589	0.589	0.589

D5. Absolute scope 1 and 2 emissions

Table D8: Effect of Emission Intensity and Green Patenting on Yield Spreads

*This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). Absolute Emissions is defined as scope 1 and scope 2 emissions, measured in CO_2e, and is measured as natural logarithms. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total and is measured in %. 'Abs × GPR' is the interaction of absolute scope 1+2 emissions and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Absolute Emissions$_{f,t-1}$	0.139*		0.148**	0.190**	0.189**
	(0.073)		(0.067)	(0.085)	(0.085)
Green Patent Ratio$_{f,t-1}$		0.206	0.215*	0.915**	0.926**
		(0.124)	(0.127)	(0.403)	(0.408)
Abs$_{f,t-1}$×GPR$_{f,t-1}$				-0.043*	-0.043*
				(0.025)	(0.025)
Green Bond$_{i,t-1}$					-0.473**
					(0.190)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	39,014	39,014	39,014	39,014	39,014
R-squared	0.452	0.452	0.453	0.453	0.454

(b) Firm and Industry-Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Absolute Emissions$_{f,t-1}$	0.251**		0.254**	0.304**	0.304**
	(0.121)		(0.120)	(0.129)	(0.129)
Green Patent Ratio$_{f,t-1}$		0.126	0.132	1.206***	1.233***
		(0.109)	(0.110)	(0.448)	(0.440)
Abs$_{f,t-1}$ × GPR$_{f,t-1}$				-0.064**	-0.065***
				(0.024)	(0.024)
Green Bond$_{i,t-1}$					-0.461**
					(0.198)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	38,954	38,954	38,954	38,954	38,954
R-squared	0.536	0.535	0.536	0.536	0.537

D6. Robustness to General Investments and CSPP

Table D9: General investments and CSPP

*This table reports the OLS estimation results of robustness tests for Equation (1), estimated with firm and industry-time fixed effects. The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in $CO_2e/USDm$. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. '$EI \times GPR$' is the interaction of emission intensity and the green patent ratio. Patents is the natural logarithm of the total number of patents filed by a firm. '$EI \times Invest$' is the interaction of emission intensity and the investment ratio, one of our control variables. The R&D-ratio measures the firm's annual R&D expenditures relative to its annual revenue (obtained from Orbis) and '$EI \times R\&D-ratio$' is the interaction of emission intensity and the firm's R&D-ratio. CSPP is a dummy which indicates whether a bond is eligible for purchase under CSPP (Column 4) or whether the bond has been purchased under the CSPP (Column 5). "$EI \times GPR' \times CSPP'$ is the interaction of emission intensity, the green patent ratio and the CSPP-dummy. While not shown, we include all pairwise interactions as controls. We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio, as well as bond characteristics, i.e., the outstanding amount, a dummy for fixed coupon bonds, a dummy for euro denominated bonds, and a dummy for green bonds. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

	Investments and Innovation			CSPP	
	(1)	(2)	(3)	(4)	(5)
	Patents	Investments	R&D	Eligibility	Purchase-dummy
Emission Intensity$_{f,t-1}$	0.197***	0.215**	0.178***	0.192***	0.188***
	(0.061)	(0.088)	(0.039)	(0.065)	(0.061)
Green Patent Ratio$_{f,t-1}$	0.554***	0.518***	0.588***	0.516***	0.530***
	(0.099)	(0.091)	(0.105)	(0.100)	(0.094)
EI$_{f,t-1}\times$ GPR$_{f,t-1}$	-0.031***	-0.028***	-0.032***	-0.029***	-0.029***
	(0.007)	(0.004)	(0.008)	(0.007)	(0.006)
Patents$_{f,t-1}$	-0.535				
	(0.335)				
EI$_{f,t-1}\times$ Invest-Ratio$_{f,t-1}$		-0.363			
		(0.435)			
R&D-Ratio$_{f,t-1}$			0.787		
			(1.469)		
EI$_{f,t-1}\times$ R&D-Ratio$_{f,t-1}$			2.694		
			(2.001)		
CSPP$_{i,t-1}$				-0.376***	-0.479***
				(0.130)	(0.110)
EI$_{f,t-1}\times$ GPR$_{f,t-1}\times$ CSPP$_{i,t-1}$				-0.008	-0.116
				(0.075)	(0.106)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Double Interactions	-	-	-	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Observations	38,954	38,954	32,897	38,954	38,954
R-squared	0.541	0.541	0.496	0.545	0.546

D7. Evolution of bond supply

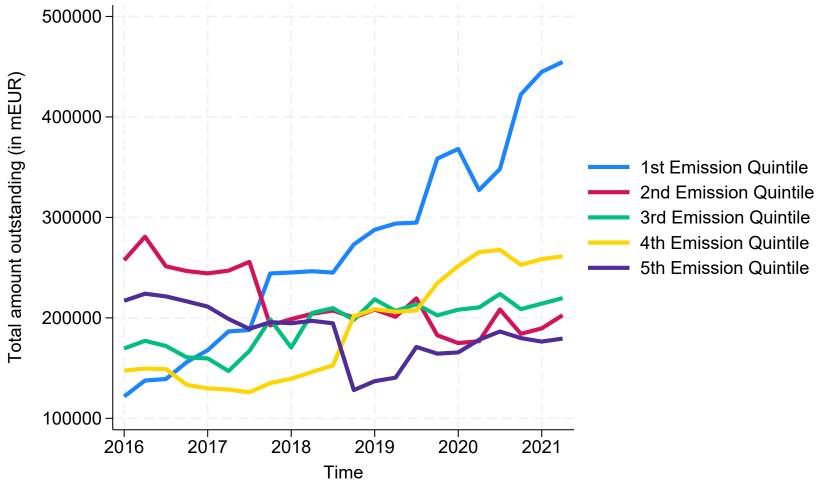

Figure D2: Evolution of bond supply

This figure shows the evolution of the total amount outstanding (in m EUR) by emission quintile over our sample period.

D8. Main results excluding the utilities sector

Table D10: Effect of Emission Intensity and Green Patenting on Yield Spreads

This table reports the OLS estimation results of Equation (1) with firm and time fixed effects (Panel A) and firm and industry-time fixed effects (Panel B). The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). Emission intensity is defined as scope 1 and scope 2 CO_2 emissions relative to the firm's revenue and is measured in CO_2e/USDm. The green patent ratio is defined as the number of green patents filed by a given firm relative to the number of patents filed in total, and is measured in %. 'EI $\times$ GPR' is the interaction of emission intensity and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. We include a set of corporate fundamentals (profitability-ratio, leverage-ratio, cash-ratio, investment-ratio) as well as bond characteristics (outstanding amount, fixed coupon dummy, euro denomination dummy). Standard errors are reported in parentheses and are clustered at the industry-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

(a) Firm and Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.223***		0.219***	0.225***	0.225***
	(0.032)		(0.033)	(0.032)	(0.033)
Green Patent Ratio$_{f,t-1}$		0.521***	0.428**	0.602***	0.608***
		(0.154)	(0.195)	(0.129)	(0.127)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-0.034***	-0.035***
				(0.008)	(0.008)
Green Bond$_{i,t-1}$					-0.218***
					(0.047)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Observations	33,693	33,693	33,693	33,693	33,693
R-squared	0.489	0.483	0.490	0.490	0.490

(b) Firm and Industry-Time Fixed Effects

	Bond Yield Spreads$_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.259***		0.255***	0.265***	0.265***
	(0.028)		(0.030)	(0.026)	(0.026)
Green Patent Ratio$_{f,t-1}$		0.454**	0.368	0.594***	0.597***
		(0.189)	(0.256)	(0.129)	(0.128)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-0.038***	-0.038***
				(0.007)	(0.007)
Green Bond$_{i,t-1}$					-0.192***
					(0.036)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes
Observations	33,648	33,648	33,648	33,648	33,648
R-squared	0.587	0.582	0.587	0.587	0.587

Appendix E. Holdership dynamics

E1. Evolution of the holder-shares

Table E1: Evolution of holder-shares (unscaled)

This table provides summary statistics on the holder shares, based on a sample of 38,987 observations reported at quarterly frequency and bond-level. We distinguish between EU-holders, institutional investors (insurance companies, mutual funds, pension funds), and banks. The (unscaled) holder-share is defined as the holdings of a specific European investor sector of a given bond relative to the total amount outstanding (at market values) in a given period.

Period	EU	Instit.	Insur.	Mfund	Pfund	Bank
2016-Q2	0.357	0.298	0.158	0.135	0.010	0.033
2016-Q3	0.353	0.296	0.154	0.137	0.010	0.032
2016-Q4	0.353	0.295	0.157	0.133	0.011	0.032
2017-Q1	0.353	0.301	0.162	0.137	0.013	0.034
2017-Q2	0.347	0.295	0.159	0.134	0.012	0.034
2017-Q3	0.343	0.291	0.156	0.133	0.012	0.034
2017-Q4	0.336	0.287	0.148	0.136	0.012	0.032
2018-Q1	0.333	0.286	0.149	0.134	0.012	0.031
2018-Q2	0.325	0.278	0.140	0.134	0.012	0.031
2018-Q3	0.327	0.281	0.142	0.135	0.012	0.031
2018-Q4	0.325	0.278	0.142	0.131	0.012	0.033
2019-Q1	0.320	0.274	0.137	0.131	0.012	0.032
2019-Q2	0.332	0.283	0.142	0.136	0.012	0.034
2019-Q3	0.323	0.276	0.136	0.134	0.012	0.033
2019-Q4	0.322	0.276	0.139	0.133	0.013	0.033
2020-Q1	0.312	0.268	0.133	0.128	0.012	0.031
2020-Q2	0.313	0.269	0.133	0.128	0.013	0.031
2020-Q3	0.304	0.263	0.126	0.129	0.013	0.029
2020-Q4	0.298	0.261	0.126	0.135	0.019	0.031
2021-Q1	0.299	0.259	0.125	0.129	0.017	0.030
2021-Q2	0.293	0.256	0.126	0.126	0.016	0.031
2021-Q3	0.288	0.250	0.121	0.124	0.016	0.031
2021-Q4	0.286	0.249	0.120	0.122	0.017	0.031
Total	0.322	0.275	0.139	0.132	0.013	0.032

Table E2: Bond Yield Spreads and Holder Dynamics

*This table reports the OLS estimation results of Equation (3), estimated with industry-time fixed effects. The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk-free rate). We include Emission intensity, which is measured in $CO_2e/USDm$, the green patent ratio (%) and their interaction ('$EI \times GPR$'). The first Column reports the effect of EU-holdership, which is measured as the total bond value held by EU-investors as a fraction of the amount outstanding. $'EI \times GPR \times EU'$ is the interaction of emission intensity, the green patent ratio and the EU-share. While not reported, we include all pairwise interactions as controls. We re-estimate Equation (3) using the share of institutional investors in Column 2, the share of holdings of insurance companies in Column 3, the share of holdings of mutual funds in Column 4, the share of holdings of pension funds in Column 5, the share of holdings of banks in Column 6, and we include the share of each institutional investor (including banks) separately in Column 7. We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio, as well as bond characteristics, i.e., the outstanding amount, a dummy which indicates if the bond has a fixed coupon, a dummy which indicates whether the bond is denominated in euro, and a dummy for green bonds. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

	Bond Yield Spreads$_{i,t}$						
	EU (1)	Instit. (2)	Insur. (3)	Mfund (4)	Pfund (5)	Bank (6)	All (7)
EU-share$_{i,t-1}$	0.109						
	(0.127)						
EI$_{f,t-1}$×GPR$_{f,t-1}$xEU$_{i,t-1}$	-0.028***						
	(0.010)						
Instit.-share$_{i,t-1}$		0.213*					
		(0.126)					
EI$_{f,t-1}$×GPR$_{f,t-1}$xInstit.$_{i,t-1}$		-0.028***					
		(0.010)					
Insur.-share$_{i,t-1}$			-0.144				-0.194*
			(0.114)				(0.114)
EI$_{f,t-1}$×GPR$_{f,t-1}$xInsur.$_{i,t-1}$			-0.024**				0.004
			(0.011)				(0.011)
Mfund-share$_{i,t-1}$				0.576**			0.344**
				(0.284)			(0.155)
EI$_{f,t-1}$×GPR$_{f,t-1}$xMfund$_{i,t-1}$				-0.018**			-0.019***
				(0.008)			(0.006)
Pfund-share$_{i,t-1}$					0.216		0.033
					(0.158)		(0.102)
EI$_{f,t-1}$×GPR$_{f,t-1}$xPfund$_{i,t-1}$					-0.005		-0.009
					(0.012)		(0.014)
Bank-share$_{i,t-1}$						-0.227	-0.388***
						(0.140)	(0.126)
EI$_{f,t-1}$×GPR$_{f,t-1}$xBank$_{i,t-1}$						0.008	0.009
						(0.018)	(0.015)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Double Interactions	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	38,987	38,987	38,987	38,987	38,987	38,987	38,987
R-squared	0.448	0.447	0.456	0.448	0.446	0.446	0.465

E3. Summary statistics of the stock regressions

Table E3: Summary statistics

This table provides summary statistics for our stock return regressions, based on 11,611 observations reported at monthly frequency and the firm-level. Stock returns is winsorized at the 99th percentile. The RoE is defined as net income divided by shareholders' equity. The book-to-market ratio is defined as (book value per share times shares outstanding) divided by (market price per share times shares outstanding). The leverage ratio is defined as total debt over total assets. The investment ratio is defined as the year-over-year growth rate of tangible assets, and is winsorized at 2.5 percent. PPE is defined as tangible assets. Sales growth is defined as the year-over-year growth rate of the firm's revenue. EPS growth is defined as the annual change in the firm's EPS normalized by the firm's stock price. The market beta is defined as the CAPM beta calculated over a 12-month period using daily data. The volatility of the firm's stock is defined as the standard deviation of stock returns based on the past 12 months of monthly returns. All ratio's are reported in percentages.

	Mean	Median	SD	P10	P90
Stock Return (in %)	0.531	0.733	8.543	-8.149	9.382
Market Capitalization (in bEUR)	42.967	13.699	125.272	1.600	92.613
RoE	11.467	9.903	43.923	-5.374	30.290
Book to Market	0.610	0.484	0.538	0.114	1.207
Leverage-Ratio (%)	29.036	27.637	12.861	13.856	46.520
Investment-Ratio (%)	7.382	2.692	23.537	-11.211	28.006
PPE (in log)	8.437	8.558	1.714	6.147	10.615
Sales growth (%)	6.810	3.383	36.475	-14.704	28.705
EPS-growth (%)	0.285	0.253	19.554	-8.580	8.102
Beta	1.016	0.997	0.406	0.496	1.559
Volatility	0.075	0.063	0.043	0.034	0.130
Climate Innovations	0.089	0.013	0.375	-0.255	0.651

Table E4: Climate Beta

This table provides summary statistics of the Climate Beta, reported at quarterly frequency and the firm-level. Climate Beta is the firm-specific exposure to aggregate climate risk, measured as the innovations in the Climate Change News Index of Engle et al. (2020).

	Mean	Median	SD	P10	P90
Climate Beta	0.030	0.029	0.135	-0.079	0.142

Appendix F. Corporate environmental performance

A recent, growing literature studies whether green innovation improves environmental performance. Cohen et al. (2023) find that firms with lower ESG-scores are key innovators in the United States' green patent landscape. Also Leippold and Yu (2023) document that firms that engage in green innovation reduce carbon emissions over time. ElBannan and Löffler (2024) document a significantly negative relationship between the volume of issued green bonds and future carbon intensity. This effect is concentrated among financially constrained firms, highlighting that the issuance of green bonds relaxes financial constraints, which enhances green innovations by issuing firms.

On the contrary, Bolton et al. (2023) find that there is path-dependency in innovation, as green innovation is predominantly undertaken by firms that are already green, while brown firms tend to innovate in brown technologies. Consequently, they find that green innovation does not reduce carbon emissions. This is confirmed by Dugoua and Gerarden (2025) and Hege et al. (2024).

Following Bolton et al. (2023), we estimate the impact of green innovation on corporate environmental performance by linking a companies' future emissions to its contemporaneous green innovation activity. That is, we estimate the following regression at the firm-year level:

$$\text{Environ. Performance}_{f,t} = \beta \text{Green Patent}_{f,t-h} + \delta' X_{f,t-1} + \eta_f + \lambda_t + \upsilon_{f,t} \tag{F.1}$$

where we use absolute scope 1 and 2 emissions (in logarithms) as our main measure of environmental performance. We also verify the robustness of the results against using emission intensity as measure of environmental performance. We use either the green patent ratio as main explanatory variable in Equation (F.1) or the amount of green patents (in logarithms). We include the vector of corporate fundamentals ($X_{f,t}$) and incorporate firm- (η_f) and time-fixed effects (λ_t).[57] For the regressions with absolute scope 1 and 2 emissions as dependent variable, we additionally include revenue (in logarithms) as control variable. We estimate the effect over a horizon of one-, two- and three-years, i.e., $h \in \{1, 2, 3\}$. As before, standard errors are clustered at the industry-level. In each specification, Column 1-3 report the results when considering the green patent ratio as explanatory variable, and Column 4-6 report the results when using the (logarithms) number of green patents as explanatory variable.

F1. Absolute emissions

Following Bolton et al. (2023), we estimate the impact of green innovation on corporate environmental performance by linking a companies' future emissions to its contemporaneous green innovation activity. As shown in Table F1, we fail to find evidence that an increase in the amount of green patents leads to lower emissions. The estimates in Column 1-3 indicate that the green patent ratio is mostly positively associated with a company's future emissions. However, the relationship is statistically insignificant at

[57] Remark that firm-fixed effects control for the average emission intensity of a given company over the sample period.

Table F1: Linking green patenting to environmental performance

*This table reports the OLS estimation results of Equation (F.1), estimated with firm- and time fixed effects. We estimate the relationship between the natural logarithm of absolute scope 1 and 2 emissions (measured in CO_2e) and the 1-, 2- and 3-year lag of the green patent ratio (measured in %, Column 1-3), and the amount of green patents (measured in natural logarithms, Column 4-6). We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, investment-ratio, and the natural logarithm of revenue. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

	Absolute Scope 1 and 2 Emissions$_{f,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Green Patent Ratio$_{f,t-1}$	0.045					
	(0.034)					
Green Patent Ratio$_{f,t-2}$		-0.016				
		(0.033)				
Green Patent Ratio$_{f,t-3}$			0.055			
			(0.097)			
Green Patents$_{f,t-1}$				0.117		
				(0.095)		
Green Patents$_{f,t-2}$					0.117	
					(0.133)	
Green Patents$_{f,t-3}$						0.036
						(0.156)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,321	987	700	1,223	907	638
R-squared	0.959	0.958	0.960	0.966	0.967	0.970

the one- and two- and three-year horizon for the green patent ratio. We find comparable results when considering the number of green patents as explanatory variable.

F2. Emission Intensity

We verify the robustness of our results using emission intensity as outcome variable in Table F2. Again, we find no evidence that the green patent ratio or the number of green patents is associated with future emission intensities. This suggests that green innovation is not associated either with an improvement in the production efficiency of firms, at the horizons we consider.

Table F2: Linking green patenting to environmental performance

*This table reports the OLS estimation results of Equation (F.1), estimated with firm- and time fixed effects. We estimate the relationship between emission intensity (measured in CO_2e/USDm) and the 1-, 2- and 3-year lag of the green patent ratio (measured in %, Column 1-3), and the amount of green patents (measured in natural logarithms, Column 4-6). We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, investment-ratio, and the natural logarithm of revenue. Standard errors are reported in parentheses and are clustered at the industry-level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.*

	Emission Intensity$_{f,t}$					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Green Patent Ratio$_{f,t-1}$	0.260					
	(0.155)					
Green Patent Ratio$_{f,t-2}$		0.221				
		(0.306)				
Green Patent Ratio$_{f,t-3}$			0.231			
			(0.442)			
Green Patents$_{f,t-1}$				0.323		
				(0.231)		
Green Patents$_{f,t-2}$					0.685*	
					(0.386)	
Green Patents$_{f,t-3}$						0.020
						(0.551)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,321	987	700	1,223	907	638
R-squared	0.949	0.950	0.966	0.958	0.961	0.978

F3. GMM

Though we control for firm specific effects and exploit lagged green patent activity, there may still be reverse causality issues leading to bias in the fixed effects OLS estimator. This is because emission-intensive firms may have stronger incentives to innovate in green technologies than less emission-intensive firms. We therefore also estimate the relationship using the Arellano and Bond (1991) two-step GMM estimator. The results using absolute scope 1 and 2 emissions are reported in Table F3 and the results emission intensity as outcome variable are reported in Table F4. This procedure does not provide conclusive evidence either. We find a statistically significant and positive relationship between absolute scope 1 and 2 emission levels and the number of green patents at the one- and three-year horizon. This association remains present at the three-year horizon when considering emission intensity.

Overall, our results thus do not provide a clear answer to whether green innovation improves environmental performance. This is qualitatively in line with Bolton et al. (2023), who do not find that green innovation materializes into future emission reductions.

Table F3: Linking green patenting to environmental performance

*This table reports the GMM estimation results of Equation (F.1), estimated with time fixed effects. We estimate the relationship between the natural logarithm of absolute scope 1 and 2 emissions (measured in CO_2e) and the 1-, 2- and 3-year lag of the green patent ratio (measured in %, Column 1-3), and the amount of green patents (measured in natural logarithms, Column 4-6). We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, investment-ratio, and the natural logarithm of revenue. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

	Absolute Scope 1 and 2 Emissions$_{f,t}$					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Green Patent Ratio$_{f,t-1}$	0.073					
	(0.045)					
Green Patent Ratio$_{f,t-2}$		-0.018				
		(0.126)				
Green Patent Ratio$_{f,t-3}$			0.643**			
			(0.267)			
Green Patents$_{f,t-1}$				-0.149		
				(0.221)		
Green Patents$_{f,t-2}$					0.549	
					(0.549)	
Green Patents$_{f,t-3}$						1.828
						(2.367)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value	0.377	0.495	0.281	0.204	0.342	0.068
AR(1) p-value	0.097	0.118	0.106	0.131	0.161	0.220
AR(2) p-value	0.278	0.998	-	0.466	0.744	-
Observations	1,321	987	700	1,223	907	638

Table F4: Linking green patenting to environmental performance

*This table reports the GMM estimation results of Equation (F.1), estimated with time fixed effects. We estimate the relationship between emission intensity (measured in $CO_2e/USDm$) and the 1-, 2- and 3-year lag of the green patent ratio (measured in %, Column 1-3), and the amount of green patents (measured in natural logarithms, Column 4-6). We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, investment-ratio, and the natural logarithm of revenue. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

	Emission Intensity$_{f,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Green Patent Ratio$_{f,t-1}$	0.438					
	(0.700)					
Green Patent Ratio$_{f,t-2}$		0.364				
		(1.177)				
Green Patent Ratio$_{f,t-3}$			2.962**			
			(1.178)			
Green Patents$_{f,t-1}$				-0.676		
				(0.457)		
Green Patents$_{f,t-2}$					-0.556	
					(0.722)	
Green Patents$_{f,t-3}$						1.824
						(3.088)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value	0.208	0.237	0.445	0.941	0.859	0.764
AR(1) p-value	0.239	0.219	0.389	0.538	0.416	0.602
AR(2) p-value	0.066	0.915	-	0.054	0.217	-
Observations	1,321	987	700	1,223	907	638

*Note: This table reports the GMM estimation results of Equation (F.1), estimated with time fixed effects We estimate the relationship between emission intensity, measured in $CO_2e/USDm$, and the green patent ratio using a 1-, 2- and 3-year lag of the green patent ratio (Column 1-3), and the amount of green patents measured in natural logarithms (Column 4-6). We include a set of corporate fundamentals, i.e., the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*