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When Nature Counts: Corporate Biodiversity Attention and Access to Bank Finance

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ABSTRACT

This paper investigates whether corporate attention to biodiversity influences firms' access to bank loans, an overlooked question in the emerging biodiversity–finance literature. Using a novel, text-based measure constructed from 446 biodiversity-related keywords and applied to Chinese A-share listed firms from 2000 to 2023, we show that firms with higher biodiversity attention obtain significantly larger bank loans. The economic magnitude of these loans is large. A quasi-natural experiment based on the 2012 *Green Credit Guidelines* confirms a causal positive effect. Mechanism analyses reveal that corporate reputation, information transparency, and R&D investment strengthen banks' lending willingness. Heterogeneity tests demonstrate that the effect is stronger under stricter environmental regulation, in low-carbon pilot cities, in nonpolluting industries, among more competitive firms, for key monitoring units, and for firms with high green-innovation capacity. The findings highlight biodiversity as a financially material strategic attribute and underscore its growing relevance in credit allocation.

JEL Classification: L25, M14, Q5, Q54

1 | Introduction

Biodiversity loss is a pressing global environmental challenge with profound implications for firms, investors, and financial institutions. Mounting research shows biodiversity degradation poses material economic and financial risks, potentially at par with climate change risks (Karolyi and Tobin-de la Puente 2023; Nedopil 2023). Crucially, they are increasingly viewed as an interconnected "twin crisis," each amplifying the other's impacts (Pörtner et al. 2023). This creates compound risks that spread across ecosystems and economies (Chen et al. 2025), yet their implications for corporate finance, especially bank lending, remain understudied.

Extant literature confirms that firms' environmental and social investments influence financing access and costs. Early work by Goss and Roberts (2011) shows that lenders charge higher spreads to borrowers with CSR concerns, whereas Magnanelli and Izzo (2017) find that stronger corporate social performance reduces the cost of debt. Subsequent research narrows the focus from broad CSR to environmental performance and from loan pricing to credit access: Shen et al. (2021) demonstrate that superior environmental performance reduces borrowing costs and improves bank loan access, and Zhang (2021) further shows that eco-friendly firms face lower collateral requirements.

Despite these advances, this literature largely relies on aggregated CSR or environmental metrics that obscure heterogeneity across environmental dimensions, with biodiversity typically subsumed within broader indicators. Emerging evidence suggests that biodiversity-related risks are financially material: Becker et al. (2025) show that biodiversity risk is priced in loan contracts, Garel et al. (2026) find that firms' nature dependence elevates downside risk, and Li et al. (2025) document that policy signals such as the Kunming Declaration affect credit markets. However, these studies focus primarily on risk exposure or policy-induced awareness rather than proactive firm-level biodiversity investments and remain limited in scope and generalizability. This gap is critical because biodiversity risks are uniquely local, multidimensional (Clément and Grenon 2025), and difficult to quantify (Nedopil 2023), and biodiversity loss can disrupt essential ecosystem services—such as pollination, water purification, and natural hazard regulation—creating risks that climate-centric frameworks fail to fully capture (Hadji-Lazaro et al. 2024). Given the unique characteristics of biodiversity, including its measurement challenges, location-specificity, and limited standardization, it is not clear whether existing findings on environmental performance extend to biodiversity-related initiatives. This motivates a dedicated investigation into the financial implications of firm-level biodiversity strategies.

This study examines whether and how corporate biodiversity attention (BRC) facilitates bank loan access. Using a novel text-based BRC measure derived from corporate disclosures, we analyze Chinese A-share listed firms over 2000–2023. We find that firms with higher BRC obtain significantly larger bank loans. The economic effect is substantial: A one-standard-deviation increase in BRC raises total lending by ~3.83%, equivalent to an extra 16.7 million yuan in average loan financing. This effect is especially pronounced for green loans (18.89% increase, or 15.13 million yuan) and intensifies after China's 2012 Green Credit Guidelines, indicating a causal policy impact. We identify three underlying channels: enhanced reputation, improved information transparency, and increased R&D investment. The relationship is heterogeneous: stronger for firms in regions with strict environmental regulation, low-carbon pilot cities, and those with higher innovation capacity, but weaker for heavily polluting industries.

This research question is particularly salient in China. China hosts rich biodiversity and faces associated risks, while also emerging as a proactive green finance policy incubator. National policies such as the Green Credit Guidelines, alongside local pilots (e.g., Huzhou Green Finance Reform Pilot Zone, where banks have trialed biodiversity-linked loans), create a unique setting to examine how regulation shapes financial rewards for corporate environmental stewardship, including biodiversity attention. Additionally, China's National Biodiversity Conservation Strategy and Action Plan (2023–2030) provides policy support for integrating biodiversity into credit evaluation.

Our study contributes to the literature in four major ways. First, we contribute to the broader literature on environmental and CSR-related financing outcomes. Prior work shows that environmental and social performance affects borrowing conditions, with lenders penalizing firms with CSR concerns and rewarding stronger sustainability performance (Goss and Roberts 2011; Magnanelli and Izzo 2017; Shen et al. 2021; Zhang 2021). We extend this literature by isolating biodiversity as a distinct environmental dimension and demonstrating its independent financial relevance beyond aggregate ESG measures. Existing studies such as Becker et al. (2025), Garel et al. (2026), and Gjerde et al. (2026) document biodiversity risk or perceptions, but none examine whether biodiversity-related strategies translate into improved credit access. We show for the first time that banks reward biodiversity attention through expanded lending. Second, we contribute to the corporate sustainability and strategic management literature by identifying biodiversity as a financially material strategic dimension. Although prior work highlights the reputational or operational value of biodiversity (Bassen et al. 2024; White et al. 2023; Smith et al. 2020), we demonstrate its direct, quantifiable impact on firms' financing conditions. Third, we develop a novel, scalable text-based measure of biodiversity attention, grounded in academic biodiversity research and applied to corporate disclosures. This advances methods used in environmental finance (Giglio et al. 2026) by expanding textual ESG measures into the biodiversity domain. Fourth, we enrich the literature on green credit and sustainable banking by uncovering the mechanisms—reputation, information transparency, and R&D—that link biodiversity strategies to lending decisions. These findings underscore how biodiversity engagement can reduce ecological, informational, and technological risks in ways that banks incorporate into credit decisions.

The paper proceeds as follows. Section 2 reviews the literature and develops hypotheses. Section 3 describes the data, variables, and empirical methodology. Section 4 presents the main results, robustness checks, and mechanism analyses. Section 5 concludes with implications and future research directions.

2 | Review of Literature and Hypothesis Development

2.1 | Review of Literature

Recent biodiversity-finance literature is rapidly growing but fragmented (Dang et al. 2026). Foundational studies (Karolyi and Tobin-de la Puente 2023; Nedopil 2023) frame biodiversity loss as a major economic and financial challenge. Empirical work on risk transmission links ecosystem degradation to financial outcomes (Lucey et al. 2025): Becker et al. (2025) find that higher biodiversity exposure correlates with wider loan spreads, confirming that banks now price nature-related risks.

Crucially, emerging research reframes climate change and biodiversity loss as interconnected "twin crises" that mutually amplify harms (Pörtner et al. 2023). Dinerstein et al. (2020) provide spatial evidence: 92% of high-carbon conservation areas overlap with biodiversity targets, confirming their deep interdependence. However, existing studies focus almost exclusively on biodiversity as a risk, not as a signal of proactive corporate management. Whether biodiversity attention, an observable risk-mitigation signal, shapes banks' core lending decisions remains untested, especially in China, where green finance policies actively direct credit to eco-friendly firms.

Biodiversity-related financial risk falls into two distinct dimensions: systemic and idiosyncratic. Systemic risk research frames biodiversity loss as a macroprudential threat. Hadji-Lazaro et al. (2024) show that banks' concentrated exposure to nature-dependent sectors (agriculture, forestry, tourism) creates contagion risks: ecosystem collapse in one sector can trigger correlated loan defaults. Mies (2025) provides global evidence that biodiversity loss drivers (land-use change, drought, water scarcity) elevate banks' systemic risk metrics (SRISK, SES). Concentrated lending amplifies this vulnerability: 42% of French banks' securities and 36% of Dutch banks' investments are tied to nature-dependent issuers. Eurozone studies further show that a few major banks finance most of the region's biodiversity footprint, creating severe concentration risk.

Parallel research examines idiosyncratic risk at the firm-bank level. Becker et al. (2025) link higher firm biodiversity exposure to wider loan spreads, reflecting banks' concerns over supply chain disruptions, regulatory penalties, and reputational damage. Garel et al. (2026) develop firm-level "Nature Dependence" scores and find that greater ecosystem reliance correlates with higher operational downside risk, a key credit signal. Gjerde et al. (2026) identify a firm-investor information gap, suggesting that actual biodiversity risks are underpriced.

Market pricing studies confirm biodiversity risk is increasingly embedded in asset valuations: Garel et al. (2024) document an equity "biodiversity footprint premium" post-Kunming Declaration, and Guidolin and Pedio (2026) find higher biodiversity-footprint agricultural commodities carry larger spot-market risk premia. Flammer et al. (2025) review emerging biodiversity-focused financing instruments. However, these studies focus on pricing existing contracts or designing new instruments, not on how corporate biodiversity strategies affect credit access.

Notably, both systemic and idiosyncratic risk literatures focus almost exclusively on risk exposure, not proactive corporate biodiversity engagement. No studies examine whether firms adopting conservation strategies, setting nature-positive targets, or disclosing biodiversity governance enjoy better credit access—a critical gap, as banks' core lending decision remains unexplored. Compounding this is a severe firm-bank information asymmetry: Firms underestimate lenders' perception of nature-related risks, whereas banks lack standardized metrics to assess biodiversity exposures (Garel et al. 2026; Gjerde et al. 2026; Lang et al. 2023). This asymmetry makes observable biodiversity attention and disclosure (e.g., textual mentions in annual reports) a valuable, credible signal: Firms can reduce information frictions by signaling stronger environmental governance and lower risk, thereby influencing lending decisions. Thus, although banks now price biodiversity risk (Becker et al. 2025), whether they reward active corporate biodiversity management and disclosure remains unanswered.

2.2 | Biodiversity Focus of Firms and Bank Loan Access

Biodiversity, a core metric of ecosystem sustainability, has made its associated risks and benefits central to corporate strategy and financial market attention. Existing studies focus on two dimensions. At the firm level, biodiversity risks elevate financial distress probability, especially for climate-sensitive and financially constrained firms; Chinese firms face significantly higher exposure than US peers, justifying localized research. Conversely, biodiversity conservation enhances corporate reputation (Bassen et al. 2024), financial performance (White et al. 2023), and firm value (Smith et al. 2020) and reduces stock price crash risk (Bassen et al. 2024). At the market level, biodiversity risks trigger stock market spillovers and systemic financial risks, yet corporate biodiversity attention hedges volatility (Giglio et al. 2026), indicating investor recognition of such performance. Prior research on bank credit determinants focuses on internal bank traits (operational efficiency, capital adequacy) and external factors (policy uncertainty, environmental regulation) but rarely examines corporate biodiversity attention. Systematic evidence on how this attention affects Chinese firms' loan access and its mechanisms remains absent—our core research gap.

Based on environmental risk management theory, banks systematically assess borrowers' ecological risks. Higher biodiversity attention enables firms to cut compliance costs via protection systems and restoration projects, sending positive signals that reduce banks' risk premiums. Per signaling theory, firms disclosing Convention on Biological Diversity–compliant reports demonstrate stronger environmental governance (De Oliveira et al. 2011), lowering banks' information costs and mitigating credit misallocation (Stiglitz and Weiss 1981). Additionally, biodiversity-related R&D builds green competitive advantages, stabilizes future cash flows, and boosts lending willingness. Post-Kunming–Montreal GBF, firms with strong biodiversity performance are more likely to enter banks' green whitelists and receive preferential credit (Mulder and Koellner 2011). Hence, we propose the following hypothesis:

Hypothesis 1. *The higher the corporate attention to biodiversity, the greater the bank loan access.*

2.3 | Why Corporate Biodiversity Focus May Not Influence Loan Access

Despite rising regulatory and investor attention to biodiversity risks, banks may not systematically integrate biodiversity into lending decisions for four key reasons.

First, biodiversity impacts and dependencies are inherently local, multidimensional, and hard to quantify, making them difficult to translate into "bankable" metrics (Nedopil 2023). Most ecosystem services do not directly affect short-term cash flows, remaining external to financial decisions and creating uncertainty for banks that rely on standardized, comparable risk indicators.

Second, banks may not perceive biodiversity risks as financially immediate. Gjerde et al. (2026) document a disconnect: Firms view nature risk as material but believe lenders pay little attention to its cash flow or capital cost impacts. Banks' risk models often lag behind emerging environmental risks, and high ecosystem-dependent firms rarely disclose these exposures (Garel et al. 2026), leaving banks unable to reliably differentiate borrower risk.

Third, banks prioritize traditional credit determinants (profitability, leverage, collateral, industry stability) over biodiversity. Even studies documenting biodiversity risk pricing (e.g., Becker et al. 2025) only examine loan spreads for existing borrowers, meaning biodiversity affects pricing marginally but not the fundamental lend-or-not decision. In competitive markets, banks have little incentive to screen for biodiversity strategies unless mandated by regulation or risks directly threaten repayment.

Finally, biodiversity-positive actions lack clear short-term financial payoffs for banks. Unlike climate investments, which often deliver measurable energy savings or compliance benefits, biodiversity initiatives rarely have transparent near-term financial returns (Karolyi and Tobin-de la Puente 2023). Since banks primarily assess default risk rather than environmental stewardship, a firm's biodiversity focus may not improve loan access. Hence, we propose the following hypothesis:

Hypothesis 2. *Corporate biodiversity focus may not influence loan access.*

3 | Research Design

3.1 | Sample Selection and Model Construction

In our sample, we include Chinese A-share listed companies during the period 2000–2023, excluding ST stocks, listed companies in the financial industry, and companies with incomplete indicator data and extreme values, and finally retain the annual data of 3572 listed companies. Annual data on bank loans and control variables are obtained from the CSMAR database.

To explore whether corporate attention to biodiversity increases the amount of bank loans it obtains, we construct the following benchmark regression model:

$$LNLoans_{i,t} = \beta_0 + \beta_1 BRC_{i,t} + \beta_k Control_{i,t} + \varphi_t + \mu_i + \varepsilon_{i,t} \tag{1}$$

$LNLoans_{i,t}$ is the natural logarithm of the year-end loan balance of commercial banks to listed company i in year t, $BRC_{i,t}$ is the degree of attention to biodiversity of listed company i in year t, $Control_{i,t}$ is a series of control variables, φ_t represent year fixed effects and μ_i firm fixed effects, and $\varepsilon_{i,t}$ is the random disturbance term. In addition, the standard errors of all regression coefficients are clustered at the firm level.

3.2 | Variable Selection

3.2.1 | Dependent Variable

The explained variable is bank loans, and the core indicator is the natural logarithm of the year-end loan balance of commercial banks to listed companies (LNLoans), referring to the measurement methods of (Ma et al. 2025). To further explore the impact differences, seven subdivided types are added: short-term loans (LNSLoans), long-term loans (LNLLoans), credit loans (LNcreLoans), pledge loans (LNPleLoans), guaranteed loans (LNGuaLoans), mortgage loans (LNMorLoans), and green loans (LNGreLoans), all of which are included in the regression in the form of natural logarithms.

3.2.2 | Independent Variable

Our core explanatory variable is corporate biodiversity attention (BRC),[1] a quality-adjusted text-based measure that effectively distinguishes genuine environmental commitment from empty rhetoric or greenwashing by integrating both the breadth and substantive quality of corporate disclosure. This indicator is systematically constructed in four sequential steps:

Following Chen (2026), we first build an exclusive biodiversity dictionary. We retrieve 38,260 core academic papers on biodiversity from the China National Knowledge Infrastructure (CNKI); extract high-frequency keywords using text mining techniques; and after two rounds of manual screening and cross-verification, finalize 446 core terms covering policy, technology, action, and risk dimensions.

Second, we calculate the raw breadth of biodiversity disclosure. Taking listed firms' annual reports as the analytical text, we split the full document into independent semantic units (sentences) by periods and count the total number of sentences containing at least one keyword from our dictionary. A higher count indicates more extensive discussion of biodiversity issues in corporate disclosures.

Third, we quantify the substantive quality of disclosure. To avoid the “form over substance” problem caused by solely counting volume, we use a fine-tuned BERT pretrained language model to automatically classify all biodiversity-relevant sentences into four categories: (i) substantive positive statements describing specific environmental investments or projects; (ii) rhetorical positive statements expressing only general commitments; (iii) negative statements disclosing environmental risks or ecological damage; and (iv) neutral statements presenting objective facts. Based on this classification, we compute the Biodiversity Sentiment Score as the number of substantive positive sentences minus the number of negative sentences, which captures the net quality of a firm's disclosure.

Fourth, we integrate breadth and quality and standardize the measure. We multiply the raw sentence count by (sentiment score + 1) to organically combine disclosure volume and quality. This calculation has three key advantages: Firms with neutral disclosures (sentiment score = 0) retain their original sentence count; firms with net positive actions receive an upward weighting; and firms dominated by negative risk disclosures are discounted. Finally, we standardize this product to have a mean of 0 and a standard deviation of 1 to obtain our final core explanatory variable, BRC. The standardized BRC measures a firm's quality-weighted biodiversity attention relative to the sample average, with positive values indicating above-average attention and negative values indicating below-average attention.

Our choice of sentences as the basic unit of measurement follows established practice in the literature (Chen 2026). Compared with raw word counts (which can be inflated by boilerplate language and repetitive phrases) and hand-coded disclosure indices (which are subjective and difficult to scale for large samples), the sentence-count approach more accurately captures meaningful information disclosure while ensuring objectivity and consistency across large datasets.

It is important to clarify the clear measurement boundary of the BRC indicator: it does not measure a firm's actual physical biodiversity footprint or third-party ESG ratings. Instead, it quantifies the importance of biodiversity as a strategic topic in official corporate communications, weighted by the substantive quality of that communication. Following the theoretical perspective of Deutsch et al. (2000), making the "invisible" biophysical support systems of economic activity "visible" is a critical prerequisite for integrating them into corporate decision-making. The BRC indicator serves this function precisely by reflecting whether management has incorporated biodiversity into strategic consciousness, which is the core feature that distinguishes this study from literature relying solely on lagging environmental indicators.

Admittedly, text-based measures have certain limitations and should be used complementarily with physical measurement methods. Physical footprint models rely on objective data such as land use and carbon emissions to directly assess a firm's ecological impact, but they face severe data availability challenges in long-term, large-sample studies and cannot capture managerial strategic intent. The BRC indicator precisely addresses this gap: the strategic cognition and action willingness it reflects is a critical dimension of risk signaling to financial intermediaries that purely physical metrics cannot capture.

After merging with sentiment score data, our final sample for BRC-related analyses includes 39,205 firm-year observations from 2000 to 2023. Descriptive statistics for BRC are presented in Table 1.

3.2.3 | Control Variables

Drawing on the research methods of (Yang and Li 2025), we adopt company-level indicators as control variables: natural logarithm of total assets (LnTa), book-to-market ratio (BM),

TABLE 1 | Summary statistics.

Variable	*N*	Mean	Std.	Min	Median	Max
Dependent variables						
LNLoans	48,981	19.891	2.038	8.870	19.939	27.223
LNSLoans	46,381	19.443	1.845	0.693	19.540	25.839
LNLLoans	32,158	19.180	2.267	7.851	19.121	26.850
LNcreLoans	32,265	19.020	2.368	4.730	19.089	26.840
LNPleLoans	17,070	18.495	2.111	8.987	18.421	26.376
LNGuaLoans	30,559	19.080	1.885	9.033	19.158	25.983
LNMorLoans	26,662	18.451	1.785	6.128	18.445	25.750
LNGreLoans	45,322	18.199	1.785	6.354	16.685	25.082
Independent variable						
BRC	39,205	0.000	1.000	−1.234	0.056	5.678
Control variables						
LnTa	59,468	22.061	1.488	14.158	21.807	31.431
BM	57,933	0.649	0.245	0.001	0.656	1.636
Lev	59,467	0.440	0.620	0.007	0.427	124.022
Capex	59,418	0.053	0.054	−0.113	0.036	0.749
Ppe	59,468	0.218	0.169	−0.206	0.184	0.971
Roa	59,467	0.062	3.700	−14.293	0.050	901.750
Assgro	62,934	0.212	0.896	−1.000	0.092	107.128
Mechanism variables						
RPU	39,547	5.350	1.800	1.000	5.400	10.000
Trans	36,597	0.650	0.220	0.100	0.680	1.000
RDSpend	32,811	17.800	1.950	12.000	17.850	24.000
Moderating variables						
HERI	39,205	0.468	0.499	0.000	0.000	1.000

(Continues)

TABLE 1 | (Continued)

Variable	N	Mean	Std.	Min	Median	Max
LERI	39,205	0.532	0.499	0.000	1.000	1.000
LCPC	38,778	0.437	0.496	0.000	0.000	1.000
NPC	38,778	0.563	0.496	0.000	1.000	1.000
HPI	29,417	0.299	0.458	0.000	0.000	1.000
NHPI	29,417	0.701	0.458	0.000	1.000	1.000
HFC	30,303	0.500	0.500	0.000	0.000	1.000
LFC	30,303	0.500	0.500	0.000	0.000	1.000
KU	30,142	0.200	0.400	0.000	0.000	1.000
NKU	30,142	0.800	0.400	0.000	1.000	1.000
H_GPR	28,705	0.500	0.500	0.000	0.000	1.000
L_GPR	28,705	0.500	0.500	0.000	0.000	1.000
Other variables						
BRC_pre	33,000	8.500	22.000	0.000	2.000	389.000
BRC_Clean	39,206	0.000	1.000	−1.200	−0.270	5.650
BRC_IV	39,206	0.000	~0.450	~−1.200	~−0.050	~2.500
BRS	39,205	0.468	0.499	0.000	0.000	1.000
WdE_Scores	62,961	0.763	0.537	0.000	0.693	2.303
Ret	62,961	0.025	0.462	−2.573	0.000	3.115
Growth	62,563	0.177	0.579	−10.382	0.091	10.992
Penalty_Dummy	45,258	0.075	0.263	0.000	0.000	1.000
Penalty_Count	45,258	0.100	0.320	0.000	0.000	1.000
Treat	29,417	0.299	0.458	0.000	0.000	1.000
Post	29,417	0.701	0.458	0.000	1.000	1.000
Treat×Post	30,303	0.500	0.500	0.000	0.000	1.000
Post×BRC_pre	39,547	3.800	8.500	0.000	0.000	389.000
BRC×HERI	39,205	2.700	8.000	0.000	0.000	389.000
BRC×LCPC	38,778	2.600	8.000	0.000	0.000	389.000
BRC×KU	30,142	1.400	5.000	0.000	0.000	389.000
BRC×H_GPR	28,705	3.200	8.000	0.000	0.000	389.000

Note: This table presents the summary statistics. The sample period is 2000–2023, at yearly frequencies. All variables are defined in Appendix B.

asset-liability ratio (Lev), ratio of capital expenditure to total assets (Capex), ratio of net fixed assets to total assets (Ppe), return on total assets (Roa), and total asset growth rate (Assgro). We include the ratio of net fixed assets to total assets (Ppe) to control for firm-level asset tangibility and capital intensity. This is a standard practice in empirical corporate and environmental finance research to account for heterogeneity in firms' collateral capacity, operational scale, and exposure to physical investment cycles, thereby isolating the effect of our variable of interest (biodiversity attention). The use of such asset-structure controls is well-established in studies ranging from corporate investment analysis (Moon and Sharma 2014) and environmental policy evaluation (Gong and Lin 2020) to assessments of industrial competitiveness (Ying 2023) and corporate financial strategy (Paranita 2006). Descriptive statistics of the key variables are presented in Table 1. BRC exhibits substantial variability across listed companies (maximum = 389, minimum = 0, mean = 5.933), with a similar disparity observed in bank loan amounts. Accordingly, multiple strategies should be adopted to enhance enterprises' attention to and actions on biodiversity, thereby increasing their access to loans. In particular, this would assist small- and medium-sized enterprises (SMEs) in securing more financing and alleviating uneven loan distribution.

4 | Empirical Results

4.1 | Benchmark Results

First, we investigate the effect of listed companies' BRC on their access to various bank loans. Benchmark regression results are presented in Table 2. Column (1) reports results with only the core explanatory variable included, where BRC exhibits a significantly positive correlation with LNLoans. Column (2) incorporates firm and year fixed effects, and the positive relationship remains statistically significant. Column (3) further adds firm-level control variables, and the positive impact of BRC on total bank loans remains significant. These findings indicate that higher BRC is associated with greater total bank loan access for firms.

Columns (4) to (10) present regression results of BRC on segmented loan types. Column (5) shows that BRC has the most prominent effect on long-term loans (LNLLoans). Columns (4), (6), (8), and (10) report the impacts of BRC on short-term loans (LNSLoans), credit loans (LNcreLoans), guaranteed loans (LNGuaLoans), and green loans (LNGreLoans), respectively, all of which are significantly positive. Column (7) indicates a positive but relatively weak effect of BRC on pledged loans (LNPleLoans), whereas Column (9) shows a negative yet insignificant effect of BRC on mortgage loans (LNMorLoans).

To gauge the economic magnitude of the biodiversity attention variable (BRC), we translate the coefficient estimates into changes in actual loan amounts. In Column (3), the coefficient on BRC is 0.0376. Since BRC is standardized (standard deviation = 1), a one-standard-deviation increase in BRC raises the natural logarithm of total loans by 0.0376, corresponding to an increase in total loan amount of approximately 3.83% [$e^{0.0376}-1=0.0383$]. Using the sample mean of LNLoans (19.891), the average loan balance corresponds to 4.36×10^{8} yuan. Thus, a 3.83% increase in lending implies that firms receive, on average, an additional 9.5 million yuan in bank credit [$0.0383\times436{,}000{,}000=16{,}698{,}800$].

The economic significance is well pronounced for green loans. In Column (10), the coefficient on BRC is 0.1730, implying that a one-standard-deviation increase in BRC increases green lending by roughly 18.89% [$e^{0.1730}-1=0.1889$]. Given the mean LNGreLoans of 18.199, the corresponding average green loan balance equals 8.01×10^{7} yuan. Multiplying this by the estimated percentage change shows that green loans rise by approximately 13.77 million yuan following a one-standard-deviation increase in BRC [$0.1889\times80{,}100{,}000=15{,}130{,}890$].

4.2 | Difference-In-Differences (DiD) Analysis Based on the Green Credit Guidelines

To more rigorously identify the causal effect of corporate attention to biodiversity on bank loans, this study employs the *Green Credit Guidelines* issued by the former China Banking Regulatory Commission in 2012 as a quasi-natural experiment. As a foundational document for China's green finance system, this policy systematically guides the allocation of credit resources toward environmentally friendly activities, providing an exogenous policy shock for our research.

4.2.1 | Model Specification and Variable Definitions

To identify the causal effect of the green credit policy on corporate bank loans, this paper utilizes the implementation of the 2012 *Green Credit Guidelines* as a quasi-natural experiment and constructs a DiD model. The core explanatory variable is the interaction term between a policy dummy variable (Treat) and a time dummy variable (Post). The policy shock timing is set at 2012, with Post equaling 1 for sample years ≥ 2012, and 0 otherwise. The treatment group is defined by matching firms' main businesses with the Green Industry Guidance Catalogue (2019 Edition); firms involved in green projects are defined as green firms (Treat = 1). To exclude interference from the policy's inhibitory effects on polluting firms, this study excludes firms in clearly defined heavily polluting industries, using the remaining neutral firms as the control group (Treat = 0). This design can effectively isolate the net incentive effect of the policy on green firms, providing a reliable foundation for causal identification in subsequent mechanism analysis.

$$LNLoans_{i,t}=\alpha_0+\alpha_1\left(Treat_i\times Post_t\right)+\alpha_k Control_{i,t}+\varphi_t+\mu_i+\varepsilon_{i,t} \tag{2}$$

Among them, the coefficient α_1 of the interaction term is the focus, reflecting the difference in bank loan access between green firms and neutral firms after the implementation of the *Green Credit Guidelines*.

Table 3 presents the baseline DiD estimates evaluating the effect of the green credit policy on firms' access to bank loans. Across all model specifications, the coefficient on the interaction term $Treat\times Post$ remains positive and statistically significant at the 5% level, indicating that green firms experienced an increase in bank lending following policy implementation. This finding holds even as the regression progressively incorporates firm-level controls and fixed effects, suggesting that the policy impact is robust to concerns about omitted variable bias and time-invariant firm heterogeneity.

In the fully specified model (Column 3), the coefficient of 0.179 implies a meaningful improvement in bank loan access for green firms relative to non-green counterparts, consistent with the policy's intended objective of steering financial resources toward environmentally aligned enterprises. Overall, these results provide compelling evidence that green credit policies effectively incentivize financial institutions to allocate credit toward environmentally responsible firms, reinforcing the strategic role of green finance instruments in promoting sustainable corporate behavior. Although the above specification identifies the average effect of the policy on green firms, it does not directly test whether the policy amplified the effect of biodiversity attention. We address this question using a continuous treatment DiD design.

4.2.2 | Parallel Trend Test

The parallel trend assumption is tested using an event study approach. The model is specified as follows:

$$LNLoans_{i,t}=\gamma_0+\sum_{j\neq2011}\gamma_j\left(Treat_i\times Post_j\right)+\gamma_k Control_{i,t}+\varphi_t+\mu_i+\varepsilon_{i,t} \tag{3}$$

TABLE 2 | Results of benchmark regression.

	(1) LNLoans	(2) LNLoans	(3) LNLoans	(4) LNSLoans	(5) LNLLoans	(6) LNcreLoans	(7) LNPleLoans	(8) LNGuaLoans	(9) LNMorLoans	(10) LNGreLoans
BRC	0.3972***	0.1738***	0.0376**	0.4031**	0.9162***	0.0621***	0.0206	0.0361*	−0.0088	0.1730***
	(14.35)	(8.32)	(2.03)	(1.75)	(2.34)	(2.59)	(1.12)	(3.08)	(−0.52)	(3.77)
LnTa			1.0680***	1.1364***	2.2177***	0.9341***	0.7393***	0.7937***	0.5579***	1.3928***
			(43.21)	(47.71)	(8.32)	(26.33)	(21.85)	(36.64)	(20.09)	(50.87)
BM			0.3574***	0.0150*	6.9235***	0.6488***	0.1339	0.4468***	0.3019***	1.8021***
			(7.09)	(1.50)	(11.46)	(5.43)	(1.34)	(6.51)	(3.75)	(17.00)
Lev			3.0851***	1.9383***	4.0963***	2.6054***	1.5199***	2.5945***	1.7497***	1.7892***
			(10.63)	(14.44)	(4.33)	(8.67)	(3.97)	(17.51)	(7.78)	(12.50)
Capex			1.1290***	1.8590***	7.1955***	0.4992	0.2251	0.9536***	0.2645	0.5551***
			(8.83)	(7.91)	(4.31)	(1.57)	(0.75)	(4.77)	(1.26)	(3.67)
Ppe			0.9950***	−0.8489***	−3.5721***	1.4537***	−0.0845	0.7477***	1.1826***	2.7518***
			(13.52)	(−6.37)	(−3.19)	(8.41)	(−0.55)	(6.63)	(9.32)	(−18.76)
Roa			0.3265	0.2928*	−0.1225	0.9904*	−0.1087	0.9194***	0.1561	−10.0723***
			(0.82)	(1.80)	(−0.14)	(1.85)	(−0.94)	(2.67)	(1.28)	(−3.07)
Assgro			−0.0624***	0.0712***	0.4572***	−0.0596**	−0.0060	−0.0628***	−0.0052	−0.2444***
			(−3.99)	(4.98)	(3.21)	(−2.35)	(−0.22)	(−3.70)	(−0.47)	(−1.678)
_Cons	18.9994***	17.8902***	−5.0711***	9.1890***	8.1295***	−2.9129***	0.1257	−0.9260	4.5285***	−4.3823***
	(617.06)	(44.97)	(−9.68)	(11.38)	(10.29)	(−3.76)	(0.18)	(−1.54)	(7.67)	(−35.51)
Year FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	39,206	39,206	39,206	38,795	26,500	26,580	13,800	24,550	21,140	23,020
Adj. R^2	0.0173	0.1416	0.7142	0.3371	0.3784	0.5357	0.4562	0.6487	0.2351	0.222

Note: The benchmark regression model is $LNLoans_{i,t} = \beta_0 + \beta_1 BRC\_Adj_{i,t} + \beta_k Controls + \varphi_t + \mu_i + \varepsilon_{i,t}$. Where *LNLoans* is the natural logarithm of the year-end loan balance of commercial banks to listed company *i* in year *t*; is the degree of attention to biodiversity of listed company *i* in year *t*; is a series of control variables; represent year fixed effects and firm fixed effects, respectively; and is the random disturbance term.
*, **, and *** denote that the individual coefficient is at the 10%, 5%, and 1% level, respectively. *t*-values are in parentheses. Standard errors are clustered at the firm level.

TABLE 3 | Difference-in-differences (DiD) regression results.

Panel A: DiD estimates

	LNLoans		
	(1)	**(2)**	**(3)**
$Treat_i \times Post_t$	0.136**	0.112**	0.179**
	(2.25)	(2.33)	(2.10)
Controls	No	Yes	Yes
Constant	4.027**	0.744**	1.470**
	(2.45)	(1.98)	(1.96)
Year FE	No	Yes	Yes
Firm FE	No	No	Yes
N	39,547	39,547	39,547
Adj. R^2	0.20	0.46	0.63

Panel B: PSM-DiD and ETB matched estimates

	(1)	**(2)**
	PSM-DiD	***Entropy Balancing***
Treat × *Post*	0.1734**	0.1901**
	(2.36)	(2.04)
_Cons	−1.4237***	−1.5672**
	(−3.66)	(2.51)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	39,547	39,547
Adj. R^2	0.1319	0.3276

Note: This table reports the benchmark regression results examining the impact of the green credit policy on enterprises' access to bank loans. Panel A, Column (1), includes no control variables and does not control for individual or time fixed effects. Column (2) introduces firm-level control variables. Column (3) further controls for both individual and year fixed effects in addition to the control variables. The dependent variable is the natural logarithm of total bank loans (*LNLoans*). The core explanatory variable is the interaction term *Treat*×*Post*, where *Treat* indicates green firms (treatment group) and *Post* indicates the post-policy period. Panel B reports the results of tests conducted to mitigate potential sample selection bias in the difference-in-differences (DiD) analysis of the *Green Credit Guidelines* policy. Column (1) presents results using Propensity Score Matching combined with DiD (*PSM-DiD*), where treatment and control firms are matched based on observable characteristics. Column (2) reports results using the Entropy Balancing method, which reweights the control group to match the treatment group in the first three moments (*mean*, *variance*, and *skewness*) of all covariates. All regression specifications are based on Equation (2) as outlined in the main text. Standard errors are clustered at the firm level.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
t-statistics are reported in parentheses.

Here, the year before the policy implementation is set as the base period. The estimation results are plotted in Figure 1. As shown in the figure, before the policy implementation, the coefficients of the interaction term for each year fluctuate around 0 and are insignificant, indicating that the treatment and control groups satisfy the parallel trend assumption regarding loan trends. In the year of policy implementation and thereafter, the coefficients become significantly positive, and the effect shows a sustained

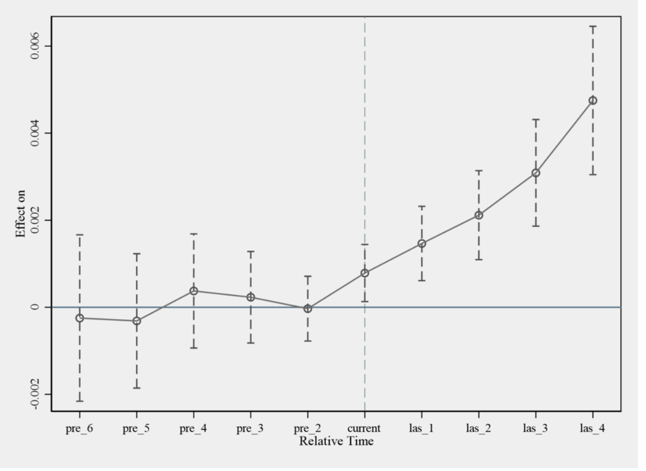

FIGURE 1 | Dynamic effects test for parallel trends.

strengthening trend, indicating that the *Green Credit Guidelines* significantly increased the bank loans obtained by green firms, and the policy effect is persistent.

4.2.3 | Placebo Test

To rule out interference from unobservable factors or randomness, a placebo test is conducted. The specific steps are as follows: Randomly select the same number of companies as the real treatment group from the sample to form a "pseudo-treatment group," and randomly assign a "pseudo-policy year" within the sample period, then perform the DiD regression. This process is repeated 500 times to obtain 500 estimated pseudo-interaction term coefficients. Figure 2 shows the kernel density distribution of these pseudo-coefficients. The real estimated value is far from the distribution center of the pseudo-coefficients, and most pseudo-coefficients are insignificant, indicating that the benchmark regression results are unlikely to be driven by chance factors.

4.2.4 | Matched Sample Test: Propensity Score Matching Combined with Difference-in-Differences (PSM-DiD) and Entropy Balancing Method

To mitigate potential selection bias caused by systematic differences between the treatment and control groups, this paper follows the approach of Rosenbaum and Rubin (1983) by using PSM-DiD and the Entropy Balancing method for verification.

Using all control variables from the benchmark regression as covariates, a logit model is used to estimate the propensity score, and the nearest neighbor 1:1 matching with replacement is employed to match the most similar control group firm for each treatment group firm. The balance test after matching shows that the standardized bias of all covariates is less than 10%. The DiD regression is then performed on this matched sample, with results shown in Column (1) of Table 3, Panel B. After addressing selective bias using the PSM method, the *Green Credit Guidelines* still significantly increase the bank loans obtained by green firms, demonstrating the robustness of our conclusions.

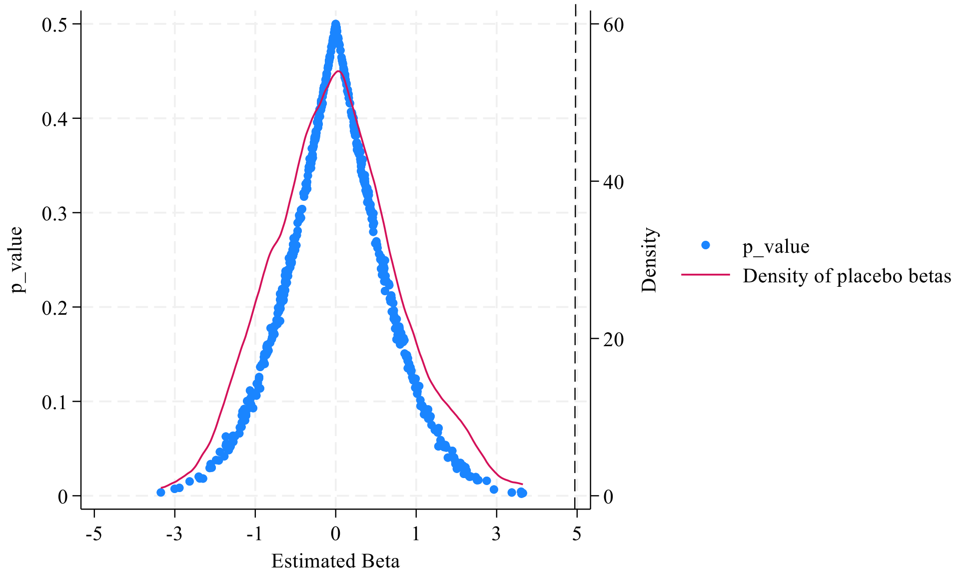

FIGURE 2 | Placebo test.

As a precise reweighting method, the Entropy Balancing method directly weights the control group samples so that the weighted control group matches the treatment group exactly in terms of the mean, variance, and skewness of all covariates. The DiD regression results based on the entropy-balanced weighted sample are shown in Column (2) of Table 3, Panel B.

Whether using PSM-DiD or the Entropy Balancing method, the coefficient of the interaction term is significantly positive at the 5% level, and its magnitude is similar to the benchmark DiD result. This indicates that after controlling for systematic differences in observable characteristics, the promoting effect of the *Green Credit Guidelines* on green firms' access to bank loans remains robust.

4.2.5 | Continuous Treatment DiD: Connecting the Policy Shock to Biodiversity Attention

To directly test whether the *Green Credit Guidelines* amplified the effect of biodiversity attention on bank loans—rather than merely benefiting green firms irrespective of their biodiversity focus—we employ a continuous treatment DiD specification. This approach interacts the post-policy dummy with firms' prepolicy biodiversity attention scores, allowing the treatment intensity to vary with the firm's existing level of biodiversity engagement.

Specifically, we estimate the following model:

$$LNLoans_{i,t} = \alpha_0 + \alpha_1 \left(Post_t \times BRC_i^{pre}\right) + \alpha_2 BRC_i^{pre} + \alpha_3 Post_t + \alpha_k Control_{i,t} + \varphi_t + \mu_i + \varepsilon_{i,t}$$

where $Post_t$ equals 1 for years ≥ 2012, and BRC_i^{pre} is the firm's raw biodiversity attention score measured in 2011 (the year before the policy). This measure is based on the original product of biodiversity-related sentence count and sentiment score, prior to standardization, ensuring that the continuous treatment intensity reflects prepolicy engagement levels.

TABLE 4 | Continuous DiD results.

	(1) *LNLoans*	(2) *LNLoans*	(3) *LNLoans*
Post × BRC_pre	0.0114**	0.0125***	0.0103**
	(2.33)	(2.71)	(2.15)
BRC_pre	0.0081*	0.0065	0.0054
	(1.89)	(1.52)	(1.41)
Post	0.112***	0.098***	0.087**
	(3.45)	(2.98)	(2.54)
Controls	No	Yes	Yes
Year FE	No	Yes	Yes
Firm FE	No	No	Yes
N	39,547	39,547	39,547
Adj. R^2	0.2152	0.4728	0.6412

Note: This table reports continuous treatment DiD estimates from the following equation: $LNLoans_{i,t} = \alpha_0 + \alpha_1 \left(Post_t \times BRC_i^{pre}\right) + \alpha_2 BRC_i^{pre} + \alpha_3 Post_t + \alpha_k Control_{i,t} + \varphi_t + \mu_i + \varepsilon_{i,t}$. The dependent variable is the natural logarithm of total bank loans (*LNLoans*). *Post* is a dummy variable equal to 1 for years ≥ 2012 (the year the guidelines were implemented) and 0 otherwise. BRC^{pre} is the firm's raw biodiversity attention score measured in 2011, calculated as the product of biodiversity-related sentence count and (1 + BRS), prior to standardization. The key explanatory variable is the interaction term $Post_t \times BRC_i^{pre}$. All regressions include the control variables as defined in Table 1. Column (1) includes no fixed effects; Column (2) adds year fixed effects; Column (3) further adds firm fixed effects. Standard errors are clustered at the firm level.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.
t-statistics are reported in parentheses.

The coefficient of interest, α_1, captures whether firms with higher pre-existing biodiversity attention experienced larger loan increases after the policy. We measure BRC_i^{pre} using 2011 values to avoid mechanical endogeneity; results are robust to excluding firms listed after 2011. The estimation results are presented in Table 4. Across all specifications, the coefficient on $Post_t \times BRC_i^{pre}$ remains positive and statistically significant at least at the 5% level. In Column (1), which includes no controls or fixed effects, the coefficient is 0.0114 and significant at the 5% level. Column (2) adds firm-level control variables and year fixed effects, and the coefficient remains positive and significant. In the fully specified model with firm fixed effects (Column 3), the coefficient is 0.0103 and significant at the 5% level, with a magnitude very similar to the baseline DiD estimate. This confirms that the *Green Credit Guidelines* amplified the lending effect specifically for firms already attentive to biodiversity before the policy, providing clean evidence that biodiversity attention, rather than green industry status alone, drives the observed increase in loan access.

4.3 | Endogeneity Issues

To rule out endogeneity concerns, we conduct a series of tests: lagged regression, instrumental variable (IV) estimation, System GMM, and Heckman two-step correction.

First, we use the one-period lag of corporate biodiversity attention (L.BRC) to mitigate simultaneity. As shown in Column (1) of Table 5, the coefficient of L.BRC is significantly positive, confirming robustness.

Second, to address reverse causality and omitted variable bias, we employ a Two-Stage Least Squares (2SLS) estimator. We use the annual average biodiversity attention (BRC) of other firms in the same industry (BRC_IV) as an instrumental variable. This variable plausibly affects a firm's own strategic focus through industry norms but is unlikely to be directly correlated with the idiosyncratic component of its bank loan access, satisfying the relevance and exclusion restrictions. As shown in Columns (2) and (3) of Table 5, the first-stage coefficient of BRC_IV is significantly positive, and the second-stage coefficient of BRC remains positive and significant at the 1% level. Tests reject the weak instrument hypothesis.

Third, to account for dynamic panel bias and unobserved heterogeneity, we employ the System GMM estimator. This approach is

TABLE 5 | Results of endogeneity tests.

	L.BRC	*2SLS*		*GMM*	*Heckman*	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
		First	**Second**		**First**	**Second**
	LNLoans	***BRC***	***LNLoans***	***LNLoans***	***CF***	***LNLoans***
BRC			1.734***	0.402**		2.637**
			(12.18)	(2.21)		(2.26)
L.BRC	0.217*					
	(1.81)					
BRC_IV		0.3176**				
		(2.33)				
L.LNLoans				0.0265***	0.239**	
				(9.62)	(2.36)	
IMR						0.138*
						(1.92)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
N	38,100	38,800	38,800	38,800	39,206	39,206
Adj. R^2	0.3611	0.7431	0.7056	0.3251	0.5762	0.6082
Identification test		Hausman $p = 0.000$		AR(1): $p = 0.015$		
		Kleibergen–Paap rk LM: 102.115		AR(2): $p = 0.965$		
		Kleibergen–Paap rk Wald *F* 87.972		Hansen J: $p = 0.971$		

Note: This table reports the results of endogeneity tests conducted to address potential reverse causality, omitted variable bias, and sample selection issues in the baseline regression. Column (1) presents results using the one-period lagged biodiversity attention variable (*L.BRC*) to mitigate reverse causality. Columns (2)–(3) report Two-Stage Least Squares (*2SLS*) estimates, with BRC_IV (the average BRC of other firms in the same Firm and year) used as the instrumental variable in the first stage; the second-stage results confirm a positive effect of instrumented BRC on LNLoans. Columns (4)–(5) present System GMM estimates, which control for dynamic endogeneity by including the lagged dependent variable (*L.LNLoans*) and using internal instruments; the *AR(1)*, *AR(2)*, and *Hansen J* statistics support the validity of the instruments. Column (6) reports *Heckman two-step* correction results to address sample selection bias, where the Inverse Mills Ratio (*IMR*) is constructed from a probit model of firm loan eligibility; the positive and significant coefficient of BRC persists after correction. All regressions include the full set of control variables, year fixed effects, and firm fixed effects. Standard errors are clustered at the firm level.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, with *t*-statistics in parentheses.

particularly valuable because access to bank loans is often persistent, and corporate biodiversity attention may adjust dynamically. The System GMM estimator uses internally constructed instruments (lagged levels and differences) to control for these dynamics and for time-invariant unobserved firm characteristics, providing robust assurance against dynamic endogeneity. The results (Column 4 of Table 5) show that the coefficient of BRC remains significantly positive after controlling for the lagged dependent variable. Diagnostic tests support the model's validity.

Finally, to control for potential sample selection bias from excluding ST and financial firms, we employ the Heckman two-step method, using "Green Factory" certification as the selection variable. After controlling for the Inverse Mills Ratio, the coefficient of BRC remains positive and significant (Column 6 of Table 5),

TABLE 6 | Results of robustness tests.

Panel A: Results of substituting the explanatory variable

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
BRS	0.0583**	0.0472**	0.0637***				
	(2.38)	(2.31)	(2.80)				
WdE_Scores				0.0258*	0.0124*	0.0272*	0.0148
				(1.86)	(1.94)	(1.87)	(1.08)
BRC							0.0165**
							(2.15)
_Cons	1.2953***	1.3748***	1.3921***	1.3284***	1.4929***	1.5225***	1.1255***
	(8.19)	(7.23)	(7.29)	(9.39)	(10.24)	(5.32)	(4.13)
Controls	No	No	Yes	No	No	Yes	Yes
Year FE	No	Yes	Yes	No	Yes	Yes	Yes
Firm FE	No	Yes	Yes	No	Yes	Yes	Yes
N	27,894	27,894	27,894	25,482	25,482	25,482	25,482
Adj. R^2	0.0803	0.2472	0.3827	0.0156	0.2663	0.3791	0.1845

Panel B: Results of adjusting the sample period

	(1)	(2)	(3)
BRC	0.8077**	0.8781**	1.4613**
	(2.41)	(2.21)	(2.39)
_Cons	0.0436*	0.0294*	0.0583*
	(1.99)	(2.28)	(1.93)
Controls	No	No	Yes
Year FE	No	Yes	Yes
Firm FE	No	Yes	Yes
N	33,900	33,900	33,900
Adj. R^2	0.0036	0.2833	0.3719

Panel C: Results of adding control variables

	(1)	(2)	(3)
BRC	0.8112**	0.9505**	1.2817**
	(2.01)	(2.39)	(2.17)
Ret	0.0030***		0.0239***
	(11.84)		(14.33)

(Continues)

TABLE 6 | (Continued)

Panel C: Results of adding control variables			
	(1)	**(2)**	**(3)**
Growth		0.0183***	0.0218***
		(23.56)	(25.16)
_Cons	0.0829*	0.0290*	0.0611*
	(1.69)	(1.63)	(1.73)
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	39,200	39,150	39,150
Adj. R^2	0.3323	0.3431	0.4528

Panel D: Results of conducting quantile regression									
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	Q10	**Q20**	**Q30**	**Q40**	**Q50**	**Q60**	**Q70**	**Q80**	**Q90**
	LNLoans	***LNLoans***	***LNLoans***	***LNLoans***	***LNLoans***	***LNLoans***	***LNLoans***	***LNLoans***	***LNLoans***
BRC	0.3126**	0.3922**	0.4504***	0.5129**	0.5724***	0.7134**	0.7847**	0.8331**	0.8661**
	(2.11)	(2.32)	(2.93)	(2.29)	(3.31)	(2.48)	(2.24)	(1.98)	(1.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	39,206	39,206	39,206	39,206	39,206	39,206	39,206	39,206	39,206
Adj. R^2	0.0373	0.0158	0.1993	0.0861	0.3689	0.0742	0.1659	0.3852	0.2827

Panel E: Excluding litigation-related keywords		
	(1)	**(2)**
	LNLoans	***LNLoans***
BRC	0.0376**	
	(2.03)	
BRC_Clean		0.3371**
		(2.24)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	39,206	39,206
Adj. R^2	0.7142	0.7146

Note: This table reports the results of robustness checks. The dependent variable is the natural logarithm of total bank loans (*LNLoans*), unless otherwise specified. Panel A presents results using two alternative proxies for biodiversity attention: the Biodiversity Sentiment Score (*BRS*) and the Wind ESG Environmental Score (*WdE_Scores*). Panel B reports results after excluding the COVID-19 pandemic period (2020–2022) to ensure that our findings are not driven by this extraordinary event. Panel C reports results after augmenting the baseline model with two additional control variables—annual stock return (*Ret*) and revenue growth rate (*Growth*)—to account for other potential determinants of bank loans. Panel D presents quantile regression estimates at the 10th to 60th percentiles of the loan distribution (results for the 70th–90th percentiles are available upon request). Panel E reports results from a robustness check that excludes trouble-related keywords from the biodiversity dictionary. *BRC_Clean* is the biodiversity attention score recomputed using a "trouble-free" dictionary that removes terms associated with illegal activities, pollution, degradation, endangerment, overexploitation, and desertification. For comparison, baseline estimates for the original *BRC* are shown alongside. All regressions include the full set of firm-level control variables as defined in Table 1, as well as year and firm fixed effects unless otherwise noted. Standard errors are clustered at the firm level. *t*-statistics are in parentheses. The consistently positive and significant coefficients across all panels confirm that our main finding is robust to alternative measurements, sample periods, model specifications, distributional assumptions, and potential confounding from defensive disclosure.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

indicating that our main finding is robust to sample selection concerns. In the second stage (outcome equation), the IMR is incorporated into the baseline regression model. As shown in Column (6) of Table 6, the coefficient of IMR is 0.138 and significant at the 10% level. After controlling for IMR, the coefficient of the core explanatory variable BRC remains 2.637 and is significantly positive at the 5% level. These results demonstrate that, after accounting for sample selectivity related to "Green Factory" certification, the positive relationship between corporate attention to biodiversity and bank loans persists robustly.

4.4 | Robustness Tests

We implement a battery of robustness tests to verify the reliability of our baseline results. First, we construct an alternative measure—the Biodiversity Sentiment Score (BRS)—using a fine-tuned BERT model. Based on the same keyword dictionary and sentence identification method, we classify biodiversity-related sentences into substantive positive, nonsubstantive positive, negative, and neutral categories. BRS is defined as the number of substantive positive sentences minus negative sentences, excluding hollow commitments and neutral statements to reflect net substantive environmental performance. We also use the environmental dimension score of the Wind ESG (WdE_Scores) as a second alternative indicator. As shown in Panel A of Table 6, the coefficients for BRS (Columns 1–3) are significant at the 5% level, and WdE_Scores is significant at the 10% level only (Columns 4–6). The results confirm that our findings are robust to alternative variable measurements. In Column (7), to ensure that our results are specifically driven by biodiversity attention rather than broader ESG or environmental factors, we augment our baseline specification by controlling for WdE_Scores. The coefficient on BRC remains positive and statistically significant. This implies banks appear to differentiate biodiversity attention from broader sustainability initiatives and incorporate it independently into their lending decisions.

Second, to rule out confounding effects from the COVID-19 pandemic, we drop observations from 2020 to 2022. As reported in Panel B of Table 6, the BRC coefficients remain significantly positive at the 5% level, indicating our results hold in the non-pandemic period. Third, we extend the baseline model by adding two additional controls: annual stock return (Ret) and revenue growth rate (Growth). Results in Panel C of Table 7 show that BRC coefficients remain significantly positive, further supporting the stability of our main findings.

Fourth, we perform quantile regression from the 10th to 90th percentiles of bank loans to examine heterogeneity across loan scales. Panel D of Table 6 shows that BRC coefficients are significantly positive at all quantiles and rise with loan size, suggesting the positive effect is consistent across firms of different borrowing levels.

Finally, to address concerns that BRC may reflect defensive disclosure of environmental problems rather than proactive attention, we construct a trouble-free keyword dictionary by removing terms associated with violations, pollution, degradation, and endangerment. We recompute a cleaned BRC index (BRC_Clean) and re-estimate the model. As shown in Panel E of Table 6, the coefficient of BRC_Clean remains significantly positive, confirming our results capture proactive strategic attention rather than reactive risk disclosure.

TABLE 7 | External validation—BRC and environmental penalties.

	(1)	(2)
	Penalty_Dummy	***Penalty_Count***
BRC	−0.0012**	−0.0084***
	(−2.31)	(−3.05)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	45,258	45,258
Pseudo R2	0.078	0.112

Note: Column (1) reports linear probability model estimates; the dependent variable equals 1 if the firm received at least one environmental penalty in year *t*. Column (2) reports Poisson regression estimates; the dependent variable is the number of environmental penalties. All regressions include the control variables defined in Table 1, as well as year and firm fixed effects. Standard errors are clustered at the firm level. *t*-statistics are in parentheses.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4.5 | External Validation: BRC and Environmental Penalties

To empirically confirm that our text-based BRC measure reflects substantive corporate biodiversity commitment rather than greenwashing (Gan 2025), we link BRC to objective environmental misconduct indicators from independent regulatory data. We collect 2000–2023 environmental penalty data for listed firms from China's local Ecology and Environment Bureaus, including a dummy variable (Penalty_Dummy) for whether a firm was penalized and a count variable (Penalty_Count) for the number of penalties. Unlike self-disclosed information, these regulatory records are exogenous to corporate reporting and serve as a credible ground truth for actual environmental compliance.

Column (1) of Table 7 reports linear probability model estimates for Penalty_Dummy, and Column (2) reports Poisson regression estimates for Penalty_Count. Across both specifications, the coefficients on BRC are negative and statistically significant at the 1% level. In Column (1), the coefficient is −0.0012, and in Column (2), the coefficient is −0.0084. These results indicate that firms with higher biodiversity attention are significantly less likely to be penalized for environmental violations and receive fewer penalties. This negative association strongly confirms that our BRC measure reflects genuine environmental commitment rather than hollow rhetoric or greenwashing.

5 | Mechanism Analysis

5.1 | Reputation Risk

Biodiversity degradation increases firms' reputational risk, as supply chain disruptions in biodiversity-sensitive areas trigger public scrutiny, stakeholder pressure, and perceived governance

TABLE 8 | Mediation results for corporate reputation, information transparency, and R&D investment.

Panel A: Corporate reputation		
	(1)	**(2)**
	RPU	***LNLoans***
BRC	0.3489**	0.0376**
	(2.23)	(2.03)
RPU		0.0023**
		(2.13)
_Cons	5.3528***	0.1503***
	(5.20)	(8.74)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	39,206	39,206
Adj. R^2	0.1337	0.7142
Panel B: Information transparency		
	(1)	**(2)**
	Trans	***LNLoans***
BRC	0.2841**	0.6401**
	(2.51)	(2.21)
Trans		0.0035**
		(1.98)
_Cons	4.7392***	2.7483***
	(5.22)	(5.19)
Controls	Yes	Yes
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	36,597	36,597
Adj. R^2	0.2438	0.3847
Panel C: R&D investment		
	(1)	**(2)**
	RDSpend	***LNLoans***
BRC	0.3790*	0.7124**
	(1.84)	(2.25)
RDSpend		0.0048**
		(2.02)
_Cons	2.8273**	3.9362***
	(2.01)	(3.03)
Controls	Yes	Yes

(Continues)

TABLE 8 | (Continued)

Panel C: R&D investment		
	(1)	**(2)**
	RDSpend	***LNLoans***
Year FE	Yes	Yes
Firm FE	Yes	Yes
N	32,811	32,811
Adj. R^2	0.2321	0.3136

Note: This table (Panel A) reports the results of the mediation mechanism test for corporate reputation. The dependent variable in Column (2) is the natural logarithm of total bank loans (*LNLoans*). In Column (1), the dependent variable is the Reputation Rating Score (*RPU*). Panel B reports the results of the mediation mechanism test for information transparency. The dependent variable in Column (2) is the natural logarithm of total bank loans (*LNLoans*). In Column (1), the dependent variable is the information transparency index (*Trans*). Panel C reports the results of the mediation mechanism test for R&D investment. The dependent variable in Column (2) is the natural logarithm of total bank loans (*LNLoans*). In Column (1), the dependent variable is R&D investment (*RDSpend*). The key explanatory variable is corporate attention to biodiversity (*BRC*). The estimation follows a two-step mediation test approach. All regressions control for the full set of firm-level control variables (as defined in Table 1) and include year and firm fixed effects. Standard errors are clustered at the firm level. The significantly positive coefficient of BRC on RPU in Column (1) and of RPU on LNLoans in Column (2) supports the mediation hypothesis that enhanced corporate reputation is a channel through which greater biodiversity attention increases bank loan access.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively, with *t*-statistics in parentheses.

gaps—impairing credit quality and tightening bank lending standards. Strengthening biodiversity attention helps firms mitigate such risks by improving internal risk management, adopting green technologies, and building reputational capital (e.g., green certifications and sustainability index inclusion) (Bassen et al. 2024). These commitments signal strong governance to financial markets, boosting banks' confidence. We hypothesize that higher biodiversity attention improves loan access by enhancing corporate reputation and reducing reputation-related credit risk.

Biodiversity risks harm corporate credibility and tighten loan terms, while higher BRC mitigates these risks via internal control optimization and green innovation. We measure reputation using the Reputation Rating Score (RPU), with higher scores indicating better reputation (referencing Rudin and Lee 2020; Walker and Dyck 2014; global reputation rankings). Results in Table 8, Panel A, show that the coefficient of BRC on RPU is 0.3489 (significant at the 5% level), and the coefficient of RPU on LNLoans is 0.0023 (significant at the 5% level). These findings confirm that BRC increases loan access by enhancing corporate reputation. In the Chinese context, lending decisions may reflect both market-based reputation and policy alignment, implying that biodiversity attention could partly capture firms' compliance with evolving state priorities rather than purely market-driven effects.

5.2 | Information Transparency

Biodiversity degradation raises supply chain uncertainty and stakeholder scrutiny, worsening information asymmetry about firms' ecological risks and management. Strengthening biodiversity attention reduces this asymmetry through more comprehensive environmental disclosure, improved risk-reporting systems, and clearer governance explanations. This alleviates moral hazard and adverse selection by providing credible, decision-useful information to lenders (Healy and Palepu 2001), optimizing governance, lowering financing costs, and reducing banks' risk uncertainty—ultimately boosting lending willingness. We hypothesize that higher biodiversity attention improves loan access by enhancing information transparency.

We examine the information transparency transmission mechanism (Bushman et al. 2004): Higher BRC reduces asymmetry via improved financial disclosure, optimizing governance, and lowering financing costs (Zhang et al. 2024). We construct the information transparency (Trans) indicator as the percentile average of comprehensive earnings quality and Shenzhen Stock Exchange Information Disclosure Rating (MEG). Results in Table 8, Panel B, show that the coefficient of BRC on Trans is 0.2841 (significant at the 5% level), and the coefficient of Trans on LNLoans is 0.6401 (significant at the 5% level). This indicates that BRC strengthens banks' lending willingness by improving information transparency.

5.3 | R&D Investments

Heightened biodiversity attention encourages firms to increase R&D in biodiversity protection and mitigation technologies. Such R&D enhances innovation capacity and economic returns via productivity improvements (Griliches 1986; Hall and Mairesse 1995). Government interventions (tax incentives, fiscal subsidies) reduce ecological innovation risks, motivating banks to lend to R&D-intensive firms (Goeschl and Swanson 2002). Scaled-up biodiversity R&D boosts productivity, investment prospects, and financial resilience—increasing expected cash flows and reducing lender uncertainty, prompting banks to expand loan supply. We hypothesize that higher biodiversity attention improves loan access by promoting R&D investment.

We explore R&D's mediating role: higher BRC increases biodiversity-related R&D expenditure. Government policies (tax incentives, subsidies) encourage bank support for such R&D (Goeschl and Swanson 2002), and R&D-driven productivity gains enhance firm value. We use R&D investment amount (RDSpend) from the CSMAR database as the indicator. Results in Table 8, Panel C, show that the coefficient of BRC on RDSpend is 0.3790 (significant at the 10% level), and the coefficient of RDSpend on LNLoans is 0.7124 (significant at the 5% level). These findings confirm that BRC helps firms secure more bank loans by increasing related R&D investment.

6 | Heterogeneity Analysis

First, stricter environmental regulation increases firms' incentives to strengthen biodiversity management and heightens banks' attention to ecological compliance; hence, we examine how regulation intensity influences the relationship between firms' biodiversity focus and bank loan access. Following the approach of Jing and Liu (2024), we measure the intensity of environmental regulation in each region using "industrial pollution source control investment per 10,000 yuan of industrial output value." Based on the sample period average, we divide the sample into high- and low-regulation groups (constructing a dummy variable HERI, with the high-regulation group assigned a value of 1 and the low-regulation group assigned 0). Subsequently, we incorporate the interaction term "BRC × HERI" into the benchmark model for regression analysis. The model is specified as follows:

$$LNLoans_{i,t} = \delta_0 + \delta_1 BRC_{i,t} + \delta_2 HERI + \delta_3 (BRC \times HERI)_{i,t} + \delta_k Control_{i,t} + \varphi_t + \mu_i + \varepsilon_{i,t} \quad (4)$$

The regression results are reported in Table 9, Panel F. The coefficient of the interaction term BRC × HERI is 0.5539, significantly positive at the 5% level. The subsample regressions show that for the HERI group, the coefficient of BRC on bank loans is 0.8341, significantly positive at the 5% level; for the LERI group, the coefficient is 0.3323, significant at the 10% level. These results collectively confirm that higher environmental regulation intensity can significantly enhance the promoting effect of BRC on bank loans. This suggests that stringent regulatory environments strengthen the credibility and perceived financial value of firms' biodiversity efforts, thereby encouraging banks to provide greater credit support.

Next, the sample is divided into low-carbon pilot city (*LCPC*) and non-pilot city (*NPC*) groups, and the interaction term $BRC \times LCPC$ is introduced. Drawing on the "twin crises" framework (Pörtner et al. 2023), which posits that climate and biodiversity risks are not separate but compound one another, we examine the moderating role of LCPC status. We hypothesize that in LCPCs—where regulatory and financial attention to climate risk is heightened—banks become more sensitized to this interdependence. Consequently, a firm's biodiversity attention (BRC) serves as a stronger signal of risk (or corporate responsibility) in these contexts. Dinerstein et al. (2020) provide the spatial corollary: Conserving biodiversity and stabilizing the climate require protecting the same places—the "Global Safety Net" where carbon-rich, species-rich ecosystems coincide. In LCPCs, where climate policy is at the forefront, banks are more likely to recognize that a firm's biodiversity attention signals its capacity to manage the compound risks emerging from this nexus.

The regression results in Table 9, Panel G, strongly support this view. The coefficient on BRC × LCPC is 0.4020, significant at the 5% level. Subsample regressions show that the BRC coefficient for the LCPC group is 0.5741, significantly positive at the 1% level, more than double that of the NPC group. This finding is striking: The financial premium for biodiversity attention is substantially amplified in cities where climate policy is at the forefront.

This result elevates our analysis beyond simple policy evaluation. It suggests that banks are beginning to price the interaction between climate transition policy and nature-related risks. In low-carbon pilot cities, climate policy salience makes lenders more vigilant

TABLE 9 | Heterogeneity analysis results.

Panel F: Environmental regulation intensity

	(1) Full sample	(2) *LERI*	(3) *HERI*
BRC	0.3323*	0.3323*	0.8341**
	(1.72)	(1.72)	(2.71)
HERI	0.1291		
	(1.12)		
BRC×HERI	0.5539**		
	(2.13)		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	39,205	20,843	18,362
Adj. R^2	0.328	0.223	0.178

Panel G: Low-carbon pilot cities

	(1) Full sample	(2) *NPC*	(3) *LCPC*
BRC	0.2156**	0.2156**	0.5741***
	(2.42)	(2.42)	(5.71)
LCPC	0.2054		
	(1.43)		
BRC×LCPC	0.4020**		
	(2.32)		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	38,778	21,843	16,935
Adj. R^2	0.316	0.291	0.329

Panel H: Firm pollution level

	(1) Full sample	(2) *NHPI*	(3) *HPI*
BRC	0.5102***	0.5102***	0.2574***
	(3.91)	(3.91)	(3.01)
HPI	−0.382**		
	(−2.55)		
BRC×HPI	−0.2581**		
	(−2.23)		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

(Continues)

TABLE 9 | (Continued)

Panel H: Firm pollution level

	(1) Full sample	(2) *NHPI*	(3) *HPI*
Firm FE	Yes	Yes	Yes
N	29,417	20,625	8792
Adj. R^2	0.2718	0.2252	0.4231

Panel I: Moderating effect of firm competitiveness

	(1) Full sample	(2) *LFC*	(3) *HFC*
BRC	0.4211*	0.4211*	0.5883***
	(1.83)	(1.83)	(5.31)
HFC	0.174		
	(1.22)		
BRC×HFC	0.1778*		
	(1.83)		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	3003	20,031	10,272
Adj. R^2	0.3081	0.2210	0.3925

Panel J: Moderating effect of pollution monitoring unit status

	(1) Full sample	(2) KU	(3) NKU
BRC	0.3825**	−0.3825**	0.7925***
	(2.41)	(−2.41)	(3.41)
KU	0.4083**		
	(4.56)		
BRC×KU	−0.4503**		
	(−2.07)		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	30,142	24,113	6029
Adj. R^2	0.3043	0.2891	0.3231

Panel K: Green innovation quality

	(1) Full sample	(2) *L_GPR*	(3) *H_GPR*
BRC	0.3058*	0.3058*	0.5774***

(Continues)

TABLE 9 | (Continued)

Panel K: Green innovation quality

	(1) Full sample	(2) *L_GPR*	(3) *H_GPR*
	(1.92)	(1.92)	(3.82)
H_GPR	0.1927		
	(1.41)		
BRC×H_GPR	0.0342		
	(1.17)		
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
N	28,705	14,352	14,353
Adj. R^2	0.3041	0.2936	0.3125

Note: This table presents the results of heterogeneity analyses examining how the relationship between corporate attention to biodiversity (*BRC*) and bank loans (*LNLoans*) varies across different firm and regional characteristics. The dependent variable is the natural logarithm of total bank loans. Each panel estimates a variant of the baseline model, incorporating interaction terms or subsample analyses. Panel F examines the moderating role of environmental regulation intensity (*HERI*: high intensity, *LERI*: low intensity). Panel G analyzes the effect of being located in a low-carbon pilot city (*LCPC* vs. *NPC*). Panel H investigates firm heterogeneity based on pollution level (*HPI*: heavily polluting industries, *NHPI*: non–heavily polluting industries). Panel I explores the moderating effect of firm competitiveness (*HFC*: high competitiveness, *LFC*: low competitiveness). Panel J tests the role of a firm's status as a key pollution monitoring unit (*KU* vs. *NKU*). Panel K assesses the influence of green innovation quality (*H_GPR*: high green patent ratio, *L_GPR*: low green patent ratio). All regressions include the full set of control variables, as well as year and firm fixed effects. Standard errors are clustered at the firm level.
*, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

about all environmental risks. As Pörtner et al. (2023) warn, failing to address coupled crises increases vulnerability. Our evidence suggests financial markets are responding: banks recognize that firms attentive to biodiversity in climate-active regions are better positioned to navigate compound risks. A firm signaling biodiversity awareness in this context reveals its capacity to manage the climate–biodiversity nexus, earning greater trust and credit.

Then, because industry pollution characteristics shape firms' environmental risk profiles and influence how banks evaluate biodiversity-related initiatives, we further examine whether industry type moderates the relationship between firms' biodiversity focus and bank loan access (Liu et al. 2025). The sample is divided into heavily polluting industries (HPI) and non–heavily polluting industries (NHPI), and the interaction term *BRC×HPI* is constructed. The regression results are shown in Table 9, Panel H. The coefficient of the interaction term is −0.2581, significantly negative at the 5% level. Subsample regressions show that the BRC coefficient for the NHPI group is 0.5102, significantly positive at the 1% level, whereas for the HPI group, it is 0.2574, also significant at the 1% level but notably smaller. The interaction term result indicates that the attribute of being a heavily polluting industry significantly weakens the financing enhancement effect brought by BRC. This suggests that banks discount the value of biodiversity initiatives among high-pollution industries due to their elevated environmental risks, leading to more cautious credit allocation despite firms' biodiversity efforts.

Because competitive market environments motivate firms to differentiate themselves through sustainability initiatives and influence how banks evaluate firms' strategic capabilities, we further examine whether firm competitiveness moderates the relationship between biodiversity focus and bank loan access (Carroni 2016). Based on industry market share, the sample is divided into high-competitiveness firms (HFC) and low-competitiveness firms (LFC) groups, and the interaction term BRC×HFC is added. The regression results are reported in Table 9, Panel I. The coefficient of the interaction term is 0.1778, significantly positive at the 10% level. Subsample regressions show that the BRC coefficient for the high-competitiveness group is 0.5883, significantly positive at the 1% level; the coefficient for the low-competitiveness group is 0.4211, significant at the 10% level. This suggests that higher firm competitiveness can strengthen the positive influence of BRC on bank loans. Overall, the findings imply that competitive firms are better positioned to translate biodiversity initiatives into financial advantages, as banks perceive these firms as more capable of leveraging environmental strategies for long-term performance.

Additionally, the use of a key pollution monitoring unit reflects stronger environmental oversight and encourages firms to adopt higher biodiversity and compliance standards, thereby improving how banks assess their environmental credibility. We examine how such monitoring status affects the relationship between biodiversity focus and bank loan access. The sample is classified into key pollution monitoring units (KU) and non-key pollution monitoring units (NKU), and the interaction term BRC×KU is introduced. The regression results are shown in Table 9, Panel J. The coefficient of the interaction term is −0.4503, significantly negative at the 5% level. Although biodiversity attention generally improves loan access, banks discount this effect for heavily polluting firms, likely because their higher environmental risk offsets the benefits of biodiversity engagement.

Finally, firms with stronger green innovation capabilities are better equipped to transform biodiversity initiatives into credible technological progress and long-term value, thereby enhancing banks' confidence in their environmental and financial prospects. We examine how green innovation affects the relationship between biodiversity focus and bank loan access. The sample is divided into a high green patent ratio group (H_GPR) and a low green patent ratio group (L_GPR) based on the median green patent ratio, and the interaction term BRC×H_GPR is constructed. The regression results are presented in Table 9, Panel K. The coefficient of the interaction term is 0.0342. Subsample regressions show that the BRC coefficient for the high green patent ratio group is 0.5774, significant at the 1% level; for the low green patent ratio group, the coefficient is 0.3058, significant at the 10% level. This demonstrates that a firm's green innovation quality is a key moderating factor in the financing utility generated by BRC, with high-quality green innovation significantly boosting bank trust and credit support for the firm. Overall, the results indicate that firms capable of coupling biodiversity efforts with strong innovation outputs are better positioned to convert environmental commitment into tangible financial advantages.

7 | Conclusion and Implications

This study provides new empirical evidence that biodiversity—long viewed as an ecological/ethical concern—now carries material financial relevance in corporate credit markets. Examining Chinese listed firms, we show that proactive biodiversity engagement increases bank financing across total volume, green loans, and long-term credit, signaling reduced environmental and operational risk.

Our findings make three key contributions. First, we advance biodiversity-finance research by shifting focus from risk exposure (Becker et al. 2025) to proactive corporate action, demonstrating that banks reward biodiversity-positive behaviors with expanded lending. Second, we complement the environmental investment-capital access literature. Building on Goss and Roberts (2011), who established CSR pricing in loan terms, prior work has identified critical enabling factors: information accessibility via infrastructure (Du et al. 2024), judicial efficiency, and strong institutional environments/high-quality FDI (Li and Ramanathan 2020). We extend this by showing that proactive biodiversity disclosure itself reduces information asymmetries and unlocks bank financing—a mechanism complementary to these external drivers. Collectively, these findings confirm that corporate environmental responsibility requires a multi-pronged approach integrating firm-level initiatives and supportive external conditions.

Our heterogeneity analyses align with these insights. The stronger biodiversity-lending effect in low-carbon pilot cities supports Li and Ramanathan's (2020) finding that robust institutional environments boost environmental investment returns. Similarly, the amplified effect for firms with high green innovation capacity echoes Du et al.'s (2024) emphasis on green knowledge accumulation. Together, these results confirm that both policy contexts and firm capabilities shape the financial returns of environmental engagement.

The results yield actionable insights for managers. First, biodiversity governance and innovation deliver tangible financial dividends alongside ecological benefits. Integrating biodiversity into strategic communication reduces lender information asymmetries, signaling superior environmental risk management. Managers should frame biodiversity as a value-creation opportunity, not just compliance, especially in progressive policy regions like low-carbon pilot cities. Second, biodiversity engagement enhances credit access via improved reputation, transparency, and R&D. Third, consistent with Du et al. (2024), accessing external environmental knowledge and investing in information infrastructure can amplify the impact of internal environmental strategies.

The results of this study offer important policy insights. Our results highlight the critical role of regulation in incentivizing corporate biodiversity stewardship. China's Green Credit Guidelines amplified lending to biodiversity-attentive firms, showing well-designed policies can redirect credit to sustainable activities. As countries implement the Kunming–Montreal Global Biodiversity Framework, integrating biodiversity (not just climate) into credit assessments will improve risk management and align finance with nature-positive goals. Standardized biodiversity disclosure frameworks are essential to reduce information asymmetries and combat greenwashing. Complementary policy tools include information infrastructure investments to expand environmental knowledge access (Du et al. 2024); improved judicial efficiency to ease financial constraints; and stronger institutional environments to amplify environmental investment returns (Li and Ramanathan 2020). A holistic approach combining disclosure mandates, infrastructure, institutional reforms, and targeted incentives will best advance sustainable economic development.

In conclusion, biodiversity, long overshadowed by climate in financial discourse, has emerged as a material factor in corporate finance. Amid accelerating biodiversity loss, firms' and financial institutions' ability to act on nature-related information will be critical to both environmental sustainability and financial system resilience.

Author Contributions

Ruxiao Li: software, investigation. **Bo Zhang:** conceptualization, methodology, data curation. **Zhang-Hangjian Chen:** project administration, supervision, writing – original draft. **Hafiz Hoque:** writing – original draft, writing – review and editing, project administration, visualization, resources.

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Conflicts of Interest

The authors declare no conflicts of interest.

Endnotes

[1] Compared with He et al. (2024), whose measures rely on keyword frequency or binary indicators, our measure captures sentence-level disclosure breadth and incorporates semantic quality using a BERT-based classification.

References

Bassen, A., D. Buchholz, K. Lopatta, and A. R. Rudolf. 2024. "Biodiversity Management and Stock Price Crash Risk." *Business Strategy and the Environment* 33, no. 5: 4788–4805.

Becker, A., F. E. Di Girolamo, and C. Rho. 2025. "Loan Pricing and Biodiversity Exposure: Nature-Related Spillovers to the Financial Sector." *Research in International Business and Finance* 75: 102724.

Bushman, R. M., J. D. Piotroski, and A. J. Smith. 2004. "What Determines Corporate Transparency?" *Journal of Accounting Research* 42, no. 2: 207–252.

Carroni, E. 2016. "Competitive Customer Poaching With Asymmetric Firms." *International Journal of Industrial Organization* 48: 173–206.

Chen, G., X. Xing, and J. Deng. 2025. "Climate-Biodiversity-Finance Nexus: Comparative Evidence From the U.S. and China." *Finance Research Letters* 86: 108271.

Chen, Z. H. 2026. "Biodiversity Risk and the Cost of Equity Capital: Implications for Sustainable Development." *Sustainable Development* 34, no. 2: 2184–2206.

Clément, A., and G. Grenon. 2025. "Mapping Biodiversity Risk Metrics in Finance: A Comparative Analysis of MSCI and LSEG Using the ENCORE Framework." *Journal of Sustainable Finance and Accounting* 7: 100020.

Dang, T. N., M. Nandy, S. Lodh, and K. Hussainey. 2026. "Nature at Risk, Finance at Stake: A Systematic Literature Review of Biodiversity Risk in Finance Research." *Business Strategy and the Environment* 35, no. 3: 4256–4276.

De Oliveira, J. A. P., O. Balaban, C. N. H. Doll, et al. 2011. "Cities and Biodiversity: Perspectives and Governance Challenges for Implementing the Convention on Biological Diversity (CBD) at the City Level." *Biological Conservation* 144, no. 5: 1302–1313.

Deutsch, A., R. Frost, A. Pollatsek, and K. Rayner. 2000. "Early Morphological Effects in Word Recognition in Hebrew: Evidence from Parafoveal Preview Benefit." *Language and Cognitive Processes* 15, no. 4–5: 487–506.

Dinerstein, E., A. R. Joshi, C. Vynne, et al. 2020. "A "Global Safety Net" to Reverse Biodiversity Loss and Stabilize Earth's Climate." *Science Advances* 6, no. 36: eabb2824.

Du, P., M. H. Parikh, X. Fan, X. Y. Liu, and J. X. Wang. 2024. "Conditional Neural Field Latent Diffusion Model for Generating Spatiotemporal Turbulence." *Nature Communications* 15, no. 1: 10416.

Flammer, C., T. Giroux, and G. M. Heal. 2025. "Biodiversity Finance." *Journal of Financial Economics* 164: 103987.

Gan, Y. 2025. "When Green Claims Turn Brown: The Impact of Corporate Greenwashing on Biodiversity Risk in China." *Quarterly Review of Economics and Finance* 104: 102067.

Garel, A., A. Romec, Z. Sautner, and A. Wagner. 2024. "Do Investors Care About Biodiversity?" *Review of Finance* 28, no. 4: 1151–1186.

Garel, A., A. Romec, Z. Sautner, and A. Wagner. 2026. "Firm-Level Nature Dependence." *Review of Finance* 30, no. 1: 231–272.

Giglio, S., T. Kuchler, J. Stroebel, and X. Zeng. 2026. "Biodiversity Risk." *Review of Finance* 30, no. 1: 131–161.

Gjerde, S., Z. Sautner, A. F. Wagner, and A. Wegerich. 2026. "Corporate Nature Risk Perceptions." *Review of Finance* 30, no. 1: 11–42.

Goeschl, T., and T. Swanson. 2002. "The Social Value of Biodiversity for R&D." *Environmental and Resource Economics* 22: 477–504.

Gong, X., and C. Lin. 2020. "Analysis of Employment Effect of Environmental Regulation: Based on the Pilot Policy of SO2 Emission Trading." In *The 3rd International Conference on Economy, Management and Entrepreneurship*, 315–320. Atlantis Press.

Goss, A., and G. S. Roberts. 2011. "The Impact of Corporate Social Responsibility on the Cost of Bank Loans." *Journal of Banking & Finance* 35, no. 7: 1794–1810.

Griliches, Z. 1986. "Productivity, R&D, and Basic Research at the Firm Level in the 1970s." *American Economic Review* 76, no. 1: 141–154.

Guidolin, M., and M. Pedio. 2026. "The Pricing of Biodiversity Risk in Commodity Markets." *Review of Finance* 30, no. 1: 351–389.

Hadji-Lazaro, P., M. Salin, R. Svartzman, et al. 2024. "Biodiversity Loss and Financial Stability as a New Frontier for Central Banks." *Ecological Economics* 223: 108246.

Hall, B. H., and J. Mairesse. 1995. "Exploring the Relationship Between R&D and Productivity in French Manufacturing Firms." *Journal of Econometrics* 65, no. 1: 263–293.

He, F., X. Guo, and P. Yue. 2024. "Media Coverage and Corporate ESG Performance: Evidence From China." *International Review of Financial Analysis* 91: 103003.

Healy, P. M., and K. G. Palepu. 2001. "Information Asymmetry, Corporate Disclosure, and the Capital Markets: A Review of the Empirical Disclosure Literature." *Journal of Accounting and Economics* 31, no. 1–3: 405–440.

Jing, R., and R. Liu. 2024. "The Impact of Green Finance on Persistence of Green Innovation at Firm Level: A Moderating Perspective Based on Environmental Regulation Intensity." *Finance Research Letters* 62, no. PB: 105274.

Karolyi, G. A., and J. Tobin-de la Puente. 2023. "Biodiversity Finance: A Call for Research Into Financing Nature." *Financial Management* 52, no. 2: 231–251.

Lang, Q., F. Ma, N. Mirza, and M. Umar. 2023. "The Interaction of Climate Risk and Bank Liquidity: An Emerging Market Perspective for Transitions to Low-Carbon Energy." *Technological Forecasting and Social Change* 191: 122480.

Li, J., Y. Jin, and P. Zhou. 2025. "Do Banks Price Firms' Biodiversity Risk? Evidence From the Kunming Declaration." *International Review of Financial Analysis* 106: 104557.

Li, R., and R. Ramanathan. 2020. "Can Environmental Investments Benefit Environmental Performance? The Moderating Roles of Institutional Environment and Foreign Direct Investment." *Business Strategy and the Environment* 29, no. 8: 3385–3398.

Liu, L., Y. Xin, B. Liu, Y. Pang, and W. Kong. 2025. "The Panel Threshold Analysis of Digitalization on Manufacturing Industry's Green Total Factor Productivity." *Scientific Reports* 15, no. 1: 4336.

Lucey, B., A. Urquhart, and S. Vigne. 2025. "Biodiversity, Financial Markets, and Systemic Risk: A Synthesizing Review." *Journal of Climate Finance* 13: 100078.

Ma, D., Q. Ji, D. Zhang, and W. Zhao. 2025. "Spillover Among Biodiversity Attention, Climate Policy Uncertainty and Global Stock Markets." *Finance Research Letters* 73: 106627.

Magnanelli, B. S., and M. F. Izzo. 2017. "Corporate Social Performance and Cost of Debt: The Relationship." *Social Responsibility Journal* 13, no. 2: 250–265.

Mies, M. 2025. "Biodiversity Finance: Sovereign Biodiversity Loss Drivers and Financial Stability." *Journal of Industrial Ecology* 29, no. 3: 937–954.

Moon, J., and A. Sharma. 2014. "Factors Influencing Fixed Assets Investments in the U.S. Hospitality Industries." *Journal of Hospitality Financial Management* 22, no. 2: 75–88.

Mulder, I., and T. Koellner. 2011. "Hardwiring Green: How Banks Account for Biodiversity Risks and Opportunities." *Journal of Sustainable Finance & Investment* 1, no. 2: 103–120.

Nedopil, C. 2023. "Integrating Biodiversity Into Financial Decision-Making: Challenges and Four Principles." *Business Strategy and the Environment* 32, no. 4: 1619–1633.

Paranita, E. S. 2006. "Analisis Pengaruh Kebijakan Hedging Dengan Instrumen Derivatif Valuta Asing dan Variabel-Variabel Value Drivers Terhadap Nilai Kekayaan Pemegang Saham." *Jurnal Bisnis Strategi* 15, no. 1: 1–21.

Pörtner, H. O., R. J. Scholes, A. Arneth, et al. 2023. "Overcoming the Coupled Climate and Biodiversity Crises and Their Societal Impacts." *Science* 380, no. 6642: eabl4881.

Rosenbaum, P. R., and D. B. Rubin. 1983. "The Central Role of the Propensity Score in Observational Studies for Causal Effects." *Biometrika* 70, no. 1: 41–55.

Rudin, J., and J. Lee. 2020. "The Impact of Corporate Reputation Ratings on CEO Compensation Under Diverse Economic Conditions." *Corporate Reputation Review* 24, no. 3: 1–127.

Shen, H., H. Wu, W. Long, and L. Luo. 2021. "Environmental Performance of Firms and Access to Bank Loans." *International Journal of Accounting* 56, no. 2: 2150007.

Smith, T., L. Beagley, J. Bull, et al. 2020. "Biodiversity Means Business: Reframing Global Biodiversity Goals for the Private Sector." *Conservation Letters* 13, no. 1: e12690.

Stiglitz, J. E., and A. Weiss. 1981. "Credit Rationing in Markets With Imperfect Information." *American Economic Review* 71, no. 3: 393–410.

Walker, K., and B. Dyck. 2014. "The Primary Importance of Corporate Social Responsibility and Ethicality in Corporate Reputation: An Empirical Study." *Business and Society Review* 119, no. 1: 147–174. https://doi.org/10.1111/basr.12028.

White, T. B., N. Mukherjee, S. O. Petrovan, and W. J. Sutherland. 2023. "Identifying Opportunities to Deliver Effective and Efficient Outcomes From Business–Biodiversity Action." *Environmental Science & Policy* 140: 221–231.

Yang, G., and Y. Li. 2025. "Research on Biodiversity Risk and Corporate Short-Term Debt for Long-Term Use under Disclosure Regulation." *Finance Research Letters* 77: 107049. https://doi.org/10.1016/j.frl.2025.107049.

Ying, W. 2023. "Technological Innovation, Industrial Integration and Global Competitiveness of Manufacturing Business." in Proceedings of the 20th International Conference on Innovation and Management 8–15.

Zhang, D. 2021. "How Environmental Performance Affects Firms' Access to Credit: Evidence From EU Countries." *Journal of Cleaner Production* 315: 128294.

Zhang, S., G. Xu, Y. Shu, and J. Zhu. 2024. "Corporate ESG Competitive Disadvantage and Cost of Debt Financing." *Finance Research Letters* 69, no. PA: 106102.

Appendix A

Construction of Biodiversity Risk Indicators

A.1 | Construction of the Biodiversity Dictionary

To measure stakeholders' attention to biodiversity and the biodiversity risks faced by listed companies, we first constructed a biodiversity dictionary tailored to the Chinese context. Given the broad scope of biodiversity—encompassing the richness and variability among living organisms and the ecological complexes of which they are part—and the complexities of the Chinese language, we aimed to cover as many biodiversity-related terms as possible. Using "biodiversity" as the keyword, we employed Python to retrieve all relevant studies from the CNKI database. This process yielded 38,260 studies published between 2000 and 2023. Keywords from these studies were manually screened to eliminate terms unrelated to biodiversity, ultimately retaining 446 keywords directly associated with biodiversity. The final dictionary is presented in Table A1.

A.2 | Measurement of Biodiversity Attention and Risk

Following the approach of Giglio et al., we measured biodiversity attention at the macro (government) level as follows. First, we segmented the text of prefecture-level city government work reports for year t into sentences using periods as delimiters. We then counted the number of sentences containing at least one biodiversity keyword ($BIO_{c,t}^{Gov-Atte}$) as a measure of biodiversity attention for city c in year t. For the listed company i, its government-level biodiversity attention ($BIO_{ic,t}^{Gov-Atte}$) is proxied by the attention score of its registered city.

For institutional investor site visit records, which comprise both investor questions and company responses, we similarly segmented each record into sentences using periods. We counted the number of sentences containing at least one biodiversity keyword across all site visit records for company i in year t. This count ($BIO_{ic,t}^{Gov-Atte}$) captures the extent of institutional investors' attention to company i's biodiversity practices.

Given that posts and replies on stock message boards (e.g., Guba) are typically short texts that cannot be reliably segmented into sentences, we performed word frequency analysis instead. Individual investor attention to biodiversity for company i in year t is measured as the frequency of biodiversity keywords appearing in the company's corresponding stock message board in that year ($BIO_{ic,t}^{Gov-Atte}$).

The firm-level biodiversity risk measure was constructed through the following steps:

First, we segmented the annual reports of listed companies into sentences using periods as delimiters and counted the number of sentences containing at least one biodiversity keyword. Across 46,101 annual reports, we identified a total of 369,762 sentences containing biodiversity-related terms.

Second, we performed sentiment classification on these sentences using an improved BERT (Bidirectional Encoder Representations from Transformers) model. This model captures contextual information by considering both preceding and following words, making it particularly suitable for the complexity of Chinese texts. We randomly selected 30,000 sentences from the total pool for manual sentiment annotation, which served as the training set. The remaining sentences were then classified using the trained model. Among the classified sentences, neutral, positive, and negative sentiments accounted for 92.2%, 7.1%, and 0.7%, respectively. Table A2 reports the classification accuracy of the BERT model, and Table A3 provides representative examples of neutral, positive, and negative sentences.

From this classification, we observe that the number of positive sentences in annual reports substantially exceeds the number of negative sentences—by a factor of more than 10. However, a preponderance of positive statements does not necessarily indicate genuine effort in biodiversity conservation. A substantial body of literature documents the existence of pseudo-social responsibility behaviors such as "greenwashing," whereby listed companies may exaggerate their environmental performance in annual reports to influence public perception and behavior. To accurately measure the biodiversity risk faced by listed firms, we conducted an additional manual classification of the positive sentences. These were divided into two categories: (1) sentences describing concrete actions related to biodiversity conservation, which directly reflect the firm's actual efforts, and (2) sentences mentioning biodiversity without specifying any substantive action.

Finally, we constructed the firm-level biodiversity risk indicator ($BIO_{i,t}^{Firm-Risk}$) for company i in year t as the difference between: (i) the number of biodiversity-related negative sentences and (ii) the number of biodiversity-related positive sentences that describe substantive actions. A larger value of this indicator signifies a higher level of biodiversity risk faced by the listed company.

TABLE A1 | Biodiversity lexicon.

Abundance, Dark Diversity, Semi-Enclosed Bay, Semi-Arid Area, Semi-Arid Region, Semi-Natural Habitat, Semi-Natural Vegetation, Protected Area, Protected Area Management, Protected Area Target, Protected Area System, Protected Animal, Protected Area, Protected Area Management, Protected Area Construction, Ecological Environment Protection, Biodiversity Conservation, Conservation Biology, Protected Species, Conservation Grazing, Conservation Tillage, Protective Development, Protective Development and Construction, Conservation Biological Control, Conservation Priority, Protected Plant, Conservation Governance, Nature Conservation, Endangered, Herbaceous Plant, Herbaceous Diversity, Herbaceous Plant, Herbaceous Plant Diversity, Herbaceous Plant Community, Grassland, Grassland Multifunctionality, Grassland Restoration, Grassland Establishment, Grassland Community, Grassland Ecology, Grassland Ecosystem, Grassland Organism, Grassland Degradation, Grassland Resource, Lawn Spontaneous Plant, Steppe, Steppe Region, Steppe Zoning, Steppe Ecological Compensation, Steppe Ecological Environment, Steppe Ecosystem, Steppe Biodiversity, Steppe Degradation, Steppe Restoration, Steppe Management, Evergreen Broad-Leaved Forest, Evergreen and Deciduous Broad-Leaved Mixed Forest, Picoplanktonic Eukaryote, Tidal Creek System, Intertidal Zone, Submerged Plant, Urban Remnant Forest, Urban Animal Habitat, Urban River and Lake Wetland, Urban Mangrove, Urban Lake, Urban Green Space System, Urban Greening, Urban Bird, Urban Forest, Urban Habitat, Urban Ecology, Urban Organism, Urban Wetland, Urban Soil and Water, Urban Wildness, Urban Wildlife, Urban Wild Landscape, Urban Vegetation, Urban Plant, Urban Nature, Red Tide Species, Livestock and Poultry Genetic Resource, Pollination, Vertical Belt, Secondary Metabolite, Secondary Forest, Secondary Natural Forest, Clump Cutting, Vulnerability, Village and Town Ecological Construction, Macrobenthos, Macrobenthic Invertebrate, Macrobenthic Animal, Large Marine Protected Area, Macroalgae, Large Carnivore, Macrobenthic Invertebrate, Macroinvertebrate, Macrofungus, Large and Medium-Sized Mammal, Strip Cutting, Single Ecosystem Function, Freshwater, Freshwater Ecosystem, Freshwater Biodiversity, Island and Reef Waters, Island, Island Ecosystem, Road Green Space, Road Ecology, Epigeic Arthropod, Epigeic Arthropod Diversity, Surface Water Environment, Surface Water Ecological Environment, Geographical Resource, Landform, Ground-Dwelling Arthropod Community, Ground-Dwelling Moss, Terrestrial Bird, Earth's Critical Zone, Earth Environmental Diversity, Community of Shared Future for Life on Earth, Earth System Science, Aboveground Biomass, Underground Forest, Belowground Biomass, Groundwater Pollution Prevention, Groundwater System, Groundwater Remediation, Topographically Steep Watershed, Geological Heritage, Low-Carbon, Low-Carbon City, Low-Carbon Technology, Low-Carbon Green, Low-Carbon Transition, Epibenthic Macroinvertebrate, Demersal Fishery Organism, Benthic Shellfish, Benthic Animal, Benthic Organism, Typical Habitat, Typical Habitat, Typical Ecosystem, Litter, Leaf Litter, Water Diversion Project Protection Forest, Butterfly, Butterfly Diversity, Butterfly Community, Butterfly Habitat, Butterfly Species, Dynamic Environment, Dynamic Collapse, Animal, Animal Protection, Zoogeographical Regionalization, Animal Diversity, Animal Welfare, Animal Activity, Animal Group, Fauna, Animal Community, Animal Production Management, Animal Bioacoustics, Animal Passage, Animal Breeding, Animal Resource, Flora and Fauna, Flora and Fauna Resource, Multi-Scale Biodiversity, Multi-Purpose Reserve Forest, Multi-Functional Agriculture, Multi-Functional Forest, Multi-Stage Constructed Wetland, Multi-Dimensional Diversity, Multi-Dimensional Biodiversity, Multi-Dimensional Synergy, Multi-Species Care, Diversity Conservation, Diversity Conservation and Management, Statutory Protected Area, Illegal Fishing, Illegal Mining, Illegal Sand Mining, Non-Flying Small Mammal, Non-Cultivated Habitat, Non-Agricultural Habitat, Non-Human Species, Zooplankton, Zooplankton Diversity, Zooplankton Community, Zooplankton and Phytoplankton, Plankton, Plankton Community Structure, Bacterioplankton, Phytoplankton, Phytoplankton, Phytoplankton Community Characteristic Difference, Perception and Cognition, Higher Plant, Alpine Grassland, Alpine Meadow, Alpine Shrub, Alpine Region, Alpine Ecosystem, Alpine Degraded Grassland, Alpine Ecosystem, Alpine Kobresia Meadow, Alpine Plant, High Carbon Sink Forestry, Plateau Lake, Plateau Wetland, Rhizosphere, Rhizosphere Bacterium, Root Exudate, Root Biomass, Park Ecosystem, Functional Insect Group, Functional Group, Functional Microorganism, Functional Trait Diversity, Symbiosis and Integration, Symbiotic Microorganism, Archaeal Community Structure, Paleoecology, Paleobotany, Trunk River Channel, Backbone Tree Species, Key Ecosystem Service, Key Biodiversity Area, Keystone Species, Critical Ecological Space, Keystone Species Loss, Canopy Structure, Shrub-Herb Layer, Shrub-Encroached Grassland, Shrub, Shrub Layer, Shrub Survival, Shrub Willow, Naturalized Plant, Siliceous Algae, Overfishing, Overgrazing, Coastal Zone, Ocean, Marine Protection, Marine Ecology, Marine Organism, Marine Genetic Resource, Marine Fish, Marine Nature Conservation, River Ecology, River and Lake Ecological Protection and Restoration, River and Lake Aquatic Ecosystem, Estuarine Ecosystem, Horizontal Ecological Compensation, Lake Ecology, Lake Ecosystem, Lake Biodiversity, Lake Wetland, Environmental Protection, Environmental Pollution, Desert, Desertification, Wilderness, Extremely Small Population, Extremely Small Population Species, Extremely Small Population Wild Plant, Near-Nature, Mine Environmental Restoration, Mining, Mining Development, Mine Ecology, Insect Diversity, Timber Harvesting, Forest Tree Resource, Understory Herb, Understory Layer, Understory Vegetation, Understory Plant, Forestry Ecology, Forestry Carbon Sink, Watershed Ecology, Terrestrial Ecological Carbon Sink, Green Mining, Bird, Birds and Mammals, Habitat, Regional Community Scale, Regional Ecology, Community, Tropical, Forest, Forest Protection, Forest Harvesting, Deforestation, Forest Community, Forest Ecology, Forest Organism, Forest Carbon Sink, Forest Degradation, Forest Species, Forest Vegetation, Desertification, Mountain, Coral, Deep Sea, Deep-Sea Mining, Habitat, Habitat Protection, Ecological Security, Ecological Shoreline, Ecological Protection, Ecological Change, Ecological Compensation, Ecological Sustainability, Ecological Vulnerability, Ecological Function, Ecological Environment, Ecological Restoration, Ecological Health, Ecosphere, Ecological Degradation, Ecological Crisis, Ecosystem, Ecosystem Service, Ecological Restoration, Biosafety, Biodiversity, Biosphere, Wetland, Wetland Ecology, Mammal Diversity, Tree Species Diversity, Water Environment, Aquatic, Aquatic Ecology, Soil Erosion, Soil and Water Ecology, Carbon Sink, Endemic Species, Endemic Plant, Natural Grassland, Natural Forest, Soil Protection, Soil Fauna, Soil Habitat, Soil Ecology, Grain for Green, Returning Farmland to Wetland, Degradation, Degraded Grassland, Degraded Steppe, Degraded Forest, Degraded Ecosystem, Degraded Wetland, Degradation and Restoration, Returning Pond to Forest, Returning Pond to Wetland, Microorganism, Pollution Prevention, Pollution Hazard, Species, County Ecology, Rural Habitat, Rural Wetland, Native Grass Species, Native Plant, Wildland, Wild, Wildlife, Wild Fauna and Flora, Dominant Species, Priority Conservation, Fish, Fish Ecology, Fishery Reserve, Rainforest, Protozoan, Protist, Primitive Ecological Protection, In-Situ Ecological Restoration, Rare and Endangered, Rare and Endangered Bird, Rare and Endangered Species, Rare and Endangered Plant, Rare Animal, Rare Animal Protection, Rare Wildlife, Rare Fish, Rare Germplasm Resource, Vegetation, Vegetation Protection, Vegetation Diversity, Vegetation Community, Afforestation, Plant, Plant Protection, Plant Diversity, Flora, Plant Community, Plant Community Diversity, Plant Ecology, Phytoremediation, Plant Species, Plant Species, Plant Population, Population, Population Protection, Population Dynamics, Population Diversity, Population Reproduction, Population Regeneration, Population Size, Population Recovery, Population Structure, Population Density, Population Quantity, Population Characteristic, Population Composition, Priority Protection, Key Protected Animal, Key Protected Wildlife, Key Protected Wild Plant, Key Protected Plant, Key Ecological Function Area, Key Biological Species, Resource Protection, Resource Management, Resource and Environment, Resource Ecology, Resource Depletion, Resource Conservation, Resource Plant, Resource Plant Diversity, Nature Protection, Nature Conservation, Natural Ecological Protection, Natural Ecological Space, Natural Ecological Element, Natural Resource.

TABLE A2 | Accuracy of the improved BERT model.

	Precision	Recall	F1-score
Negative sentences	0.86	0.67	0.75
Neutral sentences	0.94	1.00	0.91
Positive sentences	0.74	0.69	0.71

TABLE A3 | Examples of various biodiversity-related sentences in annual reports of listed companies.

	Year	Company code	Sentence
Positive sentences	2009	600900	During the year, the company carried out the “Xiluodu-Xiangjiaba-Three Gorges” joint ecological regulation experiment, using regulatory means to create conditions suitable for fish spawning and reproduction.
	2023	601005	The company organized the promotion of the Evaluation Index System for Green Urban Steel Plants, improved the responsibility system for promoting green indicators, actively created a “zero-waste steel plant” with “ultra-low waste gas emissions, zero wastewater discharge, and zero solid waste,” avoided negative impacts on the natural ecological environment, adhered to the coordinated development of the ecological environment and the surrounding environment, protected biodiversity, and avoided the occurrence of environmental pollution accidents.
Negative sentences	2021	600116	The company's steam supply, manganese ore mining, and electrolytic manganese processing businesses involve the emission of pollutants such as dust, noise, waste gas, and wastewater. With the increasing national emphasis on environmental protection in recent years, if stricter laws, regulations, systems, and rules are introduced to raise the environmental protection standards of related industries, the company will face the risk of increased environmental protection investment or possible environmental penalties.
	2021	600116	The company's steam supply, manganese ore mining, and electrolytic manganese processing businesses involve the emission of pollutants such as dust, noise, waste gas, and wastewater. With the increasing national emphasis on environmental protection in recent years, if stricter laws, regulations, systems, and rules are introduced to raise the environmental protection standards of related industries, the company will face the risk of increased environmental protection investment or possible environmental penalties.
Sentences without substantive action	2019	002166	The company adheres to the concept of synchronous development of production and environmental construction, balancing long-term sustainable development with actively fulfilling environmental protection responsibilities.
Sentences with substantive action	2014	002717	In 2014, the company focused on resource conservation and environmental friendliness, emphasizing the development of new technologies and new products with independent intellectual property rights. The company combined landscape design and construction concepts with technological innovation, investing 39.3716 million yuan in R&D for several scientific research projects. These included projects such as “Research on the Application of Near-Natural Ecological Landscape Technology,” “Research on Landscape Biology and Engineering Technology in Saline-Alkali Land,” and “Evaluation of Wetland Restoration Effects in Dongguan Ecological Park.”

Appendix B

Definition of All Variables

Category	Variable	Label	Data source
Dependent variables			
LNLoans	Total bank loans	Natural logarithm of the year-end loan balance of commercial banks to listed companies	CSMAR
LNSLoans	Short-term loans	Natural logarithm of total short-term bank loans	CSMAR
LNLLoans	Long-term loans	Natural logarithm of total long-term bank loans	CSMAR
LNcreLoans	Credit loans	Natural logarithm of total credit loans	CSMAR

Category	Variable	Label	Data source
LNPleLoans	Pledged loans	Natural logarithm of total pledged loans	CSMAR
LNGuaLoans	Guaranteed loans	Natural logarithm of total guaranteed loans	CSMAR
LNMorLoans	Mortgage loans	Natural logarithm of total mortgage loans	CSMAR
LNGreLoans	Green loans	Natural logarithm of total green loans	CSMAR
Independent variable			
BRC	Corporate attention to biodiversity	A standardized index constructed from annual reports by counting sentences containing biodiversity keywords and adjusting for sentiment using a fine-tuned BERT model.	CNKI and annual reports
Control variables			
LnTa	Firm size	Natural logarithm of total assets	CSMAR
BM	Book-to-market ratio	Ratio of book value to market value	CSMAR
Lev	Leverage ratio	Total liabilities divided by total assets	CSMAR
Capex	Capital expenditure ratio	Capital expenditure divided by total assets	CSMAR
Ppe	Net fixed assets ratio	Net fixed assets divided by total assets	CSMAR
Roa	Return on assets	Net profit divided by total assets	CSMAR
Assgro	Asset growth rate	(Closing total assets – Opening total assets)/Opening total assets	CSMAR
Mechanism variables			
RPU	Corporate reputation	Reputation rating score constructed from global corporate reputation rankings	Global corporate reputation rankings
Trans	Information transparency	Percentile average of comprehensive earnings quality and Shenzhen Stock Exchange information disclosure rating (MEG)	CSMAR
RDSpend	R&D investment	Natural logarithm of R&D expenditure	CSMAR
Moderating variables			
HERI	High environmental regulation intensity	Dummy = 1 if regional industrial pollution control investment per 10,000 yuan of industrial output is above the sample mean	China Environmental Yearbook
LERI	Low environmental regulation intensity	Complementary dummy to HERI	China Environmental Yearbook
LCPC	Low-carbon pilot city	Dummy = 1 if the firm is registered in a low-carbon pilot city	Lists of low-carbon city pilot programs released by the National Development and Reform Commission in 2010, 2012, and 2017.
NPC	Non-pilot city	Complementary dummy to LCPC	Lists of low-carbon city pilot programs released by the National Development and Reform Commission in 2010, 2012, and 2017.
HPI	Heavily polluting industry	Dummy = 1 if the firm belongs to a heavily polluting industry (official classification)	National Bureau of Statistics and China Statistical Yearbook on the Environment

Category	Variable	Label	Data source
NHPI	Non–heavily polluting industry	Complementary dummy to HPI	National Bureau of Statistics and China Statistical Yearbook on the Environment
HFC	High-competitiveness firm	Dummy = 1 if the firm's market share within its industry is above the sample median	CSMAR
LFC	Low-competitiveness firm	Complementary dummy to HFC	CSMAR
KU	Key pollution monitoring unit	Dummy = 1 if the firm is designated as a key pollution monitoring unit	Ministry of Ecology and Environment (MEE) classification
NKU	Non-key monitoring unit	Complementary dummy to KU	Ministry of Ecology and Environment (MEE) classification
H_GPR	High green patent ratio	Dummy = 1 if the firm's ratio of green patents to total patents is above the sample median	CNIPA and CSMAR
L_GPR	Low green patent ratio	Complementary dummy to H_GPR	CNIPA and CSMAR
Other variables			
BRC_pre	Pre-policy corporate attention to biodiversity	The firm's raw biodiversity attention score measured in 2011, the year immediately before the implementation of the Green Credit Guidelines. This measure is based on the original product of biodiversity-relevant sentence count and the sentiment score (BRS), prior to standardization, to preserve the prepolicy variation in engagement levels and avoid mechanical endogeneity in the continuous treatment DiD model.	CNKI and annual reports
BRC_Clean	Trouble-free biodiversity attention	Biodiversity attention score recomputed using a “trouble-free” dictionary that excludes keywords associated with negative environmental events or defensive disclosure (e.g., illegal activities, pollution, degradation, endangerment, overexploitation, desertification). This variable is employed in robustness checks to ensure results are not driven by discussions of environmental violations or penalties.	CNKI and annual reports
BRS	Biodiversity sentiment score	BRS (Biodiversity Sentiment Score) is a measure of net sentiment in corporate biodiversity disclosures, calculated as the difference between sentences describing substantive positive actions and those disclosing negative impacts.	CNKI and annual reports
WdE_Scores	Wind ESG environmental score	Environmental dimension score of the Wind ESG	Wind database
Ret	Stock return	Annual stock return with cash dividend reinvestment	CSMAR
Growth	Revenue growth rate	Main business income growth rate	CSMAR
Penalty_Dummy	Environmental penalty dummy	Equals 1 if the firm received at least one environmental penalty in year *t*, 0 otherwise (local bureaus of Ecology and Environment)	Local bureaus of Ecology and Environment

Category	Variable	Label	Data source
Penalty_Count	Number of environmental penalties	Total number of environmental penalties received by the firm in year *t* (local bureaus of Ecology and Environment)	Local bureaus of Ecology and Environment
Treat	Green firm dummy	Dummy = 1 if the firm's main business matches the Green Industry Guidance Catalogue (2019 Edition)	Green Industry Guidance Catalogue
Post	Post-policy dummy	Dummy = 1 for years ≥ 2012	Annual reports
Treat × Post	DiD interaction term	Interaction term used in difference-in-differences estimation	Green Industry Guidance Catalogue
Post × BRC_pre	Interaction term between post-policy dummy and Pre-policy corporate attention to biodiversity	Equals Post × BRC_pre, where Post = 1 for years ≥ 2012 and BRC_pre is the firm's biodiversity attention score in 2011	CNKI and annual reports
BRC × HERI	Interaction term between corporate attention to biodiversity and high environmental regulation intensity	Equals BRC × HERI, where HERI indicates above-average regional environmental regulation	CNKI; Annual reports; National Bureau of Statistics; China Statistical Yearbook on the Environment
BRC × LCPC	Interaction term between biodiversity attention and low-carbon pilot city status	Equals BRC × LCPC, where LCPC indicates location in a low-carbon pilot city	Lists of low-carbon city pilot programs released by the National Development and Reform Commission in 2010, 2012, and 2017.
BRC × KU	Interaction term between corporate attention to biodiversity and key pollution monitoring unit status	Equals BRC × KU, where KU indicates designation as a key pollution monitoring unit	CNKI; Annual reports; Ministry of Ecology and Environment (MEE) classification
BRC × H_GPR	Interaction term between corporate attention to biodiversity and high green patent ratio	Equals BRC × H_GPR, where H_GPR indicates above-median ratio of green patents to total patents	CNKI; Annual reports; CNIPA; CSMAR