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ORIGINAL PAPER

Do Banks Value Borrowers' Environmental Record? Evidence from Financial Contracts

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Abstract
Banks play a unique role in society. They not only maximize profits but also consider the interests of stakeholders. We investigate whether banks consider firms' pollution records in their lending decisions. The evidence shows that banks offer significantly higher loan spreads, higher total borrowing costs, shorter loan maturities, and greater collateral to firms with higher levels of chemical pollution. The costly effects are stronger for borrowers with greater risk and weaker corporate governance. Further, the results show that banks with higher social responsibility account for their borrowers' environmental performance and charge higher loan spreads to those with poor performance. These results support the idea that banks with higher social responsibility can promote the practice of business ethics in firms.

Keywords Chemical emissions · Pollution record · Bank sustainability performance · Corporate governance · Business ethics

Introduction

Banks play a unique role in society. On the one hand, they maximize profits for their shareholders. On the other hand, they allocate resources and funds to firms that support their operating strategy and contribute to their economic development (Levine 2005; Scholtens 2009). As most funds are sourced from depositors, banks serve as a custodian of society's resources and a delegated monitor of loan borrowers (Diamond 1984; Gao et al. 2017; Herbohn et al. 2019). They use their expertise in to screen prospective borrowers, monitor them, and to ensure they repay the banks.

Facing rapid and extreme climate change around the world, many banks have made commitments to integrate social and environmental considerations into their operations and financing decisions (Scholtens and Dam 2007; Cogan 2008; Scholtens 2009; Goss and Roberts 2011).[1] For example, since the early 2000s, banks have increasingly adopted the Equator Principles when financing projects (Jung, Herbohn, and Clarkson 2018).[2] Banks have also renewed loan contracts with favorable terms that have provided lenders with greater access to inside information about high-risk carbon firms (Herbohn et al. 2019), or they have offered lower loan costs to firms with superior performance in corporate social responsibility (Cheung et al. 2018). In addition,

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[1] According to Scholtens (2009), every eight dollars invested is subject to social or ethical screening. In many OECD countries, banks offer savings accounts to the public while promising that the funds are being used for environmentally sound projects.

[2] Proposed by the World Bank in 2002, the Equator Principles represent a risk-management framework that provides a minimum standard for due diligence and monitoring to support responsible risk decisions. To date, 97 financial institutions in 37 countries that cover more than 70% of the global lending volume in emerging markets have adopted the Equator Principles (Gupta 2018).

they have designed loan contracts that advocate for a firm's environmental performance. One bank reported that Kerima, a Helsinki-based specialty chemical company, signed a deal to borrow up to $450 million under terms that would vary according to its environmental performance. This deal was co-arranged with several large multinational commercial banks, such as BNP Paribas, Citibank, and Swedbank (Meskin 2019; Scott 2019). These facts show that some banks could play a critical role in promoting the practice of business ethics in their borrowers through their lending decisions. In this paper, we thus investigate whether banks incorporate a firm's environmental pollution record, especially its level of chemical emissions, into their lending decisions.

Recent studies have found that stronger corporate environmental policy is associated with significantly lower costs of debt and equity capital (Schneider 2011; Attig et al. 2013; Chava 2014; El Ghoul et al. 2018).[3] Firms that consider the interests of and benefits to their stakeholders are better able to build mutual trust and cooperative relationships that enable them to gain a competitive advantage over those that do not have the same focus (Freeman 1984; Jones 1995). As such, a firm with a better environmental policy should be associated with a lower cost of capital. Our study shares the theme of these studies but is distinctive from them for two reasons. First, we focus on the unique ability of financial institutions to value a company's environmental policy, specifically its level of chemical emissions. A company's emissions level is difficult to quantify, but such information can be collected and verified over time. Therefore, financial institutions should be well situated to redress any information asymmetry between lenders and borrowers.[4]

Second, to specifically investigate whether and how financial institutions value firms' environmental policy, we use the Toxic Release Inventory (TRI) from the US Environmental Protection Agency (EPA) as our measure of environmental performance. The US requires the facilities that emit toxic chemicals above a given threshold to report these emissions to the EPA. Therefore, the TRI clearly identifies the magnitude of emissions for each industrial facility. The studies that investigate the issue of environmental performance have frequently used data on ratings from Kinder, Lydenberg, and Domini Research & Analytics (KLD),[5] or environmental performance data from Trucost,[6] such as Attig, El Ghoul, Guedhami, and Suh (2013), or Chava (2014). Different from those studies, our measure can directly capture the extent to which a firm considers its stakeholders' interests since it indicates the amount of chemicals emitted into a community. Furthermore, by using TRI data in our analyses, we consider the effect of lending policy on all firms that emit chemical pollution regardless of their size.[7]

To examine how firms' chemical emissions affect the loan decisions of banks, we collect and match data from several sources. First, we collect data regarding the quantity and toxicity levels of chemicals from the data in the TRI that the EPA publishes on its website. Second, we obtain loan data on the borrowers' financial information from Reuters' DealScan. Third, we collect firms' accounting data from the Compustat database. We merge all data based on the borrowing firms and lending banks' trading IDs. The final merged database covers 8,331 loan contracts for 836 individual firms over the period from 1988 to 2015.

We conduct baseline panel regressions of loan spreads on chemical emissions (*CE*) that control for firm characteristics, loan characteristics, macroeconomic variables, loan purpose and type, and firm and year fixed effects. Our empirical analyses show that the coefficients for *CE* are positive and significant in all specifications at the 1% level. These findings support that the firms with greater chemical emissions pay higher interest rates.

We then provide evidence on the possible channels through which chemical emissions affect the cost of bank loans. Our findings show that the association between chemical emissions and the cost of bank loans is more pronounced in firms with higher risk and a weaker corporate governance structure. In particular, the costly effect of chemical emissions on loan spreads derives mostly from firms with a lower Z-score, higher expected default frequency, higher idiosyncratic volatility, lower board independence, higher proportion of busy directors on the board, dual role of CEO

[3] The main argument behind these studies is that firms should consider the interest of a broader group of stakeholders, such as customers, employees, creditors, and other concerned members of their community.

[4] Prior studies on the corporate bond spread or credit rating as a proxy for the cost of debt have not been able to highlight the role of banks in valuing a company's environmental policy.

[5] The KLD score considers broad dimensions of how a company behaves in society and is often viewed as a general score of corporate social responsibility. KLD data come from surveys, financial statement information, media reports, government documents, and other legal journals to rank companies on 13 dimensions of corporate social responsibility (CSR). Therefore, the score of KLD can be viewed as an indirect measure of corporate environmental performance.

[6] Trucost contains data about a broad range of corporate social and environmental performances. The variables cover the amount of emissions, waste production, water abstractions, natural resource use, and raw material extraction. The data span from 2004 through 2008 and comprise a sample of 1,200 publicly traded firms in the US (Delmas et al. 2015). Although it covers a wide range of variables, the data period is limited.

[7] The KLD database only typically covers large listed companies in the US and does not cover all firms that report data to TRI. Thus, about 3,890 observations, or 46.35% of our TRI data sample, are contained in the KLD database.

and chairman of the board, and a higher proportion of directors who attend less than 75% of board meetings. These findings show that firms' environmental issues can exacerbate debtholder concerns regarding the borrowers' high risk and weak governance.

We also conduct various sensitivity analyses to reduce potential endogeneity problems. First, we use regressions with firm and year fixed effects, instrumental variables via two-stage least squares, and propensity score matching to alleviate possible endogeneity induced by omitted variables and self-selection between chemical emissions and the cost of borrowing. Additionally, we consider two alternative measures of chemical emissions and find similar results. Last, we use the total cost of borrowing as an alternative to the loan spread to account for potential measurement error.

Furthermore, we find additional evidence to support our hypotheses. First, our analyses show that banks are likely to impose unfavorable nonprice loan terms on polluting firms, such as shorter maturities and more collateral requirements. Second, we find that banks with higher social responsibility (proxied by CSR score) place more importance on their borrowers' environmental performance and charge higher loan spreads for firms with chemical emissions. Last, our analyses still hold after controlling for the effect of social norms in the regression model.

Our study contributes to the literature from two perspectives. First, we focus on whether banks consider firms' pollution records in their lending decisions. Unlike the capital raised from public equity markets, business entities commonly adopt debt financing that banks typically monitor more closely (Scholtens 2009). Specifically, most firms rely relatively more heavily on bank loans (Denis and Mihov 2003; Bharath et al. 2008). Banks play an important role as delegated monitors in lending activities because they have a comparative advantage in collecting information on firms through private channels that are unavailable to other stakeholders, which helps reduce information asymmetry between borrowers and lenders (Coulson and Monks 1999). Our empirical results show that banks offer significantly higher loan spreads, shorter loan maturities, higher total borrowing costs, and more collateral requirements to firms with higher levels of chemical emissions. These results highlight a strong policy implication that some banks could have a critical role in promoting the practice of business ethics in their borrowers.

Second, our study contributes to the literature on stakeholders and bank social responsibility. Studies have shown that financial institutions' lending policies take into account stakeholders' interests (Gao et al. 2017), firms' exposure to carbon-related risk (Jung et al. 2018; Herbohn et al. 2019), and county-level social capital (Hasan et al. 2017). Our findings complement those studies and provide direct evidence that banks charge significantly higher loan spreads to high polluting firms, indicating that banks account for stakeholders' interests in their lending decisions. Furthermore, we find evidence that banks with higher social responsibility place more importance on their borrowers' environmental performance when making loans, while it does not hold for banks with lower social responsibility. The results are similar to those in Hauptmann (2017) and Cheung, Tan, and Wang (2018) who highlight that banks with higher social responsibility value community interests when making loans and they charge their borrowers with high social or environmental risks higher loan spreads.

The remainder of our study is organized as follows: In section "Literature Review and Hypothesis Development," we review the findings in the current literature and develop testable hypotheses. We discuss the data sources in section "Data and Descriptive Statistics." Section "Empirical Results" presents the main empirical results; and section 5 is the "Conclusion."

Literature Review and Hypothesis Development

The Role of Banks in Firms' Environmental Performance

Banks play a unique and important role in the commercial world by accepting deposits and making loans to borrowers. Since the majority of banks' funds come from depositors, they are responsible to their depositors (and to their shareholders) to both generate profits and minimize any potential loss from making loans. Unlike capital market investors, such as corporate debtholders and equity shareholders, banks are better able to reduce information asymmetry not only by assessing hard information in a firm's annual report but also by using soft information for making lending decisions (Agarwal and Hauswald 2010; Du et al. 2017). They can use this knowledge to screen prospective investment projects, monitor borrowers, and even to enforce lending contracts should they be breached by the borrowers (Scholtens 2009). Therefore, studies have shown that banks translate the needs and preferences of depositors into appropriate capital investments that thereby contribute to economic development.

Many global banks have adopted the Equator Principles to consider social and environmental issues in project financing to mitigate the undesirable factors in the environment (Chava 2014). From the perspective of the stakeholder theory, banks' lending policies should take environmental issues into account as they highlight the importance of active management of the business environment as well as the relationships with and promotion of the common interests of shareholders, employees, customers, creditors, and the community at large (Freeman 1984). Building mutual trust and cooperative relationships between firms and their stakeholders help the firms to gain a competitive advantage over those that do not (Jones 1995). Better relationships with stakeholders can even strengthen a firm's sustainability and financial performance (Whitehouse 2006). Since their lending resources come mainly from depositors at a cost, commercial banks should encourage making loans to firms with more environmentally sensitive and responsible performance according to the stakeholder theory.

Empirical evidence also shows that banks across the world have incorporated environmental concerns in their lending decisions (Cogan 2008; Du et al. 2017; Herbon et al. 2019). Thus, if a firm has poor environmental performance, banks will incorporate such environmental concerns in their lending decisions.[8] Thus, information on chemical emissions is typically not in the public domain; however, it becomes available to banks through potential borrowers after the banks carry out pre-loan screening and monitoring activities. Therefore, we expect that banks will retain this information advantage of understanding the magnitude of a firm's risk exposure from chemical emissions and use it to inform their lending decision.

Effect of Chemical Emissions on Bank Loan Spreads

Chemical emissions cause environmental concerns and endanger residential health and as such they impose specific risks. First, firms that engage in environmental misconduct may incur the opportunity costs related to complying with burdensome environmental regulations such as fines and cleaning costs as well as the profits lost due to reputational damage, production restrictions, or termination (Schneider 2011; Attig et al. 2013). Thus, firms with poor environmental performance should experience higher financial risk.

Second, firms with weak environmental performance encounter higher regulatory, compliance, and litigation risks; each of which affects their default risk and causes concern on the part of both financial and nonfinancial stakeholders. In addition, banks experience higher litigation risk if they lend to firms with environmental concerns, as these environmental liabilities not only impose potential solvency risks but also make debtholders responsible for environmentally related legal obligations (e.g., Balkenborg 2001). Third, lending to firms with high levels of chemical emissions may conflict with community interests or social norms that tarnish the bank's public image or reputation (Hong and Kacperczyk 2009).[9] Many banks have adopted and published policies regarding their refusal to finance environmentally harmful businesses and projects that mitigates their reputational risk (see, e.g., Davis and Worthington 1993; Kitson 1996).

All these factors affect a bank's total credit risk and can lead to unpredictable losses. The bank industry's environmental awareness has increased since the "Statement by Banks on the Environment and Sustainable Development." This statement was part of a United Nations Environment Programme (UNEP 1992) that was launched in May 1992. It was amended to become the "UNEP Statement by Financial Institutions on the Environment & Sustainable Development" in 1995. In this statement, signatories commit to becoming pivotal contributors to sustainable development and to making environmental considerations an essential part of normal credit appraisals. Thus, banks are increasingly considering environmental responsibility in their risk assessments and management procedures.

Prior studies document a negative relation between a firm's environmental performance and its cost of debt capital. Schneider (2011) investigates the pulp and paper and chemical industries and shows that the misconduct of those firms increases the future costs of clean-up and compliance that affects their interest solvency and results in a higher cost of debt. Similarly, we argue that a firm's chemical emissions are likely to influence the costs of private bank loans. Hence, we expect that banks are more likely to charge higher spreads on loans to firms with higher chemical emissions to compensate for potential liability and greater risk. We therefore propose our first hypothesis:

Hypothesis 1: Banks charge higher loan spreads to firms with higher chemical emissions.

Firm risk, Corporate Governance, and the Effect Of Chemical Emissions

In this subsection, we examine the circumstances that make the relation between chemical emissions and loan spreads more pronounced. Our reasoning is that the harmful effects of chemical emissions should be stronger for firms with

[8] For example, Herbohn, Gao, and Clarkson (2019) investigate whether banks consider carbon risk in their lending decisions and find positive and significant excess announcement-period returns for loan-renewal announcements for high-risk carbon firms that involve favorable revisions to the loan terms. Du et al. (2017) use hand-collected data on corporate environmental performance and a sample of privately-owned Chinese firms to show that the interest rate of on debt is significantly and negatively associated with their environmental performance.

[9] In this related literature, El Ghoul et al. (2019) also examine the role of the media in corporate social responsibility. Bhojraj and Sengupta (2003) indicate that firms with greater institutional ownership and more outside directors on the board benefit from better monitoring, and in turn they enjoy lower bond yields and higher credit ratings on their public debt.

higher risk or weaker corporate governance because they increase the cost of loans that exacerbates default risk. Because the banks' exposure to default risk is the primary concern in their lending policies, banks must identify, measure, monitor, and control such risks. Thus, for a firm with higher risk, such as higher uncertainty of cash flows or financial difficulty, it becomes harder for banks to assess its future cash flows or repayment of the loan. Therefore, they offer higher loan spreads when they consider the environmental performance of borrowers are bad. Meanwhile, a borrower with weak governance is less likely to provide transparent information that allows banks to evaluate the potential risk of making a loan to the firm based on environmental performance. Thus, we expect that banks will *ceteris paribus* charge a borrower a higher spread if it has a weak governance structure.

Firm risk, Chemical Emissions, and Pricing of Bank Loan

If chemical emissions contribute to an increase in loan costs that exacerbates default risk, then their effect on loan spreads should be more discernible in firms with higher risk. Different firms have various risks that cause variations in future cash flows and solvency. Studies suggest that firms with higher volatility in cash flows are associated with higher idiosyncratic volatility or risk (Irvine and Pontiff 2009). Firms with high cash- flow volatility are more likely to default when they face a shortfall and cannot cover their debt service requirements (Minton and Schrand 1999). Therefore, banks are less able to assess the default risk of borrowers due to their risk feature and may offer higher loan prices or spreads (Campbell and Taksler 2003; Kirschenmann and Norden 2012).

In addition, the problem associated with opaque information about firm-level characteristics also makes firms harder to value for banks, exaggerates the asymmetric information between the firms and banks, and increases the price terms of bank loans (Strahan 1999). To compensate for higher specific risk, banks will require higher loan spreads from firms.

When a borrower has poor environmental performance, banks are more likely to charge higher spreads on loans to compensate for potential liability and greater default. The more risky that a borrower is, the more uncertain its future repayment of principal and interest is. From a risk-management perspective, Sharfman and Fernando (2008) and Chava (2014) both propose that firms that mitigate their exposure to environmental risk have lower overall systematic risk; subsequently the market is likely to reward such "green" behavior with a lower cost of capital. Following their line of reasoning, we expect the effect of chemical emissions on loan spreads to be particularly strong for firms with higher risk.

Corporate Governance, Chemical Emission, and Pricing of Bank Loan

Studies indicate that agency risk and information risk between management and outside stakeholders affect default risk (e.g., Bhojraj and Sengupta 2003; Francis et al. 2012; Ge et al. 2012). When banks make loans to a company, they face two facets of agency risk. One is the agency problem between managers and the lenders (Jensen and Meckling 1976; Jensen 1986; Murphy 1985). Managers may neglect duties and pursue their own benefits at the expense of shareholders and creditors once they raise funds from a bank. As corporate governance is designed as a set of effective mechanisms for aligning the interests of managers and stakeholders (e.g., Shleifer and Vishny 1997; Tirole 2001), a firm with better governance can mitigate this type of agency problem by strengthening the monitoring of management and preventing their self-dealing. Since the manager's interests are aligned with stakeholders in better governed firms, banks have less concern about agency risk in firms that pollute the environment and are able to assess the potential default risk based on the information that the management team provides.

However, banks may face a second type of agency risk that arises from the conflicts of interests between shareholders and debtholders when they make loans. According to literature, shareholders may use self-dealing strategies to maximize their share values at the expense of lenders in certain circumstances.[10] These inappropriate actions affect the cash-flow volatility or lower the cash flows of the firm that increases the default risk.[11] A firm with a high level of chemical emissions may or may not explicitly increase the financial burden but may implicitly encounter higher regulatory, compliance, or litigation risks that raises a bank's concern about the loan repayment. Under this situation, a firm with poorly aligned interests between shareholders and debtholders may transfer the risk to the debtholders. Banks that consider the possible effect of a wealth transfer will charge higher loan spreads even if the firms have a good governance structure. Based on the potential agency conflicts among managers, shareholders, and creditors, no clear prediction

[10] For example, they may choose to invest in risky but potentially high-return projects (Jensen and Meckling 1976), or underinvest in positive NPV projects to grab more benefits from the firm, particularly when they are under takeover threats or financial difficulties.

[11] Cremers et al. (2007) find that the bond spread increases when the firm has stronger control over shareholders and face a high vulnerability for takeover. They explain this phenomenon as the bondholders' concern about the possible future default risk for those firms that may engage in mergers and acquisitions, and then add more debt to the firm.

about the pricing of bank loan contracts can be made for a better governed firm with poor environmental performance.

Nevertheless, a firm with a board that closely monitors its operations by requiring transparent financial reporting also reduces the information risk that further reduces the cost of debt (Beasley 1996; Klein 2002; Easley and O'hara 2004; Lambert et al. 2007; Bharath et al. 2008). Therefore, from the information risk standpoint, a well-governed firm with high chemical emissions that provides transparent information helps its banks to assess its future default risk.

Taken together, although the agency theory of debt argues that shareholders may not necessarily act in the interest of debtholders in certain circumstances, the benefits of better governance outweigh the costs of a governance structure from the information risk standpoint. We expect that strong corporate governance that promotes accountability to stakeholders contributes to more information transparency. Therefore, a better governance structure should facilitate commercial banks in assessing the potential risk associated with making loans based a firm's environmental performance.

Therefore, we hypothesize that weak governance and high firm risk magnify the effect of chemical emissions on the cost of bank borrowing. Thus, we propose our second hypothesis:

Hypothesis 2: The effect of chemical emissions on loan spreads is stronger for firms with higher risk or weaker corporate governance.

Data and Descriptive Statistics

Data

Our main explanatory variable is measured in metric tonne of toxic chemical emissions from the Toxic Release Inventory (TRI). This rich US database was created under the Emergency Planning and Community Right-to-Know Act of 1986 (EPCRA) and has been available and accessible to the public online and in other formats since 1989 (Doa 1992). The Act requires US manufacturing facilities to report their production waste, transfers, and emissions of certain toxic chemicals to the EPA on an annual basis.[12]

According to the EPCRA, three criteria determine the EPA's coverage of a firm's facilities, or in its words, "establishments." First, the firm must operate in a sector listed within the North American Industrial Classification System (NAICS). Second, a facility must be sufficiently large (must employ at least 10 workers). Third, it must produce, import, process, or use a greater amount of reportable chemicals than the EPA permits. The EPA has updated the list of TRI's chemicals periodically since the inception of EPCRA; it included some 650 items as of 2015 (EPA 2015).

Following Berrone, Cruz, Gomez-Mejia, and Larraza-Kintana (2010), we aggregate the total pounds of toxic chemical releases from the TRI database for all facilities at the parent-company level. In Fig. 1, we plot the total amount of chemical releases in the United States for years 1988 to 2015. The upper panels indicate all facilities in our database. They show that most polluters are in the eastern, midwestern, and some coastal western states. The density of facilities has increased over the course of 30 years. If we sum the total release amounts across all facilities in each state, we see that most polluters were in California and Texas in 1988; they shifted to Nevada, Utah, and Texas in 2015. Some eastern states became more prominent. Overall, the magnitude of chemical emissions decreased across states as a result of intensive regulation efforts.

In this study, the main independent variable is *CE,* the ratio of the total amount of toxic chemicals emitted to the total sales of a firm. In addition, we consider two alternative measures of chemical emissions, *CE/Asset* (The ratio of the total amount of toxic chemicals emitted to the total assets of a firm) and *CE/NI* (The ratio of the total amount of toxic chemicals emitted to the total net income of a firm), to examine if the results still hold. Larger firms are typically less vulnerable than others to the negative financial effect of environmental risks. On the other hand, larger firms in multiple industries are prone to being exposed to more environmental risk. Therefore, adjusting for the firm's size or sales can quantify the environmental performance in relative, not absolute, terms.

We collect bank loan data from Reuters' DealScan database. DealScan contains information about a loan's characteristics, such as its spread, maturity, size, and nonprice terms (such as collateral and covenants) as well as its purpose and type. The main dependent variable is *Ln(Spread)* that is the natural logarithm of the loan spread. Here, loan spread is the all-in spread drawn from the DealScan database (the amount the borrower pays in basis points over LIBOR or LIBOR equivalent for each dollar drawn down). After

[12] In the United States, chemicals in household products alone cost a staggering $340 billion a year in healthcare expenditures and lost earnings (Attina et al. 2016). The primary legal institution tasked with reviewing and regulating chemicals is the EPA, which has been overburdened since its inception in 1976. In an attempt to augment the EPA's power, former President Barack Obama signed the Frank Lautenberg Chemical Safety for the 21st Century Act before leaving office in 2016, thus updating the Toxic Substances Control Act. The new law received overwhelming and rarely seen bipartisan support in both the US House of Representatives and the Senate. The Act requires more effort in disclosing information on toxic chemical emissions and making them accessible to the public via the TRI database.

Footnote 12 (continued)

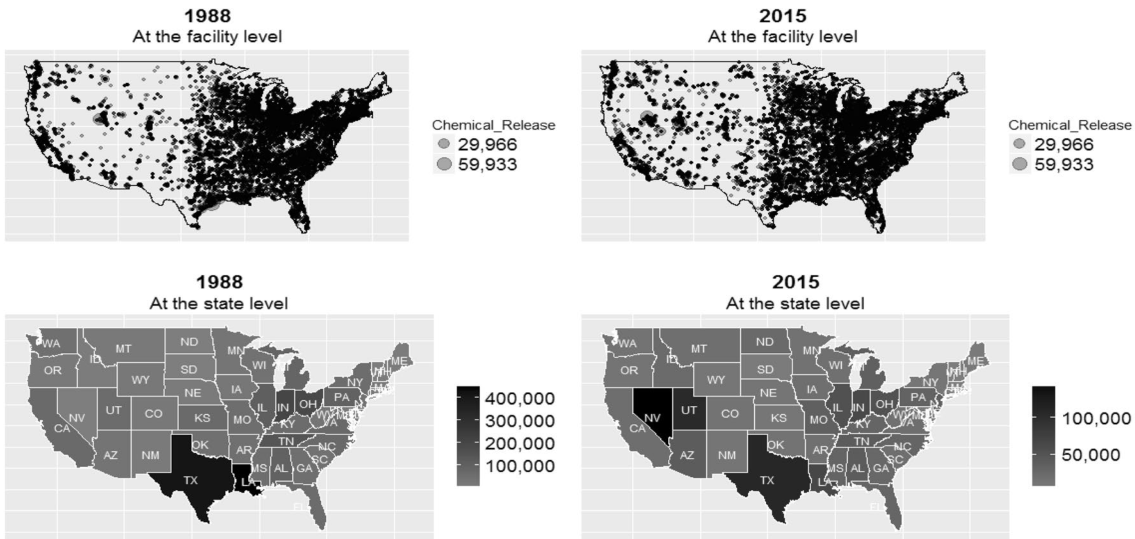

Fig. 1 Map of facilities with chemical releases in 1988 and 2015, United States. This figure presents and compares the density of the total amount of chemical emissions in the US at the beginning and the end of our sample. The data are plotted at two levels: facility (where each point indicates one facility/plant) and state (where data are summed over all facilities in a state). To aid the presentation, we only show the 48 contiguous states and exclude Alaska et al. territories. All units are in metric tonne. The darker the color, the higher the chemical emissions observed. *Source* Plotted using latest data from the US Environmental Protection Agency

merging the chemical-emission data (*CE*) with the bank loan data, we obtain the final sample of 8,331 loan contracts for 836 unique US firms between 1988 and 2015. We use the one-year lagged values of *CE* when predicting the cost of bank loans.

We also control for firm and loan characteristics and macroeconomic factors in the regression analyses. The data on firm characteristics are obtained from Compustat and comprise *Ln(Assets)*, *Market-to-book (MB)*, *Leverag*e, *Tangibility*, *Profitability*, and *Cash-flow volatility (CF-volatility)*. The loan characteristics are *Ln(Maturity)*, *Ln(Loan size)*, *Performance*, and *Collateral*. The macroeconomics factors are *Credit spread* and *Term spread*. "Appendix" provides the definitions of the variables.

To develop alternative explanations for the effects of chemical emissions on the cost of bank loans, we test two possible channels (firms' risk and governance) by partitioning the full sample into subsamples based on proxies for these channels. With respect to the risk channel, following the study of Bui et al. (2018), we adopt four default risk variables in the regression models: *Z-score* (Altman's Z-score index), *EDF* (expected default frequency measure of the firm),[13] *Idiovol* (firm's idiosyncratic volatility, the standard deviation of the residuals obtained from a market model), and *Beta* (firm's equity beta).

Regarding the governance channel, following the study of Hoechle et al. (2012), we use the essential governance variables in the regression models: *Independent* (the percentage of outside directors), *Busy* (the percentage of busy directors, where a busy director equals one if a majority of directors hold three or more directorships), *Instown* (percentage share of ownership by institutional investors), *Boardsize* (board size), *Duality* (a dummy variable for cases in which the CEO also holds the position of chairman of the board), *CEOTC* (the natural log of total compensation of the CEO), and *Attende* (a variable that measures attendance problems in the board of directors that equals the fraction of directors who attend less than 75% of board meetings). Additionally, we construct a corporate governance measure (*Governance*) that uses the first principal component from a PCA based on seven governance variables.

Descriptive Statistics

Table 1 presents the distribution of the sample across industries that are based on the first two-digit Standard Industrial Classification (SIC) codes. It shows that the chemical industry (SIC 28) is the most numerous, with 946 firm-year observations that accounts for 11.36% of the firms. Electric, gas, and sanitary services (SIC 49) follow, as does transportation equipment (SIC 37) at 10.69% and 10.26%, respectively. The distribution is consistent with general expectations, as the three are pollution-intensive industries. The smallest number of firms is in the service industries (SIC 70 to SIC 89).

[13] It is the percentile ranking of a firm's default risk based on its distance to default drawn from Bharath and Shumway (2008).

Table 1 Industry distribution

2-digit SIC	Description	Number of obs	% of obs
10	Metal mining	60	0.72%
12	Coal mining	83	1.00%
13	Oil and gas extraction	69	0.83%
14	Mining and quarrying of nonmetallic minerals, except fuels	28	0.34%
15	Construction—General contractors and operative builders	2	0.02%
16	Heavy construction, except building construction, contractor	15	0.18%
17	Construction—special trade contractors	15	0.18%
20	Food and kindred products	429	5.15%
21	Tobacco products	50	0.60%
22	Textile mill products	114	1.37%
23	Apparel, finished products from fabrics and similar materials	79	0.95%
24	Lumber and wood products, except furniture	64	0.77%
25	Furniture and fixtures	115	1.38%
26	Paper and allied products	358	4.30%
27	Printing, publishing and allied industries	86	1.03%
28	Chemicals and allied products	946	11.36%
29	Petroleum refining and related industries	166	1.99%
30	Rubber and miscellaneous plastic products	182	2.18%
32	Stone, clay, glass, and concrete products	192	2.30%
33	Primary metal industries	400	4.80%
34	Fabricated metal products	380	4.56%
35	Industrial and commercial machinery and computer equipment	732	8.79%
36	Electronic and other electrical equipment and components	761	9.13%
37	Transportation equipment	855	10.26%
38	Measuring, photographic, medical, and optical goods, and clocks	479	5.75%
39	Miscellaneous manufacturing industries	84	1.01%
40	Railroad transportation	3	0.04%
42	Motor freight transportation	2	0.02%
44	Water transportation	8	0.10%
45	Transportation by air	20	0.24%
46	Pipelines, except natural gas	23	0.28%
47	Transportation services	2	0.02%
48	Communications	17	0.20%
49	Electric, gas and sanitary services	891	10.69%
50	Wholesale trade—durable goods	114	1.37%
51	Wholesale trade—nondurable goods	126	1.51%
52	Building materials, hardware, garden supplies and mobile homes	11	0.13%
53	General merchandise stores	9	0.11%
54	Food stores	36	0.43%
56	Apparel and accessory stores	5	0.06%
58	Eating and drinking places	12	0.14%
59	Miscellaneous retail	6	0.07%
60	Depository institutions	10	0.12%
61	Nondepository credit institutions	50	0.60%
62	Security and commodity brokers, dealers, exchanges and services	30	0.36%
63	Insurance carriers	14	0.17%
65	Real estate	11	0.13%
67	Holding and other investment offices	39	0.47%
72	Personal services	1	0.01%
73	Business services	56	0.67%
75	Automotive repair, services and parking	6	0.07%

Table 1 (continued)

2-digit SIC	Description	Number of obs	% of obs
79	Amusement and recreation services	9	0.11%
80	Health services	18	0.22%
81	Legal services	3	0.04%
87	Engineering, accounting, research, and management services	21	0.25%
89	Services, not elsewhere classified	1	0.01
99	Nonclassifiable establishments	33	0.40
Total		8331	100

This table presents the distribution of sample firms by industry that is based on the first two digits of their Standard Industrial Classification (SIC) codes. The sample consists of 8,331 firms-year observations between 1988 and 2015 from 836 individual firms

Table 2 summarizes the descriptive statistics for the loan spreads, chemical emissions, and other control variables in this study. We winsorize all variables at the 1st and 99th percentiles to reduce the effects of extreme values. The mean values of chemical-emission measures (*CE, CE/Asset,* and *CE/NI*) are 0.0013, 0.0012, and 0.0107 with large standard deviations of 0.0196, 0.0155, and 0.1846 that indicate a very large dispersion in the total emissions after controlling for firm sales. The mean of *Ln(Spread)* is 5.1348, or 169.84 basis points (hereafter bp), and shows a sample variation with a standard deviation of 134.17 bp.

In terms of other loan characteristics, the mean of *Ln(Maturity)* is 3.6544 (or equivalently, 38.64 months or 3.22 year) and the mean of *Ln(Loan size)* is 5.2310 (about $186.98 million). The mean value of *Collateral* is 42.59% that indicates about 40% of the borrowers in our sample are required to pledge collateral. Regarding firm attributes, the average *Ln(Assets)*, *MB*, *Leverage*, *Tangibility*, *Profitability*, and *CF-volatility* are 7.7538, 1.6317, 0.3600, 0.3349, 0.1290, and 0.2157, respectively.

Next, Table 3 presents the results of univariate tests on the differences in the mean (and median) of the loan and firm characteristics for firms with high and low chemical emissions. The sample is divided into two groups based on the median value of *CE*. We adopt the *t*-test to test the significance of the differences in means between the two groups. Most of the differences are significant at the 1% level. In terms of loan characteristics, the test results show that firms with high chemical emissions are likely to have significantly higher spreads than those with low chemical emissions; they are higher by 24.73 bp ($= e^{4.8778} - e^{4.6692}$) in the mean test.

In addition, high-emission firms obtain smaller loans, pledge more collateral, and have a lower likelihood of performance pricing compared to more environmentally responsible firms. High-emission firms also have loans with shorter maturities, but the difference is not significant. In terms of characteristics, high-emission firms are associated with a smaller size, lower profitability, higher leverage, higher tangibility, and a higher market-to-book ratio. The majority of the signs of the differences are consistent with the literature.

Empirical Results

Effects of Chemical Emissions on Bank Loan Spreads

Following Graham et al. (2008) and Hasan et al. (2014, 2017), we use an ordinary least squares (OLS) test to investigate how chemical emissions affect the cost of bank loans. The regression equation is specified as follows:

$$\begin{aligned} Ln(Spread)_{i,t} &= \alpha_0 + \alpha_1 CE_{i,t-1} + \beta' FIRM_{i,t-1} \\ &\quad + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

in which the dependent variable $Ln(Spread)_{i,t}$ is the natural logarithm of the loan spread for firm *i* in year *t*. $CE_{i,t-1}$ represents the ratio of the total amount of toxic chemical emissions to total sales for firm *i* in year $t-1$. $FIRM_{i,t-1}$ is a vector of control variables for firm *i* in year $t-1$. $Z_{i,t}$ is the vector of the control variables for loan and macroeconomic factors *i* in year *t*. The γ_i and μ_t represent the firm and year fixed effects, respectively; and $\varepsilon_{i,t}$ is a random error. Each observation in the sample represents a single loan. In all specifications, the *t*-statistics are heteroskedastic, and the sample is clustered at the firm-level robust standard errors (White 1980; Petersen 2009).

Table 4 presents the regression results for the effect of chemical emissions on loan spreads following Eq. (1). Consistent with our expectations, the coefficients for *CE* on the log loan spread are positive and significant in all specifications at the 1% level that indicates the firms with greater chemical emissions pay higher interest rates. This finding is robust when we control for firm and year fixed effects and all other variables. Thus, our empirical analyses show that bigger polluters generally pay higher loan spreads.

We also consider two alternative measures of chemical emissions to examine if the results still hold: $CE/Asset_{i,t-1}$ and $CE/NI_{i,t-1}$ are the ratios of the total amount of toxic chemicals emitted to the total assets and to the total net income, respectively, for firm *i* in year $t-1$. We also find both coefficients remain positive and significant at the 1% level in Models (4) and (5). This additional evidence means

Table 2 Summary statistics of variables

Variables	Mean	SD	Q25	Median	Q75
Ln(Spread)	5.1348	4.8991	4.1351	5.0106	5.5214
	[169.84 bp]	[134.17 bp]	[62.50 bp]	[150.00 bp]	[250.00 bp]
CE	0.0013	0.0196	0.000046	0.000038	0.0003
CE/Asset	0.0012	0.0155	0.000055	0.000057	0.0004
CE/NI	0.0107	0.1846	0.000038	0.0004	0.0034
Ln(TCB)	4.3286	0.9531	3.5868	4.3110	5.0396
Ln(Maturity)	3.6544	0.7177	3.2581	4.0775	4.0943
Ln(Loan size)	5.2310	1.5178	4.3175	5.3230	6.2146
Performance	0.4106	0.4920	0.0000	0.0000	1.0000
Ln(Covenant)	1.3124	0.9331	0.0000	1.6094	2.0794
Collateral	0.4259	0.4945	0.0000	0.0000	1.0000
Ln(Assets)	7.7538	1.8122	6.4282	7.7425	9.0947
MB	1.6317	0.8153	1.3089	1.4476	1.6554
Leverage	0.3600	0.1999	0.2249	0.3345	0.4682
Tangibility	0.3349	0.1888	0.1840	0.2935	0.4548
Profitability	0.1290	0.0672	0.0888	0.1237	0.1629
CF-volatility	0.2157	0.9444	0.0354	0.0711	0.1524
Credit spread	0.9058	0.2778	0.7167	0.8467	1.0250
Term spread	1.1351	0.8825	0.3820	1.0208	1.9892
Z-score	4.4668	6.2248	2.0806	3.1789	5.0667
EDF	0.0669	0.1795	0.0000	0.0001	0.0156
Idiovol	0.3556	0.4753	0.2201	0.2954	0.3951
Beta	1.0080	0.6893	0.5785	0.9132	1.3135
Independent	0.7521	0.1499	0.6667	0.7778	0.8750
Busy	0.1019	0.1221	0.0000	0.0833	0.1667
Instown	0.6898	0.1842	0.5788	0.6988	0.8067
Boardsize	10.3217	2.5163	9.0000	10.0000	12.0000
Duality	0.7934	0.4051	1.0000	1.0000	1.0000
CEOTC	8.2033	1.0799	7.4321	8.1711	8.9113
Attend	0.0121	0.0361	0.0000	0.0000	0.0000
Governance	− 0.0000	0.3790	− 0.2204	0.0000	0.2207
Bank_SR	− 0.0117	0.3171	− 0.1806	− 0.0029	0.1380
SK	− 0.2837	0.8775	− 0.8486	− 0.2297	0.2976

This table presents the summary statistics of all research variables used in this study. The sample period is from 1988 to 2015. "Appendix" provides the definitions of all variables. All continuous variables are winsorized at the 1% and 99% percentiles to control for outliers. "Q25" and "Q75" denote the first and third quartiles, respectively

that a significantly positive relation exists between chemical emissions and the loan spread.

Regarding the economic significance of pollution records, we find that the effect of chemical emissions is around 40% compared to the effect of corporate tax avoidance in Hasan et al. (2014), who find that the effect of corporate tax avoidance is around $1 million per a one-standard-deviation increase in corporate tax avoidance.[14] In addition, in the unreported results of the standardized regression, we find that the effect of chemical emissions is similar to the effects of *MB* and *CF-volatility* but smaller than the effect of *Ln(Assets)* and *Leverage*. Overall, this unfavorable effect of chemical emissions on loan spreads is not only statistically significant but it is also economically important.

[14] In our study, given that the average loan spread of the sample firms is 169.84 bp, a one-standard-deviation increase in chemical emissions *(CE)* is associated with a 6.7169 bp ($e^{0.7020} \times 0.0196 \times 169.84 = 6.7169$) increase in the loan spread. As the average loan size is \$186.98 ($e^{5.2310} = 186.98$) million and the average loan time to maturity is 3.2204 ($e^{3.6544} / 12 = 3.2204$) years, a one-standard-deviation increase in chemical emissions leads to an average increase of \$0.4045 million (6.7169 bp × 186.98 × 3.2204) in interest payments.

Footnote 14 (continued)

Table 3 Loan and firm characteristics for firms with high and low chemical emissions

	High CE group	Low CE group	Difference in mean (High-Low)	*t*-statistics
	Mean	Mean		
Ln(Spread)	4.8778	4.6692	0.2086***	(10.56)
Ln(TCB)	4.4307	4.2089	0.2218***	(8.25)
Ln(Maturity)	3.6537	3.6630	− 0.0094	(− 0.59)
Ln(Loan size)	5.0412	5.4937	− 0.4525***	(− 13.99)
Performance	0.3876	0.4430	− 0.0554***	(− 5.13)
Ln(Covenant)	1.3070	1.3187	0.0116	(0.31)
Collateral	0.4448	0.4024	0.0424***	(3.91)
Ln(Assets)	7.6701	7.8703	− 0.2002***	(− 5.08)
MB	1.6521	1.6065	0.0456**	(2.54)
Leverage	0.3717	0.3422	0.0295***	(6.94)
Tangibility	0.3897	0.2650	0.1247***	(31.99)
Profitability	0.1240	0.1358	− 0.0118***	(− 8.50)
CF-volatility	0.1385	0.1825	− 0.0440***	(− 6.05)
Credit spread	0.9319	0.9384	− 0.0066	(− 0.57)
Term spread	2.2857	2.0379	0.2479***	(2.78)

This table presents the mean comparison of loan and firm characteristics between firms with high and low toxic chemical emissions. We split the sample by the median of *CE* that is a measure of the total pounds of toxic chemicals emitted and is adjusted for firm sales. We use the *t*-test for difference in means. "Appendix" provides the definitions of all variables

Superscripts *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively

Possible Channels

Our findings so far confirm that environmentally irresponsible firms generally incur higher costs for their bank debt. We further investigate whether the harmful effects of chemical emissions are stronger in firms with higher risk or weaker corporate governance (Hypothesis 2).

Firm Risk Channel

If chemical emissions contribute to an increase in loan costs that exacerbates default risk, then their effect on loan spreads should be more discernible in firms with higher default risk. Following Bui et al. (2018) and Neanidis (2019), we adopt four default risk variables in the regression models: *Z-score*, *EDF*, *Idiovol*, and *Beta*. We then define high-risk dummies for firms (*HR*) that use the median value of the sample: *Z-score_low*, *EDF_high*, *Idiovol_high*, and *Beta_high.*

To test this issue, we add one interaction term ($CE_{i,t-1} \times HR_{i,t-1}$) and the variable $HR_{i,t-1}$ to Eq. (1). The regression equation is specified as follows:

$$Ln(Spread)_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \alpha_2 CE_{i,t-1} \times HR_{i,t-1} + \alpha_3 HR_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

in which $HR_{i,t-1}$ are high firm risk dummies that are either *Z-score_low*, *EDF_high*, *Idiovol_high*, or *Beta_high* for firm *i* in year *t* −1, respectively.

Table 5 presents the regression results. The coefficients for *CE* × *Z-score_low*, *CE* × *EDF_high*, and *CE* × *Idiovol_high* are positive and significant at the 1% level. These results indicate that the effect of chemical emissions on loan spreads is more discernible in firms with high risks. Because misbehavior leads to future legal problems that may influence the firms' ability to pay interests or even principals, the increased risk of environmentally irresponsible firms dramatically raises concern among debtholders. Consistent with this argument, our findings indicate that banks are aware of borrowers' potential environmental risks when they determine lending decisions, especially when the borrowers have high risk.

Corporate Governance Channel

If chemical emissions contribute to increasing loan costs by exacerbating agency risk, their effect on loan spreads should be more discernible in firms with weak corporate governance. We follow Hoechle, Schmid, Walter, and Yermack (2012) and adopt essential governance variables in the regression models: *Independent*, *Busy*, *Instown*, *Boardsize*, *Duality*, *CEOTC*, *Attende* and *Governance*. We then define weak corporate governance dummies for firms

Table 4 Chemical-emission effect on bank loan spread

	(1)	(2)	(3)	(4)	(5)
CE	0.9497***	0.7558***	0.7020***		
	(3.29)	(4.41)	(3.88)		
CE/Asset				0.7416**	
				(2.10)	
CE/NI					0.0764***
					(4.38)
Ln(Assets)		− 0.2087***	− 0.1227***	− 0.1215***	− 0.1223***
		(− 7.63)	(− 4.17)	(− 4.33)	(− 4.37)
MB		0.0498***	0.0411***	0.0348**	0.0349**
		(2.97)	(2.71)	(2.26)	(2.26)
Leverage		0.9048***	0.7323***	0.7095***	0.7084***
		(7.95)	(6.83)	(7.19)	(7.17)
Tangibility		− 0.1271	− 0.0569	− 0.1507	− 0.1566
		(− 0.74)	(− 0.34)	(− 0.93)	(− 0.97)
Profitability		− 2.1339***	− 1.7940***	− 1.8508***	− 1.8482***
		(− 8.98)	(− 7.80)	(− 8.34)	(− 8.34)
CF-volatility		0.0882***	0.0612*	0.0634**	0.0635**
		(2.76)	(1.83)	(1.99)	(1.99)
Ln (Maturity)			− 0.0385*	− 0.0293	− 0.0292
			(− 1.70)	(− 1.28)	(− 1.28)
Ln (Loan size)			− 0.0742***	− 0.0766***	− 0.0765***
			(− 5.30)	(− 5.96)	(− 5.95)
Performance			− 0.0021	− 0.0080	− 0.0077
			(− 0.11)	(− 0.43)	(− 0.41)
Collateral			0.3389***	0.3311***	0.3311***
			(11.00)	(11.64)	(11.64)
Credit spread			− 0.0833	− 0.1412	− 0.1390
			(− 0.51)	(− 0.94)	(− 0.92)
Term spread			− 0.1166***	− 0.1154***	− 0.1154***
			(− 4.59)	(− 4.57)	(− 4.57)
Constant	4.4113***	5.3119***	6.3304***	6.3892***	6.3910***
	(36.09)	(20.35)	(25.36)	(26.08)	(26.12)
Control for					
Firm FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.7390	0.7800	0.7999	0.7948	0.7949
Obs	7476	7263	7263	7263	7263

This table presents the regression results of toxic chemical emissions (*CE*) on loan spreads via the following equation:

$$Ln(Spread)_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}$$

in which $Ln(Spread)_{i,t}$ is the natural logarithm of the spread for loan i in year t;$CE_{i,t-1}$ is the ratio of the total amount of toxic chemicals emitted to total sales for firm i in year *t-1*. $FIRM_{i,t-1}$ is a vector of control variables for firm i and its characteristics in year *t-1*. $Z_{i,t}$ is the vector of the control variables for loan and macroeconomic factor i in year t. γ_i and μ_t represent the fixed effect of firm and year, respectively; $\varepsilon_{i,t}$ is an error term. We also consider two alternative measures of chemical emissions to examine if the results still hold: $CE/Asset_{i,t-1}$ and $CE/NI_{i,t-1}$. $CE/Asset_{i,t-1}$ is the ratio of total amount of toxic chemicals emitted to total assets for firm i in year $t-1$;$CE/NI_{i,t-1}$ is the ratio of the total amount of toxic chemicals emitted to total net income for firm i in year $t-1$

Appendix provides the definitions of all variables. In all specifications, the *t*-statistics are based on heteroskedasticity and clustering the sample at the firm-level robust standard errors (White 1980; Petersen 2009)

Superscripts *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively. To save space, in this table and subsequent tables, we do not report the coefficients for firm and year dummies

(*WCG*) that use the median value of the sample: *Independent_low*, *Busy_high*, *Instown_low*, *Boardsize_small*, *Duality, CEOTC_low*, *Attend_high*, and *Governance_low.*

To test this issue, we add one interaction term ($CE_{i,t-1} \times WCG_{i,t-1}$) and the variable $WCG_{i,t-1}$ to Eq. (1). The regression equation is specified as follows:

$$Ln(Spread)_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \alpha_2 CE_{i,t-1} \times WCG_{i,t-1} + \alpha_3 WCG_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}, \tag{3}$$

in which $WCG_{i,t-1}$ are weak corporate governance dummies that are either *Independent_low*, *Busy_high*, *Instown_low*, *Boardsize_small*, *Duality, CEOTC_low*, *Attend_high*, or *Governance_low* for firm i in year $t-1$, respectively.

Table 6 presents the regression results. The coefficients for *CE* × *Independent_low*, *CE* × *Busy_high*, *CE* × *Duality, CE* × *Attend_high*, and *CE* × *Governance_low* are significantly positive and significant at the 5% or 1% level. This finding shows that the costly effect of chemical emissions on loan spreads is mostly due to firms with weak governance that supports the idea that chemical emissions can worsen lenders' concerns when borrowers have poor governance structures.

Sensitivity Analyses

A possible caveat to our main findings is endogeneity for three reasons: simultaneity, measurement errors, and omitted variables. First, simultaneity or reverse causality can confound the results when a firm obtains a higher loan spread and then increases its chemical emissions to reduce its operating costs. We address this simultaneity bias with a 2SLS estimation (e.g., Berger and Hannan 1998).

Second, measurement error in firms' chemical emissions can influence the results by creating inconsistent coefficient estimations in the regression. The 2SLS method can control for the possibility that measurement errors contaminate our results (e.g., Rajgopal and Shevlin 2002). In addition, we use the total cost of borrowing from Berg et al. (2016) as an alternative measure of loan spread to examine this issue.

Third, unobservable variables that are common to banks can also generate a positive relation between firms' chemical emissions and loan spreads (the omitted-variable bias). If firms' chemical emissions are correlated with a variable not in the analysis but that partly determines the loan spreads, then the regression estimator will be biased and inconsistent. We eliminate this type of bias by controlling for firm and year fixed effects in all equations in this study (Roberts and Whited 2013).

Simultaneity and Measurement Errors

We use two-stage regressions with instrumental variables to account directly for the endogeneity of firms' chemical emissions. Specifically, we instrument chemical emissions with two variables: the average *CE* of borrowers in the counties where the firms' polluting facilities operate (denoted as *County_CE*) and at the city level (denoted as *City_CE*).[15] These variables strongly correlate with the total amount of chemical emissions; but there is no link to the pattern of loan spreads, because counties and cities' environmental policies are more likely to constrain firms rather than banks.[16]

In fact, banks base their loan pricing on an individual firm's level of chemical emissions, not on the average emissions in the community where that firm operates. Geographic location identifies the effects of endogenous variables in many studies, as it is fixed and more likely to be exogenous. As Jiraporn, Jiraporn, Boeprasert, and Chang (2014) point out, the US Postal Service allocates zip codes exclusively based on efficiency in postal delivery, not on corporate financial policies or outcomes. For these reasons, our instrument plausibly meets the relevance and exclusion requirements.[17] Thus, the variation in *CE* across counties does not directly affect loan spreads (except via firm-specific *CE*), and it can be used to estimate the effect of *CE* on loan spreads, as shown in Table 7. Models (1) and (3) of Table 5 present the results of the first-stage regressions, and the coefficients for *County_CE* and *City_CE* are significant and in agreement with the relevance requirement. The second-stage results in Models (2) and (4) mirror those of Model (3) in Table 4 and support Hypothesis 1 (i.e., chemical emissions significantly increase loan spreads).

Accounting for Selection Bias: Propensity Score Matching

In financial studies, biased estimators can emerge by overlooking unobservable characteristics or including biased observable factors. Specifically, unlike controlled experiments, most financial and business decisions are not random;

[15] Note that there may be differences across the locations where the firms are headquartered. Further, the environmental policies of polluting counties (cities) should be more relevant to the firms' operation than the policies of headquarter counties. This difference also applies to cross-border investments, as some firms in our sample have headquarters outside the United States.

[16] We construct similar IVs using official US zip code data. Alternatively, we use the total chemical emissions instead of total chemical emissions to net income as the base variable to construct the IVs. Using these IVs does not substantially change our estimates.

[17] Unreported tests of weak instruments using the Cragg-Donald F-statistic (Cragg and Donald 1993) and underidentification (using the Anderson canonical correlation LM statistic (Anderson 1951) indicate that our instrument is not weak and our specification is not underidentified. The results are available on request.

Table 5 Chemical-emission effect and firm risks

	(1)	(2)	(3)	(4)
CE	0.7023***	− 6.5797***	− 4.8515**	− 2.7593
	(3.87)	(− 6.84)	(− 2.06)	(− 1.43)
CE × Z-score_low	1.9006***			
	(3.11)			
Z-score_low	0.0023			
	(0.06)			
CE × EDF_high		6.3103***		
		(6.63)		
EDF_high		0.1917***		
		(8.41)		
CE × Idiovol_high			4.5828**	
			(1.97)	
Idiovol_high			0.1004***	
			(3.72)	
CE × Beta_high				2.4802
				(1.30)
Beta_high				0.0364
				(1.36)
Constant	6.3358***	6.4691***	6.4655***	6.5591***
	(25.49)	(28.13)	(27.43)	(28.01)
Control for				
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes
Adj R^2	0.7539	0.7867	0.8104	0.8104
Obs	5512	5081	4923	4923

This table presents the regression results of toxic chemical emissions (*CE*) on loan spreads by considering the role of firm risk:

$Ln(Spread)_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \alpha_2 CE_{i,t-1} \times HR_{i,t-1} + \alpha_3 HR_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}$

in which $Ln(Spread)_{i,t}$ is the natural logarithm of the spread for loan i in year $t.CE_{i,t-1}$ is the ratio of the total amount of toxic chemicals emitted to total sales for firm i in year $t-1$. $HR_{i,t-1}$ are high default risk dummies that are either *Z-score_low*, *EDF_high*, *Idiovol_high*, or *Beta_high* for firm i in year $t-1$ respectively. Default risk dummies are sorted by the median value of the sample. $Z_{i,t}$ is the vector of the control variables for loan and macroeconomic factor i in year t. γ_i and μ_t represent the firm and year fixed effects, respectively; $\varepsilon_{i,t}$ is an error term

"Appendix" provides the definitions of all variables. In all specifications, the *t*-statistics are based on heteroskedasticity and clustering the sample at the firm-level robust standard errors (White 1980; Petersen 2009)

Superscripts *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively

rather, they are deliberate, and firms or their managers "self-select" their preferred choices, which is termed the "self-selection bias." In our case, if the choice to increase the level of chemical emissions (the treatment) is affected by some observable characteristics that also affect profitability, then the inferences about the treatment effect can be misleading.[18] Although we include firm fixed effects in Eq. (1) to control for a potential omitted-variable problem, this inclusion cannot fully rule out the self-selection bias. To alleviate this concern, we use propensity score matching to construct an

[18] It is very important to stress that we only consider the selection bias due to observables and use propensity score matching to account for it. This approach is not designed to address the self-selection bias due to unobservables (Tucker 2010; Park and Shin 2020). Unobservable factor-related biases can be remedied by the 2SLS approach and by incorporating firm fixed effects.

Table 6 Chemical-emission effect and corporate governances

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CE	0.5878***	− 5.4245***	0.6783***	0.7230***	− 13.4588**	0.6493***	− 3.8816**	− 13.3532***
	(4.73)	(− 3.58)	(3.82)	(4.52)	(− 2.31)	(4.90)	(− 2.32)	(− 2.74)
CE × Independent_low	11.5135***							
	(6.43)							
Independent_low	− 0.0278							
	(− 0.71)							
CE × Busy_high		5.1794***						
		(3.51)						
Busy_high		0.0073						
		(0.27)						
CE × Instown_low			− 0.2957					
			(− 0.14)					
Instown_low			− 0.1263***					
			(− 2.81)					
CE × Boardsize_small				− 1.1874				
				(− 0.34)				
Boardsize_small				0.0374				
				(1.13)				
CE × Duality					17.2740***			
					(4.16)			
Duality					− 0.0026			
					(− 0.06)			
CE × CEOTC_low						3.3534		
						(0.89)		
CEOTC_low						− 0.0261		
						(− 0.92)		
CE × Attend_high							3.6216**	
							(2.22)	
Attend_high							0.0597**	
							(2.09)	
CE × Governance_low								14.0548***
								(2.86)
Governance_low								− 0.0715**
								(− 2.28)
Constant	6.3417***	6.5929***	6.3120***	6.3140***	5.7943***	6.3476***	6.5246***	6.4060***
	(25.21)	(27.73)	(25.58)	(25.39)	(13.97)	(25.33)	(27.52)	(24.72)
Control for								
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.7539	0.7867	0.8104	0.8104	0.7867	0.8104	0.8104	0.8004
Obs	5512	5081	4923	4923	5081	4923	4923	4923

This table presents the regression results of toxic chemical emissions (*CE*) on loan spreads by considering the role of corporate governance:

$$Ln(Spread)_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \alpha_2 CE_{i,t-1} \times WCG_{i,t-1} + \alpha_3 WCG_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}$$

in which $Ln(Spread)_{i,t}$ is the natural logarithm of the spread for loan i in year $t.CE_{i,t-1}$ is the ratio of the total amount of toxic chemicals emitted to total sales for firm i in year $t-1$. $WCG_{i,t-1}$ are weak corporate governance dummies that are either *Independent_low*, *Busy_high*, *Instown_low*, *Boardsize_small*, *Duality, CEOTC_low*, *Attend_high*, or *Governance_low* for firm i in year $t-1$, respectively. Corporate governance dummies are sorted by the median value of the sample. $Z_{i,t}$ is the vector of the control variables for loan and macroeconomic factor i in year t. γ_i and μ_t represent the firm and year fixed effects, respectively; $\varepsilon_{i,t}$ is an error term

"Appendix" provides the definitions of all variables. In all specifications, the *t*-statistics are based on heteroskedasticity and clustering the sample at the firm the firm-level robust standard errors (White 1980; Petersen 2009)

Superscripts *, **, and *** denote significance levels of 10%, 5%, and 1%, respectively

Table 7 Chemical-emission effect: Two-stage least squares regressions

Dep. Var	First stage CE	Second stage Ln(Spread)	First stage CE	Second stage Ln(Spread)
	(1)	(2)	(3)	(4)
County_CE	0.0619***			
	(70.59)			
City_CE			0.0636***	
			(72.71)	
$\widehat{CE}$		1.1426**		1.2541***
		(2.36)		(2.64)
Ln(Assets)	− 0.0006	− 0.1217***	− 0.0004	− 0.1215***
	(− 1.60)	(− 8.95)	(− 1.04)	(− 8.94)
MB	− 0.0001	0.0412***	− 0.0001	0.0412***
	(− 0.35)	(4.04)	(− 0.41)	(4.04)
Leverage	− 0.0046***	0.7340***	− 0.0047***	0.7348***
	(− 2.88)	(13.33)	(− 2.93)	(13.35)
Tangibility	− 0.0069***	− 0.0518	− 0.0053**	− 0.0506
	(− 2.72)	(− 0.60)	(− 2.15)	(− 0.59)
Profitability	− 0.0023	− 1.7906***	− 0.0014	− 1.7896***
	(− 0.62)	(− 14.17)	(− 0.38)	(− 14.16)
CF-volatility	− 0.0001	0.0614***	− 0.0001	0.0614***
	(− 0.12)	(2.75)	(− 0.09)	(2.75)
Ln(Maturity)	0.0005	− 0.0396***	0.0006	− 0.0396***
	(1.22)	(− 2.75)	(1.34)	(− 2.75)
Ln(Loan size)	− 0.0001	− 0.0741***	− 0.0001	− 0.0741***
	(− 0.55)	(− 10.99)	(− 0.71)	(− 10.98)
Performance	0.0002	− 0.0020	0.0002	− 0.0021
	(0.60)	(− 0.16)	(0.45)	(− 0.17)
Collateral	0.0001	0.3386***	0.0001	0.3386***
	(0.15)	(21.25)	(0.14)	(21.25)
Credit spread	0.0008	− 0.1211	0.0000	− 0.1217
	(0.09)	(− 0.39)	(0.00)	(− 0.40)
Term spread	0.0082	− 0.0511	0.0092	− 0.0520
	(0.87)	(− 0.16)	(1.00)	(− 0.16)
Constant	0.0012	6.3501***	0.0002	6.3493***
	(0.16)	(24.84)	(0.03)	(24.83)
Control for				
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes
Adj R^2	0.7145	0.7998	0.7224	0.7998
Obs	7263	7263	7263	7263

This table examines the effect of environmental performance (*CE*) by using two-stage least squares regressions (2SLS). In the first stage, we use the average *CE* of borrowers at the county level where the firms' polluting facilities operate (*County_CE*) and at the city level (*City_CE*) as instruments to explain the dependent variable, *CE*. We report the results in Models (1) and (3), respectively. In the second stage, we use the fitted value of the dependent variable, $\widehat{CE}$, from the first stage to estimate the relation to *Ln(Spread)*. The results are presented in Models (2) and (4), respectively

"Appendix" provides the definitions of all variables. In all specifications, the *t*-statistics are based on heteroskedasticity and clustering the sample at the firm-level robust standard errors (White 1980; Petersen 2009)

Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively

Table 8 Chemical-emission effect: propensity score matching

Panel A: Matching estimation: Difference in *Ln(Spread)* between treatment and control firms

Matching method	Treatment firms	Control firms	Difference	*t*-statistic
Near Neighbor (n = 1)	4.8752	4.5792	0.2960***	(4.46)
Mahalanobis	4.8752	4.5857	0.2894***	(4.68)
Kernel Gaussian	4.8752	4.6570	0.2182***	(5.81)
Radius (0.1)	4.8752	4.6622	0.2129***	(5.65)

Panel B: Regression estimation: Based on matching samples

	(1) NN (n = 1)	(2) Mahalanobis	(3) Kernel Gaussian	(4) Radius (0.1)
D_{CE}	0.1016***	0.1181***	0.1171***	0.1154***
	(6.47)	(7.90)	(7.55)	(5.42)
Ln(Assets)	− 0.1115***	− 0.1071***	− 0.1085***	− 0.1082***
	(− 15.50)	(− 14.89)	(− 15.29)	(− 11.89)
MB	0.1107***	0.1143***	0.1043***	0.1031***
	(9.78)	(11.99)	(11.45)	(5.68)
Leverage	0.8785***	0.9693***	0.9112***	0.9072***
	(17.01)	(19.30)	(18.78)	(14.17)
Tangibility	− 0.0271	0.0094	− 0.0162	− 0.0153
	(− 0.65)	(0.23)	(− 0.40)	(− 0.29)
Profitability	− 3.0182***	− 2.7281***	− 2.7609***	− 2.7576***
	(− 22.83)	(− 18.16)	(− 20.94)	(− 13.46)
CF-volatility	0.1913***	0.1789***	0.1623***	0.1601***
	(5.28)	(5.17)	(5.08)	(3.86)
Ln(Maturity)	0.0189	− 0.0535**	− 0.0440**	− 0.0429
	(0.88)	(− 2.36)	(− 2.29)	(− 1.42)
Ln(Loan size)	− 0.0960***	− 0.1077***	− 0.0892***	− 0.0898***
	(− 11.02)	(− 11.90)	(− 10.62)	(− 8.18)
Performance	− 0.0107	0.0286*	− 0.0120	− 0.0126
	(− 0.60)	(1.73)	(− 0.72)	(− 0.54)
Collateral	0.4270***	0.4098***	0.5011***	0.5010***
	(20.29)	(20.18)	(25.15)	(18.23)
Credit spread	0.2197	0.2334	0.0911	0.0979
	(0.52)	(0.79)	(0.27)	(0.31)
Term spread	− 0.1188***	− 0.1381***	− 0.1309***	− 0.1303***
	(− 4.52)	(− 7.30)	(− 6.99)	(− 4.34)
Constant	5.6663***	5.9232***	5.8760***	5.8716***
	(18.07)	(25.01)	(22.51)	(22.17)

Table 8 (continued)

Panel B: Regression estimation: Based on matching samples

	(1) NN (n = 1)	(2) Mahalanobis	(3) Kernel Gaussian	(4) Radius (0.1)
Control for				
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes
Adj R^2	0.7177	0.7288	0.7053	0.7043
Obs	4677	4710	4729	4029

This table presents a check on the chemical-emission effect by using propensity score matching to examine our hypotheses. Specifically, we use *CE* to sort firms into quartiles. We retain only the top quartile that represents the firms with the highest chemical emissions (treatment firm) and the bottom quartile that represents the firms with the lowest chemical emissions (control firm). Matching is done with a probit function of various characteristics (*Ln(Assets), MB, Leverage, Tangibility, Profitability,* and *CF-volatility*) of the firms in the top and bottom quartiles. For robustness, we use several different matching methods: Nearest neighbors (n = 1), Mahalanobis, Gaussian Kernel, and Radius (radius = 0.1). Panel A presents the matching estimation of the loan spread between treatment firms and control firms. Panel B presents estimates of the regression equation:

$$Ln(Spread)_{i,t} = \alpha_0 + \alpha_6 D_{CE\,i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}$$

in which $Ln(Spread)_{i,t}$ is the natural logarithm of the spread for loan i in year t; $D_{CE\,i,t-1}$ equals one when firms are in the treatment group and zero when they are in the control group in year $t-1$. $FIRM_{i,t-1}$ is a vector of firm characteristics for firm i in year $t-1$. $Z_{i,t}$ is a vector of control variables for firm i in year t-1. γ_i and μ_t represent the firm and year fixed effects, respectively

"Appendix" provides the definitions of all variables. In all specifications, the *t*-statistics are based on heteroskedasticity and clustering the sample at the firm-level robust standard errors (White 1980; Petersen 2009)

Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively "optimal" control sample. This approach was developed by Rosenbaum and Rubin (1983) and Heckman, Ichimura, and Todd (1997).

Specifically, we sort firms into subsamples based on the quartiles of *CE*, and we retain only the top quartile that represents the firms with the highest *CE* (treatment firms) and the bottom quartile that represents the firms with the lowest *CE* (control firms). Matching is done with a probit function of various firm characteristics for the top and bottom quartile firms[19] that provides the so-called "propensity" (or probability) of an individual firm going into the treatment group. We use several different matching schemes with different parameters: Nearest neighbors ($n=1$); Mahalanobis, Gaussian Kernel, and Radius ($radius=0.1$).[20] Reviews of these methods and further discussions are in Abadie and Imbens (2011).

Using these four alternative matching methods, Panel A of Table 8 presents the average *Spread* of the treatment and control groups as well as the difference in *Ln(Spread)* between the two groups that is consistently positive and significant. Compared to control firms, treatment firms pay higher loan spreads.

In addition, we construct a dummy variable for treatment firms (D_{CE}) that equals one when firms belong to the treatment group and zero when firms belong to the control group. We then use D_{CE} in place of the *CE* variable in Eq. (1). The regression equation is specified as follows:

$$Ln(Spread)_{i,t} = \alpha_0 + \alpha_6 D_{CE\,i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}, \tag{4}$$

Panel B of Table 8 presents the results of the new regression analysis based on the sample with four matching methods. The coefficients for D_{CE} indicate a persistently positive and significant relation between chemical emissions and the loan spread. Therefore, we conclude that our main findings are robust to selection bias.

[19] Matching over a large number of characteristics for which treated and nontreated firms differ is difficult or infeasible (Tucker 2010). Rosenbaum and Rubin (1983) propose matching with a probit function of covariates rather than by each covariate.

[20] To confirm the parallel-trends assumption for the PSM estimator, we examine the univariate comparisons between treatment and control firms' characteristics used in the matching process. Unreported results show that none of the observed differences is statistically significant. This preliminary diagnostic test provides some evidence that differences in loan spreads are caused primarily by differences in the level of chemical emissions.

Additional Evidence

Effects of Chemical Emissions on Nonprice Loan Terms

The research provides evidence that nonprice loan terms also affect total borrowing costs (Qian and Strahan 2007). Therefore, we investigate how firms' chemical emissions affect the loan's maturity, size, and collateral as well as the syndicate size. We then use various regression methods to test the association between chemical emissions and different proxies of nonprice loan terms. We use the OLS method to estimate the dependent variables for the loan's maturity, size, total covenants, and collateral. The model for our analysis is as follows:

$$Y_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}, \tag{5}$$

in which the dependent variables, $Y_{i,t}$, are either *Ln(Maturity)* (the natural logarithm of loan maturity in months), *Ln(Loan size)* (the natural logarithm of the amount of loan in US$ millions) for firm *i* in year *t*, or *Ln(Covenant)* (the natural logarithm of number of total covenants in the contract) for firm *i* in year *t*, respectively.

Moreover, to model the probability of being required to pledge collateral, we apply a probit regression to examine how corporate environmental practices affect the probability of pledging collateral. Specifically, the probit model is as follows:

$$\begin{aligned} &\Pr(Collateral_{i,t} = 1 | CE_{i,t-1}, FIRM_{i,t-1}, Z_{i,t}) \\ &= \Phi\left(\alpha_0 + \alpha_1 CR_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t\right), \end{aligned} \tag{6}$$

in which *Φ(.)* is the cumulative distribution function of the standard normal distribution. The dependent variable, *Collateral*, is a dummy that equals one for the firms that pledge collateral, and zero otherwise.

Table 9 presents the results of the effect of chemical emissions on nonprice loan terms. In Model (1), we find that the coefficient for *CE* is negative and significant and indicate that in general, firms with substantial pollution potential obtain loans with shorter maturities. In terms of *Collateral*, Model (4) shows the coefficient for *CE* is positive and significant that indicates that higher collateral is required from polluting firms. The findings show that banks impose unfavorable nonprice loan terms on borrowers with weaker environmental practices. This result is consistent with our expectation that firms that emit toxic chemicals are subject to unfavorable nonprice terms from bank lenders.

Alternative Measure of Borrowers' Cost of Debt

In this subsection, we consider an alternative measure of borrowing costs to examine if our results still hold. Berg,

Table 9 Effect of chemical emissions on nonprice loan terms

Dep. Var	OLS Ln (maturity)	Probit Ln (loan size)	Ln (covenant)	Collateral
	(1)	(2)	(3)	(4)
CE	− 1.0551**	0.2237	− 0.3642	22.1945**
	(− 2.04)	(0.60)	(− 1.07)	(2.33)
Constant	− 1.0155**	1.9301***	1.7688***	2.5561
	(− 2.52)	(11.04)	(5.38)	(1.15)
Control for				
Control variables	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes
Adj R^2	0.7204	0.7550	0.6188	
Pseudo R^2				0.4714
Obs	6518	6518	6518	3066

This table presents the results of an OLS estimate and probit regression models in various nonprice loan terms on the ratio of the total amount of toxic chemicals emitted to total net income (*CE*). Models (1) to (3) follow the equation:

$Y_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}.$

in which the dependent variables, $Y_{i,t}$, are either *Ln(Maturity)* (the natural logarithm of loan maturity in months), *Ln(Loan size)* (the natural logarithm of the amount of loan in $US millions) for firm *i* in year *t*, or *Ln(Covenant)* (the natural logarithm of number of total covenants in the contract) for firm *i* in year *t*, respectively.

Model (4) follows a probit regression model of the probability that Collateral (a dummy variable that equals one for secured loans and zero otherwise) is required when firm i takes a loan in year t:

$Pr(Collateral_{i,t} = 1 | CE_{i,t-1}, FIRM_{i,t-1}, Z_{i,t}) = \Phi\left(\alpha_0 + \alpha_1 CE_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t\right),$

in which $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution. In all equations, CEi, $t-1$ represents the ratio of the total amount of toxic chemicals emitted to total net income for firm i in year $t-1$. $FIRM_{i,t-1}$ is a vector of control variables for firm i and its characteristics in year $t-1$. $Z_{i,t}$ is the vector of the control variables for loan and macroeconomic factor i in year t. γ_i and μt represent the firm and year fixed effects, respectively. $\varepsilon_{i,t}$ is an error term

"Appendix" provides the definitions of all variables. In all specifications, the t-statistics are based on heteroskedasticity and clustering the sample at the firm-level robust standard errors (White 1980; Petersen 2009)

Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively

Saunder, and Steffen (2016) indicate that loan contracts normally include a menu of spreads and different fees, and over 80% of US syndicated loans contain at least one fee. To account for various lender fees, we use a measure of the total cost of borrowing (hereafter *TCB*) from Berg, Saunder, and Steffen (2016).

Following this approach, we use *TCB* as the dependent variable and perform the same regression as in Models (1) to (3) of Table 4. The results are reported in Panel A of Table 10. We find that the coefficients for three chemical-emission measures (*CE, CE/Asset,* and *CE/NI*) remain positive and significant in all specifications. This result shows that a significantly positive relation exists between chemical emissions and the cost of private debt, which still holds when we use the *TCB* measure.

Effects of Bank Social Responsibility

Since few banks were involved in the account scandals, money laundering, or even overly risky activities that triggered the financial crisis, a question arises as to whether our results change for banks with different levels of social responsibility.[21] As discussed previously, banks aim to maximize the shareholders' value and have a low obligation to carry out any action that is good for society or that even hurts the creditor's interests. On the other hand, a socially responsible bank takes stakeholders' interests into account and balances them with the loan policy for a borrower that concerns of environmental performance (Freeman 1984). Because a bank has the expertise to assess information and

[21] We thank an anonymous reviewer for suggesting this analysis.

Table 10 Robustness checks

Dep. Var	Panel A: total cost of borrowing Ln (TCB)			Panel B: bank social responsibility High *Bank_SR* sample Ln (Spread)	Low *Bank_SR* sample	Panel C: control for social norms Ln (spread)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CE	1.0455***			0.4165**	0.0623	1.0189***	1.2155**
	(6.92)			(2.31)	(0.03)	(3.78)	(2.33)
CE/Asset		1.0272**					
		(2.39)					
CE/NI			0.0696***				
			(5.39)				
SK						0.0469	0.0485
						(0.66)	(1.48)
CE × SK							− 0.0412
							(− 0.52)
Constant	4.7600***	4.8557***	4.8886***	6.2419***	5.2797***	6.2906***	6.2906***
	(6.27)	(6.39)	(6.38)	(19.89)	(25.00)	(16.34)	(16.34)
Equality test for the coefficients of CE							
[p-value]				[0.0496]**			
Control for							
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan type	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj R^2	0.8807	0.8795	0.8794	0.7950	0.7484	0.8100	0.8099
Obs	4303	4657	4657	924	1201	4923	4924

This table examines the results of robustness checks. First, we use an alternative measure of the total cost of borrowing (hereafter *Ln(TCB)*) as an alternative measure for *Ln(Spread)* in the Models (1) to (3). Second, we also present the regression results on a subsample analysis based on the median value of bank social responsibility in the Models (4) and (5). Last, we present the regression results by considering social norms in the Models (6) and (7)

$$Ln(TCB)_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}$$

$$Ln(Spread)_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}$$

$$Ln(Spread)_{i,t} = \alpha_0 + \alpha_1 CE_{i,t-1} + \alpha_2 CE_{i,t-1} \times SK_{i,t-1} + \alpha_3 SK_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}.$$

in which $Ln(TCB)_{i,t}$ is the natural logarithm of the total cost of borrowing for loan i in year t; $Ln(Spread)_{i,t}$ is the natural logarithm of the spread for loan i in year t; $CE_{i,t-1}$ is the ratio of total amount of toxic chemicals emitted to total net income for firm i in year $t-1$.$SK_{i,t-1}$ is social capital measure for firm i in year $t-1$ that is the first principal component from a PCA based on *Pvote, Respn, Nccs, and Assn* (Hasan et al. 2017). In here, *Pvote* is the percentage of voters who voted in presidential elections, *Respn* is the response rate to the Census Bureau's decennial census, *Nccs* is the sum of tax-exempt non-profit organizations per 10,000 people, and *Assn* is the sum of social organizations per 100,000 people.$FIRM_{i,t-1}$ is a vector of characteristics for firm i in year $t-1$. $Z_{i,t}$ is the vector of the control variables for loan and macroeconomic factor i in year t. γi and μt represent the firm and year fixed effects, respectively; $\varepsilon_{i,t}$ is the random error

"Appendix" provides the definitions of all variables. In all specifications, the *t*-statistics are based on heteroskedasticity and clustering the sample at the firm-level robust standard errors (White 1980; Petersen 2009)

Superscripts *, **, and *** denote the significance levels of 10%, 5%, and 1%, respectively

evaluate risk and profit of the loan, a more socially responsible bank is expected to thoroughly appraise a borrower with environmental concerns and charge prices according to the risk (De la Cuesta-González et al. 2006). Few studies investigate the effect of the social responsibility of financial institutions on their loan terms, except Hauptmann (2017). Hauptmann (2017) finds that superior loan terms due to the sustainability performance of borrowers only occurs when banks also have high sustainability performance. She further investigates the reason for the difference in loan spreads and finds that it is not to reward better sustainability performance but to charge a higher premium to those firms with low sustainability performance.

Therefore, we divide our sample by the median value of bank social responsibility. We use the *Bank_SR* as a measure for bank social responsibility, which is equal to CSR strength minus CSR concern.[22] Panel B of Table 10 presents the results. The coefficient for *CE* in model (4) is significantly positive at the 5% level, while the coefficient for *CE* in model (5) is not significant. The results show that banks with higher social responsibility place more importance on their borrowers' environmental performance and charge their borrowers of high social or environmental risk with higher loan spreads; while there is no significant difference in loan spreads for banks with lower social responsibility.

Effects of Chemical Emissions and Social Norms

We investigate whether the observed result holds when considering the social norms of the place in which a firm is located. Social norms are prescriptive rules that could be understood by reference to visible characteristics of a society or community, such as family structures or participation in the social processes (Boytsun et al. 2011). They are generally enforced by members of the community and not always out of self-interest (Elster 1989). Hong and Kacperczyk (2009) argue that banks with diverse constituents are exposed to public scrutiny and therefore subject to the pressure of social norms. Similarly, Hasan et al. (2017) find evidence that banks judge the trustworthiness of their clients based on where they are located and that firms headquartered in high social capital counties pay lower loan spreads. Levine, Lin, and Xie (2018) find that firms in high trust countries obtain more trade credit during banking crises. Further, since 2000, banks have increasingly adopted the Equator Principles that consider social and environmental issues in project financing (Jung et al. 2018). Therefore, we control for the level of social norms in which a firm operates and examine whether the empirical results still hold.[23]

To test this issue, we follow the study of Hasan, Hoi, Wu, and Zhang (2017) to collect county-level data on social capital from the Northeast Regional Center for Rural Development (NRCRD) at Penn State University. We then add one interaction term ($CE \times SK$) and the variable *SK* to Eq. (1) in which *SK* is the social capital measure for firm *i* in year $t-1$, which is the first principal component from a PCA based on *Pvote, Respn, Nccs, and Assn*.[24] The regression equation is specified as follows:

$$\begin{aligned} Ln(Spread)_{i,t} &= \alpha_0 + \alpha_1 CE_{i,t-1} + \alpha_7 CE_{i,t-1} \times SK_{i,t-1} \\ &+ \alpha_8 SK_{i,t-1} + \beta' FIRM_{i,t-1} + \theta' Z_{i,t} + \gamma_i + \mu_t + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

Panel C of Table 10 presents the results of the chemical-emission effect after controlling for social norms. We find that the coefficients for the chemical-emission measures (*CE*) remain positive and significant in two specifications. However, the coefficients for *SK* and $CE \times SK$ are insignificant. Therefore, we do not find evidence to support the idea that the chemical-emission effect becomes larger in firms that operate in states, counties, or areas where the social norms are high.

Conclusions

Facing rapid and extreme climate change around the world, more and more banks have made commitments to integrate social and environmental considerations into their operations and lending. We investigate whether banks consider a firm's environmental pollution record when they make lending decisions. Specifically, we examine whether banks with greater social responsibility can promote the practice of business ethics in their borrowers through their lending decisions.

To test this issue, we collect data from the Toxic Release Inventory of the US Environmental Protection Agency to examine how chemical emissions affect the cost of loans from banks. Our sample includes 8,331 bank loan contracts from 836 individual firms between 1988 and 2015. After controlling for firm attributes, loan characteristics, macroeconomic factors as well as firm and year fixed effects, we find strong evidence that loan spreads increase when the level of a borrower's chemical emissions rises. This result also indicates that banks account for the interests of the firms' stakeholders in their lending decisions.

Furthermore, this relation is much stronger for firms with higher risk and weaker corporate governance. We also find that banks impose more stringent nonprice loan terms, such as shorter maturities and more collateral requirements, on high polluting firms. Additional results show that banks with greater social responsibility place more importance on their

[22] CSR strength (concern) is the sum of the ratios of the number of CSR strengths (concerns) of firm *i* to the total number of strength indicators across the seven rating dimensions in the KLD dataset.

[23] We thank an anonymous referee for making this suggestion.

[24] In here, *Pvote* is the percentage of voters who voted in presidential elections, *Respn* is the response rate to the Census Bureau's decennial census, *Nccs* is the number of tax-exempt non-profit organizations per 10,000 people, and *Assn* is the number of social organizations per 100,000 people.

borrowers' environmental performance when placing loans, but not for banks with a lower level of social responsibility.

In sum, we find that banks charge various unfavorable loan terms in contracts when firms increase their toxic chemical emissions. In particular, banks with greater social responsibility account for their borrowers' environmental performance more and charge polluting borrowers higher loan spreads Thus, these results confirm that banks with greater social responsibility can promote the practice of business ethics in firms.

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Appendix: Definitions of variables

Variable group	Definition	Data source
A. Dependent variables		
Chemical emissions (CE)	The ratio of the total amount of toxic chemicals emitted to the total sales of a firm. Data include approximately 300 selected toxic chemicals from domestic manufacturing facilities owned by the firm or its subsidiaries and whose emissions are required to be disclosed under the Emergency Planning and Community Right-to-Know Act	TRI (EPA) and Compustat
CE/Asset	The ratio of the total amount of toxic chemicals emitted to the total assets of a firm	TRI (EPA) and Compustat
CE/NI	The ratio of the total amount of toxic chemicals emitted to the total net income of a firm	TRI (EPA) and Compustat
B. Loan characteristics		
Ln(Spread)	Natural logarithm of the loan spread. Here, the loan spread is the all-in spread drawn from the DealScan database (the amount the borrower pays in terms of basis points over LIBOR or LIBOR equivalent for each dollar drawn down)	DealScan
Ln(Maturity)	Natural logarithm of the loan maturity in months	DealScan
Ln(Loan size)	Natural logarithm of the loan amount in US$ millions	DealScan
Performance	Dummy variable that is equal to one if the loan facility uses performance pricing, and zero otherwise	DealScan
Ln(Covenant)	Natural logarithm of the number of total covenants	DealScan
Collateral	Dummy variable that is equal to one if a loan is secured, and zero otherwise	DealScan
Ln(TCB)	Total cost of borrowing that is calculated as the natural logarithm of the total costs of a bank loan that include spread and other fees in the loan contracts	BSS (2016)
C. Firm characteristics		
Ln(Assets)	Natural logarithm of the total assets in US$ millions	Compustat
Leverage	Ratio of long-term debt plus debt in current liabilities to total assets	Compustat
MB	Ratio of market value of net assets to book value of net assets	Compustat and CRSP
Tangibility	Ratio of net property, plant, and equipment to total assets	Compustat

Variable group	Definition	Data source
Profitability	Ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to total assets	Compustat
CF-volatility	Ratio of standard deviation of quarterly cash flows from operations over the four fiscal years prior to the loan initiation year, scaled by total debt	Compustat
D. Macroeconomic factors		
Credit spread	Difference between the US AAA corporate bond yield and the BAA corporate bond yield	Datastream
Term spread	Difference between the 10-year and 2-year US Treasury yields	Datastream
E. Firm risk		
Z-score	Altman's Z-score index. Z-score = 1.2 × (working capital/total assets) + 1.4 × (retained earningsl/total assets) + 3.3 ×(earnings before interest and taxl/total assets) + 0.6 ×(market value of equityl/total liabilities) + 1.0 ×(salesl/total assets)	Comp and CRSP
EDF	Expected default frequency measure of the firm. It is the percentile ranking of a firm's default risk based on its distance to default drawn from Bharath and Shumway (2008)	Comp and CRSP
Idiovol	The standard deviation in the residuals obtained from a market model of daily returns that exceed the three-month T – bill by using the previous two-year data, where the market is represented by the value-weighted CRSP index	CRSP
Beta	Firm's equity beta from a market model of daily returns that exceed the three-month T-bill by using the previous two-year data, where the market is represented by the value-weighted CRSP index	CRSP
F. Corporate governance		
Independent	The percentage of outside directors	RiskMetrics
Busy	A dummy variable for whether a director is busy that equals one if a majority of directors hold three or more directorships	RiskMetrics
Instown	Percentage share of ownership by institutional investors	13F
Boardsize	The number of board members	RiskMetrics
Duality	A dummy variable for when the CEO also holds the position of chairman of the board	RiskMetrics
CEOTC	The natural log of total compensation of the CEO. Total compensation (TDC1) includes salary, bonus, stock awards, option awards, long-term incentive plans, and other annual compensation such as perquisites and other personal benefits	ExecuComp

Variable group	Definition	Data source
Attend	A variable to measure attendance problems for the board of directors that equals the fraction of directors who attend less than 75% of board meetings	RiskMetrics
Governance	A variable to measure corporate governance that is the first principal component from a PCA based on seven governance variables	Authors
G. Bank social responsibility		
Bank_SR	The social responsibility of a bank. Bank_SR = CSR strength – CSR concern. CSR strength (concern) is the sum of the ratios of the number of CSR strengths (concerns) of firm i to the total number of strength indicators across the seven rating dimensions in the KLD dataset	KLD
H. Social norm		
SK	The social capital measure of a firm that is the first principal component from a PCA based on Pvote, Respn, Nccs, and Assn (Hasan et al. 2017). In here, Pvote is the percentage of voters who voted in presidential elections, Respn is the response rate to the Census Bureau's decennial census, Nccs is the sum of tax-exempt non-profit organizations per 10,000 people, and Assn is the sum of social organizations per 100,000 people	NRCRD

TRI: Toxic Release Inventory (EPA: US Environmental Protection Agency). CRSP: Center for Research in Security Prices. BSS: Berg, Saunder, and Steffen (2016). NRCRD: Northeast Regional Center for Rural Development at the Pennsylvania State University.

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