BIODIVERSITY DISCLOSURES AND STOCK PRICE CRASH RISK: FIRM-LEVEL EVIDENCE

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Master Thesis

Stockholm School of Economics

2024

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Abstract

We examine the relationship between biodiversity disclosures and stock price crash risk using a large sample of European firms from 2012 to 2023. Our analysis reveals no significant correlation between biodiversity-related information disclosures and stock price crash risk. In addition, while we also observe that positive tones in biodiversity disclosures tend to correlate with decreased crash risk, and risk disclosures tend to be associated with increased crash risk, these relationships are not statistically significant. Our cross-sectional analyses further support these findings, showing no significant relationship between biodiversity disclosures and stock price risk across multiple dimensions: firms located in countries with heightened public attention to biodiversity issues, firms in high resource exploitation industries, and the pre- or post-2019 periods. Overall, our study suggests that biodiversity disclosures currently have no substantial impact on stock price crash risk. Despite growing global concerns about biodiversity challenges, investors do not yet consider biodiversity-related information as a significant factor affecting financial stability.

Keywords:

Biodiversity disclosures, Stock price crash risk, Financial stability

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Acknowledgements:

We would like to express our warmest gratitude to our supervisor Ting Dong, Assistant Professor at the Department of Accounting at the Stockholm School of Economics, for her insights, supportive guidance and helpful feedback throughout the research process.

Master Thesis
Master Program in Accounting, Valuation and Financial Management
Stockholm School of Economics

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1. Introduction

In this paper, we investigate whether and how the disclosures of biodiversity[1]-related information are useful in predicting firms' stock price crash risk (i.e., extreme downside risk in returns). This investigation is motivated by emerging research on whether firms' disclosures of biodiversity impact and risk exposure influence market reactions and financial stability (e.g. Bassen et al., 2024; Garel et al., 2024; Giglio et al., 2023). Stock price crash risk serves as a critical indicator of financial stability by measuring a firm's vulnerability to extreme downside events. Such crashes not only inflict severe losses on investors but can also threaten overall market stability (Chen et al., 2001; Hutton et al., 2009). Understanding and predicting crash risk is essential for several reasons: it helps protect against catastrophic wealth destruction, allows for early detection of potential market-wide contagion effects, and contributes to maintaining the stability of the broader financial system.

Earlier research on firms' stock price crash risk primarily focused on financial determinants, such as financial reporting opacity, tax avoidance, and earnings management (Hsu & Liao, 2022; Hutton et al., 2009; Kim et al., 2019). More recent studies have expanded to examine the effects of non-financial metrics, particularly ESG-related performance (Chebbi, 2024; Kim et al, 2014; Kim et al., 2020). However, there remains a notable gap in understanding how biodiversity impact and risk exposure affect stock price crash risk, despite biodiversity being a specific environmental issue that has gained increasing attention as a global threat[2] (WEF, 2020).

The unprecedented uncertainty surrounding biodiversity change has already begun to affect firms' operations. While firms face operational challenges from disrupted supply chains and resource scarcity (Dempsey, 2013), they also suffer stricter regulations by governments and reputational damage among environmentally conscious consumers and investors due to their contribution to biodiversity loss[3]. (Dempsey, 2016; Whelan & Fink, 2016)

The relationship between the disclosures of a firm’s biodiversity information and stock price crash risk presents a complex picture with competing theoretical predictions. On the one hand, recent evidence indicates that investors increasingly recognize and price biodiversity risks in stock markets (Bassen et al., 2024; Giglio et al., 2023), indicating that disclosures of such information could significantly influence market behavior and

[1] Biodiversity is defined as ‘the variability among living organisms from all sources including, inter alia, terrestrial, marine, and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species, and of ecosystems’ (United Nations, 1992).

[2] According to the "Nature Risk Rising" report published by the World Economic Forum in 2020, 44 trillion of economic value generation is potentially threatened by biodiversity loss.

3 According to Panwar et al. (2023), firms can cause biodiversity loss through various activities such as land use change, pollution, and overexploitation of resources.

price dynamics. On the other hand, some studies suggest that a significant portion of investors still view biodiversity-related risks as peripheral to their investment decisions (Garel et al., 2024), potentially limiting the impact of such disclosures on stock price crash risk. Given these conflicting perspectives, how biodiversity disclosures are related to stock price crash risk is ultimately an empirical question. In this paper, we aim to provide evidence on this contentious research question.

In conducting our empirical analyses, we follow existing papers[4] and use two established measures to quantify stock price crash risk: the negative coefficient of skewness of firm-specific weekly returns (NCSKEW) and the asymmetric volatility ratio comparing negative to positive firm-specific weekly returns (DUVOL). To assess biodiversity disclosures, we conduct textual analysis of earnings call transcripts, examining three key dimensions: the presence of biodiversity information, sentiment analysis of biodiversity discussions, and associated risk disclosures. We believe that the choice of textual analysis on earnings call transcripts offers distinct advantages over alternative measures such as third-party biodiversity ratings (Bassen et al., 2024; Carvalho et al., 2023) or annual report analyses (Giglio et al., 2023). This is because earnings calls represent the most crucial platform for company-investor communication (Brown et al., 2019) and provide comprehensive, widely available data across our sample companies (Li et al., 2024).

Our analysis of 8,826 observations of European-listed companies[5] from 2012 to 2023 reveals no statistically significant relationship between biodiversity disclosures and stock market crash risk. We conduct additional analysis of the relationship between specific disclosure characteristics, such as sentiment and risk discussions and stock price crash risk. While we observe results suggesting that positive tones of biodiversity disclosures correlate with decreased crash risk, and transition risk[6] disclosures are associated with increased crash risk, these relationships lack statistical significance. These findings, to some extent, align with the view that investors generally assign limited importance to sustainability-related information, including biodiversity disclosures (Eccles & Serafeim, 2013; Eckerle et al., 2020; Tomlinson et al., 2021).

Next, we perform two sets of further analyses to validate our results. First, acknowledging that earnings calls may be influenced by management's strategic disclosure choices (Bloomfield, 2002; Fu et al., 2021; Loughran & McDonald, 2016), we address this limitation by employing alternative biodiversity disclosure measurements from Refinitiv: the biodiversity impact reduction score and the environmental restoration initiatives score. Correlation analysis revealed strong positive associations between these Refinitiv scores and our original measurement, providing validation of our construction. However,

[4] See, for example, Chen et al., (2001) and Kim et al., (2019).
[5] A firm's European classification is determined by the geographical location of its headquarters.
[6] Although we also identified physical risks related to biodiversity, we excluded them from our empirical analysis due to the limited number of sample observations.

consistent with our baseline results, we found no significant relationships between biodiversity disclosures and stock price crash risk in these alternative analyses.

Furthermore, we conduct subsample analyses to investigate whether the relationship between biodiversity disclosures and stock price crash risk varies across different firm characteristics or market conditions. This additional examination provides deeper insights into the circumstances under which biodiversity disclosures might become more relevant for crash risk. Our analysis focuses on three specific contexts. First, we focus on countries where biodiversity receives heightened public attention, measured through Google search volumes for the term "biodiversity," assuming investors place greater emphasis on biodiversity issues for firms operating in these regions. Second, we examine this relationship within industries characterized by high environmental exploitation, as identified by Boiral & Heras-Saizarbitoria (2017), where investors are expected to be more sensitive to biodiversity concerns. Third, we analyze the relationship between biodiversity disclosures and stock price risk in the period after 2019, hypothesizing a stronger correlation due to increasing investors' concerns about biodiversity challenges in recent years. The results remain insignificant across all subsamples, further providing evidence that biodiversity disclosures continue to receive limited attention from investors.

Taken together, our results show that, at the current moment, biodiversity disclosures do not significantly influence stock market crash risk. Despite growing concerns about biodiversity challenges, our analysis suggests that investors continue to assign relatively low importance to biodiversity-related information, and as a result, it does not have a substantial effect on financial stability.

Our study contributes to existing literature in several ways. First, we expand the understanding of how ESG information influences stock price crash risk. While previous research has primarily focused on broad ESG metrics and their aggregate impact on stock price crash risk (Chebbi, 2024; Kim et al., 2014; Kim et al., 2020), our study takes a more focused approach by examining a specific environmental metric: biodiversity. Our findings reveal that biodiversity-related risks have been largely overlooked by markets, suggesting that while overall ESG metrics may affect financial stability, individual ESG components can exhibit varying effects. This heterogeneity in market response highlights the importance of analyzing specific ESG factors rather than relying solely on composite measures.

Second, our study advances the methodology for measuring biodiversity-related information disclosures. While previous research relied on third-party biodiversity scores, our textual analysis approach enables a more nuanced examination of biodiversity information. Specifically, our method captures multiple dimensions including sentiment analysis, risk exposure assessment, and financial impact metrics. This comprehensive analytical framework provides deeper insights into how firms communicate their

biodiversity impacts and risk exposures to the market, offering a more sophisticated understanding than traditional measurement approaches.

Last but not least, we expand the geographical scope of biodiversity disclosure research beyond the U.S. market. Building upon the work of Giglio et al. (2023), who focused on U.S.-listed firms, our study provides the first comprehensive analysis of biodiversity disclosures among European public companies. To the best of our knowledge, this represents the first large-scale examination of biodiversity reporting practices across European firms, offering valuable insights into regional variations in corporate biodiversity disclosure practices and their market implications.

The rest of the paper is organized as follows. In Section 2, we review related literature and develop our hypothesis. In Section 3 we discuss our data and methodologies. Section 4 presents our empirical results, and Section 5 concludes. Finally, in Section 6, we come up with several implications for future research.

2. Literature Review & Hypothesis Development

Stock price crash risk is an essential concern in financial markets that refers to the possibility of sudden severe drops in stock prices caused by the disclosures of previously accumulated negative information. This risk could have a significant impact on investor confidence, market stability, and overall economic health. Understanding stock price crash risk is essential since it exposes the consequences of insufficient transparency and selective disclosure. According to research, stock price crashes are frequently caused by the withholding of material information, which results in sharp market corrections when revealed (Chen et al., 2001). These sudden price declines underscore the importance of complete and accurate disclosures in maintaining market stability and mitigating unexpected shocks.

The study of stock price crash risk determinants relies on two fundamental theoretical concepts: information asymmetry and materiality. Information asymmetry is an imbalance in which one party has more or better information than the other, resulting in market inefficiencies (Akerlof, 1970). In his landmark work, Akerlof established how adverse selection occurs in the used vehicle market when sellers have private information, resulting in lower market quality and buyer distrust. This concept applies to financial markets, where insufficient or ambiguous disclosures can undermine investor trust and market inefficiencies. Stiglitz (2000) elaborated on these concepts by describing how information asymmetry causes moral hazard, which allows people with more information to act in ways that harm the less informed.

Materiality complements the idea of information asymmetry by determining the significance of disclosed information. While transparency aims to close information gaps, materiality eliminates unnecessary data to focus on what is most important for investment choices (Khan et al., 2016). By defining what is material, firms can achieve a balance between thorough reporting and clarity, allowing stakeholders to focus on data that genuinely drives economic decisions. Khan et al. (2016) found that concentrating on crucial ESG issues improves financial performance, demonstrating that focused disclosures are more successful than generic ones. Schaltegger & Burritt (2015) investigate how materiality influences corporate sustainability initiatives, which might differ depending on motives such as reactionary, reputational, responsible, or collaborative. These strategic decisions influence how companies handle disclosures, defining their long-term sustainability and stakeholder relationships.

Moving on from theoretical foundations to financial factors influencing stock price crash risk, research has shown that financial opacity and earnings management contribute to this issue. Financial opacity, defined as insufficient or opaque reporting, has been linked to a significant increase in stock price crash risk (Hutton et al., 2009). When eventually exposed, the hiding of negative information causes significant market corrections,

underlining the significance of comprehensive and transparent disclosures to reduce the risks. Building on this, Hsu & Liao (2022) identify aggressive profit management strategies as another important component related to increased crash risk. Companies manipulating results to indicate a misleadingly positive financial position face severe consequences when their actual financial condition is revealed, stressing the importance of transparent financial reporting to minimize market disruptions. Furthermore, research has shown that managerial incentives and financial rewards are linked to stock price crashes (Kim et al., 2011). Executives driven by short-term financial advantages may conceal unfavorable information to sustain personal benefits, resulting in a buildup of suppressed data that might cause a significant market correction when it is released. This underlines the importance of aligning executive remuneration with long-term success to reduce crash risk and maintain market stability.

Beyond financial factors, non-financial elements such as ownership structures, CSR initiatives, and ESG performance all have an impact on stock price crash risk. Kim et al. (2019) reveal that firms with significant foreign ownership have a lower crash risk due to institutional investors' rigorous assessment and demand for transparency. This active monitoring neutralizes hidden negative information, supporting the agency theory's assertion that external management can reduce information asymmetry. Comprehensive CSR programs are also associated with reducing crash risk as they frequently involve transparent and consistent reporting, thereby preventing the emergence of unexpected negative information (Kim et al., 2014). By fostering long-term trust and engagement, CSR activities align with sustainable growth and lower crash risk. Chebbi (2024) enhances this research by demonstrating that superior ESG performance correlates with reduced crash risk, especially when bolstered by robust governance structures. Companies that prioritize ESG disclosures benefit from enhanced transparency, which reduces speculative risk and solidifies market confidence.

These insights naturally extend to the under-explored area of biodiversity disclosure, being an emerging field within sustainability reporting. Research on the financial market implications of biodiversity information remains limited, with several recent studies exploring this relationship through different approaches and metrics. On the one hand, some researchers found that biodiversity risk has been regarded as a material risk and is priced in the stock markets. For instance, Bassen et al. (2024) find that firms with better biodiversity management, measured by Vigeo Eiris scores, experience lower stock market crash risks. Giglio et al. (2023) analyze biodiversity risk exposure in U.S. financial markets, revealing that equity markets respond to biodiversity-related news through positive covariance between industry-sorted portfolio returns and biodiversity news, though they find minimal evidence of such pricing in municipal bond markets. Adamolekun (2024) finds that exposure to biodiversity risk increases the likelihood of financial distress. On the other hand, some studies suggest that investors still treat biodiversity risks as minor factors in their investment decision-making processes. For

example, Maroun & Ecim (2024) document that biodiversity is not being factored into valuations, cost assessments and project appraisals for UK-listed companies. Similarly, Garel et al. (2024) use the Corporate Biodiversity Footprint (CBF) as a measurement of firm's negative biodiversity impact and find no consistent relationship between CBF and stock returns during 2019-2022; however, they document significant market reactions to key biodiversity policy events, with high-footprint stocks declining in value following the Kunming Declaration and TNFD launch in 2021, suggesting emerging investor attention to regulatory and litigation risks related to biodiversity preservation.

Overall, the impact of biodiversity disclosures on stock price crash risk remains uncertain. On the one hand, according to the information asymmetry theory, biodiversity disclosures could significantly affect crash risk in both directions - comprehensive reporting may reduce crash risk by increasing transparency and allowing better risk assessment, while sudden revelations of negative biodiversity impacts could trigger sharp market corrections if previously hidden risks are exposed. On the other hand, according to the materiality theory, biodiversity disclosures might have a minimal impact on crash risk since investors may view biodiversity information as less financially material compared to traditional metrics (Eccles & Serafeim, 2013; Eckerle et al., 2020; Tomlinson et al., 2021), making biodiversity-specific disclosures less likely to cause significant market movements. Building on the contrasting perspectives, we propose the following null hypothesis:

H1: Disclosure of biodiversity information is associated with stock price crash risk.

3. Methodology & Data

3.1. Measuring Stock Price Crash Risk

To assess stock price crash risk, we apply financial methods based on firm-specific return analysis to our dataset sourced from Thomson Reuters Refinitiv Eikon for the period 2011 to 2023, covering several economic cycles to reflect the effects of different market conditions. This approach is based on methodologies that use return distributions to estimate the extent and probability of such extremely negative outcomes. Two major metrics, (I) Negative Conditional Skewness (*NCSKEW*) and (II) Down-to-Up Volatility (*DUVOL*), are used, as described in previous financial research (Chen et al., 2001; Kim et al., 2021).

To calculate the measures of firm-specific crash risk, we first estimate firm-specific weekly returns for each firm and year, utilizing the following regression model:

$$r_{i,t} = \alpha_1 + \beta_1 r_{m,t-2} + \beta_2 r_{m,t-1} + \beta_3 r_{m,t} + \beta_4 r_{m,t+1} + \beta_5 r_{m,t+2} + \epsilon_{i,t} \quad (1)$$

In this equation, $r_{i,t}$ reflects the firm i return during week t, while $r_{m,t}$ denotes the market return for the week t, for which the MSCI Europe index serves as the benchmark. The term $\epsilon_{i,t}$ represents the residual. This model incorporates market returns from the surrounding weeks to account for non-synchronous trading effects (Dimson, 1979; Kim et al., 2020). The firm-specific weekly return, $W_{i,t}$ is then derived using the natural logarithm of one plus the residual:

$$W_{i,t} = \ln(1 + \epsilon_{i,t}) \quad (2)$$

This return calculation lays the groundwork for evaluating stock price crash risk using specific measures. One such metric is *NCSKEW*, introduced by Chen et al. (2001), which quantifies the asymmetry in the distribution of a firm's returns by focusing on the degree of negative skewness. The *NCSKEW* measure helps capture the likelihood of extremely negative outcomes, providing insights into potential risks in a firm's stock performance. The following formula defines the *NCSKEW*:

$$NCSKEW_{i,t} = -\frac{n \times (n-1)^{\frac{3}{2}} \times \sum W_{i,t}^3}{(n-1) \times (n-2) \times (\sum W_{i,t}^2)^{\frac{3}{2}}} \quad (3)$$

Here, n represents the number of weekly observations for the firm i over the year. A higher *NCSKEW* value indicates a greater chance of extreme negative returns, revealing possible vulnerabilities in the company's stock. Down-to-up volatility (*DUVOL*), which measures the difference in volatility between negative and positive weekly returns, adds another viewpoint on downside risk. *DUVOL* is useful in determining how a company's stock performs under various market conditions. The metric is calculated as follows:

$$DUVOL_{i,t} = \ln\left[\frac{(n_u - 1) \times \sum_{DOWN} W_{i,t}^2}{(n_d - 1) \times \sum_{UP} W_{i,t}^2}\right] \quad (4)$$

Under this framework, n_d and n_u correspondingly show the number of weeks with negative and positive returns. A larger *DUVOL* score indicates more volatility on the downside than on the upside, thereby indicating greater downside risk relative to potential upside (Chen et al., 2001).

3.2. Measuring Biodiversity Disclosures

3.2.1. Approach Selection

Measuring corporate effects on biodiversity remains an emerging field, hindered by its complexity and multidimensional nature. Assessments of biodiversity information require distinct approaches and data sources. Two primary approaches have emerged in this field: directly using biodiversity data from third-party agencies and directly conducting textual analysis to extract biodiversity-related information based on firms' disclosures such as annual reports and earning transcripts. Each method has its own advantages and disadvantages.

Nowadays, increasing institutions have expanded their services to include specialized assessments of biodiversity-related factors. These targeted evaluations offer researchers convenient access to meaningful data on companies' biodiversity impacts and practices. For instance, Bassen et al. (2024) examined global firms' biodiversity management using Vigeo Eiris's firm-level biodiversity scores covering 2009 to 2021. Focusing on European markets, Haque & Jones (2020) evaluated firms across 13 European countries using Thomson Reuters' metrics, specifically the disclosure of biodiversity initiatives (DBI) and biodiversity impact assessment (BIA) scores. In the United States, Carvajal et al. (2022) employed two key metrics from Refinitiv Eikon to assess corporate biodiversity disclosure: the Biodiversity Impact Reduction Score and the Environmental Restoration Initiatives Score. Most recently, Issa & Zaid (2023) utilized Refinitiv Eikon's biodiversity conservation reporting score to measure biodiversity disclosures among non-financial firms operating in 13 European countries.

However, the agency-provided data has some drawbacks. Firstly, biodiversity data from third-party agencies may only cover a limited number of firms in depth. (Giglio et al., 2021). Secondly, like other ESG data, the criteria used by agencies for valuing biodiversity may not always be transparent and can be subjective, leading to potential inconsistencies and biases in the assessment. (Berg et al., 2022)

Textual analysis of firms' disclosures, such as annual reports and other public documents, provides researchers with a more nuanced view of sustainability-related information. Giglio et al. (2023) utilize textual analysis to evaluate biodiversity risk at both national and corporate levels in the U.S. For country-level assessment, they develop a biodiversity

news index using New York Times articles. This index is created by identifying biodiversity-related sentences and applying the BERT[7] model for sentiment analysis. At the firm level, they employ a similar approach, analyzing 10-K statements to pinpoint biodiversity-related content. The BERT model is then applied to conduct sentiment analysis and categorize risks into physical and transition risks based on these identified sentences.

Nevertheless, the method's effectiveness based on textual analysis relies heavily on the quality and consistency of corporate disclosures. The management obfuscation theory suggests that managers have incentives to obscure information, particularly when performance is poor. Companies might unbalance their disclosure, highlighting positive aspects while minimizing or excluding negative details to make disclosures less transparent, with the aim of mitigating or postponing negative reactions from the capital markets (Bloomfield, 2002; Li, 2008). Additionally, firms may not disclose all relevant information, potentially leading to incomplete analysis. These limitations can impact the reliability and comprehensiveness of the insights gained (Loughran & McDonald, 2016).

Based on our analysis of various measurement approaches, we employ textual analysis of European firms' earnings call transcripts to examine biodiversity-related disclosures, which allow us to reveal patterns in companies' awareness and risk exposure regarding biodiversity. Earning calls' transcripts document interactions where company executives discuss strategic direction, operational performance, and financial results with market participants including analysts, investors, and media representatives. This methodology is particularly suitable for two reasons. Firstly, earnings call is identified as the most important venue in which companies communicate their company's story to the capital markets (Brown et al., 2019), making them ideal for studying how biodiversity disclosures affect stock price risk. Secondly, the widespread availability of earnings call transcripts for public firms enables us to construct a comprehensive biodiversity disclosure measure across firms, avoiding the selection bias that might occur with third-party scores or other limited measures (Giglio et al., 2021). Our study extends previous research by Giglio et al. (2023) on U.S. listed firms' biodiversity disclosures by analyzing earnings call data from 2012 to 2023 for 1,937 European public firms. While acknowledging that earnings calls, like any disclosure source, may be influenced by management's strategic choices regarding the timing and content of biodiversity-related discussions, we address this limitation by using Refinitiv's biodiversity scores to validate our findings in Section 4.5.

[7] The BERT (Bidirectional Encoder Representations from Transformers) model is an advanced natural language processing tool increasingly used in accounting research. Developed by Google, BERT excels at understanding context and nuance in text, making it particularly valuable for analyzing complex financial documents. In accounting studies, it's applied to tasks such as sentiment analysis of financial statements, risk assessment in corporate disclosures, and information extraction from lengthy reports. (Bingler et al., 2024; Giglio et al., 2023; Huang et al., 2023)

3.2.2. Extraction of Biodiversity-related Information

We extract biodiversity information from firms' earnings calls' transcripts. Our study primarily relies on earnings call transcripts sourced from Thomson Reuters Refinitiv Eikon, with additional data from Capital IQ. We collected transcripts from quarterly, semi-annual, and annual earnings conference calls of European publicly listed companies spanning 2012 to 2023. Since ESG-related discussions are not uniformly distributed across quarterly calls, we aggregated the transcript data at the firm-year level. This aggregation approach is supported by Goldman Sachs (2020), which notes that ESG discussions predominantly occur during fourth-quarter earnings calls, particularly among European companies, as year-end calls typically focus on strategic initiatives and long-term planning.

Following Giglio et al. (2023), we identify biodiversity-related discussions in earnings call transcripts using a two-step approach. First, we employ regular expression searches based on a biodiversity dictionary (detailed in **Figure 1**) containing specific biodiversity-related terms. A sentence is classified as biodiversity-related only when it contains a term in the dictionary. Then, we aggregate the data at the firm-year level, categorizing a firm as having biodiversity discussions in a given year if its aggregated earnings transcripts contain at least one biodiversity-related sentence.[8]

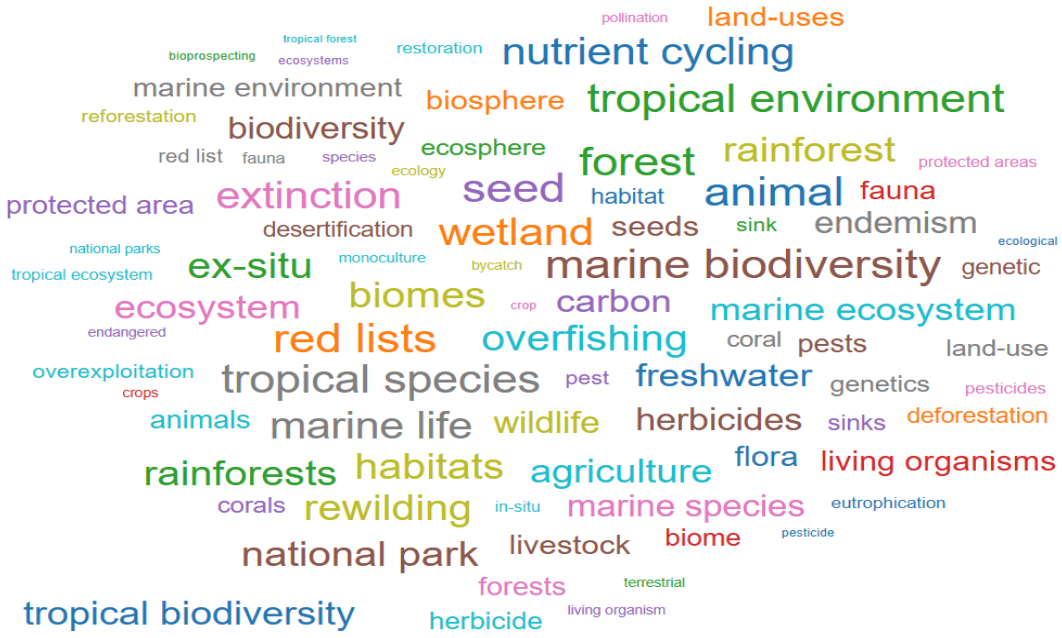

Figure 1 Biodiversity Word Dictionary

[8] To ensure accurate context and meaningful interpretation of biodiversity discussions, we extract not only the sentences containing biodiversity-related vocabulary but also the immediately preceding and following sentences. This three-sentence window approach provides comprehensive contextual understanding and enables more accurate verification of biodiversity-related content.

However, as Giglio et al. (2023) note, while certain terms like "deforestation" reliably identify biodiversity-related content, others have broader connotations that may lead to false positives[9]. To address this ambiguity and minimize misclassification, we follow Giglio et al. (2023) by employing additional qualifying terms (see **Table 1**) to refine our identification of biodiversity-related sentences when dealing with these less precise terms.

Table 1 Terms Used to Narrow Down the Biodiversity-Related Sentences

Words	**Terms used to narrow down**
Ecosystem(s)	Coast; Forest; Micro; Nature; Sustainability; Water
Marine	Biodiversity; Ecosystem; Environment; Life; Species
Tropical	Biodiversity; Ecosystem; Environment; Forest; Species
Species	Aquatic; Biodiversity; Bird; Endangered; Environment; Fish; Habitat; Invasive; List; Marine; Protect; Threat; ESA; EPA

Despite our refined machine extraction approach, we are aware that potential misclassifications can still exist. These can arise from several sources: speakers may use biodiversity-related terms metaphorically (e.g., "forest" in figurative speech), discussions may reference general biodiversity facts unrelated to the firm's operations, or biodiversity terms may appear in company names (see **Table 13** in Appendix B for specific examples of such misclassifications). To address these challenges and ensure classification accuracy, we manually reviewed all extracted sentences and eliminated those that did not represent genuine biodiversity-related discussions. Our final dataset comprises 1,042 firm-year observations containing biodiversity-related discussions, representing 8% of the total firm-year observations.

The industrial analysis presented in **Figure 2** reveals that utilities lead in biodiversity discussions, followed by mining, quarrying, oil and gas, construction, agriculture, forestry, and fishing, and manufacturing, which also aligns with the findings of Giglio et al. (2023) for U.S. firms. **Figure 3** illustrates the evolution of biodiversity discussions in the earnings calls among European firms over the past decade. During the period 2012-2016, biodiversity disclosure remained relatively low and stable, with only 3-4% of firms addressing the topic. However, a notable upward trend emerged around 2017, followed by a sharp acceleration between 2019 and 2021, ultimately reaching over 10% of firms by 2023. This trajectory parallels the pattern observed by Giglio et al. (2023) in their analysis of U.S. firms' 10-K filings. However, our findings indicate that European firms consistently maintain higher levels of biodiversity-related discussions, with approximately twice the percentage of reporting firms compared to their U.S. counterparts (10% versus 5% by 2023).

[9] For instance, the term "ecosystem" might refer to a "software ecosystem" rather than a “biological system”.

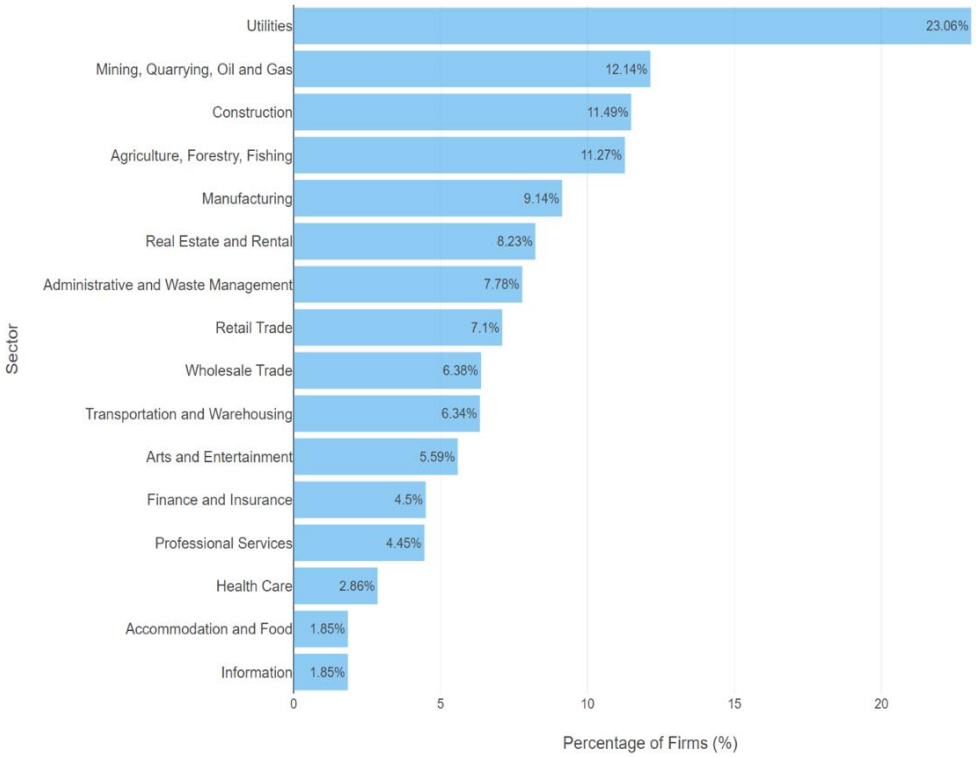

Figure 2 Industry Rankings Based on Biodiversity Disclosures in Earnings Call Transcripts

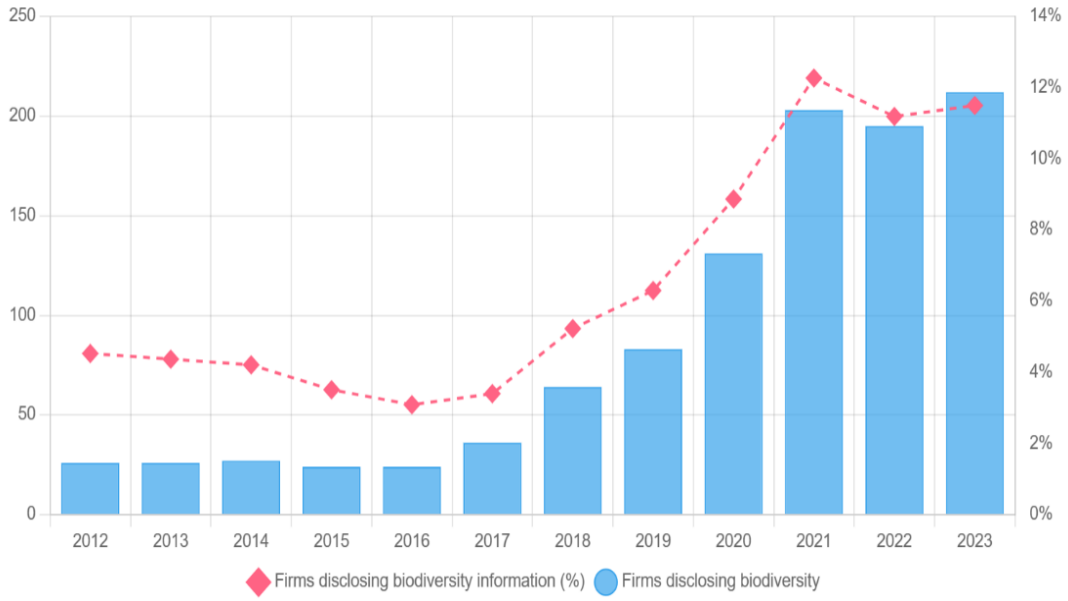

Figure 3 Trend of Biodiversity Disclosures in Earnings Call Transcripts

Additionally, we investigate the distribution of biodiversity disclosures between presentation and Q&A sessions[10] (see **Figure 4**). While biodiversity mentions have increased significantly overall (from approximately 5% before 2019 to 12% overall), the growth patterns differ between these two communication channels. The presentation sections show substantial growth in biodiversity-related content, reaching about 10% after 2019 compared to roughly 4% before 2019, whereas Q&A sessions exhibit only modest increases from approximately 2% to 3% after 2019. This disparity suggests that while companies are increasingly proactive in addressing biodiversity issues during their prepared remarks, the limited growth in Q&A discussions may indicate that investors and analysts continue to pay less attention to ESG factors, including biodiversity. This pattern is consistent with previous research (e.g., Eccles & Serafeim, 2013; Eckerle et al., 2020; Tomlinson et al., 2021), which demonstrates that ESG information is perceived as less quantifiable and more qualitative compared to traditional financial metrics, resulting in reduced attention from financial analysts.

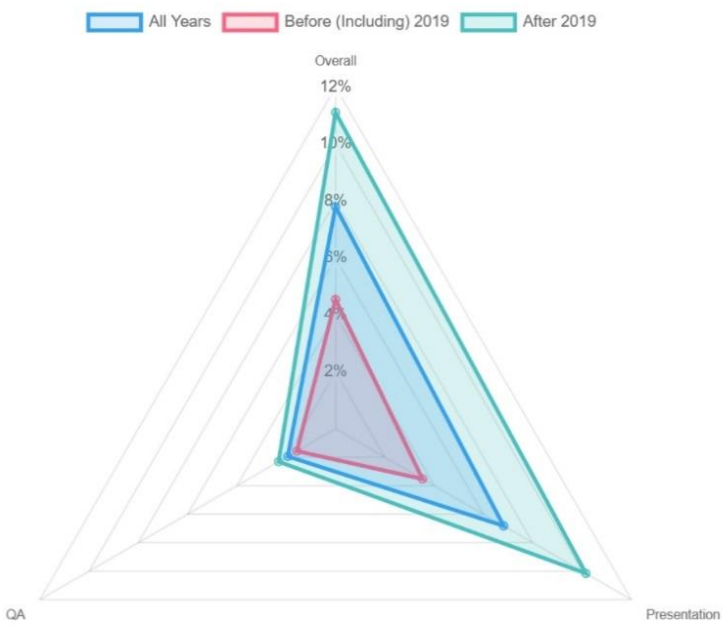

Figure 4 Distribution of Biodiversity Disclosures between Presentation and Q&A Sessions

[10] An earnings call typically contains two sessions: first, the presentation session where executives present financial results and company updates, followed by a Q&A session where analysts can inquire about specific aspects of the business performance and future outlook.

3.2.3. Categorization of Biodiversity-related Information

Through manual analysis of the extracted sentences, we developed a comprehensive classification framework that categorizes biodiversity discussions across multiple dimensions. This categorization includes sentiment analysis, risk assessment, and financial implications. Detailed examples of our classification methodology and criteria are provided in **Table 14**, Appendix B.

Sentiment analysis: Adopting the sentiment classification methodology developed by Bingler et al. (2024) for climate risk analysis, we evaluate both the content and tone of biodiversity-related discussions. Our sentiment classification framework consists of three categories: opportunity, neutral, and risk. Paragraphs are classified as opportunities when they primarily discuss business opportunities or positive impacts associated with biodiversity mitigation and adaptation strategies. Neutral classification is assigned to factual statements that lack explicit positive or negative framing. Risk classification is applied to discussions focusing on business risks or negative impacts related to biodiversity issues.

Risk assessment: Following the established framework used in climate risk literature (Giglio et al., 2021; Li et al., 2024; Stroebel & Wurgler, 2021), we classify biodiversity-related risks into two main categories: **physical risks** and **transition risks**. This classification aligns with recent biodiversity risk research (Bassen et al., 2024; Carvalho et al., 2023; Giglio et al., 2023). Physical risks encompass the financial and economic impacts stemming directly from biodiversity loss and ecosystem service degradation. These include disruptions to essential services such as raw material supply (food, fiber, and fuel), deterioration of environmental quality (water, soil, and air), and disruption of critical ecological processes (pollination, nutrient cycling, and soil formation). Transition risks arise from societal responses to biodiversity challenges, including regulatory changes (such as land-use regulations and sustainable forestry requirements), shifting consumer preferences (for example, avoiding palm oil due to deforestation concerns), and legal or reputational exposure. These risks reflect the broader institutional and market adaptations to biodiversity concerns.

Financial-related discussions: A persistent challenge in ESG and sustainability disclosures is the limited integration with financial information (Eccles & Serafeim, 2013; Eckerle et al., 2020; Tomlinson et al., 2021). We also analyze whether biodiversity discussions are connected to financial considerations. We classify a sentence as financially related when biodiversity mentions are explicitly linked to financial metrics or performance indicators, such as specific monetary values, cost savings, revenue generation, or sales performance.

Forest-related discussions: During our analysis, we observed that forest-related initiatives are common among corporate biodiversity discussions. Companies frequently

address topics such as deforestation prevention and forest conservation, noting that these efforts can serve multiple environmental objectives beyond biodiversity protection, including carbon sequestration. We classify discussions as forest-related when they specifically address forest ecosystems, deforestation, reforestation, or forest conservation initiatives.

Figure 5 reveals several distinct patterns in corporate biodiversity discussions. First, companies increasingly adopt an optimistic narrative, with 80% of all biodiversity-related discussions expressing positive sentiments, while 36% contain negative mentions. Second, among all biodiversity discussions, physical risks appear in only 15% of mentions, whereas transition risks are addressed in 30%, suggesting companies talk more about regulatory and market-related changes than direct environmental impacts. Third, only 12% of biodiversity-related discussions incorporate financial metrics, reflecting the broader challenge of translating biodiversity impacts into conventional financial measures. Finally, forest-related topics appear in 40% of all biodiversity discussions, indicating that deforestation remains a central concern in corporate biodiversity.

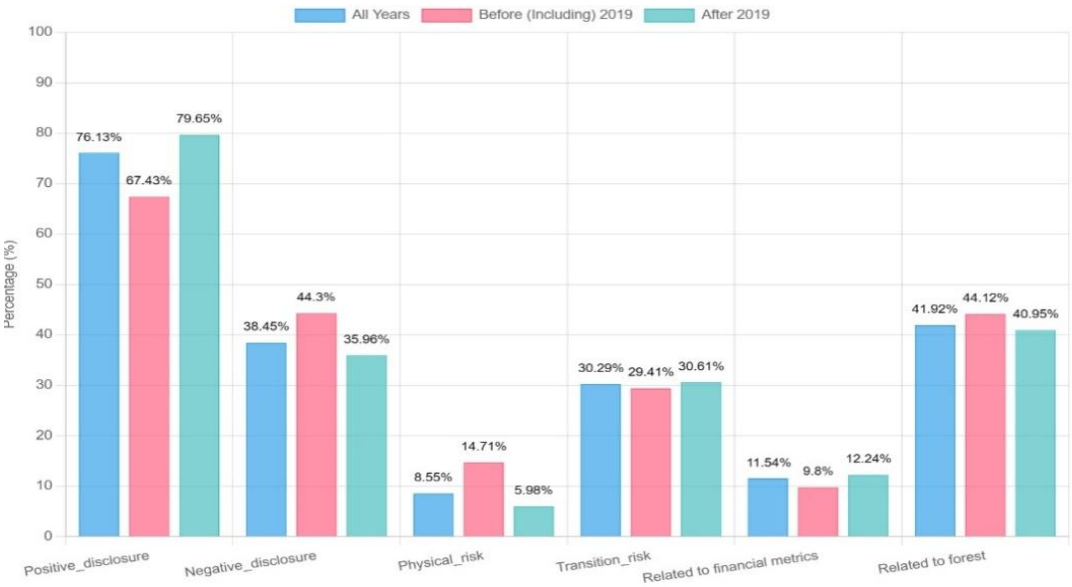

Figure 5 Biodiversity Disclosure Metrics

3.3. Empirical Model

We use the following OLS model to test the association between biodiversity disclosures and stock price crash risk (H1):

$$SPCR_{i,t} = \beta_0 + \beta_1 BIODIS_{i,t-1} + \beta_2 SPCR_{i,t-1} + \sum \beta_k CONTROLS_{i,t-1} + Fixed\ Effects + \varepsilon_{i,t} \quad (5)$$

Where *SPCR* represents the stock price crash risk, measured through either *NCSKEW* or *DUVOL*. The variable $BIODIS_{i,t-1}$ captures whether a firm disclosed biodiversity-related information in the previous year.

The model includes a set of control variables $CONTROLS_{i,t-1}$ that prior literature has shown to influence stock price crash risk (e.g. Bassen et al., 2024; Kim et al., 2020). First, we control the one-year lag of stock price crash risks (*LAGNCSKEW* or *LAGDUVOL*). For the firm fundamentals, with larger firms frequently demonstrating greater price stability, firm size (*SIZE*) helps quantify the effect of firm scale on stock price behavior. Leverage (*LEV*) is included to reflect financial risk, as higher leverage can amplify a firm's vulnerability to market shocks. Since companies with great growth potential may react more sensitively to new information, the market-to-book ratio (*MB*) shows development possibilities and can also indicate different risk profiles. Return on assets (*ROA*) serves as a profitability indicator that could influence investor views and stock price stability. Weekly return volatility (*SIGMA*) is used to capture the firm's trading and return behavior. While growth in total assets (*GROWTH*) shows the firm's pace of expansion, past stock returns (*RET*) offer insight into momentum effects. In addition, following Bassen et al. (2024), we control ESG scores (*ESG)* to prevent possible overlaps with metrics tailored to specific biodiversity. These control variables collectively contribute to a more robust analysis by addressing potential confounding influences. **Table 13** in Appendix A provides comprehensive definitions of all variables. We extract the firm fundamental data from Capital IQ and Compustat and the ESG scores from Refinitiv Eikon.

Finally, we incorporate fixed effects at the firm and year levels to account for unobserved heterogeneity across these dimensions.

3.4. Sample Selection

Table 2 summarizes the sample selection procedures for the regression models that test the association between biodiversity disclosures and the stock price crash risk. The sampling procedure begins with 49,516 individual earnings call transcripts downloaded from Refinitiv and Capital IQ spanning 2012-2023. These transcripts are first aggregated at the firm-year level, resulting in 16,648 firm-year observations. The sample is then refined through several exclusion steps: 3,285 observations are removed due to company delisting, reducing the sample to 13,363 observations. Next, 2,258 observations are excluded due to missing values for dependent variables (*NCSKEW* and *DUVOL*), followed by the removal of 25 observations with missing lagged values of these variables. Further reductions include 898 observations with missing turnover data and 11 observations lacking basic financial control variables (market-to-book ratio, size, growth, leverage, and ROA). Finally, 1,345 observations are excluded due to missing ESG data.

The final sample consists of 8,826 firm-year observations, representing 1,937 unique firms.

Table 2 Sampling Procedure

Total earnings call transcripts downloaded from Refinitiv and Capital IQ (2012-2023)	**49,516**
Total firm-year aggregated observations of earnings call transcripts (2012-2023)	**16,648**
Less: observations excluded due to company delisting	(3,285)
The final number of firm-year transcript observations	13,363
Less: missing values for dependent variables (*NCSKEW* & *DUVOL*) used in the regressions	(2,258)
Less: missing values for controls (*LAGNCSKEW* & *LAGDUVOL*) used in the regressions	(25)
Less: missing values for controls (*DTUNROVER*) used in the regressions	(898)
Less: missing values for controls (*MB, SIZE, GROWTH, LEV & ROA*) used in the regressions	(11)
Less: missing values for controls (*ESG*) used in the regressions	(1,345)
Final Sample (2012-2023)	**8,826**
Number of firms	**1,937**

4. Analysis of Results and Discussion

4.1. Descriptive Statistics and Correlations

This section provides descriptive statistics and correlation analysis, establishing a foundational understanding of data distribution and interrelationships among the examined variables. As **Table 3** shows, the two main indicators of stock price crash risk, *NCSKEW* and *DUVOL*, have mean values of 0.186 and 0.132, respectively, accompanied by standard deviations of 1.016 and 0.759. The metrics correspond with established findings in the literature, including Bassen et al. (2024), where the magnitudes of analogous measures highlight a similar distribution of risk proxies. For the independent variable, *BIODIS* exhibits a mean value of 0.082, indicating a restricted level of biodiversity disclosure within the sampled firms.

The correlation matrix demonstrates significant relationships among the variables. As **Table 4** shows, *NCSKEW* and *DUVOL* demonstrate a strong positive correlation of 0.92, reflecting their common conceptual basis as measures of firm-specific downside risk. *BIODIS* exhibits a weak positive correlation with *DUVOL* (0.02), whereas its association with *NCSKEW* is approximately zero (0.01). This indicates that biodiversity disclosures are linked to slight variations in volatility, but their direct connection to extreme negative values is minimal.

These findings resonate with the complexity identified by Kim et al. (2011) and further explored by Bassen et al. (2024), where non-financial disclosures were found to have a limited immediate impact on financial outcomes in the absence of broader institutional and market-level factors. Control variables such as leverage and return on assets exhibit correlations with the expected signs and magnitudes, underscoring their role in accounting for firm-specific risk factors and minimizing multicollinearity concerns. These are consistent with prior literature patterns validate the robustness of the dataset and reinforce the credibility of the subsequent analyses.

Table 3 Descriptive Statistics

	N	*Mean*	*Median*	*Std. Dev.*	*p25*	*p75*
NCSKEW	8826	0.186	0.122	1.016	-0.436	0.702
DUVOL	8826	0.132	0.108	0.759	-0.369	0.597
LAGCSKEW	8826	0.153	0.077	1.011	-0.470	0.667
LAGDUVOL	8826	0.100	0.073	0.761	-0.402	0.562
BIODIS	8826	0.082	0.000	0.275	0.000	0.000
SENTIMENT	728	0.798	1.000	1.715	0.000	1.000
TRANRISK	725	0.295	0.000	0.456	0.000	1.000
RET	8826	-0.001	-0.001	0.006	-0.004	0.002
MB	8826	2.969	1.816	3.699	0.992	3.520
SIZE	8826	8.273	8.302	1.576	7.238	9.335
GROWTH	8826	0.083	0.046	0.223	-0.019	0.126
SIGMA	8826	0.041	0.036	0.022	0.027	0.049
DTUNROVER	8826	-0.017	-0.001	0.167	-0.012	0.008
LEV	8826	0.177	0.158	0.139	0.062	0.265
ROA	8826	0.038	0.037	0.085	0.008	0.071
ESG	8826	0.600	0.612	0.175	0.482	0.738
BIOIMP	6638	0.348	0.000	0.413	0.000	0.813
RESTOR	8079	0.223	0.000	0.380	0.000	0.721
HIGHATTEN	8826	0.506	1.000	0.500	0.000	1.000
EXPLOIT	8826	0.441	0.000	0.497	0.000	1.000

Notes: (1) This table reports descriptive statistics of key variables (see **Table 13** in Appendix A for the definition of variables); (2) All continuous variables are winsorized at the 1st and 99th percentiles.

Table 4 Correlations Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1)	*NCSKEW*	1																			
(2)	*DUVOL*	**0.92**	1																		
(3)	*LAGCSKEW*	0	0	1																	
(4)	*LAGDUVOL*	-0.01	-0.01	**0.92**	1																
(5)	*BIODIS*	0.01	**0.02**	0.01	0.01	1															
(6)	*SENTIMENT*	0.03	0	-0.01	-0.01	.	1														
(7)	*TRANRISK*	0	0.02	0	0	.	**-0.34**	1													
(8)	*RET*	**0.07**	**0.08**	**-0.58**	**-0.69**	0	-0.04	0.04	1												
(9)	*MB*	0.01	**0.02**	**-0.08**	**-0.09**	**-0.04**	0.02	-0.02	**0.12**	1											
(10)	*SIZE*	**0.07**	**0.08**	-0.01	**-0.02**	**0.09**	0	0.05	**0.22**	**0.08**	1										
(11)	*GROWTH*	**0.04**	**0.05**	**-0.1**	**-0.08**	0	**0.09**	0.01	**0.1**	**0.14**	-0.01	1									
(12)	*SIGMA*	**-0.06**	**-0.06**	**0.11**	**0.09**	**-0.06**	0.02	-0.05	**-0.31**	**0.04**	**-0.51**	**0.06**	1								
(13)	*DTUNROVER*	-0.01	-0.01	-0.01	-0.01	0.02	0.03	0	**0.06**	0.02	**0.08**	0.01	**-0.29**	1							
(14)	*LEV*	-0.01	-0.02	0.01	0.01	**0.02**	-0.04	**0.15**	-0.01	**-0.09**	**0.03**	**-0.05**	**-0.04**	**-0.02**	1						
(15)	*ROA*	**0.04**	**0.05**	**-0.02**	**-0.03**	**0.04**	0.03	0.05	**0.22**	**0.06**	**0.35**	**0.09**	**-0.45**	**0.11**	-0.01	1					
(16)	*ESG*	**0.02**	0.02	**0.03**	**0.02**	**0.1**	0.03	0.06	**0.07**	**-0.1**	**0.52**	**-0.11**	**-0.23**	-0.02	0.01	**0.06**	1				
(17)	*BIOIMP*	0.01	0.01	0	0	**0.19**	**0.1**	0.02	**0.04**	**-0.16**	**0.31**	**-0.05**	**-0.14**	**-0.03**	**0.03**	-0.01	**0.44**	1			
(18)	*RESTOR*	0	0	0	0	**0.13**	**0.1**	-0.03	0.01	**-0.06**	**0.27**	**-0.03**	**-0.09**	0	**0.04**	0	**0.31**	**0.4**	1		
(19)	*HIGHATTEN*	-0.01	-0.01	-0.01	-0.01	**0.03**	**0.11**	0.01	0.02	**-0.04**	**0.09**	**-0.03**	**-0.05**	**0.03**	0.01	0	**0.13**	**0.19**	**0.11**	1	
(20)	*EXPLOIT*	**-0.02**	**-0.02**	**-0.02**	**-0.03**	**0.07**	0	0	0.01	**0.03**	**0.04**	**-0.04**	0	0	**-0.09**	**0.07**	**0.09**	**0.03**	**0.05**	**-0.11**	1

Notes: (1) This table presents the Pearson correlation coefficient between pairs of key variables; (2) All continuous variables are winsorized at the 1st and 99th percentiles; (3) Values in bold represent correlations significant at the 5% level; (4) The correlations between biodiversity disclosure (*BIODIS*) and transition risk (*TRANRISK*) and sentiment (*SENTIMENT*) - are not reported because these two variables are only calculated for firms that provide biodiversity disclosures (*BIODIS*=1).

4.2. Univariate Analysis

The univariate analysis investigates the relationship between biodiversity-related variables and stock price crash risk by comparing *NCSKEW* and *DUVOL* across subsamples defined by disclosure practices. The results, detailed in **Table 5**, provide insights into the extent of these associations.

Table 5 Univariate Analysis

Panel A: Univariate analysis of the stock price crash risk and biodiversity disclosures					
	(1)	(2)	(3)	(4)	(5)
	NO	YES	Diff.	t	Obs.
	N=7,980	N=846			
NCSKEW	0.184	0.206	-0.022	-0.596	8,826
DUVOL	0.131	0.146	-0.015	-0.541	8,826
Panel B: Univariate analysis of the stock price crash risk and biodiversity disclosure sentiment					
	Score below median	Score above median	Diff.	t	Obs.
	N=592	N=136			
NCSKEW	0.217	0.221	-0.004	-0.043	728
DUVOL	0.176	0.166	0.010	0.137	728
Panel C: Univariate analysis of the stock price crash risk and transition risk					
	NO	YES	Diff.	t	Obs.
	N=511	N=214			
NCSKEW	0.216	0.224	-0.008	-0.107	725
DUVOL	0.162	0.202	-0.040	-0.675	725

Notes: (1) This table presents the results of univariate analyses examining the relationship between stock price crash risk and biodiversity-related variables. Panel A compares firms with and without biodiversity disclosures. Panel B categorizes firms based on the biodiversity sentiments score, which is calculated as the difference between the number of positive and negative sentences. Panel C analyzes firms with and without biodiversity-related transition risk disclosures. (2) The dependent variables are *NCSKEW* and *DUVOL*, which measure firm-specific downside risk. (3) The "Diff." column reports the mean difference between groups, and the "t" column reports the t-statistic for the difference in means. (4) All variables are defined in Appendix B. (5) Significance levels are reported at *0.10, **0.05, and ***0.01.

Companies that provide biodiversity-related information show an average *NCSKEW* of 0.206, whereas those that do not disclose this information have an average *NCSKEW* of 0.184. The average *DUVOL* for disclosing firms is 0.146, exceeding the 0.131 observed for non-disclosing firms. The differences of -0.022 and -0.015 for *NCSKEW* and *DUVOL*, respectively, indicate that biodiversity-related disclosures are linked to marginally increased crash risk measures. The observed differences lack statistical significance, evidenced by t-values of -0.596 for *NCSKEW* and -0.541 for *DUVOL*.

The preliminary findings from the univariate analysis indicate nuanced yet limited direct relationships between biodiversity-related disclosures and stock price crash risk. To

deepen the understanding of these relationships, the following sections employ regression analyses to explore the association between biodiversity disclosures and SPCR, accounting for control variables and firm-specific factors that may influence these outcomes.

4.3. Baseline Results

Table 6 presents the results of estimation using model (5). The coefficient for *BIODIS* in the *NCSKEW* model is 0.0220, whereas in the *DUVOL* model, the coefficient is 0.00999. The positive coefficients indicate that firms disclosing biodiversity-related information are associated with marginally elevated stock price crash risk. The coefficients lack statistical significance at conventional levels. The findings correspond with the univariate analysis, indicating that biodiversity disclosures were linked to slightly elevated crash risk metrics, though lacking statistical significance.

The control variables in the models behave as anticipated and correspond with theoretical predictions. *SIZE* demonstrates a significant positive effect with both *NCSKEW* and *DUVOL*, indicating that larger firms may experience increased volatility attributed to their enhanced visibility and complexity. In contrast, *RET* and *SIGMA* demonstrate significant negative correlations with both crash risk indicators, aligning with existing literature that indicates firms exhibiting greater performance stability are likely to encounter reduced crash risks.

The results for *BIODIS*, although lacking statistical significance, suggest a positive trend that prompts debate regarding the potential signaling effects of biodiversity disclosures. These disclosures may cause market uncertainty by bringing attention to previously understated risks, subsequently affecting investors' risk perceptions. The absence of significance highlights the necessity for additional analysis to validate these observations.

Table 6 The Association between Biodiversity Disclosures and Stock Price Crash Risk

	NCSKEW		*DUVOL*	
	Coeff.	*Std*	*Coeff.*	*Std*
BIODIS	0.0220	(0.05)	0.00999	(0.04)
LAGCSKEW	-0.0722***	(0.02)		
LAGDUVOL			-0.0442***	(0.02)
RET	-2.246	(2.78)	1.637	(2.35)
MB	-0.00730	(0.01)	-0.00776	(0.00)
SIZE	0.372***	(0.04)	0.329***	(0.03)
GROWTH	0.153**	(0.06)	0.121***	(0.05)
SIGMA	-5.075***	(1.12)	-3.241***	(0.84)
DTUNROVER	-0.102	(0.16)	-0.0752	(0.12)
LEV	-0.0533	(0.26)	-0.148	(0.19)
ROA	0.0671	(0.27)	0.127	(0.20)
ESG	0.105	(0.18)	0.126	(0.13)
Year FE	YES		YES	
Firm FE	YES		YES	
Observations	8,734		8,734	
Adjusted R-sq	0.038		0.031	

Notes: (1) This table reports results of regressions estimating the association between biodiversity disclosures and firms' stock price crash risk. The following model (5) is estimated: $SPCR_{i,t} = \beta_0 + \beta_1 BIODIS_{i,t-1} + \beta_2 SPCR_{i,t-1} + \sum \beta_k CONTROLS_{i,t-1} + Fixed\ Effects + \varepsilon_{i,t}$, $SPCR_{i,t}$ is two measurements of stock price crash risk for firm *i* in year *t*, including: Down-to-up volatility of firm specific weekly returns (*NCSKEW*) and negative conditional firm specific weekly return skewness (*DUVOL)*. $BIODIS_{i,t-1}$ is a binary variable that equals 1 if firm *i* mentions biodiversity-related information in its earnings call transcripts during year *t-1*, and 0 otherwise. We include a set of control variables $CONTROLS_{i,t}$ (Refer to **Table 13** in Appendix A for variable definitions). Sample period is from 2012 to 2023; (2) The sample size in our regression analysis is smaller than in our descriptive statistics due to singleton observations being dropped by the high-dimensional fixed effects model; (3) In the untabulated tests, we verified the robustness of our findings by running an alternative specification that includes industry and year level fixed effects. The results remained consistent across both approaches; (4) Robust standard errors are in parentheses and clustered at firm level; (5) Significance levels are *0.10, **0.05, and ***0.01.

4.4. Additional Analysis

In this section, we conduct additional analysis of the relationship between two specific disclosure characteristics, such as sentiment and risk discussions and stock price crash risk to provide further evidence for our baseline findings.

4.4.1. The Association between Biodiversity Disclosures Sentiment and SPCR

Studies on corporate narratives, including those by Bloomfield (2002) and Li (2008), indicate that positive framing may diminish uncertainty and enhance market confidence. In biodiversity disclosures, we expect conveying information with a positive sentiment may indicate proactive management and dedication to objectives, thus mitigating concerns regarding concealed risks. Based on this reasoning, we propose that sentiment in biodiversity disclosures may be negatively associated with stock price crash risk. In **Table 4**, *SENTIMENT* shows a weak correlation with *NCSKEW* (0.03) and an even weaker association with *DUVOL* (0.00), suggesting that a positive tone in disclosures may marginally reduce perceptions of crash risk. We also conduct a univariate analysis to investigate the differences in SPCR between groups with biodiversity disclosure sentiment scores above and below the median. **Table 5** reports that firms exhibiting above-median positivity in *SENTIMENT* demonstrate a slightly higher average *NCSKEW* of 0.221, in contrast to 0.217 for those with below-median sentiment. However, the effect size remains small and statistically insignificant. In contrast, firms with above-median sentiment demonstrate a lower average *DUVOL* of 0.166, in contrast to 0.176 for firms with below-median sentiment, resulting in a difference of 0.010 (t = 0.137), which is statistically insignificant too.

Finally, we develop the following model to test the association between sentiment and SPCR:

$$SPCR_{i,t} = \beta_0 + \beta_1 SENTIMENT_{i,t-1} + \beta_2 SPCR_{i,t-1} + \sum \beta_k CONTROLS_{i,t-1} + Fixed\ Effects + \varepsilon_{i,t} \quad (6)$$

In this model, $SENTIMENT_{i,t-1}$ represents the net sentiment of biodiversity disclosures, calculated as the difference between the number of positive and negative sentences in a company's biodiversity-related disclosures within one year. Other elements of the model remain consistent with the specification in Model (5). **Table 7** presents the results. In the *NCSKEW* model, the coefficient for *SENTIMENT* is -0.00142, while in the *DUVOL* model, the coefficient is -0.0182. The negative coefficients indicate that a more positive tone in biodiversity-related disclosures correlates with a minor decrease in stock price crash risk. Nonetheless, similar to the results presented in the preceding section, these relationships lack statistical significance at conventional thresholds. The control variables in the models demonstrate consistent and anticipated relationships with SPCR.

Despite the coefficients for *SENTIMENT* lacking significance, their negative direction is consistent with theoretical expectations that positive sentiment could alleviate investors' apprehensions about firm risks. A constructive tone in biodiversity discussions may

mitigate uncertainty and stabilize investor perceptions. Nonetheless, the small effect sizes and absence of significance highlight that sentiment of biodiversity disclosures may not be a critical determinant in influencing SPCR.

Table 7 The Association between Biodiversity Disclosure Sentiment and Stock Price Crash Risk

	NCSKEW		*DUVOL*	
	Coeff.	*Std*	*Coeff.*	*Std*
SENTIMENT	-0.00142	(0.02)	-0.0182	(0.02)
LAGCSKEW	-0.268***	(0.06)		
LAGDUVOL			-0.198***	(0.07)
RET	9.488	(11.43)	11.44	(10.28)
MB	-0.0124	(0.04)	0.00330	(0.02)
SIZE	0.490***	(0.18)	0.380***	(0.14)
GROWTH	0.338	(0.37)	0.0895	(0.25)
SIGMA	-0.142	(6.24)	-0.286	(4.97)
DTUNROVER	-1.902***	(0.63)	-1.282***	(0.44)
LEV	-1.329	(1.12)	-1.217	(0.96)
ROA	1.100	(1.43)	1.052	(1.16)
ESG	-0.0480	(0.79)	-0.278	(0.66)
Year FE	YES		YES	
Firm FE	YES		YES	
Observations	515		515	
Adjusted R-sq	0.162		0.106	

Notes: (1) This table reports results of regressions estimating the association between biodiversity disclosure and firms' stock price crash risk. The following model is estimated: $SPCR_{i,t} = \beta_0 + \beta_1 SENTIMENT_{i,t-1} + \beta_2 SPCR_{i,t-1} + \sum \beta_k CONTROLS_{i,t-1} + Fixed\ Effects + \varepsilon_{i,t}$, $SPCR_{i,t}$ is two measurements of stock price crash risk for firm *i* in year *t*, including: *NCSKEW* and *DUVOL*. $SENTIMENT_{i,t-1}$ measures the net sentiment of biodiversity disclosures, calculated as the difference between the number of positive and negative sentences in a company's biodiversity-related disclosures. We include a set of control variables $CONTROLS_{i,t}$ (Refer to the **Table 13** in Appendix A for variable definitions). Sample period is from 2012 to 2023; (2) The sample size in our regression analysis is smaller than in our descriptive statistics due to singleton observations being dropped by the high-dimensional fixed effects model; (3) In the untabulated tests, we verified the robustness of our findings by running an alternative specification that includes industry and year level fixed effects. The results remained consistent across both approaches; (4) Robust standard errors are in parentheses and clustered at firm level; (5) Significance levels are *0.10, **0.05, and ***0.01.

4.4.2. The Association between Biodiversity Risk Disclosures and SPCR

When companies disclose their biodiversity-related risks, particularly those involving physical impacts like resource depletion and ecosystem disruption, or transition challenges such as regulatory changes and market shifts, these revelations can trigger adverse market reactions if the disclosed risks surpass investors' prior expectations. The subsequent release of this negative information to the market, whether driven by regulatory pressures or stakeholder demands, may lead to sudden and significant declines in stock prices as investors adjust their valuations based on the newly revealed environmental risks and their potential impact on future business performance. Hence, we investigate the relationship between biodiversity risk disclosures and stock price crash risk. We focus on transition risks in our analysis. Although we identified physical risks related to biodiversity, we excluded them from our empirical analysis due to the limited number of sample observations in this risk category. In **Table 4**, *TRANRISK* exhibits minimal correlations with *NCSKEW* and *DUVOL*, recorded at 0.00 and 0.02, respectively, indicating the intricate nature of converting risk disclosures into financial results. In the univariate analysis reported in **Table 5**, transition risk disclosures indicate minimal variations in crash risk metrics. Firms that recognize transition risks exhibit an average *NCSKEW* of 0.224, whereas firms that do not disclose these risks show an average of 0.216, resulting in a difference of -0.008 (t = -0.107). The average *DUVOL* for firms with transition risk disclosures is 0.202, while for those without, it is 0.162, yielding a difference of -0.040 (t = -0.675). The findings demonstrate a lack of significant association between transition risk disclosures and elevated crash risk, with observed differences being minimal and statistically insignificant.

Furthermore, we develop the following model to test the association between transition risks and SPCR:

$$SPCR_{i,t} = \beta_0 + \beta_1 TRANRISK_{i,t-1} + \beta_2 SPCR_{i,t-1} + \sum \beta_k CONTROLS_{i,t-1} + Fixed\ Effects + \varepsilon_{i,t} \quad (7)$$

Where $TRANRISK_{i,t-1}$ is a binary variable that indicates whether a firm mentioned biodiversity-related transition risks in its disclosures during the prior year. Other elements of the model remain consistent with the specification in Model (4). **Table 8** provides the regression results. The coefficient for *TRANRISK* in the *NCSKEW* model is 0.0128, whereas in the *DUVOL* model, it is 0.0170. The presence of small positive coefficients indicates that firms disclosing biodiversity transition risks may face a marginally increased crash risk, introducing a level of uncertainty to the market; disclosures may indicate potential costs or disruptions linked to regulatory changes or stakeholder expectations, which could affect investor sentiment and perceived risk. Nonetheless, similar to earlier sections, these coefficients lack statistical significance, suggesting a weak and non-robust relationship within the sample. The control variables in the models align with theoretical expectations and previous findings.

Table 8 The Association between Biodiversity Risk Disclosures and Stock Price Crash Risk

	NCSKEW		*DUVOL*	
	Coeff.	*Std*	*Coeff.*	*Std*
TRANRISK	0.0128	(0.11)	0.017	(0.09)
LAGCSKEW	-0.267***	(0.06)		
LAGDUVOL			-0.199***	(0.07)
RET	9.458	(11.44)	11.35	(10.29)
MB	-0.0126	(0.04)	0.00285	(0.02)
SIZE	0.491***	(0.18)	0.381***	(0.14)
GROWTH	0.338	(0.37)	0.0699	(0.25)
SIGMA	-0.13	(6.22)	-0.517	(4.91)
DTUNROVER	-1.903***	(0.63)	-1.274***	(0.44)
LEV	-1.339	(1.12)	-1.098	(0.96)
ROA	1.087	(1.45)	1.03	(1.16)
ESG	-0.0546	(0.79)	-0.264	(0.67)
Year FE	YES		YES	
Firm FE	YES		YES	
Observations	514		514	
Adjusted R-sq	0.160		0.103	

Notes: (1) This table reports results of regressions estimating the association between biodiversity disclosure and firms' stock price crash risk. The following model is estimated: $SPCR_{i,t} = \beta_0 + \beta_1 TRANRISK_{i,t-1} + \beta_2 SPCR_{i,t-1} + \sum \beta_k CONTROLS_{i,t-1} + Fixed\ Effects + \varepsilon_{i,t}$, $SPCR_{i,t}$ is two measurements of stock price crash risk for firm *i* in year *t*, including: *NCSKEW* and *DUVOL*. $TRANRISK_{i,t-1}$ is a binary variable that equals 1 if firm *i* mentions biodiversity-related transition risk in its earnings call transcripts during year *t-1*, and 0 otherwise. We include a set of control variables $CONTROLS_{i,t}$ (Refer to **Table 13** in Appendix A for variable definitions). Sample period is from 2012 to 2023; (2) The sample size in our regression analysis is smaller than in our descriptive statistics due to singleton observations being dropped by the high-dimensional fixed effects model; (3) In the untabulated tests, we verified the robustness of our findings by running an alternative specification that includes industry and year level fixed effects. The results remained consistent across both approaches; (4) Robust standard errors are in parentheses and clustered at firm level; (5) Significance levels are *0.10, **0.05, and ***0.01.

4.5. Alternative Measurement of Biodiversity Disclosures

To ensure the robustness of the findings on the association between biodiversity disclosures and SPCR, this section examines alternative measurements of biodiversity disclosures. Specifically, following Carvajal et al. (2022), two additional biodiversity disclosure scores by Refinitiv are considered: the Biodiversity Impact Reduction Score (*BIOIMP*), which captures firms' disclosure of efforts to mitigate biodiversity-related impacts, and the Environmental Restoration Initiatives Score (*RESTOR*), reflecting disclosure of the extent of activities aimed at restoring ecosystems. A significant and positive relationship between these external scores and our constructed *BIODI*S measurement confirms the validity of using earnings call data to capture biodiversity-related disclosures, enhancing the credibility of our pre-selected approach (See **Table 4**). **Table 9** presents the regression results using equation (5) with these alternative measurements as independent variables, and *NCSKEW* and *DUVOL* as the dependent variables. The findings indicate that the coefficient for *BIOIMP* in the *NCSKEW* model is -0.00718, while in the *DUVOL* model, it is 0.0414. For *RESTOR*, the coefficients are -0.0370 for *NCSKEW* and -0.0239 for *DUVOL*. The coefficients are small and statistically insignificant, suggesting that neither *BIOIMP* nor *RESTOR* demonstrates a meaningful or consistent association with crash risk measures. The control variables in the models exhibit expected behavior and maintain consistency with previous sections.

The lack of notable relationships between the alternative biodiversity disclosure measures and SPCR, to some extent, provides evidence that the preliminary results for *BIODIS* are not affected by the selection of measurement methods. The absence of statistical significance between *BIOIMP* and *RESTOR* suggests that biodiversity-related information may not significantly influence stock price crash risk.

Table 9 Regression Results Using Alternative Measurements of Biodiversity Disclosures

	(1) *NCSKEW*	(2) *DUVOL*	(3) *NCSKEW*	(4) *DUVOL*
Alternative measurements of biodiversity disclosure				
BIOIMP	-0.00718	0.0414		
	(0.0685)	(0.0518)		
RESTOR			-0.0370	-0.0239
			(0.0552)	(0.0421)
Controls				
LAGCSKEW	-0.0731***		-0.0730***	
	(0.0181)		(0.0162)	
LAGDUVOL		-0.0474**		-0.0428**
		(0.0187)		(0.0172)
RET	-0.843	3.096	-3.220	1.198
	(3.199)	(2.697)	(2.896)	(2.445)
MB	-0.00836	-0.00725	-0.00708	-0.00711
	(0.00769)	(0.00571)	(0.00719)	(0.00547)
SIZE	0.406***	0.335***	0.392***	0.339***
	(0.0485)	(0.0346)	(0.0471)	(0.0339)
GROWTH	0.143*	0.107**	0.166**	0.133***
	(0.0758)	(0.0546)	(0.0686)	(0.0472)
SIGMA	-4.467***	-2.840***	-5.016***	-3.314***
	(1.276)	(0.950)	(1.160)	(0.869)
DTUNROVER	0.132	0.126	-0.0781	-0.0649
	(0.151)	(0.106)	(0.159)	(0.119)
LEV	-0.110	-0.276	-0.0378	-0.137
	(0.300)	(0.224)	(0.283)	(0.211)
ROA	-0.0279	0.0542	0.0466	0.120
	(0.300)	(0.225)	(0.286)	(0.213)
ESG	0.230	0.135	0.155	0.151
	(0.204)	(0.152)	(0.193)	(0.143)
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Observations	6,578	6,578	8,001	8,001
Adjusted R-sq	0.047	0.043	0.039	0.031

Notes: (1) This table reports results of regressions estimating the association between alternative biodiversity disclosure measures and firms' stock price crash risk. The following model is estimated: $SPCR_{i,t} = \beta_0 + \beta_1(BIOIMP_{i,t-1}\ or\ RESTOR_{i,t-1}) + \beta_2 SPCR_{i,t-1} + \sum \beta_k CONTROLS_{i,t-1} + Fixed\ Effects + \varepsilon_{i,t}$, $SPCR_{i,t}$ is two measurements of stock price crash risk for firm *i* in year *t*, including: Down-to-up volatility of firm specific weekly returns (*NCSKEW*) and Negative conditional firm specific weekly return skewness (*DUVOL)*. $BIOIMP_{i,t-1}$ is a Refinitiv's Biodiversity Impact Reduction Score, scaled by 100. $RESTOR_{i,t-1}$ is a Refinitiv's Environmental Restoration Initiatives Score, scaled by 100. We include a set of control variables $CONTROLS_{i,t}$ same as model (5) (Refer to **Table 13** in Appendix A for variable definitions). Sample period is from 2012 to 2023; (2) The sample size in our regression analysis is smaller than in our descriptive statistics due to singleton observations being dropped by the high-dimensional fixed effects model; (3) In the untabulated tests, we verified the robustness of our findings by running an alternative specification that includes industry and year level fixed effects. The results remained consistent across both approaches; (4) Robust standard errors are in parentheses and clustered at firm level; (5) Significance levels are *0.10, **0.05, and ***0.01.

4.6. Cross-sectional Tests

To provide further insights into the relationships between biodiversity disclosures and stock price crash risk, this section presents cross-sectional tests across three distinct panels: (A) countries with high biodiversity attention, where biodiversity-related issues are prioritized; (B) industries characterized by high exploitation of natural resources; and (C) post-2019 observations, reflecting a period of heightened regulatory and societal focus on biodiversity.

4.6.1. High Public Attention Countries

Countries exhibiting significant biodiversity focus typically demonstrate rigorous environmental regulations, increased public awareness, and demand from stakeholders to mitigate biodiversity risks. Companies in these countries may encounter heightened demands for the disclosures of biodiversity-related information, rendering this an important context for analyzing the relationship between biodiversity disclosures and SPCR. In this section, we test the relationship between biodiversity disclosures and SPCR for companies located in high public attention countries.

To measure public attention to biodiversity issues, we utilize Google search volumes as a proxy. This methodological approach builds on foundational research by Da et al. (2011) and Drake et al. (2012), who demonstrated that Google search volumes for company tickers effectively measure investor attention. The application of Google search data has since expanded to various attention-measurement contexts. For instance, Marmrora (2023) employed Google search volumes of financial terms to gauge investor attention toward emerging market economies, while Ferguson et al. (2023) analyzed country-level Google search activity to measure stakeholder attention to sustainability reports.

We measure public attention to biodiversity across countries and time, by extracting Google Trends data for the term "biodiversity" and its equivalents in major languages. Specifically, we collect country-year level absolute search volumes[11], incorporating both the English term "biodiversity"[12] and its translations in the most used languages within each country[13](See **Table 15** in Appendix C). We report the average search volumes from 2012-2023 for each country in **Figure 6**. With France, Portugal, the United Kingdom, Spain, and Germany ranking in the top five, we define these countries as "high-biodiversity attention countries" and investigate the relationship between biodiversity disclosures and stock price crash risk in these countries.

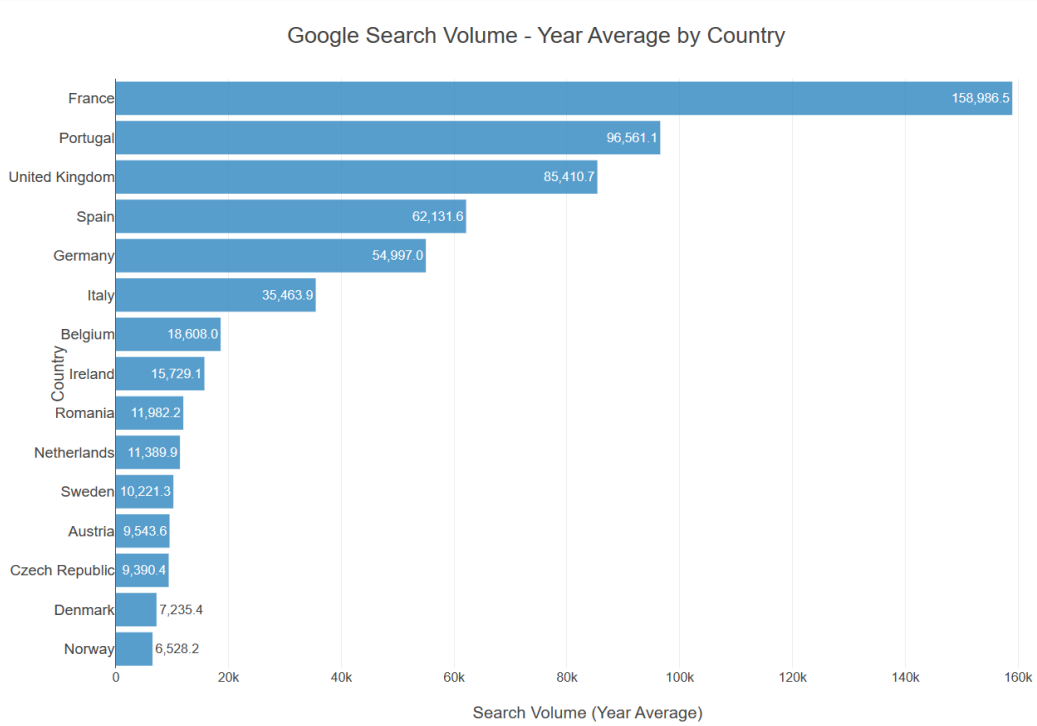

Figure 6 Country Rank of Public Attention Regarding Biodiversity

[11] Standard Google Trends data presents search activity on a relative scale from 0 to 100, where values are normalized against the peak search volume in the specified period. This normalized format does not provide actual search counts. To obtain absolute search volumes, we utilize the Glimpse Google Trends Chrome Extension, which converts the relative metrics into absolute search volumes.

[12] We specifically use only the term "biodiversity" rather than the broader biodiversity-related vocabulary from our constructed dictionary for two key reasons. First, using additional terms could introduce noise by capturing searches unrelated to biodiversity concerns, as we cannot effectively filter out irrelevant search contexts. Second, we avoid using compound phrases such as "biodiversity loss" or "biodiversity risk" because these multi-word expressions may not have direct equivalents across different languages, potentially introducing translation bias in our cross-country analysis.

[13] We attempted to measure public attention at the firm-year level by conducting search queries combining the term 'biodiversity' (translated into multiple languages) with company names or ticker symbols. However, this search methodology yielded negligible search volumes.

As **Table 10** shows, in this subsample, the coefficient for *BIODIS* is 0.0152 for *NCSKEW* and 0.0134 for *DUVOL*. The results indicate a marginal positive correlation between biodiversity disclosures and crash risk, aligning with previous sections that demonstrated a weakly positive association between *BIODIS* and *SPCR*. *SENTIMENT* exhibits a negative association with SPCR, indicated by coefficients of -0.0239 (*NCSKEW*) and -0.0405 (*DUVOL*), implying that a positive tone could potentially reduce crash risk. *TRANRISK* coefficients are 0.0124 (*NCSKEW*) and 0.0137 (*DUVOL*), indicating a negligible influence and supporting previous findings that *TRANRISK*'s impact on SPCR is largely insignificant.

Table 10 Firms Locate in High Biodiversity Attention Countries

Panel A: Biodiversity Disclosure				
	NCSKEW		*DUVOL*	
	(1)	(2)	(3)	(4)
	Low Attention	*High Attention*	*Low Attention*	*High Attention*
BIODIS	0.0184	0.0152	-0.00137	0.0134
	(0.0735)	(0.0620)	(0.0544)	(0.0474)
Observations	4,311	4,423	4,311	4,423
Adjusted R-sq	0.053	0.025	0.044	0.023
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Panel B: Sentiment				
	Low Attention	*High Attention*	*Low Attention*	*High Attention*
SENTIMENT	0.00787	-0.0239	-0.00584	-0.0405
	(0.0342)	(0.0315)	(0.0279)	(0.0248)
Observations	222	293	222	293
Adjusted R-sq	0.239	0.197	0.214	0.137
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Panel C: Transition risk

	Low Attention	*High Attention*	*Low Attention*	*High Attention*
TRANRISK	0.106	0.0124	0.0510	0.0137
	(0.149)	(0.149)	(0.127)	(0.115)
Observations	221	293	221	293
Adjusted R-sq	0.239	0.195	0.212	0.127
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Notes: (1) This table presents the results of regression analyses examining the association between biodiversity disclosure variables and stock price crash risk (SPCR) across subsamples that focus on countries with low and high biodiversity attention using model (5); (2) The dependent variables are *NCSKEW* and *DUVOL*, which measure firm-specific downside risk. The independent variables include BIODIS (presence of biodiversity disclosures), *SENTIMENT* (net sentiment of biodiversity-related disclosures), and *TRANRISK* (biodiversity-related transition risk); (3) Control variables are defined in **Table 13** in Appendix A. Year and firm fixed effects are included; (4) In the untabulated tests, we verified the robustness of our findings by running an alternative specification that includes industry and year level fixed effects, the results remained unchanged; (5) The sample size varies across panels due to data availability and subgroup criteria; (6) Robust standard errors, clustered at the firm level, are reported in parentheses; (7) Significance levels are reported at *0.10, **0.05, and ***0.01.

4.6.2. High Exploitative Industries

Given their extensive reliance on natural resources, industries with high exploitation characteristics are inherently more exposed to biodiversity-related risks (Boiral & Heras-Saizarbitoria, 2017). This heightened exposure suggests that biodiversity disclosures would play a particularly crucial role in these industries. When companies in high-exploitation industries inadequately disclose their biodiversity risks and management practices, they are more likely to accumulate negative information about potential regulatory sanctions, operational disruptions, or supply chain vulnerabilities. The greater magnitude and probability of these concealed risks in high-exploitation industries increase the likelihood that their eventual revelation will trigger severe stock price crashes. Therefore, we can expect the relationship between biodiversity disclosures and stock price crash risk to be more pronounced in high-exploitation industries.

As **Table 11** shows, the coefficient for *BIODIS* in this subsample is -0.0824 for *NCSKEW* and -0.0741 for *DUVOL*. In contrast to other subsamples, *BIODIS* exhibits a weakly

negative correlation with SPCR, indicating that biodiversity disclosures in resource-intensive industries may marginally decrease crash risk. This contrasts with the broader findings of Section 4.3, which indicated that *BIODIS* was linked to an increased risk. The influence of *SENTIMENT* is minimal, evidenced by coefficients of 0.000197 for *NCSKEW* and -0.0187 for *DUVOL*, indicating an insignificant role of tone in this context. *TRANRISK* displays mixed coefficients across exploitation levels. For high exploitation firms, the coefficients are negative (-0.109 and -0.0195), while low exploitation firms show positive coefficients (0.142 and 0.0418). However, these coefficients are statistically insignificant. The findings suggest that the relationship between biodiversity-related transition risks and crash risk varies depending on exploitation levels, though the statistical insignificance makes it difficult to draw firm conclusions.

Table 11 Firms Operate in High Exploitation Industries

Panel A: Biodiversity disclosure				
	NCSKEW		*DUVOL*	
	(1)	(2)	(3)	(4)
	Low EXPLOIT	*High EXPLOIT*	*Low EXPLOIT*	*High EXPLOIT*
BIODIS	0.0750	-0.0824	0.0471	-0.0741
	(0.0588)	(0.0628)	(0.0407)	(0.0458)
Observations	4,867	3,859	4,867	3,859
Adjusted R-sq	0.320	0.059	0.446	0.063
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Panel B: Sentiment				
	Low EXPLOIT	*High EXPLOIT*	*Low EXPLOIT*	*High EXPLOIT*
SENTIMENT	-0.00931	0.000197	-0.0195	-0.0187
	(0.0432)	(0.0285)	(0.0377)	(0.0255)
Observations	207	308	207	308
Adjusted R-sq	0.205	0.160	0.142	0.071
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Firm FE	YES	YES	YES	YES

Panel C: Transition risk

	Low EXPLOIT	*High EXPLOIT*	*Low EXPLOIT*	*High EXPLOIT*
TRANRISK	0.142	-0.109	0.0418	-0.0195
	(0.208)	(0.145)	(0.157)	(0.120)
Observations	207	307	207	307
Adjusted R-sq	0.208	0.161	0.141	0.068
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Notes: (1) This table presents the results of regression analyses examining the association between biodiversity disclosure variables and stock price crash risk (SPCR) across subsamples that investigate industries characterized by low and high natural resource exploitation; (2) The dependent variables are *NCSKEW* and *DUVOL*, which measure firm-specific downside risk. The independent variables include BIODIS (presence of biodiversity disclosures), *SENTIMENT* (net sentiment of biodiversity-related disclosures), and *TRANRISK* (biodiversity-related transition risk); (3) Control variables are defined in **Table 13** in Appendix A. Year and firm fixed effects are included; (4) In the untabulated tests, we verified the robustness of our findings by running an alternative specification that includes industry and year level fixed effects, the results remained unchanged; (5) The sample size varies across panels due to data availability and subgroup criteria; (6) Robust standard errors, clustered at the firm level, are reported in parentheses; (7) Significance levels are reported at *0.10, **0.05, and ***0.01.

4.6.3. Post-2019 Period

In recent years, biodiversity loss has emerged as one of the foremost environmental challenges endangering economic systems, as highlighted by the WEF (2020). This period marks a critical turning point in how biodiversity risks are perceived and managed. Major global initiatives, including the Kunming Declaration and the establishment of the Taskforce on Nature-related Financial Disclosures, have significantly elevated regulatory attention to biodiversity issues. This intensified regulatory and societal focus, combined with growing stakeholder awareness, suggests that biodiversity disclosures may have become more important for corporate risk assessment and market behavior. In this section, we investigate the effect of biodiversity disclosures on stock price crash risk during the post-2019 period, when biodiversity concerns have gained unprecedented attention.

As **Table 12** reports, in the post-2019 subsample, the coefficients for *BIODIS* are 0.0112 for *NCSKEW* and 0.00404 for *DUVOL*. The small positive coefficients suggest a weak association between biodiversity disclosures and increased crash risk in the recent period; however, the results are statistically insignificant. This corresponds with the main findings in Section 4.3, where *BIODIS* demonstrated a positive yet insignificant relationship with SPCR throughout the entire sample. *SENTIMENT* exhibits a negative correlation with crash risk, indicated by coefficients of -0.0199 (*NCSKEW*) and -0.0400 (*DUVOL*). The relationship between *SENTIMENT* and *DUVOL* is significant at the 10% level, indicating a potential mitigating effect of positive tone on crash risk. Nonetheless, this significance seems to be an anomaly when contrasted with other regressions involving *SENTIMENT* and *DUVOL* across various subsamples and the complete sample, where no significant relationship was detected. This anomaly indicates the need for caution in interpreting this result as anything beyond a context-specific deviation. *TRANRISK* demonstrates minimal effects, with coefficients of -0.0359 (*NCSKEW*) and 0.00133 (*DUVOL*), indicating slight variations relative to earlier results.

Table 12 Post-2019 Period

Panel A: Biodiversity disclosure				
	NCSKEW		*DUVOL*	
	(1)	(2)	(3)	(4)
	2012-2019	*2020-2023*	*2012-2019*	*2020-2023*
BIODIS	-0.0592	0.0112	-0.0194	0.00404
	(0.0995)	(0.0569)	(0.0740)	(0.0439)
Observations	3,910	4,662	3,910	4,662
Adjusted R-sq	0.061	0.079	0.041	0.076
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Panel B: Sentiment				
	2012-2019	*2020-2023*	*2012-2019*	*2020-2023*
SENTIMENT	0.0723	-0.0199	0.0324	-0.0400*
	(0.0851)	(0.0280)	(0.0670)	(0.0220)
Observations	110	344	110	344

Adjusted R-sq	0.136	0.253	0.272	0.221
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Panel C: Transition risk

	2012-2019	*2020-2023*	*2012-2019*	*2020-2023*
TRANRISK	-0.0805	-0.0359	-0.0213	0.00133
	(0.380)	(0.142)	(0.265)	(0.118)
Observations	109	344	109	344
Adjusted R-sq	0.131	0.252	0.270	0.210
Controls	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Notes: (1) This table presents the results of regression analyses examining the association between biodiversity disclosure variables and stock price crash risk (SPCR) across subsamples that analyze the pre- and post-2019 period; (2) The dependent variables are *NCSKEW* and *DUVOL*, which measure firm-specific downside risk. The independent variables include BIODIS (presence of biodiversity disclosures), *SENTIMENT* (net sentiment of biodiversity-related disclosures), and *TRANRISK* (biodiversity-related transition risk); (3) Control variables are defined in **Table 13** in Appendix A. Year and firm fixed effects are included; (4) In the untabulated tests, we verified the robustness of our findings by running an alternative specification that includes industry and year level fixed effects, the results remained unchanged; (5) The sample size varies across panels due to data availability and subgroup criteria; (6) Robust standard errors, clustered at the firm level, are reported in parentheses; (7) Significance levels are reported at *0.10, **0.05, and ***0.01.

Overall, the effects of *BIODIS, SENTIMENT*, and *TRANRISK* on SPCR are consistently small and statistically insignificant across all subsamples, with limited exceptions. The significance of *SENTIMENT* with *DUVOL* in the post-2019 subsample at the 10% level is notable; however, it seems to function more as an outlier in light of the overall insignificance observed in other regressions. The variations in the direction and magnitude of these coefficients indicate that the effect of biodiversity disclosures is contingent upon context. Post-2019 observations in countries with high biodiversity attention indicate that *BIODIS* exhibits a weakly positive correlation with SPCR, whereas industries characterized by high exploitation show a marginal trend toward risk reduction. *SENTIMENT* consistently demonstrates a mitigating effect on crash risk, while

TRANRISK exhibits minimal influence, except in high exploitation industries, where it seems to slightly reduce risk. The findings highlight the necessity of considering contextual factors, including temporal changes, geographic focus, and industry characteristics, in the analysis of the financial implications of biodiversity-related disclosures.

5. Conclusions

The connection between biodiversity disclosures and the stock price crash risk illustrates a nuanced interaction between environmental factors and financial markets, with significant consequences for corporate transparency and overall market stability. Previous investigations highlight the significance of tackling information asymmetry (Akerlof, 1970) and materiality (Khan et al., 2016; Schaltegger & Burritt, 2015), influencing the financial relevance of non-financial disclosures. This study structured its analysis around one hypothesis, targeting the main research question and concentrating on the influence of biodiversity disclosures on stock price crash risk.

Drawing on the theoretical framework of information asymmetry, we hypothesized that biodiversity disclosures could have effects on stock price risk either by reducing crash risk through comprehensive transparency and better risk assessment, or by triggering sharp market corrections when risks are suddenly exposed. However, our analysis found no statistically significant relationship between biodiversity disclosures and crash risk. Materiality theory provides a compelling explanation: while biodiversity issues are gaining attention at societal and regulatory levels, they lack the immediate financial relevance prioritized by markets. It appears that investors often view information related to biodiversity as somewhat indirect or abstract, which may hinder its impact on risk assessments. This viewpoint is supported by the findings of Garel et al. (2024) and Maroun and Ecim (2024), who observe that biodiversity continues to be a marginal consideration in financial evaluations. Consequently, Hypothesis 1 is not confirmed, highlighting the disconnect between biodiversity disclosure practices and stock price crash risk.

In our additional test, we propose that positive sentiment in biodiversity disclosures will have a negative correlation with stock price crash risk. Although descriptive statistics suggested a potential link between positive sentiment and reduced crash risk, the relationship lacked statistical significance. This absence of confirmation can again be linked to materiality theory, underscoring the limited influence of sentiment in biodiversity-related corporate communication. Moreover, no significant associations were found between transition risk disclosures and stock price crash risk, emphasizing the minimal financial significance currently attributed to biodiversity-related transition risks by the market.

To conclude, this study addresses the main research question of whether investors factor in biodiversity-related disclosures and associated risks when assessing the potential for stock price crashes. Based on empirical evidence, we conclude that investors do not currently integrate biodiversity-related disclosures and biodiversity-related risks into their evaluations of a company's potential for extreme downside stock price movements. Despite the growing global awareness of biodiversity challenges indicating the potential

future significance of these disclosures, our findings reveal that investors currently do not consider biodiversity-related information as a factor in the stock price crash risk.

6. Implications for Future Research

The results of this study indicate that disclosures related to biodiversity presently do not possess the economic importance necessary to impact stock price crash risk significantly; however, this field is evolving and may experience future developments. As regulatory frameworks related to biodiversity disclosures become more robust and standardized, it may be beneficial to revisit this relationship in the coming years to evaluate whether heightened regulatory oversight increases the financial significance of these disclosures.

Furthermore, subsequent investigations might employ a difference-in-difference methodology to examine the effects of particular regulatory implementation. Through the examination of corporate biodiversity disclosures alongside investor reactions prior to and following the implementation of regulations, it is possible to obtain a more nuanced understanding of the impact that biodiversity disclosures have on market perceptions in specific time periods.

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Appendices

Appendix A: Definition of Variables

Table 13 Definition of Variables

Variables	*Definition*
Dependent Variables	
NCSKEW$_{i,t}$	Down-to-up volatility of firm-specific weekly returns.
DUVOL$_{i,t}$	Negative conditional firm-specific weekly return skewness.
Biodiversity Related Variables	
BIODIS$_{i,t}$	A binary variable that equals 1 if firm i mentions biodiversity-related information in its earnings call transcripts during year t-1, and 0 otherwise.
SENTIMENT$_{i,t}$	The net sentiment of biodiversity disclosures, calculated as the difference between the number of positive and negative sentences in a company's biodiversity-related disclosures within one year.
TRANSRISK$_{i,t}$	A binary variable that equals 1 if firm i mentions biodiversity-related transition risk in its earnings call transcripts during year t-1, and 0 otherwise.
Control Variables	
RET$_{i,t}$	Weekly return, measured as the yearly mean of firm-specific weekly returns.
MB$_{i,t}$	Market to book ratio, measured as the market value of equity divided by the book value of equity.
SIZE$_{i,t}$	Natural logarithm of the market value of equity for firm i in year t.
GROWTH$_{i,t}$	Growth of the total assets, measured as the percentage change of the total assets over the year.
SIGMA$_{i,t}$	Weekly return volatility, calculated as the standard deviation of weekly returns over the year.
DTUNROVER$_{i,t}$	Change in monthly turnover, defined as the difference of average monthly share turnover between the current year and the previous year. Monthly share turnover is defined as the monthly trading volume divided by the total number of shares outstanding.
LEV$_{i,t}$	Leverage, defined as the total long-term debts divided by total assets.
ROA$_{i,t}$	Return on assets, defined as the income before extraordinary items divided by lagged total assets.
ESG$_{i,t}$	The total Thomson Reuters ESG Refinitiv score for firm i in year t.
Variables in Additional Tests	
BIOIMP$_{i,t}$	Refinitiv's Biodiversity Impact Reduction Score, scaled by 100. Measure a company's disclosures of impact on biodiversity or activities to reduce its impact on the native ecosystems and species, as well as the biodiversity of protected and sensitive areas.
RESTOR$_{i,t}$	Refinitiv's Environmental Restoration Initiatives Score, scaled by 100, which quantifies a company's disclosures of efforts to implement environmental restoration projects.[14]
HIGHATTEN$_{i,t}$	Dummy=1, if the company operates in countries with high public attention to biodiversity: Portugal, France, Germany, Spain, and the United Kingdom.
EXPLOIT$_{i,t}$	Dummy=1, if the company belongs to high exploitation industries including agriculture, forestry and fishing, mining, construction and manufacturing, as highlighted by Boiral & Heras-Saizarbitoria (2017).

14 According to Refinitiv's description, restoration initiatives include any initiatives like restoration, rehabilitation, clean up, and remediation activities. A company's own operation disturbing the environment and restoring the same later is not qualified as a restoration initiative.

Appendix B: Classification of Biodiversity Mentions

Table 14 Classification Examples

Labels	*Examples*
Panel A: Misclassifications by the word-dictionary method	
Use as metaphors	Remember the story, I mean, the joke I was telling you five or six years about the squirrels in the **forest**. I mean, if they mutualize the nuts, they survive the winter.
Unrelated to the firm's activity	Local community, I said it at the beginning, move away from taking something from local community, do exactly the opposite, contribute, whether it is **biodiversity**, whether it's education, whether it is craftsmanship, whether it is supplies, just do something for them.
Use as company name	By the end of last year, **Forest** had achieved approximately 65% coverage of those patients with commercial insurance plans, and about 50% coverage of those patients under Medicare Part D.
Panel B: Classifications of positive and negative disclosures	
Positive	I'm very delighted that, again in 2017, Metsä Board received a lot of recognition for its responsible business operations. In CDP, we were on the A Lists in both climate and water and got leadership status in the **forest** program.
Positive	These are not only ambitious in terms of the -- of carbon reduction but also in terms of water usage, **biodiversity**, our engagement with and effectiveness of creating enduring value for local communities and all of our stakeholders.
Physical risk	For the Salmon of Irish Origin, we made a loss of EUR 3 million in the quarter, following previously announced issues with **pancreas disease** compounded by compromised gill pathology due to **micro-jellyfish**, the same **species** as for Scotland Atlantic.
Physical risk	There have been two **storms** in the north of Sweden covering our **forests** and we have about 1m cubic meters -- a little bit more than 1m cubic meters that has been felled during 2014.
Transition risk	By developing technology that enables operations in areas with optimal biological conditions, we aim to take the industry further out into the ocean, the **natural habitat** of the salmon. Due to

	regulatory uncertainty, SalMar Aker Ocean has decided that further work on offshore farming in Norway is currently on hold.
Transition risk	And we also know from talking to **shareholders**, one of the most important areas for them in terms of the improvement of **biodiversity**.
Panel C: Classifications of other metrics	
Financial related	I talked earlier about our award-winning catchment management approach, which has secured a **GBP 20 million** ODI benefit for K7 as we take a Green First approach to investment and apply natural solutions to reduce the agricultural impact on **biodiversity** and water quality.
Financial related	We have had some **higher costs** in our **forest** operation due to -- you remember that we had the -- more than 5 million cubic meters that was storm felt and of course it's much more expensive to go in to take care of that forest than it is to -- when you can do it in an organized way. And the storm also made us buy somewhat more external forest than using our own forest and that had an impact on the **cost side**.
Forest related	We are stepping up our sustainability efforts and investments into the raw material supply chains, our full supply chain, so communicating and committing to **100% verified deforestation**, free palm and soy supply chain by 2025 as well as 100% stability to plantation by 2025.
Forest related	And a lot of the focus this year will be on biodiversity work to actually **plant trees** and shrubs, grass seeds and work with the community to improve the relationships that we have ongoing.

Appendix C: Different Linguistic Contexts of "Biodiversity"

Table 15 Different Linguistic Contexts of "Biodiversity"

Country	*Words Used for Google Trend Search*
France	Biodiversity; Biodiversité
Portugal	Biodiversity; Biodiversidade
United Kingdom	Biodiversity
Spain	Biodiversity; Biodiversidad
Germany	Biodiversity; Biodiversität
Italy	Biodiversity; Biodiversità
Belgium	Biodiversity; Biodiversité; Biodiversiteit
Ireland	Biodiversity
Romania	Biodiversity; Biodiversitate
Netherlands	Biodiversity; Biodiversiteit
Sweden	Biodiversity; Biologisk mångfald; Biodiversitet
Austria	Biodiversity; Biodiversität
Czech Republic	Biodiversity; Biodiverzita
Denmark	Biodiversity; Biodiversitet
Norway	Biodiversity; Biodiversitet; Biologisk mangfold
Poland	Biodiversity; różnorodność biologiczna
Russia	Biodiversity; биологическое разнообразие; биоразнообразие
Switzerland	Biodiversity; Biodiversité; Biodiversità
Finland	Biodiversity; Biodiversiteetti; Luonnon monimuotoisuus
Ukraine	Biodiversity; біорізноманіття; видове різноманіття
Greece	Biodiversity; βιοποικιλότητα
Hungary	Biodiversity; Biodiverzitás; Biológiai sokféleség
Slovenia	Biodiversity; Biodiverziteta
Luxembourg	Biodiversity; Biodiversité

Cyprus	Biodiversity
Estonia	Biodiversity; Elurikkus
Iceland	Biodiversity
Lithuania	Biodiversity
Malta	Biodiversity

Notes: This table presents the various linguistic translations and contexts of "biodiversity" used in our Google Trends search across different countries. It's important to note that we only include terms that yield actual search records. While we investigated all common notations of "biodiversity" in each country's most frequently used language(s), acknowledging the diversity of expressions, some translations and variations had no search data and were consequently omitted from our analysis. For example, the Luxembourgish term "Biodiversitéit" was excluded due to the lack of search records.

Appendix D: Usage of AI in Thesis Writing

During the writing process of this thesis, we utilized a couple of services that provide Artificial Intelligence solutions. In this thesis, the following resources were used: ChatGPT 4o by OpenAI, QuillBot by Learneo, and Grammarly. Mainly, these services were employed to advance the writing level of the paper by improving the flow of the written thoughts, and by detecting spelling and grammar errors in the text. To eliminate any factual inaccuracies, we followed the approach of carefully selecting the proposed corrections and rephrasing that are suggested by selected AI providers before applying any changes to the initially written text.

Additionally, ChatGPT 4o, to other services which do not have such technical solution, was used as an additional source of information to comprehend the knowledge about the concepts and code writing. This way of exploiting the service is comparable to the usage of any other consulting resources such as Wikipedia or academic references for comprehensive understanding. Specifically, ChatGPT proved instrumental in generating initial code outlines, iteratively assisting with minor coding issues. This significantly streamlined the development process, reducing the time required for code creation while improving quality by acting as a brainstorming tool for problem-solving.

To comply with the licensing requirements and intellectual property rights, all AI services were used under the paid licenses' agreements with listed parties. The necessary approvals for using the licensed versions of the services were gathered from the thesis supervisor.

In conclusion, AI services proved to be useful tools for improving the thesis's writing quality. Their application was carefully designed to minimize risks such as inaccuracies or overly broad outputs by using only precise and well-structured prompts.