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

Martijn A. Boermans [†], Maurice J. G. Bun [‡], Yasmine van der Straten [§]

Updated version: February 26, 2025
First version: January 11, 2024

Abstract

We examine whether climate transition risk affects the cost of capital and how investors value green innovation. Using confidential bond-level holdings and global firm data, we find evidence of a positive transition risk premium. This premium is lower for emission-intensive firms that actively engage in green innovation, suggesting that investors recognize and reward efforts to mitigate climate change. While investors divest from emission intensive firms, our findings suggest that those with greater risk-bearing capacity play a crucial role in the green transition by channeling capital toward emission-intensive firms that actively invest in green innovation. European institutional investors, particularly mutual funds, demonstrate a stronger demand for bonds issued by these firms, reducing their cost of capital relative to other emission intensive firms.

Keywords — Climate Change, Climate Transition Risk, Carbon Premium, Greenium, Green Innovation, Bond Markets, Institutional Investors.

JEL codes — G12, G15, G23, Q51, Q54.

*DNB Working Paper No 797. The views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank nor the Eurosystem. Data have been cleared by the Eurosystem for non-disclosure of confidential data. Details are available at www.ecb.europa.eu/stats/financial_markets_and_interest_rates/securities_holdings/html/index.en.html. For helpful comments and suggestions we thank Aleksandar Andonov, Thibault Cezanne, Jeroen Derwal, Jens Dick-Nielsen, Tim Eisert, Eline Jacobs, Marcin Kacperczyk, Marleen de Jonge, Stefano Lugo, Christoph Meinerding, Benjamin Schneider, and Thomas Walther. This paper further benefited from discussions with participants of the 7th Annual GRASFI Conference (2024), IFCAB Southampthon (2024), ESCB Research Cluster Climate Change (2024), RCEA International Conference in Economics, Econometrics, and Finance (2024), IAAE conference (2024), IPDC conference (2024), the Dutch Economist Day (2024), and seminar participants at Imperial College Business School (2024), Tilburg University (2024), Utrecht University (2024), University van Amsterdam (2024), De Nederlandsche Bank (2024), and Robeco Asset Management (2024).

[†]De Nederlandsche Bank. E-mail: m.a.boermans@dnb.nl.
[‡]De Nederlandsche Bank and University of Amsterdam. E-mail: m.j.g.bun@dnb.nl.
[§]Corresponding Author. University of Amsterdam and Tinbergen Institute. E-mail: y.vanderstraten@uva.nl

I. Introduction

Achieving net-zero emissions by 2050 presents a significant challenge for the global economy, as current public policies and actions are falling short to contain global warming to 1.5-2 degrees Celsius (UNEP, 2023). Such delays increase the likelihood of a disorderly transition, contributing to significant uncertainty and exposing firms to climate transition risks. Forward-looking financial investors may anticipate these risks and adjust their cost of capital accordingly, potentially contributing to the green transition by providing cheaper financing to firms undertaking sustainable activities.

In this paper, we investigate the role of corporate bond investors in pricing climate transition risks and how they value companies' efforts to mitigate climate change since the adoption of the Paris Agreement in 2015. Specifically, we investigate whether corporate bond investors demand a positive transition risk premium from emission-intensive firms, whether this premium is mitigated for firms actively investing in green innovation, and which investors influence yield spreads in response to climate transition risk. We provide evidence of a positive transition risk premium in the corporate bond market, as a firm's emission intensity increases bond yield spreads. By adopting a forward-looking perspective, we show that the magnitude of this carbon premium depends on the efforts firms make to transition to greener technologies. We find that emission-intensive firms with a higher share of green patents face significantly lower bond yield spreads, indicating that investors reward firms actively engaging in green innovation compared to their non-green peers. Our findings reveal that European institutional investors exhibit a relatively higher demand for bonds from emission-intensive firms that engage in green innovation. Mutual funds, in particular, influence bond yield spreads related to climate transition risks, suggesting that investors with greater risk-bearing capacity are essential in supporting the green transition by offering lower-cost financing to firms investing in greener technologies.

We derive these findings by combining global firm-level data on greenhouse gas emissions from Trucost Environmental with confidential bond-level holdings data. We focus on corporate bonds due to the pivotal role the corporate bond market plays in firm financing, serving as the marginal source of capital for many firms globally (Gourio, 2013). This is particularly true for emission-intensive firms, which rely heavily on bond issuance to fund their operations (Papoutsi et al., 2022). Moreover, climate risks primarily pose downside risks, which have more significant implications for bond investors (Ilhan et al., 2021; Hoepner et al., 2024). Our data on bond holdings comes from the ECB Securities Holdings Statistics Sectoral, which provides detailed information on aggregate security-level portfolio holdings by financial and non-financial holders from all European countries. This dataset includes bond holdings from insurance companies, pension funds, mutual funds, banks, other financial institutions, non-financial corporations, governments, and households, representing approximately 58 percent of all security holdings reported for European investors in non-financial corporate issuers. Our regression analysis, covering the period from 2016-Q1 to 2021-Q4, provides evidence of a positive carbon premium that increases with a company's emission intensity. To isolate the effect of climate transition risk on bond yield spreads, we control for a comprehensive set of firm and bond characteristics, as well as firm fixed effects and industry-time fixed effects. This enables us to account for unobserved, persistent firm characteristics and industry-wide shocks over time. We further confirm that this premium is not driven by bond credit risk, liquidity, or maturity. Moreover, we rule out alternative explanations, such as a disproportionate expansion in bond supply by emission-intensive firms (Ivanov et al., 2024). We also rule out the possibility that our results are driven by green-labeled bonds. These findings underscore the central role of carbon emissions in shaping firms' cost of capital.

While the green transition necessitates a reduction in future emissions, conventional emission data—which capture firms' past and present environmental footprint—offer a limited view of firms' forward-looking efforts to transition to greener technologies. Notably, Cohen et al. (2023) find that firms with lower Environmental, Social, and Governance (ESG) scores are often key innovators in green patent development. To account for this, we incorporate firms' green innovation efforts alongside their historical and current carbon emissions in our bond pricing analysis. We enhance our dataset with firm-level data on (green) patents from Orbis Intellectual Property to assess how investors value firms' efforts to mitigating climate change. We collect data on the total number of patents per company and identify those 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 19,399,500 patents, of which 221,930 are classified as 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). We find that emission-intensive firms with a higher share of green patents face significantly lower bond yield spreads. In other words, the carbon premium declines for firms actively engaging in green innovation compared to their non-(green-)innovative peers. A one standard deviation increase in the green patent ratio reduces the yield spread of a bond issued by a company with average emission intensity by 20.6 basis points, effectively lowering the carbon premium by approximately 20 percent. This suggests that investors reward emission-intensive firms that make an effort to transition to greener technologies and mitigate climate change.

We confirm that this result holds through various robustness tests. We show that our results are robust against adopting a stricter classification for green patents, focusing on those aimed at reducing greenhouse gas emissions related to energy generation, transmission, or distribution (Acemoglu et al., 2023). We also verify that our results are not driven by investments or patenting in general. Instead, we demonstrate that green innovation activities hold particular significance to investors, as it is not merely the overall involvement in green innovation that matters, but also the incremental addition of new green patents. Since the Corporate Sector Purchase Programme (CSPP) of the ECB has led to a significant easing in financing conditions in the euro area corporate debt market, we further verify that our results are not driven by bond eligibility for purchase under the CSPP, nor by actual purchases made by the ECB. While CSPP lowered yields for eligible bonds, we show that it did not disproportionately favor emission-intensive companies that also innovate in the green space. Our results remain robust when excluding firms in the utilities sector and small bonds with low outstanding amounts. They also hold when using absolute emissions as an explanatory variable instead of emission intensity.

Overall, our results indicate that investors consider whether firms are "fit" for the green transition. To address concerns that our results may be driven by the joint determination of bond credit ratings and environmental performance (Carbone et al., 2021), we investigate whether the impact of credit ratings on bond yield spreads differs based on a firm's environmental performance. We find no such differential effect. Instead, the combined effect of emission intensity and green innovation remains significant, even after accounting for potential interactions with credit ratings. Moreover, we find no evidence of a joint effect between bond ratings and environmental performance, alleviating concerns regarding a joint-hypothesis problem. We also rule out that our results are driven by a differential effect of bond liquidity on bond yield spreads based on firms' environmental performance. Additionally, we find that the yield discount associated with green innovation is comparable for both short- and long-maturity bonds.

Given the European Union's efforts to promote green transition goals and the strong public concern about climate change within Europe compared to other regions [1], we examine whether European investors are more inclined to incorporate climate transition risk into their investment decisions. Specifically, we assess whether European investors are more likely to demand bonds issued by emission-intensive firms that engage in green innovation activities, and which investors are driving this trend.

To elicit investor demand, we follow the methodology of Khwaja and Mian (2008) and Acharya et al. (2024). More precisely, we compare the demand of different investor types for bonds issued by firms with a similar exposure to climate transition risk, 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 consider all European investors, and focus specifically on the role of institutional investors and banks. Our results demonstrate that European institutional investors, and mutual funds in particular, have a higher demand for bonds issued by emission-intensive firms that engage in green innovation. Also European banks have a higher demand for bonds of these firms.

We assess whether European investors directly influence corporate bond spreads in relation to firms' environmental performance. That is, we examine whether our key variables of interest vary with the holdership of bonds by different European investors. We measure the holdings of specific European investors relative to the total outstanding amount (at market values) for a given bond and period, accounting for the relative size of each investor sector (Crosignani et al., 2020). We find that European institutional investors are more likely to price a company's exposure to climate transition risk, confirming the regional focus of climate mitigation efforts. In line with our demand estimation, European mutual funds play a dominant role in this pricing, providing lower-cost financing to firms that, while currently brown, are actively investing in greener technologies to mitigate climate change. Our findings suggest that while investors divest from emission-intensive firms, those with greater risk-bearing capacity play a

[1] See https://www.eib.org/en/infographics/eu-climate-change-peer-us-china.

crucial role in the green transition by channeling capital to firms that, despite their current environmental performance, are actively engaging in green innovation and long-term sustainability efforts.

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, which has focused mainly on stock markets. 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 CO2-related emissions, and show that environmental policy uncertainty helps price the cross-section of stocks returns. On the contrary, Loyson et al. (2023) do not find evidence that carbon risk is being priced in the European equity market. Aswani et al. (2024) and Zhang (2024) suggest that the association between corporate emissions and stock returns disappears when using emission intensity rather than unscaled emission levels. Boermans and Galema (2023) affirm this result for European stock, but find a carbon premium for non-European stocks using emission intensity. Pástor et al. (2022) and Ardia et al. (2023) empirically test whether green firms outperform brown firms when concerns about climate change increase unexpectedly using ESG scores (Pástor et al., 2021).[2] Eskildsen et al. (2024) run a large replication study and propose a new measure of a firm's environmental performance, combining information on firms absolute emissions, their emission intensities, and their E(SG) scores. The authors find evidence of a small, yet significant carbon premium, which is higher in greener countries and rises over time.

A more recent literature studies whether this risk is accounted for in bank lending decisions (e.g., Sastry et al., 2024; Ivanov et al., 2024; Altavilla et al., 2023; Kacperczyk and Peydró, 2022; Delis et al., 2024). Using syndicated loan data, D'Arcangelo et al. (2023) show that that the costs of debt are lower for firms with lower emission intensity, especially in countries where climate-change mitigation policies become more stringent (e.g., Ali et al., 2023; Heinkel et al., 2001). Using administrative credit registry data from Europe, Altavilla et al. (2023) provide evidence that loan spreads are higher for emission-intensive firms. This effect is particularly driven by banks that publicly commit to environmentally responsible lending practices. Sastry et al. (2024), however, 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, given that these banks continue their relationships with existing brown borrowers, especially with those that exhibit financial underperformance.

Less research has been conducted on the pricing of climate transition risk in the corporate bond

[2] 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.

market.[3] Exploiting the Paris Agreement as a shock to climate regulation, Seltzer et al. (2022) provide evidence that climate regulatory risks causally affect bond yield spreads and bond ratings. Broeders et al. (2024) also find evidence of a carbon premium that investors demand for bonds issued by firms with high emissions in the euro area. 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 more carbon-intensive firms earn significantly lower returns due to investor underreaction to the predictability of emission intensity for firm's financial performance. We contribute to the literature by considering the forward-looking efforts firms undertake to transition to greener technologies in our bond pricing analysis. Our findings indicate that the 'carbon premium is smaller for emission-intensive companies that engage in green innovation, indicating that investors value firm's efforts to mitigate climate risk.

Second, this paper also relates to the literature on green innovation and financial performance.[4] Battiston et al. (2023); Leippold and Yu (2023) focus on the association between green innovation and stock returns. Leippold and Yu (2023) show that stocks of firms with higher green innovation measures have lower expected returns. Battiston et al. (2023) find that the adoption of sustainable technologies is associated with better future financial and operating performance. Considering credit supply, Accetturo et al. (2022) show for Italian SMEs that there is a large positive elasticity of green investments to credit supply. Our contribution to this literature is twofold. First, we show that while corporate bond investors do not price green innovation in isolation, they do value green innovation efforts when undertaken by emission-intensive firms. That is, investors *asymmetrically* reward green innovation efforts, which leads to a reduction in carbon premia. This suggests that investors specifically reward efforts to mitigate climate change from firms that are currently among the highest emitters. Second, our detailed bond holdings data allows us to uniquely identify investors demand for bonds of firms with varying environmental profiles. That is, our data uniquely allows us to compare the demand of different investor types for bonds issued by firms with a similar exposure to climate transition risk, 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 show that European institutional investors, and particularly mutual funds, are more likely to price a company's exposure to climate transition risk, by offering lower-cost financing to firms that, despite being emission-intensive today, are actively investing in greener technologies to mitigate climate change.

[3]While we focus on the corporate bond market as a whole and do not focus on corporate green bonds exclusively, our paper also relates to studies in this literature (e.g., Flammer, 2021; Pietsch and Salakhova, 2022; Zerbib, 2019; ElBannan and Löffler, 2024)) as we find evidence of a substantive 'greenium'.

[4]Our paper somewhat relates to the literature on the effect of green innovation on environmental performance (see e.g., Hartzmark and Shue, 2023; Dugoua and Gerarden, 2023; Leippold and Yu, 2023; ElBannan and Löffler, 2024; Bolton et al., 2023; Cohen et al., 2023).

Table 1: Summary statistics

	Mean	Median	SD	P10	P90
Environmental Variables					
(Scope1 + Scope2) Emission Intensity	2.805	0.509	4.908	0.191	8.958
(Scope1 + Scope2) Absolute Emissions (in log)	14.670	14.242	2.101	12.297	17.448
Green Patent Ratio	0.006	0.001	0.018	0.001	0.013
Bond Characteristics					
Yield to Maturity (%)	2.131	1.809	2.256	0	4.368
Spread (%)	1.516	1.020	1.993	0.253	3.168
Bond Holding Value (in m EUR)	201.837	55.825	304.245	2.990	630.378
Amount Outstanding (in m EUR)	663.315	504.572	541.098	109.731	1300
Fixed Coupon	0.902	1	0.298	1	1
EUR	0.346	0	0.476	0	1
USD	0.509	1	0.500	0	1
Green bond	0.012	0	0.111	0	0
Corporate Fundamentals					
Revenue (in bn EUR)	57.994	30.138	84.247	4.903	152
Total Assets (in bn EUR)	92.182	54.122	94.005	8.922	277
Total Debt (in bn EUR)	29.229	17.057	32.151	2.389	67.499
Profitability-Ratio (%)	5.061	4.042	5.819	-0.217	11.992
Leverage-Ratio (%)	32.393	30.480	12.994	17.910	50.748
Cash-Ratio (%)	5.536	3.320	8.224	0.323	9.557
Investment-Ratio (%)	12.593	7.444	14.586	1.160	34.271

Note: Based on 38,374 observations, reported at quarterly frequency and the security-by-security level. Absolute emissions levels are measured in CO2e and are reported in natural logarithms. Emission intensity, measured in CO2e/USDm, is scaled by a factor 1/100 and winsorized at the 2.5 percent level. Yield to maturity is winsorized at the 1 percent level. 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.

II. Data

We construct a comprehensive dataset by compiling data from various sources. Our sample covers the period 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.[5] 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.[6]

[5]Securities are identified by unique security codes, most commonly using ISIN codes, which we use to match the holdings data with the firm-level data.

[6]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

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 (denoted by c), as well as six other European Union countries not part of the euro area. SHS is operated by the European System of Central Banks (ESCB) and data is collected by national statistics offices of the ECB itself. The data is reported quarterly at the security-by-security level for bonds issued globally.[7] In each period, we observe the bond holdings value held by a specific holder (j), which is identified at the country-sector level for each period t. Investors are classified into 8 distinct investor sectors (denoted by s). Specifically, we observe the bond holdings of insurance companies, pension funds, mutual funds, banks, other financial institutions (including securitizations vehicles), non-financial corporations, governments and households (including non-profit institutions serving households). From the SHS data, we thus observe how much of each unique security each sector in a given European country holds. The magnitude of holdings (as measured by total bond holdings at market value) within our sample encompasses 1.05 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 for euro area investors for non-financial corporate issuers.[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 also contains a time series of the yield to maturity and the amount of the debt security that is outstanding in a given quarter. To reduce the impact of outliers, we winsorize the yield to maturity at the 1 percent.[9] Since we are interested in estimating risk premia, we determine the return in excess of the risk free rate. We subtract from the yield to maturity the maturity-matched Eurozone Central Government Bond Par Yield Curve Spot Rate.[10] The CSDB also provides us with data on bond credit ratings. Rating data is directly reported by ratings agencies Fitch, Moody's, S&P and DBRS to the ECB.[11] Bond credit ratings range from 1 to 22 within our 'carbon premium' sample. A bond rating of 1 indicates that the bond is of the highest quality and has an AAA-rating. A bond rating of 22 indicates that the bond is near-default, with a CC-rating. Within our main sample, the average credit rating is 7.350 (standard deviation of 2.539), which corresponds to an upper medium-grade (A-) bond. We also obtain information on the coupon rate, the currency in which the bond is denominated, and the residual maturity of our bonds. To take into account a bond's residual maturity in our regressions, we construct a dummy variable

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.

[7] Data is reported at market value. Nominal values are also available, which are given the aggregated nominal amount of the security, excluding accrued interest.

[8] 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 dropped 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] The percentage of bonds within our sample which are denominated in euros is 31.57 percent. Since a large amount of bonds within our sample is denominated in US dollars (52.16 percent), we use Treasury Rates when determining the spread for these bonds. Bonds denominated in other currencies are benchmarked against the euro area rates.

[11] Ratings data is only available for 16,889 observations, which is 44 percent of our main sample.

which indicates whether the residual maturity of the bond is longer than 10 years. Within our sample, approximately 24 percent of bonds have a residual maturity longer than 10 years. The CSDB also contains information on green bond labels. From the 3,313 bonds within our sample, 69 bonds have a green bond label (2 percent of all bonds) and these are issued by 34 distinct companies (9 percent of all companies).

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 heightened climate change awareness and emphasized the importance of measuring and reporting environmental data (Bolton and Kacperczyk, 2021).[12] 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 CO2e) and emission intensities, which are given a company's emissions relative to its revenue, measured in tons of CO2 emissions per million dollars of revenue (CO2e/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 and consumption of heat, steam and electricity by a company. Scope 3 emissions cover indirect emissions, which are 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. Companies with higher emissions face higher regulatory and operational costs as they adapt to stricter environmental policies. Emission intensity, which measures these costs relative to a company's revenue, gives insight into the potential impact of environmental regulation on the firm's financial health and the risk of default, which is particularly relevant for corporate bond investors. Therefore, our focus is on emission intensity and we measure a companies' emissions relative to its size, determined by its revenue for the same year:

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

where emission intensity is reported in tons of CO2e/USDm. We scale 'Emission Intensity' by a factor 1/100 and winsorize it at the 2.5 percent level (Bolton and Kacperczyk, 2021).[13] We plot the evolution of

[12]Although Trucost primarily reports emissions data for private companies, our study is limited to public companies for which we have bond data available.

[13]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., Andersson et al., 2016; Boermans and Galema, 2023; Aswani et al., 2024). We do not correct revenue for

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.[14] In our analysis below, we study whether this decline is partly explained by green innovation by emission-intensive firms.

C. (Green) patent information

We obtain information on (green) patents from Orbis IP, which provides global data of patent of public and private companies filed at the European Patent Office (EUPO), the US Patent Office (USPO) 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 identify all patents registered by a given company within our sample. We identify 19,399,500 patents associated with 1,241 unique companies, which is approximately 83 percent of all firms on which we obtain information in SHS and Trucost. We gather information on the total number of patent publications of a given firm, as well as the number of patent publications and explorations in each year. We use this information to determine the total amount of active patents in a specific year.

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 the entire class on Climate Change Mitigation and Adaptation (with CPC-code Y02).[15][16] We obtain information on the publication number, the current owners, the description of the patent, the priority - and application date, as well as the classification of each green patent according to its CPC-code. We identify green patents for a specific company and year based on the application date and the identifier of current owners. This process results in 221,930 green patents, held by 383 unique companies. Hence, green patents represent only 1.1 percent of the total number of patents within our dataset and among the companies in our sample engaged in patenting, only 33 percent also hold green patents. However, these companies collectively hold 89.7 percent of all patents, amounting to 17,396,360 patents out of the total 19,399,500. This suggests a strong correlation between a company's involvement in green patenting and patenting in general.

To address this correlation, we construct a relative measure of green innovation, the green patent ratio. This measure calculates the number of patents related to green technologies relative to the total

inflation rates as inflation was very low in our sample period 2016-2021

[14]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.

[15]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).

[16]Bolton et al. (2023) argue that this classification does not always distinguish between patents on renewable energy technologies ("green") and brown efficiency improvement patents. Therefore, the authors classify patents into 3 categories: i) "green" patents for environmental technologies; ii) "general efficiency improvement" patents that deal with technologies that improve process efficiency and therefore could reduce emission intensity; iii) "brown" patents that deal with technological innovation for fossil fuel-based technologies. This classification relies on four technology classification sources on patents relating to the environmental impact of technologies, in particular: the International Patent Classification (IPC) Green Inventory (for green patents), the efficiency-improving fossil fuel-technology categories of Lanzi et al. (2011), as well as a self-identified classification based on patents from the Corporate Knights Clean 200. The OECD classification is used for robustness (Bolton et al., 2023).

Table 2: Number of Patents and Green Patents Filed over the Sample Period

Variable	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
Patents^a	641,047	650,080	648,820	627,067	565,062	476,300
Patents^g	556,190	566,459	564,623	546,625	491,318	413,546
Green Patents	7,001	6,827	7,201	7,435	5,649	7,317

Note: Patents^a represents the number of patents filed by all companies in our sample. Patents^g refers to the number of patents (green, brown, and other) filed by companies that have at least one green patent in our sample. Green patents indicates the number of green patents filed by companies within our sample.

number of patents held by a specific company (Bolton et al., 2023):

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

We focus on companies that have at least one green patent in our main sample. The resulting sample consists of 3,313 unique bonds (i), issued by 383 unique companies (f) from 37 countries worldwide, which gives us 38,374 observations (N). We compare the summary statistics of firms with green patents (as reported in Table 1) to those of firms with *any* patent. This sample consists of 8,256 unique bonds, issued by 1,176 unique firms from 52 countries worldwide, resulting in 90,867 observations. The summary statistics for this sample are reported in Table C2 in Appendix C. Compared to firms with any patent, firms that patent in green technologies (and which patent relatively more in general) tend to be larger in terms of their revenues and assets.

D. Corporate Fundamentals and Bond Characteristics

We collect information on corporate fundamentals via Refinitiv, which is also available at a quarterly frequency.[17] The data includes details on companies' total assets, revenue, equity, long-term debt, capital expenditures, cash-holdings, as well as sector - and industry classification based on the Global Industry Classification Standard (GICS). We 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 53 distinct industries. There is large variation in the green patent ratio across industries. The green patent ratio is highest in the utilities sector, which also has the highest emission intensity on average. The green patent ratio is lowest in the health care sector, which has the lowest emission intensity on average. Table 3 underscores the importance of considering the number of green patents relative to the overall number of patents, as e.g., the utilities industry has the highest green patent ratio, but the number of green patents is among the lowest. We also provide an overview of the issuer-countries within our sample in Appendix

[17] There are a few companies for which data is missing in a given quarter quarters. These are filled with the most recent observation of the specific variable of the firm.

Table 3: Distribution of observations across sectors

GIC Sector	Observations	Emission Intensity	Green Patent Ratio	#Green Patents
Basic Materials	879	7.195	0.109	40.850
Consumer Cyclicals	614	0.669	0.010	2167.720
Consumer Non-Cyclicals	411	1.626	0.009	344.202
Energy	444	4.684	0.025	43.788
Healthcare	494	0.324	0.002	85.747
Industrials	1,080	1.026	0.011	198.309
Real Estate	45	1.039	0.010	3.333
Technology	924	0.478	0.005	875.560
Utilities	542	10.219	0.033	181.220

Note: Observations are reported at the quarterly frequency and firm-level. We report the distribution of observations across GIC Sectors and the mean of emission intensity, the green patent ratio and the number of green patents by sector.

B. Approximately 23 percent of the distinct firms in our sample are established in the United States, and 38 percent in the European Union.

We also obtain data on daily bid- and ask prices via Refinitiv. 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.[18]

III. Empirical Analysis

A. *Primer: The Carbon Premium*

We start with estimating the 'carbon premium', i.e., whether bond yield spreads are larger for bonds issued by companies with a higher emission intensity. Establishing whether a 'carbon premium' exists in bond markets serves as the first step in our analysis, given that this question remains subject to debate in the literature. While some studies document a positive relationship between carbon intensity and bond yields (e.g., Seltzer et al., 2022), suggesting investors demand compensation for transition risks, others argue that bond market investors do not price climate transition risks (e.g., Duan et al., 2023). 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:

$$\text{Spread}_{i,t} = \beta \text{ Emission Intensity}_{f,t-1} + \delta' X_{f,t-1} + \gamma' Z_{i,t-1} + FE + \epsilon_{i,t} \tag{1}$$

[18] We obtain the bid-ask spread for approximately 93 percent of the bonds in our sample. We express the bid-ask spreads in percentages. The mean bid-ask spread is 0.404, with a standard deviation of 0.442.

where

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

where emission intensity is measured at the firm level in tons of CO2 emissions per million dollars of revenue (CO2e/USDm). We include the lagged value of emission intensity because emission data becomes available to investors with a lag (Zhang, 2024). The vector of one-period lagged corporate (f) fundamentals ($X_{f,t-1}$) includes the profitability-ratio, leverage-ratio, cash-ratio, and investment-ratio. We also include a vector of lagged bond (i) characteristics, $Z_{i,t-1}$, which includes 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 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.[19] We estimate Equation (1) using three different sets of fixed effects. We first use (i) time fixed effects (α_t) to account for general time trends in bond yield spreads. Second, to strengthen our inference, we estimate the relation with (ii) firm fixed effects (η_f) and time fixed effects. This allows us to further control for unobserved, persistent firm characteristics.[20] Finally, we tightens the identification by estimate the relation with (iii) industry-time fixed effects ($\mu_{g,t}$) and firm fixed effects. This allows us to absorb industry-wide shocks over time, which is crucial as 80 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.[21] 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.

The estimation results of Equation (1) are displayed in Table 4. For each of the three fixed effects specifications, the first column reports the results for the regression in which only our main explanatory variable of interest, i.e., the emission intensity, is incorporated. The second column reports the results once we include our control variables. We find evidence of a carbon premium, indicating that corporate bonds issued by higher-emission firms are associated with larger yield spreads. The results remains broadly consistent across specifications, indicating that the positive association is neither driven by 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

[19] Since we take a corporate perspective, we do not incorporate bond factors. For related approaches in the literature that analyze determinants of corporate bond spreads, see e.g., Dick-Nielsen et al. (2012); Helwege et al. (2014); Huang and Petkevich (2016); Bauer et al. (2021). Note that for yield spread regressions, bond factors are absent as control variables.

[20] Note that the industry dimension is nested in the firm dimension, f.

[21] Companies have on average 17.4 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 103.

Table 4: The Effect of Emission Intensity on Yield Spreads

	Time FEs			Firm + Time FEs			Firm + Industry-Time FEs		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Emission Intensity$_{f,t-1}$	0.115***	0.088**	0.089**	0.129**	0.128**	0.129**	0.136**	0.154*	0.155**
	(0.035)	(0.036)	(0.036)	(0.056)	(0.056)	(0.056)	(0.066)	(0.077)	(0.076)
Green Bond$_{i,t-1}$			-0.427**			-0.489**			-0.479**
			(0.190)			(0.211)			(0.225)
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	38,386	38,374	38,374	38,356	38,344	38,344	38,296	38,284	38,284
R-squared	0.141	0.213	0.214	0.429	0.443	0.444	0.508	0.525	0.526

Note: OLS estimation results for Equation (1). 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 measured in CO2e/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.

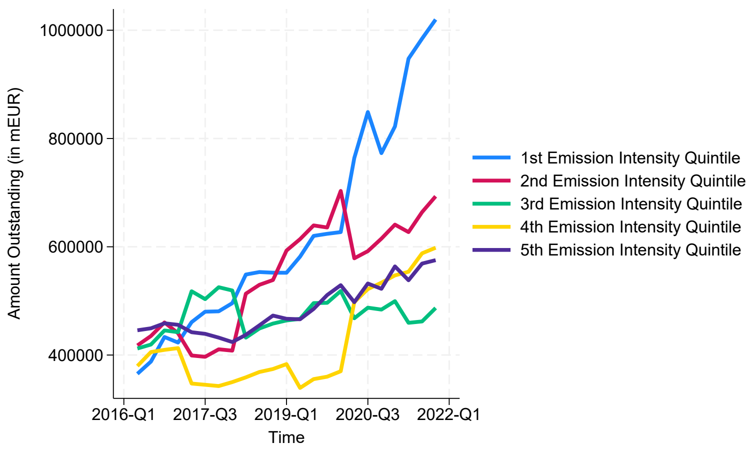

Figure 1: The evolution of total amount outstanding (in m EUR) by emission quintile over the sample period.

spreads by 76 basis points, highlighting a robust and economically meaningful carbon premium.[22]

To disentangle the carbon premium (i.e., the positive risk premium for exposure to carbon risk) from the 'greenium' (i.e., the yield discount associated with green bonds), and thus prevent that the results are driven by the green bonds within our sample, we additionally control for whether a bond has a green bond label.[23] Controlling for whether a bond has a green bond label does not change the effect of emission intensity on yield spreads, as our results remain comparable in terms of magnitude and significance.

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., Ivanov et al., 2024; Degryse et al., 2023; Altavilla et al., 2023).[25] As lending conditions become more stringent, or loan supply declines, 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 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 (in million euros). We split the sample based on the emission intensity of the issuing company and plot the total amount outstanding for each emission intensity quartile. We do not find evidence of a disproportionate expansion in bond supply of emission-intensive companies. Figure 1 shows that the trends are comparable for firms in the second, third and fourth emission intensity quartile. In contrast, 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

[22]This effect can be interpreted as the long-run effect. For the short-run effect, the within-firm standard deviation is used, which is 25.8 percent of the overall standard deviation.

[23]The results in column 3 indicate that bonds that qualify as green bond are associated with a large and highly significant yield discount.[24] Note that 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).

[25]Giannetti et al. (2023); Sastry et al. (2024) do not find evidence that banks are adjusting their lending behavior based on firm's environmental performance.

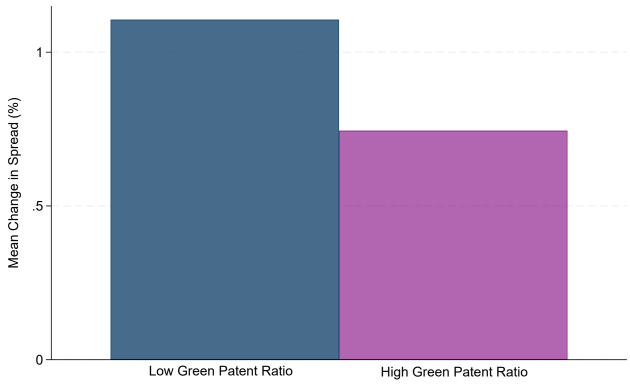

FIGURE 2: THE MEAN DIFFERENCE IN OBSERVED BOND YIELD SPREADS (IN PERCENTAGE POINTS) BETWEEN BONDS ISSUED BY HIGH- AND LOW-EMISSION FIRMS. THE MEAN DIFFERENCE IS REPORTED SEPARATELY FOR FIRMS WITH A BELOW-MEDIAN GREEN PATENT RATIO (LEFT BAR) AND THOSE WITH AN ABOVE-MEDIAN GREEN PATENT RATIO (RIGHT BAR).

firms that appear in our sample. This observation is in line with previous literature (e.g., Bolton and Kacperczyk, 2021).

B. Main Results: Emission Intensity and Green Innovation

The previous section provided evidence of a carbon premium, showing that bonds issued by high-emission firms tend to have higher yield spreads. To further illustrate this, we plot the difference in mean bond yield spreads (in raw data) between firms in the upper and lower quintiles of the emission distribution. This 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). The figure suggests that the carbon premium is more pronounced for firms with lower green patenting activity, while firms with higher green patent ratios exhibit a smaller spread differential. This indicates that green innovation may play a role in mitigating the higher financing costs associated with emission intensity.

To formally assess whether corporate bond investors reward emission-intensive firms for their efforts to transition towards greener technologies, we next examine this relationship parametrically. We interact emission intensity with firm's relative engagement in green innovation. That is, we estimate the following regression at the bond-period level:

$$\begin{aligned}\text{Spread}_{i,t} = {} & \beta_1 \text{Emission Intensity}_{f,t-1} + \beta_2 \text{Green Patent Ratio}_{f,t-1} + \beta_3 \text{Emission Intensity}_{f,t-1} \\ & \cdot \text{Green Patent Ratio}_{f,t-1} + \delta' X_{f,t-1} + \gamma' Z_{i,t-1} + FE + \varepsilon_{i,t} \qquad (2)\end{aligned}$$

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, the green patent ratio and the interaction between the two. We include a similar vector of corporate fundamentals, $X_{f,t-1}$, bond characteristics, $Z_{i,t-1}$. We estimate Equation (2) using (i) firm fixed effects (η_f) and time fixed effects (α_t), and (ii) firm fixed effects and industry-time fixed effects ($\mu_{g,t}$).[26] We cluster standard errors at the industry level (see Table B2 in Appendix B for a list of industries).

Table 5 reports the estimation results of Equation (2). For each specification, the first column reports the results when emission intensity is included as explanatory variable, whereas the second column reports the results when the green patent ratio is included as explanatory variable. Column 3 shows the results when we include both variables and column 4 adds the interaction between the green patent ratio and emission intensity, which is our main explanatory variable of interest (β_3). Finally, in column 5 we add the green bond indicator as well.

Table 5 shows that the interaction between the green patent ratio and emission intensity (labeled '$EI \times GPR$') is significantly negative at the 1 percent level. A one-standard deviation increase in the green patent ratio reduces bond yield spreads by 20.6 basis points for a company with a mean emission intensity. This constitutes a reduction in the carbon premium of approximately 20 percent, indicating that investors reward emission-intensive companies that make efforts to become more green.[27] We further explore the dynamic evolution of the interaction term over time. Figure C1 in Appendix C plots the coefficient on the interaction between the green patent ratio and emission intensity, along with the 90 percent confidence interval. The reference period is 2016. While the interaction term is not significantly different from zero in 2017, the figure reveals that it becomes significantly negative in subsequent years, with the coefficient remaining stable thereafter.

This reduction in the carbon premium for emission-intensive companies engaging in green innovation cannot be attributed to unobserved firm-specific characteristics or industry-specific shocks, as we control for both firm fixed effects and industry-time fixed effects. Finally, columns 2 and 3 show that the green patent ratio alone does not have a statistically significant effect on bond yield spreads. The coefficient becomes statistically significant only when the interaction term is added, highlighting the importance of jointly considering green innovation and environmental performance.

The utilities sector is characterized by being highly emission-intensive, yet it also has a relatively high green patent ratio (see Table 3). To ensure that our results are not disproportionately influenced by this, we re-estimate Equation 2 excluding utility sector firms. The results are shown in Table C1 in Appendix C. In this case, emission intensity, and the interaction term with the green patent ratio, remain statistically significant at the 1 percent level. The combined effect of emission intensity and green patenting also remains similar in terms of magnitude in this sample.

[26] While our main specification includes both industry-time and firm fixed effects, we verify that our results remain robust when using only industry-time fixed effects. Given that 80 percent of firms operate in tradable industries, controlling for industry-wide shocks over time is crucial (see Table B1 in Appendix B).

[27] For the short-run effect, we again use the within-firm standard deviations. The within-firm standard deviation of the green patent ratio is 19.2 percent of the overall standard deviation. Hence, based on within-firm standard deviations, the reduction in the carbon premium is approximately 15 percent.

Table 5: Effect of Emission Intensity and Green Patenting on Yield Spreads

(a) Firm and Time Fixed Effects

	(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$_{f,t-1}$		18.871	14.012	55.971***	55.642***
		(15.732)	(13.151)	(15.964)	(16.285)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-2.724***	-2.701***
				(0.809)	(0.817)
Green Bond$_{i,t-1}$					-0.485**
					(0.206)
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	38,344	39,571	38,344	38,344	38,344
R-squared	0.443	0.494	0.443	0.445	0.446

(b) Firm and Industry-Time Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.154*		0.152*	0.207***	0.208***
	(0.077)		(0.077)	(0.059)	(0.058)
Green Patent Ratio$_{f,t-1}$		10.659	4.882	70.203***	69.895***
		(10.152)	(9.568)	(16.094)	(16.115)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-4.092***	-4.076***
				(0.970)	(0.970)
Green Bond$_{i,t-1}$					-0.476**
					(0.221)
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	38,284	39,504	38,284	38,284	38,284
R-squared	0.525	0.566	0.525	0.527	0.528

Note: OLS estimation results of Equation (2) 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 measured in CO2e/USDm. The green patent is defined as the number of green patents owned by a given firm relative to the number of patents owned in total. '$EI \times GPR$' is the interaction between 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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. To assess the robustness of our findings, we extend the analysis to include all companies for which patent information is available, including those with no green patents, effectively incorporating firms with a green patent ratio of zero. This expands our sample to 1,176 unique firms and 90,867 observations.[28] The results, presented in Table C3 in Appendix C, reveal that the combined effect of emission intensity and green patenting remains statistically significant, consistent with our main specification.[29]

[28] We provide summary statistics for this sample in Table C2 in Appendix C. Compared to firms with green patents, firms without green patents (but with other patents) tend to be smaller in terms of their revenues and assets.

[29] Note that the introduction of many zeros in the green patent ratio diminishes the magnitude of the effect.

B.1 Alternative explanations

Our estimation results indicate that investors reward emission-intensive companies that make efforts to transition towards greener technologies, as measured by their relative engagement in green innovation. We examine whether our main results continues to hold against several alternative explanations. First, our green patent definition may be too broad, given that the YO2 class in patent classification includes all technologies related to climate change mitigation. To ensure that we capture innovation in greenhouse gas emission reduction technologies, we verify the robustness of our results against the adoption of a more stringent classification of green patents in a subsample. We follow Acemoglu et al. (2023) who only consider a subset of innovations in the technological subclass Y02E of the CPC as green innovations.[30] This subclass, Y02 of the CPC, consists of green patents aimed to reduce carbon emissions related to energy generation, transmission or distribution. This classification reduces the amount of green patents on which we obtain information to 32,174 patents, which are held by 177 unique companies.[31] The results are reported in column 1 of Table 6. The results indicate that the combined effect of emission intensity and green patenting remains similar in magnitude and is statistically significant at the 5 percent level. This suggests that green innovations specifically aimed at the reduction of carbon emissions are effective in lowering corporate bond yield spreads for emission-intensive firms.

Second, we verify the robustness of our results by examining the annual change in green patents relative to the change in total patents (Δ GPR).[32] The results, which are reported in column 2 of Table 6, show that the combined effect of emission intensity and the change in green patents relative to the change in total patents is statistically significant and is negative. This implies that green innovation activities hold particular importance for investors, as it is not solely the overall involvement in green innovation that matters, but also the incremental addition of a green patent. This underscores the value investors place on the continuous expansion of a firm's green innovation efforts in the context of emission reductions.

Third, in column 3 and column 4 of Table 6 we rule out that the Corporate Sector Purchase Programme (CSPP) of the ECB, which commenced in 2016, explains our results. We generate a dummy which indicates whether a given bond in our sample is eligible for purchase under the CSPP.[33] Within our sample, 10.3 percent of bonds are eligible for purchase under CSPP. We interact emission intensity and the green patent ratio (both separately and jointly) with the eligibility-dummy. The results reported in column 3 indicate that eligibility for purchase under CSPP significantly reduces bond yield spreads. Eligibility under CSPP is not driving our main results, as the interaction of emission intensity, the green

[30] 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.

[31] Under the stricter classification, the green patent ratio has a mean of 0.003 (s.d. of 0.012). Companies with green patents under the stricter classification have higher emissions on average. Specifically, the mean of emission intensity is 3.799 CO_2 (s.d. of 5.575 CO_2e).

[32] We observe the change in the green patent ratio for 32,652 observations. Δ GPR has a mean of 0.007 (s.d. of 0.022).

[33] 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/press/economic-bulletin/html/eb201803.en.html.

Table 6: Robustness: Joint Effect of Emission Intensity and Green Patenting on Bond Yield Spreads

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Classification	ΔGPR	CSPP		Patents	Investments	No Small Bonds	No weights
			Eligiblity	Purchases				
Emission Intensity$_{f,t-1}$	0.202**	0.103	0.213***	0.210***	0.211***	0.225**	0.206***	0.148***
	(0.079)	(0.087)	(0.062)	(0.058)	(0.059)	(0.085)	(0.059)	(0.037)
Green Patent Ratio$_{f,t-1}$	88.254***		69.347***	70.946***	67.730***	63.967***	51.156	47.239***
	(16.272)		(16.891)	(15.954)	(14.835)	(12.614)	(23.451)	(15.205)
EI$_{f,t-1}$ xGPR$_{f,t-1}$	-4.517**		-4.071***	-4.102***	-3.924***	-3.654***	-3.290***	-2.660***
	(2.161)		(1.021)	(0.976)	(0.900)	(0.630)	(1.224)	(0.689)
ΔGreen Patent Ratio$_{f,t-1}$		-1.950						
		(4.678)						
EI$_{f,t-1}\times\Delta$ GPR$_{f,t-1}$		-0.904*						
		(0.538)						
Green Bond$_{i,t-1}$	-0.551**	-0.498**	-0.464**	-0.466**	-0.478**	-0.476**	-0.510**	-0.334*
	(0.224)	(0.238)	(0.207)	(0.210)	(0.220)	(0.222)	(0.249)	(0.174)
CSPP$_{i,t-1}$			-0.387***	-0.413***				
			(0.131)	(0.121)				
EI$_{f,t-1}$ xGPR$_{f,t-1}\times$CSPP$_{i,t-1}$			0.224	-3.126				
			(3.770)	(10.385)				
Patents$_{f,t-1}$					-0.573*			
					(0.338)			
EI$_{f,t-1}\times$Invest-ratio$_{f,t-1}$						-0.302		
						(0.422)		
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Double interactions CSPP	-	-	Yes	Yes	-	-	-	-
Firm-FEs	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,446	32,652	38,284	38,284	38,284	38,284	32,745	38,284
R-squared	0.531	0.457	0.536	0.536	0.528	0.528	0.528	0.607

Note: Robustness tests for Equation (2), estimated by OLS 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 measured in CO2e/USDm. The green patent is defined as the number of green patents owned by a given firm relative to the number of patents owned in total. $''EI \times GPR''$ is the interaction between emission intensity and the green patent ratio. Δgreen patent ratio is defined as the change in the number of green patents relative to the change in the number of total patents owned by the firm on an annual basis. $'EI \times \Delta GPR'$ is the interaction between emission intensity and Δgreen patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. CSPP indicates whether a bond is eligible for purchase under CSPP (column 6) or whether the bond has been purchased under the CSPP (column 7). $''EI \times GPR' \times CSPP'$ is the interaction between emission intensity, the green patent ratio and CSPP. While not shown, we include all pairwise interactions as controls. Patents is the natural logarithm of the total number of patents owned by a firm. 'Invest' is the interaction between emission intensity and the investment ratio, which is one of our 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. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.

patent ratio and the CSPP dummy is insignificant. We run a similar test using data of the euro system on the actual purchases made under CSPP in column 4. Again, the key interaction between emission intensity and green patent ratio for the yield spread regression remains significant, while the interaction with CSPP is not.[34] This indicates that CSPP is not a mechanism driving our main findings.

Fourth, we test the robustness of our results against the inclusion of the total number of patents (in logarithms) in column 5 of Table 6. The results show that the effect of our interaction between emission intensity and the green patent ratio remains consistent in size and statistically significant at the 1 percent significance level. In column 6 of Table 6, we also include an interaction of emission intensity and the investment ratio as control variable, which is statistically insignificant. Both findings underscore the significance of green innovation activities by emission-intensive companies, as neither innovation nor investments in general explain our results.

To rule out that the results are driven by issuers of bonds with low values, we re-estimate Equation (2) for a sample which only includes bonds with an outstanding amount larger than 200 million euro. This reduces our sample by 15 percent. The results are reported in column 7. In this specification, the interaction term remains statistically significant. Finally, we verify the robustness of our results against the exclusion of sampling weights in column 8.

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, 2024; 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. We test the robustness of our main results by considering absolute emissions instead of emission intensity. The results, reported in Table C4 in Appendix C, show that the combined effect of absolute emissions and green patenting remains statistically significant at the 1 percent level. Furthermore, the effect becomes substantially larger in magnitude when we consider absolute Scope 1 and 2 emissions, suggesting that the impact of emissions on bond yield spreads is stronger when absolute emissions are considered. This robustness check provides further confidence in the robustness of our findings, regardless of whether emissions are measured in intensity or absolute terms.

B.2 The Role of Ratings, Liquidity and Maturity

Bond yield spreads are known to be 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, to ensure that our findings are not driven by the joint determination of these bond characteristics and firm's environmental performance. We include interactions between our main variables of interest and each of these relevant bond characteristics. The results are presented in Table 7.

[34] Focusing on the subset of bonds issued by firms located in the euro area results in similar outcomes.

Table 7: Effect of Emission Intensity and Green Patenting on Yield Spreads

	(1) Ratings	(2) Ratings	(3) Ratings	(4) Liquidity	(5) Liquidity	(6) Liquidity	(7) Maturity	(8) Maturity	(9) Maturity	(10) All
Emission Intensity$_{f,t-1}$	0.271***	0.271***	0.251***	0.247***	0.247***	0.254***	0.216***	0.217***	0.217***	0.288***
	(0.083)	(0.081)	(0.074)	(0.052)	(0.052)	(0.052)	(0.058)	(0.058)	(0.058)	(0.096)
Green Patent Ratio$_{f,t-1}$	142.939**	143.707**	132.627**	76.842***	80.326***	81.598***	70.414***	69.238***	69.730***	130.002**
	(63.324)	(68.347)	(55.598)	(17.045)	(15.373)	(15.484)	(16.352)	(16.701)	(16.150)	(56.169)
EI$_{f,t-1}$×GPR$_{f,t-1}$	-8.062**	-8.030**	-6.557***	-4.469***	-4.332***	-5.202***	-4.131***	-4.179***	-4.312***	-6.828***
	(3.663)	(3.462)	(1.811)	(0.950)	(0.932)	(0.981)	(0.945)	(0.988)	(0.991)	(2.183)
Bond Rating$_{i,t-1}$	-0.017	-0.015	-0.041							-0.031
	(0.083)	(0.076)	(0.106)							(0.101)
EI$_{f,t-1}$ xRating$_{i,t-1}$	0.023	0.023	0.029							0.022
	(0.037)	(0.038)	(0.045)							(0.035)
GPR$_{f,t-1}$×Rating$_{i,t-1}$		-0.421	3.554							4.522
		(3.399)	(3.242)							(3.678)
EI$_{f,t-1}$×GPR$_{f,t-1}$×Rating$_{i,t-1}$			-0.473							-0.374
			(0.747)							(0.599)
Liquidity$_{i,t-1}$				1.250***	1.319***	1.419***				0.649***
				(0.140)	(0.108)	(0.132)				(0.139)
EI$_{f,t-1}$×Liquidity$_{i,t-1}$				-0.055***	-0.053***	-0.076***				-0.044*
				(0.014)	(0.014)	(0.015)				(0.026)
GPR$_{f,t-1}$×Liquidity$_{i,t-1}$					-15.158	-28.433***				-20.013***
					(9.688)	(3.391)				(7.092)
EI$_{f,t-1}$×GPR$_{f,t-1}$×Liquidity$_{i,t-1}$						2.608***				-0.156
						(0.373)				(3.366)
Maturity$_{i,t-1}$							1.000***	0.992***	1.017***	0.756***
							(0.092)	(0.093)	(0.095)	(0.103)
EI$_{f,t-1}$×Maturity$_{i,t-1}$							-0.019	-0.024	-0.030*	0.017
							(0.014)	(0.016)	(0.016)	(0.057)
GPR$_{f,t-1}$×Maturity$_{i,t-1}$								8.633	-2.136	12.629
								(7.015)	(7.670)	(11.385)
EI$_{f,t-1}$×GPR$_{f,t-1}$×Maturity$_{i,t-1}$									0.963*	0.407
									(0.530)	(2.657)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bond Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,182	16,182	16,182	35,619	35,619	35,619	38,284	38,284	38,284	15,613
R-squared	0.624	0.624	0.624	0.592	0.593	0.596	0.592	0.592	0.592	0.703

Note: Robustness tests for Equation (2), estimated by OLS 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 measured in CO2e/USDm. The green patent is defined as the number of green patents owned by a given firm relative to the number of patents owned in total. "$'EI \times GPR'$ " is the interaction between emission intensity and the green patent ratio. Green bond is a dummy variable indicating whether a bond has a green bond label. The bond rating is continuous variable which increases with the credit risk associated with the bond. 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. 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. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.

Column 1-3 reports the results when we control for the interactions between our main variables of interest and the bond's credit rating. The combined effect of emission intensity and green innovation remains statistically significant at the 5 percent level. Moreover, all interactions with bond credit ratings are insignificant, suggesting that traditional credit risk models do not fully account for the impact of climate risk yet. This mitigates concerns regarding a joint-hypothesis problem. In column 4-6, we assess whether there is a differential effect of a bond's liquidity on bond yield spreads based on firm's environmental performance. We use the bid-ask spread as proxy for a bond's liquidity. Once we account for liquidity, the combined effect of emission intensity and the green patent ratio on bond yield spreads remains significant at the 1 percent level, reinforcing the robustness of our results. We also explore the differential effect of a bond's maturity in column 7 of Table 7. While the results show that yield spreads tend to be higher for bonds with a residual maturity of more than 10 years, the yield discount associated with green innovation is comparable for both short- and long-maturity bonds.

In summary, the combined effect of emission intensity and the green patent ratio remains highly statistically significant, even after taking into account potentially differential effects of credit risk, liquidity, and maturity based on a firm's environmental performance. This supports the robustness of our findings and alleviates concerns that these bond characteristics might be driving the observed effects.

B.3 Linking Green Innovation and Corporate Environmental Performance

Our findings indicate that investors "reward" emission-intensive companies that engage in green innovation, as these firms experience a significantly lower carbon premium compared to their non-innovative counterparts. This suggests that investors recognize and value the efforts of emission-intensive companies to reduce their environmental impact through green innovation. To better understand the implications of this finding, we explore whether green innovation is associated with corporate environmental performance. In other words, we investigate whether investors 'fund the fittest'. 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 emission intensity, at the one-, two- and three-year horizon. The results are reported in Appendix D.

Overall, 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. One possible explanation is that investors expect emission reductions to materialize over a longer time horizon. Another plausible explanation is that the ownership of green patents signals to investors that the company possesses advanced green technologies, which have positive option value. This is particularly relevant if investors anticipate stricter climate policies in the future, as owning green patents positions the firm to better respond to increased policy stringency. In other words, it makes the firm more resilient against a rise in the stringency of climate policy. Our results may suggest that investors incorporate this option value into their investment decisions, pricing in the potential for future environmental improvements.

C. Holdership Dynamics

In light of the European Union's broader efforts to promote green transition goals, we assess 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 level[35] and estimate the following bond demand regression (e.g., Khwaja and Mian, 2008; Boermans and Vermeulen, 2020; Acharya et al., 2024):

$$\begin{aligned}\text{Holdings}_{j,f,t} = {} & \beta_1 \text{Emission Intensity}_{f,t-1} + \beta_2 \text{Green Patent Ratio}_{f,t-1} + \beta_3 \mathbb{1}_{\text{Investor Type}=j} \\ & + \beta_4 \text{Emission Intensity}_{f,t-1} \cdot \text{Green Patent Ratio}_{f,t-1} \cdot \mathbb{1}_{\text{Investor Type}=j} \\ & + \gamma' \text{Amount Outstanding}_{f,t-1} + \lambda_{f,t} + \zeta_{c,s,t} + \nu_{j,f,t} \end{aligned} \tag{3}$$

where we include all pairwise interactions between emission intensity, the green patent ratio, and the investor-indicator as controls. The parameter of interest is β_4, which we expect to be positive. This parameter captures whether certain types of European investors have a higher demand for bonds of emission-intensive firms that make an effort to become green. We consider all European investors, and focus specifically on the subset of European institutional investors and European banks. We consider insurance companies, pension funds, mutual funds and other financial institutions as institutional investors.[36] In our most stringent specification, we estimate the regression with firm-time ($\lambda_{f,t}$) and holder area-sector-time ($\zeta_{c,s,t}$) fixed effects.[37] 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 (Acharya et al., 2024). We cluster standard errors at the industry level.

The results are reported in Panel A of Table 8. 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 with firm-time- and holder-area-sector fixed effects are reported in column 1. Column 2 reports the results of our most stringent specification, with firm-time- and holder-area-sector-time fixed effects. Our interaction effect is positive and statistically significant at the one percent significance level for institutional investors, across all specifications. This indicates that European institutional investors hold more bonds of emission

[35] 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.

[36] Since we consider banks separately, we do not include those in our measure of institutional investors.

[37] Note that all corporate fundamentals are absorbed in this specification.

Table 8: Bond Demand, Emission Intensity and Green Innovation

Panel A	Inst.			Bank		
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathrm{EI}_{f,t-1}\times\mathrm{GPR}_{f,t-1}\times\mathrm{Inst.}_{j,t-1}$	1.008***	1.134***	1.125***			
	(0.245)	(0.324)	(0.343)			
$\mathrm{EI}_{f,t-1}\times\mathrm{GPR}_{f,t-1}\times\mathrm{Bank}_{j,t-1}$				0.227	0.840**	0.809***
				(0.157)	(0.316)	(0.295)
Amount Outstanding	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Holder Area-Sector FEs	No	Yes	No	No	Yes	No
Holder Area-Sector-Time FEs	No	No	Yes	No	No	Yes
Observations	181,663	181,722	181,650	181,663	181,663	181,650
R-squared	0.198	0.651	0.659	0.115	0.651	0.659

Panel B	Insur.	Mfund.	Pfund.
	(1)	(2)	(3)
$\mathrm{EI}_{f,t-1}\times\mathrm{GPR}_{f,t-1}\times\mathrm{Insur.}_{j,t-1}$	0.257		
	(0.477)		
$\mathrm{EI}_{f,t-1}\times\mathrm{GPR}_{f,t-1}\times\mathrm{Mfund.}_{j,t-1}$		0.660***	
		(0.163)	
$\mathrm{EI}_{f,t-1}\times\mathrm{GPR}_{f,t-1}\times\mathrm{Pfund.}_{j,t-1}$			0.185
			(0.384)
Corporate Fundamentals	Yes	Yes	Yes
Amount Outstanding	Yes	Yes	Yes
Firm-Time FEs	Yes	Yes	Yes
Holder Area-Sector-Time FEs	Yes	Yes	Yes
Observations	181,650	181,650	181,650
R-squared	0.659	0.659	0.659

*Note: Estimation of Equation (3), estimated by OLS with firm-time and holder country-sector(-time) fixed effects. Column 1-3 of Panel A report the regressions of bond holding of all European institutional investors on emission intensity, measured in CO2e/USDm, the green patent ratio, and their interaction. We estimate the regression with holder area-holder sector respectively holder area-holder sector-time FEs. Column 4-6 report the regressions of bond holding of European banks on emission intensity, measured in CO2e/USDm, the green patent ratio, and an indicator variable indicating whether the holder is an institutional investor. While not reported, we include all pairwise interactions as controls. In Panel B, estimate the regressions of bond holding of specific types of institutional investors on emission intensity, measured in CO2e/USDm, the green patent ratio, and an indicator variable indicating the type of the institutional investor. We include the total bond amount outstanding of the firm as control variable. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

intensive firms that engage in green innovation, relative to the average investor within our sample. To determine which of the institutional investors is driving this effect, we estimate our most stringent specification for each type of institutional investor separately in Panel B of Table 8. Our findings show that the effect of institutional investors is entirely driven by European mutual funds. We find that neither insurance companies nor pension funds have a differential demand for bonds of emission intensive firms that innovate in the green space.

Finally, in column 6-8 of Panel A of Table 8 we assess whether European banks have a differential demand for bonds issued by emission-intensive firms that engage in green innovation. Our interaction effect is again positive and statistically significant at the one percent significance level, across all specifications. This suggests that banks also hold relatively more bonds of emission-intensive firms that engage in green innovation compared to the average investor.

We assess whether European investors directly affect corporate bond spreads in relation to companies' emission intensity and their green innovation efforts. Do these investors directly affect the pricing of corporate bonds? We asses whether the combined effect of emission intensity and green patent ratio depends on the investor type holding the bond.[38] To measure the holdings of each respective investor, we follow Crosignani et al. (2020) and construct the following variable:

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

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.[39] 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.[40] For our worldwide sample of corporate bonds, the holder share of European investors has a mean equal to 0.34 (s.d. of 0.374), signifying the large ownership of European investors in corporate bond markets globally.[41] Most of the European investments in corporate bonds stem from institutional investors, of which the holder share is on average 0.32. The average holdings of banks relative to the total amount outstanding (i.e., the numerator of the holder share) in a given period is relatively small within our sample. [42] We interact emission intensity and the green patent ratio with

[38] 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.

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

[40] Consider the following example. Bank A and Bank B 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 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 bank A and B are 0.25 and 0.125, respectively. However, if Bank A is larger than Bank B, holdings should be weighted by the relative size of the bank's assets to take into account that Bank B has a stronger preferences for environmental performance relative to its size (i.e., Bank B 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 banks do not seem to value environmental performance differentially (see Crosignani et al. (2020)).

[41] Table **??** in Appendix E shows that the average holdings of each investor relative to the total amount outstanding steadily declines over our sample period.

[42] The standard deviation of the holder-share of institutional investors 0.362. For banks, the standard deviation is 0.372.

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

$$
\begin{aligned}
\text{Spread}_{i,t} = &\ \beta_1 \text{Emission Intensity}_{f,t-1} + \beta_2 \text{Green Patent Ratio}_{f,t-1} + \beta_3 \text{Holder Share}_{j,t-1} \\
&+ \beta_4 \text{Green Patent Ratio}_{f,t-1} \cdot \text{Emission Intensity}_{f,t-1} \cdot \text{Holder Share}_{j,t-1} \\
&+ \delta' X_{f,t-1} + \gamma' Z_{i,t-1} + \mu_{g,t} + \nu_{i,t}
\end{aligned} \tag{4}
$$

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. This parameter captures whether European investors charge lower yield spreads for emission-intensive firms that make an effort to become green by engaging 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 here 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 9 reports the results of Equation (4). The first column shows the effect of EU-holdership on bond yield spreads, and includes an interaction between the lagged emission intensity, green patent ratio and the share of EU-holder. The interaction effect is negative and statistically significant at the 1 percent significance level. A standard deviation increase in the share of EU-holders reduces the yield spread of a company with a mean emission intensity and mean green patent ratio by 2.8 basis points. Although the effect is marginal in economic terms, it indicates that European investors are more likely to price a company's exposure to climate transition risk, taking into consideration both the emission intensity of a firm as well as its green patent ratio.

We analyze the effect of holdership by European institutional investors on bond yield spreads in column 2. Column 2 of Table 9 shows that interaction between emission intensity, the green patent ratio, and the holder share of institutional investors is statistically significant at the 1 percent significance level. A standard deviation increase in the share of holdings of institutional investors reduces the yield spread of company with a mean emission intensity and mean green patent ratio by approximately 2.6 basis points. This aligns with our finding that institutional investors have a higher demand for bonds of emission intensive firms that engage in green innovation and thus reveals that these investors drive yield spreads in relation to climate transition risk. Column 3 reveals that the interaction of our main variables of interest with the holder share of banks is statistically significant as well, although the magnitude of the effect size is considerably smaller than the effect for institutional investors. More specifically, a standard deviation increase in the holdings share of banks only reduces the yield spread of a company with a mean emission intensity and mean green patent ratio by 0.18 basis points. This small magnitude can potentially be explained by the fact that – even though banks have a higher demand for bonds of emission intensive firms that innovate in the green space – banks' holdings are too small at a global level to significantly affect corporate bond yield spreads.

Table 9: Bond Yield Spreads and Bond Holder Dynamics

	EU (1)	Inst. (2)	Bank (3)	Insure (4)	Mfund (5)	Pfund (6)	All (7)
$\text{EI}_{f,t-1}\times\text{GPR}_{f,t-1}$	-2.880***	-2.756**	-2.595***	-2.999***	-2.572***	-2.517**	-2.587**
	(1.044)	(1.039)	(0.886)	(1.009)	(0.899)	(0.946)	(1.016)
$\text{EU-share}_{i,t-1}$	0.090						
	(0.135)						
$\text{EI}_{f,t-1}\times\text{GPR}_{f,t-1}\text{xEU}_{i,t-1}$	-4.804***						
	(1.531)						
$\text{Inst.-share}_{i,t-1}$		0.300**					
		(0.140)					
$\text{EI}_{f,t-1}\times\text{GPR}_{f,t-1}\text{xInst.}_{i,t-1}$		-4.725***					
		(1.573)					
$\text{Bank-share}_{i,t-1}$			-0.281*				-0.451***
			(0.151)				(0.134)
$\text{EI}_{f,t-1}\times\text{GPR}_{f,t-1}\text{xBank}_{i,t-1}$			-0.281*				-0.451***
			(0.151)				(0.134)
$\text{Insur.-share}_{i,t-1}$				-3.820***			0.123
				(1.365)			(1.425)
$\text{EI}_{f,t-1}\times\text{GPR}_{f,t-1}\text{xInsur.}_{i,t-1}$				-3.675***			0.291
				(1.127)			(1.451)
$\text{Mfund-share}_{i,t-1}$					0.643**		0.445**
					(0.307)		(0.194)
$\text{EI}_{f,t-1}\times\text{GPR}_{f,t-1}\text{xMfund}i,t-1$					-2.822*		-2.351**
					(1.513)		(1.160)
$\text{Pfund-share}_{i,t-1}$						0.230	0.031
						(0.166)	(0.106)
$\text{EI}_{f,t-1}\times\text{GPR}_{f,t-1}\text{xPfund}_{i,t-1}$						-0.733	-1.312
						(1.610)	(1.811)
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	38,374	38,374	38,374	38,374	38,374	38,374	38,374
R-squared	0.433	0.431	0.443	0.432	0.432	0.431	0.452

*Note: Estimation results of Equation (4), estimated by OLS with industry-time fixed effects. The dependent variable in all regressions is the bond yield spread (YTM in excess of the risk free rate). 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. $'EI \times GPR'$ is the interaction between emission intensity and the green patent ratio (which are both included as control variable). $'EI \times GPR \times EU'$ is the interaction between emission intensity, the green patent ratio and the EU-share. While not reported, we include all pairwise interactions as controls. We re-estimate Equation (4) using the share of institutional investors in column 2, the share of holdings of banks in column 3, the share of insurance companies in column 4, the share of mutual funds in column 5, the share of pension funds in column 6, and we include the share of each institutional investors (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. Standard errors are reported in parentheses and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

Similar to our demand estimation, we also estimate Equation (4) for each type of institutional investor. The results are presented in columns 4-6 of Table 9. Column 4 shows the effect of holdership by insurance companies, while the effects of holdership by mutual funds and pension funds are reported in columns 5 and 6, respectively. We find that holdership by insurance companies and mutual funds both have statistically significant effects on bond yield spreads.

We further explore the relative impact of different institutional investors, we run a horse-race by including interactions with all investor types simultaneously in column 7. In line with our demand estimation, we find that only the interaction between emission intensity, the green patent ratio, and the share of holdings by mutual funds remains statistically significant. The effect is negative, indicating that higher demand from European mutual funds for bonds of emission-intensive firms that innovate in the green space reduces their cost of capital. Unlike insurance companies and pension funds, mutual funds have a larger risk-bearing capacity. This likely explains their pivotal role in financing firms that are currently brown but actively working to mitigate climate change.

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 study whether financial investors take up this role in the period following the adoption of the Paris Agreement in December 2015.

Specifically, we aim to answer the question whether corporate bond investors value companies' efforts to mitigate climate change and which investors do so. Since emission data is inherently backward looking, our study also considers companies' green innovation efforts. We focus on the amount of green patents relative to the total amount of patents of a given company, and assess whether emission intensity and the green patent ratio jointly affect corporate bond yield spreads.

Our empirical results provide evidence of a positive carbon premium, as a firm's emission intensity positively affects the bond yield spread. At the same time, we find that investors reward those emission-intensive companies engaging in green innovation, given that the carbon premium is lower for those companies. These results are robust against controlling for factors such as bond credit ratings, liquidity and investments more generally. We find similar results when adopting a more stringent classification for green patents and when excluding firms in the utilities sector from our sample. Moreover, our results are unaffected by eligibility or purchases of corporate bonds under the Corporate Sector Purchase Program of the ECB.

Finally, our results reveal that European institutional investors have a higher demand for bonds from emission-intensive firms that engage in green innovation. This regional focus on environmental policies aligns with the broader efforts within the European Union to promote sustainable finance. We find that mutual funds, in particular, influence bond yield spreads related to climate transition risk. This suggests that investors with greater risk-bearing capacity play a crucial role in facilitating the green transition by providing lower-cost financing to firms that, while currently brown, are actively investing in greener technologies to mitigate climate change.

References

Accetturo, A., G. Barboni, M. Cascarano, E. Garcia-Appendini, and M. Tomasi (2022): "Credit supply and green investments," *Mimeo.*

Acemoglu, D., P. Aghion, L. Barrage, and D. Hémous (2023): "Climate change, directed innovation, and energy transition: The long-run consequences of the shale gas revolution," *NBER Working Paper No. 31657.*

Acharya, V. V., R. Banerjee, M. Crosignani, T. Eisert, and R. Spigt (2024): "Exorbitant privilege? The bond market subsidy of prospective fallen angels," *Journal of Financial Economics*, Forthcoming.

Ali, K., M. Nadeem, R. Pandey, and G. S. Bhabra (2023): "Do capital markets reward corporate climate change actions? Evidence from the cost of debt," *Business Strategy and the Environment*, 32, 3417–3431.

Altavilla, C., M. Boucinha, M. Pagano, and A. Polo (2023): "Climate risk, bank lending and monetary policy," *CEPR Discussion Paper No. 18541.*

Andersson, M., P. Bolton, and F. Samama (2016): "Hedging climate risk," *Financial Analysts Journal*, 72, 13–32.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht (2023): "Climate change concerns and the performance of green vs. brown stocks," *Management Science*, 69, 7607–7632.

Arellano, M. and S. Bond (1991): "Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations," *Review of Economic Studies*, 58, 277–297.

Aswani, J., A. Raghunandan, and S. Rajgopal (2024): "Are carbon emissions associated with stock returns?" *Review of Finance*, 28, 75–106.

Battiston, S., I. Monasterolo, and M. Montone (2023): "Technological greenness and long-run performance," *Mimeo.*

Bauer, M. D., D. Huber, G. D. Rudebusch, and O. Wilms (2022): "Where is the carbon premium? Global performance of green and brown stocks," *Journal of Climate Finance*, 1, 100006.

Bauer, R., J. Derwall, and N. Pankratz (2021): "Insider ownership, governance mechanisms, and corporate bond pricing around the world," *Journal of International Money and Finance*, 117, 102423.

Boermans, M. and R. Galema (2023): "Carbon home bias of European investors," *DNB Working Paper No. 786.*

Boermans, M. A. and R. Vermeulen (2020): "International investment positions revisited: Investor heterogeneity and individual security characteristics," *Review of International Economics*, 28, 466–496.

Bolton, P. and M. Kacperczyk (2021): "Do investors care about carbon risk?" *Journal of Financial Economics*, 142, 517–549.

——— (2023): "Global pricing of carbon-transition risk," *Journal of Finance*, 78, 3677–3754.

——— (2024): "Are carbon emissions associated with stock returns? Comment," *Review of Finance*, 28, 107–109.

Bolton, P., M. T. Kacperczyk, and M. Wiedemann (2023): "The CO2 question: Technical progress and the climate crisis," *Mimeo*.

Broeders, D., M. de Jonge, and D. Rijsbergen (2024): "The European Carbon Bond Premium," *DNB Working Paper No. 798*.

Carbone, S., M. Giuzio, S. Kapadia, J. S. Krämer, K. Nyholm, and K. Vozian (2021): "The low-carbon transition, climate commitments and firm credit risk," *ECB Working Paper No. 2631*.

Cohen, L., U. G. Gurun, and Q. H. Nguyen (2023): "The ESG-innovation disconnect: Evidence from green patenting," *NBER Working Paper No. 27990*.

Crosignani, M., M. Faria-e Castro, and L. Fonseca (2020): "The (unintended?) consequences of the largest liquidity injection ever," *Journal of Monetary Economics*, 112, 97–112.

Degryse, H., R. Goncharenko, C. Theunisz, and T. Vadasz (2023): "When green meets green," *Journal of Corporate Finance*, 78, 102355.

Delis, M. D., K. d. Greiff, M. Iosifidi, and S. Ongena (2024): "Being stranded with fossil fuel reserves? Climate policy risk and the pricing of bank loans," *Financial Markets, Institutions & Instruments*, 33, 239–265.

Dick-Nielsen, J., P. Feldhütter, and D. Lando (2012): "Corporate bond liquidity before and after the onset of the subprime crisis," *Journal of Financial Economics*, 103, 471–492.

Duan, T., F. W. Li, and Q. Wen (2023): "Is carbon risk priced in the cross section of corporate bond returns?" *Journal of Financial and Quantitative Analysis*, 1–35.

Dugoua, E. and T. D. Gerarden (2023): "Innovation, inventors and the energy transition," *NBER Working Paper No. 31714*.

D'Arcangelo, F. M., T. Kruse, M. Pisu, and M. Tomasi (2023): "Corporate cost of debt in the low-carbon transition: The effect of climate policies on firm financing and investment through the banking channel," *OECD Economics Department Working Paper No. 1761*.

ElBannan, M. A. and G. Löffler (2024): "How effectively do green bonds help the environment?" *Journal of Banking & Finance*, 158, 107051.

Eskildsen, M., M. Ibert, T. I. Jensen, and L. H. Pedersen (2024): "In search of the true greenium," *Mimeo.*

Flammer, C. (2021): "Corporate green bonds," *Journal of Financial Economics*, 142, 499–516.

Giannetti, M., M. Jasova, M. Loumioti, and C. Mendicino (2023): ""Glossy green" banks: the disconnect between environmental disclosures and lending activities," *ECB Working Paper.*

Gourio, F. (2013): "Credit risk and disaster risk," *American Economic Journal: Macroeconomics*, 5, 1–34.

Hartzmark, S. M. and K. Shue (2023): "Counterproductive sustainable investing: The impact elasticity of brown and green firms," *Mimeo.*

Haščič, I. and M. Migotto (2015): "Measuring environmental innovation using patent data," *OECD Environment Working Paper No. 89.*

Heinkel, R., A. Kraus, and J. Zechner (2001): "The effect of green investment on corporate behavior," *Journal of Financial and Quantitative Analysis*, 36, 431–449.

Helwege, J., J.-Z. Huang, and Y. Wang (2014): "Liquidity effects in corporate bond spreads," *Journal of Banking & Finance*, 45, 105–116.

Hoepner, A. G., I. Oikonomou, Z. Sautner, L. T. Starks, and X. Zhou (2024): "ESG shareholder engagement and downside risk," *Review of Finance*, 28, 483—-510.

Hsu, P.-h., K. Li, and C.-y. Tsou (2023): "The pollution premium," *Journal of Finance*, 78, 1343–1392.

Huang, K. and A. Petkevich (2016): "Corporate bond pricing and ownership heterogeneity," *Journal of Corporate Finance*, 36, 54–74.

Ilhan, E., Z. Sautner, and G. Vilkov (2021): "Carbon tail risk," *Review of Financial Studies*, 34, 1540–1571.

Ivanov, I., M. S. Kruttli, and S. W. Watugala (2024): "Banking on carbon: Corporate lending and cap-and-trade policy," *Review of Financial Studies*, 37, 1640—-1684.

Kacperczyk, M. T. and J.-L. Peydró (2022): "Carbon emissions and the bank-lending channel," *Mimeo.*

Khwaja, A. I. and A. Mian (2008): "Tracing the impact of bank liquidity shocks: Evidence from an emerging market," *American Economic Review*, 98, 1413–1442.

Klaassen, L. and C. Stoll (2021): "Harmonizing corporate carbon footprints," *Nature Communications*, 12, 1–13.

Lanzi, E., E. Verdolini, and I. Haščič (2011): "Efficiency-improving fossil fuel technologies for electricity generation: Data selection and trends," *Energy Policy*, 39, 7000–7014.

Leippold, M. and T. Yu (2023): "The green innovation premium," *Swiss Finance Institute Research Paper No. 23-21*.

Loyson, P., R. Luijendijk, and S. v. Wijnbergen (2023): "The pricing of climate transition risk in Europe's equity market," *DNB Working Paper No. 778*.

Papoutsi, M., M. Piazzesi, and M. Schneider (2022): "How unconventional is green monetary policy," *Mimeo*.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2021): "Sustainable investing in equilibrium," *Journal of Financial Economics*, 142, 550–571.

——— (2022): "Dissecting green returns," *Journal of Financial Economics*, 146, 403–424.

Pietsch, A. and D. Salakhova (2022): "Pricing of green bonds: drivers and dynamics of the greenium," *ECB Working Paper No. 2728*.

Sastry, P., E. Verner, and D. Marques-Ibanez (2024): "Business as usual: Bank climate commitments, lending, and engagement," *ECB Working Paper No. 2921*.

Seltzer, L. H., L. Starks, and Q. Zhu (2022): "Climate regulatory risk and corporate bonds," *NBER Working Paper No. 29994*.

European Central Bank (2024): "Climate change-related indicators," *Access via: link*.

UNEP (2023): *Emissions Gap Report 2023: Broken Record – Temperatures hit new highs, yet world fails to cut emissions (again)*, Nairobi.

Zerbib, O. D. (2019): "The effect of pro-environmental preferences on bond prices: Evidence from green bonds," *Journal of Banking & Finance*, 98, 39–60.

Zhang, S. (2024): "Carbon returns across the globe," *Journal of Finance*, Forthcoming.

Appendix A. Time Series Properties

A1. Bond Yield

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

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

where θ_i are bond fixed effects, and λ_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: Autocorrelation in Bond Yields

	OLS	FE	GMM
Yield to Maturity$_{i,t-1}$	0.737**	0.527**	0.528**
	(0.017)	(0.004)	(0.049)
Yield to Maturity$_{i,t-2}$	0.217**	0.080**	0.135**
	(0.017)	(0.004)	(0.021)

*Note: Standard errors in parentheses, ** p<0.05, * p<0.1.*

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. The fixed effects OLS and GMM estimates, however, 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.

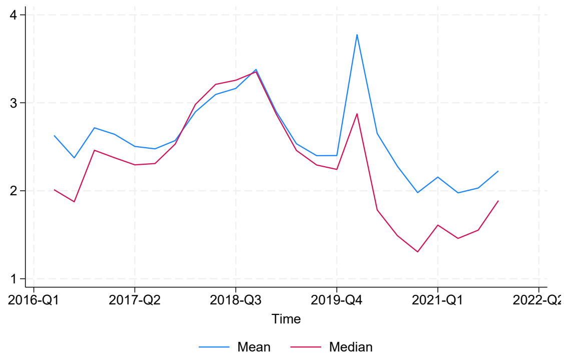

Figure A1: The evolution of the mean and median yield to maturity, reported at the quarterly-frequency and bond-level over the sample period.

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:

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

where η_f are firm fixed effects and λ_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: Autocorrelation in Emission Intensity

	OLS	FE	GMM
Emission Intensity$_{f,t-1}$	0.624**	0.006	0.142
	(0.140)	(0.026)	(0.297)
Emission Intensity$_{f,t-2}$	0.327**	0.181**	0.440**
	(0.135)	(0.029)	(0.091)

*Note: Standard errors in parentheses, ** p<0.05, * p<0.1.*

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.

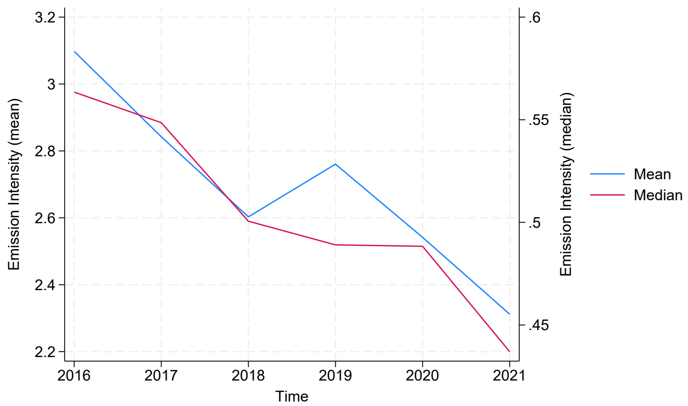

Figure A2: The evolution of the mean and median emission intensity, reported at the firm-year level over the sample period.

Appendix B. Additional Summary Statistics

Table B1: Distribution of Observations Across Industries

GICS Industry Name	Frequency	Percent	Classification
Aerospace & Defense	236	4.34	Tradable
Air Freight & Logistics	46	0.85	Tradable
Automobile Components	172	3.17	Tradable
Automobiles	213	3.92	Tradable
Beverages	66	1.21	Tradable
Biotechnology	132	2.43	Tradable
Broadline Retail	54	0.99	Non-Tradable
Building Products	72	1.33	Tradable
Chemicals	411	7.56	Tradable
Commercial Services & Supplies	36	0.66	Non-Tradable
Communications Equipment	72	1.33	Tradable
Construction & Engineering	114	2.10	Non-Tradable
Construction Materials	29	0.53	Non-Tradable
Consumer Staples Distribution & Retail	105	1.93	Non-Tradable
Containers & Packaging	47	0.87	Tradable
Diversified Telecommunication Services	157	2.89	Other
Electric Utilities	347	6.39	Tradable
Electrical Equipment	229	4.21	Tradable
Electronic Equipment, Instruments & Components	90	1.66	Tradable
Energy Equipment & Services	27	0.50	Tradable
Food Products	96	1.77	Tradable
Gas Utilities	47	0.87	Non-Tradable
Ground Transportation	47	0.87	Non-Tradable
Health Care Equipment & Supplies	70	1.29	Tradable
Health Care Providers & Services	3	0.06	Non-Tradable
Health Care Technology	12	0.22	Tradable
Household Durables	72	1.33	Tradable
Household Products	21	0.39	Tradable
IT Services	45	0.83	Other
Independent Power and Renewable Electricity Producers	68	1.25	Non-Tradable
Industrial Conglomerates	76	1.40	Tradable
Leisure Products	23	0.42	Tradable
Life Sciences Tools & Services	10	0.18	Tradable
Machinery	275	5.06	Tradable
Marine Transportation	39	0.72	Tradable
Media	46	0.85	Other
Metals & Mining	287	5.28	Tradable
Multi-Utilities	87	1.60	Non-Tradable
Oil, Gas & Consumable Fuels	339	6.24	Tradable
Paper & Forest Products	95	1.75	Tradable
Personal Care Products	23	0.42	Tradable
Pharmaceuticals	267	4.91	Tradable
Real Estate Management & Development	20	0.37	Non-Tradable
Semiconductors & Semiconductor Equipment	312	5.74	Tradable
Software	88	1.62	Other
Specialized REITs	23	0.42	Non-Tradable
Technology Hardware, Storage & Peripherals	99	1.82	Tradable
Textiles, Apparel & Luxury Goods	24	0.44	Tradable
Tobacco	22	0.40	Tradable
Trading Companies & Distributors	73	1.34	Tradable
Transportation Infrastructure	7	0.13	Non-Tradable
Water Utilities	15	0.28	Non-Tradable
Wireless Telecommunication Services	47	0.87	Other

Note: Distribution of observations across GICS Industries. Observations are reported at the quarterly frequency and firm-level.

Table B2: Emission Intensity and Green Patents across industries (mean)

GICS Industry Name	Emission Intensity	Green Patent Ratio	Green Patents
Aerospace & Defense	0.291	0.001	15.470
Air Freight & Logistics	1.466	0.001	3.500
Automobile Components	1.131	0.002	151.785
Automobiles	0.264	0.019	6056.737
Beverages	0.648	0.004	30.742
Biotechnology	0.286	0.002	15.227
Broadline Retail	0.322	0.009	6.537
Building Products	1.029	0.005	64.625
Chemicals	5.970	0.004	63.932
Commercial Services & Supplies	0.909	0.004	113.472
Communications Equipment	0.162	0.000	53.792
Construction & Engineering	0.488	0.013	10.114
Construction Materials	19.940	0.010	8.655
Consumer Staples Distribution & Retail	0.543	0.006	2.429
Containers & Packaging	1.687	0.002	4.511
Diversified Telecommunication Services	0.425	0.007	324.873
Electric Utilities	12.268	0.039	271.533
Electrical Equipment	0.789	0.025	221.485
Electronic Equipment, Instruments & Components	0.814	0.005	339.244
Energy Equipment & Services	0.773	0.010	1.519
Food Products	0.896	0.021	5.490
Gas Utilities	2.795	0.024	39.617
Ground Transportation	1.427	0.018	137.404
Health Care Equipment & Supplies	0.242	0.001	340.800
Health Care Providers & Services	0.026	0.000	0.000
Health Care Technology	0.415	0.000	20.000
Household Durables	0.624	0.011	8874.292
Household Products	0.307	0.001	67.619
IT Services	0.102	0.026	195.556
Independent Power and Renewable Electricity Producers	15.557	0.025	27.971
Industrial Conglomerates	5.693	0.007	1793.987
Leisure Products	0.462	0.010	370.913
Life Sciences Tools & Services	0.357	0.000	0.200
Machinery	0.369	0.014	533.233
Marine Transportation	11.007	0.003	1.128
Media	0.120	0.002	3.000
Metals & Mining	9.291	0.027	26.631
Multi-Utilities	1.939	0.015	2.460
Oil, Gas & Consumable Fuels	5.455	0.011	22.342
Paper & Forest Products	3.327	0.003	22.421
Personal Care Products	0.342	0.000	8.000
Pharmaceuticals	0.362	0.002	60.865
Real Estate Management & Development	0.503	0.022	4.900
Semiconductors & Semiconductor Equipment	1.934	0.017	60.603
Software	0.120	0.001	3.261
Specialized REITs	1.565	0.000	2.000
Technology Hardware, Storage & Peripherals	0.182	0.001	561.889
Textiles, Apparel & Luxury Goods	0.906	0.001	17.167
Tobacco	0.386	0.003	88.409
Trading Companies & Distributors	1.026	0.009	95.479
Transportation Infrastructure	4.688	0.007	0.571
Water Utilities	0.830	0.008	2.667
Wireless Telecommunication Services	0.418	0.007	128.404

Note: Observations are reported at the quarterly frequency and firm-level. We report the mean of emission intensity, the green patent ratio and the number of green patents. We classify industries as tradable, non-tradable and others.

Table B3: Emission Intensity and Green Patents across industries (median)

GICS Industry Name	Emission Intensity	Green Patent Ratio	Green Patents
Aerospace & Defense	0.220	0.000	4.000
Air Freight & Logistics	1.352	0.001	3.500
Automobile Components	0.563	0.001	8.000
Automobiles	0.243	0.006	228.000
Beverages	0.477	0.002	14.000
Biotechnology	0.311	0.001	9.000
Broadline Retail	0.285	0.002	3.000
Building Products	0.777	0.001	54.000
Chemicals	4.101	0.001	10.000
Commercial Services & Supplies	0.339	0.000	1.000
Communications Equipment	0.177	0.000	67.000
Construction & Engineering	0.398	0.008	2.000
Construction Materials	19.940	0.001	3.000
Consumer Staples Distribution & Retail	0.515	0.005	2.000
Containers & Packaging	1.671	0.002	5.000
Diversified Telecommunication Services	0.422	0.009	7.000
Electric Utilities	13.815	0.045	16.000
Electrical Equipment	0.466	0.001	11.000
Electronic Equipment, Instruments & Components	0.295	0.003	15.000
Energy Equipment & Services	0.205	0.001	1.000
Food Products	0.630	0.000	3.000
Gas Utilities	3.667	0.002	1.000
Ground Transportation	1.350	0.011	101.000
Health Care Equipment & Supplies	0.133	0.001	7.000
Health Care Providers & Services	0.026	0.000	0.000
Health Care Technology	0.385	0.000	20.000
Household Durables	0.349	0.011	4590.000
Household Products	0.309	0.001	68.000
IT Services	0.125	0.001	292.000
Independent Power and Renewable Electricity Producers	19.940	0.015	11.000
Industrial Conglomerates	0.637	0.001	6.000
Leisure Products	0.365	0.005	201.000
Life Sciences Tools & Services	0.284	0.000	0.000
Machinery	0.390	0.000	10.000
Marine Transportation	11.756	0.002	2.000
Media	0.130	0.002	3.000
Metals & Mining	7.456	0.003	8.000
Multi-Utilities	1.399	0.013	1.000
Oil, Gas & Consumable Fuels	4.884	0.003	10.000
Paper & Forest Products	3.074	0.002	11.000
Personal Care Products	0.332	0.000	8.000
Pharmaceuticals	0.242	0.000	21.000
Real Estate Management & Development	0.500	0.006	5.000
Semiconductors & Semiconductor Equipment	0.752	0.000	11.000
Software	0.099	0.000	3.000
Specialized REITs	1.526	0.000	2.000
Technology Hardware, Storage & Peripherals	0.110	0.000	3.000
Textiles, Apparel & Luxury Goods	0.083	0.000	17.000
Tobacco	0.391	0.004	94.000
Trading Companies & Distributors	0.735	0.009	112.000
Transportation Infrastructure	6.900	0.011	1.000
Water Utilities	0.818	0.010	3.000
Wireless Telecommunication Services	0.534	0.009	138.000

Note: Observations are reported at the quarterly frequency and firm-level. We report the median of emission intensity, the green patent ratio and the number of green patents.

Table B4: Distribution of observations across countries

Country	Frequency	Percent
Austria	58	1.07%
Australia	22	0.40%
Belgium	106	1.95%
Brazil	72	1.32%
Canada	135	2.48%
Chile	23	0.42%
China	184	3.39%
Colombia	23	0.42%
Czech Republic	23	0.42%
Denmark	23	0.42%
Spain	125	2.30%
Finland	211	3.88%
France	383	7.05%
Germany	401	7.38%
Hong Kong	23	0.42%
Hungary	23	0.42%
India	136	2.50%
Italy	160	2.95%
Japan	648	11.93%
Luxembourg	54	0.99%
Malaysia	23	0.42%
Netherlands	162	2.98%
Norway	143	2.63%
New Zealand	23	0.42%
Philippines	6	0.11%
Poland	2	0.04%
Russia	94	1.73%
Saudi Arabia	7	0.13%
South Korea	222	4.09%
Sweden	195	3.59%
Switzerland	171	3.15%
Thailand	9	0.17%
Turkey	50	0.92%
Taiwan	40	0.74%
United Arab Emirates	23	0.42%
United Kingdom	185	3.41%
United States	1,245	22.91%

Note: Distribution of observations across countries. Observations are reported at the quarterly frequency and firm-level.

Appendix C. Robustness and Additional Tests for Equation (2)

C1. Dynamic Plot of the Main Coefficient

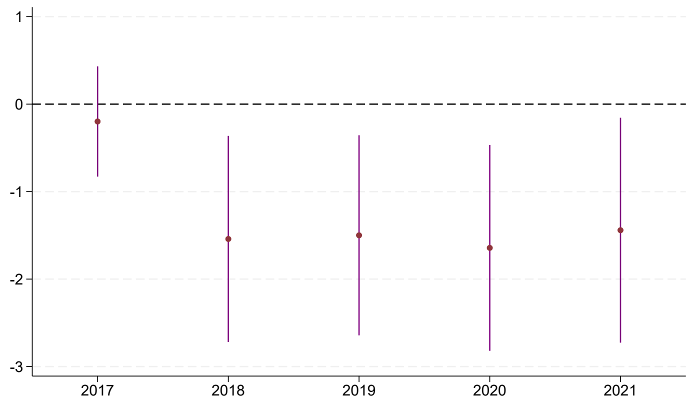

FIGURE C1: DYNAMIC PLOT OF THE COEFFICIENT FOR THE INTERACTION BETWEEN EMISSION INTENSITY AND THE GREEN PATENT RATIO ($EI \times GPR$), ALONG WITH THE 90 PERCENT CONFIDENCE INTERVALS. THE REFERENCE PERIOD IS 2016.

C2. Main Results Excluding the Utilities Sector

Table C1: Effect of Emission Intensity and Green Patenting on Yield Spreads

(a) Firm and Time Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.224***		0.220***	0.226***	0.226***
	(0.033)		(0.034)	(0.033)	(0.033)
Green Patent Ratio$_{f,t-1}$		90.312**	52.846**	74.515***	74.923***
		(34.522)	(24.237)	(16.000)	(15.874)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-3.941***	-3.956***
				(0.805)	(0.805)
Green Bond$_{i,t-1}$					-0.197***
					(0.054)
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	33,077	34,304	33,077	33,077	33,077
R-squared	0.474	0.534	0.475	0.475	0.476

(b) Firm and Industry-Time Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.266***		0.262***	0.272***	0.272***
	(0.029)		(0.031)	(0.027)	(0.027)
Green Patent Ratio$_{f,t-1}$		59.402**	50.980*	79.043***	79.085***
		(23.384)	(28.888)	(12.609)	(12.598)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-4.312***	-4.314***
				(0.624)	(0.625)
Green Bond$_{i,t-1}$					-0.154***
					(0.045)
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	33,032	34,252	33,032	33,032	33,032
R-squared	0.573	0.615	0.573	0.574	0.574

Note: OLS estimation results of Equation (2) 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 measured in CO2e/USDm. The green patent is defined as the number of green patents owned by a given firm relative to the number of patents owned in total. '$EI \times GPR$' is the interaction between 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C3. Full Sample of Patenting Firms

Table C2: Summary statistics

	Mean	Median	SD	P10	P90
Environmental Variables					
(Scope1 + Scope2) Emission Intensity	2.532	0.456	4.597	0.109	8.399
(Scope1 + Scope2) Absolute Emissions (in log)	13.825	13.870	2.313	10.895	16.962
Green Patent Ratio	0.003	0.001	0.012	0.001	0.003
Bond Characteristics					
Yield to Maturity (%)	2.575	2.238	2.651	0.037	5.218
Spread (%)	1.989	1.314	2.422	0.347	4.220
Bond Holding Value (in m EUR)	170.083	50.492	260.246	1.916	527.562
Amount Outstanding (in m EUR)	580.315	467.290	510.192	88.496	1150
Fixed Coupon	0.915	1	0.279	1	1
EUR	0.334	0	0.472	0	1
USD	0.498	1	0.500	0	1
Green bond	0.015	0	0.123	0	0
Corporate Fundamentals					
Revenue (in bn EUR)	37.467	15.596	63.973	1.652	84.798
Total Assets (in bn EUR)	62.428	28.432	80.210	3.846	171.75
Total Debt (in bn EUR)	21.190	9.611	28.192	1.208	56.846
Profitability-Ratio (%)	4.753	4.166	6.152	-0.587	11.144
Leverage-Ratio (%)	36.067	35.130	14.571	19.218	54.578
Cash-Ratio (%)	6.451	2.987	10.462	0.385	14.379
Investment-Ratio (%)	13.207	6.877	17.707	0.915	34.986

Note: Based on 90,867 observations, reported at quarterly frequency and the security-by-security level. Absolute emissions levels are measured in CO2e and are reported in natural logarithms. Emission intensity, measured in CO2e/USDm, is scaled by a factor 1/100 and winsorized at the 2.5 percent level. Yield to maturity is winsorized at the 1 percent level. 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.

Table C3: Effect of Emission Intensity and Green Patenting on Yield Spreads

(a) Firm and Time Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.105*		0.105*	0.113*	0.110*
	(0.059)		(0.059)	(0.060)	(0.061)
Green Patent Ratio$_{f,t-1}$		14.319	14.519	52.391***	51.811***
		(13.104)	(13.444)	(18.979)	(19.431)
EI$_{f,t-1}\times$ GPR$_{f,t-1}$				-2.465**	-2.427**
				(0.986)	(1.003)
Green Bond$_{i,t-1}$					-0.277***
					(0.096)
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	90,945	90,867	90,867	90,867
R-squared	0.539	0.536	0.539	0.539	0.539

(b) Firm and Industry-Time Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.115		0.114	0.126	0.125
	(0.078)		(0.078)	(0.080)	(0.080)
Green Patent Ratio$_{f,t-1}$		9.079	4.679	40.400*	39.671*
		(8.656)	(8.545)	(20.405)	(20.789)
EI$_{f,t-1}\times$GPR$_{f,t-1}$				-2.255*	-2.215*
				(1.203)	(1.222)
Green Bond$_{i,t-1}$					-0.291***
					(0.088)
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	90,825	90,885	90,807	90,807	90,807
R-squared	0.578	0.578	0.578	0.578	0.579

Note: OLS estimation results of Equation (2) 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 measured in CO2e/USDm. The green patent is defined as the number of green patents owned by a given firm relative to the number of patents owned in total. '$EI \times GPR$' is the interaction between 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

C4. Absolute Scope 1 and 2 Emissions

Table C4: Effect of Emission Intensity and Green Patenting on Yield Spreads

(a) Firm and Time Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Emission Intensity$_{f,t-1}$	0.123*		0.130**	0.235**	0.237**
	(0.066)		(0.062)	(0.091)	(0.091)
Green Patent Ratio$_{f,t-1}$		18.935	19.620	142.632***	143.262***
		(15.314)	(15.603)	(38.113)	(38.107)
EI$_{f,t-1}\times$ GPR$_{f,t-1}$				-7.177***	-7.212***
				(2.131)	(2.136)
Green Bond$_{i,t-1}$					-0.612***
					(0.219)
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	39,421	39,571	39,421	39,421	39,421
R-squared	0.495	0.495	0.495	0.496	0.498

(b) Firm and Industry-Time Fixed Effects

	(1)	(2)	(3)	(4)	(5)
Scope 1+2 Emissions$_{f,t-1}$	0.166		0.164	0.330**	0.333**
	(0.131)		(0.130)	(0.130)	(0.130)
Green Patent Ratio$_{f,t-1}$		10.715	10.436	174.543***	175.897***
		(10.024)	(10.233)	(40.316)	(39.868)
Abs$_{f,t-1}$ $\times$ GPR$_{f,t-1}$				-9.482***	-9.561***
				(2.161)	(2.140)
Green Bond$_{i,t-1}$					-0.596**
					(0.227)
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	39,351	39,504	39,351	39,351	39,351
R-squared	0.571	0.566	0.571	0.572	0.573

Note: OLS estimation results of Equation (2) 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). Scope 1+2 emissions is the natural logarithm of scope 1 and 2 emissions measured in CO2e. The green patent is defined as the number of green patents owned by a given firm relative to the number of patents owned in total. '$EI \times GPR$' is the interaction between 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix D. 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) show 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 (2023). Also Hartzmark and Shue (2023) demonstrate that brown firms face weak incentives to become more green, indicating that directing 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.

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

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

where we use emission intensity as our main measure of environmental performance. We also verify the robustness of the results against using the absolute Scope 1 and 2 emissions (in log) as measure of environmental performance. We use either the green patent ratio as main explanatory variable in Equation (D.1) or the amount of green patents (in log). We include the vector of corporate fundamentals ($X_{f,t}$) and incorporate firm- (η_f) and time-fixed effects (λ_t).[43] For the regressions with absolute scope 1 and 2 emissions as dependent variable, we additionally include revenue (in log) 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 (log) number of green patents as explanatory variable.

D.1 Emission Intensity

Following Bolton et al. (2023), we estimate the impact of green innovation on corporate environmental performance by linking a companies' future emission intensity to its contemporaneous green innovation

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

Table D1: Linking Green Innovation and Environmental Performance

	Emission Intensity$_{f,t}$					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Green Patent Ratio$_{f,t-1}$	14.632					
	(25.751)					
Green Patent Ratio$_{f,t-2}$		34.797				
		(31.313)				
Green Patent Ratio$_{f,t-3}$			53.721			
			(36.067)			
Green Patents$_{f,t-1}$				0.348		
				(0.234)		
Green Patents$_{f,t-2}$					0.348	
					(0.377)	
Green Patents$_{f,t-3}$						0.825**
						(0.363)
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	1,363	1,009	709	1,262	923	643
R-squared	0.951	0.953	0.970	0.961	0.963	0.982

*Note: OLS estimation results of Equation D.1 with firm- and time fixed effects. We estimate the relationship between emission intensity, measured in CO2e/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 errors and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

activity. We fail to find evidence that an increase in the amount of green patents leads to lower emission intensity. The estimates in Column 1-3 indicate that the green patent ratio is positively associated with a company's future emission intensity. However, the relationship is statistically insignificant at 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. In this case, we find a statistically significant, yet positive, relationship between emissions intensity and the green patent ratio at the three-year horizon.

D2. Absolute Scope 1 and 2 Emissions

We verify the robustness of our results using absolute scope 1 and 2 emission levels as outcome variable in Table D2. Again, we find no evidence that the green patent ratio or the number of green patents is associated with absolute scope 1 and 2 emissions, at the horizons we consider.

Table D2: Linking Green Patenting to Environmental Performance

	Absolute Scope 1 and 2 Emissions$_{f,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Green Patent Ratio$_{f,t-1}$	-5.104					
	(4.925)					
Green Patent Ratio$_{f,t-2}$		-0.958				
		(4.406)				
Green Patent Ratio$_{f,t-3}$			8.074			
			(8.428)			
Green Patents$_{f,t-1}$				0.134		
				(0.104)		
Green Patents$_{f,t-2}$					0.164	
					(0.132)	
Green Patents$_{f,t-3}$						0.034
						(0.138)
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	1,397	1,033	724	1,281	936	650
R-squared	0.962	0.960	0.961	0.967	0.968	0.970

*Note: Robustness tests for Equation (3), estimated by OLS including firm- and time fixed effects. We estimate the relationship between the natural logarithm of absolute scope 1 and 2 emissions, measured in CO2e, 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, investment-ratio, and the natural logarithm of revenue. Standard errors are reported in parentheses errors and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

D3. 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 more incentives to innovate in the green space. We therefore also estimate the relationship using the Arellano and Bond (1991) two-step GMM estimator. The results using emission intensity as outcome variable are reported in Table D3 and the results using absolute scope 1 and 2 emissions are reported in Table D4. This procedure does not provide conclusive evidence either. We find a statistically significant and negative relationship between emission intensity and the number of green patents at the one- and two-year horizon. However, this association disappears when considering the absolute scope 1 and 2 emission levels. In this case, we find a statistically significant and positive relationship between absolute scope 1 and 2 emissions and the green patent ratio at the one-year horizon.

Table D3: Linking Green Patenting to Environmental Performance

	Emission Intensity$_{f,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Green Patent Ratio$_{f,t-1}$	18.534					
	(18.197)					
Green Patent Ratio$_{f,t-2}$		30.180				
		(29.132)				
Green Patent Ratio$_{f,t-3}$			56.854			
			(87.770)			
Green Patents$_{f,t-1}$				-1.351**		
				(0.544)		
Green Patents$_{f,t-2}$					-1.071*	
					(0.586)	
Green Patents$_{f,t-3}$						-1.018
						(0.737)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value	0.566	0.409	0.478	0.809	0.816	0.462
AR(1) p-value	0.335	0.302	0.258	0.807	0.882	0.417
AR(2) p-value	0.031	0.630	-	0.061	0.260	-
Observations	1,363	1,009	709	1,262	923	643

*Note: Robustness tests for Equation (3), estimated by GMM with time fixed effects. We estimate the relationship between emission intensity, measured in CO2e/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 errors and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

Table D4: Linking Green Patenting to Environmental Performance

	Absolute Scope 1 and 2 Emissions$_{f,t}$					
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
Green Patent Ratio$_{f,t-1}$	7.806**					
	(3.976)					
Green Patent Ratio$_{f,t-2}$		4.504				
		(7.007)				
Green Patent Ratio$_{f,t-3}$			25.458			
			(17.346)			
Green Patents$_{f,t-1}$				-0.067		
				(0.306)		
Green Patents$_{f,t-2}$					0.211	
					(0.485)	
Green Patents$_{f,t-3}$						-0.156
						(0.634)
Corporate Fundamentals	Yes	Yes	Yes	Yes	Yes	Yes
Time-FEs	Yes	Yes	Yes	Yes	Yes	Yes
Hansen p-value	0.943	0.662	0.346	0.251	0.370	0.103
AR(1) p-value	0.096	0.122	0.147	0.177	0.177	0.222
AR(2) p-value	0.255	0.713	-	0.525	0.791	-
Observations	1,397	1,033	724	1,281	936	650

*Note: Robustness tests for Equation (3), estimated by GMM with time fixed effects. We estimate the relationship between the natural logarithm of the absolute scope 1 and 2 emissions, measured in CO2e, 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, investment-ratio, and the natural logarithm of revenue. Standard errors are reported in parentheses errors and are clustered at the industry-level. *** p<0.01, ** p<0.05, * p<0.1.*

Overall, our results 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. This raises the question why investors take green innovation into account in the bond pricing relationship. One explanation is that investors anticipate emission reductions over a longer horizon. While our data does not show that green innovation leads to emission reductions within one, two, or even three years, it is possible that implementing patented green technologies and achieving the associated emission reductions takes longer. However, extending the time frame makes it more challenging to clearly identify the effect of green innovation on corporate environmental performance. While we are not able to test this in our data, another potential explanation is that owning green patents signals to investors that the company possesses advanced green technologies. This has a positive option value, especially if investors anticipate stricter climate policies in the future, since it positions the firm to respond more effectively to increased policy stringency. Our results may suggest that investors take this option value into consideration in their investment decisions.

Appendix E. Holder-Shares

Table E1: Evolution of (Unscaled) Shares

Period	EU	Inst.	Insur.	Mfund	Pfund	Bank
2016-Q2	0.3693	0.3085	0.1658	0.1434	0.0116	0.0345
2016-Q3	0.3684	0.3098	0.1640	0.1468	0.0119	0.0336
2016-Q4	0.3635	0.3046	0.1641	0.1403	0.0120	0.0338
2017-Q1	0.3655	0.3113	0.1678	0.1437	0.0139	0.0352
2017-Q2	0.3586	0.3047	0.1639	0.1409	0.0126	0.0353
2017-Q3	0.3552	0.3023	0.1617	0.1405	0.0127	0.0355
2017-Q4	0.3510	0.3012	0.1583	0.1431	0.0133	0.0333
2018-Q1	0.3408	0.2924	0.1526	0.1391	0.0128	0.0321
2018-Q2	0.3354	0.2863	0.1462	0.1383	0.0128	0.0322
2018-Q3	0.3370	0.2899	0.1498	0.1380	0.0122	0.0320
2018-Q4	0.3287	0.2802	0.1448	0.1334	0.0121	0.0335
2019-Q1	0.3333	0.2856	0.1463	0.1362	0.0124	0.0330
2019-Q2	0.3449	0.2956	0.1496	0.1425	0.0129	0.0351
2019-Q3	0.3458	0.2965	0.1497	0.1433	0.0130	0.0349
2019-Q4	0.3369	0.2907	0.1453	0.1410	0.0145	0.0349
2020-Q1	0.3160	0.2721	0.1383	0.1294	0.0129	0.0316
2020-Q2	0.3247	0.2796	0.1392	0.1336	0.0140	0.0316
2020-Q3	0.3213	0.2799	0.1351	0.1380	0.0143	0.0304
2020-Q4	0.3216	0.2818	0.1363	0.1454	0.0203	0.0335
2021-Q1	0.3168	0.2757	0.1344	0.1386	0.0185	0.0319
2021-Q2	0.3098	0.2702	0.1332	0.1337	0.0179	0.0321
2021-Q3	0.3039	0.2640	0.1289	0.1311	0.0178	0.0324
2021-Q4	0.3014	0.2625	0.1283	0.1294	0.0181	0.0320
Total	0.3351	0.2877	0.1468	0.1384	0.0143	0.0332

Note: Based on a sample of 38,374 observations, reported at the 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.

Table E2: Evolution of (Scaled) Shares

Period	EU	Inst.	Insur.	Mfund	Pfund	Bank
2016-Q2	0.3693	0.3417	0.2796	0.2725	0.2287	0.2594
2016-Q3	0.3684	0.3418	0.2778	0.2757	0.2314	0.2625
2016-Q4	0.3635	0.3360	0.2807	0.2636	0.2312	0.2624
2017-Q1	0.3655	0.3433	0.2894	0.2642	0.2320	0.2600
2017-Q2	0.3586	0.3366	0.2880	0.2579	0.2333	0.2625
2017-Q3	0.3552	0.3337	0.2850	0.2547	0.2350	0.2624
2017-Q4	0.3510	0.3319	0.2800	0.2542	0.2320	0.2604
2018-Q1	0.3408	0.3224	0.2721	0.2474	0.2285	0.2574
2018-Q2	0.3354	0.3170	0.2690	0.2485	0.2304	0.2616
2018-Q3	0.3370	0.3202	0.2739	0.2467	0.2338	0.2592
2018-Q4	0.3287	0.3102	0.2652	0.2396	0.2280	0.2611
2019-Q1	0.3333	0.3155	0.2699	0.2443	0.2343	0.2584
2019-Q2	0.3449	0.3264	0.2771	0.2544	0.2423	0.2719
2019-Q3	0.3458	0.3263	0.2772	0.2530	0.2409	0.2745
2019-Q4	0.3369	0.3187	0.2764	0.2447	0.2423	0.2723
2020-Q1	0.3160	0.3009	0.2675	0.2312	0.2212	0.2543
2020-Q2	0.3247	0.3079	0.2760	0.2381	0.2338	0.2616
2020-Q3	0.3213	0.3081	0.2731	0.2440	0.2406	0.2651
2020-Q4	0.3216	0.3097	0.2764	0.2516	0.2497	0.2679
2021-Q1	0.3168	0.3035	0.2718	0.2418	0.2436	0.2591
2021-Q2	0.3098	0.2975	0.2731	0.2331	0.2421	0.2596
2021-Q3	0.3039	0.2913	0.2698	0.2282	0.2420	0.2604
2021-Q4	0.3014	0.2894	0.2699	0.2283	0.2239	0.2600
Total	0.3351	0.3173	0.2753	0.2476	0.2351	0.2624

Note: Based on a sample of 38,374 observations, reported at the quarterly frequency and bond level. We distinguish between EU-holders, institutional investors (insurance companies, mutual funds, pension funds), and banks. The scaled holder-share is equal to the unscaled holder share scaled by the relative size of the investor sector. 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.