

Monitoring or Selection?

Institutional Ownership and Biodiversity Incidents

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Abstract

I examine the value consequences of biodiversity incidents and their association with institutional ownership. Markets react negatively, with average shareholder losses ranging from \$76 million to \$344 million per incident. Additional stock price declines around subsequent earnings announcements are consistent with market underreaction. Institutional ownership is negatively associated with incident occurrence. Using plausibly exogenous shocks to monitoring intensity, I distinguish monitoring from selection effects. Long-term and domestic institutions, especially insurance firms and public pension funds, reduce incidents through active monitoring, whereas short-term and foreign investors, particularly investment advisors, exhibit selection behavior. Evidence from shareholder proposals supports a governance-via-voice mechanism, with withdrawn biodiversity-related proposals associated with lower incident re-occurrence. Finally, incidents are positively associated with the cost of equity capital, suggesting that investors demand compensation for biodiversity risk exposure.

JEL: G23; Q57; G14; M14

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1 Introduction

Over the past decade, academic researchers have increasingly examined the complex relationship between the modern economy and environmental degradation. Most notably, climate finance, the study of financing public and private investment to support climate change mitigation and adaptation, has evolved into an active research area (see [Hong et al. 2020](#), [Krüger et al. 2020](#), [Giglio et al. 2021](#), [Stroebe and Wurgler 2021](#) for reviews of this literature). However, climate change is only one dimension of the broader set of environmental risks associated with economic activity. Another important area that has recently gained attention in the financial economics literature is the economic and financial risks stemming from biodiversity loss, i.e., the decline in the variety of living organisms across ecosystems, largely influenced by human activity ([Heal 2004](#), [Giglio et al. 2024](#), [Flammer et al. 2025](#)).

Biodiversity loss has emerged as a topic of increasing relevance to global risk assessments. The World Economic Forum’s Global Risk Reports have consistently listed biodiversity loss among the top five global risks in terms of likelihood and impact (e.g. [WEF 2024](#)). Biosphere integrity has been identified as a breached planetary boundary ([Rockström et al. 2009](#), [Steffen et al. 2015](#)), and the World Wide Fund for Nature has reported a 73% average decline in monitored wildlife populations from 1970 to 2020 ([WWF 2024](#)). Many industries rely either directly or indirectly on biodiversity, as it supports ecosystem services such as soil fertility, crop pollination, and timber supply ([Ali et al. 2024](#), [Flammer et al. 2025](#)). According to the United Nations, more than half of global GDP is moderately or highly dependent on natural systems ([UN 2022](#)). As such, the preservation of biodiversity is increasingly viewed as relevant to long-term economic sustainability ([Giglio et al. 2024](#), [Bellon 2025](#)).

Firms are exposed to biodiversity-related risks through both physical channels (e.g., supply chain disruptions) and transition channels (e.g., evolving regulations or shifting consumer preferences) (see [IFC 2019](#), [OECD 2019](#), [Li et al. 2024](#)). In response, regulatory and market-based initiatives have begun to address these risks. For example, the Taskforce on Nature-related Financial Disclosures released a risk-based framework to guide firms in assessing and disclosing nature-related dependencies and risks ([TNFD 2023](#)). These initiatives have contributed to growing institutional expectations for firms to address biodiversity-related concerns, prompting increased stakeholder scrutiny ([Boiral and Heras-Saizarbitoria 2017](#), [Elmagrhi et al. 2019](#), [Dai et al. 2021](#)). Failure to manage biodiversity exposures may lead to reputational harm or

regulatory sanctions, including potential loss of operating licenses ([Carvajal et al. 2022](#)). Consequently, biodiversity-related risks may have material implications for firms' financial performance and long-term viability ([Fernando et al. 2017](#)).

Despite these developments, the intersection of biodiversity and finance has received limited academic attention. Biodiversity finance, the financing of biodiversity goals using public and private capital, has emerged as a potential mechanism to address these challenges ([Karolyi and Tobin-de la Puente 2023](#), [Starks 2023](#), [Flammer et al. 2025](#)). Nonetheless, leading finance journals have only recently begun to publish work in this area, as highlighted by [Karolyi and Tobin-de la Puente \(2023\)](#) and a recent special issue of the *Review of Finance*. The question of how private financing flows need to be intermediated to address biodiversity loss remains an open research gap, further echoed in Laura Stark's Presidential Address at the 2023 American Finance Association Meetings ([Starks 2023](#)). This paper contributes to the emerging literature by examining the financial implications of biodiversity incidents and their relationship with institutional ownership.

Institutional investors have both the incentives and capacity to influence corporate practices. Most institutional investors face biodiversity risks on the asset side of their portfolios; some, notably insurers, face risks on both asset and liability sides. It is therefore not surprising that institutional investors are increasingly attentive to biodiversity-related risks ([Giglio et al. 2023](#)). Compared to retail investors, they are typically more specialized and sophisticated (see [Dasgupta et al. 2021](#)). Controlling nearly 70% of U.S. equity by the end of 2020 ([Medina et al. 2022](#)), they often hold collective majority stakes, enabling effective stewardship action ([Dimson et al. 2015](#)). Existing research shows that institutional pressure can significantly reduce firms' climate risks and environmental costs ([Dimson et al. 2015](#), [Pedersen et al. 2021](#), [Stroebel and Wurgler 2021](#), [Dimson et al. 2023](#), [Pastor et al. 2023](#), [Cenedese et al. 2024](#)). Moreover, institutional ownership and engagement influence corporate behavior across environmental, social, and governance dimensions (see [Matos 2020](#), [Gillan et al. 2021](#)). These developments have coincided with a significant increase in institutional ownership of publicly listed firms globally ([Franks 2020](#), [Döring et al. 2021](#)). To date, however, no study has empirically examined the association between institutional ownership and biodiversity risk.

Based on these arguments, my main testable hypothesis is that institutional investors incorporate biodiversity risk into their investment and engagement processes, which should be reflected

in a negative relationship between institutional ownership and biodiversity incidents in their portfolio firms. To test this hypothesis, I compile a sample of over 15,000 biodiversity incident news from RepRisk, involving more than 7,000 unique firms listed on U.S. stock markets between 2007 and 2022. These incidents, captured through systematic monitoring of media and stakeholder sources, include manifestations of physical risks, such as oil spills that damaged ecosystems and led to costly settlements, and transition risks, such as activist protests targeting supply chains linked to deforestation, which led to reputational damage.

I begin by analyzing stock market reactions to biodiversity incidents using event-study methodology. The results indicate that incidents are associated with significantly negative abnormal returns, suggesting that markets perceive them as value-reducing. Estimated shareholder losses average from \$76 million to \$344 million per event, with new incidents having a more negative impact than re-occurring ones. Moreover, the initial market responses appear incomplete, with additional adverse information reflected in subsequent earnings announcements. This delayed adjustment is consistent with investor underreaction, where corrective price movements occur as longer-term consequences (such as reputational effects) become evident.

Having established that biodiversity incidents entail economically meaningful costs for shareholders, I turn to the association between institutional ownership and biodiversity incidents. Regression results indicate that higher institutional ownership is associated with a lower probability of subsequent biodiversity incidents, suggesting a potential role for institutional investors in mitigating biodiversity-related exposures. All regressions include a comprehensive set of firm and ownership control variables, saturated fixed effects at both the firm and time levels, and two-way clustered standard errors. These findings are robust across multiple biodiversity incident measures, alternative estimation methods (linear probability models, Tobit, Poisson pseudo-maximum probability regressions), and more restrictive samples. Economically, a one-standard-deviation increase in institutional ownership is associated with a 10% to 16% decrease in the likelihood of future incidents, depending on the specification.

Given that investors may endogenously avoid firms with high biodiversity risk, concerns about reverse causality and omitted variable bias arise. To address endogeneity, I implement several strategies. First, I lag all explanatory variables to mitigate simultaneity bias. Second, the results remain robust when controlling for firms' historical biodiversity profile, suggesting that institutional ownership influences risk management practices rather than simply reflecting historical

firm behavior. Third, I exploit plausibly exogenous shocks to institutional monitoring intensity (Kempf et al. 2017), allowing me to better isolate monitoring effects from selection. While these strategies cannot entirely eliminate endogeneity concerns, the collective evidence is consistent with a causal interpretation.

Ex ante, it is unclear whether the relationship between institutional ownership and biodiversity incidents is homogeneous across investor types or whether certain subgroups exhibit distinct patterns of selection and monitoring. To investigate this heterogeneity, I apply the identification strategy separately across investor subgroups classified by investment horizon (Krüger et al. 2020, Döring et al. 2021, Starks et al. 2025), geographic origin (Kim et al. 2019, Döring et al. 2023, Brockman et al. 2024), investment strategy (Bushee and Noe 2000, Bushee 2001), and legal form (Bushee 2001). The findings indicate that long-term and domestic investors reduce biodiversity incidents through active monitoring, whereas short-term investors are more likely to engage in selection. In particular, evidence of a monitoring role emerges for insurance companies and public pension funds, while independent investment advisors predominantly select into lower-risk firms.

To further examine the mechanism through which institutional investors affect biodiversity outcomes, I study shareholder proposals. Shareholders can seek to induce changes in corporate conduct through a broad spectrum of activities, including divesting, engaging in negotiations with management, or submitting shareholder proposals (McCahery et al. 2016). Focusing on the governance-via-voice channel, I estimate proposal-level multinomial logit regressions to examine the likelihood of proposal outcomes conditional on sponsor type. The results reveal that biodiversity-related proposals submitted by institutional investors are more likely to be withdrawn and less likely to be omitted, consistent with private negotiations with firm management (Carleton et al. 1998, David et al. 2007, Bauer et al. 2015). I then aggregate proposal activity at the firm level to assess its association with subsequent biodiversity incidents. The analysis indicates that a higher frequency of withdrawn biodiversity-related proposals, but not of unrelated ESG proposals, is associated with a lower likelihood of recurring, but not new, incidents. This suggests that institutional investors engage in targeted governance interventions using a voice strategy aimed at correcting misconduct by repeat offenders.

Finally, to assess the pricing implications of biodiversity risk, I analyze the cost of capital. Garel et al. (2024) provide early empirical evidence that investors demand a biodiversity risk premium. They show that firms with large corporate biodiversity footprints experienced negative

abnormal returns around the Kunming Declaration (2021)¹, followed by relatively higher returns afterward—consistent with a risk premium channel. This pattern indicates that investors have begun to anticipate future regulatory or legal challenges for such firms. In line with [Pastor and Veronesi \(2012\)](#), the increase in economic policy uncertainty following these events suggests that investors demand compensation for biodiversity-related exposures. I similarly hypothesize that greater exposure to biodiversity risk raises the cost of equity. Following prior literature ([El Ghouli et al. 2011](#), [El Ghouli et al. 2018](#), [Lee et al. 2021](#), [Garel et al. 2024](#)), I estimate firms’ implied cost of equity capital using the valuation models of [Claus and Thomas \(2001\)](#) and [Gebhardt et al. \(2001\)](#) as well as the abnormal growth models of [Easton \(2004\)](#) and [Juettner-Nauroth \(2005\)](#). The results indicate a positive relationship between biodiversity risk and the cost of capital. Similar to carbon emissions ([Bolton and Kacperczyk 2021](#), [Bolton and Kacperczyk 2023](#)), this finding suggests that markets price biodiversity-related risks.

This paper makes four contributions to the literature. First, it responds to recent calls for empirical research in biodiversity finance ([Karolyi and Tobin-de la Puente 2023](#), [Starks 2023](#)) by examining the relationship between institutional ownership and biodiversity incidents. While prior studies emphasize the need to mobilize private capital for biodiversity preservation (e.g., [Karolyi and Tobin-de la Puente 2023](#), [Coqueret et al. 2025](#), [Flammer et al. 2025](#)), empirical evidence on actual investor behavior remains limited. This study helps address that gap by documenting the role of institutional investors in mitigating biodiversity-related risks and identifying heterogeneity across investor types, particularly along dimensions of investment horizon ([Krüger et al. 2020](#), [Döring et al. 2021](#), [Starks et al. 2025](#)), geographic origin ([Kim et al. 2019](#), [Döring et al. 2023](#), [Brockman et al. 2024](#)), investment strategy ([Bushee and Noe 2000](#), [Bushee 2001](#)), and legal form ([Bushee 2001](#)).

Second, building on emerging evidence of biodiversity risk premia ([Giglio et al. 2023](#), [Garel et al. 2024](#), [Coqueret et al. 2025](#), [Garel et al. 2025](#)), the paper provides novel insights by documenting abnormal returns around biodiversity incidents and subsequent earnings announcements, as well as by linking biodiversity risk to a higher implied cost of equity. These findings contribute to the broader literature on the pricing of environmental risks, particularly in relation to carbon emissions ([Bolton and Kacperczyk 2021](#), [Bolton and Kacperczyk 2023](#)). The delayed market re-

¹On October 13, 2021, the Kunming Declaration was adopted by over 100 countries at the first part of the ongoing 15th meeting of the Conference of the Parties (COP15) to the United Nations Convention on Biological Diversity (CBD). The declaration outlines general targets for the restoration and protection of biodiversity.

action to biodiversity incidents also suggests inefficiencies in how such risks are processed, raising questions about disclosure quality and investor awareness (TNFD 2023, Ali et al. 2024).

Third, the paper contributes to research on institutional investor environmental engagement. While prior studies have primarily focused on climate-related activities (Dimson et al. 2015, Pástor et al. 2022, Ilhan et al. 2023), this study shows that institutional investors also influence biodiversity outcomes through both selection and monitoring channels. It thereby adds to the growing literature on impact investing (Kölbel et al. 2020), which examines the extent to which investor actions induce changes in corporate behavior.

Fourth, the paper complements the extant literature on the effects of shareholder activism via voice, which has mainly focused on corporate governance (e.g., Gillan and Starks (2000)) and financial performance (e.g., Becht et al. (2009); Flammer (2015)). Consistent with recent evidence that institutional voice can improve environmental outcomes (Heeb et al. 2023), the analysis of shareholder proposals suggests that targeted engagement strategies, especially those resulting in withdrawn proposals, may help reduce repeated biodiversity incidents. This complements recent evidence on the growing influence of shareholder proposals in the ESG context (Flammer et al. 2021).

The remainder of the paper is organized as follows. In Section 2, I introduce the measures of biodiversity risk and present descriptive statistics for the data. Section 3 documents the main empirical results, and Section 4 provides robustness tests. Section 5 concludes.

2 Data and descriptive statistics

2.1 Biodiversity incidents measures

Conventional ESG rating providers base their assessments, to varying degrees, on publicly available data found in the sustainability sections of firms’ annual reports or sustainability reports. This practice raises concerns over reporting bias and the potential for greenwashing, whereby firms strategically overstate their ESG efforts in self-reported disclosures ([Montgomery et al. 2024](#)). Moreover, substantial divergence in ESG ratings across providers further limits their reliability for empirical research ([Berg et al. 2022](#)).

To mitigate these concerns, I employ more objective measures of ESG risk from RepRisk, a Zurich-based ESG data provider. RepRisk adopts an event-driven, rather than firm-reported, methodology: it collects information on ESG-related incidents from more than 150,000 local, national, and international media and stakeholder sources in 23 languages. These include print and online media, NGOs, and government agencies. Each incident is classified into one of 28 predefined categories within the environmental, social, governance, and miscellaneous dimensions. As RepRisk’s data are not sourced from firms themselves, they offer a more difficult-to-manipulate signal of ESG-related events. Another key advantage of incident-based measures is their forward-looking nature.² As emphasized by [Cenedese et al. \(2024\)](#), forward-looking indicators capture a firm’s ambition and efforts to limit future biodiversity loss. Incident data, therefore, provide a useful signal of firms’ willingness to reduce their biodiversity footprint, with implications for both physical and transition risks.

For the purpose of this study, I focus on incidents classified under the category “impacts on landscapes, ecosystems, and biodiversity.” This category is the largest within the environmental pillar, accounting for 38.3% of environmental incidents and 8.5% of total ESG incidents. My choice reflects the fact that changes in land use are the main drivers of biodiversity loss ([IPBES 2019](#), [Jaureguiberry et al. 2022](#)). When a larger share of land is allocated to generate economic output, the biomass of each species falls, leading to an increase in the probability of species extinction. This loss of biodiversity reduces the productivity of the ecosystem and increases its fragility, making it more sensitive to further losses due to continued changes in land

²An alternative approach is to estimate a firm’s biodiversity footprint ([Garel et al. 2024](#)). While this method quantifies current ecological impact, it may not fully capture managerial intent to mitigate future risks, which is arguably central to investors’ assessments.

use (Cleland 2011). Examples of biodiversity incidents include repeated oil spills from Shell’s Trans-Niger pipeline, which damaged mangrove forests and aquatic ecosystems. These physical risks materialized financially when Shell agreed to a £55 million (approximately \$83 million) settlement. Transition risks are exemplified by Greenpeace’s protests targeting McDonald’s supply chain links to deforestation. In response, McDonald’s shareholders submitted a resolution in December 2024 requesting a biodiversity impact assessment of its operations and supply chains.

From the RepRisk data, I construct several biodiversity incident variables. The primary dependent variable is the binary indicator $\mathbb{1}\{\text{BI}\}$, which equals one if firm i is associated with at least one biodiversity incident in year-quarter t . I also construct two continuous measures: the count of biodiversity incidents for firm i in year-quarter t , denoted BI count, and its natural logarithmic transformation, $\ln(1 + \text{BI count})$.

In additional analyses, I also take the novelty and severity of the incidents into account. Incident novelty reflects whether a firm is exposed to a given issue for the first time in a specific location, or not. I thus construct the binary indicators $\mathbb{1}\{\text{BI new}\}$ and $\mathbb{1}\{\text{BI re-occurring}\}$, equal to one if the firm experienced a new or re-occurring biodiversity incident in year-quarter t , respectively. Incident severity, as coded by RepRisk, reflects the harshness of an incident based on its health and safety consequences, geographic or demographic scope, and underlying cause (accident, negligence, or intent). I classify incidents with a RepRisk severity level 1 as “low severity” and those with levels 2 or 3 as “high severity.”³ The corresponding binary indicators $\mathbb{1}\{\text{BI low severity}\}$ and $\mathbb{1}\{\text{BI high severity}\}$ equal one if at least one low- or high-severity biodiversity incident occurs for firm i in year-quarter t .

[INSERT FIGURE I ABOUT HERE]

Figure I presents the evolution of biodiversity incident counts over time, together with major biodiversity policy milestones. The figure displays four-quarter rolling counts of biodiversity incidents, both in total and disaggregated by severity. Between 2007 and 2015, the number of reported incidents approximately quadrupled, likely reflecting increased public awareness and media attention toward biodiversity issues. Following the adoption of the UN Sustainable Development Goals in September 2015, the overall incident level stabilizes, though subject to short-term fluctuations. Notably, severe incidents exhibit a modest decline post-2015, while less severe

³I choose this grouping given that very few incidents are assigned a severity of 3, and because the grouping yields a well-balanced distribution of observations across severity subsamples.

incidents continue a slight upward trend. In subsequent years, a series of high-profile initiatives, including the IPBES Global Assessment (May 2019), the EU Biodiversity Strategy for 2030 (May 2020), the Dasgupta Review (February 2021), the Taskforce on Nature-related Financial Disclosures (June 2021), and the Kunming Biodiversity Declaration (October 2022), highlight the growing salience of biodiversity risks in the global policy discourse.

2.2 Descriptive statistics

The sample comprises all publicly listed firms traded on the NYSE, AMEX, or NASDAQ.⁴ I match the RepRisk dataset to several standard databases. Institutional ownership is based on institutional investors' holdings of common stocks, sourced from the Thomson Reuters Financial (13F) database. Fundamentals and stock data come from Compustat and CRSP, respectively. Shareholder proposal data on Russell 3000 companies are from ISS, and analyst forecasts are from I/B/E/S. ESG ratings are obtained from Sustainalytics, MSCI, and Refinitiv. I supplement these data with institutional investor classifications and legal types, obtained from Brian Bushee's website, as well as industry returns from Kenneth French's website.

Analyses are conducted at the highest available temporal resolution. Because 13F filings are reported quarterly, most analyses are performed at the firm-year-quarter level. Exceptions include firm-year-level analyses of shareholder proposals (Table IX) and cost of equity (Table X), as shareholder proposals are observable only at annual general meetings, and precise cost of equity estimates are only available at yearly frequency. The analysis of shareholder proposal outcomes (Table VIII) is conducted at the proposal level.

[INSERT TABLE I ABOUT HERE]

Table I presents descriptive statistics. Panel A summarizes the main dataset, which comprises 206,570 firm-year-quarters from 7,252 distinct firms between January 2007 and December 2022. Within this sample, 15,005 biodiversity incidents are recorded, of which 6,977 are classified as new (46.5%), 8,028 as re-occurring (53.5%), 8,124 as low severity (54.1%), and 6,881 as high severity (45.9%). The biodiversity incident indicator equals one in 3.4% of firm-quarters. On average, firms experience 0.073 incidents per quarter, with substantial cross-sectional variation,

⁴RepRisk's dataset misses firms that never had any incident news. However, given RepRisk's event-driven methodology, the absence of incidents for these firms represent true zeros, allowing biodiversity incident variables to be set to zero. In supplementary analyses (see Section 3.3), I restrict the sample to firms with at least one reported incident during the sample period and obtain qualitatively similar results.

ranging from 0 to 41. Panel B describes the firm-year dataset. It includes 26,571 firm-years from 4,471 distinct firms for which cost of equity data are available. Panel C summarizes the proposal-level dataset, which covers 7,365 ESG shareholder proposals submitted over the period 2012 through 2022. I restrict the sample to begin in 2012, as earlier data include primarily withdrawn and omitted proposals, with voted proposals only sparsely recorded.

3 Empirical results

3.1 Abnormal returns around biodiversity incidents

I begin by assessing the potential value implications of biodiversity incidents using event-study methodology. Under the assumption of rational markets, if shareholders value biodiversity, they should respond negatively to such incidents.

Following standard methodology ([Brown and Warner 1985](#), [MacKinlay 1997](#)), I compute cumulative abnormal returns (CAR^{BI}) for each incident in excess of a market model. Consistent with [Edmans \(2011\)](#), I estimate the market model over an estimation window from 300 to 46 trading days before the incident date, using the CRSP value-weighted index as the benchmark. CARs are computed over windows ranging from three days ($[-1; +1]$) to 31 days ($[-15; +15]$), centered on the incident date. I distinguish between new and re-occurring incidents and winsorize CAR^{BI} at the 1% and 99% levels to mitigate the influence of outliers. To assess the joint significance of abnormal returns, I compute the following t -statistic:

$$t(\overline{CAR^{BI}}) = \frac{\frac{1}{N} \sum_{n=1}^N CAR_n^{BI}}{\sqrt{\frac{1}{N^2} \sum_{n=1}^N \text{Var}(CAR_n^{BI})}}, \quad (1)$$

where N is the number of events and $\text{Var}(CAR_n^{BI})$ is the variance of residuals from the estimation-window regression, scaled by the number of trading days in the event window.

[INSERT [TABLE II](#) ABOUT HERE]

Panel A of [Table II](#) reports CARs for new biodiversity incidents. Across all five event windows, from $[-1; +1]$ to $[-15; +15]$, mean CARs are consistently negative and statistically significant at the 5% level or better. The immediate negative price reaction suggests that investors are surprised by new biodiversity incidents. Moreover, the increasing magnitude of CARs over wider windows implies that the valuation effects unfold over time. In terms of economic magnitude,

these incidents are associated with average shareholder losses ranging from \$110.1 million to \$344.4 million per event, depending on the specification. These estimates are consistent with those reported in [Krüger \(2015\)](#), who finds 11-day (21-day) CARs of -0.88% (-1.31%) around environmental and social incidents from KLD (now part of MSCI), translating into losses of \$229.5 million (\$341.7 million) per incident.

For re-occurring incidents (Panel B), CARs over the immediate windows $[-1; +1]$ and $[-2; +2]$ are statistically insignificant, consistent with investors being less surprised by repeat events ([Godfrey et al. 2009](#)). However, extending the window to $[-5; +5]$ and beyond reveals significantly negative CARs, indicating delayed but adverse valuation effects. As with new incidents, the magnitude of these effects increases over time. Shareholder value losses are smaller, ranging from \$76.2 million to \$145.1 million per re-occurring incident.

Overall, the evidence suggests that biodiversity incidents are perceived as value-reducing by equity markets. These findings are in line with prior literature documenting the materiality of environmental risks for firm value (e.g., [Flammer 2013](#)). Moreover, the delayed market reaction is consistent with an underreaction hypothesis, whereby initial investor assessments are incomplete, with more adverse effects (such as reputational damage) unfolding over time.

3.2 Biodiversity incidents and earnings abnormal announcement returns

If initial stock price reactions to biodiversity incidents are incomplete, subsequent earnings announcements may lead to corrective price adjustments as longer-term, value-relevant information becomes available. I test this hypothesis by examining whether abnormal stock returns around earnings announcements are systematically related to recent biodiversity incidents.

For each quarterly earnings announcement, I calculate the three-day $[-1; +1]$ cumulative abnormal return in excess of a market model, CAR^{EA} . This time, the market model is estimated over a window ranging from 300 to 91 trading days prior to the earnings announcement, again using the CRSP value-weighted index as the benchmark. I close the estimation window at day 91 to ensure that the BI indicators, capturing incidents occurring within the 90 days prior to the event, do not overlap with the estimation period. As before, CAR^{EA} is winsorized at the 1% and 99% levels to address outliers.

To test whether recent biodiversity incidents predict earnings announcement returns, I estimate the following ordinary least squares (OLS) regression model:

$$\text{CAR}_{i,t}^{\text{EA}} = \alpha_0 + \alpha_1 \mathbb{1}\{\text{BI } 90_{i,t}\} + \alpha_2 \text{Earnings lag}_{i,t} + \alpha_3 \text{IO}_{i,t-1} + \alpha_4 \mathbf{X}_{i,t-1} + \lambda_t + \mu_i + \varepsilon_{i,t}, \quad (2)$$

where $\text{CAR}_{i,t}^{\text{EA}}$ denotes firm i 's abnormal return around the earnings announcement at time t , and $\mathbb{1}\{\text{BI } 90_{i,t}\}$ equals one if the firm experienced at least one biodiversity incident in the 90 days preceding the announcement. Control variables include the number of days since the previous earnings announcement ($\text{Earnings lag}_{i,t}$), lagged institutional ownership ($\text{IO}_{i,t-1}$), and a vector of firm-level controls ($\mathbf{X}_{i,t-1}$), all measured one quarter before the earnings announcement. Year-quarter fixed effects (λ_t) and firm fixed effects (μ_i) account for time-series trends and unobserved firm-specific heterogeneity. Standard errors are double-clustered by firm and year-quarter. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix.

[INSERT [TABLE III](#) ABOUT HERE]

The first column of [Table III](#) presents the results. The coefficient on the BI indicator is negative and statistically significant at the 1% level, indicating that recent biodiversity incidents are associated with negative CARs around earnings announcements. In economic terms, firms that experienced incidents in the prior 90 days exhibit CARs that are 46.1 basis points lower. Given the unconditional mean CAR of +0.12%, these firms shift from slightly positive to slightly negative announcement returns.

This pattern remains qualitatively unchanged when disaggregating the BI indicator by novelty (columns 2 to 4) and severity (columns 5 to 7). In the fully saturated model (column 8), which includes indicators for new, re-occurring, severe, and less-severe incidents, only new incidents retain statistical significance (coefficient = -0.443 , $p < 0.05$).

Taken together, these findings support the interpretation that markets initially under-react to biodiversity incidents, with corrective price adjustments occurring at subsequent earnings announcements, when the longer-term implications of such incidents are more fully reflected in firm valuations.

3.3 Baseline model

The findings thus far indicate that biodiversity incidents carry economic consequences observable both in short-term event windows and around subsequent earnings announcements. Building on this evidence, I now turn to the association between institutional ownership and biodiversity incidents. I begin by estimating the likelihood of biodiversity incident occurrence using a linear probability model (LPM) using OLS:

$$\mathbb{1}\{\text{BI}_{i,t}\} = \beta_0 + \beta_1 \text{IO}_{i,t-1} + \beta_2 \mathbf{X}_{i,t-1} + \lambda_t + \mu_i + \varepsilon_{i,t}, \quad (3)$$

where $\mathbb{1}\{\text{BI}_{i,t}\}$ denotes the main biodiversity incidents measure, an indicator equal to one if firm i experienced at least one biodiversity incident in calendar year-quarter t . The key regressor, $\text{IO}_{i,t-1}$, is firm i 's lagged fraction of shares held by institutional investors. $\mathbf{X}_{i,t-1}$ is a vector of lagged firm-level controls. The model includes year-quarter fixed effects, λ_t , and firm fixed effects, μ_i , to capture account for time-series trends and unobserved firm-specific heterogeneity. Biodiversity incidents are measured contemporaneously, while all explanatory variables are lagged by one quarter to mitigate potential endogeneity arising from simultaneity. Standard errors are double-clustered by firm and year-quarter. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix.

[INSERT [TABLE IV](#) ABOUT HERE]

The results for [Equation 3](#) are in the first column of [Table IV](#). The estimated IO coefficient is negative and statistically significant at the 1% level, indicating that higher levels of institutional ownership are associated with a lower likelihood of future biodiversity incident occurrence. The effect is also economically large: a one-standard-deviation increase in institutional ownership is associated with a 16.0% reduction in future biodiversity incident occurrence. As a robustness check, I employ a non-linear functional form by estimating a firm fixed-effects logit model in the second column of [Table IV](#):

$$\Pr(\mathbb{1}\{\text{BI}_{i,t}\} = 1 \mid \text{IO}_{i,t-1}, \mathbf{X}_{i,t-1}, \lambda_t, \mu_i) = \Lambda(\gamma_0 + \gamma_1 \text{IO}_{i,t-1} + \gamma_2 \mathbf{X}_{i,t-1} + \lambda_t + \mu_i), \quad (4)$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function. Unlike the LPM, the logit constrains predicted probabilities to $[0, 1]$ and permits the marginal effect of each covariate to vary with its

level. Because conditional logit omits panels with no BI variation, in column 3, I re-estimate the model on firms with at least one incident over the sample period. The IO coefficient remains negative and is statistically significant at the 5% level. I compute average marginal effects at the mean of institutional ownership and find that a one-standard-deviation increase in IO reduces the likelihood of future biodiversity incident occurrence by 8.1%, closely matching the corresponding OLS estimate of 10.0% on the same reduced sample. This confirms that my main inference is robust to the choice of functional form and remains valid when excluding all-zero panels.

To further assess robustness, I turn to alternative measures of biodiversity incidence. I begin by re-estimating the baseline model using the (continuous) count of biodiversity incidents a firm experienced in year-quarter t , $\text{BI count}_{i,t}$, as the dependent variable in column 4. Given that biodiversity counts are discrete, nonnegative, and often small, I further estimate a Poisson pseudo-maximum likelihood regression (column 5), and among firms with at least one incident over the sample period (column 6). The next two models use the natural logarithm of one plus the incident count, $\ln(1 + \text{BI count})$, as the dependent variable, estimated on the full sample (column 7) and among firms with at least one incident over the sample period (column 8). IO coefficient estimates remain qualitatively unchanged and highly statistically significant. Due to the advantages of the LPM over the alternative models, I use [Equation 3](#) as the baseline model in subsequent analyses.⁵

Taken together, the negative relationship between biodiversity incidents and lagged institutional ownership is statistically highly significant and economically meaningful, holds across alternative measures and estimation methods, and persists when restricting the sample to firms that experiences at least one incident during the study period.

3.4 Identification: Monitoring versus selection effects

The relation between biodiversity incident occurrence and institutional ownership is endogenous. In particular, reverse causality may violate the exogeneity condition and invalidate my

⁵There are at least four reasons favoring a LPM using OLS. First, the LPM allows me to include saturated fixed effects, yields directly interpretable coefficients as percentage-point changes in event probability, and facilitates the interpretation of interaction terms in the estimation ([Ai and Norton 2003](#), [Greene 2010](#)). Second, it allows estimation on the full sample without excluding all-zero panels. Third, given that biodiversity incidents occur in only about 3.4% of firm-year-quarters, the raw and log counts concentrate nearly all within-firm, over-time variation in a small subset of the sample, inducing severe heteroskedasticity, whereas the dummy distributes identifying variation more evenly. Finally, variance decomposition (see [Table A2](#) in the Appendix) shows firm fixed effects absorb just 28.4 pp of total variance in the binary outcome—versus 49.5 pp and 41.4 pp for the raw and log counts—leaving 46.9 pp of within-firm variation for identification (compared to 30.2 pp and 34.9 pp). Hence, the dummy preserves more time-varying variation and reduces persistent heterogeneity, making it the preferred outcome for my two-way fixed effects analysis.

inferences. If institutional investors strategically avoid firms with higher biodiversity risk, the negative association between IO and BI may reflect *selection* rather than *monitoring*. To address this concern, I implement an identification strategy that exploits exogenous shocks to investors' monitoring capacity (Kempf et al. 2017).

Attention is a scarce cognitive resource (Kahneman 1973). Faced with attention constraints, institutional investors must prioritize which firms to monitor. When certain industries experience extreme returns, investors shift their attention toward firms in those industries, temporarily reducing their monitoring intensity for firms in other sectors. Because these shocks originate in industries unrelated to the focal firm, they provide a source of exogenous variation in monitoring intensity (Kempf et al. 2017) and are plausibly orthogonal to the firm's idiosyncratic BI risk.

I exploit this mechanism to identify the causal effect of institutional ownership on BI. Following the methodology in Kempf et al. (2017), I first compute an investor-level distraction score for each institution k holding focal firm i in calendar quarter-year t as:

$$\text{Distraction}_{k,t} = \sum_{IND \neq IND_i} w_{k,t-1}^{IND} \times IS_t^{IND}, \quad (5)$$

where IND indexes Fama-French 12 industries, and IND_i is firm i 's Fama-French 12 industry. $w_{k,t-1}^{IND}$ denotes the weight of industry IND in investor k 's portfolio at $t - 1$, capturing the investor's exposure to that industry. IS_t^{IND} is an indicator variable that captures whether a distracting shock occurs in industry IND . Distracting shocks are defined as occurring in the two industries that exhibit the highest and lowest returns at time t . The sum of the products of $w_{k,t-1}^{IND}$ and IS_t^{IND} across all industries other than IND_i captures investor k 's distraction from focal firm i due to unrelated industry shocks.

In the second step, I aggregate distraction across all institutional investors holding firm i to construct a firm-level measure:

$$\text{Distraction}_{i,t} = \sum_{k \in I_{t-1}} \sum_{IND \neq IND_i} w_{k,i,t-1} \times w_{k,t-1}^{IND} \times IS_t^{IND} \quad (6)$$

with

$$w_{k,i,t-1} = \frac{QPFWeight_{k,i,t-1} + QPercOwn_{k,i,t-1}}{\sum_{k \in I_{t-1}} (QPFWeight_{k,i,t-1} + QPercOwn_{k,i,t-1})}, \quad (7)$$

where $w_{k,i,t-1}$ reflects the relative importance of investor k in firm i in quarter-year $t - 1$. $PFWeight_{k,i,t-1}$ is the fraction of firm i in investor k 's portfolio, and $PercOwn_{k,i,t-1}$ is the

fraction of firm i 's market value of equity held by investor k , both measured in the previous year-quarter.⁶ To constrain the impact of outliers and measurement error, I sort both terms into quintiles Q , and scale the numerator so that the weights sum to one.

The final firm-level distraction measure specified in Equation 6 depends on whether shocks occur in industries other than the focal firm's industry, whether these other industries are important to the focal firm's institutional investors, and whether these investors are important monitors in the focal firm.

To identify a causal effect of IO on BI, I re-estimate the baseline model (Equation 3), augmenting it with an interaction term between IO and Distraction.⁷ This approach yields the following extended LPM:

$$\begin{aligned} \mathbb{1}\{\text{BI}_{i,t}\} = & \delta_0 + \delta_1 \text{IO}_{i,t-1} + \delta_2 \text{Distraction}_{i,t-1} + \delta_3 \text{IO}_{i,t-1} \times \text{Distraction}_{i,t-1} \\ & + \delta_4 \mathbf{X}_{i,t-1} + \lambda_t + \mu_i + \varepsilon_{i,t}. \end{aligned} \quad (8)$$

[INSERT TABLE V ABOUT HERE]

Estimation results for Equation 8 are shown in the first column of Table V. For robustness, I estimate a Tobit version (column 2), and re-estimate the model on the restricted sample of firms with at least one incident over the sample period (column 3).⁸ Across all specifications, the IO coefficient remains negative and statistically significant at the 1% level. The interaction between IO and the distraction measure is positive and significant at the 5% level or better, indicating that the negative effect of IO on BI weakens when institutional shareholders are distracted. At high levels of distraction, the IO effect is attenuated and eventually disappears—consistent with the interpretation that institutional investors actively prevent biodiversity incidents through monitoring. A reverse causality explanation is unlikely (i.e., that low-BI firms attract only attentive but not distracted investors), as the assignment of investors into the distracted group is driven by shocks that are plausibly orthogonal to each firm's idiosyncratic BI risk.

⁶Prior literature emphasizes that monitoring effectiveness depends on both the importance of the firm to the investor (Fich et al. 2015) and the importance of the investor to the firm (Goldstein 2011). The weighting factor $w_{k,i,t-1}$ incorporates both dimensions: $PFweight_{k,i,t-1}$ proxies for the firm's relevance to the investor, while $PercOwn_{k,i,t-1}$ proxies for the investor's relevance to the firm.

⁷In all regressions, firms operating in the two shocked industries are excluded to ensure that the distraction measure does not capture extreme industry sector performance (Kempf et al. 2017).

⁸The Tobit model in column 2 of Table V corresponds to Equation 4, augmented with $\text{IO}_{i,t-1} \times \text{Distraction}_{i,t-1}$. Table Table V mirrors the models estimated earlier in Section 3, shown in columns 1 to 3 of Table IV.

Taken together, these results provide supporting evidence that the inverse relationship between institutional ownership and biodiversity incidents is at least partially causal, arising from investor monitoring capacity rather than selection alone.

3.5 Heterogeneity by investment strategy and geographic origin

I proceed by decomposing total institutional ownership to examine the heterogeneity in its association with biodiversity incidents. First, I classify institutional investors into transient, dedicated, and quasi-indexer categories, following the taxonomy introduced by [Bushee and Noe \(2000\)](#) and [Bushee \(2001\)](#). Transient investors are characterized by frequent trading based on short-term return patterns and earnings news. Dedicated investors hold large, stable positions in a small number of firms, whereas quasi-indexers maintain broadly diversified portfolios and trade infrequently. Second, I distinguish between long-term and short-term oriented investors by calculating a portfolio churn rate for each institution ([Gaspar et al. 2005](#), [Döring et al. 2021](#)). The portfolio churn rate, $CR_{k,t}$, is defined as the fraction of portfolio holdings bought or sold over a calendar year-quarter:

$$CR_{k,t} = \frac{\sum_{i=1}^{N_{k,t}} |S_{k,i,t}P_{i,t} - S_{k,i,t-1}P_{i,t-1} - S_{k,i,t-1}\mu P_{i,t}|}{\sum_{i=1}^{N_{k,t}} \frac{S_{k,i,t}P_{i,t} + S_{k,i,t-1}P_{i,t-1}}{2}}, \quad (9)$$

where $S_{k,i,t}$ denotes the number of shares of firm i held by investor k in year-quarter t , $P_{i,t}$ is the stock price of firm i at time t , and $N_{k,t}$ is the number of positions in investor k 's portfolio in that quarter. I aggregate firm-level institutional ownership by long-term and short-term investors based on the top and bottom terciles of the churn rate distribution. Third, I classify institutional investors by geographic origin: those incorporated inside (outside) the U.S. are considered domestic (foreign). This classification yields firm-level measures of domestic and foreign institutional ownership.

Ex ante, it is unclear whether the observed relationship between institutional ownership and biodiversity incidents applies uniformly across all investor types or whether certain subgroups exhibit distinct patterns of selection and monitoring. To explore this, I apply the identification strategy described in [Section 3.4](#) separately for each investor group. Specifically, I construct group-specific distraction measures (as defined in [Equation 6](#)) for each category of investors. Re-estimating the augmented model in [Equation 8](#) with these group-specific distraction terms allows identification of causal effects at a more granular level. I estimate each investor-type

specification both in isolation and in a combined model that includes all group-specific IO and distraction interactions simultaneously to assess the robustness of each effect when controlling for the presence of other investor types.

[INSERT [TABLE VI](#) ABOUT HERE]

The results in the first four columns of [Table VI](#) show that future biodiversity incidents are negatively associated with quasi-indexer ownership, statistically significant at the 1% level (coefficients = -0.028 and -0.041), while there appears to be no such effect for transient or dedicated institutions. Moreover, the negative coefficients on quasi-indexer ownership weaken when quasi-indexers are distracted (interaction coefficients = 0.106 , $p < 0.10$ and 0.181 , $p < 0.05$). This pattern is consistent with the monitoring hypothesis and indicates that quasi-indexers actively mitigate the likelihood of future biodiversity incidents.

Given the long-term investment horizons of quasi-indexer institutions ([Bushee and Noe 2000](#), [Bushee 2001](#)), this suggests that the negative relationship between institutional ownership and biodiversity incidents may be driven by long-term investors rather than short-term investors. The results in columns 5 to 7 confirm that long-term institutional ownership is negatively associated with biodiversity incidents at the 1% level of statistical significance (coefficients = -0.031 and -0.037), while the coefficients on short-term ownership are less negative and only marginally significant at the 10% level (coefficients = -0.016 and -0.019). A Wald test confirms the difference in coefficients ($p < 0.10$). Interestingly, the effect of short-term ownership does not vary with their level of distraction, whereas the negative coefficients on long-term ownership attenuate under distraction (interaction coefficients = 0.118 and 0.123). This asymmetry suggests that short-term investors may primarily select into low-risk firms without exerting a monitoring effect, whereas quasi-indexers and other long-term investors appear to actively reduce the likelihood of future biodiversity incidents through monitoring.

An explanation for these findings is that superior monitoring capabilities enable investors with a long investment horizon to effectively identify and mitigate biodiversity risks, which may only materialize over extended time horizons. Effective monitoring is costly and requires long-term commitment to the firm to realize benefits. Long-term investors can amortize these costs over longer holding periods and possess a comparative advantage in influencing managerial behavior through ongoing involvement ([Gaspar et al. 2005](#), [Chen et al. 2007](#)). Because they can process corporate information more efficiently, long-term investors also gain an informational advantage

over short-term investors ([Attig et al. 2013](#)). Furthermore, long-term institutional investors are more concerned with the reputation and legitimacy of the company, and thus they are more likely to monitor and prevent biodiversity incidents than short-term investors ([Flammer et al. 2021](#)).

Finally, I turn to ownership by domestic vis-à-vis foreign institutions in the last three columns of the same table. Domestic IO is negative and statistically significant at the 1% level (coefficients = -0.035 and -0.038), and its interactions with domestic IO distraction load significantly positive at the 10% level (interaction coefficients = 0.055 and 0.050). This indicates that the effect of domestic IO weakens under distraction, consistent with a monitoring role. By contrast, both the main and interaction coefficients for foreign IO are statistically insignificant.

Due to their proximity to local conditions, and because biodiversity loss is primarily driven by land use changes, domestic institutional investors may acquire and process monitoring information more efficiently than foreign institutions. Their “hometown advantage” enables a better understanding of local governance and operational contexts, improving monitoring effectiveness ([Kim et al. 2016](#)) and mitigating biodiversity risks. In the spirit of [Guiso et al. \(2006\)](#), it is further conceivable that domestic investors have stronger cultural and emotional ties to their home country, increasing their engagement with local biodiversity concerns. This supports the notion that their influence is driven not only by “value” but also by “values” ([Starks 2023](#)).

Overall, future biodiversity incidents are negatively associated with quasi-indexer, long-term, short-term, and domestic institutional ownership. However, only the effects of quasi-indexer, long-term, and domestic investors attenuate under distraction, consistent with a monitoring role. The stable effect for short-term investors suggests it reflects selection into lower-risk firms rather than active monitoring.

3.6 Heterogeneity by legal types

To further examine the heterogeneity in the effect of institutional ownership on biodiversity incidents, I classify institutional investors by legal type, following [Bushee \(2001\)](#). Specifically, I compute measures of institutional ownership for the following institutional legal types: investment companies, independent investment advisors, bank trusts, insurance companies, university and foundation endowments, corporate pension funds, and public pension funds.

In parallel with the previous analysis, I construct group-specific distraction measures (as defined in [Equation 6](#)) for each legal type. Re-estimating [Equation 8](#), augmented with these legal-type-specific distraction terms and their interactions with institutional ownership, allows

for the identification of causal effects at a more granular level. The estimates for each class of ownership measures are reported in [Table VII](#).⁹

[INSERT [TABLE VII](#) ABOUT HERE]

Future biodiversity incident occurrence is negatively and significantly associated with institutional ownership by independent investment advisors (coefficient = -0.031 , $p < 0.01$), insurance companies (coefficient = -0.148 , $p < 0.01$), and public pension funds (coefficient = -0.223 , $p < 0.10$), while no significant relationships are observed for the remaining legal types. However, evidence of a monitoring role, as indicated by positive and significant interaction terms with distraction, emerges only for insurance companies (interaction coefficient = 0.641 , $p < 0.10$) and public pension funds (interaction coefficient = 1.713 , $p < 0.10$). This suggests that their influence attenuates when these institutions are distracted, thereby relaxing monitoring constraints for the focal firm. By contrast, the negative coefficient for independent investment advisors appears stable under distraction, pointing toward a selection effect rather than active monitoring.

These findings are consistent with the characteristics of long-term institutional investors. Insurance companies typically maintain exceptionally long investment horizons, which increase their exposure to slow-moving but potentially severe biodiversity risks ([Giglio et al. 2023](#)). Moreover, as both investors and insurers, they face direct liability from environmental damages ([Krüger et al. 2020](#)). Consequently, they routinely apply catastrophe and environmental risk models to evaluate exposure, granting them a comparative advantage in assessing biodiversity-related risks. Public pension funds are commonly regarded as “universal owners” ([Quigley 2023](#))—large, diversified, and independent investors with a long-term investment horizon. These institutions are more likely to adopt a biodiversity lens ([Lachance and Stroeble 2023](#)) and, unlike corporate pension funds (for which no effect is observed), are subject to greater public scrutiny regarding their investment decisions. This institutional pressure may incentivize a more active role in biodiversity risk mitigation.

3.7 Channel: Governance via voice

To better understand the mechanism through which institutional investors affect biodiversity incidents, I examine governance via the voice channel by analyzing ESG shareholder proposal

⁹A simultaneous model is not feasible, as group-specific distraction measures are only available for firms with non-zero ownership from the respective legal type. Only a small number of firms are held by all seven classes simultaneously.

outcomes and their implications for corporate governance. A schematic overview of the shareholder proposal process is presented in [Figure II](#).

[INSERT [FIGURE II](#) ABOUT HERE]

Under Securities and Exchange Commission (SEC) Rule 14a-8, shareholders of publicly traded companies may exercise governance via voice by submitting proposals to be voted on at the annual general meeting (AGM). However, under specific conditions, management may petition the SEC to omit a proposal from the proxy statement.¹⁰ Omitted proposals are not subjected to shareholder vote and typically reflect managerial resistance, implying minimal opportunity for shareholder voice ([David et al. 2007](#), [Bauer et al. 2015](#)).

Even when proposals are included in the proxy and receive majority support at the AGM, management is not legally bound to implement them, as shareholder proposals are advisory under U.S. corporate law ([Levit and Malenko 2011](#)). Nonetheless, such outcomes typically trigger sustained shareholder pressure for implementation. Alternatively, the firm’s management may negotiate with the proposal’s filer before the AGM, commit to adopting the proposed changes, and thus induce the filer to voluntarily withdraw the proposal. Withdrawals, in this context, are considered to signal the highest level of shareholder activism and engagement among the three resolution outcomes ([Carleton et al. 1998](#), [David et al. 2007](#), [Bauer et al. 2015](#)).

To empirically assess the role of institutional investors in this governance process, I estimate a proposal-level multinomial logit model of the following form:

$$\begin{aligned} & \Pr(\text{Outcome}_p = j \mid \text{Inst sponsor}_p, \mathbf{Z}_{p,t-1}, \phi_t, \mu_i) \\ &= \frac{\exp(\epsilon_j \text{Inst sponsor}_p + \boldsymbol{\lambda}_j^\top \mathbf{Z}_{p,t-1} + \phi_{j,t} + \mu_{j,i})}{\sum_{k=0}^2 \exp(\epsilon_k \text{Inst sponsor}_p + \boldsymbol{\lambda}_k^\top \mathbf{Z}_{p,t-1} + \phi_{k,t} + \mu_{k,i})} \quad \text{for } j \in \{0, 1, 2\}, \end{aligned} \tag{10}$$

where Outcome_p is a categorical variable indicating the outcome of proposal p , taking values 0 if the proposal was omitted, 1 if it was voted on, and 2 if it was withdrawn. The key independent variable, Inst sponsor_p , is a binary indicator equal to one if the proposal was sponsored by an institutional investor. $\mathbf{Z}_{p,t-1}$ is a control vector of lagged firm- and proposal-level covariates. See [Table A1](#) in the Appendix for detailed variable definitions. Year and firm fixed effects, denoted

¹⁰Under SEC Rule 14a-8, permissible grounds for omission include proposals that reflect a personal grievance, require the firm to violate laws, relate to marginal aspects of business operations, or concern matters deemed part of the firm’s ordinary business activities.

by $\phi_{j,t}$ and $\mu_{j,i}$, are allowed to vary across outcome categories j to account for unobserved heterogeneity. Standard errors are double-clustered by firm and year.

[INSERT [TABLE VIII](#) ABOUT HERE]

The logit coefficient estimates for [Equation 10](#) are in the first three columns of [Table VIII](#). I begin by setting the omitted outcome ($j = 0$) as the reference category. Columns 1 and 2 thus compare the likelihood of proposals being voted on or withdrawn, relative to being omitted. In column 3, I set the voted outcome ($j = 1$) as the reference, comparing withdrawn to voted proposals. Across all models, the institutional sponsor indicator is positive and statistically significant at the 1% level, indicating that proposals sponsored by institutional investors are more likely to be voted on or withdrawn than omitted (columns 1 and 2), and more likely to be withdrawn than voted on (column 3), consistent with [Bauer et al. \(2015\)](#).

The next three columns of the same table report average marginal effects to interpret the magnitude of these results. The estimates imply that, *ceteris paribus*, proposals sponsored by institutional investors are 17.4 percentage points (pp) more likely to be withdrawn than those filed by other stakeholders. Institutional sponsorship is also associated with a 10.2 pp lower probability of omission and a 7.2 pp lower probability of a vote. All marginal effects are statistically significant at the 1% level. These effects are substantial relative to the unconditional probabilities of withdrawal (30.1%), vote (30.4%), and omission (17.9%).

Columns 7 to 12 replicate the analysis for a subsample of biodiversity-related shareholder proposals, defined as those in the ISS subcategories “Sustainability,” “Climate,” or “Pollution.”¹¹ Although the sample size is reduced to 954 from the overall 7,365 proposals, institutional sponsorship remains positively associated with the probability of withdrawal (+7.5 pp) and negatively associated with omission (−4.2 pp), both statistically significant at the 5% level. These magnitudes are again economically meaningful, given the unconditional probabilities of withdrawal (55.8%) and omission (8.8%) in this subsample.

Taken together, proposals sponsored by institutional investors are more likely to be withdrawn and less likely to be omitted, both in the full sample of ESG proposals and in the biodiversity-

¹¹The dataset contains no proposals explicitly labeled “biodiversity.” I therefore rely on ISS subcategories such as “Sustainability,” “Climate,” and “Pollution” as proxies. These subcategories encompass key dimensions of biodiversity-related risk, including ecosystem degradation and environmental externalities, and are commonly used in academic literature (e.g., [Garel et al. 2025](#)) and regulatory frameworks (e.g., TNFD) as biodiversity-relevant indicators. This approach reflects the current taxonomic limitations of shareholder proposal classifications and aligns with the conceptual overlap between these environmental subcategories and biodiversity governance.

specific subsample. Given that withdrawals (omissions) signal the highest (lowest) levels of shareholder engagement via voice (Carleton et al. 1998, David et al. 2007, Bauer et al. 2015), these findings support the view that institutional investors engage in governance via voice through behind-the-scenes negotiations on biodiversity-related issues.

To examine whether this governance channel affects future biodiversity incidents, I construct firm-level counts of proposal outcomes and use them to predict subsequent biodiversity incidents. Specifically, I estimate variations of the following LPM using OLS:

$$\mathbb{1}\{\text{BI}_{i,t}\} = \zeta_0 + \zeta_1 \text{Outcome count}_{i,t-1} + \zeta_2 \text{Total count}_{i,t-1} + \mathbf{Z}_{i,t-1} + \phi_t + \mu_i + \varepsilon_{i,t}, \quad (11)$$

where $\text{Outcome count}_{i,t-1}$ represents the number of biodiversity-related shareholder proposals in each outcome category (omitted, voted, withdrawn) targeting firm i in year $t - 1$, and $\text{Total count}_{i,t-1}$ denotes the total number of shareholder proposals targeting firm i in that year.

[INSERT TABLE IX ABOUT HERE]

The results for Equation 11 are in Table IX. While the number of omitted (column 1) and voted (column 2) proposals is not significantly associated with the likelihood of future biodiversity incidents, the number of withdrawn proposals (column 3) is negatively associated, with the coefficient statistically significant at the 1% level. In economic terms, each additional withdrawn proposal targeting a firm is associated with a 1.17 pp reduction in the probability of a biodiversity incident in the following year. This effect is substantial relative to the sample mean of biodiversity incident occurrence, which is 22.4%. The results remain qualitatively robust when all proposal types are jointly estimated in column 4.

Further analysis indicates heterogeneity in this relationship. Interestingly, the number of withdrawn proposals does not significantly affect the likelihood of new biodiversity incidents (column 5); however, it is negatively associated with the recurrence of incidents (column 6, coefficient = -0.015 , $p < 0.05$), and holds for both low-severity (Column 7, coefficient = -0.010 , $p < 0.10$) and high-severity (Column 8, coefficient = -0.010 , $p < 0.10$) incidents. As a placebo test, column 9 re-estimates the saturated model (column 4) using counts of non-biodiversity-related ESG shareholder proposals. I find that withdrawals of these proposals are not significantly associated with future biodiversity incidents.

Taken together, biodiversity-related proposals filed by institutional investors are more (less) likely to be withdrawn (omitted), indicating governance via voice through behind-the-scenes negotiations with management. A higher count of withdrawn biodiversity proposals, but not of unrelated ESG proposals targeting the focal firm, is associated with a reduced probability of re-occurring, but not new, biodiversity incidents. This suggests that institutional investors are particularly attuned to biodiversity risks that have already materialized and subsequently engage in targeted governance interventions—consistent with a voice strategy aimed at correcting misbehavior of repeated offenders.

3.8 Biodiversity incidents and the cost of equity capital

Finally, I examine the pricing consequences of biodiversity risk through the lens of the firm’s cost of capital. As investors become increasingly aware of the potential financial impacts of biodiversity risks, similar to carbon emission risks (Bolton and Kacperczyk 2021, Bolton and Kacperczyk 2023), they demand compensation for their biodiversity risk exposure (Garel et al. 2024). This risk premium likely manifests itself in the form of an increased cost of capital. In other words, I try to understand whether institutional investors care about biodiversity risks from a *value* perspective (Starks 2023).

Following recent literature (El Ghouli et al. 2011, Lee et al. 2021, El Ghouli et al. 2018), I measure a firm’s implied cost of equity (COE) capital based on analysts’ earnings forecasts and current stock prices using four different models. In particular, the COE measure is estimated taking the average implied cost of equity estimates across the valuation models of Claus and Thomas (2001) and Gebhardt et al. (2001) as well as the abnormal growth models of Easton (2004) and Ohlson and Juettner-Nauroth (2005).

To test whether biodiversity incidents are associated with the cost of equity, I estimate the following OLS model:

$$\text{COE}_{i,t} = \eta_0 + \eta_1 \mathbb{1}\{\text{BI}_{i,t}\} + \eta_2 \mathbf{W}_{i,t-1} + \psi_{i,t} + \varepsilon_{i,t}, \quad (12)$$

where $\text{COE}_{i,t}$ denotes the implied cost of equity capital for firm i in year t , and $\mathbf{Z}_{i,t-1}$ is a control vector of lagged firm-level control variables, augmented by analyst forecast bias and analyst forecast dispersion. $\psi_{i,t}$ are four-digit SIC-industry-by-year fixed effects to rule out explanations based on industry or analyst characteristics, even when they are time-varying. Standard errors

are double-clustered by firm and year. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix.

[INSERT [TABLE X](#) ABOUT HERE]

The results, shown in [Table X](#), indicate that the coefficient on the biodiversity-incident indicator is positive and significant at the 1% level (column 1). This suggests that firms with a prior biodiversity incident exhibit, on average, a 0.79 pp higher cost of equity than otherwise-identical firms. This is a sizeable effect, given the sample mean COE of 11.93%.

To analyze heterogeneity in this relationship, I turn to incident novelty (columns 2 to 4) and severity (columns 5 to 7). In model 4, which simultaneously includes indicators for both new and re-occurring incidents, I find a positive association only for new incidents (coefficient = -0.007 , $p < 0.01$). Likewise, in model 7, only high-severity but not low-severity-incidents appear to be positively associated with the cost of equity (coefficient = -0.008 , $p < 0.01$). In sum, biodiversity incidents are associated with a significantly higher cost of equity, indicating that investors demand a premium for their exposure to biodiversity risk. The effect is driven by new and high-severity incidents, suggesting investors respond more strongly to signals of emerging and material environmental risks. These findings imply that biodiversity risk is financially material and factored into investor required returns, aligning with a broader trend of ESG risks influencing capital costs.

4 Robustness tests

4.1 Biodiversity incidents and conventional ESG ratings

The main difference between an incident-based measure and conventional ESG ratings (e.g., Sustainalytics, MSCI, Refinitiv) lies in the underlying data source and methodology. While the former is derived entirely from media-reported incidents, the latter are constructed by ESG rating agencies based on analyst assessments across a predefined set of hundreds of ESG criteria.

[INSERT [TABLE XI](#) ABOUT HERE]

To explore how biodiversity incident measures relate to conventional ESG ratings, I report pairwise Pearson correlations in [Table XI](#). The binary indicator $\mathbb{1}\{\text{BI}\}$ exhibits weak to moderate correlations with standard ESG scores: 0.154 with Sustainalytics, 0.296 with Refinitiv, and a

negligible negative correlation of -0.044 with MSCI (Panel A). The two continuous biodiversity measures display similar patterns. When focusing on correlations with environmental pillar scores, results are likewise mixed: 0.215 with Sustainalytics, 0.012 with MSCI, and 0.215 with Refinitiv (Panel B). These findings suggest that biodiversity risks are partially reflected in the ESG rating methodologies.

Correlations among the conventional ESG scores range from 0.248 (Refinitiv and MSCI) to 0.651 (Refinitiv and Sustainalytics). For environmental pillar scores, correlations range from 0.346 (Refinitiv and MSCI) to 0.591 (Refinitiv and Sustainalytics). These results are consistent with the substantial divergence in ESG ratings across providers documented by [Berg et al. \(2022\)](#).

One advantage of using RepRisk incidents data is its broad coverage of over 300,000 firms, substantially exceeding that of traditional ESG rating agencies. Controlling for traditional ESG ratings in my analyses leads to sharp reductions in sample size ranging from 56% (MSCI) to 86% (Sustainalytics), and nearly 90% when all three ESG ratings are included simultaneously. Nevertheless, as a robustness test, and to assess the explanatory power of conventional ESG ratings for future biodiversity incidents, I re-estimate the baseline model ([Equation 3](#)), augmenting it with conventional ESG ratings.

[INSERT [TABLE XII](#) ABOUT HERE]

The first three columns of [Table XII](#) control for the ESG scores of Sustainalytics, MSCI, and Refinitiv, respectively. Only Sustainalytics and show statistically significant estimates (coefficients = -0.007 and -0.017 , both $p < 0.05$) indicating that these two providers, but not Refinitiv, possess some predictive power for future biodiversity incidents. When all three scores are included simultaneously in column 4, only Sustainalytics remains statistically significant (coefficient = -0.010 , $p < 0.05$). Column 5 shows that the effect appears to be driven by Sustainalytics' environmental pillar score (coefficient = -0.006 , $p < 0.05$), while none of the social or governance pillar scores from any provider demonstrate explanatory power (columns 6 and 7).

Importantly, despite the sharp reduction in sample size, the institutional ownership coefficient remains negative and statistically significant across all models. Moreover, the IO coefficient remains virtually unchanged in magnitude and statistical significance when estimated on the reduced sample including conventional ESG ratings as covariates (column 4, coefficient = -0.325 , $p < 0.05$) or on the reduced sample without controlling for conventional ESG ratings (column 9, coefficient = -0.312 , $p < 0.05$). This suggests that the decline in its statistical significance

from the 1% level in the baseline model (compare to column 1 of [Table IV](#)) to the 5% level is attributable to reduced sample size rather than confounding from omitted ESG variables.

Overall, this line of analysis confirms that omitted variable bias arising from the exclusion of these conventional measures is unlikely to threaten the validity of my inferences.

4.2 Biodiversity incidents and historical biodiversity performance

To examine whether the results are robust when controlling for historical environmental performance, and to determine whether past biodiversity incidents can predict future incidents, I augment the baseline model with lagged values of $\mathbb{1}\{\text{BI}\}$ as additional regressors. Initially, I re-estimate [Equation 3](#) by incorporating $\mathbb{1}\{\text{BI}_{i,t-1}\}$ as an explanatory variable. Next, I successively add $\mathbb{1}\{\text{BI}_{i,t-2}\}$, $\mathbb{1}\{\text{BI}_{i,t-3}\}$, and $\mathbb{1}\{\text{BI}_{i,t-4}\}$ to the model. By including lagged values of BI, I control for the firm’s historical risk profile, which may influence both current biodiversity risks and institutional investment decisions. The estimation results are in [Table XIII](#).

[INSERT [TABLE XIII](#) ABOUT HERE]

There is a strong positive relationship between past biodiversity incidents and the realization of future risk incidents. Throughout all models in Columns (1) to (4), the estimated coefficient on lagged BI is positive and statistically significant at the 1% level. Moreover, the IO coefficient remains qualitatively unchanged, both in sign and in statistical significance. Given that the IO effect persists even after adjusting for past risk incidents, the evidence suggests that IO does not merely reflect a firm’s historical environmental performance, but rather exerts a direct influence on current biodiversity risk management practices.

4.2.1 Evidence from Index reconstitution

As an alternative identification strategy, I exploit the annual reconstitution of the Russell 1000 and 2000 indexes, which generates plausibly exogenous variation in institutional ownership ([Crane et al. \(2016\)](#)). Each year, Russell reconstitutes its indexes based on a mechanical rule: the 1,000 firms with the highest market capitalizations form the Russell 1000, while the next 2,000 constitute the Russell 2000. Because firms cannot influence small variations in ranking, assignment to indexes near the cutoff is as good as random. This random assignment leads to large differences in value-weighted index weights. [Figure A1](#) in the Appendix plots average index weights by index rank. In turn, it also induces variation in institutional ownership around

the threshold, as institutions benchmarking against these indexes are more likely to hold large positions in the largest index constituents to minimize tracking error (i.e., in the largest Russell 2000 firms). I exploit this discontinuity in institutional ownership to establish a causal effect on biodiversity risk for firms close to this bandwidth.

Following the methodology of [Crane et al. \(2016\)](#), I estimate a two-stage least squares (2SLS) model, where the discontinuity in index weights around the threshold serves as an instrument for institutional ownership. In the first stage, I apply a sharp regression discontinuity design to model institutional ownership as a function of index inclusion. This instrument is unlikely to directly affect biodiversity risk, but it is expected to influence it indirectly through institutional ownership. To assess instrument validity, I perform Pearson correlation tests, F-tests, and the Sargan overidentification test.

In the second stage, I estimate the effect of instrumented institutional ownership on biodiversity risk using the exogenous variation isolated in the first stage. Formally, the second-stage model is specified as follows:

$$\mathbb{1}\{\text{BI}_{i,t}\} = \beta_0 + \beta_1 \times \widetilde{\text{IO}}_{i,t-1} + \beta_2 \mathbf{X}_{i,t-1} + \lambda_t + \mu_i + \varepsilon_{i,t}, \quad (13)$$

where $\widetilde{\text{IO}}_{i,t-1}$ is instrumented institutional ownership in firm i in the previous quarter-year.

The estimated coefficient on $\widetilde{\text{IO}}_{i,t-1}$ is negative, suggesting that exogenous increases in institutional ownership following index inclusion reduce the likelihood of future biodiversity incidents. Full results are available upon request. These findings support the robustness of the baseline inferences to this alternative identification strategy.

5 Conclusions

This paper investigates the economic and financial relevance of biodiversity risk in capital markets by analyzing over 15,000 biodiversity incidents involving more than 7,000 publicly listed U.S. firms from 2007 to 2022. I begin by documenting that biodiversity incidents are associated with economically significant negative abnormal stock returns, consistent with investor recognition of their value-reducing nature. The market response appears incomplete, with delayed adjustments around subsequent earnings announcements. These findings are consistent with initial investor underreaction, suggesting that the value implications of biodiversity incidents are not fully incorporated into stock prices at the time of their occurrence.

Building on this evidence, I examine the role of institutional investors in mitigating biodiversity risk. Higher institutional ownership is associated with a lower probability of subsequent biodiversity incidents. This relationship is economically meaningful and robust across a variety of empirical specifications, functional forms, and incident definitions. To address concerns about endogeneity, I exploit plausibly exogenous variation in institutional monitoring intensity and control for firms' historical incident profiles. Investor heterogeneity is central to the interpretation: long-term and domestic institutional investors appear to causally reduce biodiversity incidents through active monitoring, whereas short-term and foreign investors are more likely to select firms with lower ex ante risk. Insurance companies and public pension funds exhibit monitoring-driven effects, while independent advisors primarily engage in selection.

Further evidence from shareholder proposal data supports a governance-via-voice channel. Biodiversity-related proposals sponsored by institutional investors are more likely to be withdrawn, indicating private negotiations with management, and such withdrawals are associated with a lower probability of re-occurring biodiversity incidents. This is consistent with a voice strategy aimed at correcting misbehavior of repeated offenders. Finally, I document a positive relationship between biodiversity incidents and firms' implied cost of equity capital, consistent with the hypothesis that investors demand compensation for exposure to biodiversity risks.

Taken together, these findings highlight the emerging role of institutional investors in biodiversity risk management and contribute to the growing literature at the intersection of finance, environmental sustainability, and corporate governance.

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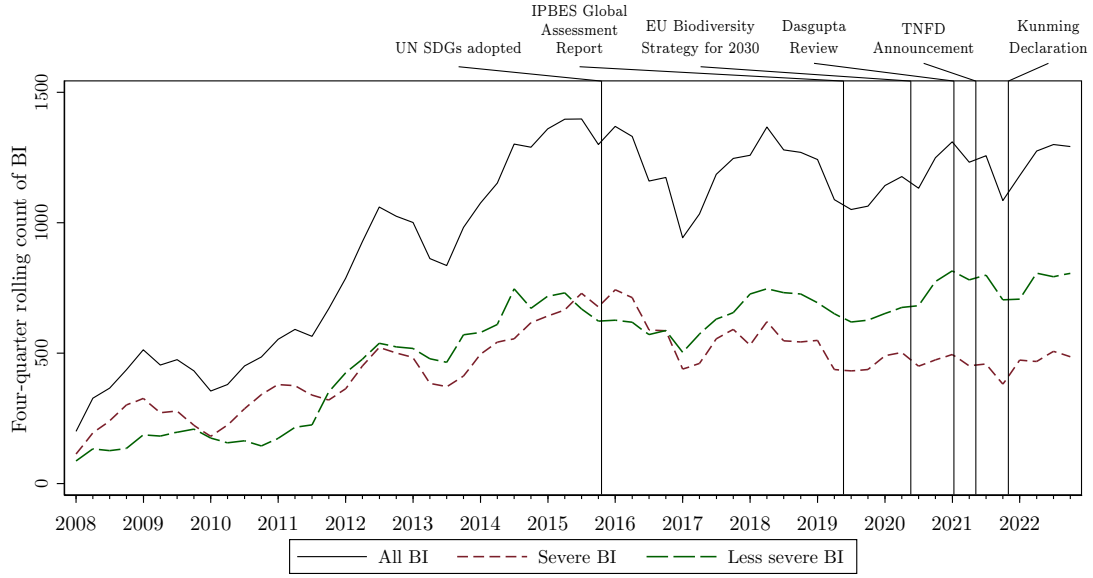
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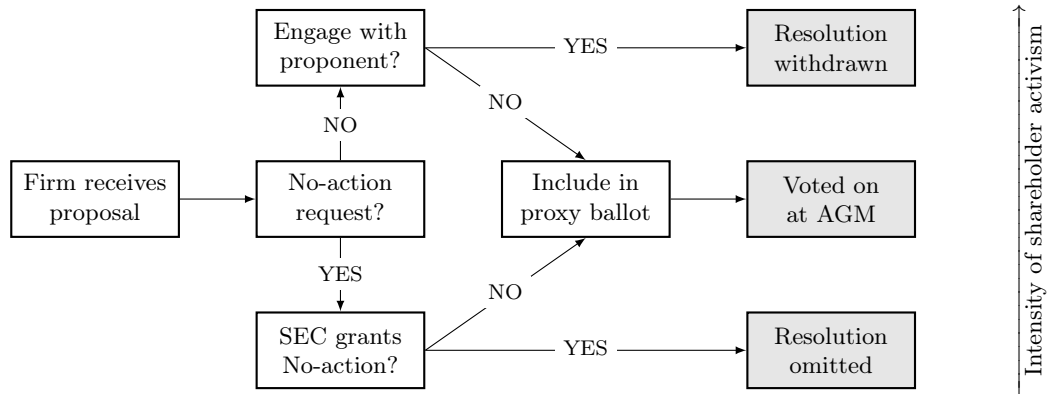
Figures and Tables

Figure I: Biodiversity incidents over time



This figure presents the four-quarter rolling count of biodiversity incidents (BI) from 2008 to 2022, disaggregated by severity (severe BI vs. less severe BI). Vertical lines denote key biodiversity policy milestones: adoption of the UN Sustainable Development Goals (September 2015), publication of the IPBES Global Assessment Report on Biodiversity and Ecosystem Services (May 2019), release of the EU Biodiversity Strategy for 2030 (May 2020), publication of the Dasgupta Review on the Economics of Biodiversity (February 2021), announcement of the Taskforce on Nature-related Financial Disclosures (TNFD; June 2021), and adoption of the Kunming Biodiversity Declaration (October 2022). Incident data are obtained from RepRisk, which employs a company-driven methodology to screen more than 150,000 information sources (including print and online media, NGOs, and government agencies) in 23 languages, linking ESG incident news to over 300,000 firms and categorizing incidents into 28 categories. I restrict attention to incidents in the “Impacts on landscapes, ecosystems, and biodiversity” category, reflecting land-use change as the primary driver of biodiversity loss. Incident severity is a function of the incident’s consequences, geographic scope, and whether it stemmed from accident, negligence, intent, or systemic causes. The sample comprises 206,570 firm-year-quarter observations containing 15,891 biodiversity incidents across 8,309 distinct firms.

Figure II: Flowchart of the shareholder proposal process



This figure presents the lifecycle of a Rule 14a-8 shareholder proposal and its implications for corporate governance. Upon receipt of a proposal, management may request no-action relief from the SEC. Reasons are, for example, the proposal reflects a personal grievance, requires the firm to violate law, relates to marginal parts of business operations, or deals with matters related to firms' ordinary business operations. If the SEC grants no-action, the proposal is omitted from the proxy statement (low activism intensity); if the request is denied or not sought, the proposal is included on the proxy ballot and voted at the AGM (moderate intensity), though these votes are nonbinding and management may still decline implementation, inviting further shareholder pressure. At any point, management may engage with the proponent and negotiate substantive changes, potentially inducing withdrawal of the proposal prior to the AGM (high intensity). The vertical arrow denotes increasing shareholder activism intensity from omission through voting to withdrawal.

Table I: Descriptive statistics

This table presents descriptive statistics for the main variables used in the study. Panel A reports summary statistics for the firm-year-quarter level dataset (applied in [Tables IV to VII, XI and XII](#)). Panel B reports summary statistics for the firm-year level dataset (applied in [Tables IX and X](#)). Panel C reports summary statistics for the proposal-level dataset (applied in [Table VIII](#)). The sample period is 2000 through 2022. It reports the number of observations (N), the mean, the standard deviation (SD), the 25% percentile (P25), the median, and the 75% percentile (P75) over the sample period. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix.

	N	Mean	SD	Min	P25	Med	P75	Max
Panel A: Firm-year-quarter level								
1{BI}	206,570	0.03	0.18	0.00	0.00	0.00	0.00	1.00
1{BI new}	206,570	0.02	0.15	0.00	0.00	0.00	0.00	1.00
1{BI re-occurring}	206,570	0.02	0.13	0.00	0.00	0.00	0.00	1.00
1{BI low severity}	206,570	0.02	0.15	0.00	0.00	0.00	0.00	1.00
1{BI high severity}	206,570	0.02	0.14	0.00	0.00	0.00	0.00	1.00
BI count	206,570	0.07	0.61	0.00	0.00	0.00	0.00	41.00
Ln(1+BI count)	206,570	0.03	0.20	0.00	0.00	0.00	0.00	3.74
Total book assets	206,570	6.82	2.15	-6.91	5.43	6.87	8.21	15.27
Book-to-market	206,570	1.68	284.78	-2,503	0.25	0.51	0.87	68,223
Return on assets	206,570	-0.01	0.89	-166.00	-0.01	0.00	0.02	147.04
Dividends	206,570	0.00	0.33	-0.01	0.00	0.00	0.00	146.03
Cash	206,570	0.19	0.24	0.00	0.03	0.09	0.25	1.00
Leverage	206,570	0.27	1.32	0.00	0.04	0.19	0.38	337.50
CAPEX	206,570	0.01	0.02	-2.31	0.00	0.00	0.01	2.38
CAPEX missing	206,570	0.01	0.10	0.00	0.00	0.00	0.00	1.00
PPE	206,570	0.20	0.24	0.00	0.02	0.10	0.28	1.00
PPE missing	206,570	0.04	0.20	0.00	0.00	0.00	0.00	1.00
RD	206,570	0.01	0.09	-0.41	0.00	0.00	0.01	22.28
RD missing	206,570	0.55	0.50	0.00	0.00	1.00	1.00	1.00
Firm age	206,570	2.48	1.22	-5.90	1.86	2.76	3.31	4.57
Institution size	206,570	9.91	1.49	-0.64	9.18	10.17	10.94	14.99
Portfolio Herfindahl	206,570	0.03	0.06	0.00	0.01	0.01	0.02	1.00
Firm Herfindahl	206,570	0.15	0.19	0.01	0.04	0.07	0.15	1.00
IO	206,570	0.48	0.25	0.00	0.28	0.54	0.69	1.00
IO TRA	206,570	0.11	0.09	0.00	0.04	0.09	0.16	0.96
IO DED	206,570	0.05	0.08	0.00	0.00	0.00	0.08	0.95
IO QIX	206,570	0.29	0.17	0.00	0.14	0.30	0.42	0.94
IO LT	206,570	0.12	0.10	0.00	0.04	0.10	0.17	0.97
IO ST	206,570	0.19	0.13	0.00	0.07	0.18	0.28	0.95
IO DOM	206,570	0.43	0.23	0.00	0.25	0.48	0.61	1.00
IO FOR	206,570	0.04	0.04	0.00	0.00	0.02	0.06	0.85
IO INV	206,570	0.02	0.04	0.00	0.00	0.01	0.04	0.62
IO IIA	206,570	0.31	0.17	0.00	0.18	0.32	0.44	0.98
IO BNK	206,570	0.06	0.05	0.00	0.01	0.05	0.10	0.82
IO INS	206,570	0.02	0.02	0.00	0.00	0.01	0.03	0.80
IO UFE	206,570	0.00	0.01	0.00	0.00	0.00	0.00	0.44
IO CPS	206,570	0.00	0.02	0.00	0.00	0.00	0.00	0.90
IO PPS	206,570	0.01	0.01	0.00	0.00	0.01	0.02	0.64
Distraction	167,164	0.11	0.07	0.00	0.05	0.09	0.14	0.90
Distraction TRA	161,288	0.11	0.07	0.00	0.05	0.09	0.14	0.74
Distraction DED	111,400	0.11	0.10	0.00	0.04	0.08	0.14	0.97
Distraction QIX	166,139	0.11	0.07	0.00	0.05	0.09	0.14	0.90
Distraction LT	161,741	0.10	0.07	0.00	0.05	0.08	0.14	0.84
Distraction ST	163,554	0.11	0.07	0.00	0.05	0.10	0.15	0.90
Distraction DOM	167,092	0.11	0.07	0.00	0.05	0.09	0.14	0.81
Distraction FOR	143,346	0.11	0.08	0.00	0.06	0.09	0.14	0.90
Distraction INV	142,323	0.12	0.08	0.00	0.06	0.10	0.16	0.70
Distraction IIA	165,990	0.10	0.07	0.00	0.05	0.09	0.14	0.90
Distraction BNK	158,794	0.11	0.07	0.00	0.05	0.10	0.14	0.63
Distraction INS	136,531	0.11	0.08	0.00	0.05	0.09	0.14	0.88
Distraction UFE	11,630	0.09	0.11	0.00	0.02	0.06	0.12	1.00
Distraction CPS	84,211	0.11	0.09	0.00	0.04	0.09	0.15	0.99
Distraction PPS	148,081	0.12	0.08	0.00	0.06	0.10	0.16	0.48

(continued)

Table I — *continued*

	N	Mean	SD	Min	P25	Med	P75	Max
Panel B: Firm-year level								
1{BI}	26,571	0.04	0.21	0.00	0.00	0.00	0.00	1.00
1{BI new}	26,571	0.03	0.17	0.00	0.00	0.00	0.00	1.00
1{BI re-occurring}	26,571	0.02	0.16	0.00	0.00	0.00	0.00	1.00
1{BI new}	26,571	0.03	0.17	0.00	0.00	0.00	0.00	1.00
1{BI low severity}	26,571	0.03	0.17	0.00	0.00	0.00	0.00	1.00
1{BI high severity}	26,571	0.03	0.16	0.00	0.00	0.00	0.00	1.00
COE	26,571	0.12	0.08	0.00	0.08	0.10	0.13	0.99
IO	26,571	0.58	0.19	0.00	0.47	0.61	0.72	1.00
Total book assets	26,571	7.45	1.87	−0.32	6.13	7.42	8.63	14.83
Book-to-market	26,571	0.56	0.60	−9.21	0.26	0.48	0.78	40.24
Return on assets	26,571	0.00	0.12	−3.00	0.00	0.01	0.02	11.84
Dividends	26,571	0.00	0.06	−0.01	0.00	0.00	0.00	6.41
Cash	26,571	0.18	0.22	0.00	0.03	0.08	0.24	1.00
Leverage	26,571	0.24	0.24	0.00	0.05	0.20	0.37	3.87
CAPEX	26,571	0.01	0.02	−0.07	0.00	0.01	0.01	0.47
CAPEX missing	26,571	0.00	0.05	0.00	0.00	0.00	0.00	1.00
PPE	26,571	0.21	0.25	0.00	0.03	0.11	0.31	0.99
PPE missing	26,571	0.05	0.21	0.00	0.00	0.00	0.00	1.00
RD	26,571	0.01	0.03	0.00	0.00	0.00	0.01	1.68
RD missing	26,571	0.56	0.50	0.00	0.00	1.00	1.00	1.00
Firm age	26,571	2.50	1.18	−5.21	1.88	2.75	3.28	4.54
Institution size	26,571	10.13	1.04	2.92	9.62	10.26	10.84	13.28
Portfolio Herfindahl	26,571	0.03	0.05	0.00	0.01	0.01	0.02	0.91
Firm Herfindahl	26,571	0.08	0.09	0.01	0.04	0.05	0.08	1.00
Forecast bias	26,571	0.06	2.51	−13.40	−0.09	−0.01	0.08	375.48
Forecast dispersion	26,571	0.15	0.79	0.00	0.02	0.04	0.09	45.00
OMIT count	6,892	0.13	0.48	0.00	0.00	0.00	0.00	11.00
VOTE count	6,892	0.38	0.87	0.00	0.00	0.00	0.00	12.00
WIDR count	6,892	0.16	0.50	0.00	0.00	0.00	0.00	19.00
Total count	6,892	0.76	1.48	0.00	0.00	0.00	1.00	19.00
OMIT count (BI)	6,892	0.01	0.13	0.00	0.00	0.00	0.00	3.00
VOTE count (BI)	6,892	0.04	0.24	0.00	0.00	0.00	0.00	5.00
WIDR count (BI)	6,892	0.05	0.24	0.00	0.00	0.00	0.00	3.00
Staggered board	6,892	0.07	0.25	0.00	0.00	0.00	0.00	1.00
Dual-class shares	6,892	0.01	0.12	0.00	0.00	0.00	0.00	1.00
Poison pill	6,892	0.02	0.13	0.00	0.00	0.00	0.00	1.00
Golden parachute	6,892	0.21	0.41	0.00	0.00	0.00	0.00	1.00
Panel C: Proposal level								
Outcome = OMIT	7,365	0.17	0.38	0.00	0.00	0.00	0.00	1.00
Outcome = VOTE	7,365	0.55	0.50	0.00	0.00	1.00	1.00	1.00
Outcome = WIDR	7,365	0.28	0.45	0.00	0.00	0.00	1.00	1.00
Outcome = OMIT (BI)	954	0.10	0.30	0.00	0.00	0.00	0.00	1.00
Outcome = VOTE (BI)	954	0.34	0.47	0.00	0.00	0.00	1.00	1.00
Outcome = WIDR (BI)	954	0.56	0.50	0.00	0.00	1.00	1.00	1.00
Inst sponsor	7,365	0.30	0.46	0.00	0.00	0.00	1.00	1.00
IO	7,365	0.58	0.14	0.00	0.50	0.58	0.67	1.00
Total book assets	7,365	10.33	1.92	3.44	9.05	10.42	11.59	15.19
Book-to-market	7,365	0.46	0.69	−12.98	0.16	0.35	0.65	43.15
Return on assets	7,365	0.01	0.03	−0.60	0.00	0.01	0.02	0.54
Dividends	7,365	0.00	0.00	0.00	0.00	0.00	0.00	0.02
Cash	7,365	0.13	0.13	0.00	0.03	0.09	0.18	0.96
Leverage	7,365	0.32	0.22	0.00	0.17	0.29	0.42	3.95
CAPEX	7,365	0.01	0.01	−0.00	0.00	0.01	0.02	0.17
CAPEX missing	7,365	0.00	0.05	0.00	0.00	0.00	0.00	1.00
PPE	7,365	0.29	0.26	0.00	0.07	0.20	0.52	0.97
PPE missing	7,365	0.03	0.18	0.00	0.00	0.00	0.00	1.00
RD	7,365	0.01	0.02	0.00	0.00	0.00	0.00	0.39
RD missing	7,365	0.59	0.49	0.00	0.00	1.00	1.00	1.00
Firm age	7,365	3.40	0.86	−0.55	2.93	3.54	4.01	4.57
Institution size	7,365	11.23	0.71	6.33	10.92	11.29	11.65	13.47
Portfolio Herfindahl	7,365	0.02	0.03	0.00	0.01	0.01	0.02	0.63
Firm Herfindahl	7,365	0.05	0.07	0.01	0.03	0.04	0.05	1.00
Staggered board	7,365	0.11	0.32	0.00	0.00	0.00	0.00	1.00
Dual-class shares	7,365	0.03	0.17	0.00	0.00	0.00	0.00	1.00
Poison pill	7,365	0.03	0.17	0.00	0.00	0.00	0.00	1.00
Golden parachute	7,365	0.42	0.49	0.00	0.00	0.00	1.00	1.00

Table II: Abnormal returns around biodiversity incidents

This table reports average cumulative abnormal returns around biodiversity incidents (CAR^{BI}) over different event windows. Column headings denote the event window (Window), number of observations (Events), mean CAR, and associated t -statistic (t -stat). CARs are estimated using the market model, centered around the biodiversity incidents, with the CRSP value-weighted index as the benchmark. The market model is calibrated over a pre-event window spanning from 300 to 46 trading days prior to the event (Edmans (2011)). To mitigate the influence of outliers, all CARs are winsorized at the 1% and 99% levels. All CARs are multiplied by 100 to express results in percentage points. Panel A (Panel B) presents results for new (re-current) biodiversity incidents. Detailed variable definitions and data sources are provided in Table A1 in the Appendix. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Window	Events	CAR^{BI}	t -stat
Panel A: New incidents			
$[-1; +1]$	2,754	-0.189	-2.90***
$[-2; +2]$	2,752	-0.234	-2.77***
$[-5; +5]$	2,744	-0.335	-2.79***
$[-10; +10]$	2,737	-0.486	-2.80***
$[-15; +15]$	2,725	-0.536	-2.53**
Panel B: Re-occurring incidents			
$[-1; +1]$	5,501	0.016	0.37
$[-2; +2]$	5,500	-0.013	-0.23
$[-5; +5]$	5,498	-0.160	-1.98**
$[-10; +10]$	5,492	-0.263	-2.36**
$[-15; +15]$	5,482	-0.441	-3.26***

Table IV: Biodiversity incidents and institutional ownership

This table reports estimation results from quarterly regressions of biodiversity incidents on institutional ownership and a set of control variables. The dependent variable in columns 1 to 3 is $1\{\text{BI}\}$, an indicator equal to one if a firm experienced at least one biodiversity incident in year-quarter t . Columns 4 to 6 use the count of biodiversity incidents a firm experienced in year-quarter t as the dependent variable. Columns 7 and 8 use the natural logarithm of one plus the incident count, $\ln(1 + \text{BI count})$, as the dependent variable. The key explanatory variable, IO, denotes the fraction of a firm's shares held by institutional investors. All explanatory variables are measured as of year-quarter $t - 1$. All models, except 2 and 5, are estimated using a linear probability model. Model 2 is estimated using logistic regression, and model 5 employs Poisson pseudo-maximum likelihood estimation. Models 1, 4, and 7 include all sample firms. The other models restrict the sample to firms with at least one biodiversity incident over the sample period. All regressions include firm and year-quarter fixed effects. Detailed variable definitions and data sources are provided in Table A1 in the Appendix. Robust standard errors, double-clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$1\{\text{BI}\}$			BI count			$\ln(1 + \text{BI count})$	
Estimator:	OLS	Logit	OLS	OLS	PPML	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IO	-0.022*** (0.006)	-0.429** (0.209)	-0.083*** (0.024)	-0.050*** (0.016)	-0.629** (0.254)	-0.189*** (0.069)	-0.023*** (0.006)	-0.087*** (0.027)
Total book assets	0.008*** (0.002)	0.855*** (0.055)	0.039*** (0.007)	0.022*** (0.008)	0.514*** (0.094)	0.101*** (0.034)	0.009*** (0.003)	0.042*** (0.011)
Book-to-market	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)
Return on assets	-0.000 (0.000)	-0.024 (0.039)	-0.001** (0.000)	-0.000 (0.000)	0.372 (0.426)	-0.002 (0.001)	-0.000 (0.000)	-0.001* (0.001)
Dividends	0.000 (0.000)	-28.965 (22.808)	-2.074 (2.746)	0.001 (0.000)	-39.697 (31.236)	-5.489 (7.304)	0.000 (0.000)	-2.218 (2.841)
Cash	0.010** (0.004)	0.971*** (0.332)	0.044 (0.030)	0.035** (0.014)	0.527 (0.397)	0.206* (0.109)	0.012** (0.005)	0.063* (0.035)
Leverage	0.000 (0.000)	0.094 (0.113)	-0.001 (0.014)	0.000 (0.000)	0.107 (0.166)	0.025 (0.058)	0.000 (0.000)	0.005 (0.019)
CAPEX	-0.025 (0.023)	0.914 (1.367)	-0.022 (0.101)	0.067 (0.070)	5.922*** (1.763)	0.579* (0.328)	0.000 (0.023)	0.109 (0.106)
CAPEX missing	-0.008* (0.005)	-0.370 (0.430)	-0.031 (0.043)	-0.015* (0.008)	-0.210 (0.174)	-0.013 (0.068)	-0.008** (0.004)	-0.022 (0.033)
PPE	0.021* (0.012)	-0.098 (0.293)	0.030 (0.039)	0.066 (0.046)	-1.017** (0.456)	0.131 (0.150)	0.021 (0.014)	0.030 (0.047)
PPE missing	0.000 (0.006)	-0.127 (0.227)	-0.007 (0.031)	-0.004 (0.013)	-0.151* (0.088)	-0.037 (0.064)	-0.001 (0.006)	-0.012 (0.030)
RD	0.004** (0.001)	-2.546 (5.119)	-0.134 (0.386)	0.008** (0.004)	-5.679 (4.855)	-0.548 (1.653)	0.004** (0.001)	-0.256 (0.558)
RD missing	0.006* (0.003)	0.142 (0.105)	0.017* (0.010)	0.017** (0.008)	0.025 (0.060)	0.046 (0.030)	0.006** (0.002)	0.015 (0.009)
Firm age	-0.003* (0.001)	0.369*** (0.061)	-0.003 (0.007)	-0.009* (0.004)	0.263*** (0.090)	-0.020 (0.023)	-0.003** (0.002)	-0.007 (0.008)
Institution size	0.001* (0.000)	0.152*** (0.033)	-0.001 (0.004)	0.001 (0.001)	0.043 (0.044)	-0.010 (0.011)	0.001* (0.000)	-0.002 (0.004)
Portfolio Herfindahl	0.028 (0.018)	2.254*** (0.524)	0.156* (0.083)	0.074* (0.044)	1.120* (0.629)	0.368* (0.208)	0.036* (0.020)	0.184* (0.092)
Firm Herfindahl	0.001 (0.003)	-0.382 (0.342)	-0.077** (0.033)	0.005 (0.011)	-0.765** (0.370)	-0.179* (0.100)	0.001 (0.004)	-0.084** (0.037)
Year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted/Pseudo R^2	0.404	0.031	0.348	0.617	0.528	0.611	0.551	0.524
Observations	206, 570	45, 851	46, 125	206, 570	46, 000	46, 125	206, 570	46, 125

Table V: Biodiversity incidents and institutional investor distraction

This table reports estimation results from quarterly regressions of biodiversity incidents on institutional ownership and a set of control variables, re-estimating the main models (see columns 1 to 3 of [Table III](#)) using exogenous variation in investor attention to assess causality. The dependent variable in all columns is $\mathbb{1}\{\text{BI}\}$, an indicator equal to one if a firm experienced at least one biodiversity incident in year-quarter t . The key explanatory variable, IO, denotes the fraction of a firm's shares held by institutional investors. Distraction captures institutional shareholders' attention away from the focal firm due to plausibly exogenous shocks ([Kempf et al. \(2017\)](#)). All explanatory variables are measured as of year-quarter $t-1$. Models 1 and 3 are estimated using a linear probability model, while model 2 is estimated using logistic regression. Model 1 includes all sample firms, whereas models 2 and 3 restrict the sample to firms with at least one biodiversity incident over the sample period. All regressions include firm and year-quarter fixed effects. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix. Robust standard errors, double-clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Estimator:	OLS	Logit	OLS
Dependent variable: $\mathbb{1}\{\text{BRI}\}$	(1)	(2)	(3)
IO	-0.026*** (0.007)	-0.677*** (0.122)	-0.104*** (0.028)
IO \times Distraction	0.057*** (0.011)	3.330** (1.468)	0.246** (0.102)
Total book assets	0.009*** (0.002)	0.835*** (0.064)	0.039*** (0.008)
Book-to-market	0.000* (0.000)	0.000 (0.000)	0.000* (0.000)
Return on assets	-0.000 (0.000)	0.006 (0.331)	-0.001** (0.000)
Dividends	0.003 (0.002)	-9.205 (27.410)	-1.258 (3.795)
Cash	0.007 (0.004)	0.667* (0.372)	0.034 (0.032)
Leverage	0.000* (0.000)	0.127 (0.119)	0.007 (0.017)
CAPEX	0.001 (0.030)	3.398** (1.621)	0.071 (0.113)
CAPEX missing	-0.006 (0.005)	-0.219 (0.485)	-0.011 (0.053)
PPE	0.014 (0.012)	-0.417 (0.337)	0.017 (0.042)
PPE missing	-0.001 (0.007)	-0.198 (0.240)	-0.008 (0.032)
RD	0.013* (0.007)	-2.468 (5.773)	0.024 (0.346)
RD missing	0.006** (0.003)	0.157 (0.117)	0.021** (0.010)
Firm age	-0.007*** (0.002)	0.407*** (0.083)	-0.012 (0.009)
Institution size	0.001 (0.000)	0.175*** (0.039)	-0.002 (0.004)
Portfolio Herfindahl	0.022 (0.021)	2.280*** (0.628)	0.139 (0.098)
Firm Herfindahl	0.000 (0.004)	-0.753* (0.422)	-0.095*** (0.036)
Year-quarter FE	✓	✓	✓
Firm FE	✓	✓	✓
Adjusted/Pseudo R^2	0.411	0.032	0.356
Observations	166,910	33,584	37,840

Table VI: Biodiversity incidents and institutional ownership heterogeneity

This table reports estimation results from quarterly regressions of biodiversity incidents on institutional ownership and a set of control variables, re-estimating the baseline model (see column 1 of [Table III](#)) to assess heterogeneity across investor types and to examine causal effects using exogenous variation in investor attention. The dependent variable in all columns is $\mathbb{1}\{\text{BI}\}$, an indicator equal to one if a firm experienced at least one biodiversity incident in year-quarter t . The key explanatory variable, IO, denotes the fraction of a firm's shares held by institutional investors. Distraction captures institutional shareholders' attention away from the focal firm due to plausibly exogenous shocks ([Kempf et al. \(2017\)](#)). Columns 1 to 4 classify IO into ownership by transient (TRA), dedicated (DED), and quasi-indexer (QIX) investors based on portfolio characteristics and trading behavior ([Bushee \(1998\)](#), [Bushee and Noe \(2000\)](#)). Columns 5 to 7 distinguish between long-term (LT) and short-term (ST) institutional ownership based on portfolio churn rates ([Gaspar et al. \(2005\)](#), [Döring et al. \(2021\)](#)). Columns 8 to 10 distinguish between domestic (DOM) and foreign (FOR) institutional ownership based on investor headquarters location. All models interact the institutional ownership types with their respective distraction measures to assess causal effects. All explanatory variables are measured as of year-quarter $t - 1$. All models are estimated using a linear probability model and include firm and year-quarter fixed effects. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix. Robust standard errors, double-clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable: $\mathbb{1}\{\text{BRI}\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IO TRA	−0.017 (0.012)			−0.023 (0.015)						
IO TRA × Distraction TRA	−0.022 (0.055)			−0.041 (0.099)						
IO DED		−0.005 (0.014)		−0.009 (0.014)						
IO DED × Distraction DED		0.063 (0.079)		0.029 (0.070)						
IO QIX			−0.028*** (0.010)	−0.041*** (0.014)						
IO QIX × Distraction QIX			0.106* (0.061)	0.181** (0.083)						
IO LT					−0.031*** (0.010)		−0.037*** (0.011)			
IO LT × Distraction LT					0.118* (0.069)		0.123* (0.069)			
IO ST						−0.016* (0.009)	−0.019* (0.009)			
IO ST × Distraction ST						−0.066 (0.050)	−0.072 (0.056)			
IO DOM								−0.035*** (0.007)		−0.038*** (0.008)
IO DOM × Distraction DOM								0.055* (0.032)		0.050* (0.031)
IO FOR									0.043 (0.041)	0.038 (0.041)
IO FOR × Distraction FOR									0.373 (0.245)	0.361 (0.249)

(continued)

Table VI — *continued*

Dependent variable: $\mathbb{1}\{\text{BRI}\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Total book assets	0.008*** (0.002)	0.010*** (0.003)	0.008*** (0.002)	0.011*** (0.003)	0.008*** (0.002)	0.008*** (0.002)	0.009*** (0.002)	0.009*** (0.002)	0.008*** (0.002)	0.009*** (0.002)
Book-to-market	0.000* (0.000)	−0.000 (0.000)	0.000*** (0.000)	−0.000 (0.000)	0.000*** (0.000)	0.000* (0.000)	0.000*** (0.000)	0.000* (0.000)	−0.000 (0.000)	−0.000 (0.000)
Return on assets	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)	0.000 (0.000)	−0.000 (0.000)
Dividends	0.003* (0.002)	0.002 (0.002)	0.002 (0.002)	0.003 (0.003)	0.002 (0.002)	0.002 (0.001)	0.003 (0.002)	0.003 (0.002)	0.003* (0.002)	0.004* (0.002)
Cash	0.008* (0.004)	0.009 (0.007)	0.006 (0.004)	0.011 (0.007)	0.007 (0.004)	0.008* (0.004)	0.009** (0.005)	0.007 (0.004)	0.012** (0.005)	0.013** (0.005)
Leverage	0.003 (0.002)	0.001 (0.002)	0.000 (0.000)	0.002 (0.005)	0.000 (0.000)	0.004 (0.003)	0.004 (0.003)	0.000* (0.000)	0.008* (0.005)	0.008 (0.005)
CAPEX	−0.003 (0.032)	0.069 (0.049)	−0.002 (0.030)	0.077 (0.050)	−0.004 (0.031)	−0.000 (0.032)	0.002 (0.033)	0.002 (0.030)	−0.001 (0.038)	0.005 (0.038)
CAPEX missing	−0.005 (0.007)	−0.004 (0.011)	−0.006 (0.005)	−0.003 (0.012)	−0.006 (0.006)	−0.006 (0.007)	−0.006 (0.007)	−0.006 (0.005)	−0.005 (0.009)	−0.006 (0.009)
PPE	0.015 (0.013)	0.003 (0.017)	0.016 (0.013)	0.002 (0.018)	0.017 (0.013)	0.014 (0.013)	0.016 (0.014)	0.014 (0.012)	0.021 (0.016)	0.020 (0.016)
PPE missing	−0.001 (0.008)	0.003 (0.011)	−0.001 (0.007)	0.003 (0.011)	−0.001 (0.007)	−0.001 (0.008)	−0.001 (0.008)	−0.001 (0.007)	−0.002 (0.009)	−0.001 (0.009)
RD	0.013* (0.007)	0.013 (0.009)	0.014* (0.008)	0.013 (0.009)	0.014* (0.008)	0.013* (0.007)	0.014* (0.008)	0.013* (0.007)	0.013* (0.008)	0.013* (0.007)
RD missing	0.007** (0.003)	0.007 (0.004)	0.007** (0.003)	0.006 (0.004)	0.007** (0.003)	0.007** (0.003)	0.007** (0.003)	0.006** (0.003)	0.007** (0.004)	0.007** (0.003)
Firm age	−0.008*** (0.003)	−0.008** (0.004)	−0.007*** (0.002)	−0.007** (0.004)	−0.007*** (0.003)	−0.008*** (0.003)	−0.008*** (0.003)	−0.007*** (0.002)	−0.010*** (0.003)	−0.008*** (0.003)
Institution size	0.000 (0.001)	−0.001 (0.001)	0.001 (0.000)	−0.001 (0.001)	0.001* (0.001)	−0.000 (0.001)	0.000 (0.001)	0.001 (0.000)	−0.001 (0.001)	−0.000 (0.001)
Portfolio Herfindahl	0.011 (0.022)	0.015 (0.027)	0.010 (0.021)	0.014 (0.027)	0.020 (0.022)	0.009 (0.022)	0.020 (0.024)	0.023 (0.021)	0.008 (0.028)	0.024 (0.029)
Firm Herfindahl	0.001 (0.005)	−0.003 (0.007)	0.004 (0.004)	−0.012 (0.009)	0.005 (0.004)	0.002 (0.004)	−0.000 (0.005)	−0.002 (0.004)	−0.003 (0.009)	−0.015 (0.010)
Year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.411	0.432	0.411	0.432	0.411	0.411	0.411	0.411	0.409	0.409
Observations	161, 028	111, 110	165, 889	110, 265	163, 291	161, 480	159, 285	166, 838	143, 043	143, 011

Table VII: Biodiversity incidents and institution legal types

This table reports estimation results from quarterly regressions of biodiversity incidents on institutional ownership and a set of control variables, re-estimating the baseline model (see column 1 of [Table III](#)) to assess heterogeneity across investor legal types and to examine causal effects using exogenous variation in investor attention. The dependent variable in all columns is $\mathbb{1}\{\text{BI}\}$, an indicator equal to one if a firm experienced at least one biodiversity incident in year-quarter t . The key explanatory variable, IO, denotes the fraction of a firm's shares held by institutional investors. Distraction captures institutional shareholders' attention away from the focal firm due to plausibly exogenous shocks ([Kempf et al. \(2017\)](#)). IO is classified into ownership by investment companies (INV), independent investment advisors (IIA), bank trusts (BNK), insurance companies (INS), university and foundation endowments (UFE), corporate (private) pension funds (CPS), and public pension funds (PPS) ([Bushee \(2001\)](#)). All models interact the institutional ownership types with their respective distraction measures. All explanatory variables are measured as of year-quarter $t - 1$. All models are estimated using a linear probability model and include firm and year-quarter fixed effects. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix. Robust standard errors, double-clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable: $\mathbb{1}\{\text{BRI}\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
IO INV	-0.022 (0.037)						
IO INV \times Distraction INV	0.423 (0.349)						
IO IIA		-0.031*** (0.007)					
IO IIA \times Distraction IIA		0.039 (0.025)					
IO BNK			-0.075 (0.054)				
IO BNK \times Distraction BNK			0.309 (0.432)				
IO INS				-0.148*** (0.050)			
IO INS \times Distraction INS				0.641* (0.339)			
IO UFE					0.410 (0.407)		
IO UFE \times Distraction UFE					-1.393 (0.930)		
IO CPS						0.126 (0.111)	
IO CPS \times Distraction CPS						-0.361 (0.227)	
IO PPS							-0.223* (0.127)
IO PPS \times Distraction PPS							1.713* (1.021)
Total book assets	0.009*** (0.003)	0.009*** (0.002)	0.009*** (0.002)	0.010*** (0.003)	0.045* (0.024)	0.014*** (0.005)	0.008*** (0.002)
Book-to-market	-0.000 (0.000)	0.000* (0.000)	-0.000 (0.000)	-0.000*** (0.000)	0.000 (0.001)	-0.000 (0.000)	-0.000 (0.000)
Return on assets	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.031 (0.030)	-0.001* (0.000)	0.000 (0.000)
Dividends	0.003 (0.003)	0.002 (0.002)	0.003* (0.002)	0.003 (0.002)	22.545* (13.347)	0.127 (4.352)	0.001 (0.002)
Cash	0.012** (0.005)	0.007 (0.004)	0.007 (0.005)	0.012** (0.006)	0.028 (0.041)	0.013 (0.011)	0.011** (0.005)
Leverage	0.008 (0.005)	0.000 (0.000)	0.002 (0.001)	0.002 (0.002)	-0.002 (0.051)	0.014 (0.012)	0.002 (0.002)
CAPEX	0.008 (0.040)	-0.001 (0.031)	-0.004 (0.032)	0.002 (0.042)	0.269 (0.360)	0.101 (0.104)	0.011 (0.037)

(continued)

Table VII — *continued*

Dependent variable: $\mathbb{1}\{\text{BRI}\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CAPEX missing	−0.006 (0.009)	−0.006 (0.006)	−0.005 (0.007)	−0.007 (0.010)	0.012 (0.063)	−0.006 (0.017)	−0.006 (0.008)
PPE	0.018 (0.017)	0.015 (0.013)	0.015 (0.014)	0.022 (0.017)	0.202 (0.154)	0.022 (0.031)	0.019 (0.016)
PPE missing	−0.001 (0.009)	−0.001 (0.007)	−0.001 (0.008)	−0.001 (0.008)	0.010 (0.064)	0.000 (0.012)	−0.000 (0.009)
RD	0.047*** (0.014)	0.014* (0.008)	0.013* (0.007)	0.012* (0.007)	0.201* (0.104)	0.048 (0.049)	0.012 (0.008)
RD missing	0.008** (0.004)	0.007** (0.003)	0.007** (0.003)	0.007** (0.004)	0.029 (0.020)	0.008 (0.005)	0.007** (0.003)
Firm age	−0.010*** (0.003)	−0.007*** (0.002)	−0.008*** (0.003)	−0.009*** (0.003)	−0.023 (0.022)	−0.020*** (0.006)	−0.010*** (0.003)
Institution size	−0.000 (0.001)	0.000 (0.000)	0.001 (0.001)	−0.000 (0.001)	−0.004 (0.009)	−0.003 (0.002)	0.000 (0.001)
Portfolio Herfindahl	0.015 (0.029)	0.012 (0.021)	0.009 (0.024)	0.009 (0.029)	0.389 (0.253)	0.018 (0.076)	0.008 (0.025)
Firm Herfindahl	−0.005 (0.009)	−0.001 (0.004)	0.009 (0.006)	−0.001 (0.011)	−0.181** (0.088)	−0.049 (0.032)	0.006 (0.007)
Year-quarter FE	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.411	0.411	0.411	0.410	0.487	0.426	0.412
Observations	142,029	165,739	158,527	136,214	11,419	83,942	147,815

Table VIII: Institutional sponsorship and shareholder proposal outcomes

This table reports estimation results from proposal-level multinomial logit regressions for shareholder proposal outcomes and the marginal effects of the logit estimates. Columns 1 to 6 include all ESG shareholder proposals, whereas columns 7 to 12 restrict the sample to biodiversity-related shareholder proposals. Columns 1 to 3 and 7 to 9 present the logit coefficient estimates for the respective sample. Columns 1 and 2, as well as columns 7 and 8, report the logit coefficient estimates for proposal outcomes of voted (VOTE) and withdrawn (WIDR), with omitted (OMIT) proposals being the reference category. Columns 3 and 9 report the logit coefficient estimates for withdrawn, with voted being the reference category. Columns 4 to 6 and 10 to 12 present the marginal effects of the logit estimates for the respective sample. The key explanatory variable, Inst sponsor, is an indicator equal to one if the proposal is sponsored by an institutional investor. All regressions include firm and year-quarter fixed effects. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix. Robust standard errors, clustered at the firm level, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	All ESG proposals						Biodiversity-related proposals					
	Multinomial logit			Marginal effects			Multinomial logit			Marginal effects		
	VOTE vs. OMIT	WIDR vs. OMIT	WIDR vs. VOTE	OMIT	VOTE	WIDR	VOTE vs. OMIT	WIDR vs. OMIT	WIDR vs. VOTE	OMIT	VOTE	WIDR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Inst sponsor	0.602*** (0.130)	1.835*** (0.155)	1.235*** (0.106)	−0.102*** (0.013)	−0.072*** (0.014)	0.174*** (0.012)	0.782 (0.570)	1.489*** (0.543)	0.716 (0.447)	−0.042** (0.017)	−0.032 (0.034)	0.075** (0.034)
IO	1.180* (0.657)	1.980** (0.804)	0.801 (0.632)	−0.151** (0.069)	0.014 (0.088)	0.137* (0.078)	−4.545 (2.994)	−3.503 (3.134)	0.953 (2.641)	0.143 (0.097)	−0.138 (0.199)	−0.005 (0.214)
Total book assets	0.076 (0.209)	−0.186 (0.277)	−0.262 (0.239)	−0.000 (0.022)	0.031 (0.031)	−0.031 (0.029)	2.454 (3.016)	3.451 (2.470)	0.805 (0.939)	−0.109 (0.094)	−0.024 (0.098)	0.133** (0.055)
Book-to-market	−0.266 (0.211)	−0.093 (0.206)	0.173 (0.162)	0.023 (0.021)	−0.037 (0.027)	0.014 (0.019)	−2.469 (2.134)	−3.207 (2.151)	−0.554 (0.845)	0.104 (0.073)	0.007 (0.070)	−0.111 (0.076)
Return on assets	−1.020 (2.693)	0.207 (2.631)	1.237 (2.223)	0.073 (0.267)	−0.197 (0.360)	0.124 (0.258)	50.374** (22.271)	37.586* (21.564)	−10.271 (9.539)	−1.561** (0.718)	1.613** (0.799)	−0.052 (0.819)
Dividends	−304.972* (159.781)	−52.681 (146.322)	252.487** (109.211)	25.190 (15.931)	−47.872** (19.666)	22.683* (12.479)	−115.034 (217.964)	275.579 (188.143)	371.726** (169.463)	−3.722 (6.514)	−26.569** (13.338)	30.291** (12.781)
Cash	0.635 (0.956)	0.899 (1.074)	0.271 (0.837)	−0.076 (0.098)	0.024 (0.124)	0.052 (0.102)	−7.489 (9.108)	−5.096 (7.435)	2.675 (5.575)	0.222 (0.272)	−0.271 (0.465)	0.049 (0.403)
Leverage	0.146 (0.441)	−0.642 (0.413)	−0.784** (0.396)	0.008 (0.042)	0.087 (0.063)	−0.095** (0.045)	8.672 (7.179)	6.212 (6.742)	−2.585* (1.393)	−0.264 (0.241)	0.294* (0.161)	−0.031 (0.138)
CAPEX	−2.012 (8.683)	−9.787 (11.770)	−7.701 (9.647)	0.452 (0.927)	0.592 (1.246)	−1.044 (1.207)	45.920 (41.962)	41.217 (41.285)	−2.018 (32.421)	−1.563 (1.365)	1.030 (2.498)	0.533 (2.600)
CAPEX missing	−0.323 (0.439)	−3.254*** (1.204)	−2.947** (1.376)	0.123*** (0.043)	0.257* (0.153)	−0.380** (0.167)	−12.124** (6.180)	−6.532 (5.827)	8.023** (3.149)	0.325 (0.201)	−0.547** (0.259)	0.222 (0.251)
PPE	−0.017 (1.031)	1.029 (1.326)	1.050 (1.147)	−0.030 (0.107)	−0.102 (0.152)	0.132 (0.140)	−12.916 (11.135)	−7.712 (10.304)	5.298 (4.439)	0.361 (0.366)	−0.536 (0.390)	0.174 (0.356)
PPE missing	0.601 (0.643)	0.307 (1.040)	−0.288 (0.433)	−0.056 (0.081)	0.075*** (0.026)	−0.019 (0.073)	3.092* (1.615)	−8.457*** (1.622)	−8.383*** (2.166)	0.121*** (0.039)	0.781*** (0.161)	−0.902*** (0.165)

Table VIII — *continued*

	All ESG proposals						Biodiversity-related proposals					
	Multinomial logit			Marginal effects			Multinomial logit			Marginal effects		
	VOTE vs. OMIT	WIDR vs. OMIT	WIDR vs. VOTE	OMIT	VOTE	WIDR	VOTE vs. OMIT	WIDR vs. OMIT	WIDR vs. VOTE	OMIT	VOTE	WIDR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
RD	−3.956 (15.693)	−21.811 (20.854)	−17.874 (16.340)	0.965 (1.683)	1.412 (2.134)	−2.377 (2.048)	−426.753*** (94.338)	−291.287** (119.619)	124.858 (118.304)	12.679*** (2.967)	−15.384* (8.264)	2.705 (9.088)
RD missing	0.015 (0.407)	1.200 (0.789)	1.185* (0.609)	−0.037 (0.050)	−0.113* (0.062)	0.150* (0.080)	−4.051* (2.217)	6.978*** (1.788)	7.863*** (2.514)	−0.076 (0.054)	−0.763*** (0.190)	0.839*** (0.185)
Firm age	−0.096 (0.386)	−0.594 (0.382)	−0.498 (0.380)	0.025 (0.037)	0.041 (0.058)	−0.066 (0.043)	−14.781* (8.529)	−15.185* (8.344)	−0.622 (2.363)	0.542* (0.289)	−0.210 (0.228)	−0.332 (0.238)
Institution size	0.142 (0.227)	−0.385 (0.292)	−0.527** (0.248)	0.001 (0.024)	0.062* (0.033)	−0.062** (0.030)	−1.619 (3.139)	−3.035 (3.185)	−1.223 (1.241)	0.087 (0.112)	0.064 (0.106)	−0.151 (0.118)
Portfolio Herfindahl	0.392 (4.251)	2.014 (3.218)	1.640 (4.019)	−0.091 (0.382)	−0.126 (0.662)	0.217 (0.431)	56.193 (90.473)	62.628 (89.515)	4.372 (28.514)	−2.159 (3.188)	0.489 (2.619)	1.670 (2.818)
Firm Herfindahl	2.309 (4.792)	3.987 (4.859)	1.850 (1.827)	−0.299 (0.510)	0.017 (0.435)	0.282 (0.255)	−89.094 (60.837)	−27.423 (55.760)	52.924* (30.207)	1.974 (2.027)	−5.326** (2.707)	3.352 (2.590)
Staggered board	−0.132 (0.223)	0.166 (0.256)	0.302 (0.236)	0.005 (0.022)	−0.039 (0.033)	0.034 (0.028)	1.670 (2.987)	2.120 (2.893)	0.355 (1.374)	−0.069 (0.102)	−0.002 (0.112)	0.071 (0.113)
Dual-class shares	−0.026 (0.375)	0.699* (0.403)	0.740* (0.419)	−0.019 (0.036)	−0.072 (0.060)	0.091* (0.048)	−7.962 (5.952)	4.438 (5.717)	9.232*** (1.824)	0.038 (0.205)	−0.912*** (0.166)	0.875*** (0.168)
Poison pill	−0.148 (0.382)	−0.035 (0.512)	0.107 (0.378)	0.012 (0.042)	−0.022 (0.049)	0.010 (0.048)	−22.241*** (6.044)	−10.868* (5.716)	9.233*** (2.216)	0.574** (0.232)	−1.075*** (0.200)	0.501*** (0.189)
Golden parachute	−0.065 (0.179)	−0.156 (0.231)	−0.091 (0.177)	0.010 (0.019)	0.004 (0.024)	−0.014 (0.022)	−0.147 (1.549)	−1.108 (1.452)	−0.876 (0.893)	0.025 (0.051)	0.059 (0.071)	−0.083 (0.069)
Year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Pseudo R^2	0.316	0.316	0.318				0.659	0.659	0.659			
Observations	7,365	7,365	7,365	7,365	7,365	7,365	954	954	954	954	954	954

Table IX: Shareholder proposal outcomes and biodiversity incidents

This table reports estimation results from yearly regressions of biodiversity incidents on proposal outcome counts and a set of control variables. The dependent variable in columns 1 to 4 is $\mathbb{1}\{\text{BI}\}$, an indicator equal to one if a firm experienced at least one biodiversity incident in year t . Columns 1 to 3 use the number of omitted proposals (OMIT count), voted proposals (VOTE count), and withdrawn proposals (WIDR count), respectively, relating to the firm in year $t - 1$ as the key explanatory variable. Column 4 includes all three measures simultaneously. Columns 5 to 8 re-estimate the specification in column 4, using as dependent variables indicators for the occurrence of new, re-occurring, low-severity, and high-severity biodiversity incidents, respectively. Column 9 presents a placebo test in which the key explanatory variable is based on the counts of shareholder proposals that are not related to biodiversity. All explanatory variables are measured as of year $t - 1$. All models are estimated using a linear probability model. All regressions include firm and year fixed effects. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix. Robust standard errors, double-clustered at the firm and year levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Proposal type:	Biodiversity related								Other ESG
Dependent variable:	$\mathbb{1}\{\text{BI}\}$				$\mathbb{1}\{\text{BI new}\}$	$\mathbb{1}\{\text{BI re-occ.}\}$	$\mathbb{1}\{\text{BI low sev.}\}$	$\mathbb{1}\{\text{BI high sev.}\}$	$\mathbb{1}\{\text{BI}\}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
OMIT count	−0.002 (0.020)			−0.004 (0.020)	0.010 (0.021)	−0.008 (0.031)	−0.008 (0.027)	0.027 (0.033)	0.007 (0.004)
VOTE count		0.008 (0.018)		0.005 (0.018)	0.018 (0.018)	−0.009 (0.030)	0.011 (0.023)	−0.002 (0.021)	0.014** (0.007)
WIDR count			−0.012*** (0.004)	−0.012** (0.005)	−0.007 (0.005)	−0.015** (0.007)	−0.010* (0.005)	−0.010** (0.005)	−0.001 (0.005)
Total count	0.005 (0.004)	0.005 (0.004)	0.007** (0.003)	0.007* (0.004)	0.005* (0.003)	0.009** (0.004)	0.005 (0.004)	0.008* (0.005)	
IO	−0.096*** (0.033)	−0.096*** (0.033)	−0.097*** (0.033)	−0.097*** (0.033)	−0.060** (0.028)	−0.070 (0.046)	−0.095*** (0.035)	−0.051 (0.036)	−0.095*** (0.033)
Total book assets	0.023* (0.012)	0.023* (0.012)	0.022* (0.012)	0.022* (0.012)	0.012 (0.012)	0.033*** (0.010)	0.016 (0.013)	0.035*** (0.012)	0.022* (0.012)
Book-to-market	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.004 (0.007)	0.006 (0.006)	0.005 (0.009)	0.011 (0.008)	0.001 (0.006)	0.004 (0.008)
Return on assets	0.010 (0.033)	0.010 (0.033)	0.010 (0.033)	0.010 (0.033)	0.003 (0.031)	−0.005 (0.030)	0.012 (0.032)	−0.020 (0.025)	0.012 (0.032)
Dividends	0.027 (0.041)	0.027 (0.041)	0.027 (0.041)	0.027 (0.041)	0.063 (0.046)	−0.050 (0.048)	0.028 (0.050)	−0.022 (0.038)	0.026 (0.041)
Cash	0.046 (0.034)	0.046 (0.034)	0.046 (0.034)	0.046 (0.034)	0.025 (0.023)	0.046 (0.040)	0.060* (0.034)	0.034 (0.030)	0.045 (0.034)
Leverage	−0.008 (0.022)	−0.008 (0.022)	−0.009 (0.022)	−0.009 (0.022)	0.005 (0.020)	0.006 (0.021)	0.044 (0.027)	−0.020 (0.029)	−0.010 (0.022)

(continued)

Table IX — *continued*

Proposal type:	Biodiversity related								Other ESG
Dependent variable:	1 {BI}				1 {BI new}	1 {BI re-occ.}	1 {BI low sev.}	1 {BI high sev.}	1 {BI}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CAPEX	0.168 (0.207)	0.171 (0.206)	0.164 (0.206)	0.166 (0.205)	0.182* (0.101)	0.266 (0.248)	0.123 (0.171)	0.368** (0.173)	0.166 (0.207)
CAPEX missing	0.113 (0.123)	0.113 (0.123)	0.113 (0.119)	0.113 (0.119)	0.026 (0.024)	0.103 (0.127)	0.022 (0.029)	0.126 (0.117)	0.110 (0.119)
PPE	0.027 (0.093)	0.026 (0.093)	0.026 (0.093)	0.026 (0.093)	−0.036 (0.070)	0.001 (0.085)	0.013 (0.078)	−0.010 (0.086)	0.025 (0.093)
PPE missing	0.108 (0.162)	0.108 (0.162)	0.108 (0.162)	0.108 (0.162)	−0.029 (0.022)	0.126 (0.158)	−0.029 (0.025)	0.118 (0.164)	0.109 (0.162)
RD	0.061 (0.050)	0.062 (0.051)	0.062 (0.050)	0.062 (0.050)	0.017 (0.043)	0.044 (0.046)	0.041 (0.048)	0.021 (0.038)	0.064 (0.049)
RD missing	0.066** (0.030)	0.066** (0.030)	0.066** (0.030)	0.066** (0.030)	−0.001 (0.032)	0.065** (0.028)	0.039 (0.039)	0.033 (0.028)	0.066** (0.030)
Firm age	−0.008 (0.013)	−0.008 (0.013)	−0.008 (0.013)	−0.008 (0.013)	−0.001 (0.011)	−0.017 (0.014)	−0.017 (0.011)	−0.005 (0.012)	−0.007 (0.013)
Institution size	0.023** (0.011)	0.023** (0.011)	0.023** (0.011)	0.023** (0.011)	0.006 (0.007)	0.019* (0.011)	0.019* (0.011)	0.013 (0.009)	0.023** (0.011)
Portfolio Herfindahl	0.478** (0.209)	0.478** (0.208)	0.483** (0.209)	0.483** (0.209)	0.384** (0.180)	0.414* (0.208)	0.470** (0.229)	0.416** (0.201)	0.490** (0.208)
Firm Herfindahl	−0.217** (0.106)	−0.217** (0.106)	−0.220** (0.105)	−0.220** (0.106)	−0.258** (0.097)	−0.126 (0.103)	−0.228* (0.130)	−0.220** (0.089)	−0.225** (0.106)
Staggered board	−0.032* (0.017)	−0.032* (0.017)	−0.032* (0.017)	−0.032* (0.017)	−0.006 (0.014)	−0.053*** (0.015)	−0.023 (0.020)	−0.029** (0.012)	−0.030* (0.017)
Dual-class shares	−0.049* (0.028)	−0.049* (0.028)	−0.049* (0.028)	−0.049* (0.028)	−0.046** (0.020)	−0.043 (0.027)	−0.052* (0.030)	−0.010 (0.025)	−0.050* (0.027)
Poison pill	0.015 (0.032)	0.015 (0.032)	0.015 (0.032)	0.015 (0.032)	0.002 (0.017)	0.004 (0.032)	0.009 (0.025)	−0.018 (0.029)	0.016 (0.032)
Golden parachute	0.007 (0.015)	0.007 (0.015)	0.006 (0.015)	0.006 (0.015)	0.007 (0.015)	0.018 (0.013)	0.008 (0.018)	0.010 (0.016)	0.006 (0.015)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.567	0.567	0.567	0.567	0.614	0.447	0.526	0.512	0.567
Observations	6, 892	6, 892	6, 892	6, 892	6, 892	6, 892	6, 892	6, 892	6, 892

Table X: Biodiversity incidents and the cost of equity capital

This table reports estimation results from yearly regressions of the cost of equity capital on biodiversity incidents and a set of control variables. The dependent variable in all columns is COE, the firm's implied cost of equity capital in year t , computed as the average of estimates across four models: [Claus and Thomas \(2001\)](#), [Gebhardt et al. \(2001\)](#), [Easton \(2004\)](#), [Ohlson and Juettner-Nauroth \(2005\)](#). The key explanatory variables are indicators equal to one if the firm experienced at least one biodiversity incident ($\mathbb{1}\{\text{BI count}\}$), a new biodiversity incident ($\mathbb{1}\{\text{BI new}\}$), a re-occurring biodiversity incident ($\mathbb{1}\{\text{BI re-occurring}\}$), a low-severity biodiversity incident ($\mathbb{1}\{\text{BI low severity}\}$), or a high-severity biodiversity incident ($\mathbb{1}\{\text{BI high severity}\}$), respectively. All explanatory variables are measured as of year $t - 1$. All models are estimated using a linear probability model and include industry-by-year fixed effects. Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix. Robust standard errors, double-clustered at the firm and year levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

[illegible]

Table XI: Correlations with conventional ESG ratings

This table reports pairwise correlation coefficients among measures of biodiversity incidents based on RepRisk data and three conventional ESG ratings: Sustainalytics, MSCI, and Refinitiv. Panel A presents correlations with aggregate ESG scores, whereas Panel B presents correlations with the environmental-pillar scores from each agency. $\mathbb{1}\{\text{BI}\}$ is an indicator equal to one if a firm experienced at least one biodiversity incident in year-quarter t . BI count is the number of biodiversity incidents in year-quarter t . $\ln(1 + \text{BI count})$ is the natural logarithm of one plus the incident count. All variables are measured in year-quarter t . Detailed variable definitions and data sources are provided in [Table A1](#) in the Appendix. Robust standard errors, double-clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: All ESG dimensions						
(1) $\mathbb{1}\{\text{BI}\}$	1.000					
(2) BI count	0.588*** (0.000)	1.000				
(3) $\ln(1 + \text{BI count})$	0.887*** (0.000)	0.858*** (0.000)	1.000			
(4) Sustainalytics	0.154*** (0.000)	0.065*** (0.000)	0.127*** (0.000)	1.000		
(5) MSCI	-0.044*** (0.000)	-0.045*** (0.000)	-0.046*** (0.000)	0.390*** (0.000)	1.000	
(6) Refinitiv	0.296*** (0.000)	0.233*** (0.000)	0.299*** (0.000)	0.651*** (0.000)	0.248*** (0.000)	1.000
Panel B: Environmental dimension						
(1) $\mathbb{1}\{\text{BI}\}$	1.000					
(2) BI count	0.588*** (0.000)	1.000				
(3) $\ln(1 + \text{BI count})$	0.887*** (0.000)	0.858*** (0.000)	1.000			
(4) Sustainalytics	0.215*** (0.000)	0.117*** (0.000)	0.189*** (0.000)	1.000		
(5) MSCI	0.012* (0.080)	-0.011 (0.120)	0.000 (0.956)	0.396*** (0.000)	1.000	
(6) Refinitiv	0.160*** (0.000)	0.088*** (0.000)	0.141*** (0.000)	0.591*** (0.000)	0.346*** (0.000)	1.000

Table XII: Controlling for conventional ESG ratings

This table reports estimation results from quarterly regressions of biodiversity incidents on conventional ESG ratings and a set of control variables. The dependent variable in all columns is $\mathbb{1}\{\text{BI}\}$, an indicator equal to one if a firm experienced at least one biodiversity incident in year-quarter t . The key explanatory variables in columns 1 to 3 are the aggregate ESG scores from Sustainalytics, MSCI, and Refinitiv, respectively. Column 4 includes all three scores simultaneously. Columns 5 to 7 re-estimate model 4 using only the E, S, and G scores from each agency, respectively. Column 8 re-estimates the baseline model (see column 1 of Table III) on the subset of firms covered by all three rating agencies. All explanatory variables are measured in year-quarter $t-1$. Detailed variable definitions and data sources are provided in Table A1 in the Appendix. Robust standard errors, double-clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dimensions:	ESG				E	S	G	w/o
Dependent var.: $\mathbb{1}\{\text{BRI}\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sustainalytics	-0.007** (0.003)			-0.010** (0.004)	-0.006** (0.002)	-0.005 (0.004)	-0.003 (0.003)	
MSCI		-0.017** (0.009)		-0.009 (0.015)	-0.007 (0.010)	0.010 (0.009)	-0.003 (0.006)	
Refinitiv			-0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)	
IO	-0.307*** (0.100)	-0.125*** (0.046)	-0.082* (0.042)	-0.325** (0.129)	-0.322** (0.131)	-0.313** (0.131)	-0.313** (0.132)	-0.312** (0.132)
Total book assets	0.041 (0.039)	0.060** (0.026)	0.042* (0.021)	0.061 (0.057)	0.060 (0.057)	0.063 (0.058)	0.060 (0.058)	0.064 (0.058)
Book-to-market	-0.002*** (0.001)	-0.000 (0.000)	-0.000 (0.000)	0.018 (0.015)	0.019 (0.015)	0.019 (0.016)	0.020 (0.016)	0.020 (0.016)
Return on assets	0.313* (0.183)	-0.001 (0.001)	-0.010 (0.021)	0.321 (0.282)	0.309 (0.278)	0.322 (0.282)	0.314 (0.280)	0.320 (0.280)
Dividends	-7.589 (29.923)	0.001 (0.001)	0.428 (0.372)	-4.353 (31.842)	-5.918 (31.191)	-5.987 (31.384)	-4.658 (31.624)	-4.979 (31.708)
Cash	0.247* (0.135)	0.075* (0.043)	0.051 (0.048)	0.175 (0.162)	0.161 (0.165)	0.143 (0.159)	0.158 (0.160)	0.151 (0.160)
Leverage	0.121 (0.125)	0.033 (0.047)	0.019 (0.053)	0.088 (0.165)	0.085 (0.169)	0.087 (0.167)	0.079 (0.165)	0.084 (0.168)
CAPEX	2.768* (1.383)	0.979** (0.401)	0.729* (0.411)	4.051** (1.945)	4.130** (2.003)	4.149** (1.970)	4.136** (2.012)	4.198** (2.023)
CAPEX missing	-0.024 (0.063)	0.008 (0.030)	-0.026 (0.037)	-0.008 (0.089)	-0.006 (0.086)	-0.003 (0.090)	0.007 (0.092)	0.006 (0.089)
PPE	-0.301 (0.248)	0.123 (0.158)	0.137 (0.163)	-0.366 (0.399)	-0.417 (0.398)	-0.366 (0.400)	-0.369 (0.400)	-0.370 (0.401)
PPE missing	0.010 (0.030)	-0.020 (0.033)	0.002 (0.035)	0.014 (0.042)	0.017 (0.041)	0.007 (0.043)	0.005 (0.042)	0.007 (0.041)
RD	1.286 (0.896)	0.287** (0.114)	0.094 (0.084)	1.331 (1.151)	1.294 (1.139)	1.336 (1.158)	1.361 (1.160)	1.385 (1.162)
RD missing	0.095* (0.052)	0.035* (0.018)	0.029 (0.022)	0.097 (0.067)	0.096 (0.067)	0.095 (0.067)	0.096 (0.067)	0.096 (0.067)
Firm age	-0.027 (0.059)	-0.015 (0.020)	-0.012 (0.011)	0.010 (0.085)	-0.009 (0.083)	0.008 (0.090)	0.004 (0.077)	-0.008 (0.085)
Institution size	0.017 (0.018)	0.001 (0.007)	-0.002 (0.005)	0.016 (0.036)	0.014 (0.035)	0.019 (0.036)	0.016 (0.036)	0.017 (0.036)
Portfolio Herfindahl	0.858* (0.465)	0.268 (0.171)	0.182 (0.143)	0.779 (0.748)	0.742 (0.744)	0.735 (0.748)	0.646 (0.734)	0.648 (0.739)
Firm Herfindahl	-0.232 (0.185)	-0.157 (0.127)	-0.034 (0.052)	-0.043 (0.413)	0.008 (0.404)	-0.038 (0.412)	-0.003 (0.406)	0.000 (0.407)
Year-quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.686	0.632	0.638	0.678	0.678	0.677	0.677	0.677
Observations	28,311	89,770	67,687	21,053	21,053	21,053	21,053	21,053

Table XIII: Biodiversity incidents and historical biodiversity performance

This table reports estimation results from quarterly regressions of biodiversity incidents on institutional ownership, past biodiversity incidents, and a set of control variables. It re-estimates the baseline model (see column 1 of Table III), augmenting it with indicators for historical biodiversity incident occurrences. The dependent variable in all columns is $\mathbb{1}\{\text{BI}\}$, an indicator equal to one if a firm experienced at least one biodiversity incident in year-quarter t . The key explanatory variable, IO, denotes the fraction of a firm's shares held by institutional investors. All explanatory variables, except the biodiversity regressors, are measured as of year-quarter $t - 1$. All models are estimated using a linear probability model and include firm and year-quarter fixed effects. Detailed variable definitions and data sources are provided in Table A1 in the Appendix. Robust standard errors, double-clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable: $\mathbb{1}\{\text{BRI}\}$	(1)	(2)	(3)	(4)
IO	−0.019*** (0.005)	−0.019*** (0.005)	−0.020*** (0.006)	−0.019*** (0.006)
$\mathbb{1}\{\text{BRI}_{t-1}\}$	0.114*** (0.013)	0.101*** (0.011)	0.095*** (0.010)	0.091*** (0.010)
$\mathbb{1}\{\text{BRI}_{t-2}\}$		0.063*** (0.012)	0.053*** (0.011)	0.048*** (0.010)
$\mathbb{1}\{\text{BRI}_{t-3}\}$			0.050*** (0.012)	0.042*** (0.012)
$\mathbb{1}\{\text{BRI}_{t-4}\}$				0.047*** (0.012)
Total book assets	0.008*** (0.001)	0.008*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
Book-to-market	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Return on assets	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)	−0.000 (0.000)
Dividends	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Cash	0.008** (0.003)	0.007* (0.003)	0.006* (0.003)	0.005 (0.003)
Leverage	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
CAPEX	−0.019 (0.022)	−0.017 (0.029)	−0.011 (0.031)	−0.005 (0.033)
CAPEX missing	−0.008* (0.004)	−0.007 (0.004)	−0.007 (0.004)	−0.007 (0.005)
PPE	0.018* (0.010)	0.015 (0.010)	0.010 (0.010)	0.008 (0.010)
PPE missing	0.000 (0.006)	−0.000 (0.006)	−0.000 (0.007)	−0.000 (0.007)
RD	0.003** (0.001)	0.003** (0.001)	0.004* (0.002)	0.004 (0.003)
RD missing	0.006* (0.003)	0.006* (0.003)	0.006* (0.003)	0.006* (0.003)
Firm age	−0.002* (0.001)	−0.004** (0.002)	−0.005* (0.002)	−0.005* (0.003)
Institution size	0.001* (0.000)	0.001* (0.000)	0.001 (0.000)	0.001 (0.000)
Portfolio Herfindahl	0.026 (0.016)	0.023 (0.016)	0.018 (0.016)	0.020 (0.016)
Firm Herfindahl	0.001 (0.003)	0.001 (0.003)	0.001 (0.003)	0.000 (0.004)
Year-quarter FE	✓	✓	✓	✓
Firm FE	✓	✓	✓	✓
Adjusted R^2	0.411	0.417	0.423	0.426
Observations	206, 570	198, 366	190, 480	182, 885

Appendix

Table A1: Variable Definitions

This Appendix provides definitions of and data sources for the main variables used in the study.

Variables	Definitions	Sources
Biodiversity incident measures		
$1\{\text{BI}\}$	A dummy variable equal to one if the firm experienced at least one biodiversity incident in a given calendar year (or quarter), and zero otherwise. Biodiversity incidents are classified under the category “impacts on landscapes, ecosystems, and biodiversity.”	RepRisk
$1\{\text{BI new}\}$	A dummy variable equal to one if the firm experienced at least one new biodiversity incident in a given calendar year (or quarter), and zero otherwise. RepRisk classifies an incident as new if it is the first time a firm is exposed to a specific ESG issue in a given location.	As above
$1\{\text{BI re-occurring}\}$	A dummy variable equal to one if the firm experienced at least one re-occurring biodiversity incident in a given calendar year (or quarter), and zero otherwise. RepRisk classifies re-occurring incidents as repeated instances of the same or similar issues involving a particular firm.	As above
$1\{\text{BI low severity}\}$	A dummy variable equal to one if the firm experienced at least one low-severity biodiversity incident in a given calendar year (or quarter), and zero otherwise. Low-severity incidents are those classified by RepRisk as severity level 1. The severity classification depends on: (1) the consequences for health and safety, (2) the extent of the incident in terms of affected people or regions, and (3) whether the incident was the result of an accident, negligence, or intent.	As above
$1\{\text{BI high severity}\}$	A dummy variable equal to one if the firm experienced at least one high-severity biodiversity incident in a given calendar year (or quarter), and zero otherwise. High-severity incidents are those classified by RepRisk as severity levels 2 or 3.	As above
BI count	The total number of biodiversity incidents experienced by the firm in a given calendar year (or quarter).	As above
$\text{Ln}(1+\text{BI count})$	The natural logarithm of one plus the total number of biodiversity incidents experienced by the firm in a given calendar year (or quarter).	As above
Abnormal return measures		
CAR^{BI}	Cumulative abnormal return (CAR) around biodiversity incidents over different event windows. CARs are estimated using the market model, centered around the biodiversity incidents, with the CRSP value-weighted index as the benchmark. The market model is calibrated over a pre-event window spanning from 300 to 46 trading days prior to the event (Edmans (2011)). To mitigate the influence of outliers, all CARs are winsorized at the 1% and 99% levels.	RepRisk, CRSP
CAR^{EA}	Three-day cumulative abnormal return around earnings announcements. CARs are estimated using the market model, centered around the earnings announcement date, with the CRSP value-weighted index as the benchmark. The market model is calibrated over a pre-event window spanning from 300 to 91 trading days prior to the event. To mitigate the influence of outliers, all CARs are winsorized at the 1% and 99% levels.	RepRisk, Compustat, CRSP
Firm characteristics		
Total book assets	The natural logarithm of total book assets (Compustat item 6) reported by the firm at the end of the fiscal year (or quarter).	Compustat
Book-to-market	The ratio of book value to market value, calculated at the fiscal year-end as the sum of common equity (Compustat item 60) and deferred taxes (item 74), divided by the market value of equity (Compustat items 24×25).	As above
Return on assets	The ratio of net income (Compustat item 172) to total book assets, reported by the firm at the end of the fiscal year (or quarter).	As above
Dividends	The ratio of common dividends (Compustat item 21) to total book assets, reported by the firm at the end of the fiscal year (or quarter).	As above

(continued)

Table A1 — *continued*

Variables	Definitions	Sources
Cash	The ratio of cash and cash equivalents (Compustat item 1) to total book assets, reported by the firm at the end of the fiscal year (or quarter).	As above
Leverage	The ratio of total debt, defined as the sum of long-term debt (Compustat item 9) and current debt (item 34), to total book assets, reported by the firm at the end of the fiscal year (or quarter).	As above
CAPEX	The ratio of capital expenditures (Compustat item 128) to total book assets, reported by the firm at the end of the fiscal year (or quarter).	As above
CAPEX missing	A dummy variable equal to one if capital expenditures data (Compustat item 128) are not reported, and zero otherwise.	As above
PPE	The ratio of net property, plant, and equipment (Compustat item 8) to total book assets, reported by the firm at the end of the fiscal year (or quarter).	As above
PPE missing	A dummy variable equal to one if PPE data (Compustat item 8) are not reported, and zero otherwise.	As above
RD	The ratio of research and development expenditures (Compustat item 46) to total book assets, reported by the firm at the end of the fiscal year (or quarter).	As above
RD missing	A dummy variable equal to one if R&D data (Compustat item 46) are not reported, and zero otherwise.	As above
Firm age	The natural logarithm of the number of years since the firm first appears in the CRSP database.	CRSP
Institution size	The natural logarithm of institutional investor's assets reported in 13F filings at the end of the calendar quarter. Holdings weights are applied to aggregate investor-level assets at the firm level.	Thomson Reuters 13F
Portfolio Herfindahl	The Investor-level weighted Herfindahl at the end of the calendar quarter, i.e., weighted institution's portfolio dispersion. Holdings weights are applied to aggregate investor-level portfolio dispersion at the firm level.	As above
Firm Herfindahl	Firm-level Herfindahl, i.e., firm's shareholder dispersion at the end of the calendar quarter.	As above
Earnings lag	The number of days between the earnings announcement date and the previous earnings announcement date.	As above
COE	The average implied cost of equity derived from the valuation models of Claus and Thomas (2001) and Gebhardt et al. (2001) as well as the abnormal growth models of Easton (2004) and Ohlson and Juettner-Nauroth (2005) .	Compustat, I/B/E/S
Forecast bias	The one-year-ahead consensus earnings forecast minus realized earnings, divided by lagged assets per share.	I/B/E/S
Forecast dispersion	The coefficient of variation of one-year-ahead earnings per share analyst forecasts.	As above
Ownership characteristics		
IO	Common shares held by institutional investors as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
IO TRA	Common shares held by transient institutional investors (Bushee and Noe (2000) , Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	Thomson Reuters 13F, Brian Bushee
IO DED	Common shares held by dedicated institutional investors (Bushee and Noe (2000) , Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
IO QIX	Common shares held by quasi-indexer institutional investors (Bushee and Noe (2000) , Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
IO LT	Common shares held by long-term institutional investors as a percentage of firm's outstanding shares at the end of the calendar quarter. Long-term investors are classified as those in the bottom tercile of the churn rate distribution (see Equation 9).	Thomson Reuters 13F

(continued)

Table A1 — *continued*

Variables	Definitions	Sources
IO ST	Common shares held by short-term institutional investors as a percentage of firm's outstanding shares at the end of the calendar quarter. Short-term investors are classified as those in the top tercile of the churn rate distribution (see Equation 9).	As above
IO DOM	Common shares held by domestic institutional investors as a percentage of firm's outstanding shares at the end of the calendar quarter. Domestic investors are those incorporated in the U.S.	As above
IO FOR	Common shares held by foreign institutional investors as a percentage of firm's outstanding shares at the end of the calendar quarter. Foreign investors are those not incorporated in the U.S.	As above
IO INV	Common shares held by investment companies (Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	Thomson Reuters 13F, Brian Bushee
IO IIA	Common shares held by independent investment advisors (Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
IO BNK	Common shares held by bank trusts (Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
IO INS	Common shares held by insurance companies (Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
IO UFE	Common shares held by university and foundation endowments (Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
IO CPS	Common shares held by corporate pension funds (Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
IO PPS	Common shares held by public pension funds (Bushee (2001)) as a percentage of firm's outstanding shares at the end of the calendar quarter.	As above
Distraction	Firm-level measure of institutional investor distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017). Distraction captures exogenous variation in monitoring intensity due to extreme industry returns unrelated to the focal firm.	Thomson Reuters 13F, Kenneth French
Distraction TRA	Firm-level measure of transient institutional investor (Bushee and Noe (2000), Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017).	Thomson Reuters 13F, Brian Bushee, Kenneth French
Distraction DED	Firm-level measure of dedicated institutional investor (Bushee and Noe (2000), Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017).	As above
Distraction QIX	Firm-level measure of quasi-indexer institutional investor (Bushee and Noe (2000), Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017).	As above
Distraction LT	Firm-level measure of long-term institutional investor distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017). Long-term investors are classified as those in the bottom tercile of the churn rate distribution (see Equation 9).	As above
Distraction ST	Firm-level measure of short-term institutional investor distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017). Short-term investors are classified as those in the top tercile of the churn rate distribution (see Equation 9).	As above
Distraction DOM	Firm-level measure of domestic institutional investor distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017). Domestic investors are those incorporated in the U.S.	As above

(continued)

Table A1 — *continued*

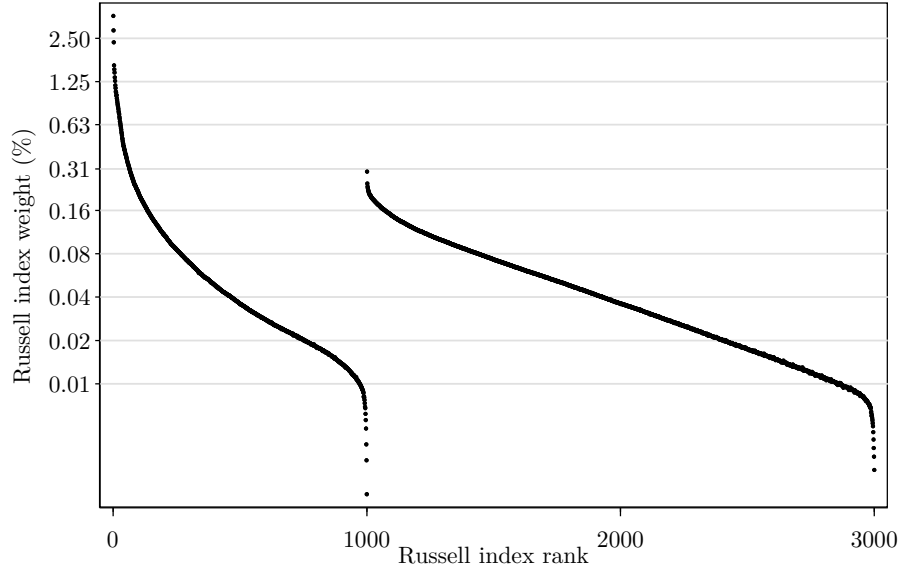
Distraction FOR	Firm-level measure of foreign institutional investor distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017) . Foreign investors are those not incorporated in the U.S.	As above
Distraction INV	Firm-level measure of investment company (Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017) .	As above
Distraction IIA	Firm-level measure of independent investment advisor (Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017) .	As above
Distraction BNK	Firm-level measure of bank trust (Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017) .	As above
Distraction INS	Firm-level measure of insurance company (Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017) .	As above
Distraction UFE	Firm-level measure of university and foundation endowment (Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017) .	As above
Distraction CPS	Firm-level measure of corporate pension fund (Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017) .	As above
Distraction PPS	Firm-level measure of public pension fund (Bushee (2001)) distraction at the end of the calendar quarter, following the methodology in Kempf et al. (2017) .	As above
Governance provisions		
Staggered board	A dummy variable equal to one if the firm has a staggered board at the end of the calendar year, and zero otherwise.	ISS
Dual-class shares	A dummy variable equal to one if the firm has dual-class shares at the end of the calendar year, and zero otherwise.	As above
Poison pill	A dummy variable equal to one if the firm has a poison pill at the end of the calendar year, and zero otherwise.	As above
Golden parachute	A dummy variable equal to one if the firm has a golden parachute at the end of the calendar year, and zero otherwise.	As above
Shareholder proposal variables		
Inst sponsor	A dummy variable equal to one if the shareholder proposal was sponsored by an institutional investor, and zero otherwise.	ISS
Outcome	A categorical variable indicating the outcome of a given shareholder proposal, taking values 0 if the proposal was omitted, 1 if it was voted on, and 2 if it was withdrawn.	As above
OMIT	A dummy variable equal to one if the shareholder proposal was omitted, and zero otherwise.	As above
VOTE	A dummy variable equal to one if the shareholder proposal was voted on, and zero otherwise.	As above
WIDR	A dummy variable equal to one if the shareholder proposal was withdrawn, and zero otherwise.	As above
OMIT count	The number of omitted shareholder proposals targeting the firm over a calendar year.	As above
VOTE count	The number of voted shareholder proposals targeting the firm over a calendar year.	As above
WIDR count	The number of withdrawn shareholder proposals targeting the firm over a calendar year.	As above
Total count	The number of shareholder proposals targeting the firm over a calendar year.	As above

Table A2: Variance decomposition of biodiversity incident measures

This table reports the incremental R^2 (in percentage points) from sequentially adding specific fixed effects to the baseline regression model (see column 1 of [Table III](#)). It shows how much additional variation in future biodiversity incidents is explained by each fixed-effect type. The dependent variable in column 1 is $1\{\text{BI}\}$, an indicator equal to one if a firm experienced at least one biodiversity incident in year-quarter t . Column 2 uses the count of biodiversity incidents a firm experienced in year-quarter t as the dependent variable. Column 3 uses the natural logarithm of one plus the incident count, $\ln(1 + \text{BI count})$, as the dependent variable. All explanatory variables are measured as of year-quarter $t - 1$. Variable definitions are provided in [Table A1](#). Robust standard errors, double-clustered at the firm and year-quarter levels, are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent variable:	$1\{\text{BI}\}$	BI count	$\ln(1+\text{BI count})$
	(1)	(2)	(3)
Year-quarter FE	0.59	0.28	0.49
Industry FE	12.91	13.34	14.42
Industry \times year-quarter FE	11.25	6.61	8.78
Firm FE	28.40	49.54	41.35
Residual variation	46.85	30.24	34.96

Figure A1: Average Russell index weights by index rank



This figure presents average Russell index weights by index rank over the study period from 2007 through 2022. Each year, Russell reconstitutes its indexes based on a mechanical rule: the 1,000 firms with the highest market capitalizations form the Russell 1000, while the next 2,000 constitute the Russell 2000. The discontinuity at the 1,000th rank reflects the mechanical break between the two indexes. Because firms cannot influence small variations in ranking, assignment to indexes near the cutoff is as good as random. This random assignment leads to large differences in value-weighted index weights. I use this discontinuity in index weights around the threshold as an instrument for institutional ownership as part of robustness tests.