Where Do Brown Companies Borrow From?*

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Abstract

We study sources of debt for companies with poor ESG performance. Using a structural model of credit risk, we show that for low-ESG-rated firms, it is less expensive to borrow from banks than from public market compared to high-ESG-rated firms. As a result, after a company experiences an adverse ESG event, it starts borrowing more from banks than from the bond market. At the same time, we find that banks have incentives to discipline brown companies that they lend to: banks' stocks drop after a public announcement that a borrower experienced an adverse ESG event. The stronger the market's reaction and the more adverse events borrowers experience, the higher loan spreads that the banks set for their brown borrowers. We conclude that both loan and bond markets offer higher costs of debt to brown firms, but the bond market's "punishment" is higher than the loan market's.

Keywords: ESG performance, debt structure, cost of debt

JEL Codes: G12, G21, D62

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1 Introduction

Social activists and non-government organizations posit that one way to regulate firms' environmental, social, and governance (ESG) performance is provide less debt funding for companies with poor ESG performance.[1] Regulators around the world consider directly regulating capital providers, especially banks, by mandatory disclosures of lending portfolio's greenness or climate stress testing.[2][3] In order to understand potential need in and effects of these regulations, it is important to understand what are the main sources of debt funding for low-ESG corporations and whether there already exists a market mechanism that "punishes" companies for not adhering to the society's standards.

In this paper, we study whether green and brown companies face different relative costs of borrowing from two debt markets – loans and bonds – and whether, as a result, green and brown companies prefer different sources of debt funding. There are two identification concerns. First, it is unobservable which factors banks consider when they originate loans. It is possible that banks originate the loan to a green company that uses the loan to mine oil and hence, becomes brown. On the other hand, banks can provide loans to brown companies that need them to transition to renewable sources of energy. Second, ex-ante ESG ratings have zero correlation since they consider different factors (Berg et al. (2022)), hence, it is not even clear if the bank finances a brown company or not. To address the concerns, we use an event-study approach and choose the setting of public announcements that a company violated one of the United Nations Global Compact (UNGC) principles.[4] The principles consist of ten rules about human rights, labor, environment, and anti-corruption that, if violated by a company, reduce its ESG performance score.

In the first step, we use a credit pricing model (Schwert (2020)) to compare premiums for borrowing from banks relative to the public market for brown and green companies.

[1]Bloomberg, November 24, 2021. Wall Street's $22 Trillion Carbon Time Bomb.

[2]Financial Times, September 22, 2021. Costs of climate change far greater than green transition, says ECB.

[3]Financial Times, March 31, 2022. Banks face new standards on carbon emissions disclosure.

[4]https://www.unglobalcompact.org/what-is-gc/mission/principles

Measuring differences in cost of borrowing from two sources is tricky because loans and bonds have different seniorities, probabilities of default, and systematic 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, to account for differences in seniority and, thus, recovery rates, we use Merton (1974) asset pricing model. We recover the asset volatility parameter using market prices of companies' bonds and then plug in the recovered parameters to find prices of these companies' loans as if they were traded on the market. The difference between actual loan spreads and the spreads suggested by the model are the premium (or the discount) that companies pay for borrowing from banks. We find that this premium is significantly smaller for firms with low ESG ratings (0.96 p.p.) than for high-ESG-rated firms (1.99 p.p.), suggesting that brown firms may find loans relatively more attractive than green firms.

Our second step is to examine whether, as a result of the different relative costs of two sources of debt, brown companies take on more debt from banks than green companies. As loans are relatively cheaper for brown firms, we expect them to borrow more from banks compared to green firms after experiencing a deterioration in ESG performance. Testing this prediction is challenging because companies with different levels of ESG performance may differ on observable and unobservable dimensions. For example, companies that often experience adverse ESG events can operate in a different industry or have lower management quality than green companies. We address these concerns by using propensity score matching. Specifically, we match firms that experience negative ESG events with firms that did not based on size, and common balance sheet characteristics, including assets and liabilities. We then compute and compare their loan originations and new bond issuances. We find that treated firms took on average \$9.66 million more in loans and issued \$719 thousand more bonds than firms in the control group. Newly originated loans 7 times exceed newly issued bonds, and the difference is statistically significant. These results are in line with the option pricing model – since loans become relatively cheaper for brown firms, their debt structure tilts towards loan financing. It is important to note that brown firms also borrow significantly more from the public debt market than green firms.

The results indicate that banks mostly finance companies with poor ESG performance. This is in contrast with ESG ratings that treat banks as green companies since they do not directly harm the society (Pástor et al. (2022)). Since instead banks provide funding for brown companies, politicians and researchers call on regulators to require banks to incorporate their borrowers' ESG performance when constructing lending portfolios. However, this regulation may not lead to desired results if there already exists a market mechanism that induces loan providers to take into account borrowers' non-financial characteristics. We next test for the existence of such a mechanism and banks' responses.

We start by documenting that investors react to banks' borrowers' ESG performance. Specifically, we show that after it is first announced that a bank's corporate borrower experienced a negative ESG event (violated a UNGC principle), share prices of both the borrower and the bank drop. The lead lender of a syndicate on average experiences a negative abnormal return of 30 basis points in a [0,7] days window after an announcement. The effect is significantly negative in the 1-week window as well as in shorter (2 days) and longer (up to 6 months) windows. A potential concern is that this effect is purely financial – banks' investors worry that firms that experience negative events are more likely to default on their loans. We provide additional evidence that the effect is not financial but rather ESG-related by showing that the reaction is stronger for banks with established relationships with their borrowers. Additionally, the effect persists after we control for borrowers' default rates or whether the loan is secured. Finally, banks' CDS spreads do not change after announcements, implying that banks' riskiness is not affected.

Since the market punishes banks for lending to brown firms, rational banks should consider their borrowers' ESG performance when originating loans. To examine lenders' responses, we analyze whether banks' lending portfolio's ESG and loan spreads change when the banks experience more borrowers' negative ESG events. We show that the more adverse events bank's borrowers experienced, the higher is the average ESG rating of the bank's lending portfolio. In other words, banks originate relatively fewer loans to brown borrowers after events. Loan spreads also change – the average all-in-drawn spread for the syndicated loan is larger for borrowers with poorer ESG performance. The negative relation between loan spreads and ESG performance becomes stronger after each negative ESG event that banks' borrowers experience.

This paper does not consider equity financing. The evidence in the literature indicated that the cost of capital does not change for brown firms (Berk and van Binsbergen (2022)). We also find evidence that the negative stock market reaction to non-financial companies' adverse ESG events does not persist in the long-run. 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.

Our paper contributes to several strands of the literature. First, we contribute to the literature on banks and their borrowers' ESG performance. Banks generally charge higher rates for companies that pollute environment, i.e. firms with high carbon emissions and fossil fuels (Goss and Roberts (2011); Delis et al. (2020); Chen et al. (2021); Degryse et al. (2021); Ehlers et al. (2022)). Several papers claim that such firms also get fewer loans (Nguyen and Phan (2020); Reghezza et al. (2021); Kacperczyk and Peydro (2022)) unless they have relationships with the lender (Houston and Shan (2022)). In this paper, we focus not only on carbon emissions but on all components of ESG and show how debt structure of brown firms changes when they experience adverse ESG events, and whether banks consider ESG performance when they originate loans.

We also contribute to the growing literature on ESG and climate finance.[5] This research suggests that investors value firms' ESG performance and demand premium from brown companies (Chava (2014); Engle et al. (2020); Choi et al. (2020);

[5]See Giglio et al. (2021) for a review.

Bolton and Kacperczyk (2021)).[6] Analogously, corporate bonds are subject to ESG risk and tend to yield less for brown firms (Huynh and Xia (2021); Seltzer et al. (2022)). Finally, Pástor et al. (2022) show that green stocks have lower expected return. There are also models that study firms' ESG performance and investors' reaction to it (Friedman et al. (2021); Pástor et al. (2021); Goldstein et al. (2022)). We show that not only firms' stock prices but also their lenders' drop after the adverse ESG event.

Finally, we contribute to the literature on debt structure, lending and, more broadly, banking. There are several theories on how firms choose between private and public credit (Diamond (1991); Rajan (1992); Chemmanur and Fulghieri (1994); Bolton and Scharfstein (1996)), as well as empirical studies discussing cross-sectional and time series variations in bank and bond financing (Faulkender and Petersen (2006); Rauh and Sufi (2010); Becker and Ivashina (2014); Crouzet (2018); Schwert (2020); Crouzet (2021)). Multiple papers study patterns in bank lending, including relationship borrowing and bank-borrower matching (Ivashina (2009); Schwert (2018); Houston and Shan (2022)). We analyze debt structure of firms with low ESG performance and show that they tend to borrow more from banks, since loans are relatively cheaper for them than bonds.

The rest of the paper is organized as follows. Section 2 describes the structural model of loan and bond pricing to compare how expensive loans and bonds are for brown companies. Section 3 shows how debt structure of brown companies changes after they experience an adverse ESG event. Section 4 discusses market reaction to banks whose borrowers experience adverse ESG events. Section 5 shows how banks incorporate ESG information when they decide to originate loans. Section 6 concludes.

[6]One of the largest group of investors who choose their holdings based on ESG performance are institutions (Krueger et al. (2020)).

2 Model of loan and bond pricing

We start by proposing a structural model of credit pricing to estimate loan prices as if they were traded on the market, to test how costly it is for brown and green firms to borrow from banks relative to issuing bonds. We first describe the model that is an extension of Merton (1974). Then we describe our data sources and results.

2.1 Model

To compare prices of two sources of debt for high- and low-ESG companies, we use the approach developed by Schwert (2020). The approach allows us to get valuations of firms' loans as if these loans were traded on the public bond market.

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.

In the first step, we match bonds and loans issued by the same company on the same date. Since for two debts issued on the same date timing and probability of default, as well as 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 the model developed by Merton (1974) with two classes of debt. The firm value is assumed to follow a geometric Brownian motion under the risk-neutral measure:

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

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 at 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

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

where

$$d_{1,S} = \frac{ln(V/K_S) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \quad d_{2,S} = d_{1,S} - \sigma\sqrt{T}, \tag{3}$$

and the value of the junior debt is

$$D_J = \left(V\Phi(d_{1,S}) - K_S e^{-rT}\Phi(d_{2,S})\right) - \left(V\Phi(d_1) - (K_S + K_J)e^{-rT}\Phi(d_2)\right), \tag{4}$$

where

$$d_1 = \frac{ln(V/(K_S + K_J)) + \left(r + \frac{1}{2}\sigma^2\right)T}{\sigma\sqrt{T}}, \quad d_2 = d_1 - \sigma\sqrt{T}. \tag{5}$$

Since the loan and the bond have zero coupon, 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 valuation of junior debt (4) 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 (2) and obtain the price of the loan as if it was traded on the public bond market.

2.2 Data

To estimate the model we collect data on loan and bond prices. We use LPC DealScan for loan rates. DealScan provides data on syndicated loans, i.e, loans that involve several parties. The main decision is usually made by the lead lender (Ivashina (2009); Schwert (2018, 2020)), hence, for each loan facility we keep only lead lender. We remove borrowers from financial and utilities industries. We remove loans originated for acquisitions, mergers, takeovers, or leveraged buyouts. We keep only US dollar denominated loans priced relative to LIBOR. Finally, we keep only unsponsored term loans or revolving lines of credit. For each facility we observe all-in-drawn spread, date of origination, maturity, seniority, and loan amount. We match 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).[7]

We match each loan facility with data on bond prices from TRACE. The data is transaction-level, i.e., it records the price of the bond at dates when transactions were made. We match loans and bonds by the date of origination/issuance and maturity. We keep only senior unsecured bonds following Schwert (2020).

Finally, we add risk-free rates and debt structure data necessary for the estimation of the model. We collect LIBOR data from Bloomberg and use it as a measure of risk-free rate mainly because loans in our sample are prices relative to LIBOR. 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. Our 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.

2.3 Estimation results

Results of the model estimation are presented in Table 1. Average bond spread is 2.05%, whereas average loan spread is 1.65%. However, once we account for maturity, seniority, and debt amounts, it becomes clear that bank borrowers pay premium for the loan – model-implied loan spreads are on average 0.33%. The results in consistent with findings in Schwert (2020) and shows that borrowing from banks is more expensive than borrowing

[7]We thank Michael Roberts and Michael Schwert for making their data available.

Table 1: Structural Estimation Results

	Mean	Std. dev.
	(1)	(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 structural estimation of the credit pricing model. Column 1 shows means and column 2 shows standard deviations of respective variables. The firs 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 percents.

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 rating 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 2. Firms in the full sample pay on average 1.29% premium for borrowing from banks. The reasons underlying the premium include better terms offered by banks, possible negotiations and relationships, etc.[8] Green firms also pay a significant premium for loans – 1.99%. Finally, brown firms pay 0.96% premium for borrowing from banks.

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

Table 2: Estimated Loan Premiums for Green and Brown borrowers

	All firms (1)	Green firms (2)	Brown firms (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.

Next, we test if brown firms pay a lower premium than green firms. t-test leads us to the conclusion that green firms pay 1.03% premium on top of the premium that brown firms pay. The number is both statistically and economically significant, which implies that loans are relatively cheaper for brown firms than for green firms. There could be two different interpretations of the results. First, it is possible that banks charge brown firms less than green firms for the reasons that are not captured by the model. We test this hypothesis in Section 5 and show that banks generally offer elevated loan rates to brown borrowers. Second, both banks and public market can "punish" brown borrower but market reaction is stronger. We discuss this hypothesis more in Sections 4 and 5.

Our model estimation shows that bank credit is relatively cheaper for brown borrowers than for green firms. It implies that when firms with poor ESG performance need credit, they are likely to demand it from banks and not from public markets. In the next section we aim to understand how debt structure changes for brown firms.

3 Debt structure

The credit pricing model shows that for brown firms it is relatively cheaper to borrow from banks than from public debt markets. Hence, we should expect that when brown firms need more credit (e.g., when they experience an adverse ESG event), they should borrow more from banks than from public debt markets. We formally test the hypothesis in this section.

3.1 Data and empirical strategy

Our goal is to understand if brown firms borrow more from banks than from public debt markets. The analysis is challenging for two reasons. First, being brown is endogenous. For example, firms can spend more resources on incorporating renewable sources of energy if they have enough funds to do it. Alternatively, if firms have relationships with some large banks, they have little incentives to become green, since they will likely keep the relationship and always use it to get more credit. Hence, there should be a shock that creates necessary variation is firms' ESG performance to identify the causal impact of brownness on credit provision. Second, even if there is a shock, firms can still get more credit for other reasons. We might be able to control for observable reason such as time trend but not for unobservables.

We address the first concern by exploiting the event-study approach. We use violations of UN Global Compact principles as events. When the serious violation takes place, it is usually covered in mass media. Then it appears in RepRisk database. The database contains information about the event – description and date. Description mentions which principle has been violated. UNGC specifies 10 principles. 2 of them are related to human rights, 4 – to labor, 3 – to environment, and 1 – to anti-corruption. There is little concern regarding the importance of events since all of them are covered by news outlets. 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). The only identification assumption that we make is that the event was unanticipated – hence, the shock is exogenous and effects are causal.

We address the second concern by using *propensity score matching* (Rosenbaum and Rubin (1983)). We collect quarterly balance sheet data from Compustat. We then match firms that experiences UNGC events (treated) with firms that did not (control) based on assets, liabilities, intangible assets, industry, and date.[9] For all variables except the date we find the nearest neighbor.[10] We use only dates at least 5 days *prior* to the event to avoid situation when the event impacts variables that we use to match. The matched sample contains 238 observations per firm and event.

We collect data on syndicated loans originated in the US from 2001 to 2021 from LPC DealScan. Following the literature, we remove financial and utilities borrowers (SIC codes 49, 60-69, 90-99). We keep only the lead lender as she is 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. We remove sponsored loans to alleviate the concerns that our results are driven by such events. We keep only loans that are prices relative to LIBOR. Finally, we keep only revolving loan facilities (revolvers, lines of credit) and term loans of all types.[11] Our final DealScan sample contains 22,506 observations.

We collect bond issuance data from Mergent FISD starting. The data specifies the issue date and amount for each bond. The sample contains 454,405 observations from 1984 to current. We merge FISD to DealScan using CUSIP and lender file kindly provided by Schwert (2020). We then add bond and loan issuance data to the matched sample. Specifically, we add any new bond issuances and loan originations that took place within one year after the event. We use the same event date for control firms. Note that although we technically look at ordinary differences, in fact we run difference-in-differences, because FISD and DealScan provide data on *originations* as opposed to

[9]We try different sets of variables that we use to compute propensity scores. For example, when we use only assets and liabilities, results are similar.

[10]Ideally dates should be matched exactly. However, that would leave us with very few observation, so instead we use a *caliper* matching with an extremely low width.

[11]Some term loans are securitized. We are not concerned about it since we specifically look at lead lenders. DealScan includes CLOs as participants in the syndicate.

holdings. We run the following regression:

$$y_{it} = \theta \cdot post_t + \kappa \cdot treat_i + \gamma \cdot post_t \cdot treat_i + u_{it} \tag{6}$$

where y_{it} is either bond or loan debt, $post_t$ is a dummy equal to 1 for observations after the adverse ESG event, and $treat_t$ is a dummy equal to 1 for treated firms.

Summary statistics are presented in Table 3. Panel A shows statistics in the full sample, whereas Panels B and C break the sample down to firms in the treatment and control group. We matched firms based on dates, industries, assets, liabilities, and intangible assets. In can be seen from the table that matching is very precise – average assets, liabilities, and intangible assets are close in two samples. 10th and 90th percentiles are farther apart but there is no clear pattern – intangible assets and liabilities are larger for treated firms but total assets are larger for the firms in the control group. We discuss statistics on loan and bond issuance in Section 3.2.

3.2 Matching results

Table 3 contains preliminary results of difference-in-differences estimation. Firms that experienced adverse ESG events take 2,364 loans from banks and issue 12,912 bonds within one year after the event. In contrast, firms in the control group take only 1,177 loans and issue 3,270 bonds within the same period. We also present statistics on loan and bond amounts. Specifically, treated firms take on average $11.8 million in loans and issue bonds of $1.7 million in value. This suggests that treated firms take more debt both in dollar amounts and in number of contracts.

To statistically formalize our findings, we estimate regression (6). Results are presented in Table 4. Column 1 presents results on loan originations and column 2 presents results on bond issuance. We first note that after negative ESG event firms take significantly more debt – both private and public. The reason is that firms need more credit after the shock that potentially incurred financial costs. However, firms take significantly more bank debt than public debt – they take on average $9.7 million loans in addition

Table 3: Matched Sample Summary Statistics

	Mean	Std. dev.	p10	p50	p90	Obs
Panel A: Full sample						
Total assets (mill. $)	25,684	31,600	1,966	19,844	64,194	44,834
Total liabilities (mill. $)	16,226	23,419	981	8,128	39,594	44,834
Intangible assets (mill. $)	7,730	14,389	208	4,150	15,929	44,834
Loan origination (thousand $)	8,576	6,143	1,500	10,000	15,000	3,541
Bond issuance (thousand $)	1,546	1,835	250	800	3,000	16,182
Panel B: Treated firms						
Total assets (mill. $)	27,349	15,908	16,593	21,679	64,194	22,417
Total liabilities (mill. $)	17,361	14,615	7,294	9,223	45,432	22,417
Intangible assets (mill. $)	9,174	11,566	2,284	4,735	38,874	22,417
Loan origination (thousand $)	11,788	5,012	1,650	15,000	15,000	2,364
Bond issuance (thousand $)	1,692	1,993	250	800	3,050	12,912
Panel C: Control firms						
Total assets (mill. $)	24,019	41,697	1,966	2,203	71,058	22,417
Total liabilities (mill. $)	15,091	29,678	956	1,082	32,716	22,417
Intangible assets (mill. $)	6,286	16,618	208	1,266	9,605	22,417
Loan origination (thousand $)	2,124	831	900	2,500	2,750	1,177
Bond issuance (thousand $)	972	756	350	840	2,000	3,270

Note: This table provides descriptive statistics for firms in our matched sample. Panel A shows statistics for the full sample. Panel B contains only treated firms – firms that experiences adverse ESG events. Panel C contains control firms – firms that did not experience ESG events. Assets, liabilities, and intangible assets are in millions, loans and bonds are in thousands. p10, p50, and p90 denote 10th, 50th, and 90th percentile, respectively. The last column shows number of observations.

Table 4: Debt Structure Changes after the Event

$$y_{it} = \theta \cdot post_t + \kappa \cdot treat_i + \gamma \cdot post_t \cdot treat_i + u_{it}$$

	Dependent variable:	
	Loans	Bonds
	(1)	(2)
Post	2,124***	972***
	(24)	(13)
Post · Treat	9,664***	719***
	(106)	(22)
Observations	3,541	16,182
R^2	0.549	0.025

Note: This table provides results of estimation of equation (6). Column 1 shows results with loan originations and column 2 shows results with bond issuance. The sample is constructed using propensity score matching based on balance sheet variables. Robust standard errors are in parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

to the firms in the control group and issue additional bonds of $719 thousand in value. The difference is statistically significant according to the Welch's t-test.

Results in this section are consistent with the model estimation in Section 2. Since loans are relatively cheaper for brown firms than for green firms, there are two explanations for finding in Table 4. First, brown firms are ex-ante more likely to violate UNGC principles or be generally involved in ESG-related scandals. Hence, for treated firms in our sample it is relatively cheaper to borrow from banks than for firms in the control group even without the event. Second, the events reduce firms' ESG ratings,[12] thus making it even cheaper for brown firms to borrow from banks.

To sum up, we find strong evidence that firms borrow more from banks than from public debt markets after they violate UNGC principles. It may suggest that banks indeed finance brown firms and allow them to operate further, so regulators should impose rules on banks and make them consider ESG performance in their loan origination

[12]Recall that we use RepRisk for ESG ratings in the model and we use events recorded by RepRisk in the debt structure analysis.

decisions. However, pure fact that bank loans are *relatively* cheaper for brown firms does not mean that banks do not increase loan prices for such firms. In addition, if banks provide huge loans to brown firms, investors who care about ESG should not only sell brown firms' stocks but also their lenders' stocks. The latter mechanism can serve as a disciplining device for banks to consider ESG performance in their lending decisions. We formally test these hypotheses in the next section.

4 Market reaction

The evidence so far implies that banks finance brown companies and originate loans to them after the adverse ESG events. In this section, we aim to show that investors notice such behavior and adjust their decisions. When firms violate UNGC principles, their investors have several reasons to sell their stock – including financial and ESG reasons. As a result, their stock price declines. In this section, we analyze how lenders' stock prices react to events that involve their borrowers.

4.1 Data and empirical strategy

We collect data on syndicated loans originated in the US from 2001 to 2021 from LPC DealScan. Following the literature, we remove financial and utilities borrowers (SIC codes 49, 60-69, 90-99). We keep only the lead lender as she is the one responsible for the deal. DealScan contains data on loan contracts – i.e. all-in-drawn spreads, fees, loan amounts, start and end dates, reasons for loans, maturities, types, and other characteristics. We match the DealScan data with quarterly Compustat data on borrowers using the connecting file provided by Chava and Roberts (2008). We match the data with quarterly Compustat data on lenders using the connecting file provided by Schwert (2020). Our final sample contains 101,128 loan facilities and covers 13,801 borrowers.

We use data on violations of UNGC principles from RepRisk as in the previous section. When the serious violation takes place, it is usually covered in mass media.

Then it appears in RepRisk database. The database contains information about the event – description and date. Description mentions which principle has been violated. UNGC specifies 10 principles. 2 of them are related to human rights, 4 – to labor, 3 – to environment, and 1 – to anti-corruption.[13] There is little concern regarding the importance of events since all of them are covered by news outlets. 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). We remove all duplicates. Finally, we match the RepRisk data with firm-level Compustat data using ISIN.

Finally, we create the bank event file. Specifically, we use DealScan to check who provided the credit to the firm when the event happen. We follow the literature and assume 1-quarter lag between the loan deal and its origination. Hence, for each firm we have data on the event (date and description), on its contemporaneous lenders, loan details and balance sheet entries for both firm and its lenders. The data covers 631 borrowers and 33 banks from 2001 to 2017 (the last year of facility start date).

To identify the effect of poor ESG performance on lenders' stock price, we use the event study approach. For each event we run the market model and then compute cummulative abnormal returns for 1-week window after the event. As a robustness test, we repeat the analysis using Fama-French 3-factor model (Fama and French (1992)) and CAPM.

After we compute abnormal returns, we add bank-level control variables – deposits and assets one quarter before the event, and current loan amounts. The regressions we are running is

$$CAR_{it} = \alpha + \gamma X_{it} + u_{it} \tag{7}$$

where CAR_it are cumulative abnormal returns and X_{it} is a vector of controls. The coefficient of interest is α – it shows conditional cumulative abnormal returns during 1 week after the negative ESG event.

[13] In the robustness tests, we repeat the analysis of this section for the environment-related events, our conclusions hold.

Pure fact of negative abnormal returns does not mean that banks' investors sell stocks because they are not satisfied with banks' sustainability. Alternative explanations include financial concerns and regulatory risks. When a bank's borrower experiences any negative event (not necessarily ESG-related), bank's assets are shocked. It can make investors sell bank's stocks. Regulatory risks imply that banks may be subject to regulations if they borrowers' policies are not sustainable. As a result, investors may be willing to sell stocks.

We address the concerns above in several ways. First, we test if returns are more negative when the event includes relationship borrowers. For each bank-borrower pair we compute the fraction of loans that the bank originated to the borrower in the total number of loans that the bank originated (Chodorow-Reich (2014)). We then demean the ratio to compare bank-borrowers with above average relationships to bank-borrowers with below average relationships. If negative returns are driven by financial concerns, there should be no significant difference between investors' reaction to the event experienced by a relationship to non-relationship borrower.

Next, we test if negative returns are amplified by worse financial conditions of the borrowers. For each borrower we compute Altman z-score (Altman (1968)) that is a proxy for bankruptcy rate of the firm. In addition, we collect data on whether the loan is secured or not. As before, we demean both series. If the negative reaction is driven by the financial conditions, it should be amplified by default risks of the borrowers and it should be stronger for unsecured loans.

Finally, if investors sell bank's stocks because they believe that the bank has higher probability of default, they should also invest in bank's credit default swaps (CDS). We collect CDS data for banks in our sample from Markit. We run the following regression:

$$\Delta CDS_{it} = \delta CAR_{it} + \gamma X_{it} + \theta_i + \epsilon_{it} \tag{8}$$

where θ_i is bank fixed effect. Insignificant δ would imply that stock sales are not related to fears that the bank is in financial distress.

It is more complicated and less important to separate the ESG effect from the regulatory risk. Since regulatory risk is related to ESG and makes investors punish unsustainable firms and banks, it is still consistent with our story. However, we run one test to partly address the concern. Specifically, we test if the negative reaction is stronger after 2014 IPCC report. Unlike previous report, 2014 IPCC report attracted attention of mass media and politicians due to dramatic predictions that it made. As a result, it called for urgent climate-related regulations. Hence, we can assume that regulatory risk became more important after 2014. We run (7) separately pre and post 2014.

4.2 Results

We first document the results of estimating (7). Column 1 of Table 5 shows the results. After the negative ESG event that firms experience, their lenders' stocks drop on average by 0.4 p.p. over 1 week. The drop is both statistically and economically significant. In robustness tests, we show that the results hold for alternative windows from 3 days to 6 months. This is evidence that investors pay attention not only to the firm that is involved in the violation of UNGC principle but also its lenders.

To separate cash flow effect from the ESG component, we run three regressions. Column 2 of Table 5 shows that for banks' stock drop by additional 0.5 p.p. if the bank is in relationships with the firm that experienced negative event. Such drop is not related to future cash flows or to bank's financial health – this is attributed to the ESG component. Investors punish banks more for being in relationships with brown companies. In other words, market is softer to banks whose first-time borrower is not sustainable in contrast to banks who actively lend to brown firms.

Column 3 of Table 5 show that Altman z-score does not impact the reaction. Altman z-score indicated the probability of default of the firm. When z-score is high, the firm is more solvent. Insignificant coefficient means that investors' reaction is the same for solvent and nearly distressed firms. Column 4 of Table 5 shows that market reacts similarly regardless of whether the loan is secured or not – this finding is consistent with the results with z-score. They lead us to conclusion that negative reaction cannot be explained by the fear that banks are distressed.

There is also an anecdotal evidence. Large banks' assets reach hundreds billion dollars. Even large loans are just a tiny fraction of banks' assets. That is why, the probability that the borrower may default on the loan does not distress banks' assets. To make that claim clear, we estimate (8). Results are presented in Table 6. Consistent with our results, coefficients in all columns are insignificant. Banks' CDS spreads do not change after the event.

Finally, we address the concern that our results are driven by the regulatory risk. We run (7) with relations for post-IPCC period. Column 5 of Table 5 shows the results. First, the coefficient at Post-IPCC is significant but small. In addition, the sign is positive which contradicts the regulatory risk explanation. The coefficient at Post-IPCC interacted with relations is insignificant – investors did not start worrying about banks' relationships with brown borrowers more after the 2014 IPCC report.

The evidence in this section suggests that market reacts negatively when banks' borrowers violate UNGC principles. The results indicate that banks are penalized when they lend to brown firms. We thus hypothesize that banks should consider ESG factor when they originate loans. We test the hypothesis in the next section.

5 Banks' response

Since banks experience drop in their stock prices after their borrowers violate UNGC principles, their rational response should be to include borrowers' ESG performance in their decision set when they originate loans. We formally test if that is true in this section. Specifically, we test if banks originate relatively fewer loans to brown borrowers after each event.[14] We also check if banks charge higher spreads from such borrowers.

For the analysis, we use the same data as in Section 4. ESG ratings come from

[14]They can achieve it by lending more to green borrowers or by lending less to brown borrowers.

Table 5: Market Reaction on Bank Stock: Event Study

$$CAR_{it} = \alpha + \beta_1 relations_{it} + \beta_2 zscore_{it} + \beta_3 secured_{it} + \gamma X_{it} + u_{it}$$

	Dependent variable:				
	CAR				
	(1)	(2)	(3)	(4)	(5)
Constant	-0.004^{***}	-0.006^{***}	-0.004^{***}	-0.004^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Relations		-0.005^{***}			-0.006^{***}
		(0.002)			
Z-Score			-0.0002		
			(0.0002)		
Secured				0.0001	
				(0.001)	
Post-IPCC					0.001^{*}
					(0.001)
Post-IPCC · Relations					0.003
					(0.003)
Observations	28,668	28,668	26,011	28,668	28,668
R^2	0.001	0.001	0.001	0.001	0.001

Note: This table provides results of estimation of equation (7) controlling for relations, Altman z-score, and dummy for secured loans. The first column shows benchmark result. The second column shows results controlling for relations with borrowers. The third column shows results controlling for Altman z-score. The fourth column shows results controlling for dummy for secured loans. The fifth column provides results for post-IPCC period. Standard errors are robust and displayed in the parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

Table 6: Bank CDS Spreads and Negative Market Reaction

$$\Delta CDS_{it} = \delta CAR_{it} + \gamma X_{it} + \theta_i + \epsilon_{it}$$

	Dependent variable:			
	ΔCDS			
	(1)	(2)	(3)	(4)
CAR	0.014	0.033	0.014	0.032
	(0.021)	(0.031)	(0.021)	(0.031)
Observations	10,015	5,763	10,015	5,763
R^2	0.00005	0.002	0.006	0.011
Bank controls	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes

Note: This table provides results of estimation of equation (8). Columns 1 and 2 do not include bank fixed effects. Columns 1 and 3 do not include bank controls. Standard errors are robust and displayed in the parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

RepRisk, hence, they are based on events that firms experience. We keep only lead lenders since they are responsible for decision-making (Ivashina (2009)). For each bank in every quarter we compute the event count, i.e., how many events their borrowers experienced up to date. We also compute the ESG score of the loan portfolio for each bank. Specifically, we compute weighted average ESG scores of firms that have open loan facilities at the bank. We then run the following regression:[15]

$$ESG^p_{it} = \beta EventCount_{it} + \alpha_i + \theta_t + u_{it} \tag{9}$$

where ESG^p_{it} is an ESG score of the loan portfolio, α_i are bank fixed effects, and θ_t are time fixed effects.

For the loan pricing analysis, we follow literature (Schwert (2018)) and use all-in-drawn spreads as a measure of loan price – it includes loan rate and fees net of LIBOR.

[15]Most results are same if we run LP or logit model to test if the probability of lending to a green firm increases after each event.

Table 7: Loan Portfolio ESG Scores and UNGC Events

$$ESG^p_{it} = \beta EventCount_{it} + \alpha_i + \theta_t + u_{it}$$

	Dependent variable:		
	Portfolio ESG score		
	(1)	(2)	(3)
Event count	0.044***	0.082***	0.014***
	(0.001)	(0.002)	(0.003)
Observations	3,262	3,262	3,262
R^2	0.232	0.834	0.918
Bank FE	No	No	Yes
Time FE	No	Yes	Yes

Note: This table provides results of estimation of equation (9). Columns 2 and 3 include time fixed effects. Columns 3 also includes bank fixed effects. Standard errors are robust and displayed in the parentheses. *,** , and *** correspond to 10-, 5-, and 1% significance level, respectively.

We run the following regression:

$$AIDS_{it} = \mu ESG_{it} + \beta ESG_{it} \cdot EventCount_{it} + +\iota ESG_{it} \cdot CAR_{it} + \alpha_i + \gamma_j + \epsilon_{itj} \quad (10)$$

where $AIDS_{it}$ are all-in-drawn spreads, ESG_{it} are *borrowers'* ESG scores, and CAR_{it} is market reaction on the lender.[16]

Results are presented in Tables 7 and 8. Banks whose borrowers experience more negative ESG events, lend relatively more to green companies. Specifically, additional adverse event increases the average ESG score of bank's loan portfolio. At the same time, we find strong evidence that banks charge higher spreads from brown borrowers – lower the ESG rating is, the higher all-in-drawn spread is. Moreover, column 3 of Table 8 shows that with every new adverse event, the relationship between ESG rating and spreads is stronger. Finally, column 4 shows that the effect is stronger when market reaction is more negative.

[16]We do not add time fixed effects to this regression because it is hard to tell when the loan price was negotiated.

Table 8: Loan Spreads for Brown Companies

$$AIDS_{it} = \mu ESG_{it} + \beta ESG_{it} \cdot EventCount_{it} + \iota ESG_{it} \cdot CAR_{it} + \alpha_i + \gamma_j + \epsilon_{itj}$$

	Dependent variable:			
	All-in-drawn spread			
	(1)	(2)	(3)	(4)
ESG rating	-14.415^{***}	-3.971^{***}	-5.042^{***}	-7.077^{***}
	(1.064)	(1.343)	(1.788)	(1.167)
ESG rating · Event count			-0.003^{*}	
			(0.002)	
ESG rating · CAR				-1.047^{**}
				(0.048)
Observations	6,380	5,608	5,608	5,485
R^2	0.028	0.962	0.216	0.214
Bank FE	No	Yes	No	No
Borrower FE	No	Yes	No	No

Note: This table provides results of estimation of equation (10). Columns 1, 3, and 4 do not include bank and borrower fixed effects. Standard errors are robust and displayed in the parentheses. *,**, and *** correspond to 10-, 5-, and 1% significance level, respectively.

The evidence in this section shows that commercial banks do not ignore ESG scores of their borrowers. They lend relatively less to brown borrowers after events and charge higher rates. We also find evidence that the effects are stronger when market reaction is bigger.[17] In other words, market disciplines banks and force them to make credit more expensive for firms with poor ESG performance.

These results may seem to contradict results in Sections 2 and 3 where we show that brown firms tend to borrow more from banks because it is relatively cheaper than to issue bonds. The discrepancy implies that although banks "punish" brown firms by charging higher spreads for loans, bondholders react even more. Hence, market cares more about ESG performance of firms than their lenders.

6 Conclusion

In this paper, we attempt to identify the main sources of debt for companies with poor ESG performance. First, we show that brown companies pay a significantly lower premium for borrowing from loan compared to bond market is lower than green companies. Perhaps as a result, after a company's ESG performance deteriorates, it initiates considerably more new loans than issues bonds.

We next ask whether corporate loan providers have motivation to and indeed incorporate their borrowers' ESG into their lending decisions. After a corporate borrower's negative ESG event becomes public, lender's stock price drops significantly in a short window surrounding the announcement, implying that banks' shareholders value ESG of the banks' lending portfolios. We show that this reaction is not purely a response to increased financial risk: the abnormal stock price drops remains after we include borrower-specific financial stability controls, and banks' credit rating does not change after one of the borrowers experiences an adverse ESG event. Loan providers respond to poor ESG performance of their borrowers by increasing loan spreads and reducing total

[17]These results are out of scope of the paper and moved to Online Appendix.

amounts of credit issued to low-ESG-rated firms.

Because brown companies' relative cost of borrowing from the loan market is lower, but at the same time loan providers increase loan spreads for brown borrowers, we conclude that public debt holders "punish" poor ESG firms even stronger than banks.

Our results suggest that, even though there exist market mechanisms that disciplines brown borrowers by raising their cost of debt, companies with poor ESG performance are still obtaining considerable amounts of debt, primarily from the private loan market.

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