Finance Research Letters 73 (2025) 106615

Contents lists available at ScienceDirect

Finance Research Letters

journal homepage: www.elsevier.com/locate/frl

Eco-innovation under pressure: How biodiversity risks shape corporate sustainability strategies

Ye Tian, Heng Chen *

School of Economics and Management, Harbin Engineering University, Harbin 150001, PR China

A R T I C L E I N F O

Keywords:
Biodiversity risk exposure
Eco-innovation
Agency costs
Resource dependence theory
Sustainability Strategies

A B S T R A C T

This study examines the impact of biodiversity risk exposure (BRE) on firms' eco-innovation (EI) using a sample of A-share listed firms in China from 2009 to 2021. We measure BRE through a text-analysis-based index and capture eco-innovation via ecological patents. Our findings show a significant positive effect of BRE on EI, which remains robust across various tests. External monitoring strengthens this relationship, while technology diversification weakens it. Additionally, stronger ESG performance, higher environmental regulations, less concentrated supply chain, and non-manufacturing firms enhance relationship of BRE and EI. This research contributes to understanding how biodiversity risks influence corporate innovation, with important policy implications for sustainability and risk management.

1. Introduction

With the gradual improvement of biodiversity information disclosure frameworks, such as the Taskforce on Nature-related Financial Disclosures (TNFD), the European Sustainability Reporting Standards (ESRS), GRI 101, and the C15 Biodiversity module in the CDP questionnaires, the study of biodiversity risk and its impact on firms has become a prominent research focus. Previous research has indicated that biodiversity risks can exert varying degrees of negative influence on firms' investments (Garel et al., 2024; Ma et al., 2024), financial risk (Liang et al., 2024), capital structure (Ahmad and Karpuz, 2024), and capital market performance (Giglio et al., 2023). However, unlike other types of risks, biodiversity risks uniquely affect firms' sustainability strategies by both promoting innovation in biodiversity conservation (e.g., Kalhoro and Kyaw, 2024; Li et al., 2024) and potentially weakening investments in specific ecological innovations due to the dilution of resources (Suding et al., 2024; Ziegler et al., 2022). This paper aims to address this research gap by investigating the impact of biodiversity risk exposure on corporate eco-innovation. Our empirical findings significantly enhance the understanding of how changes in information disclosure influence firms' responses to biodiversity risk, which is deemed crucial in corporate risk management (Garel et al., 2024; Giglio et al., 2023).

This paper examines the relationship between *BRE*and firms' *EI* activities, offering a comprehensive analysis of how biodiversity risks influence corporate innovation strategies. Using a detailed dataset on *BRE* (see He et al., 2024) and eco-innovation patents (see Appendix A.2), we explore whether firms exposed to higher biodiversity risks are more likely to engage in eco-innovation. Additionally, we investigate the moderating effects of external monitor and technology diversification, and the role of characteristics like the degree of environment regulation and ESG performance in shaping this relationship.

Our empirical analysis reveals a significant positive relationship between *BRE* and *EI*, which withstood a series of tests for

* Corresponding author.
E-mail addresses: tianye@hrbeu.edu.cn (Y. Tian), chenh@hrbeu.edu.cn (H. Chen).

https://doi.org/10.1016/j.frl.2024.106615
Received 7 November 2024; Received in revised form 4 December 2024; Accepted 8 December 2024
Available online 10 December 2024

endogeneity and robustness. This relationship is further strengthened by external monitoring mechanisms, such as media attention and institutional investors. Conversely, the impact of biodiversity risk on eco-innovation is weaker in firms with high technology diversification, suggesting that firms with a broader focus may be less inclined to adopt targeted biodiversity conservation measures. The heterogeneity analysis further shows that firms with stronger ESG performance, less concentrated supply chains, higher degree of environmental regulation, and non-manufacturing firms are more likely to respond to biodiversity risks with innovation.

This paper makes several important contributions to biodiversity risk and corporate innovation literature. First, we introduce an approach to defining and measuring firms' eco-innovations using patent content. This allows us to provide a more precise and comprehensive assessment of corporate innovation efforts, focusing specifically on innovations related to biodiversity conservation. Unlike previous studies that primarily use survey (Cai and Li, 2018) or environmental performance indicators (García-Granero et al., 2018), our method offers a targeted approach to capture the unique nature of biodiversity-related innovations.

Second, we extend the existing research on environmental innovation by incorporating biodiversity risk exposure as a distinct and critical factor influencing firms' innovation activities. While previous studies have confirmed that biodiversity risks are an important factor threatening business operations (Frank, 2024), our research emphasizes these challenges. By exploring the impact of biodiversity risks on corporate eco-innovation, we offer new insights into how firms respond to ecological challenges. This contribution enhances the understanding of the factors driving innovation in the context of biodiversity and sustainability.

The structure of this paper is as follows: In Section 2, we develop the hypotheses. Section 3 details our data and methodology. Sections 4 present our main findings. Finally, we conclude our study.

2. Hypotheses development

2.1. Resource dependence theory and sustainability strategies

According to Resource Dependence Theory (RDT), organizations depend on external resources for their survival and growth, and these resources play a central role in influencing strategic decisions and shaping firm behavior (Pfeffer and Salancik, 2015). RDT posits that a firm's access to valuable, often scarce and externally controlled resources is a critical source of competitive advantage that underpins long-term sustainability. To secure and maintain access to these essential resources, firms must develop the ability to manage dependencies, adapt to external demands and engage strategically with key stakeholders in their environment (Branco and Rodrigues, 2006).

For corporate sustainability strategies, RDT suggests that firms exposed to environmental risks and resource dependencies are driven to adopt sustainable practices to secure their resource needs and mitigate potential operational disruptions. Environmental risks such as resource scarcity, ecosystem degradation and increased regulatory scrutiny directly threaten a firm's ability to access vital resources. To address these challenges, firms can pursue sustainability strategies that reduce their dependence on fragile ecosystems, build resilience and enable them to thrive in a resource-constrained environment. Such sustainability efforts may include developing sustainable sourcing practices, substituting scarce resources, or implementing more efficient waste and resource management systems.

Research shows that firms committed to sustainable innovation are better able to secure their resource needs while reducing their environmental impact (Hart, 1995; Chang, 2011). In sectors that are highly dependent on natural resources, such as agriculture, mining or forestry, firms that prioritize sustainable practices can adapt more effectively to regulatory and stakeholder pressures (Guerci et al., 2016), maintaining operational stability (Wu and Pagell, 2011), and compliance with biodiversity and environmental standards (Treepongkaruna, 2024). In addition, resource-dependent sustainability efforts help firms meet regulatory requirements (Campbell Gemmell and Marian Scott, 2013) and align with the expectations of stakeholders invested in environmental stewardship (Sulkowski et al., 2018), thereby enhancing corporate reputation and building stakeholder trust.

In line with RDT, we propose that firms facing high environmental risks are more likely to adopt proactive sustainability strategies that mitigate environmental impacts and reduce reliance on vulnerable resources. Sustainability-driven innovations help firms secure essential resources and adapt to evolving regulatory and stakeholder demands. Firms that view sustainability strategically are better positioned to meet environmental challenges, while those lacking strong governance may respond inadequately. Based on the above discussion, we propose the following hypothesis:

H1: Corporate exposure to biodiversity risk is positively associated with eco-innovation.

2.2. Mechanism of external monitor

Based on external stakeholder theory, firms are not only concerned with internal resources and capabilities but also need to respond to the demands and pressures from external stakeholders, such as governments, medias, NGOs, and investors. External monitors, as key stakeholders, can influence firms by setting stringent environmental regulations, requiring sustainability reporting, or evaluating corporate social responsibility. These pressures drive firms to address biodiversity risks and invest in eco-innovation. Specifically, the presence of external monitors creates normative expectations, compelling firms to prioritize environmental sustainability in their innovation strategies. This external pressure encourages firms to adopt more proactive and effective measures to mitigate biodiversity risks, as doing so enhances their social image and brand value. As a result, external monitors can strengthen the impact of biodiversity risks on firms' eco-innovation efforts, motivating companies to innovate in ways that align with broader societal expectations for sustainability and environmental responsibility. Based on the above discussion, we propose the following hypothesis:

H2: External monitors strengthen the relationship of *BRE* and *EI*.

2.3. Mechanism of technology diversification

From the perspective of innovation theory, firms need to concentrate their resources and focus when engaging in innovation. However, technology diversification can disperse a firm's resources and attention across multiple technological domains, leading to the "Dilution of Expertise" (Lavie et al., 2010; Tushman and O'Reilly, 1996). This dilution reduces the firm's focus on eco-innovation, as resources allocated to biodiversity-related projects are spread across other technological areas. As a result, the firm may fail to concentrate on developing targeted solutions to address biodiversity challenges. Overall, the broader the scope of technological diversification, the less likely a firm is to prioritize specialized eco-innovations aimed at reducing biodiversity risks, as the innovation process becomes more dispersed and less focused on solving specific ecological issues. Based on the above discussion, we propose the following hypothesis:

H3: Technology Diversification strengthen the relationship of *BRE* and *EI*.

3. Research design and methodology

3.1. Variable definition

3.1.1. Dependent variable: firms' biodiversity risk exposure

We use the biodiversity index developed by He et al. (2024) to measure the firm's biodiversity risks exposure (*BRE*). They constructed biodiversity indices using text analysis based on Giglio et al.'s (2023) biodiversity dictionary.[1] By mining biodiversity-related terms in Chinese firms' annual reports, they developed the Biodiversity Risk Index (set to 1 if a term appears more than twice) and the Biodiversity Concern Index (ratio of biodiversity term characters to total report characters). These indices effectively capture corporate attention to biodiversity, offering a scalable measure for comparing biodiversity awareness across firms.

3.1.2. Independent variable: firms' eco-innovation

As traditional green innovations focus primarily on reducing emissions, improving energy efficiency and minimizing pollution, they tend to address climate change and broader environmental impacts rather than the specific needs of biodiversity conservation. Biodiversity loss involves complex issues such as habitat degradation, species depletion and ecosystem disruption, which traditional green measures do not fully address. We suggest that to manage biodiversity risks effectively, companies should adopt solutions that are specifically designed to address these challenges. Therefore, we constructed a dataset on adaptive ecological innovation based on corporate patent data to capture the efforts companies make to address biodiversity risks (see more detail for Appendix A.2). The patent data used comes from the China Research Data Service Platform (CNRDS), Innovation Patent Research (CIRD).

Specifically, this dataset includes innovations in genetic engineering that support agricultural biodiversity by reducing reliance on monoculture crops. Ecological protection technologies help restore habitats and control pollution in specific ecosystems. Sustainable agricultural practices promote soil health and biodiversity through biological controls, while biodiversity monitoring enables proactive risk management by tracking changes in species and ecosystems. In addition, renewable energy and green building innovations reduce habitat degradation and resource depletion. Compared to traditional green technologies, these targeted innovations offer a more comprehensive approach to biodiversity conservation.

This paper measures firm's adaptive eco-innovation (*EI*) by taking the natural logarithm of one plus the number of adaptive eco-innovation patent applications (*EInno*), invention patent applications (*EInvent*), and utility patent applications (*EUtil*).

3.1.3. Control variables

To analyze the impact of biodiversity risk on firm eco-innovation, we include several control variables that capture firm characteristics that influence innovation. *FirmAge* reflect the resources and experience available for innovation (Leoncini et al., 2019). *ROE* (Return on Equity) and *cashflow* indicate financial performance and liquidity, which influence a firm's ability to invest in eco-innovation (Akbar et al., 2022). *Lev* (leverage) and *Loss* (business loss) control for financial constraints and risk levels that may influence innovation decisions (Akbar et al., 2022). *TobinQ* and *Growth* capture market expectations and growth potential, both of which are related to incentives to innovate. *INV* (investment intensity) indicates past investment activity, and *SOE* (state-owned enterprise) accounts for potential government influence. Finally, *Indep* (Independent board ratio) controls for governance quality, which may influence strategic innovation decisions (Shan et al., 2024).

3.2. Empirical model

To examine the relationship between the *EI* and *BRE*, the model is constructed using the following specification:

$$EI_{i,t} = \beta_0 + \beta_1 BRE_{i,t} + \sum_k \alpha_k Controls_{i,t}^k + \sum year + \sum industry + \varepsilon_{i,t} \tag{1}$$

In Eq.1, the dependent variable $EI_{i,t}$ denotes the firms' eco-innovation of the firm *i* in year *t*. $BRE_{i,t}$ denote the influence of corporate biodiversity exposure. $Controls_{i,t}^k$ are the control variables. β_0 is the constant term, and $\varepsilon_{i,t}$ is the error term. We also incorporate the year

[1] For more detail, see http://www.cnefn.com/data/download/climate-attention-database

and firm fixed effects to rule out interference from other factors (see variable definition for Appendix A.1).

3.3. Sample selection and descriptive statistics

We selected A-share listed firms from 2009 to 2021 as our sample. The financial data for the firms in this study were obtained from the Wind and CNRDS databases. The data processing involved several steps: First, we excluded the financial data of firms in the financial sector; second, we excluded firms designated as ST, *ST, or PT, indicating abnormal financial conditions, for the relevant years; third, we removed all observations missing key variables; and fourth, we winsorized continuous variables at the 1 % level to mitigate the influence of outliers. The final sample consists of 19,388 observations.

Table 1 reports the descriptive statistics for the variables in our study. The descriptive statistics indicate generally low eco-innovation activity among firms, with median values of 0 for *EInno, EInven*, and *EUti*1, though some firms demonstrate higher innovation levels. Biodiversity risk exposure is also extremely low, with an average and median of 0.00009 and 0.00002 respectively, which is consistent with the data in He et al. (2024).

4. Empirical results

4.1. Baseline estimation results

The results indicate a significant positive effect of *BRE* on *EI* in all models. In all baseline models, *BRE* consistently shows positive and statistically significant coefficients on *EInno, EInven*, and *EUtil* suggesting that higher *BRE* is associated with increased eco-innovation efforts. In particular, the effect size of *BRE* decreases slightly when all controls are included, but remains significant, indicating that biodiversity risk exposure independently drives firms to engage in eco-innovation activities. This confirms H1 (see robust test for Appendix B).

4.2. Moderating analysis

4.2.1. External monitor

Firstly, we use media attention constructed by Antweiler and Frank (2004) as the proxy of external monitor. Specifically, we categorize financial news about a firm into 'positive' and 'negative' sentiment and construct a media attention index $Attention_{i,t}$ as follows:

$$Attention_{i,t} = \ln\left(\frac{1 + \sum Positive_{i,t}}{1 + \sum Negative_{i,t}}\right) \tag{2}$$

Where, $Positive_{i,t}$ is the number of positive (optimistic) News of stock i on year t, and $Negative_{i,t}$ means the number of negative (pessimistic) News of stock i on year t. The more news with optimism or pessimism within a year, the stronger the (positive or negative) emotion it represents. Depending on the news source, we constructed indicators of media attention based on all news (*Attention*).

Table 2., 3., and 4.

Secondly, we use institutional shareholding (*ESGFund*) as another proxy of external monitor. ESG funds require investee firm to disclose their ESG performance (Chen and Xie, 2022), increasing transparency and enabling external monitors—such as investors, regulators, and social organizations—to assess sustainability and compliance. Additionally, ESG fund investors pressure fund managers and companies to adopt sustainable practices, promoting accountability and advancing market-wide sustainability (Dantas, 2021). The regression results are shown in Table 5.

Table 1
Descriptive statistics
Table 1 presents the descriptive statistics for the sample from 2009 to 2020. The sample consists of 2769 firms.

Variable	N	Mean	p50	Min	Max	SD
EInno	19,388	0.89	0	0	4.53	1.18
EInven	19,388	0.61	0	0	4.09	0.97
*EUti*1	19,388	0.59	0	0	3.71	0.93
BRE	19,388	0.00009	0.00002	0	0.0088	0.00033
FirmAge	19,388	2.88	2.94	1.79	3.5	0.33
ROE	19,388	0.07	0.07	−0.44	0.34	0.11
Lev	19,388	0.45	0.44	0.07	0.87	0.2
TobinQ	19,388	2.01	1.61	0.86	7.94	1.23
Growth	19,388	0.16	0.1	−0.52	2.23	0.37
Cashflow	19,388	0.05	0.05	−0.14	0.23	0.07
INV	19,388	0.15	0.12	0	0.72	0.14
Loss	19,388	0.09	0	0	1	0.28
SOE	19,388	0.44	0	0	1	0.5
Indep	19,386	0.37	0.33	0.33	0.57	0.05

Table 2
Baseline regression
Table 2 reports the results of estimating Eq.1. Columns (1) - (3) present the estimation results that include only firm and year-fixed effects. Columns (4) - (6) build upon (1) - (3) by adding firm level control variables.

VARIABLES	Only FEs			Include all controls		
	EInno (1)	*EInven* (2)	*EUtil* (3)	*EInno* (4)	*EInven* (5)	*EUtil* (6)
BRE	272.111***	265.688***	161.872***	253.338***	247.312***	152.246***
	(3.923)	(4.229)	(3.021)	(3.719)	(4.049)	(2.829)
FirmAge				0.275	0.208	0.246*
				(1.612)	(1.364)	(1.899)
ROE				0.190**	0.091	0.167**
				(2.183)	(1.195)	(2.359)
Lev				0.304***	0.228***	0.263***
				(3.248)	(2.896)	(3.456)
TobinQ				−0.028***	−0.018***	−0.019***
				(−3.616)	(−2.754)	(−3.073)
Growth				0.025*	0.019	0.011
				(1.724)	(1.495)	(0.935)
Cashflow				−0.234**	−0.145*	−0.169**
				(−2.379)	(−1.747)	(−2.097)
INV				−0.272*	−0.319***	−0.102
				(−1.920)	(−2.708)	(−0.890)
Loss				−0.014	−0.031	0.004
				(−0.531)	(−1.353)	(0.181)
SOE				0.123**	0.133***	0.025
				(2.191)	(2.712)	(0.551)
Indep				0.095	0.054	0.027
				(0.441)	(0.288)	(0.152)
Constant	0.867***	0.584***	0.576***	−0.053	−0.106	−0.222
	(146.502)	(108.954)	(125.826)	(−0.107)	(−0.242)	(−0.585)
Observations	19,388	19,388	19,388	19,290	19,290	19,290
R^2	0.729	0.708	0.692	0.731	0.710	0.694
Year FE	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
F	15.39	17.88	9.124	5.795	5.140	4.094

Table 3
Moderation Effect of External Monitor
Table 3 reports the OLS regression results exploring the moderation of External Monitor. We use two indices to test this mechanism. ESG fund holdings and media attention are used as a proxy variable for external monitor. In models (1) - (4), we examine how external monitor influences the relationship of *BRE* − *EI*.

VARIABLES	Moderation of external monitor			
	Role of ESG fund holds		Role of media attention	
	EInno (1)	*EInven* (2)	*EInno* (3)	*EInven* (4)
BRE	221.988***	220.776***	199.321***	198.616***
	(3.898)	(4.045)	(3.080)	(3.627)
ESGFund	0.115***	0.103***		
	(6.160)	(6.307)		
BC × *ESGFund*	117.097**	107.039**		
	(2.429)	(2.525)		
Attention			0.029***	0.027***
			(2.960)	(3.340)
BC × *Attention*			66.037*	60.574*
			(1.822)	(1.910)
Constant	0.178	0.070	−0.066	−0.140
	(0.354)	(0.157)	(−0.130)	(−0.312)
Observations	18,427	18,427	18,705	18,705
R-squared	0.737	0.716	0.735	0.713
Baseline Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
F	7.828	7.753	6.651	6.179

Table 4
Moderation Effect of Technology Diversification
Table 4 reports the OLS regression results exploring the moderation of technology diversification. We use two indices to test this mechanism. TD-HHI and TD entropy index are used as a proxy variable for technology diversification. In models (1) - (4), we examine how technology diversification influences the relationship of *BRE* − *EI*.

	Moderation of technology diversification			
	Role of TD-HHI		Role of TD entropy index	
VARIABLES	*EInno* (1)	*EInven* (2)	*EInno* (3)	*EInven* (4)
BRE	494.441***	507.797***	510.695***	534.046***
	(3.852)	(3.711)	(4.137)	(4.080)
TD	−0.725***	−0.626***		
	(−13.434)	(−13.480)		
BRE × *TD*	−774.392***	−815.471***		
	(−3.765)	(−3.851)		
*TD*1			−0.204***	−0.238***
			(−7.803)	(−10.303)
BRE × *TD*1			−353.722***	−388.304***
			(−3.933)	(−4.080)
Constant	1.744***	1.352***	1.577***	1.260**
	(3.197)	(2.723)	(2.818)	(2.512)
Observations	15,124	15,124	15,124	15,124
R-squared	0.736	0.721	0.730	0.717
Baseline Controls	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
F	19.30	19.56	9.275	12.90

Table 5
Heterogeneity analysis of ESG Performance
Table 5 represents the heterogeneity analysis of ESG Performance of Eq.1.

	Heterogeneity of ESG Performance			
VARIABLES	*lowperformance* *EInno* (1)	*Highperformance* *EInven* (2)	*lowperformance* *EInno* (3)	*Highperformance* *EInven* (4)
BRE	75.273	290.541***	140.206**	277.388***
	(1.046)	(2.772)	(2.061)	(2.608)
Constant	−8.705***	−5.961***	−6.991***	−6.139***
	(−10.343)	(−4.507)	(−9.032)	(−4.980)
Observations	12,032	7258	12,032	7258
R-squared	0.725	0.819	0.704	0.798
Baseline Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
F	13.47	4.707	11.43	4.745

Table 6
Heterogeneity analysis of Supply Chain Disruption
Table 6 represents the heterogeneity of Supply chain disruption of Eq.1.

	Heterogeneity of Supply chain disruption			
VARIABLES	*HighSCC* *EInno* (1)	*LowSCC* *EInven* (2)	*HighSCC* *EInno* (3)	*LowSCC* *EInven* (4)
BRE	423.393***	104.292	441.538***	105.413
	(3.074)	(1.258)	(3.827)	(1.435)
Constant	−6.975***	−9.122***	−5.963***	−7.388***
	(−6.718)	(−8.469)	(−6.393)	(−8.175)
Observations	10,764	8526	10,764	8526
R-squared	0.790	0.716	0.770	0.692
Baseline Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
F	9.855	9.906	9.642	10.04

In columns (1) and (2), the significant coefficients for *BRE* (222 and 221, at 1 % level) indicate a positive relationship between biodiversity risk and eco-innovation. The positive coefficients for *BRE* × *ESGFund* (117, $p < 0.05$) suggest that ESG fund ownership strengthens this effect. Similarly, in columns (3) and (4), *BRE* remains significant (199, at 1 % level), and *BRE* × *Attention*(66 and 60, $p < 0.10$) indicates that media attention also enhances this relationship. These findings support our hypotheses that external monitoring amplifies biodiversity risk's positive impact on eco-innovation.

4.2.2. Technology diversification

Firstly, following Quintana-García and Benavides-Velasco (2008), we calculate the index by treating firms within the industry as a single entity and aggregating all patents applied for by these companies over the past five years. $TD_1 = 1 - \sum_{i=1}^{n} \left(\frac{P_i}{P}\right)^2$, where $\frac{P_i}{P}$ represents the proportion of the industry's total number of patents of the *i* firm. Secondly, following Subramanian et al. (2018), we use the cosine similarity method to calculate the relevance of a company's patents. $TD_2 = \frac{\sum_{k=1}^{n} p_{ik}p_{jk}}{\sqrt{\sum_{k=1}^{n} p_{ik}^2 \sum_{k=1}^{n} p_{jk}^2}}$, where p_{ik} represents the frequency of the *k*-th type of patent among all patents applied for by firms in industry *i* over the past five years, while p_{jk} represents the frequency of the *k*-th type of patent among patents applied for by company *j* in the same industry over the past five years. *n* denotes the total number of patent types within the industry over this five-year period. The regression results are shown in Table 6.

In columns (1) and (2), the positive and significant coefficients of *BRE* (494.441 and 507.797) indicate a strong relationship between biodiversity risk exposure and eco-innovation. However, the negative coefficients for *TD* (−0.725 and −0.626) and *BRE* × *TD* (−774.392 and −815.471) suggest that technology diversification weakens this relationship. Similarly, in columns (3) and (4), *BRE* remains significant and positive, while both *TD*1 and *BRE* × *TD*1 are negative and significant, indicating that higher technology diversification reduces biodiversity risk's positive impact on eco-innovation.

4.3. Heterogeneity analysis

The results confirm that higher biodiversity risk exposure is associated with increased levels of corporate eco-innovation. However, the influence of biodiversity risk varies in magnitude, firms have different characteristics, and they operate within diverse industry environments. Specifically, we focus on four dimensions that can influence a firm's response to biodiversity risk: (1) ESG performance, (2) supply chain concentration, (3) environmental regulation, and (4) industry heterogeneity. Under these varying circumstances, does the impact of biodiversity risk on corporate innovation differ? This section examines whether the effect of biodiversity risk on firms' eco-innovation varies across these channels.

4.3.1. ESG performance

Firms with high ESG ratings typically face greater scrutiny from investors, regulators and the public (Raghunandan and Rajgopal, 2022) for meeting their sustainability commitments. This reputational accountability motivates them to address biodiversity risks (Kopnina et al., 2024) through innovation as part of their broader ESG strategies. High ESG performers are likely to invest in eco-innovation not only to mitigate immediate biodiversity risks (Ziegler et al., 2022), but also to enhance their competitive advantage and align with long-term environmental goals (Srivastava et al., 2013).

We use a firm's ESG rating to represent its ESG performance, classifying firms with ratings of A, AA, BB, or BBB and above as the high ESG group, and all others as the low ESG group. Table 5 show significantly impact of ESG performance on relationship of *BRE-EI*.

4.3.2. Supply chain disruption

Biodiversity risks, such as resource depletion (Matopoulos et al., 2015), raw material shortages (Alonso et al., 2007), or transportation disruptions (Wilson, 2007), prompt companies to adopt innovative strategies to strengthen their supply chains. For instance, firms may invest in the development of alternative materials to reduce dependency on specific resources, thereby making the supply chain more resilient. Additionally, diversifying and multi-regionalizing supply chains become crucial strategies to mitigate risks associated with single-source disruptions (Wang et al., 2023). Firms may also adopt more flexible inventory management approaches to prepare for sudden interruptions (Kleindorfer and Saad, 2005). These innovations not only strengthen supply chain resilience but also improve firms' adaptability to biodiversity risks, allowing them to maintain a competitive edge in complex environments.

Following prior studies (e.g., Chen et al., 2023; Tang and Rai, 2012), We calculated supplier and customer concentration to measure the risk of supply chain disruption. Based on the percentage of purchases from a company's top five suppliers, we classified firms with values above the average as high concentration and those below the average as low concentration. Table 6 shows the channels through which supply chain concentration affects the *BRE-EI* relationship.

4.3.3. Environment regulation

When governments and international organizations recognize the impact of biodiversity loss, they are more likely to implement environmental policies or mandatory compliance standards aimed at mitigating these risks, such as the Kunming Declaration and the

Table 7
Heterogeneity analysis of Environmental Regulation
Table 7 represents the heterogeneity analysis of environmental regulation of Eq.1.

VARIABLES	Heterogeneity of environmental regulation			
	lowER *EInno* (1)	*HighER* *EInven* (2)	*lowER* = 0 *EInno* (3)	*HighER* *EInven* (4)
BRE	147.229	173.689**	110.456	225.827***
	(1.466)	(1.979)	(1.267)	(3.139)
Constant	−9.280***	−7.440***	−7.870***	−6.700***
	(−8.801)	(−8.238)	(−8.612)	(−8.218)
Observations	8471	10,819	8471	10,819
R-squared	0.809	0.748	0.793	0.730
Baseline Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
F	11.23	9.747	9.986	10.62

Table 8
Heterogeneity analysis of industry
Table 8 represents the heterogeneity analysis of industry of Eq.1.

VARIABLES	Heterogeneity of industry			
	Non − manufacturing *EInno* (1)	*Manufacturing* *EInven* (2)	*Non − manufacturing* *EInno* (3)	*Manufacturing* *EInven* (4)
BRE	193.388***	188.853	171.630***	235.991**
	(3.177)	(1.496)	(3.035)	(2.009)
Constant	−6.279***	−9.057***	−5.336***	−7.653***
	(−5.217)	(−10.929)	(−5.218)	(−9.870)
Observations	7330	11,960	7330	11,960
R-squared	0.749	0.752	0.729	0.735
Baseline Control	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
F	4.807	21.51	4.679	17.90

Montreal Protocol. These regulations limit the use of certain natural resources in production (Liu, 2023), enforce stricter waste management standards (Stafford, 2000), or require more sustainable operation (Yuan and Zhang, 2020). Such compliance requirements strongly motivate firm to invest in environmentally friendly technologies and green products to avoid penalties and meet legal standards.

Following Zhang et al. (2023), this paper uses government expenditure to measure the environmental regulation. We classify provinces with values above the average as the high environmental regulation group (high *ER*), and those below the average as the low environmental regulation group (low *ER*). Table 7 suggest that environmental regulation significantly enhance impact of *BRE* on *EI*.

4.3.4. Industry heterogeneity

Based on the analysis by He et al. (2024), the manufacturing sector among Chinese listed companies is less affected by biodiversity risks. In contrast, non-manufacturing sectors, such as agriculture, forestry, animal husbandry and fisheries, and environmental management, are more dependent on the sustainable use of natural resources and are subject to stricter biodiversity protection policies. Consequently, these non-manufacturing industries are more inclined to invest in eco-innovation to address these risks.

To test this hypothesis, we categorize the listed companies into manufacturing and non-manufacturing groups for heterogeneity analysis. Table 8 suggest that non-manufacturing significantly enhance impact of *BRE* on *EI*.

5. Conclusion

This study examines the impact of *BRE* on *EI*, revealing a significant positive relationship. Firms facing higher biodiversity risks are more likely to invest in eco-innovation. Several factors influence this *BRE-EI* relationship: external monitoring strengthens the impact, driving firms to address biodiversity risks more proactively. Conversely, technology diversification weakens the relationship, as firms with diverse technology may allocate fewer resources to biodiversity-focused innovations. Additionally, ESG performance, environmental regulations, supply chain disruption risks, and firms' sectors are channels in affecting the impact of biodiversity risk exposure on eco-innovation.

From a policy perspective, Chinese firms should emphasize managing biodiversity risks and actively engage in innovation related to biodiversity conservation. Such eco-innovations help firms cope with ecological challenges and enhance their competitive advantage in the global market. Specifically, firms can focus on developing technologies for ecological restoration, sustainable agricultural practices, and biodiversity monitoring to reduce their negative impacts on ecosystems and ensure resource stability. Additionally, firms should improve transparency and engage more actively with external stakeholders, including investors, regulators, and the public, to promote their sustainability efforts and ensure long-term success.

For policymakers, strengthening environmental regulations, particularly in biodiversity protection, is crucial to encouraging firms to increase their investments in eco-innovation. China can draw on international frameworks like the Kunming Declaration and the Montreal Protocol to strengthen national biodiversity policies while encouraging firms to adopt innovation-driven approaches to mitigate biodiversity risks. Furthermore, the government can provide incentives, such as green finance support and tax breaks, to foster the adoption of eco-innovations and accelerate the transition to a sustainable economy.

Despite these contributions, there are limitations to this study. First, our sample focuses on A-share listed firms in China, and future research could expand to include firms in other emerging markets or developed economies to compare how different economic contexts influence the relationship between biodiversity risks and eco-innovation. Developed economies may have better technological resources and institutional frameworks to address biodiversity risks, whereas emerging markets face more challenges related to governance and infrastructure, which would affect the relationship between BRE and EI. Second, this study does not delve deeply into the heterogeneity of industries in responding to biodiversity risks. Different industries face unique ecological challenges, and the focus of eco-innovation varies across sectors such as agriculture, energy, and manufacturing. Future research could explore industry-specific strategies for addressing biodiversity risks and developing tailored eco-innovation solutions.

CRediT authorship contribution statement

Ye Tian: Writing – review & editing, Writing – original draft, Visualization, Validation, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Heng Chen:** Validation, Supervision, Resources, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Variable Definition and Eco-Innovation

Table A.1 and A.2.

Table A.1
Variable definitions
This table provides detailed variable definitions. All firm characteristics are measured as of the end of the fiscal year. All continuous variables are winsorized at the 1st and 99th percentiles.

Variable	Definition
Dependent variables	
BRE	Measured by the frequency and ratio of biodiversity-related terms in firms' annual reports, using the biodiversity index by He et al. (2024).
Independent variable	
EI	Firm's efforts to address biodiversity risks through innovations tailored to biodiversity conservation, measured by the natural logarithm of one plus the number of adaptive eco-innovation patents (*EInno*), invention patents (*EInvent*), and utility patents (*EUtil*).
Control variable	
FirmAge	The length of time since a company was constructed.
ROE	A measure of a firm's profitability calculated as net income divided by equity asset.
Lev	The proportion of a firm's total liabilities to its total assets or equity.
TobinQ	Financial ratio that compares a firm's market value to the replacement cost of its assets.
Growth	The ratio of incremental revenue to revenue.
Cashflow	Cash flow to profit ratio.
INV	The proportion of a firm's inventory to its total assets.
Loss	A binary variable indicating if the firms are loss.
SOE	A binary variable indicating if the firms are state-owned enterprises.
Indep	The proportion of the board composed of external directors.

Table A.2
Eco-Innovation
The following table details the selection and rationale for the firm's eco-innovation patents.

Technology Category	IPC Classification	Reason for Addressing Biodiversity Risk
Gene Technology	A01H (Plant Breeding), C12 N (Genetic Engineering), C12Q 1/68 (Nucleic Acid Detection), C07 K 14/00 (Protein Engineering)	Gene technology, including gene editing and genetic modification, enhances crop resilience, disease resistance, and adaptability. This reduces dependence on single crop varieties, helping to maintain agricultural biodiversity. By developing crops better adapted to climate change and resistant to pests, companies contribute to ecosystem stability and protect biodiversity. Additionally, gene detection technologies help identify and preserve critical species, enabling businesses to participate actively in biodiversity conservation efforts.
Ecological Protection Technology	A01 N 63/00 (Microbial Biocides), C02F (Water Treatment), B09C (Soil Reclamation), A61 L 2/00 (Disinfection & Sterilization)	Ecological protection technologies, such as ecosystem restoration, pollution control, and disease prevention, mitigate the negative environmental impacts of industrial activities. For example, microbial preparations restore ecosystems by protecting habitats for plants and animals, while water pollution control technologies prevent harmful substances from entering aquatic ecosystems. Soil restoration technologies help recover polluted soils, supporting biodiversity in the ground. Disinfection technologies manage pathogens to prevent habitat degradation, protecting the diversity of ecosystems. These measures enable companies to safeguard and restore natural ecosystems, which is crucial for biodiversity conservation.
Sustainable Agriculture	A01 N (Biocides & Plant Regulators), A01 G 22/00 (Fungi Cultivation), A01C 3/00 (Seed Treatment), C05F (Waste-Derived Fertilizers)	Sustainable agriculture techniques, including eco-friendly pesticides, resource management, and organic fertilizers, help maintain biodiversity in agricultural ecosystems by reducing the use of chemical fertilizers and pesticides. Using biocompatible pesticides and plant growth regulators avoids harming non-target species, protecting diverse agricultural ecosystems. Integrated pest management and organic agricultural methods support biodiversity by reducing chemical inputs, preserving soil and aquatic diversity. Organic fertilizers not only improve soil health but also support soil microbial diversity, fostering a sustainable ecosystem. Through these practices, companies can protect biodiversity while enhancing agricultural productivity.
Biodiversity Monitoring Technology	G01 N 33/50 (Biological Chemical), C12Q 1/68 (Nucleic Acid Detection), G01 W 1/10 (Environmental Measurement), A01 M 17/00 (Pest Control Apparatus)	Biodiversity monitoring technologies enable companies to assess and track biodiversity changes in the environment, identify critical species, and respond to potential ecological risks in a timely manner. For example, immunological and microbiological sample analysis technologies help evaluate the health of species within ecosystems. Genetic monitoring can identify endangered species, supporting informed biodiversity conservation decisions. Environmental monitoring tracks ecosystem changes, identifying early signs of biodiversity loss. Pest and pathogen control equipment allows businesses to monitor harmful species and prevent interference with beneficial populations. These technologies support companies' efforts in biodiversity management and risk prevention.
Other Relevant Technologies	E04 (Construction), F03D (Wind Power), F24S (Solar Power), F24F (Air Conditioning)	Innovations in construction and renewable energy, such as green building, wind, and solar energy, help companies reduce reliance on natural resources and lessen ecological stress. These technologies lower greenhouse gas and pollutant emissions, benefiting biodiversity and environmental health. For example, green building minimizes habitat encroachment, supporting urban biodiversity. Wind and solar power provide low-carbon energy, avoiding the ecological damage of conventional energy extraction. Air conditioning technologies improve air quality, reducing pollution that can harm plants and animals. Through these technologies, companies decrease environmental disturbances and resource use, indirectly supporting biodiversity.

Appendix B. Robust Test

B.1 Instrumental-Variable Method

There are concerns about potential endogeneity and confounding factors that may affect the assessment of the impact of *BRE* on *EI*. Specifically, firm-level *BRE* may be influenced by unobserved factors that also influence its eco-innovation activities. For example, a firm's environmental strategy or positive attitude towards sustainability may simultaneously raise awareness of biodiversity risks and lead to higher levels of eco-innovation. This creates a bidirectional causality in which *BRE* and *EI* mutually determine each other, making causal inference difficult. In addition, a firm's *BRE* may be related to internal characteristics, such as management's environmental priorities or the availability of resources, which also influence its approach to innovation. Furthermore, *BRE* and *EI* may be influenced by confounding factors at the regional and industry levels, such as local regulatory pressures, environmental standards and public awareness of biodiversity issues. To correct estimation bias, we use the province-level density of ecological protection zones ($Edensity = numberofecologicalprotectionzones/area$) as an instrumental variable to identify the relationship between *BRE* and *EI*.

Specifically, for exogeneity, the *Edensity* in a province is largely determined by regional environmental policies and natural conservation priorities, which are external to any individual firm's operations or strategic decisions. This density reflects governmental and regional efforts to preserve biodiversity but does not directly influence a specific firm's eco-innovation initiatives, thus reducing the likelihood of reverse causality. For relevance, *Edensity* is likely to be positively correlated with a firm's *BRE*. Regions with higher densities of protected areas typically have stricter biodiversity conservation standards and greater regulatory scrutiny, increasing firms' awareness and perceived risk of biodiversity-related issues. This environmental context shapes firms perceived *BRE*, as they are more likely to recognize the importance of biodiversity risk when operating within or near areas with strong ecological protection measures.

Table B.1 presents the results using IV, with columns (1) reporting the first-stage regression findings. The *Edensity* shows a significant positive effect on *BRE* ($p < 0.01$), confirming that *Edensity* is strongly associated with firm's biodiversity risk exposure. These results align with expectations, regions with higher *Edensity* heighten firms' awareness and perceived biodiversity risks. The IV passed the overidentification test ($p < 0.0000$) and Weak identification ($Cragg - DonaldWaldF > 10$).

In the second stage, the predicted *BRE* shows a positive and statistically significant impact on eco-innovation measures (*EInno, EInven*, and *EUtil*), with coefficients of 986.275, 858.362, and 813.997, respectively. This suggests that higher biodiversity risk exposure leads to increased eco-innovation efforts. Therefore, we use *Edensity* to address potential endogeneity issues, thereby making the results of the study more robust.

B.2. Eliminate reverse causality

To address potential reverse causality in our analysis, we use a one-year lag of *BRE* as an alternative measure. Specifically, we examine the impact of BRE_{t-1} in year $t-1$ on its current eco-innovation activities. By using a lagged measure of biodiversity risk exposure, we aim to ensure that the observed relationship reflects the influence of past levels of biodiversity risk on current eco-innovation efforts, ruling out the influence of eco-innovation on the level of biodiversity risk exposure.

The results remain consistent with those of the baseline model, indicating that the relationship between biodiversity risk exposure and eco-innovation is unlikely to be driven by reverse causality. This approach enhancing the robustness of our conclusions.

B.3. Alternative measure of eco-innovation

In the baseline model, we use the annual number of eco-innovation patents filed by firms to represent eco-innovation. Acknowledging that not all patent applications may be approved, we use the number of granted eco-innovation patents as an alternative indicator for robustness checks. Specifically, *EInnoA, EInvenA*, and *EUtilA* represent the natural logarithms of the number of eco-innovation patents, invention patents, and utility model patents granted to firm. The reported results for these alternative indicators align closely with our benchmark regression results (see Columns (4) - (6) of Table B.2).

B.4. High dimension fixed effects regression

To mitigate potential endogeneity problems due to omitted variable bias, we use a high-dimensional fixed effects model. Specifically, we include industry-year fixed effects in the model. The results in columns (7) - (9) of Table B.2 show that the coefficients on *EInno, EInven* and *EUtil* are 190.848, 186.767 and 94.405 respectively, all of which are significant at the 1 % level. This indicates that our results are robust to the inclusion of industry trends characteristics, which do not affect our results.

B.5. Evidence from CSRC's enhanced environmental disclosure

Since the publication of the "Guiding Opinions on Building a Green Financial System" in 2016, China has gradually implemented mandatory environmental information disclosure for listed companies and bond-issuing enterprises as part of its green financial policy. This policy aims to enhance corporate environmental responsibility and transparency. In June 2017, the China Securities Regulatory Commission (CSRC) and the former Ministry of Environmental Protection signed an agreement to promote environmental information disclosure, followed by revisions to disclosure standards in 2017, which established a layered disclosure system. Key polluting companies are required to disclose environmental information, while other companies follow a "comply or explain" principle. Voluntary disclosure for ecological protection and pollution prevention is also encouraged.[2] These regulatory changes serve as an exogenous policy shock, providing a natural experiment to analyze how changes in environmental disclosure influence corporate

[2] For more details, please see http://www.csrc.gov.cn/csrc/c101800/c1003858/content.shtml.

behavior, especially how biodiversity risk exposure affects eco-innovation.

Specifically, we use the changes in China's environmental information disclosure regulations as an exogenous policy shock to identify the causal relationship between biodiversity risk exposure (BRE) and eco-innovation. The policy is exogenous because it was driven by external regulatory decisions, not by firms' internal characteristics or behaviors, making it a natural experiment. For example, the mandatory disclosure for high-polluting companies and the "comply or explain" principle for others were implemented regardless of individual firms' prior actions or innovation capacity. The policy is also highly relevant, as it directly impacts how firms manage and report environmental risks, providing strong incentives for eco-innovation. Firms exposed to higher biodiversity risks are more likely to innovate to meet disclosure requirements, creating a clear link between biodiversity risk and eco-innovation. This external and relevant policy shock allows us to isolate the causal effect of biodiversity risk exposure on eco-innovation, minimizing endogeneity concerns.

In this study, we use the policy changes related to environmental information disclosure to identify the causal effect of biodiversity risk exposure (BRE) on corporate eco-innovation, employing the Difference-in-Differences (DID) methodology. While all firms are affected by the environmental disclosure policy, we hypothesize that the impact varies across firms due to heterogeneous responses. Specifically, firms with higher levels of biodiversity risk disclosure before the policy implementation are expected to be more influenced by the regulatory change. Based on this assumption, we classify the firms into two groups: a high-disclosure group (*Post_H*) and a low-disclosure group (*Post_L*), depending on their level of biodiversity risk disclosure before the policy was enacted. By comparing the changes in eco-innovation between the high and low disclosure groups before and after the implementation of the policy, we can more accurately identify how changes in *BRE* affect firms' EI. Following Lins et al. (2017), we use the following regression equation based on Eq.1 to test these proposed channels:

$$BRE_{i,t} = \beta_0 + \beta_1 Treat_i \times Post\_L_{i,t} + \beta_2 Treat_i \times Post\_H_{i,t}$$
$$+ \sum_k \alpha_k Controls^k_{i,t} + \mu_i + \delta_t + \varepsilon_{i,t} \tag{3}$$

Where, $BRE_{i,t}$ and $Controls^k_{i,t}$ are the same as in Eq.1. $Post\_H_{i,t}$ and $Post\_L_{i,t}$ are indicator variables, which, after policy implementation, are equal to the companies in the high group and low group, respectively. The high group and low group are defined based on the following three partition variables. $Treat_i$is a binary indicator variable that takes the value of 1 if the year is greater than 2016 for the firm, and 0 otherwise.

We aim to identify the impact of biodiversity risk exposure on corporate eco-innovation using the policy change those mandates enhanced environmental information disclosure. This policy provides a unique opportunity to isolate the effect of biodiversity risk exposure, as it specifically increases firms' disclosure of biodiversity risks without influencing other factors. The empirical results align with this approach. Firms with higher biodiversity risk disclosure (the high-disclosure group) show a significant increase in eco-innovation, as indicated by the positive and statistically significant coefficients for *Post_H* × *Treat* across all innovation measures (*EInno, EInven*, and*EUtil*). This suggests that the policy's effect on disclosure directly influences eco-innovation outcomes in firms that were already transparent about their environmental risks.

In contrast, firms with low biodiversity risk disclosure (the low-disclosure group) did not exhibit significant changes in innovation outcomes, as the coefficients for *Post_L* × *Treat* are not statistically significant. This further supports our argument. Thus, the policy allows us to cleanly estimate the causal relationship between biodiversity risk exposure and eco-innovation, by focusing on the exogenous change in disclosure levels while holding other factors constant.

Table B.1
Instrumental-variable method
Table B.1 reports 2*SLS* regressions using density of ecological protection zones.

	IV-2SLS method solves the endogeneity problem			
	First-stage		Second-stage	
VARIABLES	*BRE* (1)	*EInno* (2)	*EInven* (3)	*EUtil* (4)
Edensity	0.001***			
	(6.36)			
$\widehat{BRE}$		986.275**	858.362***	813.997**
		(2.42)	(2.66)	(2.16)
Observations	19,388	19,388	19,388	19,388
R^2	0.900	0.0457	0.0448	0.0281
Baseline Control	N	Y	Y	Y
Year FE	Y	Y	Y	Y
Industry FE	Y	Y	Y	Y
Under identification		24.103	24.103	24.103
P-value		(0.0000)	(0.0000)	(0.0000)
Weak identification		27.192	27.192	27.192

Table B.2
Robust test
Table B.2 reports the results of the estimation of Eq.1. In Column (1), we use rice suitability as a proxy for clan culture. Column (2) excludes natural monopoly industries, such as energy, power, and telecommunications. Column (3) removes firms located in municipalities directly under the central government. Columns (4) - (7) re-estimate Eq.1 using Poisson regressions.

	Inverse Causation			Alternative Green Innovation			Ommit variables		
VARIABLES	*EInno* (1)	*EInven* (2)	*EUtil* (3)	*EInnoA* (4)	*EInvenA* (5)	*EUtilA* (6)	*EInno* (7)	*EInven* (8)	*EUtil* (9)
BRE_{t-1}	213.835***	209.308***	104.026*						
	(3.916)	(4.153)	(1.939)						
BRE_t				225.708***	96.950***	223.625***	190.848***	186.767***	94.405***
				(3.696)	(2.941)	(6.587)	(4.533)	(5.158)	(2.669)
Constant	0.207	0.069	−0.099	−0.550	−0.575*	−0.461*	0.925***	0.895***	0.197
	(0.396)	(0.147)	(−0.253)	(−1.195)	(−1.825)	(−1.881)	(3.026)	(3.404)	(0.767)
Observations	17,372	17,372	17,372	19,290	19,290	19,290	19,290	19,290	19,290
(Pseudo)R^2	0.744	0.725	0.707	0.738	0.656	0.703	0.754	0.733	0.722
Baseline Control	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Industry-Year FE	N	N	N	N	N	N	Y	Y	Y
F	4.818	4.392	3.084	4.434	3.764	11.26	7.623	6.558	5.570

Table B.3.

Table B.3
Evidence from CSRC's Enhanced Environmental Disclosure
This table presents the results of estimating Eq. (3). Following the methodology of previous studies (Lins et al., 2017), we classify firms into two groups based on their level of biodiversity risk disclosure before the policy implementation. Firms are categorized into high-disclosure and low-disclosure groups, depending on whether their biodiversity risk disclosure is above or below the mean level. *Post_H* is a dummy variable indicating firms in the high-disclosure group before the policy change. Table A1 provides the definitions of the variables.

VARIABLES	(1) *EInno*	(2) *EInven*	(3) *EUtil*
Post_H × *Treat*	0.217***	0.190***	0.152***
	(3.170)	(3.409)	(2.828)
Post_L × *Treat*	0.078	0.064	0.073
	(1.152)	(1.155)	(1.365)
Constant	−0.108	−0.302	−0.156
	(−0.230)	(−0.727)	(−0.437)
Observations	19388	19388	19388
R-squared	0.726	0.704	0.688
Baseline Control	Y	Y	Y
Year FE	Y	Y	Y
Firm FE	Y	Y	Y
F	7.098	6.560	4.732

Data availability

Data will be made available on request.

References

Ahmad, M.F., Karpuz, A., 2024. Beyond climate change risk: biodiversity and corporate cash holdings. Econ. Lett. 236, 111608.
Akbar, A., Jiang, X., Akbar, M., 2022. Do working capital management practices influence investment and financing patterns of firms? J. Econ. Administr. Sci. 38 (1), 91–109.
Alonso, E., Gregory, J., Field, F., & Kirchain, R. (2007). Material availability and the supply chain: risks, effects, and responses.
Antweiler, W., Frank, M.Z., 2004. Is all that talk just noise? The information content of internet stock message boards. J. Fin. 59 (3), 1259–1294.
Branco, M.C., Rodrigues, L.L., 2006. Corporate social responsibility and resource-based perspectives. J. Bus Ethic.s 69, 111–132.
Cai, W., Li, G., 2018. The drivers of eco-innovation and its impact on performance: evidence from China. J. Clean. Prod. 176, 110–118.
Campbell Gemmell, J., Marian Scott, E., 2013. Environmental regulation, sustainability and risk. Sustain. Account., Manage. Policy J. 4 (2), 120–144.
Chang, C.H., 2011. The influence of corporate environmental ethics on competitive advantage: the mediation role of green innovation. J. Bus. Ethics 104, 361–370.
Chen, M., Tang, X., Liu, H., Gu, J., 2023. The impact of supply chain concentration on integration and business performance. Int. J. Prod. Econ. 257, 108781.
Chen, Z., Xie, G., 2022. ESG disclosure and financial performance: moderating role of ESG investors. Int. Rev. Financ. Anal. 83, 102291.
Dantas, M. (2021). Are ESG funds more transparent?. *Available at SSRN 3269939*.
Frank, E.G., 2024. The economic impacts of ecosystem disruptions: costs from substituting biological pest control. Science 385 (6713), eadg0344.

García-Granero, E.M., Piedra-Muñoz, L., Galdeano-Gómez, E., 2018. Eco-innovation measurement: a review of firm performance indicators. J. Clean. Prod. 191, 304–317.
Garel, A., Romec, A., Sautner, Z., Wagner, A.F., 2024. Do investors care about biodiversity? Rev. Financ. 28 (4), 1151–1186.
Giglio, S., Kuchler, T., Stroebel, J., Zeng, X., 2023. *Biodiversity Risk* (No. w31137). National bureau of economic research.
Guerci, M., Longoni, A., Luzzini, D., 2016. Translating stakeholder pressures into environmental performance–the mediating role of green HRM practices. The Int. J. Human Res. Manage. 27 (2), 262–289.
Hart, S.L., 1995. A natural-resource-based view of the firm. Acad. Manage. Rev. 20 (4), 986–1014.
He, F., Chen, L., Lucey, B.M., 2024. Chinese corporate biodiversity exposure. Financ. Res. Lett., 106275
Kalhoro, M.R., Kyaw, K., 2024. Manage biodiversity risk exposure? Financ. Res. Lett. 61, 104989.
Kleindorfer, P.R., Saad, G.H., 2005. Managing disruption risks in supply chains. Prod. Oper. Manage 14 (1), 53–68.
Kopnina, H., Zhang, S.R., Anthony, S., Hassan, A., Maroun, W., 2024. The inclusion of biodiversity into Environmental, Social, and Governance (ESG) framework: a strategic integration of ecocentric extinction accounting. J. Environ. Manage. 351, 119808.
Lavie, D., Stettner, U., Tushman, M.L., 2010. Exploration and exploitation within and across organizations. Acad. Manage Ann. 4 (1), 109–155.
Liang, C., Yang, J., Shen, L., Dong, D., 2024. The role of biodiversity risk in stock price crashes. Financ. Res. Lett. 67, 105856.
Leoncini, R., Marzucchi, A., Montresor, S., Rentocchini, F., Rizzo, U., 2019. Better late than never': the interplay between green technology and age for firm growth. Small Bus. Econ. 52, 891–904.
Lins, K.V., Servaes, H., Tamayo, A., 2017. Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis. J. Fin. 72 (4), 1785–1824.
Liu, X., 2023. Tourism development, environmental regulations, and natural resource management: evidence from G20 countries. Resour. Policy. 86, 104224.
Ma, F., Wu, H., Zeng, Q., 2024. Biodiversity and stock returns. Int. Rev. Financ. Anal., 103386
Matopoulos, A., Barros, A.C., Van der Vorst, J.G.A.J, 2015. Resource-efficient supply chains: a research framework, literature review and research agenda. Int. J. 20 (2), 218–236.
Pfeffer, J., Salancik, G., 2015. External control of organizations-Resource dependence perspective. Organizational behavior 2. Routledge, pp. 355–370.
Quintana-García, C., Benavides-Velasco, C.A., 2008. Innovative competence, exploration and exploitation: the influence of technological diversification. Res. Policy. 37 (3), 492–507.
Raghunandan, A., Rajgopal, S., 2022. Do ESG funds make stakeholder-friendly investments? Rev. Account. Stud. 27 (3), 822–863.
Shan, H., Zhao, K., Liu, Y., 2024. ESG performance and the persistence of green innovation: empirical evidence from Chinese manufacturing enterprises. Multinat. Bus. Rev.
Srivastava, M., Franklin, A., Martinette, L., 2013. Building a sustainable competitive advantage. J. Techn. Manage. Inn. 8 (2), 47–60.
Stafford, S.L., 2000. The impact of environmental regulations on the location of firms in the hazardous waste management industry. Land. Econ. 569–589.
Subramanian, A.M., Bo, W., Kah-Hin, C., 2018. The role of knowledge base homogeneity in learning from strategic alliances. Res. Policy. 47 (1), 158–168.
Suding, K.N., Collins, C.G., Hallett, L.M., Larios, L., Brigham, L.M., Dudney, J., Spasojevic, M.J., 2024. Biodiversity in changing environments: an external-driver internal-topology framework to guide intervention. Ecology. 105 (8), e4322.
Sulkowski, A.J., Edwards, M., Freeman, R.E., 2018. Shake your stakeholder: firms leading engagement to cocreate sustainable value. Organ. Environ. 31 (3), 223–241.
Tang, X., Rai, A., 2012. The moderating effects of supplier portfolio characteristics on the competitive performance impacts of supplier-facing process capabilities. J. Operat. Manage. 30 (1–2), 85–98.
Treepongkaruna, S., 2024. Corporate sustainability and biodiversity reporting: a proactive business strategy to mitigate litigation and reputational risks. Bus. Strategy. Environ.
Tushman, M.L., O'Reilly, C.A., 1996. Ambidextrous organizations: managing evolutionary and revolutionary change. Calif Manage. Rev. 38 (4), 8–30.
Wang, Q., Zhou, H., Zhao, X., 2023. The role of supply chain diversification in mitigating the negative effects of supply chain disruptions in COVID-19. *Int. J. Operat. Prod. Manage.*, (ahead-of-print).
Wilson, M.C., 2007. The impact of transportation disruptions on supply chain performance. Log. Transp. Rev. 43 (4), 295–320.
Wu, Z., Pagell, M., 2011. Balancing priorities: decision-making in sustainable supply chain management. Jf Operat. Manage. 29 (6), 577–590.
Yuan, B., Zhang, Y., 2020. Flexible environmental policy, technological innovation and sustainable development of China's industry: the moderating effect of environment regulatory enforcement. J. Clean. Prod. 243, 118543.
Li, Yulin, Liu, Xiaohui, Canil, Jean, Cheong, Chee Seng, 2024. Biodiversity risk and firm efficiency. Financ. Res. Lett. 106414. ISSN: 1544-6123.
Zhang, X., Huang, S., Li, W., Wang, Y., 2023. Directors' and officers' liability insurance, environmental regulation and firms' environmental responsibility. Ecolog. Econ. 208, 107796.
Ziegler, R., Balzac-Arroyo, J., Hölsgens, R., Holzgreve, S., Lyon, F., Spangenberg, J.H., Thapa, P.P., 2022. Social innovation for biodiversity: a literature review and research challenges. Ecol. Econ. 193, 107336.