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The role of biodiversity risk in shaping bank lending decisions

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Abstract

We examine whether banks incorporate firm-level biodiversity risk into their lending decisions. Using a large sample of syndicated loans matched to firm-level biodiversity risk measures, we document that borrowers with higher biodiversity risk face significantly higher loan spreads. Evidence on loan volumes is weaker, suggesting that banks primarily adjust along the pricing margin rather than restricting credit supply. To capture biodiversity risk exposure, we develop a novel text-based indicator derived from corporate disclosures that incorporates the contextual content of environmental risk. To strengthen identification, we exploit firm-level environmental violations as shocks to environmental credibility. In a stacked difference-in-differences framework, we show that such violations increase the sensitivity of loan pricing to biodiversity risk. Overall, our findings provide evidence that biodiversity risk is a financially material dimension of environmental risk in credit markets.

Keywords— Bank-firm relationship, syndicated loans, biodiversity risk, textual analysis, financial stability

JEL Classification: G21, Q51, Q57

Non-technical Summary

Biodiversity loss has emerged as a critical source of environmental and economic risk. The degradation of ecosystems threatens the availability of essential natural resources such as water, soil quality, and biological inputs that underpin production processes across many industries. At the same time, firms whose activities contribute to biodiversity loss face increasing regulatory scrutiny, potential liability, and reputational costs. These channels imply that biodiversity loss may affect firms' financial performance and risk profiles, raising the question of whether financial intermediaries incorporate such risks into their risk management and portfolio adjustments. The widespread exposure of banks to biodiversity-related risks raises important questions for financial stability and potential systemic vulnerabilities. Recent evidence highlights that 72% of firms in the euro area depend on at least one ecosystem service, while among approximately 2,500 analyzed banks, 100 account for 87% of exposures to these firms (Ceglar et al., 2025). Moreover, as emphasized by Elderson (2026) in a recent speech: "if we keep destroying nature, we keep destroying economic activity," highlighting important implications of biodiversity loss and nature degradation for rising risks and potential threats to financial stability. These developments confirm the growing relevance of biodiversity risk for financial supervisors and policymakers.

This paper investigates whether banks incorporate firm-level biodiversity risk when determining loan pricing and lending volumes in the syndicated loan market. To measure biodiversity risk, we rely on textual analysis of corporate disclosures. We begin with an existing biodiversity risk indicator proposed by Giglio, Kuchler, Stroebel, and Zeng (2023) and extend this approach by moving beyond a traditional bag-of-words method to an embedding-based framework, which more effectively captures contextual and indirect language in corporate reports. In addition to constructing an overall biodiversity risk measure, we develop four granular indicators that capture the main drivers of biodiversity loss: air pollution, climate change, land use, and water pollution. This approach allows us to capture biodiversity-related risks at a more granular and contextual level, including exposures not explicitly identified by traditional measures, and to account for indirect language in corporate disclosures. In our analysis, we account for a range of loan, firm, and lender characteristics that may influence bank lending decisions, and include various fixed effects as controls for broader economic conditions. This helps ensure that our results more accurately capture the impact of biodiversity risk. Additionally, we explore borrower and lender heterogeneity by interacting our biodiversity risk measures with indicators capturing firms' environmental performance, including environmental violations and ESG environmental score, as well as bank characteristics such as sustainability commitments and the environmental vulnerability of banks' headquarters countries.

We use syndicated loan data from Dealscan for U.S. borrowing firms, covering the period 2007–2023 at an annual frequency. This dataset captures global lending relationships for large firms through syndicated loan markets. While borrowers are U.S. firms, lenders are internationally diversified and include banks from Europe and other regions. We use this setting to examine how banks price and allocate credit and how biodiversity-related risks are reflected in lending decisions.

Overall, we provide evidence that biodiversity risk is already reflected in credit market outcomes, with effects most pronounced in loan pricing. Exploring borrower and lender heterogeneity, we find that the pricing of biodiversity risk is amplified for firms with a history of environmental violations, consistent with these risks becoming more salient following such events. We find similar patterns when using firms' environmental performance, as measured by ESG environmental score. On the lender side, we show that biodiversity risk is priced more strongly by sustainability-committed banks. In contrast, we do not find robust evidence that lenders headquartered in more environmentally vulnerable countries respond differently.

Nature degradation can adversely affect firms' production processes and creditworthiness, thereby impairing banks' loan portfolios and raising financial stability concerns. Although still at an early stage compared to climate-related regulation, the interaction between biodiversity loss and financial sector is receiving growing attention in global financial policy debates. It is therefore important to clarify whether financial institutions lending to firms quantify and manage biodiversity-related risks. The findings contribute to the understanding of how environmental risks beyond climate change are transmitted into financial decision-making and highlight biodiversity as an emerging dimension of financially relevant environmental risk. Our results provide important insights for policymakers on both the measurement of firm-level biodiversity risk and banks' lending responses. We show that semantically rich measures more effectively capture biodiversity risk exposures, revealing pricing effects in credit markets that are not detected by traditional approaches.

1 Introduction

"Humanity needs nature to survive, and so do the economy and banks. The more species become extinct, the less diverse are the ecosystems on which we rely. This presents a growing financial risk that cannot be ignored."

Frank Elderson (2023), European Central Bank

Scientists warn that species extinction rates are currently up to 1,000 times higher than the natural rate. Over the past four decades, wildlife populations have declined by approximately 60%, while even non-endangered species are losing genetic diversity due to habitat degradation and local extinctions (Karolyi & Tobin-de la Puente, 2023). This depletion of natural capital has far-reaching economic and societal consequences. According to European External Action Service (2022), sustained overuse of natural resources since the 1970s has exposed more than 300 million people to heightened risks of extreme weather events such as floods and hurricanes.

Beyond its ecological implications, biodiversity loss imposes substantial economic costs by reducing the availability of essential natural inputs and increasing production costs across industries (Becker, Di Girolamo, & Rho, 2025). Economic activity depends on ecosystem services, giving rise to what is often referred to as "double materiality." On the one hand, biodiversity loss generates physical risks by disrupting production and destroying capital. On the other hand, firms contribute to biodiversity degradation, creating transition risks in the form of stricter regulation, higher compliance costs, and changes in business practices (Becker et al., 2025).

Firms are therefore exposed to multiple biodiversity-related risks, including direct ecological impacts, liability risks, and regulatory pressures (OECD, 2023). These risks have important financial implications. Physical risks can disrupt value chains and reduce asset values, while transition risks—arising from policy interventions such as restrictions, quotas, or environmental standards—require costly adjustments in the reallocation and adaption of business activities and may render certain activities unviable. The World Bank estimates that the collapse of ecosystem services could reduce global GDP by up to $2.7 trillion by 2030 (Arlt, Berg, Hut, & Streitz, 2024; Becker et al., 2025; Johnson et al., 2021).

Despite growing recognition of biodiversity loss as a material source of firm risk, empirical evidence on how financial markets respond remains limited. Existing work largely focuses on conceptual frameworks or macroeconomic implications, while evidence on how biodiversity risk affects financial contracting at the firm level is scarce. In particular, although banks are often viewed as key intermediaries in managing environmental risks, it remains unclear whether they price or ration credit based on firms' biodiversity risk.

A central challenge in addressing this question is measurement. Unlike climate risk, biodiversity risk is difficult to quantify using standard data sources. Corporate disclosures rarely contain standardized biodiversity metrics, and keyword-based approaches struggle to distinguish meaningful risk disclosures from generic environmental language. As a result, the lack of reliable firm-level measures has hindered empirical research on biodiversity risk in financial markets.

In this paper, we address this gap by developing a novel text-based measure of firm-level biodiversity risk using transformer-based sentence embeddings. This approach captures both explicit and implicit references to biodiversity-related risks in corporate disclosures. Unlike conventional bag-of-words methods, which treat words as isolated tokens, our framework leverages semantic similarity to identify context-dependent biodiversity exposure. This allows us to construct both an aggregate biodiversity risk indicator and four granular measures reflecting key environmental pressure channels: air pollution, climate change, land use, and water pollution (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), 2020).

We then examine how biodiversity risk affects bank lending decisions in the syndicated loan market, focusing on both loan pricing and credit supply. In addition, we investigate the mechanisms underlying these effects by analyzing heterogeneity across borrowers and lenders.

On the borrower side, we study the role of environmental violations and environmental performance. In particular, we exploit firm-level environmental violations and implement a stacked difference-in-differences design around violation events to assess how banks adjust lending terms when environmental risks become more salient.

On the lender side, we examine whether banks' sustainability commitments and geographic exposure to environmental risks shape their response to biodiversity risk. We further explore whether biodiversity exposure affects banks' participation decisions in loan syndicates.

Our empirical analysis builds on the hypothesis that banks incorporate biodiversity risk into lending decisions. Biodiversity loss can impair firms' profitability, asset values, and collateral by constraining the natural resources on which production depends, thereby reducing creditworthiness. These risks may therefore be priced through higher loan spreads, analogous to the carbon premium documented in prior work (Becker et al., 2025; Ehlers, Packer, & de Greiff, 2022). Banks may face regulatory scrutiny and reputational costs stemming from environmental harm caused by their borrowers. As a result, banks may avoid lending to firms with higher biodiversity risk. More broadly, they may adjust credit supply by reducing exposure to such firms or limiting their participation in syndicated loans, with stronger effects among environmentally committed lenders or those exposed to higher environmental risks (Fard, Javadi, & Kim, 2020).

Our results show that biodiversity risk is significantly priced in syndicated loan markets. Firms with higher biodiversity exposure face higher loan spreads and, in some specifications, lower loan volumes. Biodiversity risk becomes particularly salient following environmental violations: using a stacked difference-in-differences design, we provide causal evidence that firms with higher biodiversity exposure experience a larger increase in loan spreads after violation events. At the same time, banks do not systematically withdraw credit, suggesting that adjustment occurs primarily through pricing. We further find that the pricing effect is stronger for firms with weaker environmental performance and for sustainability-committed banks, while we find no robust evidence that lenders in more environmentally vulnerable countries respond differently.

Finally, we examine whether biodiversity risk affects the participation decisions of sustainability - committed banks in syndicated loans. We find limited evidence that biodiversity exposure influences participation, suggesting that banks primarily adjust along the pricing margin rather than the extensive margin of credit supply.

Using novel embedding-based measures that capture both aggregate biodiversity risk and its underlying drivers, our findings provide the first systematic evidence that biodiversity risk constitutes a financially material dimension of environmental risk that is incorporated into bank lending decisions.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and the construction of our biodiversity measures. Section 4 outlines the empirical framework. Section 5 presents the main findings. Section 6 provides additional analyses, and Section 7 concludes.

2 Related Literature

While climate risk has been extensively studied in finance, biodiversity risk has only recently begun to receive attention, despite growing recognition of its importance and its role as climate change's "twin risk" (KPMG, 2023).[1] International organizations such as UNEP and the World Economic Forum (United Nations Environment Programme, 2022), along with initiatives like COP15 (UN Biodiversity Conference 2022) and the Kunming–Montreal Global Biodiversity Framework, further emphasize biodiversity loss as a key challenge alongside climate change.

Despite growing research on biodiversity-related risk premia (Coqueret, Giroux, & Zerbib, 2024), investor perceptions (Garel, Romec, Sautner, & Wagner, 2024, 2025), asset valuation (Cornaggia, Liang, Iliev, & Wang, 2025; Giglio et al., 2023), private capital and blended finance structures (Flammer, Giroux, & Heal, 2025) and the impact on corporate operations, environmental performance, and financial outcomes (Ng, Pham, Yu, & Akbari, 2025), a notable gap remains in understanding how biodiversity risks specifically influence banks and their lending behavior.[2]

[1]The extensive Environmental, Social, and Governance (ESG) literature reflects the broader shift towards sustainability in finance (Avramov, Cheng, Lioui, & Tarelli, 2022; Edmans, 2023; Heeb, Kölbel, Paetzold, & Zeisberger, 2022; Pedersen, Fitzgibbons, & Pomorski, 2021) alongside critical evaluations (F. Berg, Fabisik, & Sautner, 2020; F. Berg, Koelbel, Pavlova, & Rigobon, 2022).

[2]More recent contributions include Guidolin and Pedio (2025) focusing on transitions risk find that

Banks are exposed to biodiversity risk through lending, investment, and off-balance-sheet activities involving firms that depend on or impact natural ecosystems. Understanding how these exposures translate into credit, market, and liquidity risks is key for assessing financial stability implications and aligning financial intermediation with environmental sustainability.

Some studies have begun to address this gap, focusing on biodiversity-related risks for businesses and the financial sector. Recent methodologies have significantly advanced the assessment of biodiversity risk in the financial sector. Berger et al. (2018) developed a biodiversity footprinting methodology, while Barker, Mulholland, and Onifade (2020) introduced a framework for evaluating biodiversity-related financial risks, highlighting the increased vulnerability of institutions linked to ecosystem dependent firms (Becker et al., 2025). Calice, Skamnelos, and Valderrama (2021) found that Brazilian banks have substantial exposure to biodiversity loss, with nearly half of corporate loan portfolios in sectors dependent on ecosystem services. van Toor, Piljic, Schellekens, van Oorschot, and Kok (2020) assessed Dutch financial institutions' exposure and illustrated the systemic risk biodiversity loss poses to the sector. Ceglar et al. (2025) further underscore this risk, showing that nearly 72% of euro area companies depend on at least one ecosystem service. At the same time, the top 100 banks (out of 2,500 analyzed) account for approximately 87% of the total biodiversity footprint. This concentration highlights the central role of major banks in financing biodiversity-impacting activities and underscores potential implications for financial stability, emphasizing the need to incorporate biodiversity considerations into lending and risk assessment. Additionally, other scholars found that deregulation led banks to decrease the environmental risk consideration in their loan pricing (Erten & Ongena, 2024).

A small but growing literature examines biodiversity risk in lending decisions. Becker et al. (2025) analyze syndicated loans from 2017 to 2022, uncovering that biodiversity risk significantly affects loan pricing, with lenders imposing a risk premium akin to the 'carbon premium' for emissions. The authors use a location-based measure to gauge the firms' exposure to biodiversity risk by looking at geographic segments of their operations. More recent work by Deng and Lin (2025) and Canipek, Kundu, Tresl, and Zimmermann (2024) examines the effect of firm-level nature-related risks on loan pricing. The former uses biodiversity exposure metrics developed by Giglio et al. (2023) and exploits biodiversity-related litigations as exogenous shocks to assess causal effects. The latter leverages amendments to the U.S. Endangered Species Act (ESA) and finds that regulatory loosening leads to lower

commodities with higher biodiversity footprints command a risk premium, particularly those consumed in more regulated European markets. Cao, Karolyi, Xiong, and Xu (2025) explore biodiversity-linked startups and find that they raise less capital but attract value driven investors. T. Liu, Constantz, Hale, and Beck (2025) find that the proximity of housing properties to mangroves, which are shown to reduce flood risk and mitigate the adverse effects of hurricanes, attenuates the decline in home prices and reduces price dispersion, leading to smaller value losses. Gjerde, Sautner, Wagner, and Wegerich (2025) survey companies worldwide on their perceptions of nature-related risks and find that a substantial share of firms already experience financial impacts linked to these risks.

loan spreads for nature-dependent firms.

Unlike these prior studies, we develop novel, granular text-based measures of firm-level biodiversity risk using an embeddings approach that captures both overall exposure and its key drivers—including air pollution, climate change, land use, and water pollution—and accounts for risk conveyed through indirect corporate disclosures. This enables us to link distinct biodiversity-related risk channels to bank lending decisions. In addition to loan spreads, we examine loan volumes, providing a more comprehensive view of banks' credit allocation. For causal identification, we exploit firm-level environmental violations in a stacked difference-in-differences framework. We further examine heterogeneity across borrower and lender characteristics, including ESG performance, UNEP-FI membership, and lenders' exposure to environmental vulnerability. Finally, we investigate whether the probability that environmentally conscious banks participate in syndicated loans depends on borrowers' biodiversity risk.

Our study relates to the literature on environmental risk and bank lending but differs from work on climate-related risks, such as CO2 emissions. CO2 emissions are quantifiable in terms of carbon footprints and are scrutinized by banks to assess a borrower's environmental impact and alignment with climate change goals. Conversely, biodiversity, which encompasses the diversity within and among species and ecosystems, is critical to ecosystem productivity, resilience, and the provision of services such as pollination, water purification, and disease regulation. In lending practices, biodiversity considerations may highlight potential impacts on local ecosystems, endangered species, and habitat conservation. These features imply more heterogeneous and less observable risk channels, with implications for how banks assess and price environmental risk in lending.

Our work is still related to the literature on climate change and bank lending. Significant contributions to this literature include: Kacperczyk and Peydró (2022), who analyze how firm-level carbon emissions affect the bank lending channel while also investigating how banks' commitments to sustainability goals affect this relationship; Delis, Greiff, Iosifidi, and Ongena (2024), who find that green banks charge higher interest rates to fossil fuel companies; Degryse, Goncharenko, Theunisz, and Vadasz (2023), who find that green banks charge lower interest rates for loans to green firms especially after the Paris Agreement in 2015; Altavilla, Boucinha, Pagano, and Polo (2024), who analyze the relationship between climate risk and bank lending policies and find that banks charge lower interest rates for loans to firms with lower emissions, while these effects are exacerbated by monetary tightening. For a recent comprehensive review of the literature in this area, see (de Haas, 2023).

3 Data and Summary Statistics

3.1 Data Overview

We next describe the datasets used to address the research questions. The dataset covers the period 2007–2023, with further details provided in the corresponding subsections.

A. Loan Level Data

We use the LoanConnector module of the DealScan database, which provides global syndicated loan data from 1988 onward, including detailed information on borrower identity, industry, lead arrangers, syndicate participants, and tranche-level terms such as size, pricing, maturity, and covenants. Each deal typically includes multiple tranches, which we treat as separate observations following standard practice (e.g., Acharya, Gopal, and Steffen (2025); Chava and Roberts (2008); Golden and Liu (2025)).

We retain only observations involving publicly listed, non-financial borrowers and restrict to bank lenders.[3] At this stage, the sample comprises 32,420 tranche-level observations.

To merge firm financial data, we map DealScan borrower identifiers to GVKEYs using Chava and Roberts (2008). Lender financial data are linked by mapping DealScan Lender IDs to Legacy IDs and subsequently to BvDIDs, following Schwert (2018). Where BvDIDs are unavailable, we apply fuzzy name matching to merge lenders with BankFocus data (with a similarity threshold of 0.75 and manual cross checks).[4]

Since our focus is on loan pricing and monitoring decisions, we restrict the sample to loans where the bank acts as a lead arranger, as lead arrangers play the central role in negotiating loan terms, screening borrowers, and organizing the syndicate (Sufi, 2007). For syndicated loans with multiple lead arrangers, we compute averages across these institutions. A summary of all third party datasets is presented in Table 1.

Table 1 about here

To analyze changes in the loan volume, we restructure the data to generate a second dataset at the bank-firm level. This dataset we denote as *Borrower - Lender Level dataset.* This sample includes the annual loan volume (in USD) computed for each bank, as detailed below.

$$\text{Loan Volume}_{\text{lender}} = \text{Total Loan Amount} \times \frac{\text{Lender Share (\%)}}{100}. \tag{1}$$

[3] We exclude firms with SIC codes 6000–6999 (financial firms) due to their distinct regulatory environment and capital structure characteristics (Fama & French, 1992, 1993; Rajan & Zingales, 1995).

[4] DealScan identifies lenders using internal Lender IDs and Legacy IDs, which do not directly correspond to standard bank identifiers. Following Schwert (2018), we use the Legacy ID as an intermediate step to obtain Bureau van Dijk identifiers (BvDIDs), which allow us to merge DealScan lenders with BankFocus financial data.

If the *Lender Share (%)* is unavailable, we assume an equal distribution of the total loan amount among all identified lead arrangers (de Haas & van Horen, 2013; Doerr & Schaz, 2021). For N lead arrangers, the loan volume for each bank is:

$$\text{Loan Volume}_{\text{lender}} = \frac{\text{Total Loan Amount}}{N}. \tag{2}$$

After computing the loan volumes for individual loans per lender, we aggregate the data to compute the total annual loan volume to firm held by each lender. This is achieved by grouping the data by *Bank Name* and *Year*, and summing up the loan volumes:

$$\text{Annual Loan Volume}_{\text{lender, firm, year}} = \sum_{\text{loans}} \text{Loan Volume}_{\text{lender, firm}}. \tag{3}$$

We restrict the sample to tranches classified as *Origination*, and furthermore, as syndicated lending is characterized by different lender types, we follow the approach of Ivashina (2009) and Degryse et al. (2023) by retaining only deals where the lender is listed as *Admin Agent*, *Agent*, *Mandated Arranger*, *Co-arranger*, *Bookrunner*, *Mandated Lead Arranger*, *Lead Arranger*, or *Manager*. This leaves us with the number of lead arrangers between 1 and 24 and 14,291 observations for the Borrower-Tranche Level dataset. We show the distribution of Lead Arrangers in Figure 1.

Figure 1 about here

B. Firm-level Biodiversity Risk Measures

According to the Global Biodiversity Framework, Target 15 mandates that "large and transnational companies and financial institutions: (a) regularly monitor, assess, and transparently disclose their risks, dependencies, and impacts on biodiversity; (b) provide information needed to consumers to promote sustainable consumption patterns; and (c) report on compliance with access and benefit-sharing regulations and measures, as applicable" (Convention on Biological Diversity, 2026). Recent literature proposes two primary approaches to quantify firm-level biodiversity risk exposure. The first is textual analysis of firm disclosures, such as 10-K filings, as introduced by Giglio et al. (2023). The second is based on estimates of firms' material biodiversity footprints, such as those developed by Iceberg Data Lab (2023) and used in empirical applications like Sautner, van Lent, Vilkov, and Zhang (2023). Both approaches have limitations, as discussed in Sautner et al. (2023).

Moreover, in line with broader concerns over ESG data divergence (e.g. see F. Berg, Kölbel, and Rigobon (2022)), Roeder and Utz (2025) document substantial disagreement in biodiversity footprint estimates across leading data providers, including ISS ESG, Iceberg Data Lab, and the Impact Institute, due to methodological and data input inconsistencies.

Biodiversity footprint measures provide a backward-looking assessment of firms' ecological impacts but offer limited insight into future risk exposure. By contrast, textual analysis, while subject to reporting bias and noise, can capture forward-looking disclosures related to physical, transition, and regulatory biodiversity risks (Cenedese, Han, & Kacperczyk, 2024). Our primary empirical strategy builds on a textual analysis approach. We introduce a novel firm-level biodiversity risk measure, described in detail in Section 3.1, which leverages an embedding-based methodology to capture forward-looking biodiversity risk disclosures. To assess the robustness of our findings, we benchmark our results against the biodiversity exposure scores developed by Giglio et al. (2023).

B1. Existing Firm-level Biodiversity Risk Text Measures

For comparison with the existing literature, we include two indicators from Giglio et al. (2023), who construct firm-level biodiversity exposure measures using textual analysis of 10-K filings. Specifically, we use the *Biodiversity Count* and *Biodiversity Regulation* scores, which are based on regular expression searches over a biodiversity dictionary. The dictionary terms are selected based on their cosine similarity to "biodiversity" in Google's word2vec model. The count score equals one if at least two sentences in the filing contain biodiversity-related terms. The regulation score applies the same logic but additionally requires that at least one of these sentences explicitly refers to regulatory language.[5]

B2. Improved and Granular Textual Measures of Firm-Level Biodiversity Risk

We develop a novel approach to capturing firm-level biodiversity risk based on contextual language embeddings.

Traditional keyword-based (bag-of-words) methods, as previously discussed, treat biodiversity-related terms as isolated tokens and disregard the semantic context in which they appear. As a result, they cannot reliably distinguish between material disclosures, generic boilerplate language, or unrelated uses of similar vocabulary. In contrast, our framework captures the semantic content of full sentences, enabling a more accurate identification of biodiversity-related risk exposures.

We introduce two methodological innovations. First, we construct a firm-level biodiversity index based on contextual sentence embeddings, which accounts for linguistic variation and captures meaning beyond keyword frequency. Second, we develop a set of granular indicators that map firm disclosures to specific environmental pressures associated with biodiversity loss, namely air pollution, climate change, land use, and water pollution.

[5]Giglio et al. (2023) also introduce a *10-K Biodiversity Negative Score*, defined as the difference between the number of negative and positive biodiversity-related sentences, where sentiment is classified using a BERT model. We exclude this measure from our analysis, as sentiment-based indicators fall outside the scope of our study and the remaining scores are more directly comparable to our textual measures.

This approach allows us to distinguish between explicit biodiversity disclosures and indirect references to underlying environmental pressures. Because firms often do not explicitly refer to "biodiversity", keyword-based methods may underestimate true exposure. By capturing indirect references—such as mentions of emissions, deforestation, or water scarcity—and linking them to their corresponding ecological pressures, our framework uncovers latent biodiversity risk embedded in corporate disclosures.

An illustrative example can be found in Keurig Dr. Pepper's 2018 10-K statement:

> *"We also may be faced with water availability risks. Water is the main ingredient in substantially all of our products. Climate change may cause water scarcity and a deterioration of water quality in areas where we maintain operations. [...] We may incur increased production costs or face manufacturing constraints which could negatively affect our business and financial performance."*

This excerpt highlights exposure to water scarcity and declining water quality—key environmental pressures associated with biodiversity loss—yet does not explicitly reference biodiversity. Instead, such disclosures embed biodiversity-related risks within broader environmental narratives, including ecosystem degradation, resource constraints, and supply chain vulnerabilities. This raises an important question: *Do firms underreport biodiversity risk, or is it implicitly conveyed through related environmental disclosures?* Distinguishing between these possibilities is critical for accurately measuring firm-level biodiversity exposure.

Motivated by this observation, we construct granular indicators of biodiversity risk based on its underlying drivers. The life sciences literature identifies four primary anthropogenic pressures contributing to biodiversity loss: land use change, water pollution, air pollution, and climate change (GLOBIO Consortium, 2024; Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), 2020). Land use change drives habitat loss, while pollutants affect biodiversity across terrestrial and aquatic systems. Climate change drives biodiversity loss by altering habitats, temperatures, and ecosystems faster than species can adapt.

To operationalize these dimensions, we employ a transformer-based sentence embedding model.[6] This embedding approach enables us to classify firm disclosures not only into an *Biodiversity Overall* indicator, but also into four topic-specific indicators: *Air Pollution*, *Climate Change*, *Land Use*, and *Water Pollution*, following the taxonomy used in Sautner et al. (2023) and Iceberg Data Lab (2023).

[6]Following Devlin, Chang, Lee, and Toutanova (2019), a range of transformer architectures have been developed. We use sentence transformers (Reimers & Gurevych, 2019), which are specifically optimized for capturing semantic similarity at the sentence and paragraph level while remaining computationally efficient.

Our framework yields (i) a comprehensive firm-level overall biodiversity risk index and (ii) four disaggregated measures aligned with scientifically grounded environmental pressures. Together, these indicators provide a more context-sensitive and forward-looking assessment of biodiversity-related discourse in corporate filings.

Text Extraction

As our input data, we extract relevant content from Items 1, 1A, and 7 of firms' annual 10-K filings. These filings, submitted to the U.S. Securities and Exchange Commission (SEC), provide standardized disclosures on firm operations, risks, and performance. Item 1 describes the firm's business activities, competitive environment, and regulatory context. Item 1A outlines material risks that could adversely affect the firm's financial position or stock performance. Item 7 contains Management's Discussion and Analysis (MD&A), which offers narrative insights on business strategy, financial drivers, and forward-looking risks. Together, these sections provide a rich textual representation of a firm's operations, strategic outlook, and disclosed risk exposures.

We retrieve the 10-K filings in HTML format from the SEC's EDGAR system and parse the relevant sections using a custom extraction tool based on the approach developed by Breitung and Müller (2025).[7] The extracted text is segmented into sentences, and adjacent sentences are merged when semantic continuity is evident, following the method used in Breitung and Müller (2025).

For sentence-level representation, we generate 768-dimensional embeddings using the pre-trained *all-mpnet-base-v2* model from the Sentence Transformers framework.[8] This model is specifically designed to capture the contextual meaning of sentences, enabling robust classification of biodiversity-related disclosures even in the absence of direct keyword matches.

Topic Construction and Sentence Allocation

First, we construct a reference corpus for each category using GPT-5.1. For each of the five dimensions, we generate 250 synthetic sentences designed to capture the respective concept in isolation.[9] These sentences serve as an initial semantic benchmark. We embed both the reference corpus and all sentences from 10-K filings in 2006 using the sentence embedding model described in the previous section. For each topic, we compute the cosine similarity between firm-level sentences and the reference embeddings:

[7] We limit our sample to filings from 2006 onward, the year in which the SEC standardized the 10-K structure, making Item 1A consistently reported across firms.

[8] Model available at: `https://huggingface.co/sentence-transformers/all-mpnet-base-v2`. The model is optimized for semantic similarity tasks and offers a favorable trade-off between accuracy and computational efficiency. See Hugging Face (2024) for benchmark comparisons.

[9] The prompt used to generate these sentences is available upon request.

$$\text{Cosine Similarity}(\mathbf{A}, \mathbf{B}) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \, \|\mathbf{B}\|} \tag{4}$$

Here, $\mathbf{A}$ and $\mathbf{B}$ denote embedding vectors, $\mathbf{A} \cdot \mathbf{B}$ their dot product, and $\|\mathbf{A}\|$ and $\|\mathbf{B}\|$ their Euclidean norms.

For each topic, we rank firm-level sentences by similarity and retain the top 1,000 most relevant observations. We use this subset to refine the reference corpus, thereby aligning it with the language observed in actual filings. We then use these refined reference sets to obtain topic-specific semantic representations, which are subsequently applied to the full sample period from 2007 to 2023.

In the second stage, we compute cosine similarity between the re-embedded topic-specific benchmarks and all sentence embeddings from 10-K filings spanning 2007 to 2023. We classify a sentence into a category if its similarity exceeds the 75th percentile of the topic-specific similarity distribution. Sentences not exceeding any threshold remain unclassified. The 75th percentile cutoff was selected based on manual inspection of classification accuracy: higher thresholds excluded relevant sentences, while lower thresholds admitted semantically unrelated content.

We aggregate sentence classifications at the firm-year level to construct count-based measures of biodiversity exposure across all five dimensions following the dummy construction of Giglio et al. (2023). When compared over time, both our embedding-based biodiversity indicator and the keyword-based binary measures developed by Giglio et al. (2023) display a pronounced upward trend (see Figure 2), consistent with the growing prominence of biodiversity in corporate disclosure practices.

Figure 2 about here

Using the loan activation year from DealScan and the borrower's CUSIP identifier, we match both biodiversity exposure measures—ours and that of Giglio et al. (2023)—to LoanConnector borrower data. Our final dataset contains 1,316 unique firms for which our embedding-based biodiversity indicators are available. By comparison, the matched Giglio et al. (2023) dataset includes 1,043 firms over the same period.

Because our sample is restricted to borrowers with at least one active syndicated loan in a given year, we observe 15,880 firm-year loan records with our sentence-based measure and 13,184 observations with the Giglio et al. (2023) measure. The overlap between the two datasets—where both measures are simultaneously available—consists of 11,888 matched firm-year observations. Figure 3 presents the time-series coverage of both measures.

Figure 3 about here

To better understand how the two measures compare at the sentence level, Table 2 presents a confusion matrix of the binary biodiversity indicators. While the two approaches largely agree in identifying non-biodiversity-related sentences (true negatives = 1,148), they diverge substantially in positive classifications. Our embedding-based classifier identifies a significantly larger number of biodiversity-related sentences, capturing 10,245 observations that are not detected by the Giglio et al. (2023) measure, while only 403 sentences are jointly classified as positive.

This discrepancy highlights the limitations of keyword-based methods in capturing indirect or context-dependent language and underscores the greater sensitivity of our semantic approach.

Table 2 about here

Consistent with these results, our approach systematically identifies more biodiversity-related disclosures. This pattern aligns with the earlier examples and reflects the ability of the sentence-level method to capture both explicit and implicit references that keyword-based classifications often overlook. To further illustrate this distinction, we provide an example from Kimball Electronics Inc.'s 2020 10-K filing:

> *"Natural disasters or other catastrophic events such as the COVID-19 pandemic may impact our production schedules and, in turn, negatively impact profitability."*

Although biodiversity is not explicitly mentioned, this statement reflects exposure to environmental pressures closely linked to biodiversity loss and ecosystem degradation. Events such as natural disasters and pandemic outbreaks can be interpreted as manifestations of reduced ecological resilience. A growing body of scientific evidence shows that biodiversity loss, habitat destruction, and ecosystem fragmentation weaken natural pathogen barriers and increase the risk of infectious disease transmission (Brema, Gautam, & Singh, 2022; Keesing et al., 2010; Schmeller, Courchamp, & Killeen, 2020). In particular, zoonotic diseases such as COVID-19 have been linked to land-use change and biodiversity depletion, which increase interactions among wildlife, livestock, and humans (Lawler et al., 2021). From a financial perspective, ecosystem-driven risks have direct implications for supply chains, production processes, and firm profitability. Accordingly, exposure to biodiversity-related environmental pressures is a relevant consideration for lenders in assessing long-term credit risk.

A traditional bag-of-words method fails to classify this disclosure as biodiversity-related because it lacks any of the canonical keywords (e.g., "biodiversity," "ecosystem," "habitat"). It treats "natural disaster," "catastrophic event," and "pandemic" as isolated tokens without recognizing their underlying environmental drivers. By contrast, contextual embeddings capture the semantic relationship between catastrophic events and biodiversity loss, mapping this disclosure to the environmental pressures that give rise to such risks. As a result, embedding-based models can classify indirect but material biodiversity risk disclosures that would be systematically missed by keyword-based approaches.

To further validate our approach, we compare our measures to the 75 reports identified as biodiversity-related by Giglio et al. (2023). While these reports receive a non-zero score under their keyword-based framework, our overall biodiversity measure assigns a value of zero to all 75 cases, as indicated in Table 2. Importantly, however, all but eight of these reports still contain sentences that our model classifies into one of the four environmental pressure categories.

This pattern suggests that firms discuss risks related to biodiversity loss primarily through specific underlying environmental pressures rather than by explicitly referencing "biodiversity" or similar terms. Taken together, these findings support our interpretation of biodiversity risk as an underlying dimension of firms' exposure to environmental and natural risks, typically conveyed through specific pressure channels rather than explicit disclosure.

An illustrative example is provided by Edison International's 2008 10-K filing:

> *"New environmental regulations, particularly those that limit emissions of CO2 and other GHG by electric generators, could put coal-fired power plants at a disadvantage compared with plants utilizing other fuels."*

This disclosure does not mention biodiversity directly and therefore receives a zero under our overall biodiversity measure. However, it highlights risks associated with greenhouse gas emissions and the transition costs of carbon regulation, which are central drivers of climate change. Climate change is widely recognized as a primary driver of biodiversity loss through its effects on ecosystems, species habitats, and ecological resilience (Alkemade, Bakkenes, & Eickhout, 2010; IPCC, 2022; Mokany, Giljohann, & Ware, 2024). By assigning this sentence to the climate change category, our semantic framework captures the relevant environmental risk signal that keyword-based approaches would overlook.

This example shows that firms often communicate biodiversity-related risks through references to underlying environmental pressures rather than explicit biodiversity terminology. Our approach captures latent biodiversity exposure embedded in broader environmental disclosures, providing a more accurate measure of firms' environmental risk.

3.1.1 Implications and Distribution of Lenders' Exposure to Biodiversity Risk

The World Bank in 2021 reported that projected biodiversity loss could reduce global real GDP by 225 billion USD by 2030, with a stress scenario involving a collapse of ecosystem services leading to a 2.7 trillion USD loss (Arlt et al., 2024; Johnson et al., 2021). ECB research as outlined in Bolton, Després, Pereira da Silva, Samama, and Svartzman (2020) and Ceglar et al. (2025) finds that around 72% of non-financial corporations in the euro area are significantly dependent on ecosystem services. Furthermore, Elderson (2024) highlights that 75% of bank loans in the euro area are connected to non-financial businesses that depend heavily on nature.

As such, nature degradation could significantly harm the creditworthiness of these enterprises, by harming their business operations. This poses risks to banks that lend to these firms, potentially negatively affecting their asset quality through higher default rates, increase in non performing assets, credit losses or also cause reputational damage.

To illustrate this point in our dataset, we highlight two examples on banks' exposure to biodiversity-related risks based on our geospatial mapping of syndicated loan connections and firm-level biodiversity risk.

Figure 4 about here

We begin with Deutsche Bank in the year 2018 (see Figure 4a). The black rectangle indicates the location of the bank's headquarters, while the colored circles represent U.S.-based borrowing firms. The color of each circle corresponds to the firm's biodiversity risk exposure, measured as the ratio of biodiversity-related sentences to the total number of sentences in Items 1, 1A, and 7 of their 10-K filings. This serves as a proxy for biodiversity-related financial and reputational risk. As shown in the figure, Deutsche Bank lends to firms with varying degrees of biodiversity exposure. This heterogeneity suggests that financial institutions may face differing levels of indirect biodiversity risk through their lending relationships, highlighting the relevance of integrating such metrics into credit risk assessment and sustainable finance strategies.

To illustrate this point further, we analyze Citigroup's lending portfolio in 2020 (see Figure 4b). Similar to the previous figure, the black rectangle marks Citigroup's headquarters, while the lines represent the loan connections to borrowing firms. Again, the color gradient reflects the biodiversity risk of these firms. The visualization shows that even within a single year and country, biodiversity risk exposure is unevenly distributed across borrowers. Several firms demonstrate relatively high biodiversity-related disclosures, indicating potential exposure to environmental scrutiny or regulatory developments.

Together, these visualizations highlight the importance of incorporating borrower-level biodiversity risk into lending decisions, enabling banks to better manage environmental risk and align portfolios with emerging sustainability standards.

To better understand our measure and identify the industries most exposed to biodiversity risk, we examine the industry distribution of firms with the highest overall biodiversity risk scores.[10]

Out of the top 10 industries presented in Figure 5, the industries ranking highest, such as oil and gas extraction, chemicals, machinery, transportation equipment, and food products, are characterized by either direct environmental footprints or strong dependencies on natural systems. In these sectors, biodiversity concerns arise through regulatory compliance, land-use impacts, and exposure to environmental litigation, all of which must be disclosed when

[10]The ranking is based on the loan spread sample and industries are defined at the two-digit SIC level (see Table A2).

financially relevant. At the same time, the presence of downstream and service-oriented industries, including wholesale trade, engineering services, and business services, suggests that biodiversity risk is also transmitted through supply chains and broader regulatory environments. Firms in these sectors are exposed to biodiversity-related risks indirectly, for example through sourcing constraints, input price volatility, or compliance requirements affecting upstream suppliers. Unlike voluntary ESG reporting, 10-K filings are subject to legal scrutiny, implying that the observed patterns reflect firms' assessments of material risk rather than reputational signaling. The inclusion of large, disclosure-intensive service industries further indicates that firm size and reporting sophistication may amplify the likelihood of biodiversity-related mentions. Consequently, the measure captures not only direct ecological exposure but also the extent to which biodiversity considerations are embedded in firms' operational and regulatory risk environments. This broader pattern is consistent with biodiversity risk propagating across production networks rather than being confined to primary sectors. Overall, the measure proxies for financially material biodiversity risk reflected in firms' disclosures, encompassing both direct and indirect channels of exposure.

Conversely, industries at the lower end of the ranking, including legal services, public administration, and social services, exhibit limited biodiversity-related disclosure, consistent with lower perceived materiality, less formalized reporting, or more indirect exposure channels.

C. Heterogeneity Across Borrowers and Lenders

We further hypothesize that heterogeneity in borrower environmental risk exposure and lender sustainability orientation may influence the sensitivity of loan pricing to biodiversity risk. To test this, we explore four dimensions of heterogeneity.

i) Borrower History of Environmental Violations

To capture borrower-level environmental behavior, we use data from the U.S. Environmental Protection Agency's Enforcement and Compliance History Online (ECHO) database, which records violations of federal environmental laws and related enforcement actions.[11] Specifically, we draw on the EPA's Integrated Compliance Information System (ICIS), which contains compliance and enforcement information across several environmental programs. Our data include ICIS Air, ICIS NPDES, ICIS Federal Enforcement and Compliance (FE&C) cases, RCRAInfo, and Safe Drinking Water Act (SDWA) cases.[12] To identify the timing of

[11] The database is publicly available at https://echo.epa.gov/tools/data-downloads.

[12] ICIS Air contains facility-level violation and compliance information related to air pollution under the Clean Air Act (CAA). ICIS NPDES records compliance, violation, and enforcement information for facilities regulated under the National Pollutant Discharge Elimination System (NPDES) of the Clean Water Act (CWA). ICIS Federal Enforcement and Compliance (FE&C) includes federal-level enforcement cases covering

enforcement actions, we use the ICIS FE&C case number to infer the case date for federal cases and extract the corresponding year, while for the remaining datasets, we rely on the settlement or enforcement date.[13]

To link borrowers in our loan sample to the ECHO data, we rely on name matching, as no common identifier exists that would allow a direct match with external financial datasets. Within the EPA databases, however, facilities can be linked across datasets using a common facility identifier (Facility ID). This identifier also allows us to connect ECHO records with the EPA Toxic Release Inventory (TRI). Following He and Qiu (2025), we first link ECHO datasets to the TRI database using the facility identifier. An advantage of TRI is that it reports parent company names, which improves the quality of the borrower matching procedure. Specifically, we merge three ECHO datasets—ICIS Air, ICIS NPDES, and ICIS FE&C with TRI, thereby obtaining enhanced firm-name information for the facilities in our sample. The remaining datasets, SDWA and RCRAInfo, are matched separately, so the integration of the ECHO data proceeds in two stages.

We match the resulting datasets to our borrower sample using a fuzzy name-matching algorithm with a similarity threshold of 0.75. All retained matches are manually reviewed to ensure accuracy.[14]

Environmental violations occur for different firms at different points in time. We therefore identify the timing of the first environmental violation for each firm and construct a firm-year indicator capturing the occurrence of violations. Based on the year of the first violation, firms are assigned to treatment cohorts, which form the basis of a stacked difference-in-differences (DiD) framework (Cengiz, Dube, Lindner, & Zipperer, 2019; Wing, Freedman, & Hollingsworth, 2024). In this setup, treated firms are those experiencing their first violation in a given cohort year, while the control group consists of firms that have not yet experienced a violation by that time. The stacked dataset constructed from these cohorts allows us to examine not only the average effect of environmental violations on loan pricing, but also potential temporal heterogeneity in lenders' responses to borrowers' environmental compliance histories conditional on their biodiversity risk.

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multiple environmental statutes, including the CAA, the Resource Conservation and Recovery Act (RCRA), the CWA, the SDWA, and others. RCRAInfo provides information on hazardous-waste violations and compliance under the Resource Conservation and Recovery Act. SDWA cases record enforcement actions brought under the Safe Drinking Water Act. The EPA distinguishes 245 violation types, ranging from export infractions and unregulated waste disposal to microbial contamination and pesticide misuse. Restricting the analysis to selected violation categories would substantially reduce the sample size, so we adopt a more aggregated approach.

[13]For background on the ECHO data and related applications, see Lel (2023) and He and Qiu (2025).

[14]In some instances, the same case appears in multiple EPA systems, for example in ICIS Air, ICIS NPDES, or RCRAInfo, and may later also be recorded in ICIS FE&C when the case is escalated to the federal level. In such cases, we prioritize the ICIS FE&C record, as it reflects federal enforcement. To avoid double counting, we review and consolidate duplicate records across systems.

ii) Borrower Environmental Performance

As a complementary measure of borrower-level environmental performance, we use the Environmental (E) Pillar Score from LSEG (formerly Refinitiv/Eikon) (London Stock Exchange Group, 2026). This score provides a comprehensive assessment of firms' environmental practices and outcomes, aggregating information across multiple dimensions, including emissions, resource use, and environmental innovation.

The Environmental Pillar Score is reported as a letter grade ranging from $D-$ (lowest) to $A+$ (highest). To facilitate its use in regression analysis, we convert these letter grades into a numerical scale from 1 ($D-$) to 12 ($A+$), with higher values indicating better environmental performance. This transformation preserves the ordinal ranking of firms while allowing for a straightforward interpretation of coefficient estimates. The E-score is constructed by LSEG based on publicly available information, including company disclosures, annual reports, and third-party data sources, and is designed to be comparable across firms and over time. As such, it captures not only realized environmental outcomes but also firms' policies, targets, and governance structures related to environmental management.

In our empirical analysis, this variable serves as a complementary proxy to the violation-based measures derived from the EPA data. While violations capture realized regulatory breaches and enforcement actions within a stacked difference-in-differences framework, the E-score reflects a broader and more continuous notion of environmental performance. In specifications using the E-score, we rely on standard interaction models rather than the cohort-based DiD design. As such, these results should be interpreted as capturing cross-sectional and within-firm variation in environmental performance, rather than causal effects tied to discrete violation events.

iii) Lender Commitment to Sustainability

Lenders may differ in the extent to which they incorporate environmental considerations into lending decisions. To capture such heterogeneity, we proxy for lender-level commitment to environmental and sustainability objectives by identifying whether the lead arranger is a signatory to the Principles for Responsible Banking (PRB). The PRB were developed jointly by participating banks and the United Nations Environment Programme – Finance Initiative (UNEP-FI) and provide a global framework for aligning banking activities with the goals of the Paris Agreement and the Sustainable Development Goals. In particular, the principles emphasize the integration of environmental risks, including biodiversity loss, into financial decision-making. According to UNEP-FI, PRB signatories play "a unique and critical role in pivoting this global economic shift and achieving these objectives".[15]

[15] UNEP-FI (2021), Biodiversity Target Setting, available at: `https://www.unepfi.org/` (accessed [26.01.2026]).

We focus on PRB signatories rather than all UNEP-FI members, as the PRB represent a more formalized and targeted commitment to sustainability. UNEP-FI membership signals general engagement with environmental finance initiatives and has been used in prior studies as a proxy for environmental commitment (e.g., Ehlers et al., 2022; Degryse et al., 2023; Kacperczyk & Peydró, 2022). Thus, it encompasses a broader and more heterogeneous set of institutions. By contrast, PRB signatories commit to aligning their business strategies with sustainability objectives, including biodiversity-related targets, and are subject to disclosure and accountability requirements. As such, PRB participation provides a more stringent proxy for lender-level sustainability orientation relevant to our setting.

We manually match PRB signatories to Dealscan parent lender identifiers using bank names. Most signatories in our sample commit at the group level.[16] This allows us to construct a time-varying indicator of lender sustainability commitment at the deal level.

We use *UNEP-FI Lender* to capture lenders' sustainability orientation, but the variable is defined differently across the loan spread and loan volume regressions to reflect the structure of each dataset. In the loan spread regressions, where many loan facilities involve multiple lead arrangers, *UNEP-FI Lender* is defined at the syndicate level as the share of lead arrangers in a given deal that are PRB signatories. In the loan volume regressions, where the unit of observation is the bank-firm-year, *UNEP-FI Lender* is defined at the individual lender level and equals one if the respective bank is a PRB signatory.

iv) Lender Headquarters' Country Exposure to Environmental Vulnerability

We further examine whether lenders' geographic exposure to environmental risk moderates loan pricing. To this end, we match each lead arranger to its country of headquarters and combine this information with the ND-GAIN Country Index, which measures national climate vulnerability and adaptive capacity based on more than 40 indicators (Notre Dame Global Adaptation Initiative (ND-GAIN), 2024). The index aggregates information on exposure, sensitivity, and adaptive capacity to climate change, as well as institutional and economic readiness.

We use the overall ND-GAIN score, which is calculated as:

$$\text{ND-GAIN Score} = (\text{Readiness Score} - \text{Vulnerability Score} + 1) \times 50 \tag{5}$$

Higher values of the index indicate lower climate vulnerability and greater readiness to adapt to environmental risks.[17]

To capture lender-level exposure to environmental vulnerability, we construct a binary

[16] PRB status is assigned starting in the year a bank becomes a signatory. UNEP-FI documentation distinguishes between group and subsidiary-level signatories. We assign status at the parent level.

[17] Detailed documentation of the ND-GAIN Country Index methodology is available at: `https://gain.nd.edu/our-work/country-index/methodology/`.

variable, *Low ND-GAIN*, equal to one if the ND-GAIN score of the lender's home country is below the sample median, and zero otherwise. This specification allows us to test whether lenders headquartered in more environmentally vulnerable countries price biodiversity risk differently from those located in more resilient environments.

3.2 Descriptive Statistics

We present summary statistics for the samples used in our main regression specifications in Table 3, along with a correlation matrix for the main explanatory variables in Table 4.[18]

Because our analysis considers loan spreads, loan volumes, and lender participation, we transform the original borrower–tranche-level dataset into borrower–lender-level datasets. The unit of observation therefore differs across specifications, leading to differences in the number of observations and corresponding summary statistics across samples.[19]

Our borrower–tranche-level dataset comprises 7,670 observations across 718 unique borrowing firms. Our dependent variable is the loan spread, defined in DealScan as the All-in Spread Drawn (AISD), which measures the cost incurred by the borrower in basis points over the reference rate (historically LIBOR) for the drawn portion of the loan, including facility fees. The loan spread ranges from 17.50 to 725.00 basis points, with a mean of 176.54 basis points. Our main explanatory variables include *Biodiversity Count* and *Biodiversity Regulation* from Giglio et al. (2023), as well as five newly constructed textual measures: *Biodiversity Overall*, *Air Pollution*, *Climate Change*, *Land Use*, and *Water Pollution*. Overall, we find that the biodiversity measures by Giglio et al. (2023) are, on average, low but display notable dispersion, suggesting that while many firms have limited exposure, a non-trivial subset faces significantly higher biodiversity risks. In contrast, our measures indicate much higher exposure: about 91% of firms are classified as exposed under the Biodiversity Overall indicator, 77% for Air Pollution, 91% for Climate Change, 75% for Land Use, and 65% for Water Pollution.

All borrower and lender characteristics are measured at the annual level and lagged by one year to mitigate endogeneity concerns related to the timing of loan origination. The average deal size is 20.86 in logarithmic terms, corresponding to USD 2,061.17 million. Loan maturity has a mean of 3.79 (in log months) and a maximum of 4.50. Loan facilities have up to 27 lead arrangers, with an average of 4.11. A substantial share of facilities are arranged by a single lead bank (see Figure 1). In addition, 40% of loans are secured and 66% include financial covenants.

[18] Summary statistics are reported for the estimation samples corresponding to the main regression specifications and thus reflect the fixed-effects structure introduced in Section 4. Continuous variables are winsorized at the 1st and 99th percentiles to mitigate the influence of outliers.

[19] As an extension, we also analyze lenders' participation decisions in syndicated loans. This analysis relies on a borrower–lender-level dataset, for which the data are reconstructed based on lender shares, as described in Section 6.

Firm size is measured as the natural logarithm of total assets, with a mean of 22.10 (approximately USD 15,556.10 million). Return on assets averages 5.24%, leverage 27.94%, and tangibility 24.56%.

Lender characteristics in the facility-level regressions are averaged across lead arrangers within each syndicate. The mean (log) size of lead arrangers is 28.17 (approximately USD 1,956.16 billion). Average lender income is 49.49%, and lender capitalization is 9.29%. Approximately 12% of loans are arranged by lead arrangers that are UNEP-FI PRB signatories. Furthermore, about 48% of loans are arranged by lenders headquartered in countries classified as Low ND-GAIN, i.e., below the sample median and thus relatively more vulnerable to environmental risks. The mean Environmental Pillar Score is 6.44 (out of 12).

Our borrower–lender-level dataset comprises 2,041 observations across 456 unique borrowing firms. The dependent variable is the natural logarithm of loan volume, with a mean of 18.58 (corresponding to USD 223.63 million) and ranging from 15.36 to 21.14. The descriptive statistics of biodiversity measures are broadly consistent with those reported earlier, showing comparable distributions and magnitudes across the sample.

Borrower and lender characteristics are measured annually and lagged by one year. Firm size has a mean of 22.88 (approximately USD 29,788.87 million). Return on assets averages 6.23%, leverage 26.27%, tangibility 24.15%, and the average coverage ratio is 30.20.

Lender characteristics include capitalization (mean 9.29%) and income (mean 49.61%). The mean (log) size of lead arrangers is 28.15 (approximately USD 1,972.24 billion). Roughly 50% of loans are arranged by PRB-affiliated lenders, and around 50% of lenders are classified as Low ND-GAIN. The average Environmental Pillar Score is 7.55, with a maximum of 12.

Table 3 about here

Table 4 reports the pairwise correlations among the main explanatory variables. Biodiversity Count and Biodiversity Regulation are highly correlated (0.855), reflecting their similar construction based on closely related keyword classifications (see Figure 2a). As a result, the two measures capture largely overlapping dimensions of biodiversity exposure.

By contrast, Biodiversity Overall is only weakly correlated with both Biodiversity Count (-0.042) and Biodiversity Regulation (-0.046). This is consistent with differences in construction, as the overall measure is derived using an alternative methodology that captures broader environmental dimensions rather than relying on keyword frequency alone.

Biodiversity Overall exhibits moderate positive correlations with the four environmental pressure measures: Air Pollution (0.426), Climate Change (0.588), Land Use (0.401), and Water Pollution (0.361). These patterns are consistent with the design of the measure, which links biodiversity risk to underlying environmental stressors. Overall, the correlation structure suggests that Biodiversity Overall captures a broader dimension of environmental risk that is distinct from the keyword-based measures.

Table 4 about here

4 Empirical Approach

We organize our empirical analysis around two questions. First, does firm-level biodiversity risk affect the price of bank credit? Second, does it affect the quantity of credit supplied to firms? To address these questions, we estimate two baseline specifications. The first relates biodiversity risk to loan spreads at the tranche level. The second examines whether biodiversity exposure affects the total volume of credit extended at the bank–firm level.

We further examine heterogeneity in these effects along borrower and lender dimensions. On the borrower side, we consider firms' environmental compliance history (Section 4.2.1) and environmental performance (Section 4.2.2). On the lender side, we study whether effects vary with sustainability commitments and geographic exposure to environmental vulnerability (Sections 4.2.3 and 4.2.4).

Identification relies on variation across firms, banks, and time. Biodiversity risk is measured using both the keyword-based indicator from Giglio et al. (2023) and our sentence-based measures, while lending outcomes are obtained from DealScan and merged with firm- and lender-level controls. Variable definitions and data sources are described in Section 3.

Finally, we examine whether biodiversity risk affects lenders' participation decisions in syndicated loans. In particular, we test whether banks with sustainability commitments, proxied by UNEP-PRB signatory status, are differentially likely to participate in loans to firms with higher biodiversity risk. This analysis captures the extensive margin of credit supply and is presented in Section 6.

4.1 Do Banks Account for Firm Biodiversity in their Lending Decisions?

Loan Spreads

To examine the effect of biodiversity risk on loan pricing, we estimate the following specification at the borrower–tranche level:

$$\begin{aligned}\text{Loan Spread}_{l,f,b,t} = \alpha + \beta\,\text{Bio Risk}_{f,t} + \gamma\,\text{Loan}_{l,f,b,t} + \delta\,\text{Firm}_{f,t-1} \\ + \zeta\,\text{Lead Bank}_{b,t-1} + \text{FE} + \varepsilon_{l,f,b,t}\end{aligned} \tag{6}$$

where Loan Spread$_{l,f,b,t}$ denotes the spread of loan l extended to firm f by bank b at time t.[20] Loan spreads are measured as the All-in Spread Drawn (AISD), defined as the spread in basis points over the reference rate for the drawn portion of the loan, including facility fees (T. Berg, Saunders, & Steffen, 2016; Gao, Hua, & Khurshed, 2021).

[20]We use the DealScan Active Deal Date to define the time index t, measured at the year level.

Bio $\text{Risk}_{f,t}$ denotes firm-level biodiversity risk. We consider both the keyword-based measures from Giglio et al. (2023), *Biodiversity Count* and *Biodiversity Regulation*, and our sentence-based measures, including *Biodiversity Overall* as well as disaggregated indicators for *Air Pollution*, *Climate Change*, *Land Use*, and *Water Pollution*.

We follow the literature in including loan and borrower-level control variables that may affect loan spreads. $\text{Loan}_{l,f,b,t}$ captures loan characteristics such as size, maturity, covenants, collateral, and the number of lead arrangers. $\text{Firm}_{f,t-1}$ includes borrower characteristics, like size (logarithm of total assets), profitability (return on assets), leverage (debt over assets), tangibility (the ratio of tangible assets to total assets) and coverage (EBITDA over interest expenses).

Given the syndicated structure of the loan market, each facility is arranged by a lead bank (lead arranger) that negotiates loan terms, performs due diligence, screens the borrower, and organizes the syndicate. Participating banks provide funding but are not directly involved in borrower screening or monitoring. As a result, the lead arranger plays a central role in loan origination and monitoring (Doerr & Schaz, 2021; Sufi, 2007). Following the literature (Degryse et al., 2023; Ehlers et al., 2022; Ho & Wong, 2023), we capture lead arranger characteristics with the vector Lead $\text{Bank}_{b,t-1}$, which includes bank characteristics, such as size (total assets), capitalization (the ratio of total equity to total assets), and income capturing the business model of the bank (net interest income over operating revenue).[21] Both borrower and lender characteristics are lagged by one period to mitigate endogeneity concerns related to loan origination timing.

In our baseline regressions, we consider specifications with separate loan purpose, borrower industry (two-digit SIC code), year, and U.S. state fixed effects.[22] Our model-of-choice specification always includes purpose and three way interacted industry × U.S. state × year fixed effects, which absorb time-varying local industry shocks and regional demand conditions. As a result, identification stems from within industry–state–year variation in how banks price and allocate credit to firms with different biodiversity risk exposure, rather than from common differences in borrower demand or local economic conditions (Chava, 2014; Degryse, De Jonghe, Jakovljević, Mulier, & Schepens, 2019; Giannetti, Jasova, Loumioti, & Mendicino, 2024). We acknowledge that firm-specific demand adjustment within these cells may still remain. As our main biodiversity risk measures vary primarily at the firm-time level and exhibit limited variation at the same level, the inclusion of borrower fixed effects is overly restrictive in most of our specifications. In all our estimations, we cluster the standard errors at the borrower level.

[21] For loans with multiple lead arrangers, we follow Heider, Saidi, and Schepens (2019) and Degryse et al. (2023) and use the average of lead bank characteristics.

[22] We provide an industry overview of the Borrower - Tranche Level dataset in Table A2.

Loan Volume

To examine whether biodiversity risk affects credit supply, we estimate the following specification at the bank–firm level:

$$\begin{aligned}\log(\text{Loan Volume})_{f,b,t} = \alpha + \beta\,\text{Bio Risk}_{f,t} + \delta\,\text{Firm}_{f,t-1} \\ + \zeta\,\text{Lead Bank}_{b,t-1} + \text{FE} + \varepsilon_{f,b,t}.\end{aligned} \tag{7}$$

The dependent variable, Loan Volume$_{f,b,t}$, measures the outstanding loan exposure of bank b to firm f at time t. Following the literature, we construct this variable by aggregating the shares of syndicated loans held by each bank across all active facilities (Chakraborty, Goldstein, & Mackinlay, 2018; Doerr & Schaz, 2021; Mueller & Sfrappini, 2025). Specifically, we allocate loan shares to individual lenders at origination and sum outstanding positions until maturity.[23] The dependent variable is defined as the natural logarithm of this measure.

We include the same set of borrower and lead arranger characteristics as in the loan spread specifications. As before, in our baseline specifications, we test models with separate borrower industry (two-digit SIC), U.S. state, and year fixed effects. In addition to controlling for lender heterogeneity using bank-level controls, we also introduce lender fixed effects, which absorb time-invariant differences across banks. We further consider specifications with lender × time fixed effects (Degryse et al., 2023; Kacperczyk & Peydró, 2022). Our main model of choice, however, includes lender fixed effects and three-way industry × U.S. state × year fixed effects, which provide a more restrictive specification to isolate credit supply effects from time-varying regional and industry shocks, while also accounting for time-invariant differences across banks (Doerr & Schaz, 2021).

4.2 Heterogeneity Across Borrowers and Lenders

4.2.1 Do Banks Adjust Lending Terms More Strongly for Biodiversity-Exposed Firms Following Environmental Violations?

While the baseline specifications include a rich set of controls and fixed effects, they remain correlational. To strengthen identification, we exploit firm-level environmental violations recorded by the U.S. Environmental Protection Agency (EPA) as shocks to firms' environmental credibility. Such violations increase regulatory scrutiny and may alter lenders' perceptions of borrowers' environmental and biodiversity-related risks.

Environmental violations occur for different firms at different points in time, which requires an empirical approach that accounts for staggered treatment timing. Due to the problems associated with traditional staggered designs in such settings (Baker, Larcker, &

[23] DealScan provides lender shares for a subset of syndicated loans. When this information is unavailable, we allocate loan amounts equally across participating banks, following Doerr and Schaz (2021).

Wang, 2022), we employ a stacked difference-in-differences (DiD) (Cengiz et al., 2019; Wing et al., 2024). Specifically, we divide the sample into cohorts based on the year of the first environmental violation. For each cohort, treated firms are those whose first violation occurs in that year, while the control group consists of firms that have not yet experienced a violation by that time (including firms that violate only later or never violate). This approach prevents late-treatment bias by ensuring that already-treated firms are not used as controls. We first identify the timing of the first environmental violation for each firm and create a firm-year indicator capturing the occurrence of violations. Using this information, we construct cohort-specific treatment groups and corresponding event-time windows around the violation year. Finally, we stack all cohort samples into a single dataset and estimate a triple difference-in-differences specification interacting treated, post and biodiversity indicator. This approach allows us to examine not only the average effect of environmental violations on loan pricing, but also potential temporal heterogeneity in lenders' responses to borrowers' environmental compliance histories conditional on their biodiversity risk.

$$\begin{aligned}
\text{Loan Spread}_{l,f,b,t} = {} & \alpha + \beta_1 \,\text{Bio Risk}_{f,t} + \beta_2 \,\text{Treated}_{f,c} + \beta_3 \,\text{Post}_{f,c,t} \\
& + \beta_4(\text{Treated}_{f,c} \times \text{Post}_{f,c,t}) \\
& + \beta_5(\text{Bio Risk}_{f,t} \times \text{Treated}_{f,c}) \\
& + \beta_6(\text{Bio Risk}_{f,t} \times \text{Post}_{f,c,t}) \\
& + \beta_7(\text{Bio Risk}_{f,t} \times \text{Treated}_{f,c} \times \text{Post}_{f,c,t}) \\
& + \gamma \,\text{Loan}_{l,f,b,t} + \delta \,\text{Firm}_{f,t-1} + \zeta \,\text{Lead Bank}_{b,t-1} \\
& + \text{FE} + \varepsilon_{l,f,b,t}.
\end{aligned} \tag{8}$$

For each cohort c, $\text{Treated}_{f,c}$ equals one for firms whose first violation occurs in cohort c, and zero otherwise. $\text{Post}_{f,c,t}$ equals one for observations in the violation year and subsequent years within the event window, and zero otherwise. In the baseline specification, we use a symmetric event window of three years before and three years after the violation, $[-3, +3]$. Firms without recorded violations remain untreated throughout the sample period. This framework allows us to compare lending outcomes before and after violation events while using not-yet-treated firms as controls, thereby identifying lenders' pricing responses to borrowers' environmental violations depending on their biodiversity risk exposures.

The coefficient of interest is β_7, which captures whether lenders differentially adjust loan pricing for biodiversity-exposed firms following environmental violations.

We include the same firm, loan, and lender-level control variables as in Equation 6. Moreover, we include cohort × year fixed effects in addition to loan purpose and three-way interacted industry × U.S. state × year fixed effects. The cohort × year fixed effects absorb time-varying shocks specific to each violation cohort in the stacked sample, ensuring that treated firms are compared with not-yet-treated firms within the same cohort and calendar year. As before, loan purpose and industry × U.S. state × year fixed effects control for differences in contract design and time-varying local demand and regional economic conditions.

Identification therefore stems from differences in lending terms between firms experiencing an environmental violation and firms that have not yet experienced a violation but operate in the same local industry–state–year environment and receive loans for similar purposes. This structure ensures that the estimated effects capture banks' responses to environmental violations rather than differences in contract characteristics or local economic conditions across borrowers.

We implement an analogous specification for loan volume:

$$\begin{aligned}\log(\text{Loan Volume})_{f,b,t} = {} & \alpha + \beta_1 \,\text{Bio Risk}_{f,t} + \beta_2 \,\text{Treated}_{f,c} + \beta_3 \,\text{Post}_{f,c,t} \\ & + \beta_4(\text{Treated}_{f,c} \times \text{Post}_{f,c,t}) \\ & + \beta_5(\text{Bio Risk}_{f,t} \times \text{Treated}_{f,c}) \\ & + \beta_6(\text{Bio Risk}_{f,t} \times \text{Post}_{f,c,t}) \\ & + \beta_7(\text{Bio Risk}_{f,t} \times \text{Treated}_{f,c} \times \text{Post}_{f,c,t}) \\ & + \delta \,\text{Firm}_{f,t-1} + \zeta \,\text{Lead Bank}_{b,t-1} \\ & + \text{FE} + \varepsilon_{f,b,t}.\end{aligned} \tag{9}$$

The loan volume regressions include all firm and lender-level control variables as in Equation 7. In addition, we incorporate cohort × year and industry × U.S. state × year fixed effects, and further include lender fixed effects as before.

4.2.2 Is the Effect of Biodiversity Risk on Bank Lending Decisions Amplified by Low Environmental Performance?

To examine borrower heterogeneity, we test whether the effect of biodiversity risk is stronger for firms with weaker environmental performance. We proxy for environmental performance using the Environmental Pillar Score (E-Score). We augment the baseline specifications by interacting biodiversity risk with the E-Score. The loan spread specification is given by:

$$\begin{aligned}\text{Loan Spread}_{l,f,b,t} = {} & \alpha + \beta_1 \,\text{Bio Risk}_{f,t} + \beta_2 \,\text{E-Score}_{f,t} \\ & + \beta_3(\text{Bio Risk}_{f,t} \times \text{E-Score}_{f,t}) \\ & + \gamma \,\text{Loan}_{l,f,b,t} + \delta \,\text{Firm}_{f,t-1} + \zeta \,\text{Lead Bank}_{b,t-1} \\ & + \text{FE} + \varepsilon_{l,f,b,t}.\end{aligned} \tag{10}$$

The corresponding loan volume specification is:

$$
\begin{aligned}
\log(\text{Loan Volume})_{f,b,t} = \alpha &+ \beta_1 \,\text{Bio Risk}_{f,t} + \beta_2 \,\text{E-Score}_{f,t} \\
&+ \beta_3 (\text{Bio Risk}_{f,t} \times \text{E-Score}_{f,t}) \\
&+ \delta \,\text{Firm}_{f,t-1} + \zeta \,\text{Lead Bank}_{b,t-1} \\
&+ \text{FE} + \varepsilon_{f,b,t}.
\end{aligned} \tag{11}
$$

The coefficient of interest is β_3, which captures whether the effect of biodiversity risk varies with firms' environmental performance.

The E-Score ranges from 1 to 12, with higher values indicating better environmental performance. Thus, the interaction term between biodiversity risk and E-Score tests whether banks price and allocate credit differently when biodiversity exposure coincides with weak environmental performance. This specification allows us to assess whether biodiversity risk becomes more salient for lenders when firms have an overall poor environmental track record. The fixed effects specification and control variables remain as in our baseline models outlined in Equations 6 and 7.

4.2.3 Do Committed Banks Account More for Firm Biodiversity Risk in Their Lending Decisions?

To examine lender heterogeneity, we test whether banks' sustainability commitments affect how they price and allocate credit to firms exposed to biodiversity risk. We proxy for sustainability commitments using participation in the United Nations Environment Programme – Finance Initiative (UNEP-FI), specifically the Principles for Responsible Banking (PRB), following Ehlers et al. (2022).

We augment the baseline specifications by interacting biodiversity risk with a lender commitment indicator. The loan spread specification is:

$$
\begin{aligned}
\text{Loan Spread}_{l,f,b,t} = \alpha &+ \beta_1 \,\text{Bio Risk}_{f,t} + \beta_2 \,\text{UNEP-FI Lender}_{b,t} \\
&+ \beta_3 (\text{Bio Risk}_{f,t} \times \text{UNEP-FI Lender}_{b,t}) \\
&+ \gamma \,\text{Loan}_{l,f,b,t} + \delta \,\text{Firm}_{f,t-1} + \zeta \,\text{Lead Bank}_{b,t-1} \\
&+ \text{FE} + \varepsilon_{l,f,b,t}.
\end{aligned} \tag{12}
$$

The corresponding loan volume specification is:

$$\begin{aligned}\log(\text{Loan Volume})_{f,b,t} = &\ \alpha + \beta_1 \,\text{Bio Risk}_{f,t} + \beta_2 \,\text{UNEP-FI Lender}_{b,t} \\ &+ \beta_3(\text{Bio Risk}_{f,t} \times \text{UNEP-FI Lender}_{b,t}) \\ &+ \delta \,\text{Firm}_{f,t-1} + \zeta \,\text{Lead Bank}_{b,t-1} \\ &+ \text{FE} + \varepsilon_{f,b,t}.\end{aligned} \tag{13}$$

The coefficient of interest is β_3, which captures whether banks with sustainability commitments differentially price and allocate credit to firms with higher biodiversity risk.

4.2.4 Do Banks Headquartered in Regions with Higher Biodiversity Exposure Account More for Firm Biodiversity Risk in Their Lending Decisions?

In this section, we examine whether banks' geographic exposure to environmental risk affects how they price and allocate credit to biodiversity-exposed firms. Environmental vulnerability varies across countries, implying that banks headquartered in more exposed regions may be more sensitive to biodiversity-related risks.

To capture cross-country differences in environmental vulnerability, we use the ND-GAIN Country Index provided by the University of Notre Dame (Notre Dame Global Adaptation Initiative (ND-GAIN), 2024). The index measures a country's vulnerability to environmental risks and its capacity to adapt, with lower scores indicating higher vulnerability.

Following Section 4.2.3, we interact firm-level biodiversity risk with an indicator for whether the lead arranger is headquartered in a country with high environmental vulnerability. Specifically, we define a dummy variable Low $\text{ND-GAIN}_{b,t}$ that equals one if the ND-GAIN score of the lender's home country is below the sample median in a given year, and zero otherwise.[24]

The coefficient on the interaction term $\text{Bio Risk}_{f,t} \times \text{Low ND-GAIN}_{b,t}$ captures whether banks headquartered in more environmentally vulnerable countries respond differently to borrower biodiversity risk. Conditional on the fixed-effects structure described above, identification relies on differences in lending behavior across banks facing different environmental pressures when lending to firms operating in the same industry–state–year environment.

[24] For applications of ND-GAIN data, see Y. Liu, Wang, Wen, and Wu (2024) and Giglio, Kuchler, Stroebel, and Wang (2024).

5 Empirical results

5.1 Do Banks Account for Firm Biodiversity in Their Lending Decisions?

Tables 5 and 6 report the baseline results from Equation 6 across alternative biodiversity measures. Focusing on Table 5, Columns (1)–(4) present results using the measures proposed by Giglio et al. (2023), namely *Biodiversity Count* and *Biodiversity Regulation*. Both measures are positively and significantly associated with loan spreads across specifications, indicating that firms with higher biodiversity risk face higher borrowing costs.

The economic magnitude is non-trivial, although only a small fraction of firms (approximately 4%) are classified as biodiversity-exposed under these measures (see Table 2). Columns (5)–(6) report results for our measure, *Biodiversity Overall*. The coefficient is not statistically significant in Column (5), but becomes positive and significant in Column (6) when employing a more restrictive fixed-effects specification.

This pattern suggests that the information captured by the *Biodiversity Overall* measure is identified primarily from within industry × U.S. state × year variation. Controlling for these high-dimensional fixed effects absorbs time-varying local industry and regional conditions, allowing for a sharper identification of firm-level biodiversity exposure.

In Table 6, we report the baseline results for the biodiversity risk drivers: *Air Pollution*, *Climate Change*, *Land Use*, and *Water Pollution*. Across specifications, all four measures are positively associated with loan spreads. While statistical significance is weaker in specifications with less restrictive fixed effects, the coefficients remain consistently positive and become statistically significant when employing the most stringent fixed-effects structure. Overall, these results indicate that exposure to biodiversity-related risk drivers is associated with higher borrowing costs.

These findings suggest that lenders respond not only to aggregate biodiversity risk but also to its underlying environmental drivers, which overlap with broader environmental risk factors. This evidence is consistent with Erten and Ongena (2024), who document that banks charge higher loan spreads to firms associated with greater environmental harm.

In terms of economic magnitude, focusing on specifications with interacted fixed effects, the estimated effects range from approximately 4% to 18% of the sample mean loan spread (176.54 basis points). The largest effect is observed for *Biodiversity Overall*, which is associated with an increase of 32 basis points in loan spreads, corresponding to approximately 18% of the average.[25]

In our estimations, we use a conservative identification strategy that accounts for various characteristics at the loan, firm, and lender levels. The estimated coefficients on control

[25] As all biodiversity risk indicators are binary variables, we assess economic significance by comparing estimated coefficients to the mean of the dependent variable, following Mitton (2022).

variables are broadly consistent with prior literature. Deal size is negatively related to loan spreads but not statistically significant. Loan maturity is negatively and significantly associated with spreads in most specifications. The presence of covenants is also negatively and significantly related to loan spreads, consistent with their role in mitigating credit risk. Secured loans are associated with higher spreads, indicating that collateral is primarily used by riskier borrowers (Golden & Liu, 2025). A larger number of lead arrangers is, when significant, positively associated with spreads.

Firm characteristics exhibit expected patterns. Larger and more profitable firms (measured by return on assets) face lower borrowing costs. Leverage is negatively and significantly associated with loan spreads, while tangibility is generally not statistically significant. Coverage is statistically significant in some specifications and enters with a positive coefficient.

Regarding lender characteristics, capitalization, income, and size are all negatively and significantly associated with loan spreads. This suggests that larger and better-capitalized banks, as well as those with greater reliance on interest-based income, provide lower-cost financing.

Table 5 about here

Table 6 about here

Turning to loan volume, Table 7 indicates that firms with higher overall and regulatory biodiversity risk tend to receive lower credit volumes. However, the estimated effects are generally not statistically significant across specifications. The magnitude of the coefficients remains relatively stable under alternative fixed-effects structures.

Table 7 about here

Table 8 about here

Among the sub-components reported in Table 8, *Water Pollution* is the only dimension that exhibits a statistically significant negative association with loan volume (Columns 10 and 12). Focusing on Column 12, the estimates imply that firms with high *Water Pollution* exposure receive approximately 12.2% lower loan volumes, corresponding to a reduction of about USD 27 million relative to the sample mean.[26]

[26] The average loan volume in the sample is USD 223.63 million. A coefficient of -0.130 in a log loan volume regression implies a percentage change of $\exp(-0.130) - 1 \approx -12.2\%$, corresponding to a reduction of approximately USD 27 million when evaluated at the sample mean.

5.2 Heterogeneity Across Borrowers and Lenders

5.2.1 Do Banks Adjust Lending Terms More Strongly for Biodiversity-Exposed Firms Following Environmental Violations?

Table 9 reports results from the stacked triple difference-in-differences design based on EPA environmental violation events introduced in Section 4.2.1. Overall, the findings suggest that biodiversity risk becomes more salient under regulatory scrutiny, leading to differential pricing responses by lenders.

The standalone biodiversity risk indicator is positive and statistically significant across all specifications, consistent with higher loan spreads for firms with greater biodiversity exposure. The coefficient on the triple interaction is positive in all specifications, but statistically significant only for the *Biodiversity Overall* measure, with an estimated effect of 51.46 basis points. This implies that, following an environmental violation, firms with higher biodiversity risk experience a larger increase in loan spreads relative to both lower-risk firms and the control group.

These results suggest that biodiversity risk is priced more strongly when environmental violations increase its salience to lenders. The stronger and more consistent effect for the *Biodiversity Overall* measure suggests that it captures aspects of biodiversity risk that become particularly relevant under heightened regulatory attention.

Table 9 about here

Turning to Table 10, we examine whether the pricing effects observed for loan spreads extend to the quantity of bank lending. The standalone biodiversity indicators are generally not statistically significant, suggesting that biodiversity exposure does not affect lending volumes prior to an environmental violation.

Following an EPA violation, however, the estimates indicate a reduction in credit supply. For the biodiversity measures of Giglio et al. (2023), the interaction terms are negative and statistically significant at the 10% level, implying that banks reduce lending to biodiversity-exposed firms once environmental misconduct becomes publicly known.

These results are consistent with lenders becoming more sensitive to firms' environmental risk profiles after violations, leading to more constrained credit access for biodiversity-exposed firms.

Table 10 about here

5.2.2 Is the Effect of Biodiversity Risk on Bank Lending Decisions Amplified by Low Environmental Performance?

We examine whether the effect of biodiversity risk on loan spreads reflects firms' overall environmental performance, as captured by the Environmental (E) score. To this end, we interact biodiversity risk measures with the continuous E-score.

For *Biodiversity Count* and *Biodiversity Regulation*, neither the main effects nor the interaction terms are statistically significant, suggesting that these measures do not capture variation in biodiversity risk beyond what is reflected in general environmental performance.

In contrast, for the *Biodiversity Overall* measure, the main effect is positive and statistically significant, while the interaction with the E-score is negative and statistically significant at the 5% level. This indicates that biodiversity risk is associated with higher borrowing costs, but that this effect is attenuated for firms with stronger environmental performance.

A similar pattern emerges for the *Land Use* indicator, where biodiversity exposure is positively associated with loan spreads and the interaction with the E-score is negative and significant. For the remaining drivers, the interaction terms are not statistically significant.

Overall, these findings suggest that biodiversity risk captures information beyond standard ESG-based environmental performance measures, while its pricing is partially moderated by stronger firm environmental performance.

Table 11 about here

Turning to loan volume in Table 12, *Biodiversity Count* and *Biodiversity Regulation* exhibit negative and statistically significant main effects, indicating that biodiversity exposure is associated with lower loan volumes. The interaction terms with the Environmental (E) score are positive and significant, suggesting that this reduction in lending is attenuated for firms with stronger environmental performance. This pattern is consistent with these measures capturing broader environmental risk reflected in ESG ratings.

In contrast, for the *Biodiversity Overall* measure, neither the main effect nor the interaction with the E-score is statistically significant. Similarly, we do not observe significant interaction effects for the individual biodiversity pressure drivers.

Taken together, these results provide no evidence that the effects associated with our biodiversity measures on loan volume vary systematically with firms' overall environmental performance.

Table 12 about here

5.2.3 Do Committed Banks Account More for Firm Biodiversity Risk in Their Lending Decisions?

Table 13 reports the results for Equation 12. Across specifications using *Biodiversity Count* and *Biodiversity Regulation*, biodiversity exposure is positively and significantly associated with loan spreads. However, the interaction terms with the UNEP-FI indicator are not statistically significant, suggesting that these keyword-based indicators do not uncover differential pricing of biodiversity risk by sustainability-committed banks.

In contrast, for the *Biodiversity Overall* measure, biodiversity exposure remains positively associated with loan spreads, and the interaction with the UNEP-FI indicator is positive and statistically significant. This implies that UNEP-FI banks charge a higher spread to firms with higher biodiversity risk relative to non-UNEP-FI lenders.

Examining the individual biodiversity pressure drivers, *Air Pollution*, *Climate Change*, and *Water Pollution* are positively and significantly associated with loan spreads. However, none of the interaction terms with the UNEP-FI indicator are statistically significant. This suggests that differential pricing by UNEP-FI banks does not operate through individual environmental dimensions but is instead captured at the aggregate level.

Finally, the standalone UNEP-FI coefficient is positive and statistically significant in some specifications, indicating that these banks tend to charge higher spreads on average. Overall, the results suggest that biodiversity risk is priced by banks, with more comprehensive measures more effectively capturing the underlying risk and thus uncovering stronger pricing by sustainability-committed banks.

Table 13 about here

Turning to loan volume in Table 14, neither the biodiversity measures nor their interactions with the UNEP-FI indicator are statistically significant across specifications. This suggests that biodiversity exposure does not affect the quantity of credit supplied by UNEP-FI banks relative to other lenders.

By contrast, the standalone UNEP-FI coefficient is negative and statistically significant in several specifications, indicating that UNEP-FI banks provide smaller loan amounts on average, independent of biodiversity exposure. This pattern reflects differences in general lending behavior rather than a biodiversity-specific response.

Overall, the results indicate that sustainability-committed banks adjust primarily along the pricing margin rather than the quantity margin. While they charge higher spreads to biodiversity-exposed firms, they do not reduce lending volumes to these borrowers.

Table 14 about here

5.2.4 Do Banks Headquartered in Regions with Higher Biodiversity Exposure Account More for Firm Biodiversity Risk in Their Lending Decisions?

Table 15 reports the results corresponding to Section 4.2.4, examining whether lenders headquartered in countries with low climate adaptation readiness, defined as being below the median of the ND-GAIN index, differentially price borrower biodiversity risk.

The *Biodiversity Overall* measure remains positively and statistically significant, consistent with the baseline results. However, the interaction term *Biodiversity Overall* × *Low ND-GAIN* is not statistically significant, indicating that the pricing of biodiversity risk does not vary systematically with lenders' exposure to environmental vulnerability. For *Biodiversity Count* and *Biodiversity Regulation*, neither the main effects nor the interaction terms are statistically significant.

A similar pattern holds for the individual biodiversity pressure drivers. *Air Pollution*, *Climate Change*, *Land Use*, and *Water Pollution* are positively associated with loan spreads, while the corresponding interaction terms with *Low ND-GAIN* are not statistically significant. The standalone *Low ND-GAIN* indicator is also not statistically significant, suggesting that lenders in more climate-vulnerable countries do not charge systematically different spreads on average.

Overall, these findings provide no evidence that lenders' geographic exposure to environmental vulnerability affects the pricing of biodiversity risk.

Table 15 about here

Turning to loan volume, Table 16 examines whether biodiversity risk exposure is associated with the quantity of credit supplied. For the *Biodiversity Overall* measure and the individual biodiversity pressure drivers, the estimated effects are generally not statistically significant. An exception is *Climate Change*, which is positively associated with loan volume at the 10% level.

For *Biodiversity Count* and *Biodiversity Regulation*, a different pattern emerges. The main effects are negative and statistically significant, indicating that biodiversity exposure is associated with lower loan volumes on average. In contrast, the interaction terms with *Low ND-GAIN* are positive and statistically significant, suggesting that this negative association is attenuated for lenders headquartered in more climate-vulnerable countries. One interpretation is that these lenders face different constraints or incentives in credit allocation, although we do not directly test this mechanism. In particular, lenders from more climate-vulnerable countries may include a larger share of foreign banks, for whom lending to U.S. firms is less tied to domestic constraints, making them less likely to reduce lending to biodiversity-exposed firms.

The standalone *Low ND-GAIN* coefficient is generally not statistically significant, indicating that lenders in more climate-vulnerable countries do not differ in their overall lending volumes independent of biodiversity exposure.

Overall, heterogeneity across lenders with respect to climate vulnerability appears more pronounced when biodiversity exposure is measured using the keyword-based indicators. In contrast, when biodiversity risk is captured by the broader *Biodiversity Overall* measure, we do not observe systematic differences in lending volumes across lenders with different levels of environmental exposure.

Table 16 about here

6 Extension: Lender Syndicate Participation

Because loan pricing and lending volumes are observed only for banks that choose to participate in a syndicated loan, the baseline specifications condition on an endogenous participation decision. To address this selection margin, we extend the analysis to examine banks' participation choices in syndicated lending. Banks may manage their exposure to biodiversity risk not only through pricing and loan quantities, but also through participation decisions. In particular, sustainability-oriented banks may mitigate exposure by opting out of deals involving borrowers with higher biodiversity risk.

We therefore study whether firm-level biodiversity risk affects banks' participation in syndicated loans, following the empirical framework of Sufi (2007). Rather than focusing on pricing or loan size, this specification captures the extensive margin of credit supply—namely, which banks choose to join a given loan syndicate as lead arrangers.

$$\begin{aligned} \text{Syndicate Participant}_{l,f,b,t} = \alpha &+ \beta_1 \,\text{Bio Risk}_{f,t} + \beta_2 \,\text{UNEP-FI Lender}_{b,t} \\ &+ \beta_3 (\text{Bio Risk}_{f,t} \times \text{UNEP-FI Lender}_{b,t}) \\ &+ \gamma \,\text{Loan}_{l,f,b,t} + \delta \,\text{Firm}_{f,t-1} + \zeta \,\text{Lender}_{b,t-1} \\ &+ \text{FE} + \varepsilon_{l,f,b,t}. \end{aligned} \tag{14}$$

The dependent variable, Syndicate Participant$_{l,f,b,t}$, equals one if bank b participates as a lead arranger in loan l to firm f at time t, and zero otherwise. As syndicated loans may involve multiple lead arrangers, this specification captures the decision of a bank to assume a lead role in a given transaction.

To construct the choice set, we restructure the loan volume dataset at the bank–firm–loan level and restrict potential participants to banks active in the syndicated loan market in year t. Following Bharath, Dahiya, Saunders, and Srinivasan (2007) and Sufi (2007), we further restrict the sample to the top 100 banks by market share in each year. This approach ensures a well-defined set of potential participants for each deal. We estimate the model using a probit specification.[27]

Table 17 reports the estimates for Equation 14. Overall, the results provide limited evidence that firm-level biodiversity risk affects banks' participation decisions in syndicated loans. The coefficients on the biodiversity measures are generally not statistically significant. An exception is the *Biodiversity Overall* measure, which is positive and statistically significant at the 10% level.

The standalone *UNEP-FI Lender* indicator is positive and statistically significant in some specifications, indicating that sustainability-committed banks are more likely to participate as lead arrangers. This pattern likely reflects the fact that these banks are larger and more active in the syndicated loan market.

The interaction terms between biodiversity risk and the UNEP-FI indicator are generally not statistically significant. The only exception is the *Water Pollution* measure, for which

[27] Sufi (2007) studies the role of information asymmetry in the formation of syndicated loan networks and argues that the empirical predictions apply symmetrically to the selection of lenders into deals.

the interaction term is negative and statistically significant, suggesting a lower likelihood of participation for sustainability-committed banks in loans to firms with higher exposure along this dimension.

Overall, the results indicate that banks' participation decisions are not systematically driven by borrower biodiversity risk.

7 Conclusion

This paper studies how biodiversity-related risks are reflected in bank lending decisions. We develop a set of text-based indicators derived from firms' disclosures using an embedding-based approach that captures the semantic content of environmental risk. This framework allows us to move beyond keyword-based measures and identify more nuanced dimensions of biodiversity exposure, including its underlying drivers such as air pollution, climate change, land use and water pollution.

We document that biodiversity risk is significantly priced in syndicated loan markets. Firms with higher biodiversity exposure face significantly higher loan spreads, while the evidence for loan volumes is weaker. This pattern suggests that banks primarily adjust along the pricing margin rather than restricting credit supply.

To better understand the mechanisms underlying these results, we examine heterogeneity across borrowers and lenders. On the borrower side, we show that the pricing of biodiversity risk is amplified following environmental violations, particularly when using our comprehensive biodiversity measure. This pattern indicates that biodiversity risk becomes more salient to lenders following adverse environmental shocks. In contrast, the effects on loan volumes remain limited, suggesting that banks do not systematically withdraw credit even after adverse environmental events. Similar patterns arise when conditioning on firms' ESG environmental performance. Consistent with this interpretation, our stacked difference-in-differences design provides causal evidence that biodiversity risk amplifies loan pricing for firms following environmental violations.

On the lender side, we find that sustainability-committed banks (UNEP-FI signatories) place greater weight on biodiversity risk in pricing, while we find no systematic evidence that banks headquartered in more environmentally vulnerable countries behave differently. In addition, biodiversity risk does not appear to materially affect banks' participation decisions in syndicated loans.

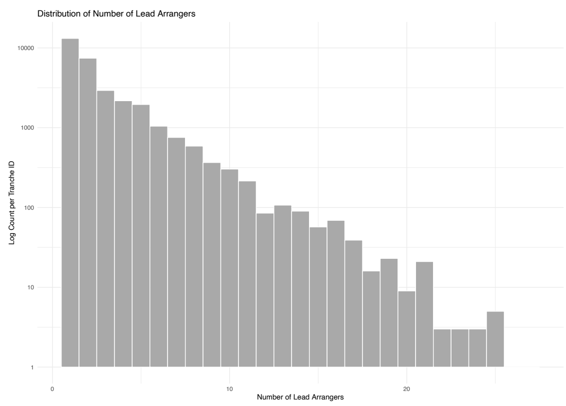
Taken together, our findings indicate that biodiversity risk is incorporated into bank lending primarily through loan pricing rather than through credit allocation or participation decisions. More broadly, the results highlight that financial institutions respond to environmental risks even when these are not directly observable through traditional metrics, but are instead embedded in firms' broader environmental footprint.

Our findings have important implications for financial regulation and supervision. As regulatory frameworks such as the Kunming–Montreal Global Biodiversity Framework evolve, understanding how biodiversity risk is transmitted through financial markets becomes increasingly important. Our results suggest that banks incorporate biodiversity risk primarily through loan pricing rather than through credit allocation, implying that such risks may affect the cost of capital without necessarily leading to a reallocation of credit. This distinction is relevant for central banks and financial supervisors concerned with the transmission of environmental risks to financial stability. Our findings suggest that biodiversity risk may play an increasingly important role in financial contracting as disclosure practices and regulatory frameworks continue to evolve.

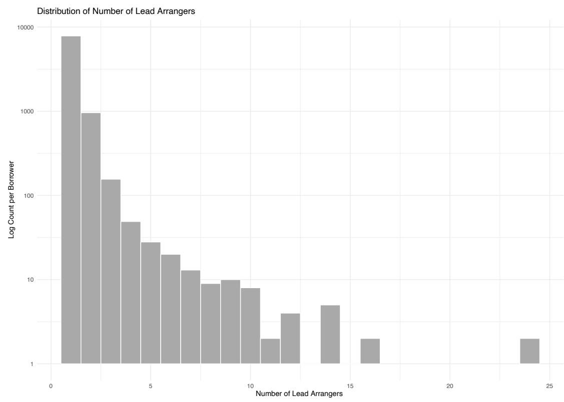
Declaration on the Use of AI

During the preparation of this paper, the authors used Grammarly and ChatGPT to assist with LaTeX formatting and, to a limited extent, support minor coding tasks, as well as to enhance the language and clarity of the text. All intellectual contributions, analyses, and interpretations remain those of the authors.

Figure 1: Overview of Lead Arrangers per year

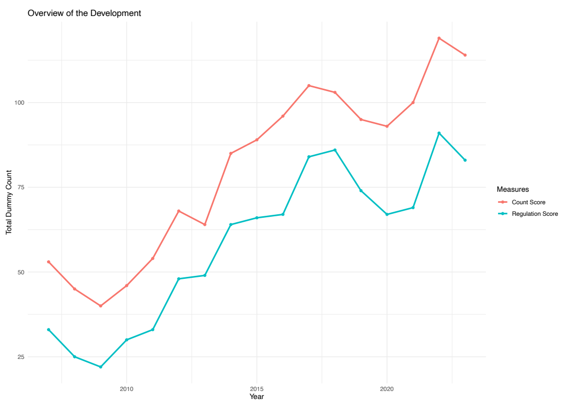


(a) Overview of Lead Arrangers in the Borrower - Tranche Dataset. For better visibility of the larger counts of lead arranges, a logarithm is used.

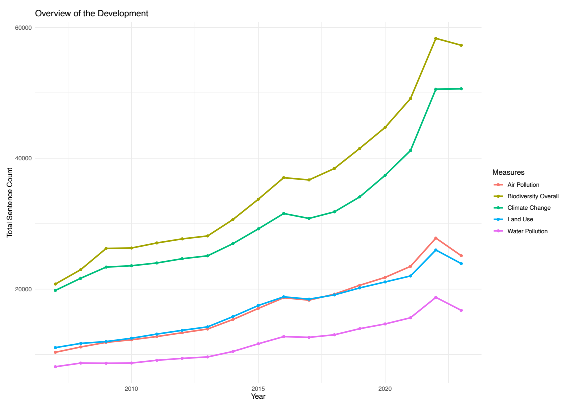


(b) Overview of Lead Arrangers in the Borrower - Lender Dataset. This is the overview after restructuring and filtering the lead arrangers. For better visibility of the larger counts of lead arranges, a logarithm is used.

Figure 2: Overview of the count of the dummy variable by (Giglio et al., 2023) versus our own measure - 2007-2023



(a) Total dummy counts by new measures per year.



(b) Total sentences counts by new measures per year.

Figure 3: Yearly coverage of observations with a biodiversity measure (own or from Giglio et al. (2023)) compared to the total number of observations in DealScan. The decline in coverage during the financial crisis period reflects the overall contraction in syndicated lending activity, as visible in the total DealScan observations, rather than changes related to biodiversity measurement.

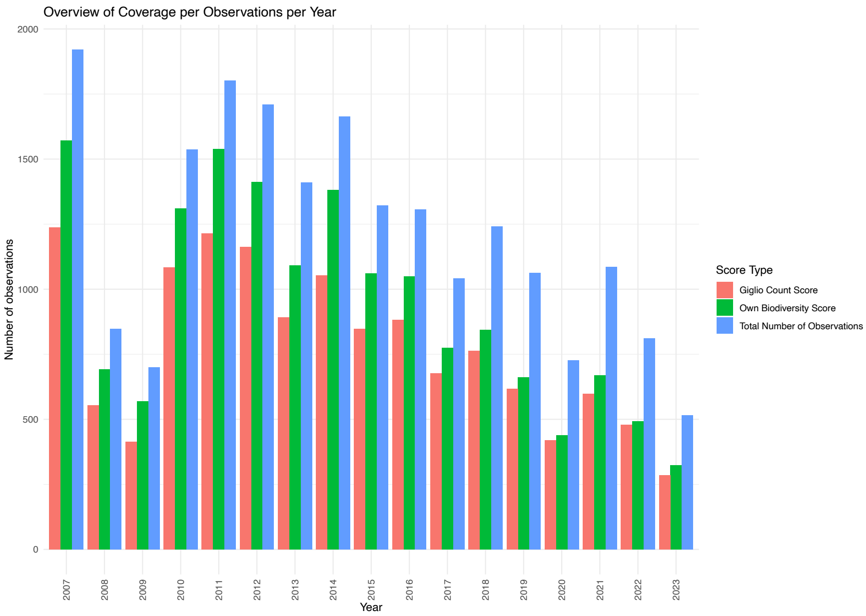
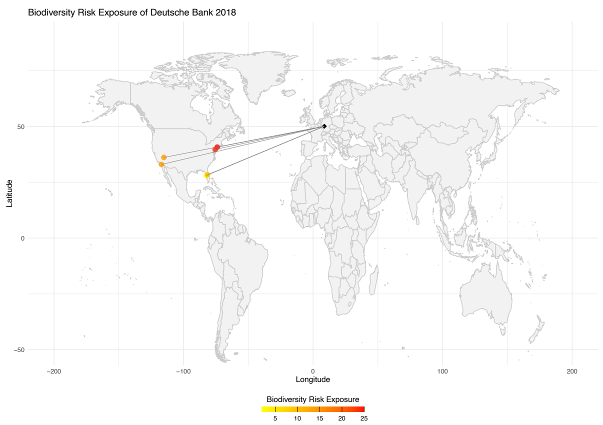
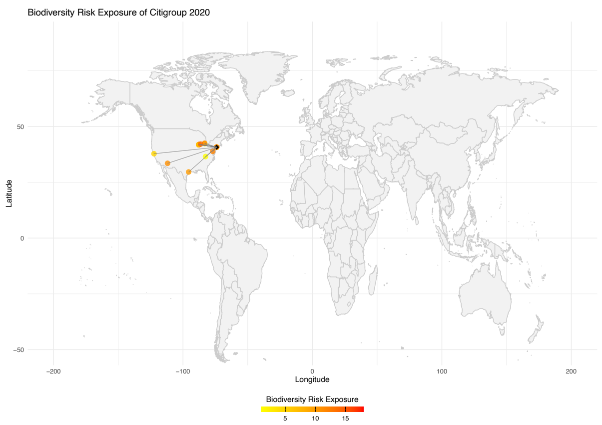


Figure 4: Overview of our own measure in Borrower - Tranche Level dataset



(a) Syndicated loan connections of Deutsche Bank in the year 2018. The black rectangle represents the headquarters of Deutsche Bank, while the colored circles indicate the U.S.-based firms the bank is lending to. The color reflects each firm's biodiversity exposure, measured as the ratio of biodiversity-related sentences to the total number of sentences in Items 1, 1A, and 7 of their 10-K filings—serving as a proxy for biodiversity-related risk.



(b) Syndicated loan connections of Citygroup in the year 2020. The black rectangle represents the headquarters of Citygroup, while the colored circles indicate the U.S.-based firms the bank is lending to. The color reflects each firm's biodiversity exposure, measured as the ratio of biodiversity-related sentences to the total number of sentences in Items 1, 1A, and 7 of their 10-K filings—serving as a proxy for biodiversity-related risk.

Table 1: Summary of datasets by third parties used in the study

Dataset	Description	Source
Loan-level data	Information on US syndicated lending relationships, including details on borrowing firms, industries, lead bank arrangers, other participating banks, and loan specifics (origination date, size, pricing terms, maturity, covenants).	DealScan Database
Firm (borrower) data	Firm characteristics, including financial characteristics of borrowing firms.	Compustat Database
Bank (lender) data	Lead-bank arranger characteristics.	BankFocus Database
Borrower biodiversity risk indicators	Firm-level biodiversity risk exposure data, spanning from 2001 to 2024, developed through textual analysis of 10-K statements. This biodiversity data is available at http://www.biodiversityrisk.org	Giglio et al. (2023)
Borrower environmental violations	Data from the EPA's Enforcement and Compliance History Online (ECHO) system, incorporating Federal Enforcement and Compliance (FE&C) data from the Integrated Compliance Information System (ICIS), as well as program-level data from ICIS-Air, ICIS-NPDES, RCRAInfo, and the Safe Drinking Water Act (SDWA), used to track environmental violations and enforcement actions.	U.S. Environmental Protection Agency (2025)
Borrower E-Score	Environmental Pillar Score provided by LSEG (formerly Refinitiv) which indicates the environmental performance of each company per year.	London Stock Exchange Group (2026)
Bank environmental commitments	Data on banks' sustainability commitments based on the Principles for Responsible Banking, covering targets in carbon emissions, production and consumption, nature-related financing, and inequality.	United Nations Environment Programme – Finance Initiative (UNEP-FI)
Lender's country vulnerability to climate change	The ND-GAIN Country Index evaluates the vulnerability and readiness to the negative effects of climate change for 182 UN countries since 1995 using 40+ core indicators.	World Bank Notre Dame Global Adaptation Initiative (ND-GAIN) (2024)

Table 2: Confusion matrix comparing the Giglio et al. (2023) classifier against our own overall biodiversity measure (spread dataset).

	Biodiversity = 0	**Biodiversity = 1**
Giglio = 0	1148	10245
Giglio = 1	75	403

Table 3: Descriptive statistics

Borrower - Tranche Level (Loan Spread dataset)					
	Count	Mean	SD	Min	Max
Loan Spread (bps)	7670	176.54	95.08	17.50	725.00
Biodiversity Count	7670	0.02	0.15	0	1
Biodiversity Regulation	7670	0.01	0.12	0	1
Biodiversity Overall	7008	0.91	0.29	0	1
Air Pollution	7008	0.77	0.42	0	1
Climate Change	7008	0.91	0.28	0	1
Land Use	7008	0.75	0.44	0	1
Water Pollution	7008	0.65	0.48	0	1
Deal Size (USD million)	7670	2,061.17	2,550.41	15.00	13,000.00
Deal Size (log)	7670	20.86	1.13	16.52	23.29
Maturity (log)	7670	3.79	0.57	0	4.50
Covenants	7670	0.56	0.50	0	1
Secured	7670	0.40	0.49	0	1
Number of Leads	7670	4.11	3.28	0	27.00
Size (Total Assets, USD million)	7670	15,556.10	35,880.21	45.41	193,694.00
Size (log)	7670	22.10	1.56	17.63	25.99
Return on Assets (%)	7670	5.24	7.25	-45.39	26.41
Leverage (%)	7670	27.94	18.09	0	103.40
Tangibility (%)	7670	24.56	20.55	1.26	88.69
Coverage	7670	31.35	84.81	-13.50	617.44
Lender Capitalization (%, Avg.)	7670	9.61	1.61	4.18	13.35
Lender Income (%, Avg.)	7670	49.49	8.84	10.86	77.69
Lender Size (Total Assets Avg., USD billion)	7670	1,956.16	699.18	49.42	3,743.57
Lender Size (log)	7670	28.17	0.65	24.62	28.95
E-Score (cont.)	7668	6.44	2.96	1	12
UNEP-FI Lender (%)	7670	11.96	31.29	0	100
Low ND-GAIN	7259	0.48	0.50	0	1
Borrower - Lender Level (Loan Volume dataset)					
	Count	Mean	SD	Min	Max
Loan Volume Amount (USD million)	2041	223.63	318.83	4.69	1,518.74
Loan volume (log)	2041	18.58	1.09	15.36	21.14
Biodiversity Count	2041	0.03	0.17	0	1
Biodiversity Regulation	2041	0.02	0.15	0	1
Biodiversity Overall	1832	0.90	0.30	0	1
Air Pollution	1832	0.76	0.43	0	1
Climate Change	1832	0.87	0.33	0	1
Land Use	1832	0.70	0.46	0	1
Water Pollution	1832	0.62	0.49	0	1
Size (Total Assets, USD million)	2041	29,788.87	47,996.30	57.14	203,631.00
Size (log)	2041	22.88	1.73	17.86	26.04
Return on Assets (%)	2041	6.23	7.55	-40.59	24.66
Leverage (%)	2041	26.27	16.58	0	90.66
Tangibility (%)	2041	24.15	20.84	1.41	90.05
Coverage	2041	30.20	72.15	-8.82	555.80
Lender Capitalization (%)	2041	9.29	1.86	3.90	13.35
Lender Income (%)	2041	49.61	11.45	10.65	83.73
Lender Size (Total Assets, USD billion)	2041	1,972.24	787.78	38.66	3,743.57
Lender Size (log)	2041	28.15	0.72	24.38	28.95
E-Score (cont.)	2031	7.55	2.90	1	12
UNEP-FI Lender	2041	0.21	0.41	0	1
Low ND-GAIN	1826	0.50	0.50	0	1

This table represents the summary statistics for two data samples used in the empirical analysis. All firm- and lender-level financial variables are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles.

Table 4: Correlation matrix of biodiversity risk scores

	Biodiversity Count	Biodiversity Regulation	Biodiversity Overall	Air Pollution	Climate Change	Land Use	Water Pollution
Biodiversity Count	1.000						
Biodiversity Regulation	0.855***	1.000					
Biodiversity Overall	-0.042***	-0.046***	1.000				
Air Pollution	0.059***	0.040***	0.426***	1.000			
Climate Change	-0.005	-0.022*	0.588***	0.354***	1.000		
Land Use	0.057***	0.038***	0.401***	0.461***	0.414***	1.000	
Water Pollution	-0.021*	0.007	0.361***	0.417***	0.326***	0.385***	1.000

Correlation matrix based on the Borrower–Tranche Level dataset. Results for the Borrower-Lender Level dataset are similar and available upon request. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Loan spreads and biodiversity risk

	Giglio et al. (2023) measures				Own measure	
	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Count	28.255***	29.032***				
	(9.133)	(10.920)				
Biodiversity Regulation			33.387**	29.570***		
			(13.154)	(9.577)		
Biodiversity Overall					2.759	32.218***
					(4.949)	(9.123)
Deal Size	-3.512	-0.595	-3.610	-0.642	-2.324	0.613
	(2.459)	(4.152)	(2.456)	(4.161)	(2.518)	(4.410)
Maturity	-8.731**	-10.438***	-8.679**	-10.438***	-8.704**	-12.837***
	(3.776)	(3.904)	(3.779)	(3.904)	(4.024)	(4.279)
Covenants	-11.810***	-5.230	-11.706***	-5.227	-11.783***	-6.173
	(2.980)	(4.134)	(2.981)	(4.132)	(3.062)	(4.179)
Secured	45.723***	16.429***	45.937***	16.357***	44.164***	15.569***
	(3.758)	(5.749)	(3.747)	(5.757)	(3.838)	(5.904)
Number of Leads	1.751**	0.742	1.735**	0.733	1.298*	0.402
	(0.680)	(0.749)	(0.680)	(0.749)	(0.697)	(0.741)
Size	-19.315***	-20.952***	-19.101***	-20.974***	-19.154***	-18.694***
	(1.700)	(3.319)	(1.698)	(3.332)	(1.756)	(3.771)
Return on Assets	-1.981***	-2.997***	-1.981***	-3.003***	-1.780***	-3.441***
	(0.357)	(0.542)	(0.357)	(0.542)	(0.377)	(0.617)
Leverage	0.779***	0.780***	0.774***	0.779***	0.832***	0.917***
	(0.118)	(0.228)	(0.119)	(0.228)	(0.130)	(0.247)
Tangibility	-0.022	0.140	-0.012	0.148	-0.054	0.130
	(0.129)	(0.224)	(0.129)	(0.225)	(0.136)	(0.266)
Coverage	-0.018	0.026	-0.019	0.026	-0.009	0.050**
	(0.018)	(0.023)	(0.018)	(0.023)	(0.021)	(0.024)
Lender Capitalization	-3.371***	-7.988***	-3.411***	-8.103***	-3.005**	-5.447**
	(1.282)	(2.633)	(1.287)	(2.653)	(1.361)	(2.310)
Lender Income	-0.703***	-1.058***	-0.701***	-1.027***	-0.678**	-0.797**
	(0.257)	(0.340)	(0.256)	(0.339)	(0.276)	(0.354)
Lender Size	-9.124***	-5.878	-9.402***	-5.993	-10.512***	-7.421
	(3.266)	(6.130)	(3.283)	(6.110)	(3.407)	(6.419)
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No
US State FE	Yes	No	Yes	No	Yes	No
Industry x US State x Year FE	No	Yes	No	Yes	No	Yes
Observations	8190	7670	8190	7670	7480	6998
R^2	0.430	0.691	0.430	0.691	0.418	0.685

This table reports the results of estimating the model in Equation 6. The dependent variable is the Loan spread measured as AISD - "All in Spread Drawn" of loan tranche i, issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Loan level controls include Deal Size, the logarithm of deal volume (in millions of USD); Maturity, the logarithm of loan maturity (in months); Covenants, a binary variable equal to 1 if loan covenants are included; Secured, a binary variable equal to 1 if loan is secured by collateral. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. If multiple lead arrangers are involved, arranger characteristics are averaged across lead banks. Columns 1, 3 and 5 include fixed effects for loan purpose, firm industry, US state where firm is located and year of the loan. Columns 2, 4 and 6 replace separate industry, US State and year fixed effects with three-way Industry × US State × Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Loan spreads and biodiversity risk triggers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Air Pollution	7.573*	15.469**						
	(3.886)	(6.961)						
Climate Change			-4.879	26.438***				
			(5.402)	(9.170)				
Land Use					0.874	14.170**		
					(4.217)	(6.237)		
Water Pollution							5.092	21.428***
							(3.458)	(7.274)
Deal Size	-2.491	0.824	-2.294	1.155	-2.332	1.292	-2.376	0.835
	(2.533)	(4.422)	(2.509)	(4.424)	(2.514)	(4.365)	(2.523)	(4.396)
Maturity	-8.764**	-12.847***	-8.756**	-12.925***	-8.736**	-12.994***	-8.815**	-13.175***
	(4.046)	(4.279)	(4.030)	(4.276)	(4.023)	(4.276)	(4.025)	(4.267)
Covenants	-11.859***	-6.335	-11.807***	-6.016	-11.784***	-6.269	-11.930***	-7.069*
	(3.061)	(4.178)	(3.056)	(4.175)	(3.065)	(4.199)	(3.085)	(4.181)
Secured	43.654***	16.234***	44.442***	15.908***	44.230***	16.002***	43.829***	15.531***
	(3.834)	(5.947)	(3.853)	(5.936)	(3.873)	(5.970)	(3.820)	(5.938)
Number of Leads	1.306*	0.547	1.313*	0.450	1.304*	0.480	1.342*	0.641
	(0.697)	(0.747)	(0.697)	(0.747)	(0.698)	(0.750)	(0.695)	(0.759)
Size	-18.991***	-20.458***	-19.300***	-19.694***	-19.195***	-20.524***	-18.987***	-19.679***
	(1.753)	(3.634)	(1.756)	(3.716)	(1.751)	(3.573)	(1.746)	(3.700)
Return on Assets	-1.750***	-3.436***	-1.763***	-3.366***	-1.774***	-3.338***	-1.781***	-3.444***
	(0.377)	(0.616)	(0.376)	(0.614)	(0.376)	(0.606)	(0.375)	(0.578)
Leverage	0.830***	0.909***	0.832***	0.949***	0.835***	0.892***	0.829***	0.889***
	(0.130)	(0.257)	(0.128)	(0.254)	(0.130)	(0.242)	(0.130)	(0.234)
Tangibility	-0.063	0.031	-0.056	0.103	-0.058	0.031	-0.053	0.100
	(0.136)	(0.271)	(0.134)	(0.266)	(0.135)	(0.265)	(0.134)	(0.250)
Coverage	-0.008	0.043*	-0.010	0.051**	-0.009	0.043*	-0.006	0.051**
	(0.021)	(0.024)	(0.021)	(0.024)	(0.021)	(0.024)	(0.021)	(0.024)
Lender Capitalization	-3.059**	-4.930**	-2.970**	-4.994**	-2.985**	-4.949**	-2.956**	-5.049**
	(1.357)	(2.390)	(1.361)	(2.383)	(1.365)	(2.354)	(1.362)	(2.345)
Lender Income	-0.670**	-0.832**	-0.676**	-0.791**	-0.678**	-0.856**	-0.681**	-0.832**
	(0.276)	(0.356)	(0.278)	(0.356)	(0.277)	(0.359)	(0.276)	(0.357)
Lender Size	-10.575***	-6.778	-10.466***	-6.702	-10.501***	-6.295	-10.500***	-8.202
	(3.433)	(6.383)	(3.411)	(6.470)	(3.409)	(6.432)	(3.424)	(6.690)
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
US State FE	Yes	No	Yes	No	Yes	No	Yes	No
Industry x US State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	7480	6998	7480	6998	7480	6998	7480	6998
R^2	0.418	0.684	0.418	0.685	0.417	0.684	0.418	0.685

This table reports the results of estimating the model in Equation 6. The dependent variable is the Loan spread measured as AISD - "All in Spread Drawn" of loan tranche i, issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions at least two sentences related to the four main topics in the firm's 10-K report, and 0 otherwise. Loan level controls include Deal Size, the logarithm of deal volume (in millions of USD); Maturity, the logarithm of loan maturity (in months); Covenants, a binary variable equal to 1 if loan covenants are included; Secured, a binary variable equal to 1 if loan is secured by collateral. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. If multiple lead arrangers are involved, arranger characteristics are averaged across lead banks. Columns 1, 3, 5 and 7 include fixed effects for loan purpose, firm industry, a US State where firm is located and year of the loan. Columns 2, 4, 6 and 8 replace industry, US State and year fixed effects with three-way Industry × US State × Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Bank lending and biodiversity risk

	Giglio et al. (2023) measures						Own measure		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Biodiversity Count	-0.139 (0.116)	-0.0731 (0.220)	-0.156 (0.121)						
Biodiversity Regulation				-0.225 (0.151)	-0.0467 (0.266)	-0.263* (0.158)			
Biodiversity Overall							-0.0644 (0.0659)	0.0247 (0.164)	-0.0847 (0.0734)
Size	0.331*** (0.0137)	0.385*** (0.0248)	0.341*** (0.0144)	0.331*** (0.0137)	0.385*** (0.0248)	0.340*** (0.0144)	0.333*** (0.0140)	0.392*** (0.0267)	0.343*** (0.0150)
Return on Assets	0.00671** (0.00271)	0.00703 (0.00465)	0.00762*** (0.00280)	0.00663** (0.00271)	0.00702 (0.00466)	0.00753*** (0.00280)	0.00823*** (0.00286)	0.00358 (0.00495)	0.00891*** (0.00307)
Leverage	0.00445*** (0.00140)	0.00200 (0.00347)	0.00461*** (0.00142)	0.00444*** (0.00139)	0.00198 (0.00347)	0.00461*** (0.00141)	0.00382** (0.00149)	-0.000155 (0.00359)	0.00387*** (0.00150)
Tangibility	0.000922 (0.00149)	-0.000889 (0.00298)	0.000870 (0.00154)	0.000939 (0.00148)	-0.000936 (0.00296)	0.000886 (0.00153)	0.000344 (0.00153)	0.000704 (0.00313)	0.000640 (0.00160)
Coverage	0.000572** (0.000251)	0.000845** (0.000418)	0.000312 (0.000193)	0.000579** (0.000253)	0.000843** (0.000417)	0.000318 (0.000194)	0.000518** (0.000247)	0.000685 (0.000430)	0.000271 (0.000194)
Lender Capitalization	0.0512 (0.0325)	-0.0901 (0.0580)		0.0514 (0.0324)	-0.0897 (0.0578)		0.0603* (0.0330)	-0.0670 (0.0657)	
Lender Income	-0.00256 (0.00410)	-0.0194** (0.00811)		-0.00240 (0.00409)	-0.0194** (0.00813)		-0.00274 (0.00418)	-0.0213** (0.00845)	
Lender Size	0.292** (0.142)	-0.184 (0.221)		0.293** (0.143)	-0.183 (0.221)		0.252* (0.144)	-0.235 (0.253)	
Lender FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry FE	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
US State FE	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Year FE	Yes	No	No	Yes	No	No	Yes	No	No
Lender x Year FE	No	No	Yes	No	No	Yes	No	No	Yes
Industry x US State x Year FE	No	Yes	No	No	Yes	No	No	Yes	No
Observations	3280	2041	3115	3280	2041	3115	2964	1811	2796
R^2	0.498	0.803	0.577	0.499	0.803	0.577	0.515	0.819	0.599

This table reports the results of estimating the model in Equation 7. The dependent variable is the log. Loan Volume issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in 10-K report. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. Columns 1, 4 and 7 include fixed effects for lender, industry, US State and year. Columns 2, 5 and 8 include lender and three way interacted industry x US State x Year fixed effects. Columns 3, 6 and 9 include industry, US State and two way interacted lender × year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Bank lending and biodiversity risk triggers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Air Pollution	-0.0703	-0.0425	-0.0740									
	(0.0462)	(0.114)	(0.0500)									
Climate Change				0.00735	0.286	-0.0483						
				(0.0622)	(0.186)	(0.0709)						
Land Use							-0.0562	0.0240	-0.0493			
							(0.0447)	(0.0893)	(0.0446)			
Water Pollution										-0.0786**	-0.0436	-0.130***
										(0.0384)	(0.104)	(0.0409)
Size	0.332***	0.389***	0.342***	0.334***	0.402***	0.344***	0.333***	0.391***	0.343***	0.331***	0.388***	0.340***
	(0.0140)	(0.0269)	(0.0151)	(0.0141)	(0.0268)	(0.0150)	(0.0140)	(0.0274)	(0.0150)	(0.0139)	(0.0267)	(0.0149)
Return on Assets	0.00807***	0.00375	0.00873***	0.00822***	0.00349	0.00897***	0.00808***	0.00360	0.00875***	0.00823***	0.00355	0.00868***
	(0.00287)	(0.00500)	(0.00307)	(0.00285)	(0.00483)	(0.00306)	(0.00286)	(0.00492)	(0.00306)	(0.00284)	(0.00494)	(0.00304)
Leverage	0.00384**	-0.000249	0.00388***	0.00373**	0.0000915	0.00377**	0.00377**	-0.0000578	0.00377**	0.00378**	-0.000211	0.00384**
	(0.00149)	(0.00372)	(0.00150)	(0.00149)	(0.00359)	(0.00150)	(0.00149)	(0.00367)	(0.00151)	(0.00149)	(0.00366)	(0.00150)
Tangibility	0.000423	0.000742	0.000711	0.000374	0.00113	0.000673	0.000425	0.000542	0.000732	0.000335	0.000599	0.000598
	(0.00152)	(0.00323)	(0.00159)	(0.00152)	(0.00308)	(0.00159)	(0.00153)	(0.00328)	(0.00160)	(0.00152)	(0.00319)	(0.00160)
Coverage	0.000512**	0.000650	0.000266	0.000520**	0.000802*	0.000276	0.000513**	0.000684	0.000268	0.000492**	0.000656	0.000241
	(0.000246)	(0.000436)	(0.000191)	(0.000246)	(0.000425)	(0.000193)	(0.000246)	(0.000428)	(0.000192)	(0.000247)	(0.000425)	(0.000194)
Lender Capitalization	0.0601*	-0.0685		0.0605*	-0.0678		0.0591*	-0.0665		0.0603*	-0.0664	
	(0.0330)	(0.0650)		(0.0332)	(0.0652)		(0.0331)	(0.0656)		(0.0330)	(0.0662)	
Lender Income	-0.00273	-0.0212**		-0.00281	-0.0214**		-0.00274	-0.0214**		-0.00236	-0.0213**	
	(0.00415)	(0.00850)		(0.00418)	(0.00834)		(0.00420)	(0.00836)		(0.00419)	(0.00851)	
Lender Size	0.238*	-0.244		0.252*	-0.246		0.245*	-0.232		0.244*	-0.235	
	(0.144)	(0.255)		(0.145)	(0.252)		(0.146)	(0.253)		(0.145)	(0.255)	
Lender FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Industry FE	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
US State FE	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes
Year FE	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
Lender x Year FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Industry x US State x Year FE	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Observations	2964	1811	2796	2964	1811	2796	2964	1811	2796	2964	1811	2796
R^2	0.515	0.819	0.599	0.515	0.821	0.598	0.515	0.819	0.598	0.515	0.819	0.600

This table reports the results of estimating the model in Equation 7. The dependent variable is the natural logarithm of Loan Volume issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on lending: Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. Furthermore, Biodiversity Total is 1 when the company mentions more than 2 of the four topics in their 10-K Statement. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. Columns 1, 4, 7 and 10 include fixed effects for lender, industry, US State and year. Columns 2, 5, 8 and 11 include lender and three way interacted industry x US State x Year fixed effects. Columns 3, 6, 9 and 12 include industry, US State and two way interacted lender × year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Loan spreads, biodiversity risk and EPA violations

	Biodiversity Count	Biodiversity Regulation	Biodiversity Overall	Air Pollution	Climate Change	Land Use	Water Pollution
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated	7.109	6.752	56.335***	22.726	0.224	22.382	15.890
	(6.489)	(6.440)	(20.952)	(14.369)	(0.505)	(14.556)	(10.750)
Treated × Post	-3.818	-3.481	-56.018***	-24.878	-0.225	-23.932	-10.664
	(7.090)	(7.028)	(20.608)	(15.118)	(3.204)	(15.368)	(10.829)
Biodiversity Indicator	29.310**	28.773***	33.743***	17.296**	25.560***	11.011	22.354***
	(12.291)	(11.090)	(10.353)	(7.766)	(9.301)	(6.853)	(7.162)
Biodiversity Indicator × Treated	-7.155	-7.699	-48.095**	-14.782	9.491	-16.542	-9.166
	(6.592)	(6.508)	(22.199)	(15.979)	(6.583)	(15.883)	(12.847)
Biodiversity Indicator × Post	-0.165	-1.188	0.237	1.107	-0.209	-0.514	0.351
	(1.578)	(0.963)	(1.183)	(0.942)	(1.087)	(0.692)	(0.824)
Biodiversity Indicator × Treated × Post	4.118	4.681	51.460**	21.149	-5.769	24.678	4.753
	(6.999)	(6.911)	(22.152)	(17.068)	(8.423)	(17.668)	(13.445)
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × US State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31723	31723	28905	28905	28905	28905	28905
R^2	0.732	0.732	0.728	0.728	0.727	0.727	0.728

This table reports the results of estimating the model in Equation 8. The regressions are estimated using a stacked difference-in-differences design where cohorts are defined by the year of the first environmental violation. The dependent variable is the Loan spread measured as AISD - "All in Spread Drawn" of loan tranche i, issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. The specification includes a triple interaction between Treated, Post, and the biodiversity indicator, where environmental violations are measured as a firm–year dummy. Lender Loan level controls include Deal Size, the logarithm of deal volume (in millions of USD); Maturity, the logarithm of loan maturity (in months); Covenants, a binary variable equal to 1 if loan covenants are included; Secured, a binary variable equal to 1 if loan is secured by collateral. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. If multiple lead arrangers are involved, arranger characteristics are averaged across lead banks. In all columns we include Cohort x Year, loan purpose, and three-way Industry × US State × Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Bank lending, biodiversity risk and EPA violations

	Biodiversity Count (1)	Biodiversity Regulation (2)	Biodiversity Overall (3)	Air Pollution (4)	Climate Change (5)	Land Use (6)	Water Pollution (7)
Treated	-0.0755	-0.0747	0.146	0.0357	-0.00527	0.0304	-0.0413
	(0.0766)	(0.0769)	(0.156)	(0.0316)	(0.0106)	(0.0675)	(0.0436)
Treated × Post	0.0477	0.0473	-0.303	0.117	-0.206	0.0166	0.102
	(0.0833)	(0.0836)	(0.223)	(0.0796)	(0.255)	(0.105)	(0.101)
Biodiversity Indicator	0.165*	0.174	-0.0298	-0.0822	0.170	0.0260	-0.0534
	(0.0940)	(0.112)	(0.145)	(0.108)	(0.170)	(0.0747)	(0.0915)
Biodiversity Indicator × Treated	0.165*	0.174	-0.206	-0.113	-0.0536	-0.114	-0.00939
	(0.0940)	(0.112)	(0.174)	(0.0964)	(0.0847)	(0.114)	(0.106)
Biodiversity Indicator × Post	0.111	0.122	0.00943	-0.0277*	0.00136	-0.0193	0.000530
	(0.0719)	(0.105)	(0.0186)	(0.0143)	(0.0172)	(0.0131)	(0.0129)
Biodiversity Indicator × Treated × Post	-0.262*	-0.281*	0.352	-0.0855	0.255	0.0194	-0.0893
	(0.139)	(0.149)	(0.237)	(0.128)	(0.272)	(0.145)	(0.140)
Cohort × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × US State × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12906	12906	11654	11654	11654	11654	11654
R^2	0.878	0.878	0.891	0.891	0.891	0.891	0.891

This table reports the results of estimating the model in Equation 9. The regressions are estimated using a stacked difference-in-differences design where cohorts are defined by the year of the first environmental violation. The dependent variable is the log. Loan Volume issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. The specification includes a triple interaction between Treated, Post, and the biodiversity indicator, where environmental violations are measured as a firm–year dummy. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. In all columns we include Cohort x Year, lender and three way interacted Industry x US State x Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Loan spreads, biodiversity risk and E-Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-73.410						
	(95.323)						
Biodiversity Count x E-Score	13.268						
	(12.237)						
Biodiversity Regulation		-87.986					
		(101.257)					
Biodiversity Regulation x E-Score		14.982					
		(13.020)					
Biodiversity Overall			91.228***				
			(31.307)				
Biodiversity Overall x E-Score			-7.075**				
			(3.442)				
Air Pollution				25.073			
				(20.920)			
Air Pollution x E-Score				-1.049			
				(2.530)			
Land Use					54.454**		
					(21.891)		
Land Use x E-Score					-5.110**		
					(2.568)		
Climate Change						58.953*	
						(31.414)	
Climate Change x E-Score						-3.776	
						(3.478)	
Water Pollution							3.800
							(18.999)
Water Pollution x E-Score							2.893
							(2.344)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x US State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7668	7668	6996	6996	6996	6996	6996
R^2	0.691	0.691	0.686	0.685	0.685	0.685	0.686

This table reports the results of estimating the model in Equation 8. The dependent variable is the Loan spread measured as AISD - "All in Spread Drawn" of loan tranche i, issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. E-Score (cont.) is the Refinitiv Environmental Pillar whose grades are mapped to a 12-point numeric scale, with higher values indicating better environmental performance. Loan level controls include Deal Size, the logarithm of deal volume (in millions of USD); Maturity, the logarithm of loan maturity (in months); Covenants, a binary variable equal to 1 if loan covenants are included; Secured, a binary variable equal to 1 if loan is secured by collateral. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. If multiple lead arrangers are involved, arranger characteristics are averaged across lead banks. In all columns we include fixed effects for loan purpose, and three-way Industry × US State × Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Bank lending, biodiversity risk and E-Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-1.594***						
	(0.595)						
Biodiversity Count × E-Score	0.189***						
	(0.070)						
Biodiversity Regulation		-1.803**					
		(0.701)					
Biodiversity Regulation × E-Score		0.215***					
		(0.082)					
Biodiversity Overall			0.574				
			(0.440)				
Biodiversity Overall × E-Score			-0.067				
			(0.054)				
Air Pollution				-0.114			
				(0.248)			
Air Pollution × E-Score				0.011			
				(0.032)			
Climate Change					0.796		
					(0.568)		
Climate Change × E-Score					-0.061		
					(0.070)		
Land Use						-0.115	
						(0.285)	
Land Use × E-Score						0.017	
						(0.033)	
Water Pollution							0.184
							(0.272)
Water Pollution × E-Score							-0.028
							(0.033)
E-Score	-0.034*	-0.034*	0.034	-0.035	0.028	-0.039	-0.008
	(0.019)	(0.019)	(0.056)	(0.031)	(0.070)	(0.030)	(0.031)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x US State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2031	2031	1801	1801	1801	1801	1801
R^2	0.803	0.803	0.818	0.818	0.819	0.818	0.818

This table reports the results of estimating the model in Equation 9. The dependent variable is the log. Loan Volume issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. E-Score (cont.) is the Refinitiv Environmental Pillar whose grades are mapped to a 12-point numeric scale, with higher values indicating better environmental performance. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. In all columns we include fixed effects for loan purpose, and three-way Industry × US State × Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Loan spreads, biodiversity risk and bank commitments (UNEP-FI Lender)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	40.593***						
	(12.507)						
Biodiversity Count x UNEP-FI Lender	-0.786						
	(0.676)						
Biodiversity Regulation		40.304***					
		(13.837)					
Biodiversity Regulation x UNEP-FI Lender		-0.781					
		(0.697)					
Biodiversity Overall			22.080**				
			(9.742)				
Biodiversity Overall x UNEP-FI Lender			0.375**				
			(0.171)				
Air Pollution				14.950**			
				(7.180)			
Air Pollution x UNEP-FI Lender				0.005			
				(0.171)			
Climate Change					26.069**		
					(12.075)		
Climate Change x UNEP-FI Lender					-0.006		
					(0.259)		
Land Use						10.543	
						(6.488)	
Land Use x UNEP-FI Lender						0.162	
						(0.151)	
Water Pollution							16.485**
							(7.967)
Water Pollution x UNEP-FI Lender							0.247
							(0.152)
UNEP-FI Lender	0.234**	0.220**	-0.205	0.118	0.127	0.008	-0.038
	(0.094)	(0.094)	(0.176)	(0.151)	(0.257)	(0.123)	(0.113)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x US State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7670	7670	6998	6998	6998	6998	6998
R^2	0.692	0.692	0.686	0.685	0.685	0.685	0.686

This table reports the results of estimating the model in Equation 12. The dependent variable is the Loan spread measured as AISD - "All in Spread Drawn" of loan tranche i, issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. UNEP-FI Lender represents a percentage of lead arrangers on a tranche that are UNEP-FI PRB signatories. Loan level controls include Deal Size, the logarithm of deal volume (in millions of USD); Maturity, the logarithm of loan maturity (in months); Covenants, a binary variable equal to 1 if loan covenants are included; Secured, a binary variable equal to 1 if loan is secured by collateral. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. If multiple lead arrangers are involved, arranger characteristics are averaged across lead banks. In all columns we include fixed effects for loan purpose, and three-way Industry × US State × Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: Bank lending, biodiversity risk and bank commitments (UNEP-FI Lender)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.119						
	(0.257)						
Biodiversity Count × UNEP-FI Lender	0.301						
	(0.713)						
Biodiversity Regulation		-0.102					
		(0.319)					
Biodiversity Regulation × UNEP-FI Lender		0.288					
		(0.736)					
Biodiversity Overall			0.050				
			(0.187)				
Biodiversity Overall × UNEP-FI Lender			-0.100				
			(0.332)				
Air Pollution				-0.083			
				(0.115)			
Air Pollution × UNEP-FI Lender				0.201			
				(0.147)			
Climate Change					0.264		
					(0.193)		
Climate Change × UNEP-FI Lender					0.079		
					(0.275)		
Land Use						0.045	
						(0.096)	
Land Use × UNEP-FI Lender						-0.112	
						(0.177)	
Water Pollution							-0.061
							(0.108)
Water Pollution × UNEP-FI Lender							0.086
							(0.196)
UNEP-FI Lender	-0.296*	-0.296*	-0.185	-0.352*	-0.300	-0.208	-0.324
	(0.170)	(0.171)	(0.359)	(0.185)	(0.298)	(0.203)	(0.217)
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x US State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2041	2041	1811	1811	1811	1811	1811
R^2	0.803	0.803	0.820	0.820	0.821	0.820	0.820

This table reports the results of estimating the model in Equation 13. The dependent variable is the log. Loan Volume issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. UNEP-FI Lender represents a an indicator equal to 1 if the lead arranger is a UNEP-FI PRB signatory. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. In all columns we include lender and three way interacted Industry x US State x Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15: Loan spreads, biodiversity risk and ND-GAIN Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	31.291 (24.953)						
Biodiversity Count x Low ND-GAIN	-1.349 (32.582)						
Biodiversity Regulation		23.108 (25.446)					
Biodiversity Regulation x Low ND-GAIN		14.350 (34.195)					
Biodiversity Overall			45.522*** (8.047)				
Biodiversity Overall x Low ND-GAIN			-26.080 (19.030)				
Air Pollution				19.976*** (6.824)			
Air Pollution x Low ND-GAIN				-5.689 (14.685)			
Land Use					23.198*** (7.684)		
Land Use x Low ND-GAIN					-16.352 (12.840)		
Climate Change						36.710*** (8.887)	
Climate Change x Low ND-GAIN						-21.146 (18.309)	
Water Pollution							29.892*** (9.859)
Water Pollution x Low ND-GAIN							-13.016 (14.375)
Low ND-GAIN	-15.124 (21.475)	-15.673 (21.414)	6.654 (27.085)	-13.104 (26.086)	-6.379 (21.960)	2.229 (27.661)	-10.585 (24.973)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x US State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7259	7259	6612	6612	6612	6612	6612
R^2	0.684	0.684	0.677	0.676	0.676	0.676	0.677

This table reports the results of estimating the model in Equation 12. The dependent variable is the Loan spread measured as AISD - "All in Spread Drawn" of loan tranche i, issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. Low ND-GAIN Low ND-GAIN equals one if a loan has an above-median share of lead arrangers headquartered in below-median ND-GAIN countries. Loan level controls include Deal Size, the logarithm of deal volume (in millions of USD); Maturity, the logarithm of loan maturity (in months); Covenants, a binary variable equal to 1 if loan covenants are included; Secured, a binary variable equal to 1 if loan is secured by collateral. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. If multiple lead arrangers are involved, arranger characteristics are averaged across lead banks. In all columns we include fixed effects for loan purpose, and three-way Industry × US State × Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: Bank lending, biodiversity risk and ND-GAIN Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.526* (0.317)						
Biodiversity Count × Low ND-GAIN	0.881** (0.413)						
Biodiversity Regulation		-0.737* (0.434)					
Biodiversity Regulation × Low ND-GAIN		1.161** (0.525)					
Biodiversity Overall			-0.010 (0.220)				
Biodiversity Overall × Low ND-GAIN			0.140 (0.335)				
Air Pollution				0.023 (0.147)			
Air Pollution × Low ND-GAIN				-0.222 (0.191)			
Climate Change					0.366* (0.220)		
Climate Change × Low ND-GAIN					-0.260 (0.305)		
Land Use						-0.026 (0.138)	
Land Use × Low ND-GAIN						0.074 (0.175)	
Water Pollution							0.072 (0.156)
Water Pollution × Low ND-GAIN							-0.230 (0.204)
Low ND-GAIN	0.106 (0.159)	0.110 (0.160)	0.050 (0.345)	0.309* (0.171)	0.398 (0.292)	0.137 (0.152)	0.300* (0.179)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x US State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1819	1819	1605	1605	1605	1605	1605
R^2	0.800	0.800	0.817	0.817	0.818	0.817	0.817

This table reports the results of estimating the model in Equation 13. The dependent variable is the log. Loan Volume issued to firm f by lead bank b in year t. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. We include now the interaction with Low NDGAIN measured on bank b and time t level. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets. In all columns we include lender and three way interacted Industry x US State x Year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 17: Syndicate participation, firm biodiversity risk and bank commitments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.00789						
	(0.00545)						
Biodiversity Count × UNEP-FI Lender	0.00899						
	(0.0131)						
Biodiversity Regulation		-0.0115					
		(0.00738)					
Biodiversity Regulation × UNEP-FI Lender		0.0125					
		(0.0136)					
Biodiversity Overall			0.00877*				
			(0.00528)				
Biodiversity Overall × UNEP-FI Lender			-0.0105				
			(0.00964)				
Air Pollution				0.00302			
				(0.00324)			
Air Pollution × UNEP-FI Lender				-0.00798			
				(0.00552)			
Climate Change					0.00752		
					(0.00535)		
Climate Change × UNEP-FI Lender					-0.0118		
					(0.00816)		
Land Use						0.00195	
						(0.00317)	
Land Use × UNEP-FI Lender						0.00616	
						(0.00609)	
Water Pollution							0.00463
							(0.00291)
Water Pollution × UNEP-FI Lender							-0.00999*
							(0.00549)
UNEP-FI Lender	0.0294***	0.0297***	0.0426***	0.0385***	0.0430***	0.0266**	0.0384***
	(0.0101)	(0.0102)	(0.0141)	(0.0116)	(0.0129)	(0.0114)	(0.0113)
Market share	0.0842***	0.0842***	0.0837***	0.0837***	0.0837***	0.0837***	0.0837***
	(0.00169)	(0.00169)	(0.00178)	(0.00178)	(0.00178)	(0.00178)	(0.00178)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
US State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	321590	321590	292234	292234	292234	292234	292234
Pseudo R^2	0.192	0.192	0.188	0.188	0.188	0.188	0.188

This table reports the results of estimating the syndicate participation model in Equation 12. The dependent variable Syndicate participant is an indicator equal to one if bank b is selected as a lead lender for deal i to firm f in year t, and zero otherwise. The model is estimated using a probit specification, and reported coefficients represent probit coefficients. For each loan-year, the choice set consists of the 100 banks with the highest syndicated loan market share in that year. The main variables of interest capture the impact of firm-level biodiversity risk on loan pricing: Biodiversity Count is a binary variable equal to 1 if the term "biodiversity" appears in at least two sentences in the firm's 10-K report, and 0 otherwise. Biodiversity Regulation is equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation. Biodiversity Overall is 1 when the company mentions biodiversity related sentences in at least two sentences in the firm's 10-K report. Air Pollution, Climate Change, Land Use, Water Pollution which are binary variables equal to 1 if the firm mentions any sentence related to the four main topics in the firm's 10-K report, and 0 otherwise. UNEP-FI Lender represents a an indicator equal to 1 if the lead arranger is a UNEP-FI PRB signatory. Firm-level controls include: Size, the log of total assets (in millions of USD); Return on Assets, net income as a percentage of total assets; Leverage, total debt as a percentage of total assets; Tangibility, tangible assets as a percentage of total assets; Coverage, EBITDA over interest expenses. Lead Arranger controls are defined as follows: Lender Capitalization, total equity as percentage of total assets; Lender Income, net interest income as percentage of operating revenue; Lender Size, the logarithm of total assets; Market Share measures bank's share of syndicated loan volume in the respective year. In all columns we include lender, industry, US State and year fixed effects. All firm- and lender-level controls are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors (in parentheses) are clustered at the borrower level. Statistical significance is denoted as follows: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Appendix

This appendix provides additional descriptive data analysis tables.

Table A1: Definitions and sources of the main regression variables

Variable	Definition	Source
Dependent variables		
Spread	Loan spread measured as the All-In Spread Drawn (AISD) at the tranche level.	Dealscan
Loan volume	Loan volume held by the lender at the firm-year level, measured as the logarithm of USD loan volume.	Dealscan
Biodiversity risk measures		
Biodiversity Count	Dummy variable equal to 1 if "biodiversity" is mentioned in at least two sentences in the firm's 10-K report.	(Giglio et al., 2023)
Biodiversity Regulation	Dummy variable equal to 1 if biodiversity is mentioned in at least two sentences, and at least one of those refers to regulation.	(Giglio et al., 2023)
Biodiversity Overall	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to biodiversity loss in at least two sentences in the firm's 10-K report.	Own construction
Air Pollution	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to air pollution in at least two sentences in the firm's 10-K report.	Own construction
Climate Change	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to climate change in at least two sentences in the firm's 10-K report.	Own construction
Land Use	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to land use in at least two sentences in the firm's 10-K report.	Own construction
Water Pollution	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to water pollution in at least two sentences in the firm's 10-K report.	Own construction
Loan-level variables		
Deal Size	Natural logarithm of the total deal amount at the tranche level.	Dealscan
Maturity	Natural logarithm of loan maturity measured in months.	Dealscan
Covenants	Dummy variable equal to 1 if any covenants are included in the loan contract.	Dealscan
Secured	Dummy variable equal to 1 if the loan is secured by collateral.	Dealscan
Number of Leads	Number of lead arrangers in the loan syndicate.	Dealscan
Borrower-level variables		
Size	Natural logarithm of borrower's total assets, based on lagged annual financial statements.	Compustat
Return on Assets (%)	Net income as a percentage of total assets, based on lagged annual financial statements.	Compustat
Leverage (%)	Total debt as a percentage of total assets, based on lagged annual financial statements.	Compustat
Tangibility (%)	Tangible assets as a percentage of total assets, based on lagged annual financial statements.	Compustat
Coverage	EBITDA divided by interest expenses, based on lagged annual financial statements.	Compustat
Lender-level variables		
Lender Capitalization (%, Avg.)	Lead arranger equity as a percentage of total assets, averaged across lead arrangers, based on lagged annual financial statements.	BankFocus / Dealscan / Own calculations
Lender Income (%, Avg.)	Net interest income as a percentage of operating revenue, averaged across lead arrangers, based on lagged annual financial statements.	BankFocus / Dealscan / Own calculations
Lender Size (Total Assets Avg., USD)	Log of lead arranger total assets in USD (millions), averaged across all lead banks, based on lagged annual financial statements	BankFocus / Dealscan / Own calculations
Lender Size (log)	Log of total assets of the lead arranger(s), based on lagged annual financial statements	BankFocus / Dealscan / Own calculations
Environmental scores and indicators		
E-Score (cont.)	Continuous firm-level environmental score ranging from 1 (lowest) to 12 (highest), based on LSEG ESG ratings	LSEG ESG Scores / Own construction
UNEP-FI Lender (%)	Share of lead arrangers in the syndicate that are UNEP-FI PRB signatories.	UNEP-FI membership database / Own mapping
Low ND-GAIN	Dummy variable equal to 1 if the average ND-GAIN Country Index across lead arrangers' headquarters falls below the sample median.	ND-GAIN / World Bank

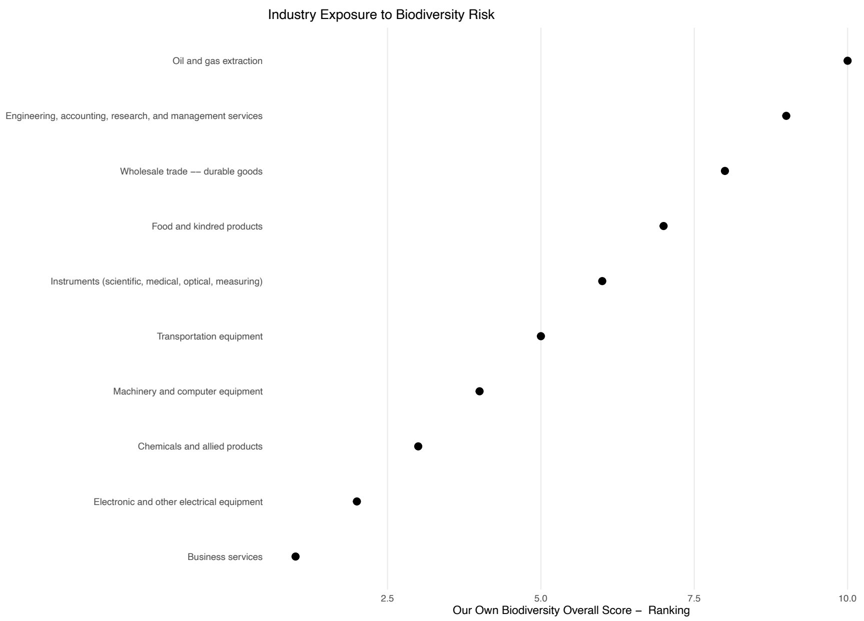
This table defines the main variables used in the empirical analysis. All firm- and lender-level financial variables are lagged by one year. Continuous variables are winsorized at the 1st and 99th percentiles. Lender-variable definitions refer to the loan spread sample. In the loan volume sample, where the unit of observation is the lender–firm–year, all lender variables are defined at the individual lender level rather than as syndicate-level shares. Accordingly, *UNEP-FI Lender* and *Low ND-GAIN* are no longer measured using shares of lead arrangers.

Table A2: Industry Coverage of the Matched Sample (Spread)

SIC2	Industry	Loans	Firms	*(continued)*			
1	Agricultural production (crops)	2	1	45	Air transportation	73	6
7	Agricultural services	17	2	47	Transportation services	52	5
13	Oil and gas extraction	248	26	48	Communications	200	12
15	Construction – general contractors and operative builders	132	13	49	Electric, gas, and sanitary services	95	10
16	Heavy construction excluding building construction – contractors	79	8	50	Wholesale trade – durable goods	283	24
17	Construction – special trade contractors	52	5	51	Wholesale trade – nondurable goods	192	14
20	Food and kindred products	345	27	52	Retail – building materials, hardware, garden supply	36	3
21	Tobacco products	39	3	53	Retail – general merchandise	78	6
22	Textile mill products	63	4	54	Food stores	40	6
23	Apparel and finished products from fabrics and similar materials	122	7	55	Auto dealers and gas stations	159	12
24	Lumber and wood products excluding furniture	25	4	56	Retail – apparel and accessory stores	77	9
25	Furniture	79	8	57	Retail – home furniture, furnishings, and equipment stores	25	3
26	Paper and allied products	129	8	58	Retail – eating and drinking places	120	13
27	Printing and publishing	132	12	59	Misc. retail	107	12
28	Chemicals and allied products	535	50	70	Hotels and lodging	121	9
29	Petroleum refining	86	8	72	Personal services	35	6
30	Rubber and plastics	95	11	73	Business services	791	76
31	Leather and leather products	51	4	75	Automotive repair, services, and parking	26	3
32	Stone, clay, glass, and concrete products	26	3	76	Misc. repair services	7	1
33	Primary metals	146	20	78	Motion pictures	14	2
34	Fabricated metals	112	11	79	Amusement and recreation services	112	7
35	Machinery and computer equipment	533	56	80	Health services	207	14
36	Electronic and other electrical equipment	503	61	81	Legal services	3	1
37	Transportation equipment	416	31	82	Education services	6	1
38	Instruments (scientific, medical, optical, measuring)	379	34	83	Social services	21	1
39	Misc. manufacturing	89	7	87	Engineering, accounting, research, and management services	259	23
40	Railroad transportation	7	2	89	Misc. services	16	2
42	Motor freight transportation	60	9	92	Public administration	7	1
44	Water transportation	6	1				
Total						**7670**	**718**

This table reports the industry composition of the matched sample used in the loan spread analysis. Industries are defined at the two-digit SIC level. Columns report the number of loan facilities and number of borrowing firms per industry.

Figure 5: Coverage of biodiversity measures over time. The figure reports the top 10 industries across all firms and years identified by our *Biodiversity Overall* measure.



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