The Role of Biodiversity Risk in Shaping Bank Lending Decisions*

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Abstract

In this study, we examine the extent to which banks incorporate firm-level biodiversity risk into their lending decisions, both in terms of loan pricing and loan volume adjustments. We use a comprehensive syndicated loan market dataset that captures lender-borrower relationships and allows for matching with firm-level biodiversity risk measures. Beyond employing existing biodiversity risk measures, we extend the methodology by developing a more granular text-based biodiversity risk measure. This novel metric is constructed using cosine similarity of textual embeddings, allowing for

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a nuanced assessment of biodiversity-related corporate disclosures. Furthermore, we explore potential transmission mechanisms through which biodiversity risk is reflected in lending decisions, analyzing whether banks explicitly price biodiversity risk or adjust credit supply based on borrowers' exposure to biodiversity-related vulnerabilities. We examine whether bank location, UNEP-FI membership, and borrower characteristics, such as low ESG scores and environmental violations, affect lending behavior. While we find clear evidence that banks penalize biodiversity risk through higher spreads and lower loan volumes, the underlying channels remain inconclusive.

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

JEL Classification: G21, Q51, Q57

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 40 years, there has been a dramatic 60 percent decline in wildlife populations. Even non-endangered species are losing genetic diversity due to habitat degradation and local extinctions (Karolyi & Tobin-de la Puente, 2023). This exhaustion of nature and the planet's resources could lead to a future with very few resources, significantly impacting human health as well. According to European External Action Service (2022), humans have been overusing Earth's resources since the 1970s, resulting in more than 300 million people being exposed to the risk of severe floods and hurricanes.

Beyond its ecological implications, biodiversity loss imposes substantial economic impacts by limiting the availability of essential natural resources, which increases costs across various industries (Becker, Di Girolamo, & Rho, 2025). Economic activities are intricately tied to ecosystem services in a two-way relationship referred to in the literature as double materiality. On one hand, economic activity relies on intact ecosystems and biodiversity to function effectively, aligning with the concept of physical risk, where biodiversity loss directly results in economic losses. On the other hand, economic activities can harm biodiversity, creating transition risks, such as stricter regulations that increase operational costs or render certain business practices unviable (Becker et al., 2025).

According to Organisation for Economic Co-operation and Development (2022), businesses face multiple biodiversity-related risks, including direct ecological impacts, liability for biodiversity loss, and the financial repercussions of regulatory changes. Recognizing biodiversity loss as a significant driver of both physical and transitional risks is critical within

the financial market context. Physical risks, such as species extinction, precipitate capital destruction and disrupt value chains. In contrast, transitional risks emerge from governmental interventions—like restrictions, quotas, and thresholds—that necessitate corporate action and investment, leading to increased operational costs and the relocation and adaptation of business activities.

The World Bank underscores the gravity of these risks, estimating that the collapse of ecosystem services could lead to a global GDP decline of $2.7 trillion by 2030 (Arlt, Berg, Hut, & Streitz, 2024; Becker et al., 2025; Johnson et al., 2021). As highlighted by Becker et al. (2025), the banking sector's engagement with biodiversity-related risks is paramount, given their implications for both environmental stability and economic sustainability. Ignoring these risks could lead to increased insurance premiums, reputational damage, or regulatory penalties, further stressing the importance of integrating biodiversity considerations into financial and operational strategies.

In this context, we analyze the impact of firm biodiversity risk on adjustments in bank lending decisions, both in terms of volume and pricing. First, we connect firm-level text-based biodiversity measures to bank lending decisions, identifying a significant and positive relationship to loan spreads and significant and negative relationship to loan volume observed at bank-firm level. Second, we enhance the overall measure by developing four distinct text-based indicators that specifically account for the language of the reports and associate it to known biodiversity triggers: air pollution, land use, climate change and water pollution, measured at the firm-level. We improve the bag-of-words approach by leveraging cosine similarity of embeddings, enabling us to capture contextual meaning beyond mere word occurrences. This approach enhances our understanding of corporate reporting practices related to biodiversity risk while also strengthening our measurement by examining multiple dimensions of biodiversity-related risks. Furthermore, it supports our empirical analysis by enabling a more precise identification of the effects on lenders, specifically in terms of their lending decisions and pricing strategies. Third, we explore the mechanism through which

our baseline findings can be explained, by exploring the effect of lender commitments to sustainability targets, as well as the exposure to biodiversity loss in the country where the lender headquarters is located. Finally, we further inspect how the effects differ between firms with a history of environmental violations and those without, as well as based on their environmental performance scores.

We find that firm-level biodiversity risk is significantly and positively linked to loan spreads, while it is significantly and negatively associated with loan volume. Bank commitments to sustainable targets seem to influence results for loan volume. In contrast, we find no robust evidence that the location of a lender's headquarters, based on country's vulnerability to environmental risk, amplifies the main relationship. We also find evidence that lower firm environmental scores amplify loan spreads. Finally, firms with a history of environmental violations seem to incur higher spreads in the three years following their first violation, particularly if exposed to biodiversity risk arising from water pollution. This environmental violation effect is more pronounced for loan volume analysis. It is important to note that when we control for different specifications of fixed effects at the industry, state, and year levels, the results are sometimes affected. Thus, the underlying mechanism behind our main findings remains somewhat inconclusive.

Our empirical analysis rests on the hypothesis that the banks account for the biodiversity risk of the borrowers in their lending decisions. Biodiversity loss can impact firms' profit and cost side and deteriorate their creditworthiness and collateral by limiting the resources they depend on. Dependency of firms' activities on biodiversity, which enables their unimpeded functioning, can be considered a physical risk, while the biodiversity loss arising due to firms' economic activities can be seen as a transition risk, such as from regulatory scrutiny as indicated in Becker et al. (2025). In terms of physical risk and dependency, banks may require compensation in terms of higher interest rates charged on loans carrying this risk, similar to a carbon premium on greenhouse gas emissions (Becker et al., 2025; Ehlers, Packer, & de Greiff, 2022).

In addition to pricing adjustments, banks may become less willing to lend to highly exposed firms. Depending on firms' contribution to biodiversity loss, which could also trigger regulatory action, banks could seek to limit their exposures to such firms on their balance sheets. The same channel could also manifest through a more direct regulatory risks to banks stemming from the biodiversity risk exposure of their borrowers. This could pressure banks to adjust their loan portfolios and reallocate their lending to lower-risk firms. Moreover, banks could also be held accountable for degrading nature through the activities of their borrowers, which could trigger regulatory scrutiny or increase their reputational risk. If concerns like this are widespread among many banks participating in the loan market, they could avoid particular firms depending on their biodiversity risk. We would expect that fewer banks are then willing to participate in such loan syndicate deals, or be inclined to decrease their shares, especially banks already committed to environmental goals and considered "green" (Fard, Javadi, & Kim, 2020). The question remains whether banks committed to environmental goals are more sensitive to biodiversity risks.

The environmental commitments of banks can serve as proxies of their attitude to environmental concerns and acknowledgment of the risks involved. Previous studies on climate risk and bank lending have shown that bank commitments are highly relevant (Bolton & Kacperczyk, 2023; Chava, 2014; Degryse, Goncharenko, Theunisz, & Vadasz, 2023; Ehlers et al., 2022; Kacperczyk & Peydro, 2022); thus, we expect committed banks might weigh the biodiversity exposure of firms more strongly. We also consider how the vulnerability of a lender's headquarters country to environmental degradation, captured by the ND-GAIN index, may affect their sensitivity to firm biodiversity risk exposure. Banks headquartered in countries with greater vulnerability may respond more strongly to the firm-level biodiversity risk in terms of their lending decisions. At the firm level, we also assess whether the ESG Environmental (E) score influences our main relationships, using poor environmental performance as a proxy for elevated risk exposure to biodiversity loss, signaling the firm unpreparedness for such risks. Finally, to explore regulatory channels, we utilize the firm-level

data on environmental violations from the U.S. Environmental Protection Agency (EPA), allowing us to test whether a firm's history of non-compliance amplifies the main effect.

2 Related Literature

Reflecting on the dual environmental challenges of our time, finance research has significantly pivoted to incorporate environmental concerns, recognizing climate change and biodiversity loss as the era's defining crises. The extensive exploration of Environmental, Social, and Governance (ESG) metrics demonstrates a significant shift towards sustainability, as seen in various studies (Avramov, Cheng, Lioui, & Tarelli, 2022; Edmans, 2023; Heeb, Kölbel, Paetzold, & Zeisberger, 2023; Pedersen, Fitzgibbons, & Pomorski, 2021) and critical evaluations (F. Berg, Fabisik, & Sautner, 2020; F. Berg, Koelbel, Pavlova, & Rigobon, 2022). Research on biodiversity risks remains less developed, even as the importance of biodiversity, highlighted by the UNEP and the World Economic Forum (United Nations Environment Programme, 2022), and efforts like COP 15 (UN Biodiversity Conference 2022) and the Kunming-Montreal Global Biodiversity Framework emphasize its critical role alongside climate change. Notably, the concept of biodiversity as climate change's "twin risk" (KPMG, 2023) requires further academic attention. Some studies have begun to address this gap, focusing on biodiversity-related risks for businesses and the financial sector (Coqueret & Giroux, 2023; Garel, Romec, Sautner, & Wagner, 2023; Giglio, Kuchler, Stroebel, & Zeng, 2023; Organisation for Economic Co-operation and Development, 2022), underlining the need for research on how the decline of biodiversity affects banks and their practices.

Despite growing research on biodiversity-related risk premia (Coqueret & Giroux, 2023), investor perceptions (Garel et al., 2023; Garel, Romec, Sautner, & Wagner, 2025), asset valuation (Cornaggia, Liang, Iliev, & Wang, 2025; Giglio et al., 2023), and the impact on corporate operations, environmental performance, and financial outcomes (Akbari, Ng, Yu, & Pham, 2025), a notable gap remains in understanding how biodiversity risks specifically

influence banks and their lending behavior.[1] This gap underscores the need for comprehensive studies that delve into the implications of biodiversity decline on financial institutions. Such research is essential for developing strategies that align financial practices with environmental conservation goals, thereby contributing to a more sustainable and resilient global economy.

We concentrate on the lending behaviors of banks towards firms with varying levels of biodiversity risk, explicitly examining how these risks influence the terms of syndicated loans. 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. Unlike their study, in our analysis, we assess both loan volume adjustments and loan pricing in bank lending decisions. 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 loan spreads for nature-dependent firms. Our study complements and extends this literature by developing novel more granular text-based measures of firm-level biodiversity risk derived with embeddings approach. In addition to examining loan spreads, we also analyze loan volumes, offering a more comprehensive view of banks' credit allocation. Furthermore, we explore heterogeneity through borrower- and

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

lender-related channels, such as environmental law violations, ESG performance, UNEP-FI membership, and lenders' exposure to environmental vulnerability. While our firm-level application is currently limited to U.S. borrowers due to data availability, we plan to extend the analysis to European firms in future work, thereby enhancing the global relevance of our findings.

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 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, Diaz Kalan, and Miguel (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, Boldrini, Lelli, Parisi, and Heemskerk (2023) further underscored this risk, revealing that the top ten euro area banks by impact on nature finance account for about 40% of the total global impact by euro-area firms, a figure that rises to 90% for the top 100 banks out of 2,500 analyzed. This concentration highlights the crucial role of major banks in financing biodiversity-impacting activities and emphasizes the need for incorporating biodiversity considerations into their lending and risk assessment processes. Additionally, other scholars found that deregulation led banks to decrease the environmental risk consideration in their loan pricing (Erten & Ongena, 2023).

Our research is situated within the discourse on biodiversity and bank lending and is distinct from the study of earlier climate-related risks, such as CO2 emissions. This distinction is crucial because CO2 emissions and biodiversity are valued differently due to their unique implications for environmental sustainability and financial risk assessment. CO2 emissions, which are central to the climate change discourse, 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 could highlight potential impacts on local ecosystems, endangered species, and habitat conservation.

Our work is still related to the literature on climate change and bank lending. Significant contributions to this literature include: Kacperczyk and Peydro (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 finds that green banks charge higher interest rates to fossil fuel companies; Degryse et al. (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 (2023), 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).

The remainder of the paper is organized as follows. Section 3 reviews the data and outlines the construction of our textual biodiversity risk measure. Section 4 presents our empirical approach. Section 5 discusses the findings and 6 concludes the study.

3 Data

In this paper, we examine how bank lending decisions in terms of loan pricing and volume are influenced by firms' exposure to the risk of biodiversity loss using DealScan's LoanConnector database. This database includes information on syndicated lending relationships worldwide, dating back to 1988 and continuing to the present. DealScan enables the identification of

lender-firm relationships, including the borrowing firm, its industry, the lead bank arranger, other participating banks, and key loan characteristics such as origination date, size, pricing terms, maturity, and covenants. A loan agreement (deal) in Dealscan typically consists of several tranches (loans). Within the same deal, different tranches can have specific credit terms. Thus, the origination and amendments to loan tranches represent distinct observations in our sample, (Acharya, Gopal, & Steffen, 2024; Chava & Roberts, 2008; Golden & Liu, 2025). We download all available data for each industry and filter only borrower-lender linkages where the lender is a bank, the borrower is non-private, and for a period after 2007, as the main global policy developments on biodiversity are also quite recent. Additionally, we also drop financial firms from data, those with SIC code in between 6021 and 6799. This leaves us with 32,420 observations. We denote the spread dataset as *Borrower - Tranche Level dataset*.

Since we only have access to the new DealScan data, we first map our Borrower ID to the Legacy ID using the mapping information from Chava and Roberts (2008). This mapping enables us to identify the corresponding GVKEY, which we then use to retrieve financial information for borrower firms from Compustat.

We then integrate financial data on the lenders. Again, we first map the Lender ID to the Dealscan Legacy ID using the mapping information from Chava and Roberts (2008). Next, we map the Legacy ID to the BvDID number, which focuses on lender identification, based on the work of Schwert (2018). For any companies without a BvDID number, we use a fuzzy name-matching algorithm to link financial information from BankFocus with the relevant banks. Since we focus on loan pricing, we restrict the DealScan sample to include only lead arrangers. For syndicated loans involving multiple lenders, we calculate averages across the lead arrangers. We present all datasets in Table 1.

Table 1 about here

To analyze changes in the loan volume of bank lending, 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.

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

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 loans 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 still means that the number of lead arrangers varies between 1 and 24 and overall leaves us with 14,291 observations for the Borrower-Tranche Level dataset.

We show the distribution of Arrangers in Figure 1.

Figure 1 about here

To account for lender commitments to sustainability targets, we obtain the data on sig-

natories of the United Nations Environment Programme – Finance Initiative (UNEP-FI). This data was previously used in several papers (Degryse et al., 2023; Ehlers et al., 2022; Kacperczyk & Peydro, 2022) as a measure of the environmental and sustainable commitment of the lender. The signatories of UNEP-FI are committed to the Principles for Responsible Banking, developed by the participating banks and the UNEP-FI. Halting biodiversity loss has been identified as a critical target for the financial institutions within these principles as stated on the UNEP-FI website: *"Signatories to the Principles for Responsible Banking have a unique and critical role in pivoting this global economic shift and achieving these objectives. And UNEP-FI is ready to support member banks in aligning their strategies and portfolios with a nature-positive future."* Moreover, in June 2021, the UNEP-FI published the Biodiversity Target Setting Guidelines for the participating banks. This suggests that identifying banks committed to UNEP-FI reasonably indicates the bank's attitude to biodiversity risks. The UNEP-FI data is manually matched using the bank's name and mapped to the lender's parent ID in Dealscan.[2]

Furthermore, as our sample contains more than one lead arranger per loan we have to adapt the measure for the UNEP-FI membership. We first create a binary variable *Member UN Lead*, which is 1 if one of the lead arrangers is a member, and then a second continuous variable *Member UN Share Lead*, which calculates the share of banks that are members of the lead arranger per deal (Degryse et al., 2023).

Furthermore, to account for how the geographic location of a lenders' headquarters and its exposure to biodiversity loss might influence the financing decisions, we use the NDGAIN Country Index provided by World Bank (Notre Dame Global Adaptation Initiative (ND-GAIN), 2024).

The NDGAIN Country Index evaluates the vulnerability and readiness of 182 UN countries since 1995 using 40+ core indicators. NDGAIN considers the importance of natural

[2]UNEP-FI data reveals whether the bank has committed at the group or subsidiary level. Most banks we observe have become signatories of UNEP-FI principles at the group level.

capital by measuring the share of renewable natural capital in a country's overall wealth, based on the World Bank's wealth accounting data. This indicator helps assess the extent to which ecosystem services constrain economic output, and the NDGAIN database provides a variety of indicators related to climate adaptation.

In our preliminary analysis we use the overall NDGAIN score which is computed as:

$$\text{NDGAIN score} = (\text{Readiness score} - \text{Vulnerability score} + 1) \times 50 \tag{4}$$

A high NDGAIN score indicates that a country has low vulnerability and high readiness, meaning it is well-prepared for climate challenges. In contrast, a low NDGAIN score suggests high vulnerability and low readiness, indicating a country is at significant risk and lacks the resources or infrastructure to adapt effectively.

We match the information on the regions with the lender information in the volume dataset (Borrower-Lender Level) and with the parent lender in the Borrower - Tranche Level dataset (Loan Spread dataset). We incorporate this information by creating a dummy variable *Low NDGAIN*, that equals 1 if the value is below the median and 0 otherwise.

To gain a deeper understanding of a company's environmental behavior and how this might impact lender decisions, we also use data from the U.S. Environmental Protection Agency (2025). Specifically, the EPA tracks violations of environmental laws.[3] The data provided shows the type and number of violations for a particular company or at a particular time. In total, there are 245 different types of violations, ranging from export violations or microbial violations of unregulated waste to microbial violations or misuse of a registered pesticide. As filtering for specific breaches would reduce our sample too much, we decide to count whether and when a company has had a breach. We use this information to create a dummy variable, called *Post3yr*, that equals 1 for the year of the violation and the following three years, otherwise zero.

[3] A detailed background can be found in Lel (2023).

We additionally include the Environmental (E) Pillar Score of the ESG score by LSEG (formerly Refinitiv/Eikon) to control for firm environmental score, (London Stock Exchange Group, 2025). The score is reported both as a percentage and as a letter grade ranging from D- (lowest) to A+ (highest). This scores gives an overall idea of the environmental performance of a company per year. We construct a dummy variable, namely *Low E Score*, equal to 1, indicating whether a firm's E Pillar Score falls below B- and 0 otherwise.

3.1 Key explanatory variables: Firm-level biodiversity risk measures

According to the Global Biodiversity Framework, Target 15 requires 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; (c) Report on compliance with access and benefit-sharing regulations and measures, as applicable"*, (on Biological Diversity, 2025).

Current literature outlines two different ways to quantify the biodiversity risk exposure of firms: 1) textual analysis of firm-related statements such as 10-K reports as in Giglio et al. (2023) and more recently, 2) firm material biodiversity footprint data from Iceberg Data Lab (2023) as already used in Sautner, Van Lent, Vilkov, and Zhang (2023). There are limits to both measures as outlined in Sautner et al. (2023). Furthermore following the discussion on the divergence among ESG data providers, Roeder and Utz (2025) highlight significant disagreement between the biodiversity footprints based on underlying methods and measurement data of three major providers namely ISS ESG, Iceberg Data Lab, and Impact Institute.

Corporate biodiversity footprint measures quantify the material impact of a firm on biodiversity but are not forward-looking, thus preventing inferring the company's future actions

associated with environmental risks. However, the textual analysis offers some inference about future firm activities related to environmental risks, including biodiversity (physical, transition, or regulatory), but is subject to reporting bias (Cenedese, Han, & Kacperczyk, 2023).

Our primary empirical approach relies on textual analysis measures. In order to achieve a more accurate assessment of biodiversity loss at the firm level, we develop a novel measure as detailed in Section 3.1.2. To ensure the robustness of our findings, we also conduct a comparative analysis using the measures developed by Giglio et al. (2023), which are outlined below. This serves to validate our measure and enhance the credibility of our results.

3.1.1 Existing firm-level biodiversity risk measures

As for our initial biodiversity risk measure, we use the biodiversity risk data of Giglio et al. (2023). The creators of this metric advocate a clear distinction between climate and biodiversity risks, noting that their impacts vary significantly across industries in ways that are both economically meaningful and distinct from climate risk exposures, (Giglio et al., 2023). These annual firm-level biodiversity scores developed by Giglio et al. (2023) are derived from textual analysis of 10-K filings as a measure of biodiversity risk. Overall, we include two out of the three measures[4] they provide: *10-K Biodiversity Count Score*: Does the company mention biodiversity related words in at least two sentences in the 10-K statements? *10-K Biodiversity Regulation Score*: Does the company mention biodiversity related words in at least two sentences and at least one of those is about regulation in the 10-K statements?

For their *10-K Biodiversity Count Score* Giglio et al. (2023) builds a Biodiversity Dic-

[4]Additionally, Giglio et al. (2023) introduce a *10-K Biodiversity Negative Score*, calculated as the number of negative biodiversity-related sentences minus the number of positive ones. The sentiment of the sentences is computed by using a BERT model. However, we chose not to include this measure in the current analysis, as the other two metrics are more directly comparable to our own textual analysis measures. In future work, we plan to explore the sentiment of company disclosures in greater depth.

tionary that contains 100 words. They chose those words using Google's word2vec3 implementation and focusing on the cosine similarity of those words to biodiversity. Then they use a bag-of words approach and count the sentences that include any of those words. The counts are transformed into a binary variable equal to 1 in case the document includes at least two sentences that mention any of the biodiversity-related words, as defined above, and zero otherwise. The *10-K Biodiversity Regulation Score* is computed in similar manner, however additional terms (namely: law(s), regulation, act, ESA, discharge, or restriction) are included in the search. The score is equal to 1 if least two biodiversity risk sentences and at least one of them is a biodiversity regulation risk sentence, zero otherwise.

Using the time variable year of the loan active date from Dealscan and CUSIP, we match Giglio et al. (2023)'s biodiversity risk exposure data to our Loan Connector data for the borrower. Figure 2 provides an overview of our main data, referred to as the *Borrower - Tranche Level dataset*, (while the *Borrower - Lender Level dataset* is structured as described above). This figure displays all three available measures. Figure 2a illustrates the 10-K Biodiversity Count Score, indicates that over time less then 10% of the companies mention biodiversity risks. Similar we see relatively few mentions of regulation, as shown in Figure 2b. Overall, Figure 2 suggests that discussions on biodiversity are limited, with companies making few references to biodiversity risk in their 10-K statements.

Figure 2 about here

3.1.2 More granular textual measures of firm-level biodiversity risk

Following this, we question whether companies explicitly discuss biodiversity-related issues or if they instead focus on its underlying drivers. Rather than directly addressing biodiversity risks, firms might highlight related environmental concerns, such as water scarcity, pollution, or climate change, which indirectly impact biodiversity.

An example of this can be seen in a statement from 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 statement highlights Keurig Dr. Pepper's concerns about water availability—a critical factor influencing biodiversity loss due to environmental changes. Although the company does not explicitly mention biodiversity, water scarcity is closely linked to ecosystem degradation, deforestation, and unsustainable resource use.

Such discussions suggest that firms may acknowledge the consequences of biodiversity loss without directly framing them as biodiversity-related risks. This raises the question of whether biodiversity concerns are being overlooked in corporate disclosures or simply embedded within broader environmental narratives.

Using this as our motivation we aim to define more granular biodiversity measures. From life sciences, we know that biodiversity risk is driven by underlying environmental pressures (GLOBIO Consortium, 2024; Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES), 2020). These drivers include factors such as land use, water pollution, air pollution and climate change[5]. For example, changes in land use often lead to habitat destruction, while pollution includes both air and water pollution. Climate change remains a significant and distinct driver affecting biodiversity.

The *10-K Biodiversity Count Score* by Giglio et al. (2023) employs a bag-of-words approach, which may not adequately capture the biodiversity risks faced by companies. This limitation arises because companies often do not use synonyms for biodiversity when dis-

[5]Also other data providers use these pressure to try and measure biodiversity (Iceberg Data Lab, 2023)

cussing their risks; instead, they may concentrate on the more specific factors that contribute to biodiversity loss.

We therefore aim to create more granular biodiversity risk measures inspired by the environmental pressures defined by Iceberg Data Lab (2023) and introduced by Sautner et al. (2023). The four key pressures — "Air Pollution", "Climate Change", "Land Use," and "Water Pollution" — collectively contribute to the overall risk of biodiversity loss. Furthermore, our measure improves upon the bag-of-words approach by using a Transformer-based model[6] that captures relationships between words, thereby incorporating context into the word embeddings.

We create four distinct textual measures based on Items 1, 1A, and 7 from firms' 10-K filings. 10-K statements are an annual reports filed by publicly traded companies with the U.S. Securities and Exchange Commission (SEC) to provide a comprehensive overview of their financial performance and operations. Its primary purpose is to ensure transparency and standardized disclosure, helping investors, analysts, and regulators make informed decisions. The report includes detailed financial statements, risk factors, management's discussion and analysis, and information on legal proceedings. The first item in a firm's 10-K report - Item 1 - outlines its business, detailing aspects such as operations, products, markets, revenue streams, and regulatory frameworks. Item 1A of a firm's 10-K filing outlines the risk factors that could significantly affect its financial condition, operations, or stock performance. These risks may arise from different conditions: macroeconomic, industry-specific challenges, regulatory changes, competitive pressures, or operational disruptions. Firms are required to

[6]Since the release of BERT (Devlin, 2018), numerous transformer-based models have followed. Although these models share the transformer architecture and can be fine-tuned for semantic similarity tasks, they differ in size, speed, and token capacity. For example, the Sentence Transformer models proposed by Reimers (2019) can process up to 512 tokens, making them suitable for embedding sentences or short paragraphs rather than entire documents. Currently, over 100 pre-trained Sentence Transformer models are available online each trained on different datasets and optimized for various tasks (see `https://www.sbert.net/docs/pretrained_models.html`). Some models excel at semantic similarity, while others are better suited for semantic search. There is always a trade-off between performance, computational intensity, and processing time.

provide clear and detailed report, focusing on the most significant risks. Item 7 outlines management's insights into the company's financial performance, including examination of trends, identification of risks, and evaluation of future prospects. All this information is crucial for various stakeholders to understand the company's organization, its standing within the industry and firm's exposure to potential uncertainties.

We obtain the 10-K statements of US firms in HTML format from EDGAR, an API managed by the U.S. Securities and Exchange Commission. Utilizing a customized parser, we extract above described Items 1, 1A, and 7 for our analysis.

First, we split the extracted Item 1, Item 1A and Item 7 sections of the 10-K filings into individual sentences, then concatenate only those that are clearly connected, following the procedure outlined by Breitung and Müller (2025). Specifically, we use the open-source sentence transformer *all-mpnet-base-v2*[7] to generate 768-dimensional embeddings. This model has been optimized for sentence embeddings and sentence similarity. We select this model because it offers the best trade-off between performance and computational efficiency while being optimized for sentence similarity tasks.[8]

Our first step is to create sets of sentences that best describe each of the four topics individually. We first describe the four main topics using 50 sentences for each topic. We then compute embeddings of these sentences as well as the sentences in the 2006 10-K statements.[9]

We then construct a cosine similarity matrix of dimensions between those example sentence embeddings and the 10-K embeddings. The cosine similarity, as shown in Equation 5, measures the similarity between two embedding vectors independently of their magnitude. It captures the cosine of the angle between the vectors in a high-dimensional space, where a

[7]Available on Hugging Face: `https://huggingface.co/sentence-transformers/all-mpnet-base-v2`

[8]Hugging Face provides a leadership board of various sentence transformers allowing for comparison of performance and other metrics. More information can be found in Hugging Face (2024).

[9]We start with 10-K statements in 2006, as Item 1A section — was introduced in Form 10-K filings beginning that year.

value closer to 1 indicates higher similarity.

$$\text{Cosine Similarity}(\mathbf{A}, \mathbf{B}) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\| \, \|\mathbf{B}\|} \tag{5}$$

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

We then rank the sentences per topic, selecting the top 1,000 sentences with the highest similarity. We manually review these sentences to remove generic or irrelevant statements. After this curation, we retain a final set of 100 sentences per topic. This process provides a more focused sample of sentences that best represent the four key pressures contributing to biodiversity risk and accounts for the specific language choices in 10-K statements. We then again create embeddings of these curated sentences.

Next, using these embeddings as well as the embeddings of the firm 10-Ks after 2006, overall, we have 54,450 reports between 2007 and 2023. We then again generate another cosine similarity matrix. In the final step, we identify the 75th percentile of the cosine similarity distribution and classify each sentence into one or none of the above categories.[10]

Finally, we aggregate the counts per category per report, year, and firm. This yields three possible metrics: (1) counting the number of sentences per report that belong to each category, (2) using a binary measure indicating whether the report focuses predominantly on one of these measures, or (3) computing the standard deviation of these counts as a dispersion measure, indicating whether firms concentrate on a single topic or address multiple topics. Currently, we convert the count measures into a binary variable similar to the *10-K Biodiversity Count Score* to make it more comparable. So currently having a single sentence mentioning one of the environmental pressures gives us a dummy of 1.

Figure 3 about here

[10]For 1982 unique borrowers in our sample, we have the 10-Ks statements for 1171.

Figure 3a shows that more than 75% of the companies mention one of the biodiversity topics when we look at the more granular measures. Furthermore, if we drill down into the specific topics discussed in Figure 3b, we can see that the four environmental pressures are consistently mentioned by companies over time. Most companies also mention more than one issue in their report. Only about 10% of the companies in our sample do not mention any of the biodiversity topics (shown in red). However, it is possible that the company mentions one of the other three topics. Conversely, the majority of companies address several other issues related to biodiversity loss.

Moreover, we create another dummy variable (called Biodiversity Total) which is 1 if more than 2 sentences related to environmental pressures (arising from mentions related to four topics: air pollution, climate change, land use or water pollution) are included in the reports and 0 otherwise. This metric serves to indicate whether companies discuss one or more environmental pressures associated to biodiversity loss.

3.1.3 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 Boldrini, Ceglar, Lelli, Parisi, and Heemskerk (2023) and Ceglar et al. (2023) 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, in-

crease in non performing assets, credit losses or also cause reputational damage. The study further reports that nearly 75% of bank loans are extended to such non-financial corporations.

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 underscore the need for lenders to consider biodiversity risks at the borrower level. By identifying and mapping these exposures, banks can better

manage their environmental risk profiles and align their portfolios with emerging sustainability expectations.

3.2 Descriptive statistics

We present the preliminary summary statistics for our two samples of data in Table 2 as well as a correlation table for the main explanatory variables in Table 3.[11]

Given that we analyze both loan spreads and loan volumes, we restructured the original Firm-Tranche Level dataset into a Firm-Lender Level dataset. As a result, the two datasets differ in the number of observations and their respective descriptive statistics.

Our variable of interest in the Borrower - Tranche Level dataset is the loan spread, defined by DealScan as AISD - "All in Spread Drawn", which quantifies the cost incurred by the borrowing firm, in basis points over LIBOR, for the portion of the loan drawn, plus any facility fees. It ranges from 17.50 to 725.00 bps, with an average of 176.30 basis points. Then we have our main explanatory variables: biodiversity dummy measures, which include the Biodiversity Count and Biodiversity Regulation from Giglio et al. (2023), as well as the five new own textual measures - Air Pollution, Climate Change, Land Use, Water Pollution and Biodiversity Total. We also include loan and borrower characteristics.

All borrower and lender characteristics are measured annually and are lagged by one year to mitigate endogeneity concerns related to the timing of loan origination. Deal Size averages at 20.62 corresponding to 1,634.61 USD million. Regarding loan characteristics, the maturity of the loans have a mean of 3.83 with a maximum of 4.50, as measured by the logarithm of maturity months at tranche level. Furthermore, the facilities in our sample have between 1 and 27 lead arrangers, with an average of 3.36 lead banks. Notably, a large share of facilities are led by a single arranger (see Figure 1). An average of 41% of the loans are secured, and 66% include financial covenants.

[11] We winsorize continuous variables at the 1st and 99th percentiles to limit the effect of spurious outliers.

Firm size is measured as the natural logarithm of total assets, with a mean of 21.82—approximately equivalent to 11,322.03 million USD. Return on assets averages 4.97%, while the mean leverage ratio is 24.98%, and average tangibility is 26.71%. Lender characteristics in the facility-level regressions are averaged across the pool of lead arrangers for each loan facility. The mean (log) size of lead arrangers is 28.05, which is equivalent to 1,730.46 billion USD. Then the average lender income is 49.54%, and lender capitalization stands at 9.07%. Approximately 12.42% of the loans are arranged by a UNEP-FI member institution.

Furthermore, about 4% of the lenders are located in areas that that are more vulnerable and not well prepared for challenges arising from climate change and roughly 33% have a low E pillar score defined as a score below B-. Only 4% of the companies have a environmental violation (Post3yr).

In the Borrower - Lender Level dataset, our outcome of interest is the natural logarithm of loan volume, which has a mean of 18.15 (corresponding to 143.43 million USD) and ranges from 15.42 to 21.14. Again we include the biodiversity-related variables as previously discussed. Then borrower and lender characteristics are again measured annually, using one-year lagged values. Firm size is calculated as the natural logarithm of total assets and has a mean of 22.26 — approximately equivalent to 19,304.63 million USD: Return on assets averages 5.82%, leverage stands at 22.53%, and tangibility averages 25.80%. The average coverage ratio is 36.95. Lender characteristics include lender capitalization (mean 8.83%) and Lender Income (mean 49.33%). On average, the (log) size of lead arrangers is 27.97, equivalent to 1,684.32 billion USD. Roughly 17% of the loans are arranged by a UNEP-FI affiliated lender. Furthermore, about 5% of the lenders are located in more vulnerable areas and less prepared for sustainability-related risks, as indicated by the Low NDGAIN dummy. Lastly, around 29% of firms are classified as having a Low E Score, based on the Environmental Pillar Score. Only 6% of the companies have an environmental violation recorded (Post3yr).

Table 2 about here

From Table 3 we can clearly see that the Biodiversity Count and the Biodiversity Regulation score are highly correlated. This is due to the design of the measure and can already be seen in Figure 2. We also find a moderate correlation for our more granular measure. Given that our measure uses an embedding approach and focuses on the four environmental pressures, it is possible that it captures additional sensitivities that would have been missed using the Biodiversity Count and Biodiversity Regulation score.

Table 3 about here

4 Empirical Approach

We begin our analysis with the base regression specification outlined in Section 4.1, where we examine the correlations between biodiversity risk at the firm level, as measured by data from Giglio et al. (2023) and our more granular biodiversity measures. We test our predictions in terms of loan pricing at the loan (tranche) level and loan volume at the bank-firm level. In 4.2, we expand our identification by including data on bank commitments to environmental goals (Degryse et al., 2023; Ehlers et al., 2022; Kacperczyk & Peydro, 2022) and test the expanded versions of the previous models. Additionally in 4.3, we also examine whether the participation of banks headquartered in countries with higher vulnerability to and low readiness (as measured by the NDGAIN index) concerning climate challenges impacts the loan terms and volume. To assess whether the impact of biodiversity risk on bank lending decisions is amplified following environmental violations (4.4, we exploit firm-level violation data from the U.S. Environmental Protection Agency (EPA) to identify treatment events and examine changes in lending outcomes before and after such violations, relative to unaffected firms, employing a quasi difference-in-difference approach. Finally, we examine how our primary explanatory variables interact with firm environmental scores as outlined in 4.5.

4.1 Baseline: Do banks account for firm biodiversity risk in their lending decisions?

We hypothesize that firms with higher exposure to biodiversity risks will experience an increase in interest rate spreads and a decrease in loan volume depending on lender sensitivity to biodiversity related risk exposures, which can arise due to various reasons such as sustainability commitments, regulatory environment, reputation concerns, risk management frameworks or concentration to specific industries which could be affected more by biodiversity loss (Arlt et al., 2024; Becker et al., 2025; DeNederlandsche Bank, 2020; Johnson et al., 2021). Our study builds on the work of Becker et al. (2025) by utilizing more detailed, firm-specific measures derived from textual analysis of the firms' annual 10-K statements. This approach allows us to categorize firms according to their vulnerability to biodiversity loss. To test our predictions, we estimate the following model on the tranche loan level:

$$\begin{aligned} Loan\ spread_{l,f,b,t} = \alpha + \beta Bio\ risk_{f,t} + \gamma LOAN_{l,f,b,t} + \delta FIRM_{f,t-1} + \zeta LENDER_{b,t-1} \\ + FE + \varepsilon_{l,f,b,t} \end{aligned} \tag{6}$$

where $Loan\ spread_{l,f,b,t}$ denotes the spread of the loan l provided to firm f by bank b at time t.[12] Defined by DealScan as AISD - "All in Spread Drawn," it quantifies the cost incurred by the borrowing firm, in basis points over LIBOR, for the portion of the loan drawn, plus any facility fees (T. Berg, Saunders, and Steffen (2016); Gao, Hua, and Khurshed (2021)). $Bio\ risk_{f,t}$ represents the binary biodiversity risk measure for firm f at time t. It can take form of one of the binary measures on the firm level created by Giglio et al. (2023): *Biodiversity Count* and*Biodiversity Regulation* core as well as one of our own computed scores: *Air Pollution, Water Pollution, Land Use and Climate Change* or *Biodiversity Total*

[12]The syndicate deals are reported via the Active Deal Date, which indicates loan activation. We use this variable to determine the time index t to be year or year quarter.

score.

We follow the literature to include loan and borrower control variables as they could affect loan spreads. $LOAN_{l,f,b,t}$ encompasses characteristics of the loan such as its size, maturity, covenants, collateral and number of lead arrangers. $FIRM_{f,t-1}$ includes control variables for the borrower, covering aspects like size (total assets), profitability (return on assets), leverage (debt over assets), tangibility (ratio of tangible assets to total assets) and coverage (EBITDA over interest expenses).

Given the syndicated nature of the loan data, each loan facility involves a lead bank or lead arranger responsible for arranging the loan and additional banks participating in the syndicate to finance it. The lead arranger takes the lead in loan issuance by negotiating the loan terms and conditions, as well as screening and monitoring by performing due diligence and organizing the syndicate deal. The other banks participate in the deal but are not in immediate contact with the borrower, thus the lead bank plays a pivotal role in loan origination and monitoring (Doerr & Schaz, 2021; Sufi, 2007). We follow the approach in existing studies (Degryse et al., 2023; Ehlers et al., 2022; Ho & Wong, 2023) and with the vector $LEAD\ BANK_{b,t-1}$ we assess the characteristics of the lead arranger, including its size (total assets), capitalization (equity over assets), and bank business model (net interest income over operating revenue). Both borrower and lender observables are lagged for one period to mitigate endogeneity concerns related to the timing of loan origination.[13]To control for data heterogeneity across firms and time, we incorporate a series of fixed effects in FE. In most of our regressions we control for loan purpose, main industry of the firm, measured by the first two digits of Standard industrial Classification (SIC) code, and year fixed effects. To isolate credit supply effects, we need to control for time-varying heterogeneity on regional and industry level. Moreover, country-industry-time fixed effects can control for time-varying

[13]For a portion of our sample, there is more than one lead bank reported for the syndicate. In those cases for bank controls we take the average of lender characteristics across all lead banks of that loan deal (Degryse et al., 2023; Heider, Saidi, & Schepens, 2019).

heterogeneity within country and industry (Doerr & Schaz, 2021). To account for lender heterogeneity, we either introduce bank controls or include a set of lender or lender-time fixed effects (Degryse et al., 2023; Kacperczyk & Peydro, 2022).

Standard errors are clustered at the borrower level.

To identify if banks adjust their credit supply to firms dependent on their exposure to biodiversity risk we employ the following empirical setting:

$$Log(Loan\ volume)_{f,b,t} = \alpha + \beta Bio\ risk_{f,t} + \delta FIRM_{f,t-1} + \zeta LENDER_{b,t-1} + FE + \varepsilon_{f,b,t}. \tag{7}$$

To measure the loan volume between bank-firm pairs we follow the literature (Chakraborty, Goldstein, & MacKinlay, 2018; Doerr & Schaz, 2021; Mueller & Sfrappinia, 2021) and construct a variable *Loan volume* that captures outstanding bank b loan volume to firm f at time t. The loan volume is a stock variable originated through sum of all loan shares held by the bank until the loan reaches maturity. This approach requires splitting loan deals into loan shares financed by each bank and then aggregating them into outstanding loan volumes between each pair.[14] Thus, $Log(Loan\ volume)_{f,b,t}$ is our dependent variable in this setting. Considering we now observe data in bank-firm-time setting, in these regressions on top of biodiversity measures, we control for borrower and lender characteristics as well as time, industry, lender and lender-time fixed effects.

[14]Dealscan provides data on lending portions of each bank in a syndicate deals. In cases this is not available we resort to splitting loan volumes among participating banks in equal shares (Doerr & Schaz, 2021).

4.2 Do *committed* banks account more for firm biodiversity risk in their lending decisions?

To account for bank environmental commitments and the role they play in bank lending decisions, we now classify lenders based on their commitment to environmental goals, which may increase their sensitivity to biodiversity-related risks, (Ehlers et al., 2022; Kacperczyk & Peydro, 2022). Equation 8 outlines our empirical approach:

$$\begin{aligned} Loan\ spread_{l,f,b,t} = \alpha + \beta_1 Bio\ risk_{f,t} + \beta_2 Commit_{b,t} + \beta_3 Bio\ risk_{f,t} * Commit_{b,t} \\ + \gamma LOAN_{l,f,b,t} + \delta FIRM_{f,t-1} + \zeta LEAD\ BANK_{b,t-1} + FE \\ + \varepsilon_{l,f,b,t}. \end{aligned} \tag{8}$$

Here we introduce the variable $Commit_{b,t}$, signifying a bank's dedication to sustainability targets.[15] We further examine the interaction between the measures of biodiversity risk and the banks' sustainability commitment to understand their collective impact on loan pricing. The rest of the variables remain the same as in Equation 6.

We also extend our Equation 7 on loan volume adjustments to include bank commitments data:

$$\begin{aligned} Log(Loan\ volume)_{f,b,t} = \alpha + \beta_1 Bio\ risk_{f,t} + \beta_2 Commit_{b,t} + \beta_3 Bio\ risk_{f,t} * Commit_{b,t} \\ + \delta FIRM_{f,t-1} + \zeta LEAD\ BANK_{b,t-1} + FE + \varepsilon_{f,b,t}. \end{aligned} \tag{9}$$

[15] As in Ehlers et al. (2022) and Degryse et al. (2023) for classification of banks in terms of their commitment to sustainability goals, we rely on the data from the United Nations Environment Programme – Finance Initiative (UNEP-FI), whose goal is to bring together banks, insurance companies, and investors towards the more sustainable economy by facilitating the active application of sustainable targets in areas such as carbon emissions, produce and consumption, financing nature and inequality.

4.3 Do banks headquartered *in regions with higher exposure to biodiversity risk* account more for firm biodiversity risk in their lending decisions?

While biodiversity is a global concern, it varies significantly across geography, as some regions are more sensitive to biodiversity loss than others. To investigate whether the bank's geographical location influence the financing decisions, we use the NDGAIN Country Index provided by the the University of Notre Dame and distributed by the World Bank Notre Dame Global Adaptation Initiative (ND-GAIN) (2024). The NDGAIN index captures a country's vulnerability to climate change and its readiness to improve resilience. A high NDGAIN score indicates that a country has low vulnerability and high readiness, meaning it is well-prepared for climate challenges. In contrast, a low NDGAIN score suggests high vulnerability and low readiness, indicating a country is at significant risk and lacks the resources or infrastructure to adapt effectively.

We follow the empirical approach outlined in Section 4.2 to run this test, but modify the interaction terms in Equations 8 and 9. Instead of focusing on UNEP-FI bank commitments, we now interact our main variable of interests with an indicator capturing whether the lead arranger bank is headquartered in a country with higher exposure to biodiversity risk. We define a dummy variable *Low NDGAIN* that equals 1 if the NDGAIN score of a lead bank's country of headquarters falls below the median at the observed time period and 0 otherwise.[16]

4.4 Do banks adjust their lending terms more strongly for firms with higher biodiversity risk after environmental violations?

We now examine violations of environmental laws as recorded by the U.S. Environmental Protection Agency (EPA). We use a quasi-difference-in-differences (DiD) approach to analyze

[16]For an application of NDGAIN data or indices see in different forms consult Y. Liu, Wang, Wen, and Wu (2024) and Giglio, Kuchler, Stroebel, and Wang (2024).

the variation in firm-level EPA violations over time. Our treatment variable, *Post3yr*, is a time-varying indicator that equals 1 starting in the year a violation occurs and remains 1 for three consecutive years, returning to 0 afterward. Firms with no recorded violations remain untreated throughout the study period. This specification enables us to compare the financing terms of firms before and after the regulatory event with those of a control group of unaffected firms.

We then interact this indicator with our biodiversity risk measures to investigate whether the effect of biodiversity risk is amplified for firms with a history of environmental misconduct. This interaction term helps us explore whether companies that have violated environmental regulations are more sensitive to—or more likely to be penalized for—exposure to biodiversity risk, potentially due to heightened scrutiny from regulators, investors, or the public.

$$\begin{aligned} Loan\ spread_{l,f,b,t} = \alpha + \beta_1 Bio\ risk_{f,t} + \beta_2 Post3yr_{f,t} + \beta_3 Bio\ risk_{f,t} * Post3yr_{f,t} \\ + \gamma LOAN_{l,f,b,t} + \delta FIRM_{f,t-1} + \zeta LEAD\ BANK_{b,t-1} + FE \\ + \varepsilon_{l,f,b,t}. \end{aligned} \tag{10}$$

$$\begin{aligned} Log(Loan\ volume)_{f,b,t} = \alpha + \beta_1 Bio\ risk_{f,t} + \beta_2 Post3yr_{f,t} + \beta_3 Bio\ risk_{f,t} * Post3yr_{f,t} \\ + \delta FIRM_{f,t-1} + \zeta LEAD\ BANK_{b,t-1} + FE + \varepsilon_{f,b,t}. \end{aligned} \tag{11}$$

4.5 Is the effect of biodiversity risk on bank lending decisions amplified by low E Scores?

Environmental Scores (E Scores) provide a comprehensive assessment of firms' environmental performance. To account for the environmental performance of a company and whether it

affects lending decisions in combination with the biodiversity risk, we follow the empirical approach outlined in Equations 10 and 11, and modify the interaction terms to include a dummy indicating low (below B-) E pillar performance.

Interacting our biodiversity measures with a dummy indicating whether a firm performs poorly in terms of its E Score allows us whether the combination of low environmental performance and high biodiversity risk leads to differentiated outcomes. It can be argued that the E Score may reflect some risk components that are also relevant for biodiversity risk, however, there may also be limited substitution between biodiversity risk and the E Score metric, as they can capture distinct aspects of environmental exposure.

5 Empirical results

5.1 Baseline

Tables 4 and 5 present the baseline results of Equation 6, using all available biodiversity measures. Focusing on Table 4, which includes the measures proposed by Giglio et al. (2023)—namely the overall biodiversity score (*Biodiversity Count*) and the score capturing firm-level mentions of biodiversity regulation-related content (*Biodiversity Regulation*)—we find a positive and statistically significant relationship between biodiversity risk measures and loan spreads. In Table 5, we show the baseline results using our own more granular measures that separate biodiversity-related mentions in firm 10-K statements based on one of the following topics: *Air Pollution, Climate Change, Land Use, Water Pollution.* To offer a more comparable approach to the Giglio et al. (2023) scores, we also estimate the model using the biodiversity measure that is calculated across the previous four measures, denoted as *Biodiversity Total.* All five biodiversity risk metrics are positively associated with loan spreads. While most coefficients are statistically significant across specifications, including different fixed effects occasionally affects significance levels, while the direction and

magnitude of the estimates remain broadly consistent. These findings are in line with Erten and Ongena (2024) who also show that banks charge higher loan prices to firms that inflict harm on the environment.

It should be noted that in our estimations, we use a conservative identification strategy that accounts for various characteristics at the loan, firm, and lender levels. Additionally, we employ a saturated fixed effects structure, incorporating loan purpose, industry, and year fixed effects. In some specifications, we include three-way fixed effects for industry, state, and year interactions. This approach helps to account for unobserved heterogeneity and isolate credit supply effects while absorbing sectoral, temporal, and geographic shocks (Chava, 2014; Degryse, De Jonghe, Jakovljević, Mulier, & Schepens, 2019; Giannetti, Jasova, Loumioti, & Mendicino, 2023).

In terms of economic significance, our results indicate that biodiversity risk is associated with economically meaningful increases in loan spreads. Given that the average spread in our sample is 176.30 basis points, the estimated effects range from approximately 5% to 33% of this mean. The largest effect is observed for the *Biodiversity Regulation* score (Table 4, Column 3). Likewise, in Table 5, the *Biodiversity Total* dummy is associated with a statistically significant increase of 23 basis points in loan spreads, corresponding to approximately 13% of the average.[17]

The results of our control variables are as expected, with the deal size and maturity having a negative relationship with loan spreads, which is statistically significant in most columns. In terms of the loan covenants, the relationship is also of negative sign and significant, indicating the existence of covenants in loan contracts leads to lower financing costs. A dummy variable indicating whether the loan is secured is, in most columns, statistically significant and positively associated with the dependent variable, indicating collateral is used mainly by riskier borrowers (Golden & Liu, 2025). We do not find any significant

[17]As all biodiversity risk indicators are binary variables, we assess economic significance by comparing the estimated coefficients to the mean of the dependent variable, following the approach of Mitton (2024).

relationship for the control variable indicating the number of lead arrangers. As for firm characteristics, firm size is statistically significant in most columns, while the relationship to the dependent variable is of negative sign. We find similar results for return on assets. As expected, we obtain a negative and significant association between firm leverage and the loan spread. The firm tangibility and coverage variables are not significant in most specifications. As for bank fundamentals, we find that lender capitalization, income, and size are all statistically significant and negatively associated with the dependent variable. This that larger, better capitalized banks and those with greater reliance on interest based income in their operating revenue are able to offer lower cost of financing to their clients.

While the results in Table 4 indicate a substantial increase in loan spreads for firms with elevated biodiversity risk, it is important to note that only around 10% of companies in the sample are flagged as having such risk under this measure. Nevertheless, when we turn to more granular indicators, we find that firms reporting on air pollution, water pollution, and climate change—key drivers of biodiversity loss—also face significantly higher loan spreads, albeit with smaller effect sizes. This suggests that although the individual drivers are associated with more modest increases in borrowing costs, they are already partially reflected in lenders' pricing of credit risk. Lenders might not be explicitly pricing "biodiversity risk" as a standalone concept but are responding to its underlying components, which naturally overlap with broader environmental concerns.

Table 4 about here

Table 5 about here

Moving to loan volume (presented in Equation 7), a key identification hurdle in our empirical setting is to accurately attribute the adjustments in credit volume and conditions to supply-side factors. This, at the same time, requires absorbing any factors arising from loan demand. The data allows us to employ various specifications for fixed effects that could

limit this issue. Our base model controls for variation, which is common to all firms over time (time fixed effects) and firm time-invariant unobserved heterogeneity (firm fixed effects). In all our regressions, we also control for various firm-level characteristics controlling for loan demand. To account for lender heterogeneity, we either introduce bank controls or include a set of lender or lender-time fixed effects (Degryse et al., 2023; Kacperczyk & Peydro, 2022). Moreover, in some specifications we introduce three way fixed effects at the industry-state-year level that can control for time-varying heterogeneity within a specific state and industry (Degryse et al., 2019; Doerr & Schaz, 2021; Giannetti et al., 2023).

Table 6 about here

Table 7 about here

The analyses presented in Table 6 suggests that firms with higher overall and regulatory biodiversity risk may receive lower credit volumes. The magnitude of the coefficients stays broadly constant over different fixed effect specifications. Then Table 7 focuses on the more granular biodiversity risks and confirms that the *Biodiversity Total* is negatively associated with credit volumes, although the coefficient is not statistically significant. Among the sub-components, *Water Pollution* is the only dimension showing a statistically significant and negative relationship with credit volumes (column 10), indicating that banks may be particularly attentive to firms' exposure to water-related biodiversity risks. The coefficient estimate remain stable across alternative model specifications (however not statistically significant column 11-12), lending support to the robustness of the results.

Nevertheless, given the inherent difficulty in disentangling credit supply from demand, we are currently conducting additional tests to more accurately separate these effects and ensure that our results reflect a clean measure of the impact of biodiversity risk on credit supply.

5.2 *Committed* Banks

After our baseline regressions above, we are interested to understand whether being a *committed* bank as signaled by the bank's dedication to sustainability targets, more specifically the United Nations Environment Programme – Finance Initiative (UNEP-FI) has an effect on the pricing behaviour as outline in Equation 8.

Table 8 about here

The regression results in Table 8 indicate that environmental factors play a significant role in shaping outcomes related to the dependent variable, with notable differences in the effects of specific environmental risks. *Biodiversity Count* and *Biodiversity Regulation* scores exhibit strong positive associations with loan spreads, further suggesting that firms facing higher biodiversity and biodiversity-related regulatory risks tend to incur higher loan spreads. In contrast, the interaction terms between these biodiversity measures and the *UNEP-FI Lender* dummy are statistically insignificant, suggesting that a bank's commitment to sustainability principles, as indicated by UNEP-FI membership, does not meaningfully alter the pricing of biodiversity risk in loan contracts.

By contrast, the other environmental dimensions—*Air Pollution*, *Climate Change*, *Land Use*, and *Water Pollution*—show no statistically significant effects on loan spreads. Their interaction terms with *UNEP-FI Lender* are also insignificant, indicating limited evidence that these specific environmental risks are systematically incorporated into loan pricing decisions in this context.The aggregate measure, *Biodiversity Total*, is likewise not statistically significant, and its interaction with the UNEP-FI lender indicator remains insignificant.

Our findings align with Chava (2014), who shows that firms with negative environmental externalities face significantly higher loan spreads. We find that firms with higher exposure to biodiversity-related risks, face loan spread increases of around 48 to 73 basis points. In contrast to Chava (2014) who find some evidence in bank responses to environmental

risk based on their sustainability commitments , our interactions with lender sustainability commitments (e.g., UNEP-FI membership) are generally statistically insignificant.

Overall, these results suggest that among the environmental dimensions considered, biodiversity risk—particularly when measured narrowly through mentions or regulatory exposure—plays a more salient role in shaping credit market outcomes. These findings underscore the complexity of integrating environmental risks into financial decision-making and highlight the need for further research on the role of firm-level environmental commitments in shaping economic outcomes.

Table 9 about here

Turning to loan volume in Table 9, we find that both the *Biodiversity Count* and *Biodiversity Regulation* scores, as well as their interactions with the *UNEP-FI Lender* dummy, exhibit strong negative relationships with loan volumes. These results further support our earlier findings, indicating that firms facing biodiversity and biodiversity-related regulatory risks tend to receive lower credit volumes—particularly from lenders who are signatories of the United Nations Environment Programme – Finance Initiative.

When examining the four environmental pressures—*Air Pollution*, *Climate Change*, *Land Use*, and *Water Pollution* and theit sum *Biodiversity Total*—we find that, overall, their individual effects on loan volumes are not statistically significant, with the exception of *Water Pollution*, which displays a negative and weakly significant relationship. This suggests that, among the broader set of environmental risks, biodiversity-related dimensions are more salient in influencing lending behavior. The interaction terms between these environmental pressures and the *UNEP-FI Lender* dummy are also not statistically significant, implying that UNEP-FI lenders do not consistently adjust loan volumes in response to environmental pressures.

5.3 High Biodiversity Risk Regions

The regression results in Table 10 show that countries with low climate adaptation readiness—defined as being below the 25th percentile of the NDGAIN index—experience different loan spread responses to biodiversity and more granular biodiversity risks.

We find that both the *Biodiversity Count* and *Biodiversity Regulation* scores are positively and significantly associated with higher loan spreads, suggesting that lenders perceive biodiversity-related risks as financially material. However, the interaction terms *Biodiversity Count* × *Low NDGAIN* and *Biodiversity Regulation* × *Low NDGAIN* are not statistically significant, indicating that the effect of biodiversity risk on loan pricing does not vary meaningfully across countries with different levels of climate adaptation readiness.

Among the four environmental pressures, only *Climate Change* and *Water Pollution* exhibit positive and statistically significant effects on loan spreads, but again, their interactions with *Low NDGAIN* are not significant. This suggests that while some environmental risks are priced in, this pricing does not appear to systematically differ between countries with high versus low climate adaptation capacity. Nevertheless, the interaction term *Biodiversity Total* × *Low NDGAIN* in column (7) is positive and highly significant. This suggests that in countries with low climate adaptation readiness, firms identified as facing more than 2 environmental pressures within the same year are charged substantially higher loan spreads. In contrast, such risks appear to have a less pronounced effect in more climate-resilient countries. Interestingly, the coefficient for the *Low NDGAIN* dummy is large and negative in column (7), and statistically significant, possibly capturing unobserved country-level characteristics associated with lower spreads in less climate-ready contexts.

Finally, the coefficient on *Low ND-GAIN* is negative in all specifications, with one estimate (column 7) being statistically significant at the 1% level. his suggests that banks located in countries with low climate adaptation capacity tend to offer loans at significantly lower spreads, all else equal. One possible interpretation is that banks in less climate-resilient

countries may underprice environmental and biodiversity-related risks—either due to limited internal capacity for risk assessment, weaker regulatory pressure, or greater exposure to short-term lending incentives. Alternatively, such pricing behavior could reflect broader financial market conditions, such as lower baseline interest rates or higher competition in domestic lending markets. This finding raises concerns about potential risk mispricing in more vulnerable banking systems and highlights the importance of strengthening climate risk management practices within financial institutions, especially in regions with limited adaptation readiness.

Overall, the results suggest that while biodiversity and certain environmental risks increase loan spreads, there is limited evidence that lenders systematically adjust pricing based on a country's climate adaptation readiness—at least as captured by the NDGAIN index.

Table 10 about here

Turning to loan volume in Table 9, we find that the *Biodiversity Regulation* shows statistically significant negative associations with loan volumes.

This indicates that firms facing biodiversity-related risks receive lower credit volumes, particularly when borrowing from lenders that are members of the United Nations Environment Programme – Finance Initiative (UNEP-FI).

When examining the four environmental pressures—*Air Pollution*, *Climate Change*, *Land Use*, and *Water Pollution*—we find that, overall, their individual effects on loan volumes are not statistically significant, with the exception of *Water Pollution*, which displays a negative and weakly significant relationship.

Furthermore, the only statistically significant interaction term is *Land Use* $\times$ *Low NDGAIN*. The negative and significant coefficient indicates that in countries with low climate adaptation capacity, land use-related biodiversity risks are associated with substantially reduced credit volumes. This suggests that lenders may tighten credit supply more aggressively in less climate-resilient countries when confronted with risks related to land degradation or

ecosystem conversion. However, given the challenges in disentangling credit supply effects from shifts in loan demand, these results should be interpreted with appropriate caution.

However, most of the interaction terms between with *UNEP-FI Lender* are not statistically significant, implying that UNEP-FI lenders do not consistently adjust loan volumes in response to non-biodiversity environmental pressures. This pattern underscores the distinctive role of biodiversity concerns in shaping credit allocation decisions, especially when lenders are explicitly committed to sustainable finance principles.

The coefficient on the *Low ND-GAIN* indicator is consistently positive across all specifications, although only once statistically significant (column 5). This suggests that, in general, banks operating in countries with lower climate adaptation capacity do not provide significantly different credit volumes purely due to their location.

Table 11 about here

5.4 Firm-level biodiversity risk and EPA violations

Table 12 explores how loan spreads respond to biodiversity risk in the context of firms flagged for environmental violations, as captured by the EPA-based *Post3yr* dummy (equal to 1 in the year of violation and the subsequent three years). The results suggest that biodiversity-related risks become more salient in the presence of regulatory scrutiny. Specifically, the coefficients on both *Biodiversity Count* and *Biodiversity Regulation* are positive and statistically significant, indicating that firms with higher biodiversity risk face increased loan spreads. However, their interaction terms with the *Post3yr* EPA violation dummy are negative and statistically insignificant. This suggests that, although biodiversity risk is priced in overall, its marginal effect on loan spreads does not intensify—and may even slightly diminish—during the three-year period following an environmental violation. One plausible explanation is that firms flagged by the EPA may undertake corrective measures or adopt more robust environmental policies post-violation, leading lenders to view the firm's environ-

mental risk profile as improving over time, thereby dampening the additional pricing impact of biodiversity risk.

In contrast, *Water Pollution* exhibits a different dynamic. Both the standalone coefficient and the interaction with *Post3yr* are positive and statistically significant, suggesting that loan spreads increase further for firms with water pollution exposure after an EPA violation. This may indicate that water-related risks are perceived as more severe, persistent, or harder to remediate, and thus lead to a compounding effect on borrowing costs.

While most coefficients on *Post3yr* are statistically insignificant, one specification (column 6) reveals a negative and statistically significant effect. Specifically, this indicates that, on average, loan spreads decrease in the three years following an environmental violation for firms not heavily exposed to the corresponding biodiversity risks. This could imply that firms with lower biodiversity risk profiles may benefit from relatively improved credit terms post-violation, possibly due to proactive biodiversity management or lower perceived future compliance risk. However, the lack of consistent significance across specifications suggests that this effect is not uniform and may be context-dependent. Furthermore, the absence of a positive and significant *Post3yr* effect implies that lenders do not systematically increase borrowing costs following violations, unless combined with high environmental exposure, which is more directly captured by the interaction terms in the corresponding models.

Taken together, these results do not necessarily conflict. Instead, they point to differentiated lender responses based on the nature of the environmental risk and its perceived persistence or remediation potential. Biodiversity risks may be viewed as more manageable post-violation, whereas water pollution may trigger heightened scrutiny and lasting financial penalties.

Table 12 about here

Lastly, turning to Table 13, we find that the coefficients on *Biodiversity Count*, *Biodiversity Regulation*, and *Water Pollution* are negative and statistically significant, reinforcing the

notion that firm-level biodiversity risks—particularly those related to water pollution—are associated with reduced loan volumes. These findings further underscore the financial materiality of biodiversity concerns in lending decisions. In addition, we observe that the interaction terms *Air Pollution* × *Post3yr* and *Biodiversity Total* × *Post3yr* are both negative and statistically significant. This suggests that, following an environmental violation event, lenders may become more sensitive to firms' environmental risk profiles—especially in relation to air pollution and broader biodiversity exposures—resulting in more constrained credit access.

The variable *Post3yr* is positive and statistically significant in several columns (especially columns 3, 4, 6, and 7), even though the interaction terms with specific biodiversity or pollution risks are negative and significant (e.g., *Air Pollution* × *Post3yr*, *Biodiversity Total* × *Post3yr*). This pattern suggests that, on average, firms experience a modest increase in loan volumes in the three years following an environmental violation, unless they are simultaneously exposed to certain environmental risks. In other words, the baseline effect of *Post3yr* may reflect lenders' neutral or even favorable credit treatment of firms that are not burdened by air pollution or biodiversity-related concerns. However, when these environmental risks are present, the negative interaction terms indicate that lenders tighten credit access in the post-violation period. This suggests that environmental violations do not uniformly reduce loan volumes; rather, their financial consequences are amplified for firms with high environmental risk exposure. The equations for loan spread and loan volume are outlined below.

Table 13 about here

5.5 Low Environmental (E) Score

Specifically in Table 14, we find a significant and positive interaction terms for both *Biodiversity Count* × *Low E Score* and *Biodiversity Regulation* × *Low E Score* suggest that firms

with poor environmental scores face substantially higher loan spreads when also exposed to biodiversity risks. This implies that lenders may penalize firms more harshly when biodiversity risk is coupled with generally weak environmental performance. Our findings are broadly consistent with Seltzer, Starks, and Zhu (2022), who show that firms with lower environmental performance tend to exhibit higher bond yield spreads, particularly when they are located in states with more stringent environmental regulations.

Table 14 about here

Then Table 15 show that both the *Biodiversity Count* and *Biodiversity Regulation* scores as well as *Air Pollution* are negatively and statistically significantly associated with loan volume, indicating that lenders reduce credit to firms exposed to biodiversity-related risks. However, the interaction terms *Biodiversity Count* $\times$ *Low E Score* and *Biodiversity Regulation* $\times$ *Low E Score* are not statistically significant, suggesting that the reduction in loan volume due to biodiversity risk does not vary systematically based on a firm's environmental score.

This pattern contrasts with the findings for loan spreads (Table 14), where biodiversity risks led to significantly higher spreads for firms with poor environmental performance. This may suggest that while lenders increase the cost of borrowing for environmentally weak firms exposed to biodiversity risk, they do not necessarily reduce the volume of credit extended to them.

Table 15 about here

6 Conclusion and Outlook

In this study, we make several contributions. First, we link firm-level, text-based biodiversity measures to bank lending decisions and identify a significant relationship with loan spreads and a negative and significant association of biodiversity measures with loan volumes. These findings suggest that banks adjust lending terms in response to firms' biodiversity exposure.

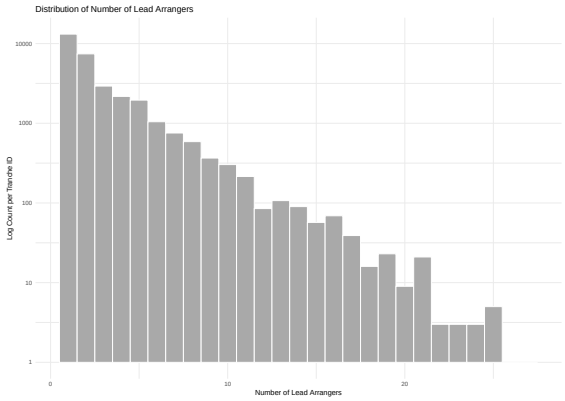
Second, we contribute to the measurement of biodiversity-related risks by developing four distinct text-based indicators using an embedding technique that accounts for the linguistic context of sustainability reports. This improves the traditional bag-of-words method by leveraging the cosine similarity of word embeddings, allowing us to capture semantic nuance beyond simple word counts. Our analysis focuses on four key environmental pressures: air pollution, water pollution, climate change, and land use, revealing notable variation across these categories and highlighting the heterogeneity of biodiversity-related risks.

To investigate the mechanisms behind our baseline findings, we extend the analysis by examining heterogeneity across both banks and firms. On the lender side, we assess whether geographical location—particularly in countries less prepared for climate change—and UNEP-FI membership shape lending behavior. On the borrower side, with low ESG scores and those with a history of environmental violations (as identified by EPA data). While we find clear evidence that banks penalize biodiversity risk through both higher loan spreads and lower loan volumes, the precise channels behind these relationships remain inconclusive. To be specific, when introducing alternative and more strict specification of fixed effects to account for potential credit demand factors (as shown in the Appendix), some coefficients lose statistical significance, raising questions about the stability of the effects. The observed patterns may reflect a combination of pricing strategies, lender risk assessments, and broader market dynamics that are difficult to fully disentangle in empirical analysis.

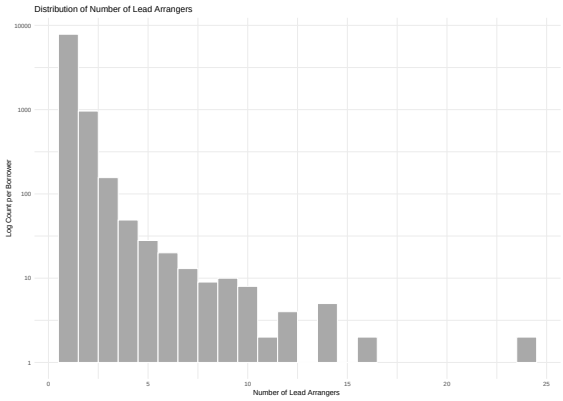
Future improvement plans include distinguishing physical risk from regulatory risk for each dimension of our measure to enhance the identification of transmission channels. We

also aim to refine our methodology for deriving the four environmental pressures by adopting a more advanced embedding model with an earlier cutoff date, further minimizing forward-looking biases and strengthening the robustness of our identification strategy.

Figure 1: Overview of Lead Arrangers per year.

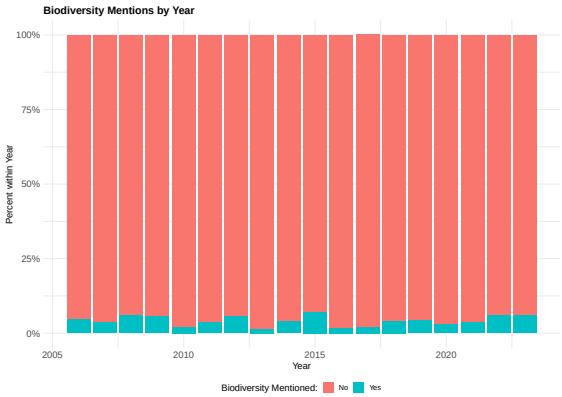


(a) Overview of Lead Arrangers in the Borrower - Tranche Dataset. For better visibility of the larger counts of lead arranges, a logarithm is used.



(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 (Giglio et al., 2023) data in Borrower - Tranche Level dataset

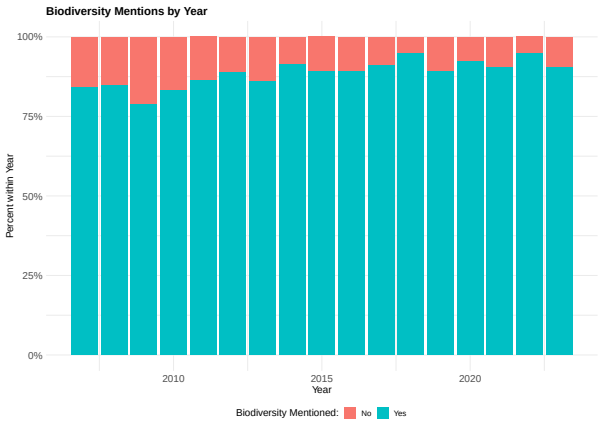


(a) 10-K Biodiversity Count Score

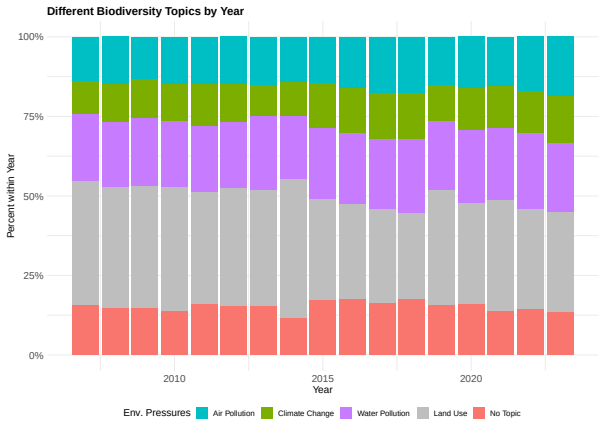


(b) 10-K Biodiversity Regulations Score

Figure 3: Overview of our own measure in Borrower - Tranche Level dataset

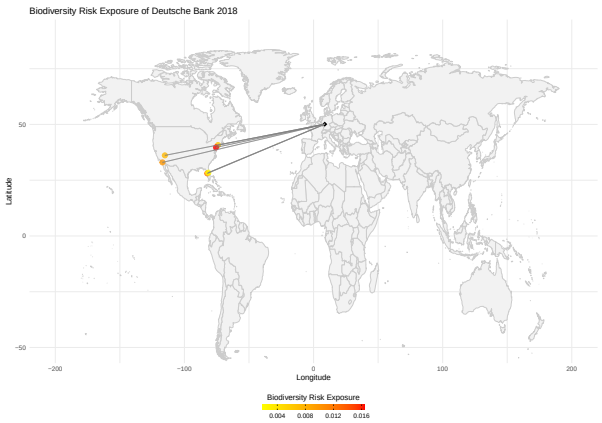


(a) Share of firms mentioning biodiversity in 10-K statements. Here the *No* indicates that the company does not mention any of the four environmental pressures.

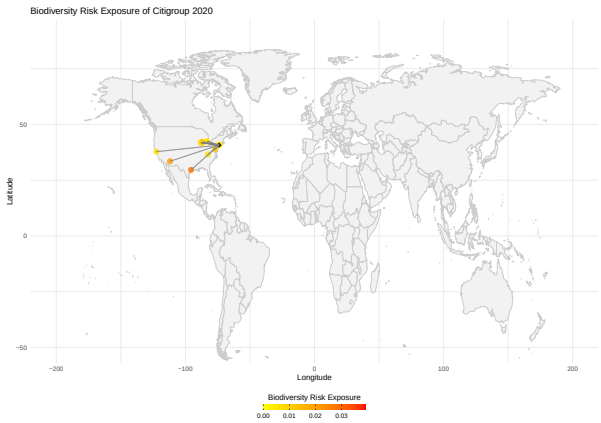


(b) Distribution of biodiversity pressure topics mentioned among firms. *No Topic* refers to partial coverage of the four key environmental pressures.

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 2020 in the year 2018. 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 2023, developed through textual analysis of 10-K statements. This biodiversity data has been recently made available at http://www.biodiversityrisk.org	Giglio et al. (2023)
Bank environmental commitments	Data on bank commitments to sustainability targets, focusing on sustainable economy initiatives in carbon emissions, production and consumption, financing nature, and inequality.	United Nations Environment Programme – Finance Initiative (UNEP-FI)
Lender's country vulnerability to climate change	The NDGAIN 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)
Borrower environmental violations	Data on National Enforcement and Compliance History Online Data. The Enforcement and Compliance History Online (ECHO) system incorporates Federal enforcement and compliance (FE&C) data from the Integrated Compliance Information System (ICIS), used to track federal enforcement cases.	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 (2025)

Table 2: Descriptive statistics

Borrower - Tranche Level (Loan Spread dataset)					
	Count	Mean	SD	Min	Max
Loan Spread (bps)	4078	176.30	101.98	17.50	725.00
Biodiversity Count	4078	0.02	0.15	0.00	1.00
Biodiversity Regulation	4078	0.01	0.12	0.00	1.00
Air Pollution	4078	0.59	0.49	0.00	1.00
Climate Change	4078	0.48	0.50	0.00	1.00
Land Use	4078	0.74	0.44	0.00	1.00
Water Pollution	4078	0.60	0.49	0.00	1.00
Biodiversity Total	4078	0.69	0.46	0.00	1.00
Deal Size (USD million)	4078	1,634.61	2,048.27	10.00	13,000.00
Deal Size (log)	4078	20.62	1.17	16.12	23.29
Maturity (log)	4078	3.83	0.53	0.00	4.50
Covenants	4078	0.66	0.47	0.00	1.00
Secured	4078	0.41	0.49	0.00	1.00
Number of Leads	4078	3.36	2.75	1.00	27.00
Size (Total Assets, USD million)	4078	11,322.03	29,120.99	45.41	193,694.00
Size	4078	21.82	1.49	17.63	25.99
Return on Assets (%)	4078	4.97	7.90	-45.39	26.41
Leverage (%)	4078	24.98	17.77	0.00	103.40
Tangibility (%)	4078	26.71	21.72	1.26	88.69
Coverage	4078	33.72	91.36	-13.50	617.44
Lender Capitalization (% , Avg.)	4078	9.07	1.58	4.17	13.68
Lender Income (% , Avg.)	4078	49.54	9.32	26.05	90.14
Lender Size (Total Assets Avg., USD billion)	4078	1,730.46	595.62	33.83	22,454.69
Lender Size (log)	4078	28.05	0.67	24.24	28.53
UNEP-FI Lender (%)	4078	12.42	31.64	0.00	100.00
Low NDGAIN	4062	0.04	0.20	0.00	1.00
Low E Score	3196	0.33	0.47	0.00	1.00
Post3yr	4078	0.04	0.19	0.00	1.00
Borrower - Lender Level (Loan Volume dataset)					
	Count	Mean	SD	Min	Max
Loan Volume Amount (USD million)	1527	143.43	230.10	5.00	1,518.74
Loan volume (log)	1527	18.15	1.02	15.42	21.14
Biodiversity Count	1527	0.03	0.17	0.00	1.00
Biodiversity Regulation	1527	0.02	0.14	0.00	1.00
Air Pollution	1527	0.55	0.50	0.00	1.00
Climate Change	1527	0.45	0.50	0.00	1.00
Land Use	1527	0.73	0.45	0.00	1.00
Water Pollution	1527	0.55	0.50	0.00	1.00
Biodiversity Total	1527	0.66	0.48	0.00	1.00
Size (Total Assets, USD million)	1527	19,304.63	38,447.30	45.41	203,631.00
Size (log)	1527	22.26	1.74	17.63	26.04
Return on Assets (%)	1527	5.82	8.14	-40.59	24.66
Leverage (%)	1527	22.53	16.32	0.00	90.66
Tangibility (%)	1527	25.80	20.94	1.41	90.05
Coverage	1527	36.95	89.97	-8.82	555.80
Lender Capitalization (%)	1527	8.83	1.80	3.81	13.68
Lender Income (%)	1527	49.33	11.84	14.44	90.44
Lender Size (Total Assets, USD billion)	1527	1,684.32	658.34	33.03	2,747.46
Lender Size (log)	1527	27.97	0.78	24.22	28.64
UNEP-FI Lender	1527	0.17	0.38	0.00	1.00
Low ND-GAIN	1512	0.05	0.23	0.00	1.00
Low E Score	1292	0.29	0.45	0.00	1.00
Post3yr	1527	0.06	0.24	0.00	1.00

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 3: Correlation matrix of biodiversity risk scores.

	Biodiversity Count	Biodiversity Regulation	Air Pollution	Climate Change	Land Use	Water Pollution	Biodiversity Total
Biodiversity Count	1.000						
Biodiversity Regulation	0.855***	1.000					
Air Pollution	0.110***	0.090***	1.000				
Climate Change	0.106***	0.089***	0.417***	1.000			
Land Use	0.024**	0.038***	0.270***	0.262***	1.000		
Water Pollution	0.058***	0.067***	0.441***	0.482***	0.328***	1.000	
Biodiversity Total	0.087***	0.073***	0.671***	0.619***	0.485***	0.682***	1.000

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

Table 4: Loan spreads and biodiversity risk

	(1)	(2)	(3)	(4)
Biodiversity Count	42.898**	53.219***		
	(17.376)	(18.499)		
Biodiversity Regulation			58.195**	43.371***
			(23.531)	(15.253)
Deal Size	-8.862**	-1.858	-8.970**	-2.242
	(3.976)	(5.573)	(3.953)	(5.602)
Maturity	-16.038**	-14.530**	-15.993**	-14.522**
	(7.034)	(6.345)	(7.055)	(6.346)
Covenants	-10.254**	-3.804	-10.237**	-3.884
	(4.655)	(5.854)	(4.668)	(5.854)
Secured	45.255***	1.483	45.030***	1.931
	(5.619)	(7.636)	(5.611)	(7.629)
Number of Leads	1.644	-0.430	1.628	-0.454
	(1.358)	(1.136)	(1.357)	(1.137)
Size	-12.418***	-23.177***	-12.155***	-22.902***
	(2.828)	(4.545)	(2.809)	(4.590)
Return on Assets	-1.421***	-2.932***	-1.390***	-2.900***
	(0.494)	(0.788)	(0.490)	(0.785)
Leverage	0.912***	0.859***	0.907***	0.862***
	(0.174)	(0.308)	(0.174)	(0.310)
Tangibility	-0.102	-0.266	-0.090	-0.225
	(0.186)	(0.297)	(0.185)	(0.298)
Coverage	-0.016	0.022	-0.018	0.023
	(0.026)	(0.027)	(0.025)	(0.028)
Lender Capitalization	-1.897	-14.278***	-1.948	-14.175***
	(1.838)	(3.982)	(1.839)	(4.045)
Lender Income	-0.481	-1.729***	-0.504	-1.790***
	(0.399)	(0.566)	(0.393)	(0.569)
Lender Size	-6.606	-15.209**	-6.489	-15.589**
	(4.919)	(6.987)	(4.899)	(6.981)
Purpose FE	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No
Year FE	Yes	No	Yes	No
Industry x State x Year FE	No	Yes	No	Yes
Observations	4078	3821	4078	3821
R^2	0.421	0.698	0.422	0.698

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. 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 and 3 include fixed effects for loan purpose, industry, and year. Columns 2 and 4 replace industry and year fixed effects with three-way industry × 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 5: Loan spreads and biodiversity risk - granular measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Air Pollution	5.176	17.905**								
	(5.292)	(7.854)								
Climate Change			8.965*	19.340**						
			(4.968)	(7.984)						
Land Use					2.478	20.349**				
					(5.490)	(9.691)				
Water Pollution							11.586**	18.770*		
							(5.597)	(10.744)		
Biodiversity Total									7.461	23.012**
									(5.858)	(9.324)
Deal Size	-9.332**	-2.127	-9.152**	-2.026	-9.304**	-2.987	-9.416**	-2.237	-9.384**	-3.316
	(4.004)	(5.751)	(3.989)	(5.636)	(3.980)	(5.676)	(4.024)	(5.634)	(4.005)	(5.706)
Maturity	-16.151**	-14.838**	-16.423**	-14.646**	-16.111**	-14.763**	-16.532**	-14.889**	-16.315**	-14.890**
	(7.050)	(6.345)	(7.039)	(6.348)	(7.066)	(6.335)	(7.053)	(6.339)	(7.045)	(6.339)
Covenants	-10.382**	-4.496	-10.665**	-4.722	-10.434**	-3.784	-11.048**	-4.512	-10.650**	-4.168
	(4.729)	(5.871)	(4.711)	(5.780)	(4.730)	(5.824)	(4.760)	(5.851)	(4.730)	(5.814)
Secured	46.111***	2.569	45.889***	2.900	46.511***	1.942	45.706***	2.519	45.992***	2.187
	(5.614)	(7.613)	(5.477)	(7.572)	(5.553)	(7.673)	(5.592)	(7.611)	(5.619)	(7.598)
Number of Leads	1.592	-0.487	1.620	-0.508	1.560	-0.573	1.638	-0.525	1.616	-0.512
	(1.345)	(1.139)	(1.331)	(1.118)	(1.359)	(1.131)	(1.343)	(1.131)	(1.340)	(1.130)
Size	-11.599***	-23.228***	-11.767***	-22.891***	-11.575***	-21.166***	-11.545***	-22.217***	-11.602***	-21.629***
	(2.803)	(4.580)	(2.766)	(4.600)	(2.791)	(4.667)	(2.818)	(4.624)	(2.800)	(4.623)
Return on Assets	-1.354***	-2.763***	-1.344***	-2.836***	-1.376***	-2.956***	-1.330***	-2.727***	-1.349***	-2.883***
	(0.489)	(0.772)	(0.488)	(0.778)	(0.488)	(0.748)	(0.486)	(0.789)	(0.487)	(0.796)
Leverage	0.920***	1.098***	0.904***	0.982***	0.915***	0.985***	0.882***	0.912***	0.905***	1.018***
	(0.177)	(0.337)	(0.178)	(0.310)	(0.175)	(0.302)	(0.178)	(0.311)	(0.177)	(0.316)
Tangibility	-0.080	-0.208	-0.097	-0.210	-0.069	-0.203	-0.075	-0.132	-0.078	-0.109
	(0.186)	(0.296)	(0.185)	(0.306)	(0.185)	(0.283)	(0.182)	(0.307)	(0.184)	(0.299)
Coverage	-0.010	0.041	-0.010	0.044	-0.011	0.040	-0.011	0.038	-0.011	0.054*
	(0.030)	(0.031)	(0.030)	(0.031)	(0.030)	(0.032)	(0.030)	(0.028)	(0.030)	(0.033)
Lender Capitalization	-1.944	-13.736***	-1.757	-13.211***	-1.904	-13.600***	-1.989	-12.925***	-2.002	-13.695***
	(1.859)	(4.045)	(1.859)	(3.993)	(1.860)	(3.943)	(1.838)	(4.028)	(1.854)	(4.009)
Lender Income	-0.532	-1.812***	-0.518	-1.841***	-0.550	-1.937***	-0.544	-1.852***	-0.536	-1.883***
	(0.425)	(0.578)	(0.416)	(0.551)	(0.423)	(0.558)	(0.418)	(0.558)	(0.422)	(0.555)
Lender Size	-6.783	-16.541**	-6.536	-17.290**	-6.790	-16.570**	-6.628	-15.730**	-6.686	-17.312**
	(5.115)	(6.904)	(5.134)	(7.102)	(5.146)	(6.742)	(5.090)	(7.047)	(5.119)	(6.819)
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
Industry x State x Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4078	3821	4078	3821	4078	3821	4078	3821	4078	3821
R^2	0.419	0.698	0.420	0.699	0.418	0.698	0.420	0.698	0.419	0.699

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 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. 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 and 3 include fixed effects for loan purpose, industry, and year. Columns 2 and 4 replace industry and year fixed effects with three-way industry × 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: Bank lending and biodiversity risk

	(1)	(2)	(3)	(4)	(5)	(6)
Biodiversity Count	-0.321**	-0.0917	-0.629**			
	(0.144)	(0.116)	(0.301)			
Biodiversity Regulation				-0.474***	-0.185	-0.820**
				(0.165)	(0.152)	(0.389)
Size	0.349***	0.349***	0.339***	0.347***	0.349***	0.337***
	(0.0226)	(0.0152)	(0.0399)	(0.0227)	(0.0151)	(0.0401)
Return on Assets	0.00151	0.00563**	0.00650	0.00134	0.00551**	0.00616
	(0.00357)	(0.00258)	(0.00855)	(0.00357)	(0.00258)	(0.00847)
Leverage	0.00487**	0.00451***	0.000897	0.00486**	0.00451***	0.000605
	(0.00230)	(0.00142)	(0.00541)	(0.00229)	(0.00142)	(0.00541)
Tangibility	0.00296	0.00175	-0.00287	0.00284	0.00178	-0.00355
	(0.00197)	(0.00155)	(0.00411)	(0.00196)	(0.00154)	(0.00405)
Coverage	0.000665**	0.000417**	0.000395	0.000667**	0.000422**	0.000381
	(0.000280)	(0.000198)	(0.000502)	(0.000281)	(0.000198)	(0.000506)
Lender Capitalization	0.0471		-0.0980	0.0486		-0.0828
	(0.0429)		(0.0919)	(0.0426)		(0.0893)
Lender Income	-0.00253		-0.0141	-0.00229		-0.0147
	(0.00472)		(0.0107)	(0.00472)		(0.0106)
Lender Size	0.592***		0.410	0.594***		0.407
	(0.192)		(0.344)	(0.193)		(0.344)
Industry FE	Yes	Yes	No	Yes	Yes	No
Lender FE	Yes	No	Yes	Yes	No	Yes
Year FE	Yes	No	No	Yes	No	No
Lender x Year FE	No	Yes	No	No	Yes	No
Industry x State x Year FE	No	No	Yes	No	No	Yes
Observations	1527	3460	929	1527	3460	929
R^2	0.536	0.577	0.847	0.537	0.577	0.848

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. 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 and 3 include fixed effects for industry, lender and year. Columns 2 and 4 include industry and lender x year fixed effects. Lastly Column 3 and 6 include lender and a three-way industry × 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 - own measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Air Pollution	0.0466	-0.0207	0.0510												
	(0.0603)	(0.0407)	(0.115)												
Climate Change				-0.00991	-0.0405	-0.0486									
				(0.0627)	(0.0413)	(0.116)									
Land Use							0.0401	0.0246	0.118						
							(0.0630)	(0.0453)	(0.130)						
Water Pollution										-0.144**	-0.0636	-0.226			
										(0.0621)	(0.0416)	(0.138)			
Biodiversity Total													0.00300	-0.0258	-0.0218
													(0.0643)	(0.0448)	(0.125)
Size	0.350***	0.348***	0.349***	0.348***	0.348***	0.348***	0.350***	0.349***	0.357***	0.344***	0.348***	0.340***	0.349***	0.348***	0.347***
	(0.0229)	(0.0152)	(0.0414)	(0.0231)	(0.0152)	(0.0407)	(0.0229)	(0.0152)	(0.0431)	(0.0226)	(0.0152)	(0.0405)	(0.0229)	(0.0153)	(0.0421)
Return on Assets	0.00172	0.00563**	0.00562	0.00148	0.00555**	0.00585	0.00157	0.00576**	0.00549	0.000914	0.00535**	0.00387	0.00152	0.00561**	0.00557
	(0.00357)	(0.00258)	(0.00843)	(0.00360)	(0.00259)	(0.00857)	(0.00356)	(0.00256)	(0.00862)	(0.00361)	(0.00259)	(0.00849)	(0.00359)	(0.00258)	(0.00849)
Leverage	0.00488**	0.00451***	0.000469	0.00484**	0.00455***	-0.0000213	0.00481**	0.00448***	0.000641	0.00500**	0.00453***	-0.0000596	0.00484**	0.00453***	0.0000212
	(0.00234)	(0.00143)	(0.00547)	(0.00233)	(0.00142)	(0.00528)	(0.00235)	(0.00143)	(0.00542)	(0.00232)	(0.00142)	(0.00519)	(0.00233)	(0.00143)	(0.00536)
Tangibility	0.00229	0.00169	-0.00399	0.00245	0.00176	-0.00401	0.00243	0.00165	-0.00375	0.00249	0.00180	-0.00467	0.00241	0.00171	-0.00408
	(0.00200)	(0.00154)	(0.00411)	(0.00200)	(0.00153)	(0.00413)	(0.00198)	(0.00153)	(0.00408)	(0.00201)	(0.00153)	(0.00413)	(0.00199)	(0.00154)	(0.00414)
Coverage	0.000665**	0.000406**	0.000366	0.000646**	0.000396**	0.000292	0.000652**	0.000414**	0.000409	0.000614**	0.000395**	0.000129	0.000653**	0.000406**	0.000312
	(0.000278)	(0.000197)	(0.000502)	(0.000281)	(0.000197)	(0.000474)	(0.000278)	(0.000198)	(0.000496)	(0.000276)	(0.000197)	(0.000518)	(0.000279)	(0.000197)	(0.000504)
Lender Capitalization	0.0471		-0.108	0.0436		-0.113	0.0429		-0.111	0.0463		-0.105	0.0441		-0.110
	(0.0440)		(0.0978)	(0.0437)		(0.0987)	(0.0435)		(0.0972)	(0.0430)		(0.0972)	(0.0436)		(0.0980)
Lender Income	-0.00312		-0.0151	-0.00285		-0.0150	-0.00297		-0.0153	-0.00200		-0.0131	-0.00290		-0.0146
	(0.00480)		(0.0110)	(0.00474)		(0.0110)	(0.00473)		(0.0110)	(0.00473)		(0.0109)	(0.00475)		(0.0109)
Lender Size	0.594***		0.436	0.586***		0.422	0.580***		0.422	0.586***		0.456	0.586***		0.429
	(0.192)		(0.347)	(0.192)		(0.347)	(0.192)		(0.350)	(0.189)		(0.349)	(0.192)		(0.347)
Industry FE	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Lender FE	Yes	No	Yes	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	Yes	No	No
Lender x Year FE	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No
Industry x State x Year FE	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Observations	1527	3460	929	1527	3460	929	1527	3460	929	1527	3460	929	1527	3460	929
R^2	0.534	0.577	0.844	0.534	0.577	0.844	0.534	0.577	0.845	0.537	0.577	0.846	0.534	0.577	0.844

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: 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, 10 and 13 include fixed effects for industry, lender and year. Columns 2,5,8, 11 and 14 include industry and lender x year fixed effects. Lastly Column 3,6,9,12 and 15 include lender and a three-way industry × 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 8: Loan spreads, biodiversity risk and bank commitments (UNEP-FI Lender).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	47.590**						
	(20.668)						
Biodiversity Count × UNEP-FI Lender	-0.294						
	(0.303)						
Biodiversity Regulation		73.244**					
		(30.556)					
Biodiversity Regulation × UNEP-FI Lender		-0.594					
		(0.407)					
Air Pollution			4.701				
			(5.771)				
Air Pollution × UNEP-FI Lender			0.039				
			(0.148)				
Climate Change				6.794			
				(5.274)			
Climate Change × UNEP-FI Lender				0.169			
				(0.133)			
Land Use					0.416		
					(5.924)		
Land Use × UNEP-FI Lender					0.159		
					(0.156)		
Water Pollution						9.088	
						(5.852)	
Water Pollution × UNEP-FI Lender						0.206	
						(0.155)	
Biodiversity Total							5.672
							(6.353)
Biodiversity Total × UNEP-FI Lender							0.138
							(0.143)
UNEP-FI Lender	-0.003	-0.010	-0.026	-0.092	-0.121	-0.135	-0.100
	(0.087)	(0.087)	(0.111)	(0.113)	(0.129)	(0.125)	(0.130)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose 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
Observations	4078	4078	4078	4078	4078	4078	4078
R^2	0.422	0.423	0.419	0.420	0.419	0.421	0.419

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. 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. We include now the interaction with UNEP-FI measured on bank b and time t level. 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. Columns 1 and 3 include fixed effects for loan purpose, industry, and year. Columns 2 and 4 replace industry and year fixed effects with three-way industry × 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 9: Bank lending, biodiversity risk and bank commitments (UNEP-FI Lender).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.258*						
	(0.148)						
Biodiversity Count × UNEP-FI Lender	-0.696**						
	(0.312)						
Biodiversity Regulation		-0.395**					
		(0.180)					
Biodiversity Regulation × UNEP-FI Lender		-0.565*					
		(0.336)					
Air Pollution			0.031				
			(0.061)				
Air Pollution × UNEP-FI Lender			0.108				
			(0.141)				
Climate Change				0.002			
				(0.063)			
Climate Change × UNEP-FI Lender				-0.071			
				(0.140)			
Land Use					0.035		
					(0.065)		
Land Use × UNEP-FI Lender					0.033		
					(0.163)		
Water Pollution						-0.120*	
						(0.063)	
Water Pollution × UNEP-FI Lender						-0.159	
						(0.141)	
Biodiversity Total							0.018
							(0.066)
Biodiversity Total × UNEP-FI Lender							-0.095
							(0.145)
UNEP-FI Lender	-0.423	-0.396	-0.469	-0.387	-0.450	-0.276	-0.334
	(0.559)	(0.558)	(0.552)	(0.567)	(0.582)	(0.555)	(0.580)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1527	1527	1527	1527	1527	1527	1527
R^2	0.537	0.537	0.534	0.534	0.534	0.538	0.534

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. 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. We include now the interaction with UNEP-FI 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. Columns 1, 4 ,7, 10 and 13 include fixed effects for industry, lender and year. Columns 2,5,8, 11 and 14 include industry and lender x year fixed effects. Lastly Column 3,6,9,12 and 15 include lender and a three-way industry × 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: Loan spreads, biodiversity risk and NDGAIN Index.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	40.036**						
	(18.852)						
Biodiversity Count × Low ND-GAIN	30.669						
	(56.317)						
Biodiversity Regulation		58.787**					
		(25.302)					
Biodiversity Regulation × Low ND-GAIN		-13.442					
		(33.773)					
Air Pollution			4.973				
			(5.402)				
Air Pollution × Low ND-GAIN			15.072				
			(24.819)				
Land Use				2.517			
				(5.584)			
Land Use × Low ND-GAIN				2.641			
				(31.084)			
Climate Change					9.515*		
					(5.134)		
Climate Change × Low ND-GAIN					6.937		
					(25.483)		
Water Pollution						10.261*	
						(5.671)	
Water Pollution × Low ND-GAIN						25.422	
						(22.874)	
Biodiversity Total							5.375
							(5.979)
Biodiversity Total × Low ND-GAIN							69.664***
							(21.048)
Low ND-GAIN	-12.888	-10.155	-18.035	-12.609	-13.860	-25.872	-66.102***
	(18.190)	(18.145)	(25.059)	(34.143)	(24.129)	(26.674)	(19.852)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose 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
Observations	4062	4062	4062	4062	4062	4062	4062
R^2	0.422	0.423	0.420	0.419	0.421	0.421	0.422

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. 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. We include now the interaction with Low NDGAIN measured on bank b and time t level. 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 and 3 include fixed effects for loan purpose, industry, and year. Columns 2 and 4 replace industry and year fixed effects with three-way industry × 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 11: Bank lending, biodiversity risk and NDGAIN Index.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.299*						
	(0.156)						
Biodiversity Count × Low ND-GAIN	-0.257						
	(0.276)						
Biodiversity Regulation		-0.455**					
		(0.182)					
Biodiversity Regulation × Low ND-GAIN		-0.224					
		(0.367)					
Air Pollution			0.042				
			(0.060)				
Air Pollution × Low ND-GAIN			-0.102				
			(0.252)				
Climate Change				0.015			
				(0.062)			
Climate Change × Low ND-GAIN				-0.305			
				(0.252)			
Land Use					0.053		
					(0.063)		
Land Use × Low ND-GAIN					-0.541**		
					(0.272)		
Water Pollution						-0.126**	
						(0.064)	
Water Pollution × Low ND-GAIN						-0.243	
						(0.256)	
Biodiversity Total							0.019
							(0.064)
Biodiversity Total × Low ND-GAIN							-0.350
							(0.245)
Low ND-GAIN	0.177	0.185	0.243	0.269	0.650***	0.351	0.458
	(0.222)	(0.222)	(0.255)	(0.274)	(0.237)	(0.298)	(0.322)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1508	1508	1508	1508	1508	1508	1508
R^2	0.530	0.531	0.528	0.528	0.529	0.531	0.528

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. 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. 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. Columns 1, 4 ,7, 10 and 13 include fixed effects for industry, lender and year. Columns 2,5,8, 11 and 14 include industry and lender x year fixed effects. Lastly Column 3,6,9,12 and 15 include lender and a three-way industry × 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: Loan spreads, biodiversity risk and EPA Violations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	45.441**						
	(19.304)						
Biodiversity Count × Post3yr	-28.720						
	(28.190)						
Biodiversity Regulation		60.784**					
		(25.398)					
Biodiversity Regulation × Post3yr		-42.200					
		(44.632)					
Air Pollution			4.775				
			(5.407)				
Air Pollution × Post3yr			12.306				
			(23.817)				
Land Use				2.388			
				(5.524)			
Land Use × Post3yr				0.061			
				(21.321)			
Climate Change					8.356*		
					(5.058)		
Climate Change × Post3yr					14.981		
					(23.286)		
Water Pollution						10.123*	
						(5.602)	
Water Pollution × Post3yr						44.546**	
						(19.576)	
Biodiversity Total							6.491
							(5.910)
Biodiversity Total × Post3yr							33.385
							(21.836)
Post3yr	5.194	5.613	-5.549	3.519	-6.287	-32.679**	-24.434
	(13.030)	(12.768)	(18.622)	(17.062)	(13.791)	(13.663)	(16.535)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose 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
Observations	4078	4078	4078	4078	4078	4078	4078
R^2	0.422	0.422	0.419	0.418	0.420	0.421	0.420

This table reports the results of estimating the model in Equation 10. 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. 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. We include now the interaction with Post3yr as a measure of environmental violation measured on firm f and time t level as a 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. Columns 1 and 3 include fixed effects for loan purpose, industry, and year. Columns 2 and 4 replace industry and year fixed effects with three-way industry × 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: Bank lending, biodiversity risk and EPA Violations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.320**						
	(0.153)						
Biodiversity Count × Post3yr	0.002						
	(0.273)						
Biodiversity Regulation		-0.475***					
		(0.172)					
Biodiversity Regulation × Post3yr		0.050					
		(0.282)					
Air Pollution			0.078				
			(0.059)				
Air Pollution × Post3yr			-0.699***				
			(0.224)				
Climate Change				0.019			
				(0.063)			
Climate Change × Post3yr				-0.550**			
				(0.225)			
Land Use					0.035		
					(0.064)		
Land Use × Post3yr					0.080		
					(0.396)		
Water Pollution						-0.130**	
						(0.063)	
Water Pollution × Post3yr						-0.403	
						(0.264)	
Biodiversity Total							0.039
							(0.064)
Biodiversity Total × Post3yr							-0.861***
							(0.240)
Post3yr	0.066	0.063	0.577***	0.386**	-0.007	0.386*	0.768***
	(0.141)	(0.139)	(0.169)	(0.151)	(0.369)	(0.219)	(0.196)
Observations	1527	1527	1527	1527	1527	1527	1527
R^2	0.536	0.537	0.538	0.537	0.534	0.539	0.539

This table reports the results of estimating the model in Equation 11. 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. 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. We include now the interaction with Post3yr as a measure of environmental violation measured on firm f and time t level as a 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. Columns 1, 4 ,7, 10 and 13 include fixed effects for industry, lender and year. Columns 2,5,8, 11 and 14 include industry and lender x year fixed effects. Lastly Column 3,6,9,12 and 15 include lender and a three-way industry × 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: Loan spread, biodiversity risk and Low E Score.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	23.599*						
	(12.423)						
Biodiversity Count × Low E Score	79.803*						
	(41.484)						
Biodiversity Regulation		15.965					
		(11.830)					
Biodiversity Regulation × Low E Score		132.353***					
		(45.656)					
Air Pollution			1.201				
			(6.129)				
Air Pollution × Low E Score			-4.282				
			(11.215)				
Land Use				0.697			
				(6.025)			
Land Use × Low E Score				-0.148			
				(12.935)			
Climate Change					3.586		
					(6.040)		
Climate Change × Low E Score					9.104		
					(11.181)		
Water Pollution						8.577	
						(6.235)	
Water Pollution × Low E Score						-5.992	
						(11.445)	
Biodiversity Total							3.969
							(7.287)
Biodiversity Total × Low E Score							-3.731
							(11.984)
Low E Score	1.418	0.634	7.613	5.179	1.140	9.051	7.947
	(6.778)	(6.749)	(9.166)	(11.545)	(9.383)	(9.853)	(11.332)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose 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
Observations	3194	3194	3194	3194	3194	3194	3194
R^2	0.467	0.470	0.459	0.459	0.460	0.460	0.459

This table reports the results of estimating the model in Equation 10. 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. 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. We include now the interaction with Low E Score measured on firm f and time t level. The dummy is 1 if the ESG score of the borrower is lower than B-. 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. Columns 1 and 3 include fixed effects for loan purpose, industry, and year. Columns 2 and 4 replace industry and year fixed effects with three-way industry × 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 15: Bank lending, biodiversity risk and Low E Score.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.440***						
	(0.165)						
Biodiversity Count × Low E Score	0.234						
	(0.330)						
Biodiversity Regulation		-0.722***					
		(0.124)					
Biodiversity Regulation × Low E Score		0.414					
		(0.356)					
Air Pollution			0.046				
			(0.083)				
Air Pollution × Low E Score			-0.148				
			(0.119)				
Climate Change				-0.005			
				(0.084)			
Climate Change × Low E Score				-0.154			
				(0.118)			
Land Use					-0.008		
					(0.085)		
Land Use × Low E Score					-0.046		
					(0.127)		
Water Pollution						-0.223***	
						(0.078)	
Water Pollution × Low E Score						-0.067	
						(0.123)	
Biodiversity Total							-0.052
							(0.085)
Biodiversity Total × Low E Score							-0.077
							(0.124)
Low E Score	-0.072	-0.075	0.011	-0.006	-0.039	-0.056	-0.029
	(0.069)	(0.069)	(0.094)	(0.096)	(0.117)	(0.095)	(0.107)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1285	1285	1285	1285	1285	1285	1285
R^2	0.543	0.545	0.540	0.541	0.540	0.548	0.540

This table reports the results of estimating the model in Equation 11. 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. 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. We include now the interaction with Low E Score measured on firm f and time t level. The dummy is 1 if the ESG score of the borrower is lower than B-. 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, 10 and 13 include fixed effects for industry, lender and year. Columns 2,5,8, 11 and 14 include industry and lender x year fixed effects. Lastly Column 3,6,9,12 and 15 include lender and a three-way industry × 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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Appendix

This appendix provides additional robustness tests for the results reported in the main article. The tables include alternative fixed effects and different variable constructions.

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 in USD.	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)
Air Pollution	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to air pollution.	Own construction
Climate Change	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to climate change.	Own construction
Land Use	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to land use.	Own construction
Water Pollution	Dummy variable equal to 1 if the firm's 10-K filing mentions risks related to water pollution.	Own construction
Biodiversity Total	Dummy variable equal to 1 if the 10-K report includes at least two mentions of any of the four biodiversity-related risk categories (air pollution, climate change, land use, water pollution, biodiversity regulation).	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		
UNEP-FI Lender (%)	Share of lead arrangers in the syndicate that are UNEP-FI members (used for Borrower-Tranche Level data)	UNEP-FI membership database / Own mapping
Low NDGAIN	Dummy variable equal to 1 if the ND-GAIN Country Index for the lead arranger's headquarters is below the sample median.	ND-GAIN / World Bank
Low E Score	Dummy variable equal to 1 if the firm's E Score falls below the sample median.	LSEG ESG Scores / Own construction
Post3yr	Dummy variable equal to 1 for loans originated in year of firm's environmental violation or 3 years after.	EPA (IC&S)

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.

Table A2: Loan spreads, biodiversity risk and bank commitments - controlling for alternative specification of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	62.498***						
	(19.587)						
Biodiversity Count × UNEP-FI Lender	-3.212						
	(3.276)						
Biodiversity Regulation		55.403***					
		(18.388)					
Biodiversity Regulation × UNEP-FI Lender		-3.173					
		(3.273)					
Air Pollution			25.916***				
			(9.485)				
Air Pollution × UNEP-FI Lender			-0.312				
			(0.216)				
Climate Change				26.467***			
				(9.151)			
Climate Change × UNEP-FI Lender				-0.405			
				(0.247)			
Land Use					24.981**		
					(11.323)		
Land Use × UNEP-FI Lender					-0.145		
					(0.217)		
Water Pollution						26.608**	
						(11.652)	
Water Pollution × UNEP-FI Lender						-0.436*	
						(0.234)	
Biodiversity Total							36.894***
							(11.005)
Biodiversity Total × UNEP-FI Lender							-0.561**
							(0.224)
UNEP-FI Lender	0.164	0.159	0.347**	0.353**	0.273	0.420**	0.530***
	(0.134)	(0.137)	(0.164)	(0.167)	(0.169)	(0.203)	(0.193)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3821	3821	3821	3821	3821	3821	3821
R^2	0.700	0.700	0.699	0.700	0.699	0.699	0.700

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Bank lending, biodiversity risk and bank commitments - controlling for alternative specification of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.656**						
	(0.312)						
Biodiversity Count × UNEP-FI Lender	0.500						
	(0.398)						
Biodiversity Regulation		-0.876**					
		(0.406)					
Biodiversity Regulation × UNEP-FI Lender		0.637					
		(0.447)					
Air Pollution			0.010				
			(0.126)				
Air Pollution × UNEP-FI Lender			0.229				
			(0.213)				
Climate Change				-0.055			
				(0.125)			
Climate Change × UNEP-FI Lender				0.041			
				(0.197)			
Land Use					0.064		
					(0.135)		
Land Use × UNEP-FI Lender					0.231		
					(0.199)		
Water Pollution						-0.274*	
						(0.145)	
Water Pollution × UNEP-FI Lender						0.293	
						(0.186)	
Biodiversity Total							-0.059
							(0.140)
Biodiversity Total × UNEP-FI Lender							0.182
							(0.191)
UNEP-FI Lender	0.176	0.137	0.175	0.299	0.098	0.156	0.155
	(0.288)	(0.276)	(0.410)	(0.376)	(0.410)	(0.348)	(0.420)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	929	929	929	929	929	929	929
R^2	0.848	0.848	0.845	0.844	0.845	0.847	0.845

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Loan spreads, biodiversity risk and ND-GAIN Index - controlling for alternative specification of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	42.596*						
	(22.522)						
Biodiversity Count × Low ND-GAIN	99.838***						
	(35.792)						
Biodiversity Regulation		26.993					
		(20.630)					
Biodiversity Regulation × Low ND-GAIN		107.064***					
		(40.184)					
Air Pollution			16.849**				
			(7.977)				
Air Pollution × Low ND-GAIN			6.661				
			(51.870)				
Land Use				19.918**			
				(9.847)			
Land Use × Low ND-GAIN				75.859**			
				(35.136)			
Climate Change					20.127**		
					(7.901)		
Climate Change × Low ND-GAIN					-32.043		
					(50.725)		
Water Pollution						22.172**	
						(10.380)	
Water Pollution × Low ND-GAIN						-105.073***	
						(25.696)	
Biodiversity Total							24.488***
							(9.445)
Biodiversity Total × Low ND-GAIN							0.000
							(.)
Low ND-GAIN	-49.110	-46.442	-33.584	-105.082***	-11.896	64.855***	-34.737
	(30.755)	(30.549)	(42.274)	(27.360)	(43.019)	(21.322)	(29.362)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3811	3811	3811	3811	3811	3811	3811
R^2	0.699	0.699	0.698	0.699	0.699	0.699	0.699

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Bank lending, biodiversity risk and ND-GAIN Index -controlling for alternative levels of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.689**						
	(0.320)						
Biodiversity Count × Low ND-GAIN	0.450						
	(0.339)						
Biodiversity Regulation		-0.968**					
		(0.436)					
Biodiversity Regulation × Low ND-GAIN		0.786					
		(0.529)					
Air Pollution			0.055				
			(0.116)				
Air Pollution × Low ND-GAIN			-0.165				
			(0.274)				
Climate Change				-0.037			
				(0.118)			
Climate Change × Low ND-GAIN				-0.342			
				(0.289)			
Land Use					0.131		
					(0.133)		
Land Use × Low ND-GAIN					-0.336		
					(0.325)		
Water Pollution						-0.224	
						(0.140)	
Water Pollution × Low ND-GAIN						-0.055	
						(0.292)	
Biodiversity Total							-0.019
							(0.126)
Biodiversity Total × Low ND-GAIN							-0.203
							(0.366)
Low ND-GAIN	0.066	-0.011	0.154	0.219	0.290	0.124	0.182
	(0.353)	(0.336)	(0.407)	(0.332)	(0.408)	(0.358)	(0.394)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	927	927	927	927	927	927	927
R^2	0.845	0.846	0.842	0.842	0.843	0.844	0.842

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Loan spreads, biodiversity risk and EPA Violations - controlling for alternative specification of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	53.092***						
	(18.432)						
Biodiversity Count × Post3yr	0.000						
	(.)						
Biodiversity Regulation		43.467***					
		(15.279)					
Biodiversity Regulation × Post3yr		0.000					
		(.)					
Air Pollution			19.965**				
			(8.191)				
Air Pollution × Post3yr			-43.425				
			(30.799)				
Land Use				22.250**			
				(9.724)			
Land Use × Post3yr				-60.935***			
				(18.651)			
Climate Change					21.230**		
					(8.280)		
Climate Change × Post3yr					-54.925*		
					(28.876)		
Water Pollution						20.268*	
						(11.291)	
Water Pollution × Post3yr						-20.980	
						(35.147)	
Biodiversity Total							25.014**
							(9.884)
Biodiversity Total × Post3yr							-26.325
							(35.277)
Post3yr	-25.159	-25.492	-5.638	25.534	-0.393	-12.904	-10.163
	(19.384)	(19.271)	(29.486)	(20.377)	(27.562)	(29.532)	(30.225)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3821	3821	3821	3821	3821	3821	3821
R^2	0.699	0.698	0.699	0.699	0.699	0.699	0.699

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Bank lending, biodiversity risk and EPA Violations - controlling for alternative specification of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.685**						
	(0.317)						
Biodiversity Count × Post3yr	0.418						
	(0.400)						
Biodiversity Regulation		-0.923**					
		(0.414)					
Biodiversity Regulation × Post3yr		0.638					
		(0.451)					
Air Pollution			0.064				
			(0.116)				
Air Pollution × Post3yr			-0.506				
			(0.443)				
Climate Change				-0.036			
				(0.117)			
Climate Change × Post3yr				-0.339			
				(0.471)			
Land Use					0.088		
					(0.126)		
Land Use × Post3yr					0.440		
					(0.355)		
Water Pollution						-0.216	
						(0.140)	
Water Pollution × Post3yr						-0.284	
						(0.527)	
Biodiversity Total							-0.004
							(0.124)
Biodiversity Total × Post3yr							-0.491
							(0.490)
Post3yr	0.434*	0.439*	0.699**	0.559*	-0.048	0.606	0.736*
	(0.248)	(0.246)	(0.308)	(0.329)	(0.243)	(0.412)	(0.382)
Observations	929	929	929	929	929	929	929
R^2	0.849	0.850	0.846	0.846	0.846	0.848	0.846

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Loan spreads, biodiversity risk and E Score - controlling for alternative specification of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	44.769						
	(31.023)						
Biodiversity Count × Low E Score	26.321						
	(36.640)						
Biodiversity Regulation		12.742					
		(14.531)					
Biodiversity Regulation × Low E Score		62.901**					
		(25.098)					
Air Pollution			15.315**				
			(7.698)				
Air Pollution × Low E Score			1.584				
			(18.515)				
Land Use				-2.711			
				(9.572)			
Land Use × Low E Score				41.572**			
				(17.481)			
Climate Change					9.015		
					(8.667)		
Climate Change × Low E Score					27.337		
					(17.060)		
Water Pollution						4.387	
						(9.917)	
Water Pollution × Low E Score						30.344*	
						(18.077)	
Biodiversity Total							8.435
							(8.634)
Biodiversity Total × Low E Score							33.879**
							(16.970)
Low E Score	-19.932*	-21.132*	-18.627	-49.620***	-29.098*	-40.581**	-42.042***
	(12.064)	(12.134)	(17.338)	(15.950)	(16.835)	(18.750)	(15.560)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2978	2978	2978	2978	2978	2978	2978
R^2	0.714	0.713	0.713	0.714	0.714	0.713	0.714

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Bank lending, biodiversity risk and E Score - controlling for alternative specification of fixed effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Biodiversity Count	-0.590						
	(0.399)						
Biodiversity Count × Low E Score	-0.061						
	(0.521)						
Biodiversity Regulation		-0.792					
		(0.538)					
Biodiversity Regulation × Low E Score		0.001					
		(0.634)					
Air Pollution			0.153				
			(0.145)				
Air Pollution × Low E Score			-0.185				
			(0.281)				
Climate Change				0.075			
				(0.138)			
Climate Change × Low E Score				-0.342			
				(0.241)			
Land Use					0.333*		
					(0.174)		
Land Use × Low E Score					-0.320		
					(0.329)		
Water Pollution						-0.136	
						(0.181)	
Water Pollution× Low E Score						-0.026	
						(0.287)	
Biodiversity Total							0.177
							(0.170)
Biodiversity Total × Low E Score							-0.287
							(0.327)
Low E Score	-0.044	-0.031	0.085	0.141	0.259	-0.041	0.188
	(0.157)	(0.157)	(0.282)	(0.204)	(0.309)	(0.281)	(0.312)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x State x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	785	785	785	785	785	785	785
R^2	0.841	0.841	0.838	0.838	0.841	0.838	0.838

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$