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By *Duc Duy Nguyen, Steven Ongena, Shusen Qi, Vathunyoo Sila, and Yibing Wang*

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Abstract

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Keywords: Biodiversity Risk, Bank Lending, Small Businesses, Kunming Declaration

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1 Introduction

Biodiversity is the foundation of our natural ecosystems, providing essential services that support economic activities and human well-being. From pollination and water purification to climate regulation and soil fertility, ecosystem services derived from biodiversity are critical for the functioning of many industries. However, rapid biodiversity losses—driven by habitat destruction, pollution, and resource exploitation—have heightened financial risks for firms reliant on natural capital. The adoption of global biodiversity initiatives, such as the Kunming-Montreal Global Biodiversity Framework, signals a shift toward integrating biodiversity considerations into financial decision-making.

Recent evidence shows that investors and lenders increasingly require a risk premium on equity and fixed income assets that are exposed to biodiversity-related risk (Garel et al., 2024; Hoepner et al., 2023). We contribute to this growing literature by providing the first systematic evidence on how biodiversity risk affects bank lending to small businesses. Our findings not only advance understanding of the extent to which financial institutions incorporate nature-related risk assessments into their lending decisions, but also shed light on how biodiversity risk impacts small businesses—firms which, compared to large public companies, are less diversified, riskier, more informationally opaque, more geographically concentrated, and more dependent on bank financing. These characteristics make them particularly vulnerable to disruptions in ecosystem services, a risk that may be further amplified by their difficulty in securing favorable credit conditions from banks (Robb and Farhat, 2013).

To examine how biodiversity risk affects lending to small businesses, we use loan-level small business lending data from the U.S. Small Business Administration (SBA) 7(a) program. The SBA 7(a) provides loan guarantees to credit-constrained small businesses[1] through qualified financial institutions. These institutions are responsible for underwriting

[1] Specifically, to qualify for 7(a) loan assistance, a small business must be unable to obtain the desired credit on reasonable terms from non-Federal, non-State, and non-local government sources.

the loans and, in many cases, are granted delegated authority to evaluate applications, make credit decisions, and disburse funds without prior SBA approval. Under the 7(a) program, lenders share loan losses with the SBA based on the guarantee percentage, incentivizing them to carefully screen borrowers and determine appropriate interest rates within the allowable range set by the SBA (DeYoung et al., 2008). The 7(a) dataset provides detailed loan-level characteristics such as the initial interest rate and other loan terms, as well as the NAICS-6 sub-industry code as indicated in the loan application.

We combine the 7(a) SBA dataset with data from the Exploring Natural Capital Opportunities, Risks and Exposure (ENCORE) platform and construct two industry-level measures (at NAICS-6 level) for biodiversity risk of small businesses: (1) *Dependency score*, which considers how significantly the industry would be affected if ecosystems services or benefits stop or are disrupted; and *Impact score*, which evaluates how economic activities in a given industry negatively affects biodiversity. ENCORE's measures are suitable proxies because, unlike large corporations, small businesses typically do not produce sustainability reports or disclose detailed information on their biodiversity dependencies and impacts. As a result, lenders seeking to understand biodiversity-related risks in small business lending are more likely to rely on industry-level proxies, such as those provided by ENCORE. Moreover, the ENCORE platform is specifically designed to help financial institutions identify nature-related risks they are exposed to through their lending and investment in high-risk industries.

Analyzing a sample of 596,436 small business loans originated under the 7(a) SBA program between January 2010 and September 2024, we document economically meaningful associations between our biodiversity risk measures and loan terms received by small businesses, indicating that lenders do integrate nature-related risk assessments in their lending decisions. Specifically, our results suggest that lenders are primarily concerned with the risk associated with borrowers' dependency on biodiversity—such as potential financial losses from operational disruptions due to biodiversity loss (biodiversity *dependency* risk). In addition, our findings indicate that the harm borrowers may cause to biodiversity (biodiversity *impact* risk) also increasingly plays a role.

All our estimations include granular NAICS-5 fixed effects, lender-SBA district office-year fixed effects, county-year fixed effects, and delivery method-subprogram fixed effects. The inclusion of NAICS-5 fixed effects allows us to compare loan spreads for borrowers within the same narrow NAICS-5 industry.[2] Lender-SBA district office-year fixed effects control for the joint responsibilities of the SBA and lenders in originating 7(a) loans, while county-year fixed effects partial out time-varying local shocks that could be correlated with both local economic conditions and small business lending. Finally, the inclusion of delivery method-subprogram fixed effects ensures that we compare loans subject to similar interest rate guidelines.

We perform various tests to shed light on the underlying economic mechanisms through which biodiversity risk is incorporated into loan prices. First, our findings suggest that *dependency* risk—the extent to which the industry would be affected if ecosystem services are disrupted—represents a source of credit risk. When firms heavily rely on ecosystem services, any decline in these services due to biodiversity loss can disrupt operations, reduce revenues, and increase costs. Small firms are particularly vulnerable to these disruptions since they lack the ability to diversify their operations or reallocate businesses to less affected regions. Small firms also lack the financial resilience to withstand biodiversity-related disruptions. The loss of firm profits, in turn, can increase the probability that small firms default on their loans and result in credit losses for lenders.

Consistent with this, we find that firms in more biodiversity-dependent industries are more likely to default on their loans. Specifically, a one standard deviation higher in *Dependency score*[3] is associated with a 2.4% higher probability of loan defaults. As a result, lenders impose a higher interest rate on loans to borrowers in industries with greater dependency risk to compensate for these potential credit losses. In particular, a one standard deviation

[2] We illustrate in Panel B of Table 1 and discuss in Section 2.3 that there is meaningful variation in our measures of biodiversity scores within a NAICS-5 industry.

[3] A one standard deviation increase in *Dependency score* is equivalent to moving from the Geothermal Electric Power Generation sub-industry to the Fossil Fuel Electric Power Generation sub-industry.

increase in *Dependency score* is associated with 5.3 basis points (= 0.01547 * 3.426) higher interest rate. This increase in interest rate translates into a $1,390 increase in financing cost for the average borrower in our sample. Moreover, we find that the elements of biodiversity dependency risk that matter for loan pricing are those likely to disrupt businesses: dependency on provisioning services (material inputs such as crops, livestock, fish, and freshwater) and dependency on regulating and maintenance services (ecosystem functions such as water purification, soil fertilization, climate regulation, and flood regulation). In contrast, dependency on cultural services, such as aesthetically pleasing landscapes or cultural sites, has no impact on loan rates.

Our further analyses show that, in addition to incorporating dependency risk in loan rates, lenders also rely on securitization to shift at-risk loans off their balance sheets and refrain from lending to firms in biodiversity-dependent industries. Moreover, lenders with greater exposure to financing these firms are more likely to price this risk, indicating a learning effect from realized credit losses. Collectively, our findings suggest that biodiversity dependency risk represents credit risk for lenders.

Second, we examine biodiversity *impact* risk—the extent to which borrowers harm biodiversity. We find no evidence that impact risk is associated with credit risk: default rates are similar across borrowers with different levels of impact risk. Instead, our findings suggest that lenders price impact risk mainly to compensate for potential reputational damage or legal consequences when financing firms that negatively affect biodiversity.

Specifically, lenders only start pricing biodiversity impact risk in the later part of our sample period. Impact risk is associated with higher loan spreads beginning in 2015, when biodiversity became a global priority with the launch of the Paris Agreement and the UN Sustainable Development Goals. The effect becomes even stronger after 2022, following the adoption of the Kunming-Montreal Global Biodiversity Framework, the decade's most significant international biodiversity treaty which increased regulatory and sanction risks for lenders supporting biodiversity-unfriendly firms. We also find that impact risk is more likely to be reflected in loan pricing in states with a governor from the Democratic party.[4] These states tend to adopt more progressive policies and often pressure lenders and investors to divest from industries that negatively affect biodiversity and the environment. Finally, we find that the pricing effect is stronger for loans linked to areas *at risk* of becoming protected—i.e., areas with high biodiversity value that have not yet been officially designated as protected areas. Collectively, our results suggest that impact risk is priced to account for the potential reputational and litigation risks associated with financing firms that negatively impact biodiversity.

We perform several tests to further validate our results. First, we show that biodiversity dependency and impact risks are distinct from climate risks. Excluding climate-related services (for example, climate regulation or GHG emissions) from our measures does not alter our results. Second, our findings hold when we focus on loans in which banks have delegated authority to make underwriting decisions (that is, loans under the Preferred Lender and SBA Express programs), suggesting that lenders themselves incorporate biodiversity risks into pricing. Finally, we find that the effects of both dependency and impact risks are stronger for larger loans and for loans with longer duration, indicating that lenders price these risks more cautiously when they have greater "skin in the game." Overall, our results suggest that biodiversity risks are relevant to the viability of small businesses and thus are priced accordingly by financial institutions.

We contribute to the emerging literature on biodiversity finance in several ways. To the best of our knowledge, our study is the first to examine the impact of biodiversity risk on small businesses' access to finance, as well as the terms and conditions of their loans. Our analyses make use of micro-level data that cover an important component of the small business lending market in the U.S.. We focus on small businesses because their general lack of diversification makes these firms particularly vulnerable to biodiversity loss and ecosystem service disruptions. Consequently, the pricing of biodiversity risk is likely to be

[4] Our results are robust across three definitions of location: (i) the state of the project for which the loan is requested, (ii) the lender's headquarters state, and (iii) the state of the SBA district office.

most pronounced in the small business lending market. Additionally, since small firms heavily rely on banks for financing, credit rationing by banks could exacerbate their vulnerability to biodiversity loss. Therefore, another important implication of our work is to shed light on the potential joint effects of biodiversity risk and credit constraints on the growth and continuity of small firms. Exploring the links between biodiversity loss, access to finance, and real outcomes can contribute to the development of effective risk assessment tools, mitigation and support strategies for small businesses, and policy frameworks that promote long-term stability.

More broadly, our paper contributes to recent studies on how financial institutions incorporate borrowers' environmental performance in their investment decisions. These studies collectively address the question of whether financial institutions should divest or engage with businesses exposed to environmental risks (Starks, 2023). Most of these studies focus on borrowers with high carbon emissions or pollution and find that banks either divest from (Kacperczyk and Peydró, 2021) or impose more stringent loan terms (Delis et al., 2024; Ivanov et al., 2024; Degryse et al., 2023) on these "brown" borrowers. In contrast, other studies find that lenders in fact increase lending to brown borrowers (Beyene et al., 2021; Giannetti et al., 2024). While there is substantial literature documenting how banks incorporate environmental risks into lending decisions, studies specifically focusing on bank lending and natural capital are limited, due to data availability and a lack of awareness (Ascui and Cojoianu, 2019). Utilizing novel data on small business lending, our paper offers new insights into biodiversity assessment and its influence on lending decisions. Importantly, we remain agnostic on whether the pricing effects come from lenders or the SBA. As long as there is a differential pricing based on a borrower's biodiversity risk, this indicates that the loan originator acknowledges this risk as relevant to their lending and pricing decisions.

Our paper contributes to the nascent literature on the pricing of biodiversity risk. Giglio et al. (2023) develop measures of U.S. firms' biodiversity risks and investigate the returns of portfolios sorted on these biodiversity measures. Garel et al. (2024) identify a biodiversity footprint premium after the Kunming Declaration in 2021. On the financing side, Flammer et al. (2025) study the use of private capital to finance biodiversity conservation and restoration. Hoepner et al. (2023) examine infrastructure firms and find that those with better biodiversity risk management have better long-term refinancing conditions. Becker et al. (2023) construct a biodiversity risk indicator at the country-level for EU lenders, and observe a positive correlation between syndicated loan pricing and the level of biodiversity exposure of large corporate borrowers. We extend this literature by studying small businesses, which make up 99.9% of companies in the U.S.. Small businesses are more vulnerable to ecosystem disruptions, and yet have received relatively less attention in the context of biodiversity risk pricing.

2 Data and Empirical Model

2.1 Biodiversity data

Our primary measures of biodiversity risk come from the ENCORE platform. This dataset provides a structured, evidence-based materiality assessment of biodiversity dependencies and impacts for 271 economic activities based on the International Standard Industrial Classification of All Economic Activities (ISIC) groups and classes.[5]

ENCORE's measures are suitable for analyzing the impact of biodiversity risk on bank lending to SMEs for at least three reasons. First, unlike large corporations, SMEs typically do not produce sustainability reports or disclose detailed information on their biodiversity dependencies and impacts. As a result, lenders seeking to understand biodiversity-related risks in SME lending are more likely to rely on industry-level proxies, such as those provided by ENCORE. Second, the ENCORE platform is specifically designed to help financial

[5] We use the 2024 version of ENCORE, which includes several key enhancements over the previous iteration: i) increased granularity in economic sectors, expanding from 152 GICS-based sub-industries to 270 ISIC-based sub-industries; ii) enhanced detail on biodiversity-related aspects; and iii) the inclusion of quantitative data to support materiality ratings. There are no major changes to the natural capital knowledge base across versions.

institutions understand how their borrowers rely on natural ecosystems for their production processes. It also provides guidance on how biodiversity risks can be embedded into credit risk assessment for lending and investment decisions.[6] Finally, the data are publicly available and endorsed by several environmental bodies, including the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), the Taskforce on Nature-related Financial Disclosures (TNFD), the Science Based Targets Network (SBTN), and the Global Reporting Initiative (GRI) Standards.

We use the ENCORE platform to produce two measures of biodiversity risks. The first measure, *Dependency score*, evaluates the extent to which an industry relies on biodiversity-related ecosystem services. The UN System of Environmental-Economic Accounting Ecosystem Accounting identifies 25 such ecosystem services, grouped into three categories: (1) provisioning services (e.g., the supply of food, fibre, livestock, and water), (2) regulating and maintenance services (e.g., the regulation and maintenance of air, water, soil, habitat, and climate), and (3) cultural services (e.g., cultural, educational, or recreational benefits).

For each ecosystem service relied on by an industry, ENCORE assesses how severely the industry would be affected if the ecosystem service were disrupted, using both a qualitative method and a blended approach that combines quantitative and qualitative assessments. For example, the qualitative method evaluates the magnitude of the dependency based on the significance of the loss of functionality in the industry if the ecosystem service were disrupted, as well as the financial cost to the industry of adapting to the disruption.[7] Based on this assessment, ENCORE classifies the outcome into one of five materiality categories (ranging from *very low* to *very high*). A *very low* or *low* materiality level indicates that

[6] See Exploring Natural Capital Opportunities, Risk and Exposure: A Practical Guide for Financial Institutions.

[7] For instance, a limited loss of functionality indicates that the industry can continue as is or with minor modifications, while a severe loss of functionality means that disruption in the ecosystem service provision prevents the economic activity; a low financial cost means that adaptation to the disruption of the ecosystem service will represent a minor cost and will not significantly affect the financial position in the long run. In contrast, a severe financial cost means that adaptation to the disruption of the ecosystem service will have a significant effect on the financial viability.

minimal or no adjustments would be required, whereas a *medium*, *high*, or *very high* level suggests that production could be significantly impaired. Based on these classifications, we define an industry's *Dependency score* as the total number of ecosystem services for which its dependency is assessed as *medium* or higher in materiality.

The second measure, *Impact score*, captures the potential adverse effect of each industry on biodiversity. This measure is based on 13 biodiversity impact drivers, which are defined as the use of a measurable quantity of a natural resource or the release of a measurable quantity of substances, as well as physical and biological agents. Examples of these drivers include the introduction of invasive species, over-exploitation of natural resources, production of disturbances (e.g., noise and light), and the release of toxic pollutants. Using both quantitative and blended approaches, ENCORE assesses the extent to which each industry exerts pressure on natural ecosystems through each impact driver based on per 1 EUR of output values (e.g., volume of pollutants emitted per 1 EUR of output, or volume of GHGs emitted per 1 EUR of output produced by the industry). Similar to the *Dependency score* measure, the classification includes five levels of materiality, ranging from *very low* to *very high*. We use ENCORE's classifications to calculate each industry's *Impact score* as the total number of impact drivers assessed at *medium* or higher materiality.

2.2 Small business lending data

We obtain loan-level small business lending data from the U.S. Small Business Administration (SBA) 7(a) program, which is the SBA's primary program for providing financial assistance to small businesses for various purposes. The SBA 7(a) loan program provides loan guarantees for small businesses that cannot secure credit through traditional channels. Specifically, to qualify for 7(a) loan assistance, a business must meet the SBA's size requirement, including having fewer than 500 employees and annual revenues under $7.5 million, and must be unable to obtain the desired credit on reasonable terms from non-Federal, non-State, and non-local government sources. As a result, this program plays a vital role in ensuring the flow of credit to financially marginal small businesses. In 2024, the 7(a) program supported 70,242 loans with a total value of $31.1 billion, accounting for nearly 70% of total SBA small business loans and 60% of total capital provided by the SBA.

The SBA provides loan guarantees to eligible small firms through qualified financial institutions, which are primarily commercial banks. For the majority of 7(a) loans,[8] the SBA delegates lending and pricing responsibilities to financial institutions, including selecting loan recipients, initiating SBA involvement, underwriting the loans in accordance with SBA program guidelines, and regularly monitoring and reporting the loans' progress to the SBA.

SBA 7(a) loan interest rates are partially regulated by the SBA, which sets a maximum allowable rate based on factors such as the loan amount, loan terms, and the current prime rate (Gupta and Ongena, 2025).[9] Although lenders cannot exceed these limits, they retain discretion to set interest rates within the allowable range. Because lenders share loan losses with the SBA, which are proportional to the outstanding loan balance at default and according to the guarantee percentage established at origination, they are incentivized to carefully evaluate borrower risk and set appropriate loan terms and loan rates (DeYoung et al., 2008). As such, lenders are able to incorporate biodiversity-related risks into loan prices, provided that the resulting rate complies with the SBA guidelines. Importantly, our conclusions do not depend on whether loan rates are set by lenders or the SBA. If we observe differential pricing based on a borrower's biodiversity risk, this would indicate that the loan underwriter—whether the SBA or the lender—acknowledges this risk as relevant to their lending and pricing decisions.

The SBA 7(a) loan-level dataset provides information on the loan disbursement date, the borrower's identity, the location and NAICS-6 sub-industry as indicated in the loan application, the initial interest rate, loan size, term to maturity, default status, and charged-off amount. We map the NAICS-6 sub-industries from the SBA with the ISIC

[8] We show in Subsection 3.4 that the pricing of biodiversity risk is more salient when lenders have greater involvement in the credit decision.

[9] For example, for a $150,000 loan with a term of 10 years and Prime at 8.5%, the maximum interest rate would be 11.25% (Prime + 2.75%).

industry groups and classes from ENCORE using the crosswalk developed by the U.S. Census Bureau. This allows each borrower in the SBA sample to receive a biodiversity dependency (impact) risk score according to its NAICS-6 sub-industry classification.[10]

To construct our sample, we begin with the universe of all small business loans originated by commercial banks and made through the SBA program between January 2010 and September 2024. The sample starts in 2010 to avoid picking up the impact of the 2008-09 Global Financial Crisis on small business lending decisions and ends in 2024, the most recent year with available 7(a) data. We exclude canceled loans, loans to borrowers in the finance and insurance industry (NAICS = 52), loans with negative interest rate spreads, and loans to borrowers in U.S. territories like Guam and Puerto Rico.

2.3 Descriptive statistics

Panel A of Table 1 presents summary statistics for our key variables. Our main sample includes 596,436 small business loans originated under the 7(a) SBA program for borrowers in 905 unique NAICS-6 sub-industries between January 2010 and September 2024. These loans are originated by 1,954 unique commercial banks across all 50 U.S. states and Washington DC. The average loan is granted for a duration of 126 months, for an amount of $387,955, and the average interest rate is 7.114%. Of the loans that have been completed, 92.4% were fully repaid, while the remaining 7.6% resulted in default. These statistics are comparable to those reported in other studies that analyze 7(a) loans (Wang and Norden, 2024).

[Insert Table 1]

[10]Our matching process uses the 2022 NAICS-to-ISIC crosswalk. Since the SBA 7(a) dataset contains some outdated NAICS codes compared to the 2022 standards, we manually correct these discrepancies. For example, the SBA 7(a) dataset contains a dated NAICS code of 233210 for the "Single Family Housing Construction" sub-industry. We correct this to the 2022 NAICS code of 236115 for the "New Single-Family Housing Construction" sub-industry. When a single NAICS code corresponds to multiple ISIC codes, we manually assign such NAICS code to the nearest ISIC. For instance, NAICS code 111219 ("Other Vegetable (except Potato) and Melon Farming") can correspond to ISIC codes 0113, 0119, or 0128. We match this NAICS code to ISIC 0113 ("Growing of vegetables and melons, roots and tubers") since it best aligns with the NAICS description.

Borrowers in our sample have an average *Dependency score* of 4.8. This indicates that their industries have 4.8 out of 25 (approximately 20%) ecosystem services assessed to face medium, high, or very high materiality risk. Moreover, there is substantial variation in the dependency score, with a standard deviation of 3.4. A one-standard deviation increase in biodiversity dependency score corresponds to the difference between, for example, the *Postal Service* sub-industry (Dependency score=2) and the *Tobacco Manufacturing* sub-industry (Dependency score=5). Furthermore, there is considerable variation in the dependency score across NAICS-6 sub-industries within the same NAICS-5 industry. To illustrate, Panel B of Table 1 displays the biodiversity dependency scores of the NAICS-6 sub-industries within the *Electric Power Generation* industry (NAICS-5: 22111). As shown in Panel B, there is significant variation in dependency scores within this industry, with the highest score of 7 in the *Fossil Fuel Electric Power Generation* sub-industry, and the lowest score of 2 in the *Other Electric Power Generation* sub-industry. This difference corresponds to 1.5 standard deviations in the dependency score.

The average *Impact score* is 2.6, suggesting that industries exert on average 2.6 out of 13 pressures (approximately 20%) on biodiversity. Our measure of biodiversity impact score similarly reveals substantial variation with a standard deviation of 1.9—equivalent to the difference in impact scores between the *Postal Service* sub-industry (Impact score=2) and the *Coffee and Tea Manufacturing* sub-industry (Impact score=4). We display in Panel B of Table 1 the biodiversity impact scores of the NAICS-6 sub-industries within the *Electric Power Generation* industry. Like the dependency score, impact scores within this industry exhibit substantial variation. The *Biomass Electric Power Generation* sub-industry has the highest impact score of 9, while the *Solar Electric Power Generation* sub-industry has the lowest at 0. The difference corresponds to 4.7 standard deviations in impact score.

2.4 Empirical model

To examine how biodiversity risk affects small businesses' loan terms, we estimate the following loan-level regression specification:

$$y_{lit} = \alpha + \beta \mathbf{x}_i + \delta_k + \delta_{lst} + \delta_{ct} + \delta_d + \varphi \mathbf{w}_{lt} + \varepsilon_{lt}, \quad (1)$$

where y_{lit} is either the interest rate spread on the loan (which is the difference between the initial annual interest rate on the loan and the 10-year treasury bond rate) or a securitization dummy (which indicates whether the loan has been sold in a secondary market) of loan l to finance a project in a NAICS-6 sub-industry i in year t. The vector $\mathbf{x}_i$ represents the biodiversity *Dependency score* and/or *Impact score* for a NAICS-6 sub-industry i, based on data from ENCORE.

Our main specification includes NAICS-5 fixed effects, lender-SBA district office-year fixed effects, county-year fixed effects, and delivery method-subprogram fixed effects. In this empirical setup, the effects of biodiversity risk are identified within the same narrow NAICS-5 industry, while controlling for time-varying lender-SBA office pair characteristics, time-varying county characteristics, and the loan's subprogram/delivery method. The inclusion of NAICS-5 fixed effects (δ_k) controls for industry-specific characteristics—such as economic trends, competition, regulatory environment, or technological advancements. The power of our tests comes from the substantial variation in biodiversity impact and dependency scores within a NAICS-5 industry, as previously discussed in Section 2.3 and illustrated in Panel B of Table 1.

The inclusion of lender-SBA district office-year fixed effects (δ_{lst}) allows us to compare small business loans originated by the same lender-SBA district office pair in the same year. This accounts for the joint responsibilities of lenders and the SBA in originating SBA loans and sharing potential loan losses. Moreover, lender-SBA district office-year fixed effects also absorb all time-varying lender specific characteristics such as size, capital level, risk appetite, regulatory differences, business models, and credit scoring technologies that may affect small business lending outcomes.

We further include county of the project for which the loan is requested interacted with year fixed effects (δ_{ct}) to remove all time-varying county-level factors, such as demographic, social, economic, and demand-side factors related to local business cycles and labor demand. County-year fixed effects also control for changes in state-level regulations that could affect small business lending behavior across different locations. Finally, we include the SBA's delivery method-subprogram fixed effects (δ_d) to control for the specific subprogram under which the loan is granted.

Following Tang et al. (2024), we include several loan-level control variables ($\mathbf{w}_{lt}$): *Loan maturity*, the length of the loan term in years; *Ln(Loan size)*, the natural logarithm of the gross approval amount; *Ln(Jobs created)*, the natural logarithm of the total number of jobs created and retained, as reported by the lender on the loan application; and *%SBA contribution*, the amount of SBA loan's guaranty divided by the gross approval amount. Loan size and the number of jobs created serve as proxies for the borrower's size.

Finally, to isolate borrowers' biodiversity risk from their general credit risk, all regression specifications control for *Altman's Z-score*, calculated as the Z-score of the median Compustat firm in each NAICS-6 sub-industry in each quarter-year.[11] We use Compustat firms because there are limited high-quality representative data on private firms to calculate Z-score. This approach assumes that the median private firm and the median Compustat firm in the same NAICS-6 sub-industry in the same quarter-year share similar credit risk. All continuous variables are winsorized at the 2.5% and 97.5% levels.

[11] Some NAICS-6 sub-industries do not have firms in Compustat. We replace these with the Z-score of the median firm in the NAICS-5 industry.

3 Biodiversity risk and the cost of small business loans

3.1 Baseline results

Table 2 reports our baseline regression results examining the effect of biodiversity dependency and impact risk on the cost of loans to small firms. The dependent variable is *Interest rate spread*, the difference between the loan's initial annual interest rate and the 10-year U.S. treasury bond yield. The independent variables are *Dependency score* and *Impact score* in Columns (1) and (2) respectively. All regression specifications control for a large set of control variables and fixed effects, as specified in Section 2.4. Standard errors are clustered at the NAICS-6 sub-industry level.

[Insert Table 2]

We find that lenders charge higher interest rate spreads on borrowers in industries with greater biodiversity dependency risk, but not on those with higher biodiversity impact risk. Specifically, as shown in Column (1), the coefficient on *Dependency score* is positive and statistically significant below the 5% level, suggesting that lenders impose higher interest rate spreads on borrowers in industries with greater exposure to biodiversity dependency risk. The magnitude indicates economically meaningful effects. Specifically, a one standard deviation increase in *Dependency score*—equivalent to an increase in dependency score from the *Geothermal Electric Power Generation* sub-industry to the *Fossil Fuel Electric Power Generation* sub-industry—is associated with 5.3 basis points (= 0.01547 * 3.426) higher interest rate. This increase in interest rate spread translates into a $1,390 increase in financing cost for the average borrower in our sample.[12]

[12]The average loan size in our sample is $387,955, the average annual interest rate (r) is 7.114%, and the average duration of the loan is 10.5 years (10.5 * 12 = 126 months). We obtain the monthly payments using the simple present value formula, where the total loan cost is the sum of all monthly payments (pmt*134). At an interest rate of 7.114%, the total loan cost is $567,359 ($4,502.85 * 126). In contrast, at an interest rate of 7.167% the total loan cost is $568,749 ($4,513.88 * 126).

Conversely, we find in Column (2) that lenders do not charge higher interest rates on loans to borrowers with higher biodiversity impact risk. In particular, the coefficient on *Impact score* is statistically insignificant, and the magnitude of the coefficient is close to zero. Our findings remain unchanged when we include both *Dependency score* and *Impact score* in the same regression in Column (3).[13]

Taken together, our baseline findings demonstrate that lenders incorporate only borrowers' biodiversity dependency risk in setting loan price. This indicates that they are primarily concerned with the credit risk associated with borrowers' dependency on biodiversity—such as potential financial losses from operational disruptions due to biodiversity loss—rather than the biodiversity harm borrowers may cause.

3.2 Robustness on baseline results

In Table 3, we present various robustness checks on our main findings, with Panel A covering *Dependency score* and Panel B *Impact score*. In Columns (1)-(2), we show that the baseline results are not sensitive to how the biodiversity scores are constructed. Specifically, instead of counting the number of ecosystem services (impact drivers) at medium and higher materiality risk, we calculate the average individual dependency (impact) scores across all ecosystem services (impact drivers) in each industry (Column (1)).[14] In Column (2), we count only the ecosystem services (impact drivers) with the highest materiality. The results remain robust.

[Insert Table 3]

In Column (3), instead of using *Altman's Z-score*, we control for five individual components of the score, namely, (i) Working capital, (ii) Retained earnings, (iii) Earnings before interest and taxes, (iv) Sales, and (v) Market value of equity.[15] This allows us to control

[13] The correlation between *Dependency score* and *Impact score* is 0.43.

[14] To do so, we convert the materiality rating to a quantitative 0-to-1 scale with intervals of 0.2 (0 for no dependency (impact) risk, 0.2 for very low to 1 for very high dependency (impact)).

[15] The first four variables are scaled by total assets while market value of equity is scaled by book value of debt.

for the potential non-linear relationships between each of these bankruptcy predictors and loan rates. Similar to Z-score, these variables are constructed at the NAICS-6-quarter-year level based on a sample of all Compustat firms. We obtain robust results, further alleviating the concern that our main findings are driven by borrowers' general credit risk.

In Column (4), to further ensure that our results are not driven by imbalances in loan characteristics across industries with different biodiversity scores, we use propensity score matching to match loans in sub-industries with high biodiversity dependency (impact) scores above the sample's median to those in sub-industries with low biodiversity scores below the sample's median. We match using all control variables specified in Equation (1). As shown in Column (4), our results remain robust.

In Columns (5)-(7), we show that our results are robust to various alternative model specifications. In particular, we use the logarithm of loan spreads as the dependent variable since interest rate spreads could have a dispersed distribution (Column (5)), double cluster standard errors at the NAICS-6 sub-industry and lender levels (Column (6)), and additionally control for *Ln(loan size)*^{2}, *Loan maturity*^{2}, and *Ln(Jobs created)*^{2} to account for possible non-linear relationships between loan characteristics and rate spreads (Column (7)).

3.3 Variations in biodiversity measures

In this subsection, we explore heterogeneity in the biodiversity measures. Our first test distinguishes between different types of biodiversity dependency risk. As discussed in Subsection 2.1, ENCORE classifies 25 ecosystem services into three categories: i) *provisioning services*; ii) *regulating and maintenance services*, and iii) *cultural services. Provisioning services* refers to the material products that ecosystems provide directly to businesses, such as crops, livestock, fish, or fresh water. Similarly, *regulating and maintenance services* support ecosystem stability, ensuring business have access to clean water, fertile soil, climate and flood regulation, and land degradation prevention. Disruptions to both these services could significantly impact a firm's production processes. In contrast, ecosystems that provide *cultural services*, such as aesthetically pleasing landscapes or cultural sites, are generally neither direct inputs to nor enablers of production for most businesses (Garel et al., 2025). Thus, we expect provisioning and maintenance services, but not cultural services, to affect loan rates.

To test our hypothesis, we calculate a separate *Dependency score* for each of the three categories (provisioning, maintenance, and cultural services) based on the number of ecosystem services in that category assessed as having medium or higher materiality, and relate these scores to loan rates. The average *Dependency score* is 0.515 for provisioning services (out of a maximum of 4), 3.322 for maintenance services (out of 17), and 0.948 for cultural services (out of 4). All these scores show meaningful variation, with standard deviations of 0.589, 2.603, and 1.309 for provisioning, maintenance, and cultural services, respectively. We display the results in Panel A of Table 4.

[Insert Table 4]

In line with our expectations, the results in Panel A show that biodiversity risks related to provisioning and maintenance services—but not cultural services—affect loan rates. In particular, a one standard deviation increase in *Dependency score (provision)* and *Dependency score (maintenance)* is associated with 4.6 and 3.4 basis points higher interest rates, respectively. Overall, our findings thus shed light on the specific ecosystem services that matter to loan pricing decisions.[16] Our results also lend support to Garel et al. (2025), who argue that cultural ecosystem services are less relevant to a firm's production and economic activities.

Our second test examines whether our biodiversity risk measures differ from climate risk measures (Altavilla et al., 2024; Islam and Singh, 2025). This is important because both the biodiversity dependency and impact measures include elements that may also reflect climate risk exposures. For instance, the dependency measure includes climate regulation services,

[16] We are unable to perform a similar analysis for biodiversity impact risk since there is no clear categorization of these risks.

while the impact measure includes greenhouse gas (GHG) emissions. Accordingly, in Panel B of Table 4, we reconstruct the *Dependency score* and *Impact score* by excluding items related to climate risk. Specifically, we remove global and local climate regulation services from the dependency measure and GHG emissions from the impact measure.

As shown in Panel B, after excluding climate-related items, the re-estimated coefficients on *Dependency score (w/o climate regulation)* (Column (1)) and *Impact score (w/o GHG emissions)* (Column (2)) remain similar to our baseline estimates. Thus, our findings are not driven by borrowers' exposure to climate-related risk, but rather reflect lenders' specific concerns about biodiversity-related risk.

3.4 Variations in lenders' involvement in making credit decisions

In this subsection, we consider heterogeneity in lenders' incentives to screen loans carefully and recognize and price biodiversity risk. Our first test exploits variation in the extent to which the SBA delegates credit decision-making authority to lenders. This variation arises from the SBA's institutional structure, which allows selected lenders to make credit decisions independently without prior SBA review. Specifically, under the Preferred Lender Program (PLP) and the SBA Express program, participating lenders are granted pre-authorization to evaluate and approve loan applications on their own.[17] This delegation effectively shifts the responsibility for borrower screening and risk assessment from the SBA to the participating lenders.

These delegated programs comprise a substantial portion of loans in our sample, with PLP loans accounting for 37% and SBA Express loans for 46% of total 7(a) loan originations. In contrast, for other types of 7(a) loans, the SBA retains centralized control over credit decisions, requiring direct review and approval through SBA Loan Guaranty Processing

[17] In the case of PLP lenders, the SBA delegates full credit evaluation and approval authority based on the lender's demonstrated track record with SBA loans. Similarly, the SBA Express program allows approved lenders to make credit decisions using their own underwriting processes and procedures.

Center. To this end, we split our sample into two subsamples: (1) delegated lending, i.e., 7(a) loans originated under the PLP and SBA Express programs, and (2) non-delegated lending.

[Insert Table 5]

Panel A of Table 5 displays the results. Consistent with our expectations, the results in Panel A indicate that dependency risk is priced in the subsample where lenders have full discretion over credit decisions (Column (1)), but not in the subsample where such authority is retained by the SBA (Column (2)). While suggestive, these results should be interpreted with caution. First, we acknowledge that there is more power to find statistically significant effects in the delegated lending subsample because this sample has more observations. Second, we remain agnostic on whether the biodiversity pricing effects come from lenders or the SBA. If we observe differential pricing based on a borrower's biodiversity risk, this would indicate that the loan underwriter—whether the SBA or the lender—acknowledges this risk as relevant to their lending and pricing decisions.

Our second test explores heterogeneity in loan characteristics, specifically in terms of loan size and loan duration. Larger loans pose greater risk for lenders, including higher potential losses when financing borrowers exposed to biodiversity dependency risk and greater reputational and litigation risk in lending to those with negative biodiversity impacts. Similarly, longer-duration loans increase lenders' exposure to future biodiversity disruptions and regulations. Since lenders have more "skin in the game" in originating large and long-term loans, they could be more likely to recognize and price biodiversity risk in these cases. We test this by interacting *Dependency score* and *Impact score* with *Ln(Loan size)* and *Loan maturity*, and display the results in Panel B of Table 5.

As shown in Panel B, all interaction coefficients are positive and statistically significant,[18] indicating that lenders are more likely to price biodiversity dependency and impact risk in larger and longer-term loans. These findings are consistent with the results in Panel

[18]The interaction between *Impact risk* and *Ln(Loan size)* is marginally statistically significant at 10% level.

A, suggesting that lenders place more emphasis on biodiversity risk when they have more authority in credit decisions and have more at stake.

3.5 Variations over time

In the final cross-sectional test, we explore heterogeneity in the effects over time. Our 2010–2024 sample period coincides with a significant increase in global attention to, and regulatory measures aimed at, biodiversity protection (Garel et al., 2024). We thus expect lenders to be more likely to incorporate biodiversity impact and dependency risk into their loan pricing decisions in the later years of our sample period.

We focus on two key periods that mark a sharp increase in attention to biodiversity: (1) *after 2015*, when the Paris Agreement and the UN Sustainable Development Goals (SDGs) came fully into effect. While the 2015 Paris Agreement primarily focuses on climate change mitigation, it is closely related to biodiversity conservation, since climate change is a major driver of biodiversity loss; and (2) *after 2022*, when the Kunming-Montreal Framework was adopted (Garel et al., 2024; Opoku, 2019). Considered the most important international treaty of the decade on biodiversity, the Kunming Declaration stresses the need to align financial flows to support the conservation of biodiversity. It also triggers biodiversity-related regulation and litigation and thus carries important implications for lenders and borrowers. To this end, we explore heterogeneity in the pricing of biodiversity risk across two periods: 2016–2022 (after Paris but before Kunming-Montreal) and 2023–2024 (after Kunming-Montreal). The 2010-2015 period serves as the base group.

[Insert Table 6]

Table 6 displays the results. As shown in Column (2), the interaction coefficients on *Impact score* × *2016–2022* and *Impact score* × *2023–2024* are both positive and statistically significant at the 1% level. Moreover, the coefficient for 2023–2024 (0.026) is twice as large as that for 2016–2022 (0.013). There is no significant relationship between biodiversity impact risk and loan pricing during the base period (2010–2015).

Our results suggest that lenders become more responsive to biodiversity impact risk after the Paris Agreement and the adoption of the UN SDGs, and even more so following the Kunming Declaration. While we do not find evidence of biodiversity impact risk being priced in the baseline, lenders are increasingly likely to recognize and incorporate this risk in more recent years—particularly after the Kunming Declaration, which significantly heightened regulatory and litigation risks associated with lending to firms that negatively affect biodiversity.

In contrast, the interaction coefficients between *Dependency score* and the time period indicators are not statistically significant below the 5% level, while the single term *Dependency score* remains positively significant (Column (1)). Thus, unlike impact risk which appears to be priced only in recent years, dependency risk has been consistently reflected in loan spreads throughout the sample period. In subsequent sections, we investigate the underlying mechanisms that may explain why lenders respond differently to these two types of biodiversity risk.

4 Mechanisms behind banks' pricing of dependency risk

In this section, we conduct various tests to understand the underlying mechanisms through which biodiversity dependency risk is incorporated into the cost of SME loans. Since dependency risk captures a firm's exposure to ecosystem service disruptions, this means firms in highly biodiversity-dependent industries would face greater risks of profitability loss and operational disruptions when ecosystem services are compromised. Small firms are particularly vulnerable to these disruptions as they lack the ability to diversify their operations or reallocate businesses to less affected regions. The loss of firm profits, in turn, can increase the probability that borrowers default on their loans and result in credit losses for lenders. Consistent with this, our collective findings in this section indicate that lenders view dependency risk as a source of credit risk.

4.1 Loan default

Our first test of this channel examines the impact of borrowers' biodiversity dependency and impact risk on the likelihood of loan default. The dependent variable is *Default*, a dummy variable that equals one if a loan defaults and zero if it is paid in full. The regression specifications include control variables and fixed effects similar to those in Equation (1).

[Insert Table 7]

Table 7 displays the results. As shown in Column (1) of Table 7, the coefficient on *Dependency score* is positive and statistically significant, indicating that borrowers in industries with higher biodiversity dependency risk are more likely to default on their loans. The magnitude of the estimate in Column (1) indicates that a one standard deviation increase in dependency risk is associated with a 0.024 or 2.4% (= 0.007 x 3.426) higher probability of loan default. Relative to the average default rate of 7.6%, this estimate corresponds to an economically substantial marginal effect of 31%.

It is worth noting that this estimate is obtained after controlling for Altman's Z-score, which captures the more general credit risk characteristics specific to the borrower's NAICS-6 sub-industry. Therefore, the association between *Dependency score* and default probability is unlikely to be confounded by industry-level financial and accounting fundamentals. Overall, our results indicate that the pricing of dependency risk reflects lenders' concerns about potential credit losses in financing firms operating in a highly biodiversity-dependent industry.

In contrast, we do not find any association between *Impact score* and default. In Column (2), the coefficient on *Impact score* is statistically insignificant, and its magnitude is close to zero. Since firms that exert negative impacts on biodiversity are not more likely to default on their loans, this finding further supports our interpretation that lenders view dependency risk—but not impact risk—as a form of credit risk. Accordingly, they impose higher interest rates on loans to firms facing greater dependency risk to compensate for potential credit losses.

4.2 Loan securitization and aggregate lending volume

In this subsection, we examine the effect of biodiversity risk on loan securitization and aggregate lending volume. If lenders view biodiversity dependency risk as credit risk, they could mitigate this risk by—alongside incorporating it in loan prices—securitizing these loans off their balance sheet (Müller et al., 2025). Similarly, due to concerns about potential credit losses, lenders may also refrain from financing borrowers in highly biodiversity-dependent industries.

Table 8 focuses on loan securitization. While lenders typically hold 7(a) loans until maturity, they have the option to sell these loans in the secondary market. In our sample, 27% of originated loans are securitized. To examine how biodiversity risk affects loan securitization, our dependent variable is *Securitized*, a dummy variable that equals one if the loan is sold on the secondary market, and zero otherwise. The regressions include control variables and fixed effects similar to those in Equation (1).

[Insert Table 8]

As shown in Column (1) of Table 8, the coefficient estimate on *Dependency score* is significantly positive and its magnitude indicates that loans to borrowers in industries with a one-standard deviation higher biodiversity dependency risk are 1% (= 3.426 x 0.003) more likely to be sold in the secondary market. Relative to the average securitization rate of 27%, this estimate corresponds to an economically meaningful marginal effect of 4%. In contrast, lenders are not more likely to securitize loans with higher impact risk (Column (2)). The findings in Table 8 therefore indicate that, in addition to incorporating dependency risk in loan rates, lenders rely on securitization to shift at-risk loans off their balance sheets. The results are consistent with the view that lenders perceive biodiversity dependency risk as credit risk.

In Table 9, we examine the effect of biodiversity risk on aggregate lending volume. If lenders perceive biodiversity dependency as a source of credit risk, we expect them to tighten credit supply by reducing the overall loan volume to borrowers with higher dependency risk. To test this, we aggregate loan-level data at the NAICS6-lender-SBA office-county-year level. Our dependent variable is *Ln(Total lending volume)*, the natural logarithm of the total dollar amount of 7(a) loans originated by a lender-SBA office pair to a given NAICS-6 sub-industry in a given county-year. Thus, this variable measures lenders' willingness to lend to a given NAICS-6 sub-industry.[19]

[Insert Table 9]

The results in Table 9 indicate that small borrowers in highly biodiversity-dependent industries receive a lower total volume of 7(a) loans. In particular, the coefficient estimate in Column (1) indicates that a one-standard deviation increase in *Dependency score* is associated with a 8.2% (= -0.024 x 3.426) lower lending volume. In contrast, borrowers' *Impact score* does not affect their access to 7(a) loans (Column (2)).

Our overall findings suggest that lenders perceive dependency risk as a source of credit risk and refrain from lending to borrowers in highly biodiversity-dependent industries. The results may also reflect borrowers' credit demand, as small borrowers exposed to biodiversity dependency risk could be self-discouraged from applying for a loan, anticipating rejection or unfavorable loan terms due to their heavy reliance on biodiversity. Regardless of the interpretation, the results in Table 9 demonstrate that dependency risk adversely affects small borrowers' access to finance. This has important implications, suggesting that biodiversity dependency risk has potential real outcomes in perpetuating borrowers' financial constraints and affecting their survival and growth.

[19] We do not perform this analysis at the loan-level and use *Ln(Loan size)* as the dependent variable because this variable directly captures borrower preferences. For example, even when lenders are willing to offer larger loans, credit markets will not clear on these terms if borrowers only require small loans.

4.3 Lender exposure to biodiversity risk

Our third test focuses on the roles of lenders' exposure to biodiversity risk. We expect lenders with greater exposure to financing firms in highly biodiversity-dependent industries to be more likely to price this risk, since they have likely "learned" from past losses in lending to these firms. We test this by interacting *Dependency score* with *Dependency exposure*, the weighted average dependency score (by loan amount) across all 7(a) loans a lender originates in a given year. We similarly interact *Impact score* with *Impact exposure*, the weighted average impact score (by loan amount) across all 7(a) loans a lender originates in a given year. Table 10 displays the results.

[Insert Table 10]

As shown in Column (1) of Table 10, the interaction coefficient on *Dependency score* x *Dependency exposure* is positive and statistically significant. This indicates that lenders with more exposure to firms in industries facing high biodiversity dependency risk are more likely to price this risk. This is consistent with a "learning channel," where past realized credit losses from lending to highly biodiversity-dependent firms feed into future lending decisions.

In contrast, the interaction coefficient on *Impact score* x *Impact exposure* in Column (2) is statistically insignificant. Thus, more lending to borrowers with negative biodiversity impact does not increase the likelihood that lenders price impact risk. As shown in the next section, the pricing of impact risk is mainly driven by perceived regulatory risks. Thus, lenders would not incorporate impact risk into their pricing, even if they have experience lending to these firms, unless they perceive regulatory risks in doing so.

Overall, our findings are consistent with the explanation that lenders view biodiversity dependency risk as a source of credit risk. This view is also in line with our earlier findings that the pricing of dependency risk is more salient among larger and longer-term loans since these loans would pose greater potential credit losses for lenders. Moreover, since dependency risk reflects credit risk, its pricing is independent of recent movements toward biodiversity protection, a finding documented in Table 6.

5 Mechanisms behind banks' pricing of impact risk

In this section, we explore the potential mechanisms through which biodiversity impact risk is incorporated into loan prices. Our findings in Table 6 indicate that while lenders do not on average price biodiversity impact risk, they have become more likely to do so in recent years, amid increased regulation and litigation against lending to firms with negative biodiversity impact. Moreover, heightened public awareness of firms' negative impact on biodiversity could also amplify reputational concerns for lenders financing these firms (Coulson, 2002; Flannery et al., 2024; Müller et al., 2025). Our findings in this section suggest that biodiversity impact risk is priced to account for the potential reputational and litigation risks associated with financing firms that negatively impact biodiversity.

5.1 Political environments

Our first test of this channel exploits variations in the political environment across states. Views on biodiversity and environmental protection have become increasingly politically polarized. While Democrats often urge lenders and investors to divest from industries making negative biodiversity and environmental impact, Republicans instead criticize those that take active stances on environmental issues (Duchin et al., 2025; Gormley et al., 2024) Thus, Democrat-leaning states are more likely to enforce regulations and sanctions on firms that harm biodiversity, as well as lenders that finance these firms. Additionally, the reputational risk of financing such firms could be higher in these states. As a result, if lenders view biodiversity impact risk as a potential regulatory or reputational concern, they would be more likely to price this risk in Democrat-leaning states.

We follow Gormley et al. (2024) and use the political affiliation of the state's governor as a proxy for the political environment in the state. Specifically, *Democrat* is a dummy variable that equals one if the state has a Democrat governor in a given year, and zero otherwise. *Democrat* is defined using three different location definitions: (1) the state of the project for which the loan is requested. Small borrowers typically seek loans from local bank branches near their project locations. As a result, the political attitudes of local loan officers, who conduct the initial borrower assessments, likely play an important role in the pricing of biodiversity risk; (2) the lender's headquarters' state. Since headquarters has the ultimate authority over loan approval and pricing, its attitudes are also likely to play a role in determining the extent to which biodiversity risk is priced; and (3) the state of the SBA district office, to account for the SBA's involvement in originating 7(a) loans.

To test our hypothesis, we interact *Democrat* with *Dependency score* and *Impact score*. We further restrict the sample to states that experience at least one political party turnover (from Republican to Democrat and vice versa) during the 2010–2024 sample period. This ensures that the state experiences meaningful changes in political values and attitudes over time. Table 11 displays the results.

[Insert Table 11]

Consistent with our expectations, the interaction coefficients between *Impact score* and *Democrat* are positively and statistically significant across all three location definitions (Columns (4)-(6)). Thus, loan rates are more likely to reflect biodiversity impact risk in Democrat-leaning states, where lenders could face greater regulatory and sanction risks for financing firms in biodiversity-unfriendly industries.

In contrast, the interaction coefficients between *Dependency score* and *Democrat* are statistically insignificant (Columns (1)-(3)), indicating that the pricing of dependency risk does not depend on the political environment in the state. This further corroborates the interpretation that lenders view dependency risk as credit risk and impact risk as potential regulatory or sanction risk.

5.2 Heterogeneity across locations

Our second test of this channel exploits variation in regulatory risk across geographical locations. In particular, we focus on areas *at risk* of being classified as protected areas, i.e., regions that are designated and managed with the aim of conserving natural environments, protecting critical habitats, and preserving global biodiversity. The scope of protected areas has grown over time. As of 2024, approximately 17% of the Earth's land surface had been designated as protected areas, compared to around 15% in 2022, and less than 10% in 2000. This trend reflects the increase in global commitments to biodiversity conservation, in line with the "30×30" target of the Kunming-Montreal Framework, which calls for the effective protection and management of 30% of the global land and sea areas by 2030.

The expansion of protected areas can have important implications for firms located in or near such regions. Once an area receives the protected status, it becomes subject to more stringent regulations, which may restrict or entirely prohibit economic activities deemed harmful to the local ecological systems. As a result, firms in biodiversity-unfriendly industries could face increased regulatory scrutiny when operating in or near these protected areas. If lenders view biodiversity impact risk as a potential regulatory concern, they would be more likely to price biodiversity risk for firms operating in areas *at risk* of becoming protected areas.

To test this hypothesis, we interact *Dependency score* and *Impact score* with *Area at risk*, a dummy that equals one if the loan proposal's designated county contains an area that is considered to be of high biodiversity value (and thus *could become* designated as a protected area), but has not yet been designated as a "protected area" (Nguyen et al., 2024).[20] In our sample, 27% counties contain areas *at risk* of being designated protected areas.

[Insert Table 12]

Table 12 displays the results. As shown in Column (2) of Table 12, the interaction coefficient between *Impact score* and *Area at risk* is positively and statistically significant. This suggests that lenders are more likely to price impact risk when the loan is for a project located near areas at risk of being designated as protected areas. In contrast, the interaction coefficient between *Dependent score* and *Area at risk* is not statistically significant. Overall, these findings imply that the pricing of biodiversity impact risk is associated with the potential exposure to more stringent regulatory environments.

6 Conclusions

This paper provides the first systematic evidence on the pricing of biodiversity risk in the context of small business lending. Using comprehensive loan-level data from the U.S. Small Business Administration's 7(a) programme and industry-level proxies for biodiversity risk from the ENCORE platform, we show that lenders primarily focus on biodiversity *dependency* risk—that is, the extent to which borrowers rely on ecosystem services—and charge higher loan spreads on borrowers in industries with high exposure to this risk. Our results suggest that lenders view dependency risk as a source of credit risk, as evidenced by higher default rates, an increased likelihood of loan securitization, and reduced credit availability for small

[20] Following Nguyen et al. (2024), we first identify areas that are considered to be of high biodiversity value, and thus *could become* designated as biodiversity protected areas. To do this, we use two widely recognized ecological data sources: (1) the Key Biodiversity Areas GIS dataset, which identifies regions that are homes of animal, fungus, and plant species at risk of extinction, based on the International Union for Conservation of Nature's Red List of Threatened Species; and (2) the Intact Forest Landscapes map, which captures both forest ecosystems as well as naturally treeless ecosystems such as grasslands, shrublands, heathlands, and tundra. We then use the United States Geological Survey Protected Areas Database to identify areas that have *already been* designated as protected areas. Finally, we define the areas *at risk* of being classified as a protected area as those that *could become* designated as protected areas but have not *already been* officially designated as protected areas.

firms in biodiversity-dependent industries. We also find that lenders with greater exposure to financing such firms are more likely to price this risk, indicating a learning effect from past lending losses.

We also show that biodiversity *impact* risk—the extent to which borrowers negatively affect biodiversity—is increasingly reflected in loan pricing, particularly as the global community becomes more concerned about environmental issues as marked by the implementation of the Paris Agreement, the United Nations Sustainable Development Goals, and the adoption of the Kunming-Montreal Global Biodiversity Framework. Our analyses further reveal that impact risk is associated with higher loan spreads only in areas with heightened regulatory scrutiny and more politically progressive states. Overall, the pricing of biodiversity impact risk appears to be driven by lenders' concerns about reputational and regulatory risks.

Our findings have important implications. For policymakers, the results highlight the growing influence of nature-related risks on financial intermediation activities, especially in response to international biodiversity commitments. For financial institutions, the study underscores the importance of developing robust tools to assess both dependency and impact risks, particularly as biodiversity regulations tighten. Lastly, our analyses raise concerns about credit access for vulnerable small firms that are dependent on ecosystem services, suggesting that biodiversity loss could exacerbate existing financing constraints, with knock-on effects for firm survival and local economic resilience. Overall, our paper contributes to the emerging field of biodiversity finance by shedding light on how biodiversity risk translates into financial risk—and how this, in turn, shapes small business lending decisions.

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Table 1: Summary Statistics

Panel A: Summary Statistics

	#Obs	Mean	StDev	Min	Max
Dependency score	596,436	4.785	3.426	0.000	18.000
Impact score	596,436	2.614	1.946	0.000	11.000
Interest rate spreads (%)	596,436	4.571	1.815	1.600	9.000
Ln(Loan size)	596,436	11.850	1.490	9.210	14.845
Loan maturity	596,436	10.494	6.326	2.000	25.000
Ln(Jobs created)	596,436	1.726	1.132	0.000	4.111
%SBA contribution	596,436	0.649	0.149	0.500	0.900
Altman Z-score	463,337	12.079	1.517	9.210	15.039
Securitized	540,708	0.272	0.445	0.000	1.000
Default	354,166	0.076	0.264	0.000	1.000
Ln(Total lending volume)	355,274	0.499	0.500	0.000	1.000

Panel B: Dependency and Impact Scores within a NAICS-5 Industry

NAICS-6	NAICS-6 Title	Dependency	Impact
221111	Hydroelectric Power Generation	6	3
221112	Fossil Fuel Electric Power Generation	7	8
221113	Nuclear Electric Power Generation	5	6
221114	Solar Electric Power Generation	7	0
221115	Wind Electric Power Generation	7	3
221116	Geothermal Electric Power Generation	4	5
221117	Biomass Electric Power Generation	3	9
221118	Other Electric Power Generation	2	1

Notes: Panel A provides descriptive statistics for the main variables used in the analyses. 'Ln' denotes that a variable is measured in natural logarithms. Variable descriptions are in Appendix Table A.1. Panel B displays the biodiversity dependency and impact scores of the NAICS-6 sub-industries within the *Electric Power Generation* industry (NAICS-5: 22111).

Table 2: Biodiversity risk and interest rate spread

Dependent variable: *Interest rate spread*	(1)	(2)	(3)
Dependency score	0.015**		0.017***
	[0.006]		[0.006]
Impact score		0.001	-0.007
		[0.012]	[0.012]
Ln(Loan size)	-0.043***	-0.043***	-0.043***
	[0.003]	[0.003]	[0.003]
Loan maturity	-0.007***	-0.007***	-0.007***
	[0.001]	[0.001]	[0.001]
Ln(Jobs created)	-0.412***	-0.412***	-0.412***
	[0.010]	[0.010]	[0.010]
%SBA contribution	0.885***	0.884***	0.885***
	[0.095]	[0.095]	[0.095]
Altman's Z-score	-0.001***	-0.001***	-0.001***
	[0.000]	[0.000]	[0.000]
Observations	596,436	596,436	596,436
NAICS-5 FE	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Subprog-Delivery method FE	Yes	Yes	Yes
Adjusted R^2	0.677	0.677	0.677

Notes: This table examines the relation between borrowers' biodiversity risk and interest rate spreads. The dependent variable is *Interest rate spread*, the difference between the loan's initial annual interest rate and the 10-year U.S. treasury bond yield. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3: Biodiversity risk and interest rate spread: Robustness checks

Panel A: Robustness checks for dependency score

Dependent variable: *Interest rate spread*

	Average Score (1)	Highest Materiality (2)	Control Altman-Z (3)	PSM (4)	Ln Loan Spread (5)	Double Clustering (6)	Quad. Controls (7)
Dependency score	0.345**	0.055**	0.015**	0.013**	0.003***	0.015*	0.021***
	[0.152]	[0.025]	[0.006]	[0.007]	[0.001]	[0.009]	[0.006]
Observations	596,436	596,436	596,436	515,588	596,436	596,436	596,436
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS-5 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subprog-Delivery method FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.677	0.677	0.677	0.674	0.676	0.634	0.691

Panel B: Robustness checks for impact score

Dependent variable: *Interest rate spread*

	Average Score (1)	Highest Materiality (2)	Control Altman-Z (3)	PSM (4)	Ln Loan Spread (5)	Double Clustering (6)	Quad. Controls (7)
Impact score	0.086	0.017	0.001	0.005	0.000	0.001	-0.001
	[0.303]	[0.079]	[0.012]	[0.014]	[0.002]	[0.012]	[0.011]
Observations	596,436	596,436	596,436	478,768	596,436	596,436	596,436
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
NAICS-5 FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subprog-Delivery method FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.677	0.677	0.677	0.678	0.676	0.634	0.691

Notes: This table reports various robustness tests on the relation between borrowers' biodiversity dependency risk (Panel A) and impact risk (Panel B) and interest rate spreads. In Column (1), the independent variables are the average individual dependency (impact) scores across all ecosystem services (impact drivers) in each industry. In Column (2), the dependent variables are the number of ecosystem services (impact drivers) with the highest materiality in each industry. Column (3) controls for five individual components of Altman's Z-Score: (i) Working capital, (ii) Retained earnings, (iii) Earnings before interest and taxes, (iv) Sales, and (v) Market value of equity. Column (4) uses propensity score matching to match loans in sub-industries with biodiversity dependency (impact) scores above the sample's median to those in sub-industries with biodiversity scores below the sample's median. Column (5) uses the logarithm of loan spreads as the dependent variable. Column (6) doubles cluster standard errors at the NAICS-6 sub-industry and lender levels. Column (7) additionally controls for *Ln(loan size)*^{2}, *Loan maturity*^{2}, and *Ln(Jobs created)*^{2}. Unless otherwise stated, the dependent variable is *Interest rate spread*, the difference between the loan's initial annual interest rate and the 10-year U.S. treasury bond yield. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. Control variables, as specified in Equation (1), are included but not reported for brevity. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4: Variations in biodiversity measures

Panel A: Different types of dependency risk			
Dependent variable: *Interest rate spread*			
	(1)	(2)	(3)
Dependency score (provision)	0.078**		
	[0.037]		
Dependency score (maintenance)		0.013**	
		[0.006]	
Dependency score (culture)			0.007
			[0.018]
Observations	596,436	596,436	596,436
Control variables	Yes	Yes	Yes
NAICS-5 FE	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Subprog-Delivery method FE	Yes	Yes	Yes
Adjusted R^2	0.677	0.677	0.677

Panel B: Excluding climate-related items		
Dependent variable: *Interest rate spread*		
	(1)	(2)
Dependency score (w/o climate regulation)	0.015**	
	[0.006]	
Impact score (w/o GHG emissions)		0.004
		[0.010]
Observations	596,436	596,436
Control variables	Yes	Yes
NAICS-5 FE	Yes	Yes
Lender-SBA office-year FE	Yes	Yes
County-year FE	Yes	Yes
Subprog-Delivery method FE	Yes	Yes
Adjusted R^2	0.677	0.677

Notes: Panel A differentiates between different types of biodiversity dependency risk. *Dependency score (provision)*, *Dependency score (maintenance)*, and *Dependency score (culture)* represent the number of ecosystem services in each category (provision, maintenance, and cultural services) assessed as having medium or higher materiality. Panel B excludes items related to climate risk from the biodiversity measures. *Dependency score (w/o climate regulation)* is the total number of ecosystem services (excluding global and local climate regulations) in each industry for which its dependency is assessed as medium or higher in materiality. *Impact score (w/o GHG emissions)* is the total number of impact drivers (excluding GHG emissions) in each industry assessed at medium or higher materiality. Control variables, as specified in Equation (1), are included but not reported for brevity. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Variations across lenders' involvement

Panel A: Lender's automony in making credit decisions		
Dependent variable: *Interest rate spread*		
Subsamples:	Delegated lending	Non-delegated lending
	(1)	(2)
Dependency score	0.018***	-0.001
	[0.007]	[0.012]
Impact score	-0.007	0.029
	[0.013]	[0.021]
Observations	514,908	65,169
Control variables	Yes	Yes
NAICS-5 FE	Yes	Yes
Lender-SBA office-year FE	Yes	Yes
County-year FE	Yes	Yes
Subprog-Delivery method FE	Yes	Yes
Adjusted R^2	0.678	0.609

Panel B: Variations over loan characteristics				
Dependent variable: *Interest rate spread*				
	(1)	(2)	(3)	(4)
Dependency score*Ln(Loan size)	0.010***			
	[0.002]			
Impact score*Ln(Loan size)		0.008*		
		[0.004]		
Dependency score*Loan Maturity			0.001***	
			[0.000]	
Impact score*Loan Maturity				0.002**
				[0.001]
Dependency score	0.018***	0.018***		
	[0.006]	[0.006]		
Impact score			0.0005	0.003
			[0.012]	[0.012]
Observations	596,436	596,436	596,436	596,436
Control variables	Yes	Yes	Yes	Yes
NAICS-5 FE	Yes	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Subprog-Delivery method FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.678	0.677	0.677	0.677

Notes: Panel A examines variations in the extent to which the SBA delegates credit decisions to lenders. Column (1) presents results for the delegated lending subsample, specifically 7(a) loans issued through the PLP and SBA Express programs. Column (2) shows results for the non-delegated lending subsample, consisting of 7(a) loans issued through all other programs. Panel B examines heterogeneity in loan characteristics. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. *Loan maturity* is the length of the loan term in years. *Ln(Loan size)* is the natural logarithm of the gross approval amount. Control variables, as specified in Equation (1), are included but not reported for brevity. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Variations over time

Dependent variable: *Interest rate spread*	(1)	(2)
Dependency score	0.016***	
	[0.006]	
Dependency score*2016-2022	-0.004*	
	[0.003]	
Dependency score*2023-2024	-0.005	
	[0.004]	
Impact score		0.001
		[0.012]
Impact score*2016-2022		0.013***
		[0.003]
Impact score*2023-2024		0.026***
		[0.005]
Observations	596,436	596,436
Control variables	Yes	Yes
NAICS-5 FE	Yes	Yes
Lender-SBA office-year FE	Yes	Yes
County-year FE	Yes	Yes
Subprog-Delivery method FE	Yes	Yes
Adjusted R^2	0.677	0.677

Notes: This table examines how the relationship between borrowers' biodiversity risk and interest rate spreads varies over time. The dependent variable is *Interest rate spread*, the difference between the loan's initial annual interest rate and the 10-year U.S. treasury bond yield. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. *2016-2022* is a dummy variable that equals one for the years 2016-2022, and zero otherwise. *2023-2024* is a dummy variable that equals one for the years 2023-2024, and zero otherwise. Control variables, as specified in Equation (1), are included but not reported for brevity. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 7: Biodiversity risk and loan default

Dependent variable: *Default*	(1)	(2)	(3)
Dependency score	0.007**		0.007**
	[0.003]		[0.004]
Impact score		0.002	-0.002
		[0.003]	[0.004]
Ln(Loan size)	-0.005***	-0.005***	-0.005***
	[0.001]	[0.001]	[0.001]
Loan maturity	-0.015***	-0.015***	-0.015***
	[0.001]	[0.001]	[0.001]
Ln(Jobs created)	-0.014***	-0.014***	-0.014***
	[0.001]	[0.001]	[0.001]
%SBA contribution	-0.058***	-0.058***	-0.058***
	[0.017]	[0.017]	[0.017]
Altman's Z-score	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Observations	354,166	354,166	354,166
NAICS-5 FE	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Subprog-Delivery method FE	Yes	Yes	Yes
Adjusted R^2	0.136	0.136	0.136

Notes: This table examines the relation between borrowers' biodiversity risk and the likelihood of loan default. The dependent variable is *Default*, a dummy variable that equals one if a loan defaults and zero if it is paid in full. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 8: Biodiversity risk and loan securitization

Dependent variable: *Securitized*	(1)	(2)	(3)
Dependency score	0.003**		0.004***
	[0.001]		[0.001]
Impact score		-0.0004	-0.002
		[0.002]	[0.002]
Ln(Loan size)	-0.008***	-0.008***	-0.008***
	[0.001]	[0.001]	[0.001]
Loan maturity	0.001**	0.001**	0.001**
	[0.000]	[0.000]	[0.000]
Ln(Jobs created)	0.006***	0.006***	0.006***
	[0.001]	[0.001]	[0.001]
%SBA contribution	0.013	0.013	0.013
	[0.013]	[0.013]	[0.013]
Altman's Z-score	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Observations	540,708	540,708	540,708
NAICS-5 FE	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Subprog-Delivery method FE	Yes	Yes	Yes
Adjusted R^2	0.735	0.735	0.735

Notes: This table examines the relation between borrowers' biodiversity risk and the likelihood of loan securitization. The dependent variable is *Securitized*, a dummy variable that equals one if the loan is sold on the secondary market and zero otherwise. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 9: Biodiversity risk and aggregate lending volume

Dependent variable: *Ln(Total lending volume)*	(1)	(2)	(3)
Dependency score	-0.024**		-0.031**
	[0.012]		[0.013]
Impact score		0.020	0.034*
		[0.019]	[0.019]
Loan maturity	0.095***	0.095***	0.095***
	[0.001]	[0.001]	[0.001]
Ln(Jobs created)	0.493***	0.493***	0.493***
	[0.006]	[0.006]	[0.006]
Altman's Z-score	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]
Observations	463,337	463,337	463,337
NAICS-5 FE	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Adjusted R^2	0.645	0.645	0.645

Notes: This table examines the relation between borrowers' biodiversity risk and the aggregate lending volume. The dependent variable is *Ln(Total lending volume)*, the natural logarithm of the total dollar amount of 7(a) loans originated by a lender-SBA office pair to a given NAICS-6 sub-industry in a given county-year. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 10: Lender exposure to biodiversity risk

Dependent variable: *Interest rate spread*	(1)	(2)
Dependency score*Dependency exposure	0.004***	
	[0.001]	
Dependency score	0.016***	
	[0.006]	
Impact score*Impact exposure		-0.001
		[0.003]
Impact score		0.001
		[0.012]
Observations	596,436	596,436
Control variables	Yes	Yes
NAICS-5 FE	Yes	Yes
Lender-SBA office-year FE	Yes	Yes
County-year FE	Yes	Yes
Subprog-Delivery method FE	Yes	Yes
Adjusted R^2	0.677	0.677

Notes: This table examines the role of lender exposure to biodiversity risk. The dependent variable is *Interest rate spread*, the difference between the loan's initial annual interest rate and the 10-year U.S. treasury bond yield. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. *Dependency exposure* is the weighted average dependency score (by loan amount) across all 7(a) loans a lender originates in a given year. *Impact exposure* is the weighted average impact score (by loan amount) across all 7(a) loans a lender originates in a given year. Control variables, as specified in Equation (1), are included but not reported for brevity. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 11: Political environments and the pricing of biodiversity risk

Dependent variable: *Interest rate spread*	(1)	(2)	(3)	(4)	(5)	(6)
Dependency score*Democrat (Loan)	0.001					
	[0.002]					
Dependency score*Democrat (Lender HQ)		0.002				
		[0.002]				
Dependency score*Democrat (SBA Office)			0.000			
			[0.002]			
Impact score*Democrat (Loan)				0.018***		
				[0.004]		
Impact score*Democrat (Lender HQ)					0.010**	
					[0.004]	
Impact score*Democrat (SBA Office)						0.020***
						[0.005]
Dependency score	0.009	-0.0002	0.009			
	[0.007]	[0.007]	[0.007]			
Impact score				-0.011	-0.010	-0.012
				[0.011]	[0.012]	[0.012]
Observations	367,710	358,839	346,265	367,710	358,839	346,265
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
NAICS-5 FE	Yes	Yes	Yes	Yes	Yes	Yes
Lender-SBA office-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Subprog-Delivery method FE	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.660	0.612	0.658	0.660	0.612	0.658

Notes: This table examines how the relationship between borrowers' biodiversity risk and interest rate spreads varies across state-level political environments. The dependent variable is *Interest rate spread*, the difference between the loan's initial annual interest rate and the 10-year U.S. treasury bond yield. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. *Democrat (Loan)* is a dummy variable which equals 1 if the state as specified in the loan application has a Democrat governor and 0 otherwise. *Democrat (Lender HQ)* is a dummy variable which equals 1 if the lender's headquarters state has a Democrat governor and 0 otherwise. *Democrat (SBA office)* is a dummy variable which equals 1 if the SBA district office's state has a Democrat governor and 0 otherwise. Control variables, as specified in Equation (1), are included but not reported for brevity. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 12: Variations across locations

Dependent variable: *Interest rate spread*	(1)	(2)
Dependency score*Area at risk	0.000	
	[0.002]	
Dependency score	0.015**	
	[0.006]	
Impact score*Area at risk		0.007**
		[0.003]
Impact score		0.000
		[0.012]
Observations	595,256	595,256
Control variables	Yes	Yes
NAICS-5 FE	Yes	Yes
Lender-SBA office-year FE	Yes	Yes
County-year FE	Yes	Yes
Subprog-Delivery method FE	Yes	Yes
Adjusted R^2	0.677	0.677

Notes: This table examines how the relationship between borrowers' biodiversity risk and interest rate spreads varies across locations. The dependent variable is *Interest rate spread*, the difference between the loan's initial annual interest rate and the 10-year U.S. treasury bond yield. *Dependency score* is the total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality and *Impact score* is the total number of impact drivers in each industry assessed at medium or higher materiality. *Area at risk* is a dummy that equals one if the loan proposal's designated county contains an area that is considered to be of high diversity value but has not yet been designated as a protected area, and zero otherwise. Control variables, as specified in Equation (1), are included but not reported for brevity. Standard errors clustered at the NAICS-6 sub-industry level are reported in brackets. Variable descriptions are in Appendix Table A.1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Appendix Table A.1: Variable descriptions

Variable	Descriptions
Data source: ENCORE	
Dependency score	The total number of ecosystem services in each industry for which its dependency is assessed as medium or higher in materiality.
Impact score	The total number of impact drivers in each industry assessed at medium or higher materiality.
Dependency exposure	The weighted average dependency score (by loan amount) across all 7(a) loans a lender originates in a given year.
Impact exposure	The weighted average impact score (by loan amount) across all 7(a) loans a lender originates in a given year.
Data source: SBA 7(a) small business loan program	
Default	= 1 if a loan defaults, = 0 if it is paid in full.
Interest rate spread	The difference between the loan's initial annual interest rate and the 10-year U.S. treasury bond yield.
Securitized	= 1 if a loan is sold in the secondary market, = 0 otherwise.
Ln(Loan size)	Natural logarithm of the loan amount.
Loan maturity	Length of the loan term in years
Ln(Jobs created)	Natural logarithm of the number of jobs created and retained as reported in the loan applications.
%SBA contribution	The amount of SBA loan's guaranty divided by the gross approval amount.
Ln(Total lending volume)	The natural logarithm of the total dollar amount of 7(a) loans originated by a lender-SBA office pair to a given NAICS-6 sub-industry in a given county-year.
Data source: Other sources	
Altman Z-score	Z-score of the median Compustat firm in each NAICS-6 sub-industry in each quarter-year.
Area at risk	= 1 if the loan proposal's designated county contains an area that is considered to be of high diversity value but has not yet been designated as a protected area, = 0 otherwise.
2016-2022	= 1 for the year 2016-2022, = 0 otherwise
2023-2024	= 1 for the year 2023-2024, = 0 otherwise
Democrat (Loan)	= 1 if the state as specified in the loan application has a Democrat governor, = 0 otherwise
Democrat (Lender HQ)	= 1 if the lender's headquarters state has a Democrat governor, = 0 otherwise
Democrat (SBA office)	= 1 if the SBA district office's state has a Democrat governor, = 0 otherwise

Notes: This table provides definitions and sources of variables used in the paper.

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25-011 **Duc Duy Nguyen and Vathunyoo Sila:** Corporate Hiring under Uncertainty.

25-010 **Lora Dimitrova and Sapnoti K. Eswar:** Does Financial Innovation Lead to Technological Innovation? Evidence from Foreign Exchange Derivatives.

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