When Nature Threatens Financial Stability: Biodiversity Risk and Bank Performance in China

Abstract

Biodiversity loss poses significant financial risks, yet its implications for banking sector remain insufficiently examined in literature. This study examines the impact of biodiversity risk on financial performance of Chinese listed banks (2007-2022). We find that biodiversity risk reduces bank performance, primarily through rising non-performing loans (NPLs). A heterogeneity analysis reveals that rural and urban banks with limited resources are more severely impacted than state owned and joint stock banks. Moreover, we observe that this adverse effect is less pronounced in banks with high ESG performance, suggesting the value of robust ESG frameworks in mitigating risk. Using China's Green Credit Guideline (2012) and Mandatory Biodiversity Disclosure (2020) as quasi-natural experiments, we demonstrate that while regulatory interventions promote sustainability, they impose short-term financial costs. Our findings remain robust across alternative measures and estimation techniques. Overall, this study underscores biodiversity risk as a critical environmental challenge for banks, emphasizing the need for integrated environmental risk management and balanced regulatory frameworks to ensure financial stability and sustainability.

Keyword: Biodiversity Risk; ESG; Bank Performance; Ownership; non-performing loans

1. Introduction

Biodiversity loss presents both environmental and financial risks, with wildlife populations declining by 69% since 1970 and over 50% of global GDP reliant on ecosystem services (WWF, 2022). This crisis, intertwined with climate risks, threatens key economic sectors, including food security, healthcare, and financial stability, with projected global GDP losses of 2.3% by 2030 (World Bank, 2021). While firms face tangible financial repercussions from biodiversity risks (Liu et al., 2025), including reputational damage, operational costs, and market penalties (Anthony & Morrison-Saunders, 2023; Bassen et al., 2024; White et al., 2023), the mechanism through which biodiversity risk transmit into financial sector remain unexplored.

Banks, as key financial intermediaries, face growing exposure to biodiversity-related financial risks through their lending and investment portfolios. Unlike broader ESG considerations, biodiversity risk encompasses specific challenges that directly threaten ecosystem services, leading to immediate financial implications for banks. Unmitigated exposure to high impact sectors like mining, agriculture and infrastructure can lead towards asset devaluation, rising non- NPLs (Hudson, 2024). While existing research has examined ESG factors in bank performance (Chiaramonte et al., 2022), and regulatory uncertainties (Ashraf & Shen, 2019; Paligorova & Santos, 2017), the direct financial implications of biodiversity risks for banks remain unaddressed. Given the growing integration of biodiversity consideration in financial regulation (e.g., Taskforce on Nature-related Financial Disclosures, 2023), understanding their implications for bank performance is critical for investors, policymakers, and financial institutions.

The Natural Resource-Based View (NRBV) of the firm (Barney, 1991) believes that firms achieve sustained competitive advantage by effectively managing environmental constraints. Additionally, risk mitigation view of stakeholder theory posits that sustainable investments serve as insurance, fostering stakeholder goodwill and moral capital (El Ghoul & Karoui, 2017; Godfrey, 2005; Godfrey et al., 2009), alleviating risks associated with adverse events, enhancing a firm's reputation and performance. In banking, biodiversity risks create financial vulnerabilities by increasing credit risk, asset impairment and regulatory capital pressures. Unlike broader climate risks, biodiversity loss directly impacts loan portfolios, investment exposures and risk weighted assets, particularly sectors reliant on ecosystem services. Empirical evidence confirms that environmental shocks weaken financial institutions, reducing bank performance and stability (Agnese & Giacomini, 2023; Andrieş & Sprincean, 2023). However, biodiversity-related financial risks remain overlooked in banking research, leaving a critical gap in understanding their distinct transmission channels and systemic implications.

China provides a compelling case for examining the financial implications of biodiversity risk, given its status as one of the world's most biodiverse economies and home to the world's largest banking sector, with assets exceeding $40 trillion (Allen et al., 2017). However, its financial system remains highly exposed to biodiversity-related risks. Recognizing the financial materiality of these risks, China has implemented extensive conservation policies, including the Biodiversity Conservation Strategy and Action Plan (2011–2030) and the establishment of the China National Committee for Biodiversity Conservation (He, Huang, et al., 2024), alongside financial-sector-specific regulations such as the Green Credit Guidelines (2012) and mandatory biodiversity-related disclosures (2020) (Cao et al., 2024). This unique combination of high biodiversity exposure, financial sector integration, and evolving regulatory frameworks makes China an ideal setting to examine how biodiversity risks affect banking performance.

In this paper, we examine the impact of biodiversity risk on performance of 37 Chinese listed banks from 2007 to 2022. We use a novel textual based measure of biodiversity risk developed by He, Chen, et al. (2024) and provided a unique lens to assess its impact on bank performance. Our empirical findings reveal that biodiversity risk reduces bank performance, primarily through NPLs as the key transmission channel. To ensure robustness, we use alternative measures and employ a range of empirical techniques, including propensity score matching, entropy balancing, quantile regression, and Lewbel's variable instrumental approach.

Our study makes several key contributions. First, we extend the banking and sustainability literature by empirically establishing biodiversity risk as a distinct environmental factor, separate from climate change that directly impact bank performance. We provide novel evidence that biodiversity risk weakens the performance of Chinese banks. Additionally, we account for the heterogeneity of China's commercial banking system and find that state-owned and joint-stock banks and banks with greater ESG performance are less prone to biodiversity risk. Second, we extend the literature on bank performance (Chiaramonte et al., 2022; Gehrig et al., 2024), by identifying NPLs as the primary transmission channel through which biodiversity risk undermines financial performance. Third, leveraging China's Green Credit Guideline (2012) and Mandatory Biodiversity Disclosure (2020) as quasi-natural experiments, we demonstrate that while regulatory interventions promote sustainability, they impose short-term financial costs which hampers bank performance. Finally, we contribute to the emerging field of climate finance (e.g., (Bolton & Kacperczyk, 2021, 2023; Flammer et al., 2025; Garel et al., 2024; Ilhan et al., 2023; Sautner et al., 2023), by positioning biodiversity risk as a critical financial determinant beyond carbon emissions and climate change.

The insights from this study can guide financial institutions integrating biodiversity considerations into their risk management frameworks, thereby enhancing resilience against environmental shocks. This paper proceeds as follows, Section 2 details research methods, Section 3 presents the results and Section 4 presents discussions and policy insights.

2. Methods

2.1 Sample selection

We analyze panel data from 37 Chinese-listed banks[1] (2007–2022), including six state-owned, nine joint-stock, 15 urban, and seven rural commercial banks, representing over 80% of China's banking assets (Cao et al., 2024).

2.2 Variables, data, and model setting

Following the finance literature, Nizam et al. (2019) , Zhou et al. (2021) and (Bennouri et al., 2018), bank performance is measured using return-on-total assets ratio (ROA) and return-on-equity ratio (ROE), with pre-tax income to total assets ratio (EBT_TA) as a robustness check. The main independent variable is biodiversity risk. Biodiversity risk exposure for Chinese banks is assessed using the Biodiversity Risk Index (Biodiversity Risk) developed by He, Chen, et al. (2024). Inspired by the work of (Giglio et al., 2023), He, Chen, et al. (2024) developed the Chinese corporate biodiversity exposure indices, utilizing annual reports from over 4,000 firms over 15 years through textual analysis. This index effectively captures the strategic characteristics and development objectives of these firms, providing an accurate measure of corporate biodiversity exposure (Zhou & Lucey, 2024). Moreover, following recent literature (Berger & Bouwman, 2013; Liang et al., 2013), we include bank size (SIZE), leverage (LEV), loan-to-deposit ratio (LOA_DEP), liquid assets ratio (LIQ_AST) and money supply (M2) as controlling factors. Data sources are Refinitiv Eikon and the World Bank. Measurement of the study's variables is provided in Appendix Table A1.

Our baseline model specification is in Eq. (1), which formulates the role of biodiversity risk in bank stability.

$$BP_{i,t} = \alpha_1 + \beta_1 BIO\_RISK_{i,t} + \sum(Controls)_{i,t} + f_i + d_t + \varepsilon_{i,t} \tag{1}$$

where $BP_{i,t}$ represents bank performance (ROA/ROE) and BIO_RIS is the biodiversity measure. Controls include bank and country-level factors, which potentially explain bank performance. Additionally, firm-fixed effects (f_i) and year-fixed effects (d_t) account for unobservable heterogeneity and time trends. Standard errors are clustered at the firm level.

[1] The choice of China as a sample for the study is supported by the immense scale of its banking sector, which is among the largest globally. In 2023, the assets of Chinese banks grew significantly, reaching approximately 417.3 trillion yuan (about $58.7 trillion USD). https://english.www.gov.cn/archive/statistics/202401/25/content_WS65b26090c6d0868f4e8e382d.html

For quasi natural experiments, we use China's Green Credit Guideline (2012)[2] and Mandatory Biodiversity Disclosure (2020)[3]. The model includes interaction terms between BIO_RISK and event dummies equation 2:

$$BP_{i,t} = \alpha_1 + \beta_1 BIO\_RIS_{i,t} + \beta_2 Event\_Dummy_{i,t} + \beta_3 (BIO\_RIS_{it} \ x \ Event\_Dummy_{i,t}) + \sum (Controls)_{i,t} + f_i + d_t + \varepsilon_{i,t} \quad (2)$$

For robustness, we apply propensity score matching (PSM), entropy balancing, Lewbel's two-stage least squares estimation (Lewbel, 2012), and alternative variables measurements.

3. Empirical results

3.1 Summary and VIF

Table 1 presents summary statistics and variance inflations factor (VIF) of the variables to offer basic insights about data distribution, variation and multicollinearity issues, essential for regression analysis (Naseer et al., 2025). BIO_RISK is a binary variable with a mean of 0.68, showing significant exposure among banks, while bank performance indicators exhibit moderate variations. The VIF values remain low (mean VIF=1.074), eliminating multicollinearity concerns, ensuring the reliability of variables for regression estimates

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3.2 Baseline results

Following the initial analysis, we conduct OLS regression with robust standard errors, both with and without bank and year effects. The results in Table 2 indicate a significant negative association between BIO_RISK and performance indicators. Specifically, BIO_RISK significantly diminishes bank performance, with a 0.189% decline in ROA and a 0.141% reduction in ROE. This association holds even with fixed effects and inclusion of fixed effects improved R-squared from 0.24 to 0.60 (ROA) and 0.28 to 0.78 (ROE). This enhances the model accuracy by controlling unobserved heterogeneity. In the case of controlling factors, size enhances while leverage reported positive association with ROE and negative with ROA. The rest of the variables exhibit insignificant association. The inclusion of

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[2] These guidelines are introduced by China Banking and Insurance Regulatory Commission (CBIRC) to enhance environmentally sustainable lending practices, encouraging banks to provide loan for green projects and restrict financing for high-pollution industries. http://www.cbirc.gov.cn/

[3] Introduced by the Ministry of Ecology and Environment (MEE) of China to enforce corporate transparency on biodiversity impacts. https://www.mee.gov.cn/

3.3 Heterogeneity analysis

3.3.1 Ownership analysis

There may be a heterogeneous effect of biodiversity risk on bank performance. Rural and urban Chinese banks hold limited resources, while state-owned and joint stock banks benefit from scale efficiency(Cao et al., 2024). To account for this, we include a state-owned bank dummy (1 for state-owned/joint-stock, 0 for rural and urban banks). These state-owned and joint stock banks operate at national level in China while rural and urban banks are local. The results in Table 3 reported that biodiversity risk significantly reduces profitability, with a more pronounced effect on rural and urban banks (ROA -0.208, significant at 1%; ROE; -0.207, significant at 1%) compared to state-owned and joint-stock banks (ROA -0.121, significant at 5% ; ROE -0.0943, n.s).

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3.3.2 Low vs high ESG performance banks

We classified banks into high and low ESG based on mean ESG scores to assess whether banks with better ESG performance perform differently and are more resilient to risks than with weaker ESG practices. Strong ESG frameworks drive better stakeholder ties and boost efficiency (Chiaramonte et al., 2022). In Table 4, the results show that biodiversity risk has significant negative effect on high ESG performance banks (ROA -0.140, significant at 5%; ROE-0.112, significant at 10%). However, this negative significant effect is stronger in lower ESG performance banks (ROA -0.140, significant at 5%; ROE-0.112, significant at 10%).

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3.4 Channel Analysis

We propose that biodiversity risk impacts performance through non-performing loans (NPL). Climate change lowers income and asset value (Fan et al., 2024), while a decline in regional GDP and income growth raises banks' NPL ratios (Ghosh, 2015). Additionally, reduced labor productivity and stricter environmental standards increase costs and lower repayment capacity (Gambhir et al., 2022). This increase in NPL further reduces bank financial performance. This rise in the NPL harms bank performance. Table 5 shows that BIO_RISK positively affects NPL, which in turn negatively impacts bank performance.

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3.5 Further analysis and robustness

3.5.1 Propensity score matching

To control for sample selection bias, we employ propensity score matching (PSM) technique (Caliendo & Kopeinig, 2008), treating firms exposed to biodiversity risk as the treatment group. Re-estimating baseline estimates with PSM samples (Table 6), we find that BIO_RISK remains negatively significant under both nearest neighbor (Columns 1-2) and caliper matching (Columns 3-4), confirming that selection bias does not drive the inverse relationship between bank performance and biodiversity risk exposure.

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3.5.2 Entropy balancing

To address the reduced sample in PSM, following Zhou and Lucey (2024), we employ entropy balancing, which holds full sample (Hainmueller, 2012). Based on biodiversity risk exposure, treatment, and control groups are matched, achieving covariate balance by considering mean, variance, and skewness. Table 7 shows that covariate variation is negligible, ensuring proper matching between groups.

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3.5.3 Environmental policy shocks as natural quasi-experiments

We use China's Green Credit Guidelines (2012) and Mandatory Biodiversity Disclosures (2020) as natural quasi experiments to investigate how these policy interventions bank performance. The results provided in Table 8 indicate that BIO_RISK exerts a consistently significant negative effect on bank performance. The implementation of Green Credit Guidelines led to a significant decline in ROA (0.210, significant at 5%) and ROE (-0.235), The findings exhibit higher biodiversity risks experiencing additional financial deterioration, as evidenced by the negative and significant interaction term BIO_RISK*Green Credit Guidelines (-0.153 for ROA and -0.149 for ROE). In a similar fashion, the introduction of Mandatory Biodiversity Disclosures resulted in substantial reductions in ROA (-0.257) and ROE (-0.420), though the interaction with biodiversity risk was not statistically significant, suggesting a uniform impact across the banking sector. These models demonstrate a moderate to strong explanatory power, with R-squared values ranging from 0.257 to 0.406.

Table_8_Here

3.5.4 Alternative measurements

We assess the robustness of our findings by using alternative measurements. First, we incorporate the lag of biodiversity risk to examine its impact on ROA and ROE. Additionally, we use an alternative measure of bank performance, EBT_TA, in column three (Table 9). Overall, the results align with the benchmark findings indicating a negative association between biodiversity risk and bank performance.

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3.5.5 Alternative estimations and endogeneity

Finally, to ensure further robustness and consistency of our results, we employ quantile regression analysis across multiple quantiles and observed that the negative bearing of BIO_RISK persists at all levels of firm performance distribution (Table 10). To cope potential endogeneity, we apply Lewbel two stage least square (L2SLS),approach which does not rely on external instruments and provides estimates similar to those using external instruments(Lewbel, 2012) as confirmed by recent studies (Acheampong et al., 2021; Awaworyi Churchill & Smyth, 2020; Fang et al., 2023). The reported findings from alternative estimations support the baseline results, confirming a negative effect of biodiversity risk on bank performance.

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4. Discussion, conclusion and policy implications

We examine biodiversity risk and bank performance nexus of Chinese listed banks over the period 2007-2022. Our findings show that biodiversity risk reduces bank performance. These outcomes with NRBV, positing that effective environmental risk management enhance long-term competitive advantage, by safeguarding important financial measures like liquidity and stability (Agnese & Giacomini, 2023; Andrieș & Sprincean, 2023). Furthermore, to capture heterogeneity of Chinese banking sector, we categorized the banks into state-owned/joint stock banks and rural/urban banks and observed that rural and urban banks are extremely affected by biodiversity risk, likely due to their limited resources and weaker risk management capabilities. In contrast, state-owned and joint-stock banks, with their larger scale and more robust infrastructures, exhibit some resilience to biodiversity-related shocks.

To check how banks ESG performance can shelter to their financial performance against biodiversity risk, we divided the banks into high and low groups considering their ESG scores. We discovered that while banks with high ESG performance are not safe to biodiversity risk, their ESG practices may help in mitigating some of the adverse financial impacts. Banks with robust ESG frameworks maintain stronger relationship with stakeholders and demonstrate enhanced operational efficiencies (Chiaramonte et al., 2022), which can buffer the detrimental impacts of environmental risks on profitability. Conversely, banks with lower ESG performance are severely affected by biodiversity risk. These findings underscore the importance of integrating ESG considerations into risk management framework, particularly for banks with lower ESG performance, to reduce vulnerability to environmental risks.

In order to check the channel through which biodiversity risk hampers banks performance, we empirically tested the NPLs as a pathway through which biodiversity risk hurts banks profitability measures. Biodiversity related risks increase the likelihood of loan defaults by affecting income levels and assets values ,raising NPL ratios (Fan et al., 2024). Since NPLs are established as a channel in adverse impacts of biodiversity risk on bank performance, banks should strengthen their credit risk assessment processes to manage NPLs. Moreover, policy makers should introduce regulations that require banks to disclose biodiversity risk exposure and incorporate these into stress testing assessments.

Most crucially, the findings from quasi natural experiments performed using China's Green Credit Guidelines (2012) and Mandatory Biodiversity Disclosure (2020) show that both policies led to declines in profitability. This aligns with the risk mitigation view (Bouslah et al., 2018),suggesting that banks with poor environmental practices bear greater financial penalties during regulatory transitions. These findings underscore the need to balance environmental goals with financial stability. Transitional support, phased regulations implementation and incentives for sustainable practices could mitigate short-term costs (Luo & Bhattacharya, 2006). Moreover, the broad-based effect of Mandatory Biodiversity Disclosures indicates that while the policy created a level playing field, it imposed a compliance cost across banking sector. By streamlining disclosure requirements and providing standardized reporting templates, it may be helpful in reducing administrative costs and ensuring transparency.

In conclusion, this study empirically establishes negative association between biodiversity risk and bank performance, offering valuable insights for policy makers to design biodiversity related regulations that promote sustainability without imposing excessive financial burden on banking sector. Bank managers should integrate biodiversity risk into credit risk assessments and capital allocation strategies for long term financial stability. By working together, policy makers and managers can ensure a sustainable and financially viable transition.

The exclusive focus of this study on Chinese banks was driven by data availability on biodiversity risk, limiting the generalizability of findings. However, given rising global recognition of biodiversity as a financial risk, our study lays the foundation for future research in other emerging and developed markets thereby advancing the literature on biodiversity finance, and bank financial performance.

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Appendix A

Table A1. Variable measurements

Variable	Definition	Source
Bank performance	Measures of ROA, ROE, and earnings before tax/total assets (EB_TA)	Refinitiv ASSET

Biodiversity risk (BIO_RISK)	Equal to 1 if biodiversity terms appear more than twice in the annual report and 0 otherwise	He, Chen, et al. (2024)
Non-performing loan (NPL)	Non-performing loans / Total loans	Refinitiv ASSET4
ESG Performance (ESG)	Composite score based on several ESG parameters	Refinitiv ASSET4
Bank Size (SIZE)	Natural logarithms of total assets	Refinitiv ASSET4
Liquid assets ratio (LIQ_AST)	Liquid assets to total assets	Refinitiv ASSET4
Loan to deposit ratio (LOA_DEP)	Loans/total deposits	Refinitiv ASSET4
Leverage (LEV)	Liabilities to total assets	Refinitiv ASSET4
Money supply (M2)	Broad Money (% of GDP)	WDI

Tables

Table 1. Summary statistics and VIF

Variable	N	Mean	Std. Dev.	Min	Max	VIF	1/VIF
	592	0.68	0.467	0.00	1.00		
ROA	592	0.009	0.009	-0.075	0.078		
ROE	592	14.493	8.132	-8.419	61.84		
EB_TA	592	0.012	0.006	-0.033	0.064		
ESG	592	44.073	15.29	6.72	88.35		
NPL	592	1.357	0.972	0.049	9.681		
BIO_RISK	592	0.68	0.467	0.00	1.00	1.035	0.966
SIZE	592	13.876	1.728	7.537	17.615	1.054	0.949
LOA_DEP	592	0.694	0.104	0.419	0.951	1.151	0.869
LIQ_AST	592	0.007	0.026	0.012	0.323	1.056	0.947
LEV	592	14.022	3.833	0.699	31.334	1.142	0.876
M2	592	191.013	21.160	148.840	227.944	1.008	0.992
Mean VIF						1.074	

In this table summary statistics and VIF of variables used in this study are provided. These variables are defined in in appendix Table A1.

Table 2. Baseline regression analysis

Variables	(1) ROA	(2) ROA	(3) ROE	(4) ROE
BIO_RISK	-0.189***	-0.158***	-0.141***	-0.130*
	(0.0212)	(0.0356)	(0.0403)	(0.0506)
SIZE	0.0810***	0.604**	0.118***	1.618***
	(0.0133)	(0.273)	(0.0124)	(0.433)
LOA_DEP	0.00935	0.0188	-0.0246	0.0264
	(0.0122)	(0.0219)	(0.0246)	(0.0379)
LIQ_AST	-0.0412	-0.140	-0.213	-0.308
	(0.0991)	(0.135)	(0.143)	(0.274)
LEV	-0.0846***	-0.0562	0.179***	0.227***
	(0.0236)	(0.0397)	(0.0333)	(0.0790)
M2	-0.00160	-0.00928	-0.0110	-0.00712
	(0.00960)	(0.0113)	(0.0321)	(0.0318)
Intercept	0.0117	0.145	0.129	0.805***
	(0.0628)	(0.158)	(0.137)	(0.247)
Bank effect	No	Yes	No	Yes
Year effect	No	Yes	No	Yes
Observations	592	592	592	592
R-squared	0.24	0.60	0.28	0.78

This table presents baseline regression results. Models 1 and 2 assess BIO_RISK impact on ROA, with Model 2 incorporating year and bank effects. Models 3 and 4 follow the same approach for ROE. Standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels.

Table:3 Analysis considering banks' ownership

Variables	State-owned / joint stock banks		Rural/Urban banks	
	(1)	(2)	(3)	(4)
	ROA	ROE	ROA	ROE
BIO_RISK	-0.121**	-0.0943	-0.208***	-0.207***
	(0.0577)	(0.0781)	(0.00957)	(0.0175)
SIZE	0.663**	1.461**	0.363*	1.194***
	(0.280)	(0.604)	(0.191)	(0.186)
LOA_DEP	0.00228	-0.0777	0.0385**	0.0452
	(0.0397)	(0.0872)	(0.0174)	(0.0296)
LIQ_AST	-0.416	-0.338	0.106	0.154*
	(0.381)	(0.423)	(0.0746)	(0.0827)
LEV	-0.0291	0.242*	-0.147***	0.0203
	(0.0777)	(0.134)	(0.0208)	(0.0372)
M2	-0.00750	-0.0188	0.0125	0.0135
	(0.00812)	(0.0519)	(0.00882)	(0.00938)
Intercept	0.651	-0.694	0.561***	1.594***
	(0.478)	(0.751)	(0.178)	(0.183)
Bank effect	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes
Observations	240	240	352	352

This table presents the impact of BIO_RISK on bank performance, comparing state-owned/joint-stock banks with other banks. Standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels.

Table:4 Analysis considering banks' ESG performance

Variables	High ESG performance banks		Lower ESG performance	
	(1)	(2)	(1)	(2)
	ROA	ROE	ROA	ROE
BIO_RISK	-0.140**	-0.112*	-0.145***	-0.133***
	(0.0506)	(0.0648)	(0.0312)	(0.0363)
SIZE	0.300	1.559**	0.510	0.715
	(0.338)	(0.621)	(0.720)	(0.950)
LOA_DE	0.0348	0.0254	0.0440	0.0227
	(0.0308)	(0.0698)	(0.0312)	(0.0572)
LIQ_AS	-0.174	-0.535	0.126	0.219
	(0.189)	(0.468)	(0.169)	(0.228)
LEV	-0.0826	0.165	-0.106	0.0458
	(0.0507)	(0.114)	(0.115)	(0.141)
M2	-0.0200*	-0.0106	0.0118	9.91e-05
	(0.0116)	(0.0456)	(0.0125)	(0.0167)
Intercept	0.151	1.221***	-0.194	0.138
	(0.239)	(0.448)	(0.803)	(0.312)
Bank effect	Yes	Yes	Yes	Yes
Year effect	Yes	Yes	Yes	Yes
Observations	480	480	112	112

This table presents the impact of BIO_RISK on bank performance, comparing banks with high and low ESG performance. Standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels.

Table:5 NPL as a channel in biodiversity risk and bank performance

	(1)	(2)	(3)
Variables	NPL	ROA	ROE
NPL		-0.0823***	-0.104***
		(0.0167)	(0.0146)
BIO_RISK	0.164***	-0.147***	-0.118***

	(0.0420)	(0.0334)	(0.0449)
SIZE	-2.716***	0.509**	1.222***
	(0.813)	(0.242)	(0.436)
LOA_DEP	-0.264***	-0.0112	-0.0131
	(0.0673)	(0.0228)	(0.0371)
LIQ_AST	0.921**	-0.153	-0.0646
	(0.464)	(0.119)	(0.282)
LEV	0.150	-0.0678*	0.270***
	(0.208)	(0.0392)	(0.0756)
M2	0.00128	-0.0120	-0.00535
	(0.0402)	(0.0160)	(0.0332)
Intercept	0.198	0.252**	0.695***
	(0.565)	(0.123)	(0.249)
Bank effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
Observations	592	592	592
Number of years	16	16	16

This table examines the role of NPL as a channel in the relationship between biodiversity risk and bank performance. Standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. Bank and year-fixed effects are included

Table:6 Biodiversity risk and bank performance for the PSM sample

	Nearest neighbor matching		Caliper matching	
	(1)	(2)	(3)	(4)
Variables	ROA	ROE	ROA	ROE
BIO_RISK	-0.158***	-0.130**	-0.158***	-0.130**
	(0.0378)	(0.0451)	(0.0378)	(0.0451)
SIZE	0.604**	1.618**	0.604**	1.618**
	(0.266)	(0.687)	(0.266)	(0.687)
LOA_DEP	0.0188	0.0264	0.0188	0.0264
	(0.0422)	(0.0953)	(0.0422)	(0.0953)
LIQ_AST	-0.140	-0.308*	-0.140	-0.308*
	(0.163)	(0.186)	(0.163)	(0.186)
LEV	-0.0562	0.227**	-0.0562	0.227**
	(0.0445)	(0.108)	(0.0445)	(0.108)
M2	-0.00928	-0.00712	-0.00928	-0.00712
	(0.00891)	(0.0172)	(0.00891)	(0.0172)
Intercept	0.145	0.805*	0.145	0.805*
	(0.171)	(0.480)	(0.171)	(0.480)
Bank effect	Yes	Yes	Yes	Yes
Year effect	386	314	386	314

This table shows the impact of biodiversity risk on bank performance using PSM. Standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. Bank and year-fixed effects are included.

Table:7 Entropy balancing

Pre-entropy-balancing		Treat			Control	
Variables	Mean	variance	skewness	mean	variance	skewness
SIZE	0.131	0.741	0.315	0.042	0.888	0.333
LOA_DE	0.115	1.124	0.283	-0.221	0.766	-0.568
LIQ_AS	-0.160	0.022	4.337	-0.184	0.007	1.967
LEV	0.049	0.354	1.041	0.219	0.811	1.474
M2	0.046	0.953	-0.521	-0.087	1.107	-0.236
Post-entropy-balancing						
SIZE	0.131	0.741	0.315	0.131	1.095	0.088
LOA_DE	0.115	1.124	0.283	0.115	0.564	-0.680
LIQ_AS	-0.160	0.022	4.337	-0.160	0.011	1.556

LEV	0.049	0.354	1.041	0.049	0.697	1.845
M2	0.046	0.953	-0.521	0.046	1.043	-0.319

This table shows the summary statistics of key variables before and after entropy balancing, highlighting improved balance between the treatment and control groups post-adjustment.

Table:8 Exogenous shocks

	(1)	(2)	(3)	(4)
Variables	ROA	ROE	ROA	ROE
BIO_RISK	-0.0948*	-0.144**	-0.216***	-0.239***
	(0.0492)	(0.0630)	(0.0305)	(0.0714)
Post Green Credit Guidelines	-0.210**	-0.235		
	(0.0935)	(0.191)		
BIO_RISK* Green Credit Guidelines	-0.153***	-0.149**		
	(0.0935)	(0.191)		
Post Mandatory Biodiversity Disclosures			-0.257***	-0.420***
			(0.0618)	(0.0937)
BIO_RISK* Post Mandatory Biodiversity Disclosures			0.0182	-0.00556
			(0.0588)	(0.0962)
Intercept	0.191*	0.181	0.0315	0.0589
	(0.106)	(0.174)	(0.0404)	(0.0859)
Controls	Yes	Yes	Yes	Yes
Observations	592	592	592	592
R squared	0.257	0.307	0.317	0.406

This table presents the results of natural quasi experiments using two important policy events during the sample period as external shocks: the issuance of green credit guidelines issued by the China Banking Regulatory Commission (CBRC) in 2012, and Mandatory Biodiversity-Related Disclosures (2020) issued by the Ministry of Ecology and Environment (MEE). Standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels. Bank and year-fixed effects are included.

Table:9 Alternative measurements

	(1)	(2)	(3)
Variables	ROA	ROE	EBT_TA
L1_ BIO_RISK	-0.0738**	-0.124**	
	(0.0372)	(0.0494)	
BIO_RISK			-0.0998***
			(0.000458)
Baseline controls	Yes	Yes	Yes
Constant	0.0562	-0.142	0.0156***
	(0.185)	(0.165)	(0.00206)
Bank effect	Yes	Yes	Yes
Year effect	Yes	Yes	Yes
Observations	592	592	592
Number of Banks	37	37	37

This table presents the results of the impact of biodiversity risk on bank performance. L1_BIO_RISK represents the lagged value of biodiversity risk. Standard errors are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels. Bank and year-fixed effects are included.

Table:10 Alternative estimations (quantile regression and Lewbel 2SLS analysis)

	(1)	(2)	(3)	(4)	(5)	6	(1)	(2)	(3)	(4)	(5)	6
	q10	**q25**	**q50**	**q75**	**q90**	**L2SLS**	**q10**	**q25**	**q50**	**q75**	**q90**	**L2SLS**
	ROA	ROA_	ROA	ROA	ROA	ROA	ROE	ROE	ROE	ROE	ROE	ROE
BIO_RISK	-0.264***	-0.226***	-0.243***	-0.272***	-0.296***	-0.318***	-0.390***	-0.275***	-0.282***	-0.317***	-0.369***	-0.417***
	(-7.08)	(-12.59)	(-16.41)	(-13.26)	(-10.87)	(0.0476)	(0.058)	(0.030)	(0.031)	(0.041)	(0.054)	(0.0731)
SIZE	0.0340	0.0473*	0.0335*	0.0609**	0.0586*	0.0649***	0.083	0.128***	0.083**	0.172***	0.156**	0.168***
	(0.84)	(2.41)	(2.07)	(2.72)	(1.97)	(0.0199)	(0.066)	(0.034)	(0.036)	(0.047)	(0.062)	(0.0345)
LOA_DEP	0.00762	-0.0502**	-0.0664***	-0.0453*	-0.0292	-0.0244	-0.120**	-0.195***	-0.155***	-0.198***	-0.239***	-0.159***
	(0.21)	(-2.85)	(-4.57)	(-2.26)	(-1.10)	(0.0202)	(0.058)	(0.030)	(0.031)	(0.041)	(0.054)	(0.0423)
LIQ_AST	0.199	0.0585	0.153	0.377**	0.456*	0.247**	0.556	0.304	0.214	0.238	0.709**	0.380**
	(0.76)	(0.46)	(1.46)	(2.60)	(2.37)	(0.109)	(0.376)	(0.195)	(0.203)	(0.265)	(0.350)	(0.148)
LEV	-0.0462	-0.100***	-0.0972***	-0.0735*	-0.0487	-0.0415	0.162*	0.126***	0.197***	0.189***	0.323***	0.228***
	(-0.86)	(-3.87)	(-4.55)	(-2.49)	(-1.24)	(0.0383)	(0.085)	(0.044)	(0.046)	(0.060)	(0.079)	(0.0609)
M2	0.0165	0.0172	0.0135	0.000953	0.0174	0.0172	-0.002	0.030	0.046	-0.030	-0.007	0.00812
	(0.47)	(1.01)	(0.97)	(0.05)	(0.68)	(0.0161)	(0.054)	(0.028)	(0.029)	(0.038)	(0.051)	(0.0425)
Intercept	-0.315***	-0.186***	-0.0350	0.163***	0.361***	-0.00312	-0.550***	-0.326***	-0.119**	0.206***	0.578***	-0.0257
	(-5.51)	(-6.72)	(-1.54)	(5.19)	(8.65)	(0.0271)	(0.088)	(0.046)	(0.047)	(0.062)	(0.082)	(0.0415)
Observations	592	592	592	592	592	592	592	592	592	592	592	592
Number of banks	37	37	37	37	37	37	37	37	37	37	37	37
Number of years	16	16	16	16	16	16	16	16	16	16	16	16

This table shows the results of alternative estimations quantile regression at 10, 25, 50 ,75, 90 percentiles and Lewbel 2SLS, evaluating the impact of biodiversity risk on bank performance. Standard errors are in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% levels.