The ESG Divide: How Banks and Bondholders Differ in Financing Brown Firms*

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Abstract

We study credit providers and costs of debt for firms with low ESG performance. First, we find that, while both banks and bondholders charge low-ESG borrowers a higher interest rate compared to high-ESG borrowers, the premium charged by banks is relatively lower. Second, while bondholders reduce the amount of financing when borrowers' ESG performance deteriorates, banks keep the size of their loans unchanged or even increase loans issued to low-ESG borrowers. We provide evidence that the difference in creditors' policies is driven by banks' superior information about how material borrowers' low ESG performance is and by lenders' different preferences regarding their borrowers' ESG performance.

Keywords: ESG performance, bank lending, debt structure, cost of debt

JEL Codes: G12, G21, D62

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1 Introduction

Social activists and non-government organizations have suggested that one way to regulate firms' environmental, social, and governance (ESG) performance is to provide less debt funding for companies with low ESG performance.[1] Policymakers around the world consider directly regulating capital providers by mandatory disclosures of lending portfolios' ESG profiles or climate stress testing.[2,3] Despite the growing attention to these proposals, we lack comprehensive evidence on debt conditions and the main debt providers of firms with low ESG performance. In this paper, we study the credit conditions that brown firms[4] face and the extent to which banks and public bondholders finance brown companies. We also examine the reasons behind lenders' different decisions in financing brown firms.

We find that while firms with poor ESG performance face higher costs of both loans and public debt, the premium for borrowing from banks is lower for low-ESG-performance firms than for high-ESG-performance firms. As a result, brown companies obtain larger loans and borrow less from the bond market. This suggests that brown firms' debt structure is tilted towards bank loans. We test two mechanisms that are consistent with our findings. First, banks have superior information about the materiality of the sustainability risk and originate loans mostly to firms with lower risks. Second, banks and bondholders have different preferences for lending to brown firms. We also consider a set of alternative mechanisms (such as borrowers' financial risk, short-term borrowing, etc) and argue that they cannot explain our findings.

We begin by studying brown firms' costs of different types of debt. We show that companies with lower ESG performance face higher costs of both bank loans and bond financing. However, simply comparing firms with high and low ESG performance has

[1] Bloomberg, November 24, 2021. Wall Street's $22 Trillion Carbon Time Bomb.
[2] Wall Street Journal, May 3, 2024. HSBC's Green Credentials Come Under Fresh Scrutiny.
[3] Financial Times, March 31, 2022. Banks face new standards on carbon emissions disclosure.
[4] Throughout the paper, we use the terms "brown" and "green" to denote firms with low and high ESG performance, respectively. In Appendix B.1, we focus only on environmental performance and demonstrate that our results hold.

at least two challenges. The first is a reverse causality issue. It is possible that a debt provider finances a company first; the company invests in profitable yet ESG-unfavorable projects (Bellon and Boualam (2024)) and becomes brown. The second issue may be that brown companies have unobservable characteristics that make them attract a specific type of debt or certain debt conditions. For example, green firms may be ruled by more liberal managers who are also more transparent, making a green company more attractive to investors in the public bond market.

To address these concerns, we employ an event study methodology, which allows us to isolate the effect of firms' ESG performance on their debt financing. As a setting, we choose news announcements about negative ESG events happening at companies. An event comprises a violation of one or more of the United Nations Global Compact (UNGC) principles – ten principles related to human rights, labor, environment, and anti-corruption that a responsible business should follow.[5] Violating a principle reduces a firm's ESG performance and at the same time, as we discuss in later in detail, does not appear to affect financial performance.[6] We find that after a firm experiences a negative ESG event, the interest rate on its next loan increases, and the yield on bonds issued by the firm rises (implying costlier borrowing).

While an event study can provide useful insights, the event study assumptions require the events to be exogenous (unrelated to unexplained part of credit conditions). In reality, some firms are more likely to have a negative ESG event than others. For example, firms in the oil industry are more likely to have an oil spill. To address the issue, we match firms that had a negative ESG event with similar firms that did not have negative ESG events around the same time by using propensity score matching.[7] The variables used in matching include pre-event ESG performance, balance sheet variables, date, and industry. We then compare the costs of debt between the two closely matched groups of firms.

[5]See the UNGC website for detailed descriptions of the ten UNGC principles.

[6]We show that a negative ESG event does not increase firms' demand for short-term funding and does not lead to harsher non-price loan terms, such as covenants or collateral.

[7]We consider an alternative matching strategy in Appendix B.2.

Our estimates suggest that the costs of borrowing from both types of lenders are higher for brown firms. Specifically, the all-in-drawn spread charged by the bank on the next loan for the firm that had a negative ESG event increases on average by 4.4 to 11.3 bps relative to the firm that did not have negative ESG events around the same time. Bond financing also becomes more expensive – bond yields rise by 1.4 to 1.8 bps following a negative ESG event.

Even though both banks and public bondholders appear to charge premiums for their borrowers' low ESG performance, these premiums may be different for the two types of creditors. In particular, loan rates are smaller than bond yields to begin with because loan investors are senior to bond investors in case of a default. To account for differences between the two types of debt, we use a credit pricing model proposed by Schwert (2020). Measuring interest charged by the two creditors is complicated because loans and bonds have different seniorities, probabilities of default, and systemic risk exposure related to default. To overcome differences in default probabilities, we match loans and bonds issued by the same company on the same date with the same maturity and other characteristics. Next, we use Merton (1974) asset pricing model to account for differences in seniority and, thus, recovery rates. We obtain the prices of firms' loans as if they were traded on the market. The difference between actual loan spreads and the spreads suggested by the model is the additional cost that companies pay for borrowing from banks. We find that the additional cost for borrowing from banks paid by brown borrowers is significantly lower (0.96 percentage points) than the additional cost paid by green borrowers (1.99 percentage points). This result suggests that, even though banks and bondholders both charge higher rates if a borrower is brown, banks do so to a lesser extent, making bank loans relatively cheaper for brown borrowers than for green borrowers.[8,9]

[8]Our paper does not consider equity financing. Prior work finds a small reaction of equityholders to ESG news (Gantchev et al. (2022)). A possible conclusion is that equity financing does not become considerably more expensive for firms with poor ESG performance and can be used to finance their operations.

[9]In additional analyses, we make sure that banks do not compensate for a lower interest rate increase with harsher other loan terms. The banks do not include more financial covenants, are not more likely

Next, we examine whether the two types of creditors – banks and bondholders – react differently to their borrowers' low ESG performance in terms of amounts of financing. Similarly to interest rates, first, we conduct an event study and show that following a negative ESG event, the amount of bank loans increases for brown firms, whereas bond financing declines. Second, we compare amounts of loan and bond credit for firms that had a negative ESG event with amounts for their matched counterparts. We find that bondholders provide less credit to brown firms compared to green firms, while banks provide the same amount or even larger loans. In particular, bond financing declines by 1.2% to 4.3% following a negative ESG event for treated firms compared to the control firms. Sizes of bank loans increase by 0.2% to 2% for firms that have had a negative ESG event compared to firms that have not.

Overall, our study documents three patterns: (1) both banks and public bondholders charge brown borrowers a higher interest rate; (2) this increase in the interest rate is smaller for banks; (3) banks provide the same or larger credit to brown firms, while bondholders provide less credit. Next, we study potential mechanisms underlying our findings. The set of potential mechanisms is limited because the mechanism cannot be entirely demand-driven (supply-driven) – otherwise, for both loans and bonds, interest rates and quantities would move in opposite (the same) directions.

We explore potential explanations for why loans are relatively cheaper for brown borrowers and why banks choose to provide financing to firms with low ESG performance while bondholders do not. We first explain why the results are unlikely to be driven by the elevated financial risk after a borrower's ESG performance deteriorates. The financial risk mechanism is unlikely to explain why banks would increase financing to such borrowers while public bondholders would decrease financing. The increased financial risk is a supply-side mechanism, and as we discuss above, if credit supply shifts such that the interest rate increases, the amount of credit should be reduced, but banks do not cut lending to firms with low ESG performance. The negative ESG events in our sample,

to require collateral, do not shorten maturity, and (as we discuss later in detail) do not reduce loan sizes when lending to brown borrowers.

while important in terms of firms' ESG profiles, are not so financially material as to move the firms close to default and thus substantially shift their capital structure. We also check that the results are not driven by firms' increased demand for short-term financing to remedy the consequences of negative ESG events. Finally, it might be the case that instead of contracting lending to financially risky firms, banks shorten maturity, impose more covenants, or demand collateral. We test all three predictions and do not find any evidence of banks tightening their credit conditions beyond increasing loan spreads.

We then provide evidence for two explanations that are consistent with our findings. The first explanation is banks' exclusive knowledge about their borrowers. Banks invest resources in screening (Ramakrishnan and Thakor (1984); Allen (1990)) and monitoring (Diamond (1984); Winton (1995)) their borrowers and consequently obtain informational advantage compared to other capital providers (e.g., public bondholders). We conjecture that banks' expertise allows them to better interpret the consequences of the borrowers' low ESG performance for the borrowers' cash flows and solvency. As a result, banks may be able to identify and provide credit to brown borrowers whose low ESG performance does not affect their financial performance. We confirm this mechanism using a moderation test with the measure of materiality of firms' ESG concerns computed by MSCI.[10] We find that banks generally issue larger loans only to borrowers whose negative ESG event is not financially material. If a negative ESG event is material, banks reduce the loan amounts, behaving in the same manner as bondholders.

The second explanation for our findings may be that public debt holders and banks have different preferences for their borrowers' ESG performance.[11] If bondholders inherently value their borrowers' ESG performance, they may require a higher premium as financial compensation for unsatisfactory non-financial performance. The preferences

[10]Importantly, MSCI launched this tool only at the end of 2020, so public bondholders do not have access to the Map for most of the time frame for our sample.

[11]The motives behind different tastes can be non-pecuniary benefits that banks' or bondholders' investors derive from holding high ESG assets, regulatory environments, or lenders' exposure to ESG risks. For example, large body of the literature argues that bondholders have preferences for green investment (Larcker and Watts (2020); Baker et al. (2024); Renjie and Xia (2023)). We do not argue that non-pecuniary benefits are the only explanation of the second mechanism and we are agnostic about potential reasons banks or bondholders have certain ESG preferences.

explanation also rationalizes why bondholders divest from brown firms. When some investors (i.e., bondholders) value ESG performance, and others (i.e., banks) do not, in equilibrium, the former will invest more in green companies and the latter more in brown companies (Pástor et al. (2021)). We test the preference mechanism on both banks and bondholders. We use two measures of banks' preferences for ESG performance: self-disclosed – whether banks' major shareholders claim to be sustainability-oriented – and action-based – whether a bank's board of directors has an ESG committee. Using both measures, we find that bank financing of brown firms is driven primarily by banks that do not have preferences for their borrowers' high ESG performance. Banks whose shareholders claim to be ESG-oriented increase loan sizes to brown firms by a smaller amount; banks that have an ESG committee even reduce loan amounts to brown borrowers. Using PRI and SBTI signatories to measure bondholders' ESG preferences, we do not find any significant difference in institutional investors' bond investing behavior for investors that do and do not have a preference for ESG. In combination, all bondholders appear to have some preference for ESG, while some banks do not value borrowers' ESG performance and thus can provide funding to brown borrowers when bondholders or ESG-conscious banks cannot.

Our paper contributes to several strands of the literature. The youngest and rapidly developing literature is about firms' non-financial performance (i.e., environmental or ESG in general) and cost of capital (see Giglio et al. (2021) for a review). Studies of equity have generally concluded that companies' high ESG performance is associated with higher realized stock returns (Chava (2014); Lins et al. (2017); Engle et al. (2020); Choi et al. (2020); Bolton and Kacperczyk (2021); Hsu et al. (2023)), while expected returns of green companies are negative (Pástor et al. (2022)). There is evidence, however, that high ESG performance is associated with lower stock returns (Bolton and Kacperczyk (2023)). Similarly to our paper, the literature on equity and ESG recognizes that investors may have preferences for their holdings' non-financial performance (e.g., Friedman and Heinle (2016); Pástor et al. (2021); Pedersen et al. (2021);

Giglio et al. (2023)) and equilibrium investor holdings and asset prices depend on these preferences. On the debt side, multiple studies have found that firms with low ESG performance face higher costs of both bank loans (Goss and Roberts (2011); Delis et al. (2020); Chen et al. (2021); Degryse et al. (2021); Ehlers et al. (2022); Altavilla et al. (2024)) and public debt (Jung et al. (2018); Huynh and Xia (2021); Seltzer et al. (2022)), unless this debt has a clear purpose of improving the firm's ESG performance (Flammer (2021)). Prior research has also examined how lenders choose the amounts they lend to brown and green firms and other contractual features (Nguyen and Phan (2020); Reghezza et al. (2021); Kacperczyk and Peydro (2022); Wang (2023); Giannetti et al. (2024); Sastry et al. (2023); Beyene et al. (2024)). Importantly, not all the studies focus on corporations' environmental performance; some have considered corporations' conduct on other ESG dimensions, such as tax avoidance or misreporting (Graham et al. (2008); Hasan et al. (2014)). Existing literature has found somewhat conflicting results: some studies claim that lenders in general reduce financing to brown borrowers (e.g., Kacperczyk and Peydro (2022); Hartzmark and Shue (2022); Wang (2023); Akey et al. (2024); Bellon and Boualam (2024)), and some claim that lenders increase their financing (e.g., Giannetti et al. (2024)). We contribute to the debate in at least two ways. First, we consider the borrower's full menu of debt options and study the relative costs of public and private debt. We highlight that, while it is true that both types of debt are more expensive for brown borrowers, bank loans become relatively more attractive as borrowers' ESG performance deteriorates. Second, we help resolve the potentially confusing conflicting results on the amounts of financing lenders provide to brown borrowers. We provide evidence for two mechanisms underlying lenders' decision to provide financing to brown borrowers: lenders' preferences for ESG and financial materiality of borrowers' low ESG performance. These mechanisms also help us understand whether debt investors value ESG qualities of assets because ESG has cash flow implications or because the investors derive non-pecuniary benefits from investing in high ESG assets. Understanding investors' motivation is an important step towards a better understanding of sustainable investing (Starks (2023)).

We also contribute to the broader literature on lending decisions (e.g., Ivashina (2009); Schwert (2018); Houston and Shan (2022)). Among many previous studies, we find that a borrower's profile beyond financial performance is important for lenders' decisions about interest rates and sizes of financing. Importantly, our evidence suggests that lenders consider borrowers' ESG performance in tandem with its financial implications.

Another large stream of research is on corporate debt and capital structure (e.g., Diamond (1991); Rajan (1992); Chemmanur and Fulghieri (1994); Bolton and Scharfstein (1996), Faulkender and Petersen (2006); Rauh and Sufi (2010); Becker and Ivashina (2014); Crouzet (2018); Schwert (2020); Crouzet (2021); Flanagan (2022)). These studies identify multiple determinants of companies' choice among different funding sources. One of the important determinants is information asymmetry between the lender and the borrower. We show that, in the ESG setting, information asymmetry continues to matter and mitigates the lenders' decision to fund a borrower with low ESG performance. Some studies have also considered the relation between firms' capital or debt structure and sustainability profile. For example, Chang et al. (2024) study how firms' ex ante capital structure affects their subsequent non-financial performance. Asimakopoulos et al. (2023) find that, after information about borrowers' ESG performance becomes available, their debt structure tilts toward more bank loans. It is important to note that we focus on borrowers whose ESG performance information is already available. Our contribution is to show how borrowers' ESG performance affects lenders' decision to finance the borrower.

The rest of the paper is organized as follows. Section 2 describes our main data sources, summary statistics, and empirical strategy. Section 3 provides the results on the cost of debt of brown companies. Section 4 shows the results on the amount of debt of brown companies. Section 5 studies the potential mechanisms underlying our findings. Section 6 concludes.

2 Data and empirical strategy

In this section, we describe our main data sources and discuss the identification strategy. Since we compare different debt sources of firms, we construct a dataset that combines loans originated by banks and bonds issued by corporations.

2.1 Data

The data on syndicated loans originated in the US from 2001 to 2021 comes from the Thompson Reuters DealScan. For each loan, we observe the lender, the borrowers, all-in-drawn spreads, loan amounts, and other loan terms such as covenants, collateral, and maturity. Following prior literature, we remove borrowers in the financial and utilities industries (SIC codes 49, 60-69, 90-99). We keep only observations for the lead lender as this lender is typically the one responsible for the deal. We keep only US dollar-denominated loans. We remove loans that are originated for acquisitions, takeovers, or leverage buyouts, even if those reasons are mentioned as secondary, and sponsored loans. We keep only loans that are priced relative to LIBOR. Finally, we keep only revolving loan facilities (revolvers, lines of credit) and term loans of all types. Our final DealScan sample contains 19,664 observations. For each loan facility, we observe an all-in-drawn spread (relative to LIBOR), date of origination, maturity, seniority, and loan amount. We merge the loan pricing data with balance sheet data on lenders and borrowers from Compustat using linking files provided by Chava and Roberts (2008) and Schwert (2020).[12]

We obtain bond issuance data from Mergent FISD. The data specifies the issue date and amount for each bond. The sample contains 454,405 observations from 1984 to 2021. We merge FISD to DealScan using CUSIP and lender file shared by Schwert (2020). We collect bond prices from TRACE and merge each loan facility with data on bond prices. The data is transaction-level, i.e., prices of the bonds are recorded at dates when

[12]We thank Sudheer Chava, Michael Roberts, and Michael Schwert for making their data available.

transactions were made. We match loans and bonds by the date of origination/issuance and maturity. Following Schwert (2020), we keep only senior unsecured bonds.

Next, we add risk-free rates and debt structure data. Because loans in our sample set interest rates relative to LIBOR, we collect LIBOR data from Bloomberg and use it as a measure of risk-free rate. We further compute bond spreads by maturity-matching LIBOR to make the base consistent with loans. Finally, we collect debt structure data from Capital IQ. We define senior debt as a sum of total bank debt and capital leases. The rest of the debt is junior.

Finally, we obtain firms' ESG performance data from RepRisk. RepRisk collects data on news announcements about firms' negative ESG events – violations of UNGC principles. When a serious violation takes place, it is usually covered in mass media. Then, it appears in the RepRisk database. The database contains information about the event – description and date. The description mentions which principle has been violated. UNGC specifies ten principles: two of them are related to human rights, four – to labor, three – to the environment, and one – to anti-corruption. In the paper, we use events themselves and ESG ratings[13] for firms that RepRisk computes based on the history of UNGC violations. For events, the original RepRisk sample covers 37,164,374 events, many of which are duplicates (e.g. if the event was covered by multiple media outlets), which we remove. For ratings, RepRisk ESG ratings are based on the number of UNGC violations a firm experienced. The more violations, the lower the rating. If a firm has not violated any principles in a long period of time, its rating improves. Unlike many other measures of ESG scores, the rating we use is ex-post, i.e., it does not measure ex-ante brownness of firms given their emissions, corporate policies, etc.

A major advantage of using RepRisk data for ESG performance is that it focuses on realized ESG events rather than on ex-ante characteristics, as many other ESG ratings do. As Berg et al. (2022) show, there is a very low correlation between ex-ante ratings. By focusing on actual events, we take a stance on how we define a brown firm – a

[13]In Appendix B.5, we consider widely used MSCI ratings and show that our results hold.

Table 1: Descriptive Statistics of RepRisk Events: Counts of Events

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Events per firm	125	8.672	13.688	1.000	1.000	10.000	90.000
Events per year	11	98.55	76.993	2.00	41.50	143.00	238.00
Events per firm-year	301	3.601	5.182	1.000	1.000	4.000	58.000

Note: This table provides summary statistics of counts of RepRisk events per firm, per year, and per firm-year. An event is recorded the first time it is covered by a public source. We drop duplicating news coverage of events after the first announcement.

Table 2: Descriptive Statistics of RepRisk Events: Event Characteristics

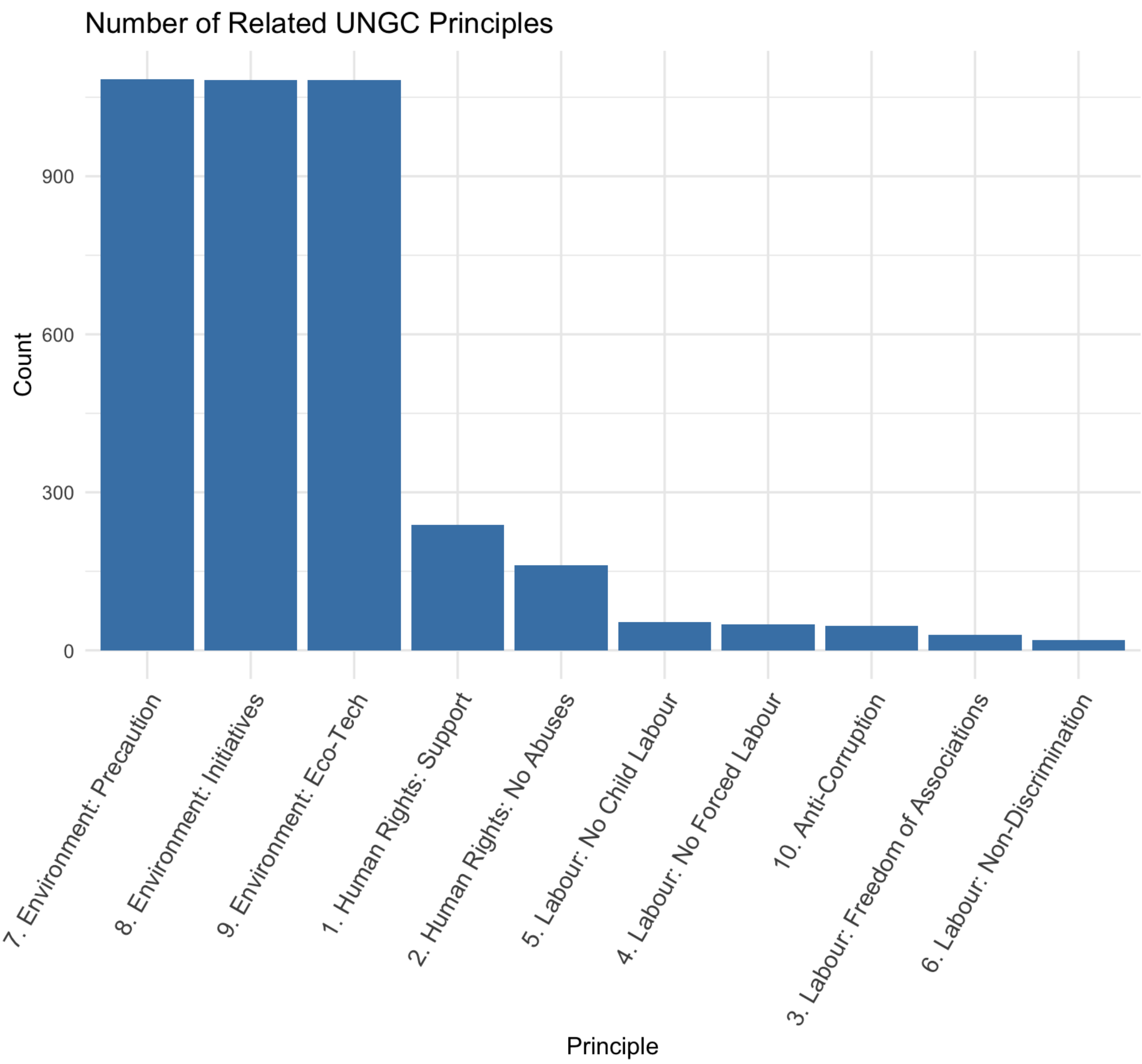
Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Severity	1,084	1.491	0.527	1	1	2	3
Novelty	1,084	1.719	0.450	1	1	2	2
Reach	1,084	1.559	0.599	1	1	2	3

Note: This table provides summary statistics of the characteristics of RepRisk events. Severity measures the harshness of the event. The higher the number, the harsher the risk incident. Novelty is the newness of the issues addressed in the news about the event. The higher the number, the more unexpected the news is. Source reach is the influence or readership of the news source in which the event was published. The higher the number, the more influential the first announcement about an event is.

company that had many negative ESG events.

We show summary statistics of negative ESG events – UNGC violations – in our sample in Tables 1 and 2. On average, we have about 9 events per firm, 99 events every year, and about 4 events per firm in a given year. Figure 1 shows the number of UNGC principles violations. Note that one event may involve violations of multiple principles. The vast majority of violations are of environmental principles. The next most popular category is human rights. In Appendix B.1, we keep only events related to climate and show that our findings are the same.

Figure 1: Histogram of UNGC Principles Violations in RepRisk Events in our Sample.



Note: The histogram shows the frequency of different UNGC principles violations in our sample. The data is from RepRisk. Note that one event may involve violations of multiple UNGC principles. For the full description of principles, see the UNGC website.

2.2 Empirical strategy

We start by examining whether firms with different ESG ratings have different prices and quantities of debt. Specifically, we estimate the following regression:

$$Y_{ibt} = \beta ESG_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \theta_t + \varepsilon_{ibt} \tag{1}$$

where Y_{ibt} is either the price of debt or the logarithm of the quantity of debt originated by bank b to firm i at time t. ESG_{it} is an ESG rating of firm i as of time t, X_{ibt} is a set of control variables (including Altman z-score, a dummy variable for secured debt, and balance sheet variables), α_i is borrower FEs, κ_b is bank FEs, and θ_t is time FEs. In case of bonds, the amount of bond financing and all characteristics are at the firm-year level (no b subscript and no bank fixed effects). In Appendix B.5, we also consider widely used MSCI ratings and show that our results hold.

Despite the fact that ESG ratings from RepRisk are not ex-ante evaluations of companies' ESG profiles but rather ex-post counts of negative ESG events, there are potential endogeneity concerns. In particular, firms that have many negative ESG events can be different from those that do not in ways that also impact loan rates and debt amounts. We implement an event study methodology to address this identification concern. As events, we take RepRisk events – violations of UNGC principles. In Appendix B.1, we show that our results hold even if we consider only climate-related events.

The assumption behind the event study is that ESG events are not driven by loan characteristics. In particular, we assume that the events are not impacted by the debt terms such as interest rates and that the events are not correlated with the error term in (1). We then run the following regression:

$$Y_{ibt} = \beta Post_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \theta_t + \varepsilon_{ibt} \tag{2}$$

where $Post_{it}$ is a dummy variable equal to 1 for firm i after it has a negative ESG event. We define the post period as the year after the event. We specifically look at the *next* debt contract after the event. For example, if the event happened before the end date of the existing loan, the loan will not be treated as the post-event debt.

In principle, loan terms can impact the events. For example, higher loan rates might force the borrower to forgo green projects as brown projects are often cheaper (Hartzmark and Shue (2022); Bellon and Boualam (2024)). To further mitigate the concerns that the events are not random (for example, because firms in some industries are more likely to violate UNGC principles), we match firms in our sample (treatment group) to firms that did not have any negative ESG events (control group) using the propensity score nearest neighbor matching where propensity scores are calculated using logit.[14] We match firms based on their balance sheet characteristics (assets, liabilities, intangibles), date, industry, and ESG rating prior to the event. For each firm-event pair, we find a matching firm from Compustat. Our final matched data contains 135,818 observations. We then merge the matched data with loan and bond data to estimate the following regression:

$$Y_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt} \tag{3}$$

where $Treat_{it}$ is a dummy equal to 1 for the firms that have a negative ESG event at time t.[15] Our main identification assumption is that absent negative ESG events, firms in two groups would have had similar debt characteristics. In Appendix B.3, we discuss the parallel trend assumption and show that there are no pre-trends: firms in the treatment and control group do not have different credit conditions prior to their events.

The matching strategy allows us to mitigate concerns related to treated firms being fundamentally different from the firms that do not experience any events. For example, a possible concern is that green firms are better monitored by the banks, and that is why green firms get, on average, better terms. Our matching strategy helps with this threat because we include ESG scores before the events in the matching set, so we compare treated firms with the firms with similar ESG ratings prior to the event but that did not experience an event. Unless the event itself triggers less monitoring, which is unlikely, more intense monitoring of green firms should not explain our results. In Appendix B.4 we plot distributions of variables in the control and treatment groups to show that the matching yields a relatively balanced sample.

Our final database contains data for treated and control firms on their balance sheets,

[14] In Appendix B.2, we show that our results are robust to alternative matching strategies, such as Mahalanobis distance matching.

[15] Most firms experience multiple events throughout our sample. For example, if Apple Inc. experiences an event in August 2002 and July 2020, its $Treat_{it}$ will be equal to 1 for the third quarter of 2002 and the third quarter of 2020. Apple Inc. can still be matched as a non-event firm for other quarters.

Table 3: Summary Statistics: Matched Sample

	All firms		Treatment		Control	
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.
Panel A: Loan characteristic (DealScan)						
Bank loan amount (th. $)	4,810	7,849	4,154	3,189	5,476	9,839
All-in-drawn spread (b.p.)	148	72	121	73	159	69
Panel B: Bond characteristics (TRACE & FISD)						
Bond yield (%)	4.49	37.30	4.08	18.96	7.61	96.03
Bond amount (th. $)	1,105	4,154	1,018	2,067	1,376	7,599
Panel C: Borrower characteristics (Compustat & RepRisk)						
Total assets (bill. $)	77	145	80	112	75	165
Total liabilities (bill. $)	55	125	50	91	60	145
Altman z-score	2.29	1.40	2.78	1.38	1.88	1.29
ESG score	1.14	1.23	1.57	1.10	0.83	1.22

Note: This table provides descriptive statistics for the data used in the main analysis of the paper. Panel A provides summary statistics for loan characteristics from DealScan. Panel B contains summary statistics for bond characteristics for TRACE and FISD. Panel C provides statistics for borrowers' characteristics from Compustat and RepRisk. The columns represent the groups – the first two show means and standard deviations for the full sample, and columns 3-6 provide means and standard deviations separately for treatment and control groups, respectively. The treatment group is the group where firms experienced negative ESG events.

loan amounts, issued bonds, prices of loans and bonds, ESG ratings, and dates of negative ESG events. Table 3 provides summary statistics for the matched sample. The variables used in matching are fairly close for treatment and control groups, as the procedure requires. Moreover, our matching technique performs well for out-of-procedure variables. For example, pre-event average all-in-drawn spreads are 128 and 159 bps for the firms in treatment and control groups, respectively.

3 Cost of debt for brown companies

In this section, we analyze the costs of loan and bond financing for brown firms relative to green firms. We first test whether bank loans have different costs for brown firms. Then, we test if the yields of bonds issued by brown companies are higher than the yields of those issued by green companies. Finally, we estimate a structural model to compare the cost of bank loans to the cost of bond financing.

3.1 Cost of bank loans

We start by testing whether loan spreads (loan rates minus LIBOR) are higher for firms with lower ESG ratings. Table 4 shows the results. Generally, loan spreads are lower for firms with high ESG ratings. The result persists even after including bank and borrower fixed effects. This finding implies that banks charge a premium when they lend to a brown firm. The reason for this premium may be brown firms' low ESG performance or that banks expect the financial performance of brown firms to be worse than that of green firms. To partly rule out the financial performance explanation, we include Altman's z-score (Altman (1968)), a dummy variable for secured loans, and loan amounts as control variables.[16] In Appendix B.5, we also consider widely used MSCI ratings and show that our results hold.

The results in Table 4 do not necessarily imply that low ESG performance is the reason for high loan spreads. There are potential confounding factors that can affect both the ESG rating and loan spread of the firm. To address the concern, we conduct an event study using news about firms having negative ESG events. The relevance assumption is that the violation of UNGC principles makes the firm more brown. The exogeneity assumption implies that the events are not influenced by loan conditions, and also common variables do not impact both the firm's loan conditions and the probability of the firm experiencing a negative ESG event.

[16]Controlling for z-score does not fully eliminate the possibility that the result is driven by financial risk. We discuss this issue more in Section 5.

Table 4: Impact of ESG Performance on the Loan Spread

$$r^{\ell}_{ibt} = \beta ESG_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:		
	All-in-drawn spread		
	(1)	(2)	(3)
ESG rating	-3.008^{*}	-8.384^{***}	-9.964^{***}
	(1.550)	(1.006)	(2.125)
Bank FE	Yes	Yes	No
Borrower FE	Yes	No	No
Controls	Yes	Yes	Yes
Observations	5,485	5,485	5,485
R^2	0.962	0.866	0.628

Note: This table provides results of the estimation of equation (1) where the dependent variable is all-in-drawn spreads. ESG ratings are based on a number of negative ESG events calculated by RepRisk. The ratings are demeaned. Bank and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Columns 1 and 2 of Table 5 show the results. Note that since in the event study we only include firms that have a negative ESG event, the variable of interest is $Post$. In one of the specifications, negative ESG events are associated with higher loan spreads charged by banks. An average event increases the all-in-drawn spread of the next loan to the borrower by 3.4 bps. This result is in line with our hypothesis that banks consider borrowers' ESG performance when determining loan spreads. The insignificant result in the other specification may occur due to the selection bias of firms that have a negative ESG event. We address this concern in the next set of tests.

The event study assumptions require that the negative ESG events are not influenced by loan conditions or common confounders. In reality, some firms may be more likely to experience a negative ESG event than other. For example, firms in the oil industry are more likely to have an oil spill, or firms with worse ESG performance ex ante are more likely to maintain this poor performance. Oil firms will also likely obtain different loan conditions. To address this issue, we match firms that experienced negative ESG events with similar firms that did not experience any negative ESG events close to the

Table 5: Impact of ESG Performance on the Loan Spread: Event Study and Matching

$$r^{\ell}_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:			
	All-in-drawn spread			
	(1)	(2)	(3)	(4)
Post	−0.034	3.387***	−3.342***	−8.131***
	(0.671)	(0.788)	(0.480)	(0.866)
Event			130.876***	−23.128***
			(3.120)	(0.894)
Post · Event			4.359***	11.283***
			(0.795)	(1.164)
Matching	No	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes
Observations	16,962	16,962	35,150	35,150
R^2	0.924	0.873	0.957	0.890

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is all-in-drawn spread. The first two columns correspond to the event-study results. The events are violations of the UNGC principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Bank and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

same date. The variables used in matching include pre-event ESG ratings, balance sheet characteristics, date, and industry. The exclusion restriction requires that variables not captured by the matching procedure do not impact the occurrence of a negative ESG event. Another way to phrase the assumption is that absent the event, firms in the treatment and control groups would have had similar debt conditions. In the Appendix B.3, we also show that there are no pre-trends – firms in the treatment and control groups have similar loan spreads before the events.

Columns 3-4 of Table 5 show the results of the test with matching. The all-in-drawn spread of the next loan for the firm that has had a negative ESG event increases on

Table 6: Impact of ESG Performance on the Bond Yields

$$r^b_{it} = \beta ESG_{it} + \gamma X_{it} + \alpha_i + \theta_t + \varepsilon_{it}$$

	Dependent variable:		
	Bond yield		
	(1)	(2)	(3)
ESG rating	-1.729^{***}	-0.335^{***}	-0.993^{***}
	(0.099)	(0.045)	(0.024)
Time FE	Yes	Yes	No
Firm FE	Yes	No	No
Observations	47,118	47,118	47,118
R^2	0.709	0.686	0.031

Note: This table provides results of the estimation of equation (1) where the dependent variable is bond yield. ESG ratings are based on a number of negative ESG events calculated by RepRisk. The ratings are demeaned. Time and firm fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

average by 11.3 bps relative to the firm that did not have any negative ESG events around the same time. At the within-firm level, the magnitude of the reduction is smaller but still statistically and economically meaningful: 4.4 bps. These results imply that negative ESG events increase the cost of bank loans for borrowers.

3.2 Cost of bonds

Next, we test how ESG ratings impact bond yields. If the yield is high, the price is low, so if borrowing from the bond market is more expensive for brown firms, the bond yields of brown companies should be higher than those of green companies. Table 6 shows the results. Lower ESG ratings are associated with higher bond yields, implying that brown companies sell their bonds at lower prices. The results are even stronger if we account for time and firm fixed effects to control for unobservable variation in bond issuers and the year of the issuance. In Appendix B.5, we also consider widely used MSCI ratings and show that our results hold.

Changes in ESG performance are generally correlated with other characteristics which

Table 7: Impact of ESG Performance on the Bond Yields: Event Study and Matching

$$r^b_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \theta_t + \varepsilon_{ibt}$$

	Dependent variable:			
	Bond yield			
	(1)	(2)	(3)	(4)
Post	1.693***	2.219***	0.033	−0.754***
	(0.033)	(0.041)	(0.131)	(0.144)
Event			−2.670***	−3.164***
			(0.139)	(0.146)
Post · Event			1.442***	1.784***
			(0.140)	(0.134)
Matching	No	No	Yes	Yes
Time FE	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Observations	1,773,731	1,773,731	2,769,450	2,769,450
R^2	0.182	0.169	0.043	0.041

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is bond yields. The first two columns correspond to the event-study results. The events are violations of the UNGC principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Time and firm fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

can also impact bond yields. For example, firms in the electric car production industry usually have higher ESG ratings, but they might also be perceived as riskier, and hence, their bond yields can be higher. To address this issue, we conduct an event study using firms' negative ESG events.

Columns 1-2 of Table 7 show the event study results. Bond yields increase on average by 1.7-2.2 bps after a negative ESG event, implying that bond prices are lower for more brown firms. This finding suggests that borrowing from public markets is more expensive for brown firms than for green firms.

The event study rests on the assumption that all changes to bond yields around the negative ESG event are attributed to the event. However, other factors can also impact bond yields. For example, financial shocks or changes in the regulation of certain industries can impact bond yields around negative ESG events. To address the issue, we match firms that experienced negative ESG events with similar firms that did not experience any negative ESG events close to the same date, following the same procedure as described above. The variables used in matching include pre-event ESG ratings, balance sheet characteristics, date, and industry. The exclusion restriction requires that variables not captured by the matching procedure do not impact the occurrence of a negative ESG event.

Columns 3-4 of Table 7 show the matching results. In both specifications, bond yields increase for firms that had negative ESG events relative to firms that did not. Bond yields increase by 1.4-1.8 bps during the one-year window around the negative ESG event, suggesting that brown firms find it more costly to borrow from the bond market.

Next, we study whether the *difference* in the cost of bank and bond debt is different for brown and green firms. To examine this question, we need to compare prices of loans and bonds for the *same* firm under the same conditions. The comparison is not straightforward since bonds are traded on the market and loans are not. We discuss how we compare prices of bonds and loans in the next subsection.

3.3 A structural model of loan and bond pricing

Comparing prices of loans and bonds is challenging because bonds are traded on the market and thus their yields are determined by trading behavior, whereas loans are originated by banks and their spreads are a result of negotiations between lenders and borrowers. Bonds and loans also have different maturities and different seniority. One approach to estimate the differences between the costs of bonds and loans is to estimate the loan premium as if loans were traded on the market like bonds. We do it by following the methodology developed by Schwert (2020).

3.3.1 Model set-up

Prices that a company pays for borrowing from the loan and the bond market are inherently difficult to compare. Bonds and loans differ in probabilities and expected times of default, expected recoveries in case of a default, and systematic risk exposures of recovery rates and default probabilities.

We estimate the differences in prices of loans and bonds in two steps. In the first step, we match bonds and loans issued (obtained) by the same company on the same date. Since for two debts issued on the same date timing and probability of default and systematic risk exposure with respect to default are the same, differences in prices for these loan-bond pairs are solely driven by expected recoveries in case of a default (Schwert (2020)).

In the second step, we account for differences in expected recoveries, or seniorities, of bonds and loans by using a structural model of credit risk. The model is an extension of Merton (1974) with two classes of debt. The firm value is assumed to follow a geometric Brownian motion under the risk-neutral measure:

$$dlnV_t = \left(r - \frac{1}{2}\sigma^2\right) dt + \sigma dW_t^Q, \tag{4}$$

where r is a risk-free rate and σ^2 is the asset volatility parameter.

Suppose a firm has two types of zero-coupon debt: a senior loan with face value K_S and a junior bond with face value K_J. The loan and the bond mature on the same date, T. The payoff of a senior debt holder is equivalent to a portfolio consisting of a risk-free bond and a short put option struck at K_S. The junior debt holder's payoff is equivalent to a portfolio of a long call option struck at K_S and a short call option struck at K_S+K_J. With these assumptions, the value of the senior debt is

$$D_S = V - \left(V\Phi(d_{1,S}) - K_S e^{-rT}\Phi(d_{2,S})\right), \tag{5}$$

where

$$d_{1,S} = \frac{ln(V/K_S) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \quad d_{2,S} = d_{1,S} - \sigma\sqrt{T}, \tag{6}$$

and the value of the junior debt is

$$D_J = \left(V\Phi(d_{1,S}) - K_S e^{-rT}\Phi(d_{2,S})\right) - \left(V\Phi(d_1) - (K_S + K_J)e^{-rT}\Phi(d_2)\right), \tag{7}$$

where

$$d_1 = \frac{ln(V/(K_S + K_J)) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \quad d_2 = d_1 - \sigma\sqrt{T}. \tag{8}$$

Since the loan and the bond have zero coupons, their yields are $y_S = \frac{1}{T}ln(K_S/D_S)$ and $y_J = \frac{1}{T}ln(K_J/D_J)$, respectively.

We use the model to obtain market prices of loans as follows. First, we use the equation for the valuation of junior debt (7) to solve for the asset volatility parameter, σ^2. Next, we plug in the recovered parameter σ^2 into the valuation equation for senior debt (5) and obtain the price of the loan as if it was traded on the public bond market.

3.3.2 Model data

To estimate the model we collect data on loan and bond prices. We use DealScan for loan rates and TRACE for bond prices. We match loans and bonds issued by the same firm on the same date. To avoid comparing low-risk bonds to high-risk bank loans, we follow Schwert (2020) and limit the sample to first-lien loans. The final sample contains 117 loan facilities from 2009 to 2016. We add ESG ratings from RepRisk to the data since our goal is to compare relative prices of credit for brown and green companies.

3.3.3 Estimation results

Results of the model estimation are presented in Table 8. The average bond spread is 2.05%, and the average loan spread is 1.65%. However, once we account for maturity, seniority, and debt amounts, it becomes clear that bank borrowers pay a premium for taking a loan instead of issuing a bond – the model-implied loan spreads are, on average,

Table 8: Structural Estimation Results

	Mean (1)	Std. dev. (2)
Bond spread	2.05	3.11
Bond yield	3.86	3.19
Loan spread (data)	1.65	1.27
Loan spread (model)	0.33	1.75
Observations	117	117

Note: This table provides results of the structural estimation of the credit pricing model. Column 1 shows means, and column 2 shows the standard deviations of respective variables. The first two rows show empirical corporate bond spreads relative to maturity-matched LIBOR and bond yields, respectively. The third row presents empirical loan spreads from DealScan. Finally, the fourth row presents recovered loan spreads from the model, i.e., loan prices relative to LIBOR as if loans were traded on the market. All numbers are in percentages.

0.33%. This result is consistent with findings in Schwert (2020) and shows that borrowing from banks is more expensive than borrowing from the market.

Next, we compute *loan premiums*, i.e., differences between observed and recovered loan spreads for all borrowers and separately for green and brown borrowers. We define green borrowers as firms that have ESG RepRisk ratings of 'A,' 'AA,' or 'AAA' on the date of origination/issuance. We define brown borrowers as firms with ESG ratings of 'BBB' or lower on the date of origination/issuance. Recall that RepRisk ratings are based on events that happened to the firm, so classic concerns of measurement error in ESG ratings (Berg et al. (2022)) are mitigated in our analysis.

Premiums and t-values from the Welch tests are presented in Table 9. Firms in the full sample pay on average 1.29 percentage points premium for borrowing from banks. The reasons underlying the premium include better terms offered by banks, possible negotiations and relationships, etc.[17] Green firms pay an above-average premium – 1.99

[17]For more detail, see Schwert (2020).

Table 9: Estimated Loan Premiums for Green and Brown borrowers

	All firms	Green firms	Brown firms
	(1)	(2)	(3)
Loan premium	1.29***	1.99***	0.96***
	(6.84)	(5.63)	(4.34)
Observations	117	39	78

Note: This table provides estimated loan premiums, i.e., differences between observed loan spreads and spreads recovered from the credit pricing model. Column 1 shows the premium for all firms. Column 2 presents the premium for firms that have ESG RepRisk ratings of 'A,' 'AA,' or 'AAA' on the date of origination/issuance. Column 3 shows the premium for firms with ESG ratings of 'BBB' or lower on the date of origination/issuance. t-values from the Welch t-test are in parentheses. All premiums are in percentage points.

percentage points. Finally, brown firms pay a below-average premium of 0.96 percentage points.

Next, we examine whether brown firms pay a lower premium than green firms. The t-test result suggests that green firms pay a 1.03 percentage points premium on top of the premium paid by brown firms. This number is both statistically and economically significant, implying that loans are relatively cheaper for brown firms than for green firms.

Our model estimation shows that bank credit is relatively cheaper for brown than for green firms. This price differential implies that when brown firms need funding, they are more likely to demand it from banks than green firms. In the next section, we aim to understand how banks and public bondholders choose the amounts of funding provided to brown and green borrowers.

4 Amounts of bank and bond financing of brown companies

In the previous section, we found that bank loans are relatively cheaper for brown firms than for green firms compared to bond financing. In this section, we study what amounts of funding banks and public bondholders provide to brown borrowers.

We utilize the same identification strategy as before to answer the questions. Specifically, we first use firms' negative ESG events. We assume that the probabilities of the violations are exogenous, i.e., firms' debt decisions do not impact the violation, as well as any unobservables that can influence loan and bond amounts. Second, we match the firms that had a negative ESG event with similar firms that did not have any negative ESG events. The matching strategy allows us to address the concern that the events are impacted by certain firm characteristics that also affect the amounts of funding provided by different creditors.

Table 14 presents results for the sizes of loans that banks provide to companies. Columns 1 and 2 show the results of the event study. Following a negative ESG event, an average firm increases its loan amounts by 1.8 to 2%. The result implies that banks provide borrowers with larger loans when borrowers' ESG performance deteriorates. The propensity score matching results are presented in Columns 3 and 4. The results show that the bank loan amounts increase by 0.2 to 0.6% for firms that had a negative ESG event relative to firms that did not. The results, however, are not statistically significant. At the very least, we can conclude that banks do not divest from brown firms, and brown firms borrow greater amounts from banks despite increased interest rates. Also note that high R^2s, even without borrower fixed effects, suggest that the borrower-specific reasons might not be enough to explain the variation in loan amounts. We discuss potential economic mechanisms for our findings in detail in the next section.

Table 11 presents results for the amount of bond financing obtained by firms. Columns 1 and 2 show the results of the event study. Following a negative ESG event, an

Table 10: Impact of ESG Performance on the Loan Amount: Event Study and Matching

$$log(Loan \quad Amt)^{\ell}_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:			
	Log (Loan Amount)			
	(1)	(2)	(3)	(4)
Post	0.020***	0.018**	0.008	0.007
	(0.006)	(0.008)	(0.008)	(0.007)
Event			4.126***	−0.045
			(0.168)	(0.181)
Post · Event			0.006	0.002
			(0.010)	(0.010)
Matching	No	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes
Observations	30,573	30,573	50,007	50,007
R^2	0.997	0.996	0.998	0.995

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is the logarithm of the bank loan amount. The number of observations is larger than in the regressions with all-in-drawn spreads because there are some loan contracts with missing price information. The first two columns correspond to the event-study results. The events are violations of the UNGC principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Bank and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

average firm reduces its bond issuance by 1.5 to 4.3%. The result implies that bondholders provide firms less financing after their ESG performance deteriorates. The matching results produce similar conclusions – bond financing declines by 1.2 to 2.9% following the negative ESG event for treated firms compared to control firms. This result implies that either bondholders divest from brown firms or that brown firms do not issue bonds, since borrowing from the banks becomes relatively cheaper.

The results in this section imply that banks provide the same or larger loans to their borrowers when the borrowers become more brown, while bondholders reduce their

Table 11: Impact of ESG Performance on the Bond Financing Amount: Event Study and Matching

$$log(Bond \quad Amt)_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \theta_t + \varepsilon_{ibt}$$

	Dependent variable:			
	Log(Bond Financing Amount)			
	(1)	(2)	(3)	(4)
Post	-0.043^{***}	-0.015^{***}	-0.023^{***}	0.036^{***}
	(0.003)	(0.004)	(0.008)	(0.007)
Event			13.337^{***}	13.340^{***}
			(0.148)	(0.079)
Post · Event			-0.012	-0.029^{***}
			(0.008)	(0.008)
Matching	No	No	Yes	Yes
Time FE	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Observations	104,075	104,075	147,294	147,294
R^2	0.999	0.998	0.998	0.997

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is bond amounts. The first two columns correspond to the event-study results. The events are violations of the UNGC principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Time and firm fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

funding. Therefore, brown firms' debt structure tilts towards bank loans, consistent with the result that bank loans become relatively cheaper for brown firms than for green firms compared to bond financing. Various mechanisms can drive our findings. For example, are brown firms demanding more bank loans and fewer bonds, or do banks increase their supply of loans while bondholders divest, i.e., is the result driven by the demand for or by the supply of funding? What are the underlying mechanisms for an increased bank loan supply and reduced bond issuance? We address these questions in the next section.

5 Potential mechanisms

Our study has documented three consistent patterns: firms with low ESG performance (1) face a larger cost of debt overall, (2) face a smaller premium for borrowing from banks, and (3) have more bank-loan-heavy debt structure than firms with high ESG performance. We have not yet offered any mechanisms that can explain these results. In this section, we discuss two broad explanations for brown companies' debt conditions and structure.

First, we discuss if the results can be solely driven by an increased demand for credit from brown firms because any adverse event might require more debt to finance the costs. Second, we discuss the opposite side – whether the results can be solely driven by increased supply from the banks and reduced supply from the bondholders. We conclude that our results must be driven by a combination of brown firms' increased demand for credit and banks' and bondholders' differential supply of credit.

Next, we study three potential mechanisms that can explain why banks supply credit in a manner different from bondholders – increased financial risks of brown companies, banks' superior information about their borrowers, and banks' and bondholders' different tastes.

5.1 Demand-driven and supply-driven explanations

The usual way to separate demand and supply explanations is to use location-time fixed effects (Mian and Sufi (2009); Khwaja and Mian (2008)). Unfortunately, our loan and bond data is at the firm-bank-time level. As an alternative approach, we separate supply and demand by observing both changes in debt amounts and changes in the cost of borrowing.

When firms have a negative ESG event, they might need more credit to compensate for financial damages. The firms then may demand more bank loans and more bond financing. If the demand drives the results, then the amounts of borrowing and costs of credit should move in the same direction, i.e., more loans and bond issuance should also imply costlier debt. In our findings, this is only true for bank loans – they stay the same or increase and become more expensive. However, bond issuance declines, at the same time becoming more costly. These observations imply that the demand alone cannot explain our results.

After firms become more brown, it is possible that their debt providers choose to divest. The debt providers may divest either because they think that the firm is financially riskier and less likely to repay the debt, or because they are concerned about potential reputation damages. If the supply drives our results, then the credit amounts and the costs should move in different directions, i.e., larger loan amounts and bond issuance should also imply a reduction in interest rates. This is true for bond issuance – bond amounts decline and bond yields rise after negative ESG events, implying that bondholders divested from the firm. However, bank loans stay the same or increase along with loan rates increases, which means that changes in loan financing cannot be purely supply-driven.

Overall, our results suggest that brown firms demand more credit to finance their costly operations. At the same time, debt holders (at least bondholders) divest from brown firms after adverse ESG events. Bank loans being unchanged or increasing likely implies both – firms demand more funding, and banks fill the gap created by bondholders who leave. This dynamic is reflected in increased loan rates, potentially suggesting higher bargaining power of the banks. In other words, since both loans and bonds become more expensive for brown firms, but loans are relatively cheaper, brown firms' debt structure tilts towards bank credit. In the next three sections, we consider potential mechanisms for why banks supply credit in a manner different from bondholders.

5.2 Financial risk

One explanation for the results we find can be that brown borrowers are financially riskier than green borrowers. For example, if the borrower has an oil spill, its cash flows likely also decline. Hence, the probability of a future default increases. In that case, the firm could only borrow at a higher interest rate.

We believe that this explanation is unlikely. First, it is not clear why a simple increase in the borrower's financial risk would affect borrowing costs differently from the two types of debt providers. If the borrower becomes riskier, then both banks and bondholders should be concerned that their debt might not be repaid, so we could expect a similar change in the costs charged by the two types of creditors. We, however, observe that the premium charged by banks is significantly lower than the premium charged by public bondholders.

Second, this mechanism cannot explain why bondholders would decrease brown borrowers' financing while banks would not. The increased financial risk is a supply-side mechanism, and as we discussed before if credit supply shifts such that the interest rate increases, the amount of credit should be reduced. We find this result for public bondholders but not for banks.

Another explanation that would be consistent with the financial risk is that firms want to borrow short-term loans to mitigate the negative impact of an event, and banks are willing to originate such loans. We consider loans with a maturity of at least 1, 2, 3, and 4 years and show that, if anything, our results get stronger. Tables 12 and 13 show the results. Banks increase loan spreads following the event in all four subsamples. Also, banks do not cut lending to firms with low ESG performance, even if we focus on longer-term loans. In fact, banks seem to provide even longer-term loans, as a positive significant coefficient in Column 4 of Table 13 suggests. Overall, our results are unlikely to be explained by short-term bank lending, which would be in line with the financial risk explanation.

Finally, banks may respond to increased financial risk by changing other terms of the loan contract. For example, they can impose stricter covenants, demand collateral, or reduce the maturity of the loan. All three policies, in principle, can help to increase the safety of the loan, so the banks might be more willing to increase the amount of loans. We test all three predictions in our matched sample using data from DealScan.

Table 12: Impact of ESG Performance on the Loan Spreads: Longer-Term Loans

$$r^{\ell}_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:			
	All-in-drawn spread			
	(1)	(2)	(3)	(4)
Post	−8.639***	−8.935***	−8.303***	−8.212***
	(0.883)	(0.877)	(0.864)	(0.875)
Event	−24.850***	−25.308***	−25.396***	−27.928***
	(0.916)	(0.923)	(0.915)	(0.908)
Post · Event	11.193***	11.525***	11.473***	10.933***
	(1.184)	(1.183)	(1.173)	(1.175)
Subset	1 year	2 years	3 years	4 years
Matching	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	34,124	33,495	32,711	30,851
R^2	0.891	0.894	0.896	0.900

Note: This table provides results of the estimation of equation (3) where the dependent variable is all-in-drawn spread. The sample contains loans of longer maturity than our benchmark results. Column 1 keeps loans longer than 1 year, column 2 – 2 years, column 3 – 3 years, and column 4 – 4 years. The events are violations of the UNGC principles. The estimates are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Bank and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

The results are in Table 14. Column 1 shows that after the event, banks do not demand more collateral from the treated firms. Column 2 shows that, if anything, there are fewer covenants after the events. We also do not find any evidence of decreased maturity of the loans after the events.

We do not argue that financial considerations are not influencing our results. We, however, claim that financial risk alone cannot explain our findings because firms' fundamentals and riskiness matter for both banks and public bondholders. This suggests that there is something different in banks' debt origination decisions, making them more willing to finance brown companies. Below we test two potential explanations. The first

Table 13: Impact of ESG Performance on the Loan Amounts: Longer-Term Loans

$$log(Loan \quad Amt)^{\ell}_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:			
	Log (Loan Amount)			
	(1)	(2)	(3)	(4)
Post	0.011	−0.003	0.004	−0.009
	(0.008)	(0.007)	(0.008)	(0.007)
Event	4.601***	6.424***	6.096***	6.719***
	(0.187)	(0.136)	(0.147)	(0.138)
Post · Event	−0.002	0.006	−0.002	0.020**
	(0.010)	(0.008)	(0.008)	(0.008)
Subset	1 year	2 years	3 years	4 years
Matching	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Observations	46,520	45,032	44,216	37,087
R^2	0.998	0.999	0.999	0.999

Note: This table provides results of the estimation of equation (3) where the dependent variable is the logarithm of the bank loan amount. The sample contains loans of longer maturity than our benchmark results. Column 1 keeps loans longer than 1 year, column 2 – 2 years, column 3 – 3 years, and column 4 – 4 years. The events are violations of the UNGC principles. The estimates are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Bank and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

explanation is that banks have superior information about borrowers' cash flows compared to public bondholders. In particular, banks can differentiate between ESG events which increase borrowers' financial risk and ESG events which do not affect borrowers' financial risk, and then issue larger loans only to brown borrowers whose financial risk does not increase. The second explanation is that banks and bondholders have different preferences for ESG performance of their holdings – while bondholders want to divest from socially irresponsible firms, banks fill in the gap.

Table 14: Impact of ESG Performance on Collateral, Covenants, and Maturity

$$Terms^{\ell}_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:		
	Collateral	Covenants	Maturity
	(1)	(2)	(3)
Post	0.007^{**}	0.027^{***}	-11.599^{**}
	(0.003)	(0.003)	(4.862)
Event	1.052^{***}	0.003	290.244^{***}
	(0.004)	(0.004)	(5.358)
Post · Event	0.008	-0.021^{***}	14.910^{**}
	(0.003)	(0.003)	(6.299)
Matching	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	50,007	49,998	50,007
R^2	0.884	0.963	0.961

Note: This table provides results of the estimation of equation (3) where the dependent variable is one of the loan terms. The dependent variable in Column 1 is an indicator of whether the next loan has collateral. The dependent variable in Column 2 is an indicator of whether the next loan has covenants. Column 3 has the next loan's maturity as a dependent variable. The events are violations of the UNGC principles. The estimates are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Bank and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

5.3 Banks' superior information

The next explanation we consider is banks' superior information about their borrowers. In contrast to public debt or equity holders, banks are known to invest a lot of resources in screening (Ramakrishnan and Thakor (1984), Allen (1990)) and monitoring (Diamond (1984), Winton (1995)) their borrowers. This close relationship allows banks to obtain a lot of information, often soft information that other investors do not possess (Bhattacharya and Chiesa (1995), Yosha (1995)).

We suggest that this information about firms also helps banks better understand their borrowers' ESG risks. In particular, banks may be able to differentiate between borrowers whose ESG risks also imply financial risks and borrowers whose ESG risks are not financially material. Banks can thus provide credit mostly to borrowers whose ESG risks are not material and offer lower interest rates to these borrowers, compared to the rates offered by the public bond market that does not differentiate between borrowers. As a result, brown borrowers with financially immaterial ESG risks would choose to borrow greater amounts from banks.

One way to test this explanation is to find a variable that captures the financial materiality of borrowers' ESG risks. If the described mechanism holds, we would expect this variable to be a moderator in the relationship between sizes of bank loans and borrowers' ESG performance: banks should provide loans of smaller sizes to brown borrowers whose ESG risks are more financially material.

We use the ESG Industry Materiality Map produced by MSCI to measure the financial materiality of ESG risks of our firms. The Map is based on the data and analysis MSCI conducts to construct its ESG ratings. The company-level ESG ratings measure how well a corporation manages its financially material ESG risks. The Map aggregates assessed materiality at the GICS (sub-)industry level, for each out of thirty-four issues related to E (environmental), S (social), or G (governance).[18] For each issue and (sub-)industry, the Map provides a weight measuring how financially harmful an issue is for a given (sub-)industry. For example, for Healthcare Equipment, the most material issue is Governance (39%), followed by Product Safety & Quality (33.6%), followed by Human Capital Development (22%), followed by Carbon Emissions (5%), Privacy & Data Security (0.2%), and Chemical Safety (0.1%). The Map is updated on a regular basis and is publicly available. Importantly, MSCI launched this tool only at the end of 2020.[19] Public bondholders do not have access to the Map for most of the time frame for our sample.

[18]To access the Map and the lists of industries, sub-industries, and issues, visit the MSCI ESG Industry Materiality Map website.

[19]See Nasdaq, November 16, 2020. MSCI launches public tool to help corporates and industry stakeholders understand its ESG Ratings model.

We merge the Map with our firm-event-level dataset in four steps. First, we identify the firms' GICS sub-industries. Second, we manually classify the thirty-four ESG issues into the ten UNGC Principles. In the final step, we assign a materiality score to each firm-event as follows. For each UNGC Principle listed as violated during an event, we sum the weights assigned in this firm's industry to ESG issues related to this Principle. If, during an event, multiple Principles were violated, we next sum all weights from all the violated Principles. Finally, we create a variable $HMateriality$ that equals 1 if the event's materiality is above the 75^{th} quantile and 0 otherwise.[20]

To examine whether financial materiality is moderating the relationship between the size of bank loans and firms' ESG performance, we interact the dummy for a financially material adverse ESG event with the main variables of interest and run the following regressions:

$$log(Loan \quad Amt)^l_{ibt} = \beta \cdot HMateriality_{it} \cdot Post_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \theta_t + \varepsilon_{ibt} \tag{9}$$

$$log(Loan \quad Amt)^l_{ibt} = \beta \cdot HMateriality_{it} \cdot Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \kappa_b + \theta_t + \varepsilon_{ibt} \tag{10}$$

We choose to test mechanisms with debt quantities rather than prices for selection bias reasons. To understand this, consider a borrower with a high MSCI risk. If banks refuse to lend to this borrower, its loan quantity will be equal to 0 and reflected in our mechanism tests without bias. However, a refused borrower will not have an interest rate – all-in-drawn spreads will enter as 0 for such borrowers, thus creating a selection bias. True counterfactual spreads for refused borrowers should be higher than for the ones who got loans.

Table 15 shows the estimation results. Note that the variable $HighMateriality$ equals $Post \cdot Event \cdot HighMateriality$ because $HighMateriality = 1$ only for firms that have an event after this event happens. Consistent with the informational advantage mechanism, the realized materiality level of adverse ESG events moderates the relationship between firms' ESG performance and bank loan amounts. The moderating relationship is present

[20] We choose the 75^{th} quantile rather than the median because the median materiality is 0 in our dataset.

Table 15: Impact of ESG Performance on the Loan Amount, Moderator Test: Effect of Events' Materiality

$$log(Loan \quad Amt)^{l}_{ibt} = \beta \cdot HMateriality_{it} \cdot Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \kappa_b + \theta_t + \varepsilon_{ibt}$$

	Dependent variable:			
	Log (Loan Amount)			
	(1)	(2)	(3)	(4)
Post	-0.007	0.077^{***}	-0.020^{*}	0.006
	(0.009)	(0.010)	(0.011)	(0.011)
Post·Event			0.048^{***}	0.063^{***}
			(0.014)	(0.015)
HighMateriality	0.013	-0.157^{***}	-0.045^{***}	-0.160^{***}
	(0.010)	(0.012)	(0.010)	(0.011)
Matching	No	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes
Observations	30,557	30,557	49,991	49,991
R^2	0.997	0.996	0.995	0.995

Note: This table provides results of the estimation of equations (9) and (10). The materiality of events is measured based on the MSCI ESG Industry Materiality Map. The first two columns correspond to the event-study results. The events are violations of the UNGC principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Time and bank fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

in the specifications without borrower fixed effects, potentially because materiality does not vary substantially over time and is borrower-specific. The outcome suggests that banks can distinguish between brown borrowers whose ESG risks are material and brown borrowers whose ESG risks are not material. In the firm-level (matching) specification, after an adverse ESG event happens, the size of newly originated bank loans increases by 7.7% (6.3%) if the event is not financially material but decreases by 8.0% (9.4%) if the event is financially material. Banks appear to issue larger loans to brown borrowers, but only if these borrowers' brownness does not affect the borrowers' financial health.

Such an advantage probably allows banks to offer credit to financially solid companies that cannot obtain enough financing in the public bond market due to the information asymmetry between investors and brown borrowers.

5.4 Preference for green investments

Our next explanation is that banks and public bondholders simply have different preferences for green investments. Specifically, public debt holders may inherently value their companies' high ESG performance, presumably because public debt holders' investors value ESG (Krueger et al. (2020); Bauer et al. (2021)), either due to the warm-glow-giving utility they obtain from investing in socially responsible firms or due to stricter regulatory environment.[21] The preference for high-ESG investments would create incentives for bondholders to divest from the firms whose ESG performance deteriorates, as we observe in the data. A large body of the literature also argues that bondholders have preferences for green investment (Larcker and Watts (2020); Baker et al. (2024); Renjie and Xia (2023)).

At the same time, banks may not value borrowers' ESG performance as strongly because of a different investor pool or because of laxer regulation.[22] So even if banks' borrowers violate UNGC principles, banks continue investing in them, and they are even able to make profits by charging higher loan spreads. Consistent with this explanation, our results suggest that the amount of bank loans increases for brown firms while loan rates rise.

When some investors inherently value ESG performance, and others do not, in equi-

[21] Public bondholders mostly consist of large institutional investors that face increasing regulatory scrutiny and public pressure to divest from poor ESG-performing corporations. In particular, the Securities and Exchange Commission has recently adopted a rule implying that an investment fund can only use an ESG-themed name if at least 80% of its portfolio aligns with the stated ESG goals (see the SEC's press release on September 20, 2023). The Commission also has increased scrutiny over financial investors' commitment to their stated policies (see the SEC's press release on November 22, 2022) and improper disclosure (see the SEC's press release on May 23, 2022).

[22] In contrast, the US banks are not (yet) regulated as heavily with respect to the greenness of their investment portfolios. The majority of ESG initiatives for banks are voluntary and not subject to external verification.

librium, the former will invest more in green companies and the latter more in brown companies (Friedman and Heinle (2016)). Interest rates, while being generally higher for brown companies, would be more favorable for investors who do not value ESG performance. The reasons for increased interest rates might be different. Bondholders increase interest rates because they reduce the supply of debt. Banks, in turn, increase loan rates because they have more bargaining power – borrowers demand more loans since bondholders divest.

To test the preferences explanation empirically, we again conduct a moderation test. If the preferences explanation is correct, the relationship between the borrowers' credit conditions and their ESG performance should be moderated by the level of the lenders' preference for ESG. Similarly, if bondholders' taste for sustainable investment drives their divestment, we should not find any significant results for bond amounts across more or less sustainable bondholders.

We come up with two measures of banks' preferences for their borrowers' ESG performance. The first measure is banks' investors' self-disclosed tastes for ESG. We construct this measure as follows. First, for each bank, we identify its three largest shareholders using the data from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system or from banks' or institutional investors' websites. Second, we use major shareholders' official websites, sustainability reports, press releases, SEC filings, documentation, and third-party ESG ratings to identify whether each shareholder claims to be high-ESG-oriented. We use ChatGPT-4o to determine whether sources of information about a shareholder mention a sustainability goal. We provide examples of sustainability goals in institutional investors' quarterly reports in the Appendix A. The ultimate measure of the bank's investors' self-disclosed preference for ESG is the number of shareholders who claim to be high-ESG-oriented. Because we only look at the three largest shareholders, our measure of banks' investors' self-disclosed preference for ESG varies from 0 to 3. A potential weakness of this measure is that self-disclosed preference for ESG may be greenwashing and may not necessarily imply an investor actually prefers high-ESG investments and pushes their bank to lend to greener borrowers.

The second measure that we construct may potentially better capture the bank's shareholders' actions to improve the greenness of their banks' portfolios – the presence of an ESG-related committee on the bank's board of directors. We obtain information on banks' boards of directors and committees from the BoardEx database. The second measure is a dummy variable, which equals 1 if the board of directors of a bank has an ESG-related committee.

For bondholders, we follow Aleszczyk and Loumioti (2024) and define a bondholder as sustainable if it is a signatory of the Principles for Responsible Investing or participates in the Science-Based Target Initiative (SBTI). We then calculate a measure for the firm – the share of its bondholders that are PRI signatories or participate in SBTI. The higher the measure is, they more sustainable the bondholders are.

We run the following regressions:

$$log(Loan \quad Amt)^{l}_{ibt} = \beta \cdot z_{bt} \cdot Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \theta_t + \varepsilon_{ibt} \quad (11)$$

$$log(Bond \quad Amt)_{ibt} = \beta ESGBondHolders_{it} \cdot Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \varepsilon_{ibt} \quad (12)$$

where z_{bt} is either the number of the bank's three major shareholders that claim to be high-ESG-oriented or a dummy variable of whether the bank's board of directors has an ESG-related committee. The second regression looks into bond amounts for firms that have more or less bondholders held by PRI signatories or investors participating in SBTI. As discussed in the previous section, we do not repeat the tests for loan interest rates because loan prices may suffer from selection bias.

Columns 1-4 of Table 16 present the results for banks. Both measures moderate the relationship between firms' ESG performance and the sizes of loans that these firms obtain, confirming our second mechanism – banks' unique preferences for their borrowers' ESG performance. Banks, on average, extend larger loans to brown borrowers, but banks with preferences for high ESG performance do not change their lending or at least increase by a smaller amount. In terms of economic magnitudes, a bank that does not have any high-ESG-oriented major shareholders extends 14.4% to 27.5% larger loans after a borrower becomes browner. This increase is reduced by 6.3% to 9.5% for each major high-ESG-oriented shareholder. For the specifications with ESG committees, a bank without an ESG-related committee on its board extends 1.5% to 5.9% larger loans after a borrower becomes more brown. If a bank has an ESG-related committee, it might reduce the size of loans extended to brown borrowers: the effect varies from -1.9% to -9.7%.

Column 5 of Table 16 presents the results for bonds. We find that regardless of the PRI signature or SBTI participation, bondholders divest from brown borrowers after the events (i.e., the coefficient as the interaction term is insignificant). The results are consistent with the taste for sustainable investment that is more pronounced for bondholders than for the banks.

Overall, in this section, we discuss potential underlying mechanisms driving our main findings. We first argue that our results cannot be fully accounted for by increased demand for credit from brown firms or by changes in the supply of credit from debt holders. We suggest that our findings are driven by increased demand from brown firms, bondholders' divestment from brown investments, and banks' will and ability to finance brown companies. We next demonstrate how at least two forces can explain our findings – banks' superior information about firms' fundamentals and the differential preference of banks compared to bondholders.

6 Conclusion

This study investigates credit conditions faced by corporations with low Environmental, Social, and Governance performance. We document multiple robust, thought-provoking patterns: companies with poor ESG performance (1) face larger costs of debt overall, however, (2) a smaller premium for borrowing from banks, and (3) borrow larger amounts from banks and smaller from the bond market. These findings collectively suggest that debt providers for brown companies are primarily banks rather than the public market.

Why do banks charge brown borrowers a lower premium than public bondholders, and why do banks lend to brown firms while bondholders divest from brown firms? We discuss multiple mechanisms that can explain our findings. First, we rule out purely supply-driven and purely demand-driven explanations because observed changes in debt amounts and borrowing costs are inconsistent with a single-sided mechanism. Next, we argue that brown borrowers simply being riskier than green borrowers is also unlikely to explain our results.

We propose and test two mechanisms that align with all our findings. The first mechanism is banks' superior knowledge about their borrowers. Because banks have closer relationships with the borrowing companies, they might be better skilled than public investors at assessing the implications of borrowers' low ESG performance for future cash flows. As a result, if banks are less uncertain about the borrower's risk, they can afford a more preferable interest rate. The second mechanism is banks' and public bondholders' different preferences for the ESG performance of their holdings. We argue that bondholders may value their holdings' ESG performance more than banks do, and thus reduce their funding to borrowers whose ESG performance deteriorates.

Our study contributes to the public debate on whether and how socially irresponsible corporations should be regulated. Multiple calls have been made to affect companies' actions indirectly through their debt providers. However, to our knowledge, so far there exists limited large-sample evidence on the main debt providers of brown companies and whether these companies already face unfavorable borrowing conditions. We fill this void and show that brown companies are increasingly financed by banks.

Table 16: Impact of ESG Performance on the Loan and Bond Amounts: ESG Committees, Shareholders, and Sustainability Funds

$$log(Loan \quad Amt)^{l}_{ibt} = \beta \cdot ESGCommittee_{bt} \cdot Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \theta_t + \varepsilon_{ibt}$$
$$log(Loan \quad Amt)^{l}_{ibt} = \beta \cdot NumESGShareholders_{bt} \cdot Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \theta_t + \varepsilon_{ibt}$$
$$log(Bond \quad Amt)_{ibt} = \beta ESGBondHolders_{it} \cdot Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \varepsilon_{ibt}$$

	Dependent variable:				
	Log (Loan Amount)				Bond Amount
	(1)	(2)	(3)	(4)	(5)
Post·Event	0.015	0.059***	0.275***	0.144	−0.451
	(0.015)	(0.022)	(0.065)	(0.119)	(0.869)
Post·Event·ESGCommittee	−0.019	−0.097***			
	(0.019)	(0.029)			
Post·Event·NumESGShareholders			−0.095***	−0.063	
			(0.022)	(0.040)	
Post·Event·ESGBondHolders					2.511
					(1.973)
Matching	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	–
Borrower FE	Yes	No	Yes	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	30,585	30,585	26,164	26,164	1,854
R^2	0.997	0.996	0.998	0.995	0.995

Note: This table provides results of the estimation of equations (11) and (12) where the moderator variable is the dummy variable that equals 1 if a bank has an ESG-related committee on its board of directors in Columns 1-2, the number of bank's shareholders who claim to be high-ESG-oriented in Column 3-4, and the share of bondholders who co-signed Principles for Responsible Investing or participate in Science Based Targets initiative in Column 5. The results are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Bank and firm fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

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Appendix

A Institutional investors' ESG focus

Below we provide some examples of sustainability goals that institutional investors mention. We use these goals and goals with similar wording to classify an investor as a high-ESG-oriented.

1. Sustainable Investment:
   (a) "Commitment to sustainable investing"
   (b) "Sustainability-focused funds"
   (c) "Sustainable investment strategies"
   (d) "Investing in sustainability"
   (e) "Long-term sustainable growth"
   (f) "Environmental, social, and governance (ESG) criteria"
   (g) "Sustainable finance initiatives"
2. Environmental, Social, and Governance (ESG):
   (a) "ESG integration in investment decisions"
   (b) "Responsible investing"
   (c) "ESG-focused investment products"
   (d) "Commitment to ESG principles"
   (e) "Incorporating ESG factors"
   (f) "Sustainable and responsible investment"
3. Climate Change and Environmental Impact:
   (a) "Climate change strategy"

(b) "Reducing carbon footprint"

(c) "Environmental stewardship"

(d) "Commitment to decarbonization"

(e) "Green bonds and sustainable finance"

(f) "Environmental impact assessment"

4. Social Responsibility:

   (a) "Socially responsible investing"

   (b) "Promoting social equity and inclusion"

   (c) "Diversity and inclusion in investments"

   (d) "Human rights in investment practices"

   (e) "Community engagement and social impact"

5. Governance:

   (a) "Strong governance practices"

   (b) "Ethical business practices"

   (c) "Corporate governance and sustainability"

   (d) "Transparency and accountability in investment"

B Additional results and robustness tests

B.1 Climate events

The main results of the paper consider negative ESG events, including environmental, social, and governance events. However, most of the focus in the media and research has been on climate issues. Most of the events in our sample are environmental and since we consider large firms with access to syndicated lending, most firms had at least one environmental event in the sample. Nonetheless, in this section, we consider a robustness test in which we keep only the events that are climate-related. We show the impact of climate events on the prices of bonds and bank loans, as well as the quantities of loans and bonds.

Tables B.1-B.4 show that our results hold if we focus only on environmental events. First, both loan spreads and bond yields increase implying that it is more expensive to borrow after negative environmental events. Second, while public debtholders divest from firms after the events, banks do not seem to cut their lending to such firms. We should also note that the number of observations in climate-only tables is not much lower than in the tables with all events because most of the events in our sample are climate-related.

B.2 Different matching method

We use nearest-neighbor propensity score matching in the main analysis. In this section, we show that our results are robust to using a different matching strategy – Mahalanobis distance matching. Tables B.5 and B.6 shows that our results are robust to the matching technique.

B.3 Parallel trends assumption

Most of our results are based on staggered difference-in-differences with matching. The main assumption for identification is that absent treatment (a negative ESG event), firms in treatment and control groups behave similarly. To add evidence to the assumption, we check if there are pre-trends – if interest rates started rising and bond amounts started declining already before events. To test this, we regress outcome variables on the sum of pre-event time periods multiplied by events.

Figure B.1 shows the results. There was no rise in loan spreads or change in loan amounts for treated firms prior to the event. There was also no decline in bond amounts. The only place where there is a small pre-trend is bond yields – there is an increase in

Table B.1: Impact of ESG Rating on the Loan Spread: Climate Events

$$r^{\ell}_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:			
	All-in-drawn spread			
	(1)	(2)	(3)	(4)
Post	0.822	5.593***	−1.928***	−2.411**
	(0.939)	(1.095)	(0.621)	(1.041)
Event			146.983***	−25.434***
			(4.546)	(1.118)
Post · Event			3.927***	6.916***
			(1.079)	(1.502)
Matching	No	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes
Observations	9,797	9,797	22,283	22,283
R^2	0.923	0.869	0.956	0.895

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is all-in-drawn spread. The first two columns correspond to the event-study results. The events are violations of the UNGC climate principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Bank and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table B.2: Impact of ESG Rating on the Bond Yields: Climate Events

$$r^b_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \theta_t + \varepsilon_{ibt}$$

	Dependent variable:			
	Bond yield			
	(1)	(2)	(3)	(4)
Post	2.235***	3.367***	−1.702***	−0.646***
	(0.052)	(0.061)	(0.123)	(0.172)
Event			0.711***	0.955***
			(0.131)	(0.132)
Post · Event			4.658***	3.496***
			(0.171)	(0.172)
Matching	No	No	Yes	Yes
Time FE	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Observations	1,367,619	1,367,619	2,039,819	2,039,819
R^2	0.198	0.155	0.044	0.039

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is bond yields. The first two columns correspond to the event-study results. The events are violations of the UNGC climate principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Time and firm fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table B.3: Impact of ESG Rating on the Loan Amount: Climate Events

$$log(Loan \quad Amt)^{\ell}_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:			
	Log (Loan Amount)			
	(1)	(2)	(3)	(4)
Post	0.018^{**}	0.008	-0.014	0.006
	(0.009)	(0.010)	(0.010)	(0.009)
Event			3.280^{***}	-0.095
			(0.132)	(0.199)
Post · Event			0.025^{**}	-0.011
			(0.012)	(0.012)
Matching	No	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Borrower FE	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes
Observations	19,032	19,032	32,556	32,556
R^2	0.997	0.995	0.997	0.994

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is the logarithm of the bank loan amount. The number of observations is larger than in the regressions with all-in-drawn spreads because there are some loan contracts with missing price information. The first two columns correspond to the event-study results. The events are violations of the UNGC climate principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Bank and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table B.4: Impact of ESG Rating on the Bond Financing Amount: Climate Event

$$log(Bond\quad Amt)_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \theta_t + \varepsilon_{ibt}$$

	Dependent variable:			
	Log(Bond Financing Amount)			
	(1)	(2)	(3)	(4)
Post	-0.029^{***}	-0.004	0.020^{**}	0.060^{***}
	(0.004)	(0.004)	(0.009)	(0.009)
Event			12.520^{***}	13.122^{***}
			(0.085)	(0.040)
Post · Event			-0.036^{***}	-0.042^{***}
			(0.010)	(0.010)
Matching	No	No	Yes	Yes
Time FE	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Observations	73,897	73,897	104,767	104,767
R^2	0.999	0.998	0.998	0.997

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is bond amounts. The first two columns correspond to the event-study results. The events are violations of the UNGC climate principles. Columns 3-4 are based on nearest-neighbor propensity score matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Time and firm fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table B.5: Impact of ESG Rating on the Bank Loans: Mahalanobis Distance Matching

$$Y_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:			
	All-in-drawn spread		Log (Loan Amount)	
	(1)	(2)	(3)	(4)
Post	-2.375^{***}	-2.791^{***}	-0.001	0.050^{***}
	(0.498)	(0.781)	(0.006)	(0.010)
Event	133.702^{***}	-20.099^{***}	4.515^{***}	-0.173^{***}
	(3.513)	(0.944)	(0.159)	(0.010)
Post · Event	3.146	4.452^{***}	0.030^{***}	-0.031^{**}
	(0.863)	(1.155)	(0.008)	(0.013)
Matching	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Observations	33,480	33,480	49,420	49,420
R^2	0.954	0.895	0.998	0.995

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is either all-in-drawn loan spreads (columns 1-2) or loan amounts (columns 3-4). The first two columns correspond to the event-study results. The events are violations of the UNGC climate principles. Columns 3-4 are based on nearest-neighbor Mahalanobis distance matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Time and firm fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table B.6: Impact of ESG Rating on Bonds: Mahalanobis Distance Matching

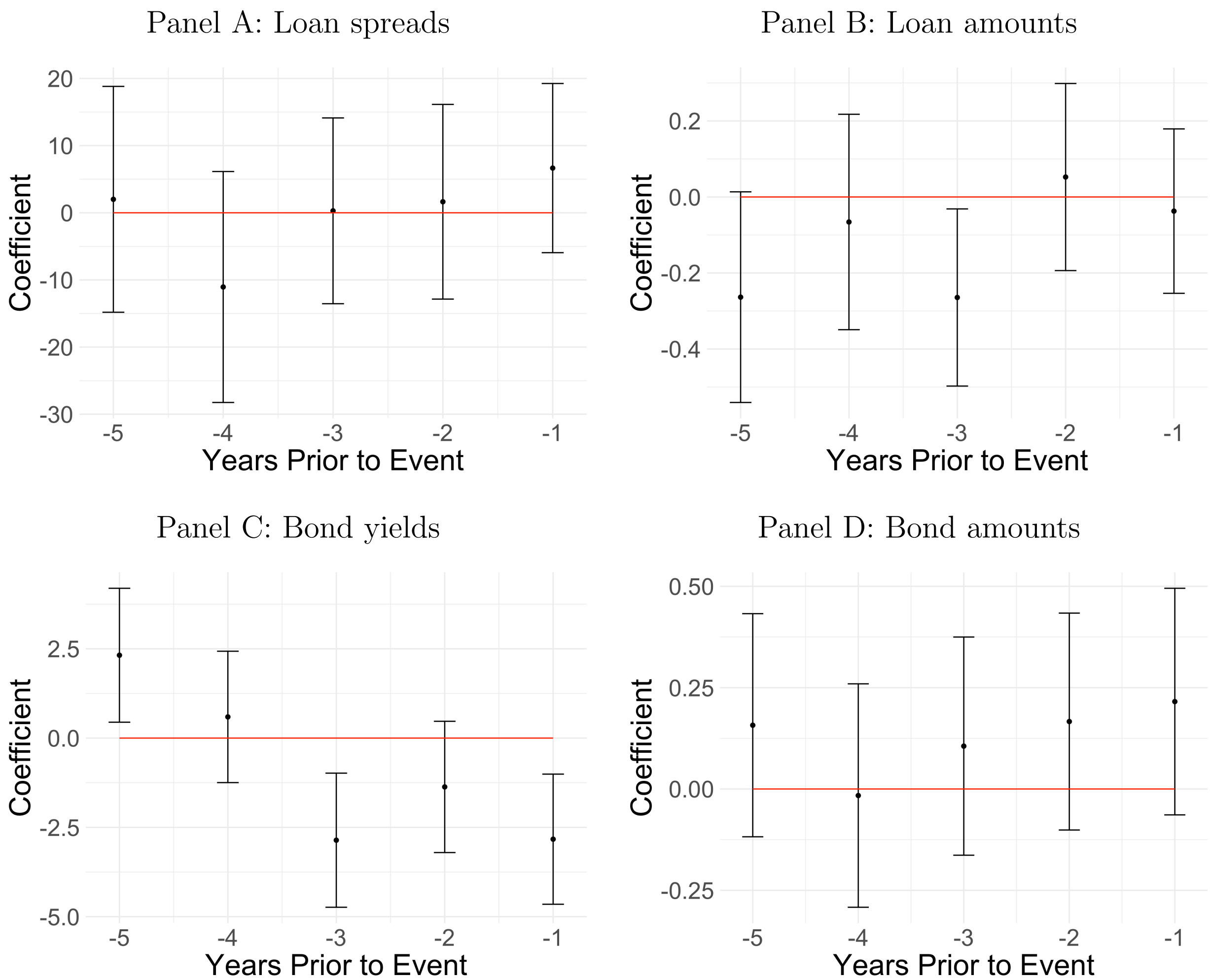
$$Y_{ibt} = \beta Post_{it} \cdot Treat_{it} + \gamma X_{ibt} + \alpha_i + \theta_t + \varepsilon_{ibt}$$

	Dependent variable:			
	Bond yield		Log(Bond Financing Amount)	
	(1)	(2)	(3)	(4)
Post	-0.280	-0.509	-0.042^{***}	0.024^{***}
	(0.343)	(0.319)	(0.007)	(0.006)
Event	-11.986^{***}	-11.462^{***}	13.413^{***}	13.337^{***}
	(0.182)	(0.182)	(0.126)	(0.079)
Post · Event	1.838^{***}	1.145^{***}	0.017	-0.015^{**}
	(0.332)	(0.310)	(0.007)	(0.007)
Matching	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	No
Firm FE	Yes	Yes	Yes	Yes
Observations	2,903,356	2,903,356	176,687	176,687
R^2	0.998	0.998	0.998	0.998

Note: This table provides results of the estimation of equations (2) and (3) where the dependent variable is either bond yields (columns 1-2) or bond amounts (columns 3-4). The first two columns correspond to the event-study results. The events are violations of the UNGC climate principles. Columns 3-4 are based on nearest-neighbor Mahalanobis distance matching. The variables used in matching include pre-event ESG ratings, balance sheet indicators, date, and industry. Time and firm fixed effects are included. Standard errors are clustered at the firm level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

bond yields of treated firms five years prior to the event. However, there is no rise in bond yields four, three, two, or one year prior to the event. The results add evidence to support our parallel trend assumption.

Figure B.1: Pre-Trends in Debt Prices and Debt Amounts

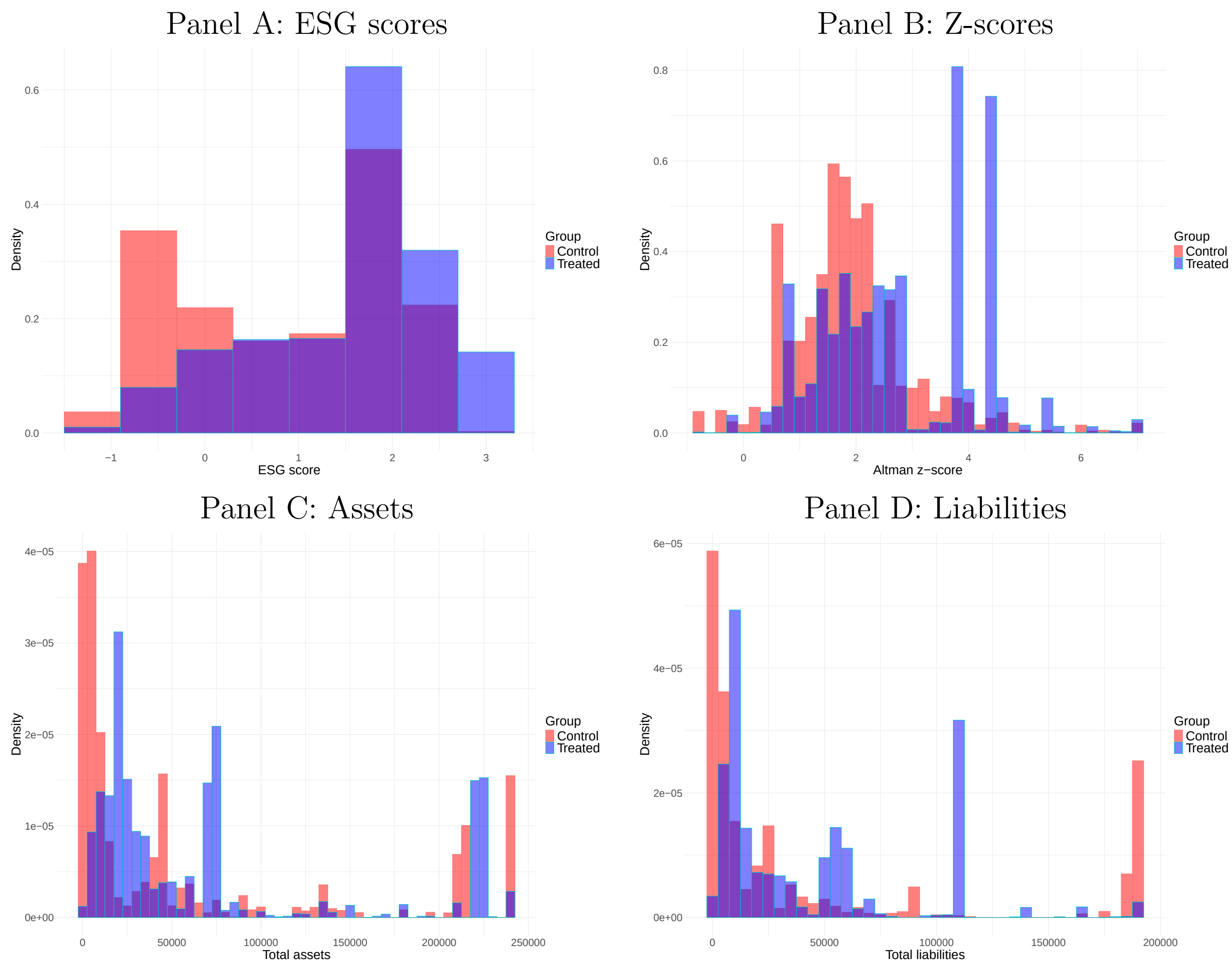


Note: This figure shows pre-trends in debt amounts and prices. Each dot represents regression coefficients when regressing dependent variables on lags of time variable (one to five years prior to events) interacted with the treatment indicator. 1% confidence intervals are included. Panels A and B show loan spreads and amounts, respectively. Panels C and D show bond yields and amounts, respectively.

B.4 Matching distributions

One way to argue that matching is good is to compare distributions of variables in the treatment and control groups. Figure B.2 shows the distribution functions. Overall, our matching strategy is doing well in matching balance sheet variables. ESG scores of treated firms appear to be higher than the ones of the control firms, so the bias is downward.

Figure B.2: Distributions of Variables after Matching



Note: This figure shows distribution histograms of variables used for propensity score matching. Red bars represent the control group, while blue bars represent the treatment group. Panels A and B show ESG scores from RepRisk and Altman z-scores, respectively. Panels C and D show total assets and total liabilities, respectively.

B.5 MSCI ESG rating

In this section, we show that our results are robust to using MSCI ratings that are widely analyzed in the literature. Table B.7 shows the results.

Table B.7: Impact of MSCI Ratings on the Loan Spreads and Bond Yields

$$r_{ibt} = \beta MSCI_{it} + \gamma X_{ibt} + \alpha_i + \kappa_b + \varepsilon_{ibt}$$

	Dependent variable:			
	All-in-drawn spread		Bond yield	
	(1)	(2)	(3)	(4)
MSCI rating	−1.675	-3.750^{***}	−0.006	-0.195^{***}
	(1.463)	(0.948)	(0.031)	(0.029)
Bank FE	Yes	Yes	No	No
Borrower FE	Yes	No	Yes	Yes
Time FE	No	No	Yes	No
Controls	Yes	Yes	Yes	
Observations	2,796	2,796	39,200	39,200
R^2	0.972	0.897	0.872	0.871

Note: This table provides results of the estimation of equation (1) where the dependent variable is all-in-drawn spreads in Columns 1-2 and bond yields in Columns 3-4. ESG ratings are calculated by MSCI. Bank, time, and borrower fixed effects are included. Standard errors are clustered at the borrower level and displayed in parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.