The Biodiversity Reporting Puzzle: Regional Heterogeneity, Industry Materiality and Stock Price Crash Risk

Gregor Dorfleitner[a,c,b,*], Julian Hunzinger[a]

[a] *Department of Finance, University of Regensburg*
[b] *Centre for Climate Resilience, University of Augsburg*
[c] *Hanken Centre for Accounting, Finance and Governance, Hanken School of Economics*

Abstract

We examine the relationship between biodiversity reporting and firm-specific crash risk across Europe, the United States and Asia over the period 2013 to 2024. We find a negative association in Europe and the U.S., though mostly significant only in Europe, while the relationship is significantly positive in Asia. These results indicate strong regional heterogeneity in how biodiversity disclosure is interpreted by capital markets. The materiality hypothesis is not supported, as the relationship is not driven by industry-level ecological exposure, suggesting that the effect is independent of sectoral materiality. Robustness checks using a Heckman two-stage model confirm the stability of the results. Overall, biodiversity reporting emerges as an economically relevant determinant of crash risk with implications for investors and disclosure regulation.

Keywords: Biodiversity Reporting, Biodiversity, Reporting, Crash Risk, ESG

*Corresponding author. Email: gregor.dorfleitner@ur.de

1. Introduction

The increasing degradation of global biodiversity has emerged as one of the most critical environmental and economic challenges of the twenty-first century. Biodiversity, commonly defined as the variability among living organisms and ecosystems, constitutes the fundamental basis of ecological resilience, economic productivity and societal well-being (Morton & Hill, 2014).

Recent studies document a severe decline in global biodiversity, with estimates suggesting a reduction in ecological species diversity of approximately 25% over the last two centuries (WWF, 2024). Beyond its ecological consequences, biodiversity loss is also increasingly considered an economic risk, as estimates suggest that more than half of global gross domestic product (GDP) is moderately or highly dependent on ecosystem services and natural capital (WEF, 2020). Consequently, biodiversity degradation not only threatens environmental sustainability but also exposes firms and financial markets to significant operational, regulatory and reputational risks.

Against this background, international policymakers and regulatory institutions have intensified efforts to integrate biodiversity considerations into corporate and financial decision-making. The *Kunming–Montreal Global Biodiversity Framework* (GBF), developed under the Convention on Biological Diversity (CBD), establishes a comprehensive global agenda aimed at halting and reversing biodiversity loss by 2050 (CBD, 2026). Simultaneously, regulatory initiatives such as the Task Force on Nature-related Financial Disclosures (TNFD) and the European Sustainability Reporting Standards (ESRS) increasingly require firms to identify, manage and disclose biodiversity-related dependencies and impacts (Elliot et al., 2024). Particularly within the European Union, biodiversity disclosure is progressively transitioning from a voluntary reporting practice toward a mandatory regulatory requirement under the Corporate Sustainability Reporting Directive (CSRD) (Adler et al., 2018; European Union 2023c; Elliot et al., 2024).

As a result, corporate biodiversity reporting has gained substantial importance in recent years. Firms disclose biodiversity-related information for various reasons extending beyond pure regulatory compliance. Prior literature suggests that biodiversity disclosure may strengthen institutional legitimacy, improve stakeholder relations, enhance investor confidence and mitigate reputational and regulatory risks (Freeman, 2010; Suchman, 1995; TNFD, 2021). At the same time, however, the quality and substance of biodiversity reporting remain highly heterogeneous. Existing evidence indicates that biodiversity disclosures often vary considerably across firms and industries and are frequently characterized by limited transparency, vague commitments and a lack of measurable outcomes, even among companies with substantial biodiversity exposure (Rimmel & Jonäll, 2013). Consequently, concerns arise that biodiversity reporting may partly function as symbolic communication rather than reflecting substantive ecological engagement.

In parallel to the growing relevance of biodiversity reporting, recent literature increasingly examines the financial implications of biodiversity-related corporate behavior. Di Tommaso et al. (2025) provide evidence for a positive relationship between biodiversity performance and firms' financial outcomes within European markets. Similarly, Bassen et al. (2024) show, using a global sample, that robust biodiversity management is significantly associated with lower future firm-specific crash risk. In line with that, Yang et al. (2025) demonstrate for U.S. listed firms that higher biodiversity risk exposure significantly increases stock price crash risk. Moreover, Minnick et al. (2025) document that substantive biodiversity protection measures reduce future crash risk internationally, particularly in firms characterized by strong governance structures and stakeholder-oriented institutional environments.

Despite growing evidence that biodiversity disclosure affects firm-specific crash risk, a key conceptual question arises: why would biodiversity reporting influence crash risk at all? More specifically, what underlying firm characteristics are reflected through biodiversity disclosure that financial markets appear to price? Existing studies implicitly assume that biodiversity reporting operates through a largely universal mechanism and therefore document an overall negative association between biodiversity disclosure and crash risk (Bassen et al, 2024). However, because prior research predominantly relies on pooled global or single-region samples, it remains unclear whether this relationship is indeed universal or instead shaped by institutional context.

This study advances the literature along three main dimensions. First, it provides the first explicit cross-regional analysis of the biodiversity disclosure–crash risk nexus across Europe, the United States and Asia, thereby addressing the lack of evidence on regional heterogeneity. Second, it examines whether biodiversity reporting is systematically associated with the biodiversity materiality of firms' industries, addressing the previously unexplored question of whether disclosure behavior reflects sector-specific biodiversity exposure. Third, the study introduces several methodological improvements to the biodiversity crash-risk literature. It applies a Heckman selection approach to mitigate potential sample selection bias associated with voluntary biodiversity disclosure. Furthermore, it uses daily rather than weekly stock return data to better capture firm-specific information accumulation around crash events and accounts for industry effects in the market-model regression (Callen and Fang, 2015a,b). Moreover, in addition to the established measures NCSKEW and DUVOL, it includes COUNT as an additional proxy for firm-specific crash risk (Jin and Myers, 2006).

The empirical findings reveal substantial regional heterogeneity. Biodiversity reporting is associated with significantly lower crash risk in Europe, exhibits mostly no significant relationship in the United States and is positively associated with crash risk in Asia. These findings suggest that the market interpretation of biodiversity disclosure is institutionally contingent rather than universal. The existence of these regional differences raises the question of whether the observed heterogeneity reflects differences in the underlying materiality of biodiversity risks across industries. However, the results indicate that biodiversity reporting is not systematically driven by industry-level biodiversity materiality. This suggests that disclosure behavior is shaped less by sector-specific financial exposure and more by broader institutional, reputational and legitimacy-related considerations. These findings challenge the implicit assumption in prior literature that biodiversity disclosure uniformly reduces firm-specific crash risk across institutional settings. Instead, the results suggest that the market interpretation of biodiversity disclosure is institutionally contingent rather than universal.

The objective of this study is therefore to examine the relationship between biodiversity reporting and firm-specific stock price crash risk while explicitly accounting for regional differences and industry materiality. More specifically, the study addresses two central research questions. First, how does biodiversity reporting relate to firm-specific crash risk across Europe, the United States and Asia when controlling for firms' general ESG performance? Second, to what extent does the relationship between biodiversity reporting and crash risk depend on the biodiversity materiality of the respective industry?

The remainder of the paper is structured as follows. Section 2 reviews the literature and develops hypotheses. Section 3 describes data, variables and methodology. Section 4 presents results. Section 5 tests the robustness of the results. Section 6 concludes.

2. Literature and hypotheses

2.1. Stock price crash risk: Concept and underlying mechanisms

Firm-specific stock price crash risk refers to the likelihood of sudden and extreme negative stock price movements at the firm level. In the empirical literature, crash risk is commonly operationalized using the negative conditional skewness of firm-specific return distributions (NCSKEW) (Chen, Hong, & Stein, 2001; Kim, Li, & Li, 2014). Additional established measures include down-to-up volatility (DUVOL) and count-based measures of extreme negative returns (COUNT). While NCSKEW captures asymmetry in the return distribution, DUVOL measures the relative volatility of negative versus positive return periods and COUNT captures the frequency of extreme negative return realizations (Chen et al., 2001; Jin & Myers, 2006; Kim, Li, & Zhang, 2011a, 2011b).

The dominant theoretical explanation for stock price crash risk is the *bad news hoarding* hypothesis (Hutton, Marcus, & Tehranian, 2009; Jin & Myers, 2006). According to this framework, managers strategically withhold adverse firm-specific information from outside investors in order to protect short-term firm value, avoid reputational damage or secure private benefits. Over time, undisclosed negative information accumulates within the firm until it reaches a tipping point at which concealment can no longer be sustained. Once the accumulated bad news is released to the market, stock prices adjust abruptly, resulting in a crash event.

Agency theory provides an important theoretical foundation for this mechanism. Jensen and Meckling (1976) argue that managers possess incentives to strategically control the timing and extent of information disclosure due to conflicts of interest between managers and shareholders. Empirical evidence further suggests that managers tend to delay the disclosure of negative information while releasing positive news more promptly (Kothari, Shu, & Wysocki, 2009).

Beyond managerial information hoarding, the literature identifies additional mechanisms contributing to crash risk. These include heterogeneous investor beliefs, limits to arbitrage, short-sale constraints and delayed information diffusion (Cao, Coval, & Hirshleifer, 2002; Hong & Stein, 2003; Zhu, 2016). Nevertheless, despite these complementary explanations, bad news hoarding remains the dominant theoretical framework in the crash risk literature (Habib et al., 2017).

As a consequence, a broad literature has emerged investigating the determinants of firm-specific crash risk. Identified determinants include financial reporting quality, disclosure transparency, managerial incentives and characteristics, corporate governance structures, financing decisions, ownership structures and institutional environments (Habib et al., 2017). This extensive body of research highlights that crash risk is shaped not only by internal disclosure policies but also by broader market and institutional mechanisms.

CSR, ESG and firm-specific crash risk

Building upon the informational perspective of crash risk, a growing literature examines whether sustainability related activities influence managerial incentives and information environments. The theoretical debate is primarily characterized by two competing views: the risk mitigation hypothesis and the agency-cost hypothesis (Kim et al., 2014; Utz et al., 2018).

The risk mitigation view argues that firms with stronger sustainability engagement operate under higher ethical standards and more transparent disclosure practices, thereby reducing information asymmetries and limiting managerial incentives to hoard bad news (Kim et al., 2014). From this perspective, CSR and ESG activities improve the firm's information environment and strengthen stakeholder trust, reducing uncertainty regarding future cash flows and ultimately lowering crash risk.

Several mechanisms support this argument. First, sustainability engagement can generate moral capital in the form of intangible assets such as reputation, trust, employee commitment, customer loyalty and legitimacy among stakeholders (Godfrey, 2005; Surroca, Tribó, & Waddock, 2010; Edmans, 2011). These intangible assets may function as an insurance-like protection mechanism during periods of distress and reduce idiosyncratic firm risk (Attig et al., 2013; El Ghoul et al., 2017).

Second, enhanced sustainability disclosure increases transparency and reduces informational opacity. Gelb and Strawser (2001) argue that firms with stronger CSR engagement tend to provide more informative disclosures and maintain superior investor relations practices. Improved transparency constrains managerial discretion and reduces the possibility of concealing adverse information.

Third, socially responsible institutional investors often exert stronger monitoring pressure on corporate management (Bollen, 2007).

In contrast, the agency-cost view argues that managers may strategically employ CSR activities to pursue private benefits, improve personal reputations, or strengthen managerial entrenchment at the expense of shareholders (Barnea & Rubin, 2010; Goss & Roberts, 2011). From this perspective, sustainability initiatives may represent inefficient investments that divert resources from core business operations and reduce profitability (Friedman, 1970; McWilliams, Siegel, & Wright, 2006).

Moreover, sustainability reporting can potentially function as a form of impression management or symbolic legitimacy rather than genuine transparency (Hemingway & Maclagan, 2004). Managers may use sustainability communication strategically to divert stakeholder attention away from operational weaknesses or hidden risks. In such settings, sustainability engagement may coincide with greater bad news hoarding and increased crash risk.

Empirical evidence suggests that both mechanisms coexist and may depend strongly on institutional context. Utz (2018) documents substantial regional heterogeneity. While CSR is associated with lower crash risk in Europe and the United States, the relationship becomes positive in the Asia-Pacific region. Li and Wu (2025) provide similar evidence for China and argue that weak institutional environments and symbolic disclosure practices reduce the credibility of sustainability reporting. In such contexts, CSR may fail to reduce information asymmetries and instead increase investor skepticism. Utz (2018) explains the positive crash-risk finding through the overinvestment hypothesis, arguing that many Asian firms attempt to adopt Western CSR standards and consequently overinvest in CSR activities. These excessive investments can impose substantial costs on firms, thereby increasing financial pressure and ultimately elevating stock price crash risk.

An important extension to this literature is provided by Dorfleitner and Zhang (2024), who show using BERT-based textual analysis that ESG-related news significantly affects stock returns and that negative ESG news has substantially stronger valuation effects than positive ESG news. This finding highlights that capital markets actively process sustainability-related information and penalize adverse sustainability signals disproportionately strongly.

Overall, prior research suggests that the relationship between sustainability engagement and stock price crash risk is context-dependent and shaped by institutional quality, regulatory environments, investor expectations and disclosure credibility.

Biodiversity and double materiality

While the previous literature primarily emphasizes how biodiversity-related risks affect firms and financial markets, the relationship between firms and biodiversity is inherently reciprocal. Corporate activities themselves exert substantial impacts on ecosystems and biological diversity. Firms that extract natural resources, alter land use or emit pollutants may directly contribute to biodiversity degradation and habitat loss.

This reciprocal interaction between firms and biodiversity forms the basis of the concept of *double materiality*. The concept requires companies not only to disclose sustainability-related risks that may affect the firm financially, but also to report how their own activities contribute to environmental and societal impacts (Lashitew, 2021). Consequently, double materiality extends beyond the traditional concept of financial materiality by integrating two complementary perspectives.

Following Senanayake et al. (2024), the first dimension refers to *financial materiality*. This perspective describes how biodiversity-related developments affect a firm's economic condition, firm value, cash flows and risk exposure. Biodiversity loss may generate operational disruptions, regulatory costs, reputational damage or supply-chain vulnerabilities that directly affect corporate financial performance.

The second dimension, commonly referred to as *impact materiality* or the *inside-out perspective*, captures the reverse relationship, namely the impact of corporate activities on biodiversity and ecosystems. This perspective recognizes firms not merely as passive recipients of environmental risks but also as active contributors to biodiversity loss through their business operations (Cooper & Michelon, 2022).

Both dimensions are connected through societal reactions and resulting transition risks. When corporate activities contribute to biodiversity degradation, stakeholders such as regulators, investors, NGOs and consumers increasingly exert pressure on firms to change their behavior. This pressure may materialize in the form of transition risks, including stricter regulation, litigation risk, reputational damage or changing consumer preferences, which subsequently affect firms' financial performance (Addoum et al., 2020; Bergmann et al., 2016; Senanayake et al., 2024). Consequently, proactive biodiversity management may reduce reputational and regulatory risks, whereas firms with poor biodiversity practices may face elevated exposure to public criticism, legal disputes and regulatory sanctions.

The interdependence between biodiversity and firms is increasingly documented in the literature. Previous studies show that biodiversity-related risks can increase production costs, reduce revenue growth and profitability and constrain firms' access to long-term financing (Bach et al., 2025; Flammer et al., 2025).

Against this background, the concept of double materiality raises the important question of whether and to what extent firms disclose information regarding their biodiversity impacts and related mitigation measures.

Biodiversity and capital markets

Compared to the extensive literature on CSR and ESG, research on biodiversity-related risks and biodiversity disclosure remains comparatively nascent. However, biodiversity risks are increasingly recognized as financially material for firms and investors.

Giglio et al. (2026) provide evidence that biodiversity-related risks already affect stock market valuations, while surveys indicate that investors perceive these risks as insufficiently priced by financial markets. Similarly, Garel et al. (2024) show that firms with stronger biodiversity management benefit from lower regulatory risk, improved operational efficiency and enhanced investor reputation, whereas firms with poor biodiversity practices face higher exposure to sanctions, reputational damage and transition risks (Carvalho et al., 2023).

Several studies further suggest that biodiversity risks command a distinct risk premium, reflecting regulatory uncertainty and increasing investor awareness regarding biodiversity-related obligations and dependencies (El Ouadghiri et al., 2025; Garel et al., 2024; Ma et al., 2025).

Regarding stock price crash risk specifically, Bassen et al. (2024) provide initial evidence that stronger biodiversity management is negatively associated with future crash risk in an international sample. Their findings suggest that firms with more developed biodiversity practices are less likely to conceal adverse information. Minnick et al. (2025) confirm this crash-reducing effect of biodiversity engagement in a global setting. Complementary evidence is provided by Yang et al. (2025), who show that greater biodiversity risk exposure significantly increases crash risk among U.S. firms, particularly through biodiversity-related regulatory transition risks.

Additional evidence suggests that biodiversity-related activities influence broader sustainability perceptions. Pokharel (2025) finds that firms with stronger biodiversity impact reduction scores tend to exhibit higher ESG ratings overall, indicating that biodiversity management contributes positively to perceived sustainability performance.

Despite these emerging findings, important research gaps remain. Existing studies largely neglect regional heterogeneity and do not systematically examine whether biodiversity disclosure exerts an independent effect beyond general ESG performance. Furthermore, the informational role of biodiversity disclosure remains underexplored, particularly regarding whether biodiversity-related reporting provides capital markets with incremental information that is not already captured by aggregate ESG measures.

These unresolved questions motivate the hypotheses developed in the following section.

2.2. Hypothesis development

Prior literature suggests that the relationship between sustainability disclosure and crash risk depends strongly on institutional and regulatory environments. Utz (2018) demonstrates that the association between CSR and crash risk differs substantially across regions and does not follow an universal pattern. Similarly, Dai et al. (2019) show for Chinese firms that the crash-risk implications of CSR disclosure depend critically on whether disclosure is mandatory or voluntary.

Biodiversity disclosure can be interpreted as a specialized dimension of sustainability communication that relies on similar informational and legitimacy-related mechanisms. Hassan et al. (2020) argue that biodiversity disclosure constitutes an extension of broader CSR engagement and serves as a source of corporate legitimacy. However, the credibility and informational value of biodiversity disclosure are likely to differ substantially across institutional settings.

In regions characterized by stronger regulatory enforcement, higher investor protection and more developed sustainability reporting frameworks, biodiversity disclosure is more likely to function as a credible transparency signal. Firms operating in such environments face stronger monitoring pressure from regulators, institutional investors and civil society actors. As a result, biodiversity disclosure may reduce information asymmetries, constrain managerial bad news hoarding and mitigate crash risk.

In contrast, in regions with weaker institutional enforcement or predominantly voluntary disclosure regimes, biodiversity reporting may function more symbolically and serve impression-management purposes. Firms may adopt biodiversity reporting practices primarily to satisfy external legitimacy demands while simultaneously concealing adverse environmental impacts or operational weaknesses. In such contexts, biodiversity disclosure could coincide with greater opacity, investor skepticism and ultimately higher crash risk.

Moreover, regional differences in investor preferences, stakeholder pressure, legal systems and sustainability cultures may further shape how biodiversity disclosure is interpreted and priced by financial markets. Existing evidence from the CSR literature indicates that sustainability-related disclosures can either reduce or increase crash risk depending on these contextual factors (Utz, 2018; Li & Wu, 2025).

Taken together, these arguments suggest that the relationship between biodiversity disclosure and firm-specific stock price crash risk is likely to vary across regions rather than follow a universally negative or positive pattern.

Hypothesis 1. *The relationship between biodiversity disclosure and firm-specific stock price crash risk differs across Europe, the United States and Asia.*

The potential existence of regional heterogeneity raises the question of which underlying mechanisms shape the relationship between biodiversity disclosure and firm-specific crash risk. One possible explanation relates to the biodiversity materiality of firms' industries.

Firms operating in high-impact industries such as mining, agriculture, forestry, energy and resource extraction are particularly dependent on ecosystem services while simultaneously exerting substantial pressure on biodiversity (Carvalho et al., 2023; Garel et al., 2024). In these industries, biodiversity-related risks are financially material and directly linked to operational continuity, regulatory exposure and reputational risk.

Under these conditions, biodiversity disclosure may function as a particularly informative signal for investors. Firms with credible biodiversity reporting may signal superior risk management capabilities, greater preparedness for future regulatory transitions and stronger operational resilience. Consequently, biodiversity disclosure could exert a stronger crash-reducing effect in high-impact industries than in sectors with limited biodiversity exposure.

At the same time, high-impact industries may also exhibit stronger incentives for impression management and strategic disclosure behavior. Hassan et al. (2020) argue that biodiversity disclosure frequently serves legitimacy and reputation-building purposes rather than substantive transparency objectives. Boiral (2016) further demonstrates that large mining companies systematically employ neutralization techniques in biodiversity reports in order to downplay adverse environmental impacts.

Related research on environmental disclosure suggests that firms operating in environmentally sensitive industries often engage in selective disclosure or greenwashing practices, thereby increasing information asymmetries and market uncertainty (Elsbach & Sutton, 1992; Fabrizio & Kim, 2019; Walker & Wan, 2012). In such settings, biodiversity disclosure may therefore become less informative and less effective in reducing information asymmetries between firms and investors, which may increase firm-specific stock price crash risk.

Given these competing mechanisms, the direction of the relationship between biodiversity disclosure and crash risk in high-impact industries remains theoretically ambiguous.

Hypothesis 2. *The relationship between biodiversity disclosure and firm-specific stock price crash risk differs between high-impact industries and industries with lower biodiversity exposure.*

3. Data and methodology

3.1. Sample and data sources

The dataset used for the crash-risk analysis is obtained from LSEG, which provides internationally comparable financial, market, ESG and biodiversity-related firm-level data (LSEG, 2026).

The sample period covers the years 2013–2024. This period is chosen because biodiversity and sustainability related disclosure becomes more systematically available and internationally comparable in LSEG from around 2013 onward. In addition, the period reflects the growing relevance of biodiversity issues in corporate reporting and financial markets.

The sample includes publicly listed firms from three major economic regions: Europe, the United States, and Asia-Pacific. Firms are drawn from the *STOXX Europe 600*, *S&P 500* and *STOXX Asia/Pacific 600*. All firms that were constituents of these indices at any point during the observation period are included in the analysis. This procedure ensures broad coverage of internationally important large- and mid-cap firms while avoiding survivorship bias that would arise from considering only firms continuously listed throughout the sample period.

Following Jin and Myers (2006) and Morck et al. (2000), a firm-year observation is only included if the respective stock is traded on at least 150 trading days within a fiscal year. This restriction reduces potential distortions caused by illiquid stocks, IPOs or temporary trading suspensions and ensures reliable estimation of crash-risk measures based on sufficiently dense daily return series.

Daily stock returns are calculated using total-return indices to account for dividends and other distributions through full reinvestment. To eliminate exchange-rate distortions within the international sample, all prices and returns are converted into euros.

Firms are assigned to industries based on their 2-digit *Standard Industrial Classification* (SIC) codes. Based on the SIC classification, value-weighted industry return indices are constructed using lagged market capitalization weights. These industry indices are later incorporated into the market-model regressions used to estimate crash-risk measures.

The final sample consists of 2,602 unique firms, including 801 European firms, 850 U.S. firms and 951 Asian firms.

3.2. Biodiversity variable

To measure corporate biodiversity reporting, this study uses the *Biodiversity Impact Reduction* (BIR) indicator provided by LSEG. The central research question of this study concerns whether the act of biodiversity disclosure itself constitutes an informational signal to capital markets. BIR is ideally suited to address this question, as it captures precisely whether a firm publicly reports biodiversity-related information or discloses measures aimed at reducing negative biodiversity impacts. The underlying information is collected by LSEG from publicly available corporate documents, including sustainability reports, annual reports and regulatory filings.

However, in its original form, the BIR indicator is delivered as a quartile-normalised score. Specifically, the score reflects the share of observations within the same industry that perform worse, formally defined as:

$$\text{Score}_i = \frac{\text{Number of observations with a lower value than } x_i}{N} \tag{1}$$

where N denotes the total number of firms in the respective industry peer group. As a result, all firms that report biodiversity-related information receive an identical industry-level score, while all non-reporting firms receive a score of zero. To illustrate: in the energy sector, *Occidental Petroleum Corp*, *ConocoPhillips*, *Marathon Petroleum Corp*, and *Phillips 66* all share an identical BIR score of 69.53 in 2024, solely because they belong to the same industry and all disclose biodiversity-related information. The score thus does not reflect the individual quality or depth of a firm's biodiversity efforts, but merely its reporting status relative to industry peers.

Since the central research question of this study concerns whether biodiversity reporting itself—rather than its quality—constitutes an informational signal to capital markets, the quartile-normalised score is not suited as the primary variable of interest. Instead, we use the binary indicator of the BIR-Score:

$$BIR_{i,t} = \begin{cases} 1 & \text{if the firm reports biodiversity-related measures or disclosures,} \\ 0 & \text{if no such disclosure is reported.} \end{cases} \tag{2}$$

Observations classified as `NA` are excluded from the baseline analysis, as missing data cannot be interpreted as intentional non-disclosure. This binary specification directly captures the research object of interest—the presence or absence of biodiversity disclosure—and is therefore the appropriate operationalisation for the empirical analysis.

3.3. Control variables

Following An and Zhang (2013), Chen et al. (2001), Hutton et al. (2009) and Kim et al. (2011b), the regression models include several firm-specific control variables to isolate the effect of biodiversity disclosure on crash risk.

Firm size (*SIZE*) is measured as the natural logarithm of the market value of equity. The market-to-book ratio ($MTBV$) captures firms' growth opportunities and is calculated as the ratio of market value to book value of equity. Leverage (LEV) is defined as total liabilities divided by total assets and reflects firms' capital structure and financial risk.

Profitability is controlled for using return on equity (*ROE*) and return on assets (*ROA*). *ROE* is calculated as income before extraordinary items divided by book equity, whereas *ROA* is measured as income before extraordinary items divided by total assets.

In addition, several return-distribution characteristics are included. Stock return volatility (*SIGMA*) is measured as the standard deviation of firm-specific daily returns. $SKEW$ and $KURT$ capture skewness and kurtosis of firm-specific daily returns, respectively, while RET measures the average daily firm-specific stock return. These variables account for differences in firms' risk profiles and past stock market performance (Hutton et al., 2009; Jin and Myers, 2006).

Finally, some specifications additionally include a lagged ESG score to ensure that the estimated biodiversity effect does not merely reflect firms' general sustainability orientation. Consistent with prior literature, most control variables enter the regressions with a one-year lag to reduce potential endogeneity concerns (El Ghoul et al., 2017; Oikonomou et al., 2014).

3.4. Empirical approach

Following Roll (1988), Hutton et al. (2009) and Callen and Fang (2015a,b), stock price crash risk is estimated based on firm-specific residual returns obtained from an expanded market model regression. In addition, the model incorporates both regional market returns and industry returns, thereby capturing a broader set of systematic influences on stock prices.

To address non-synchronous trading effects (Dimson, 1979), lagged, contemporaneous and leading market and industry returns are included in the regression specification. Specifically, for each firm i and trading day d, the following regression is estimated:

$$r_{i,k,d} = \alpha_i + \beta_{1,i} r_{m,d-1} + \beta_{2,i} r_{k,d-1} + \beta_{3,i} r_{m,d} + \beta_{4,i} r_{k,d} + \beta_{5,i} r_{m,d+1} + \beta_{6,i} r_{k,d+1} + \varepsilon_{i,d}, \tag{3}$$

where $r_{i,k,d}$ denotes the daily return of firm i in industry k, $r_{m,d}$ represents the regional market return, and $r_{k,d}$ is the value-weighted industry return. Regional benchmark indices include the Euro STOXX 600 for Europe, the S&P 500 for the United States and the STOXX Asia/Pacific 600 for Asia. The residual term $\varepsilon_{i,d}$ captures the firm-specific component of stock returns that cannot be explained by general market or industry movements.

Following Hutton et al. (2009), firm-specific residual returns are transformed as

$$w_{i,d} = \ln(1 + \varepsilon_{i,d}), \tag{4}$$

where $w_{i,d}$ denotes the transformed firm-specific daily return of firm i on day d. The logarithmic transformation reduces the skewness of residual returns and improves comparability across firms.

3.4.1. Crash risk measures

Based on the transformed residual returns, three established measures of stock price crash risk are calculated using rolling 252-trading-day windows. Using multiple crash-risk proxies allows the analysis to capture different dimensions of extreme negative stock price movements and improves the robustness of the empirical results.

First, $COUNT$ measures the difference between the number of extreme negative return days (crashes) and extreme positive return days (jumps), following Jin and Myers (2006). A crash (jump) occurs when firm-specific returns fall below (exceed) 3.09 standard deviations from the annual mean return, corresponding to the 0.1% tails of a normal distribution. The measure is defined as:

$$COUNT_{i,t} = \#\{w_{i,d} < \bar{w}_i - 3.09\sigma_i\} - \#\{w_{i,d} > \bar{w}_i + 3.09\sigma_i\}, \tag{5}$$

where $\bar{w}_i$ denotes the annual mean of firm-specific returns and σ_i their standard deviation. Higher values of $COUNT$ indicate a greater relative frequency of crash events.

Second, $NCSKEW$ captures the negative conditional skewness of firm-specific returns (Kim et al., 2011a,b). Higher values indicate a stronger left-skewed return distribution and therefore higher crash risk. The measure is defined as:

$$NCSKEW_{i,t} = -\frac{D(D-1)^{3/2}\sum_{d=1}^{D}(w_{i,d}-\bar{w}_i)^3}{(D-1)(D-2)\left(\sum_{d=1}^{D}(w_{i,d}-\bar{w}_i)^2\right)^{3/2}}, \tag{6}$$

where D denotes the number of trading days within year t. The negative sign ensures that larger values correspond to greater crash risk.

Third, $DUVOL$ compares the volatility of firm-specific returns on down days with the volatility on up days (Chen et al., 2001):

$$DUVOL_{i,t} = \ln\left(\frac{\sum_{d\in\mathrm{Down}}(w_{i,d}-\bar{w}_i)^2/(d_{\mathrm{Down}}-1)}{\sum_{d\in\mathrm{Up}}(w_{i,d}-\bar{w}_i)^2/(d_{\mathrm{Up}}-1)}\right). \tag{7}$$

Down days are defined as trading days on which firm-specific returns fall below the annual mean return, whereas up days are days with returns above the mean. Higher values of $DUVOL$ indicate that negative return periods exhibit greater volatility than positive return periods and therefore imply elevated crash risk.

Together, these measures capture different dimensions of crash risk, including the frequency of extreme negative returns, the asymmetry of return distributions and the relative volatility of negative versus positive return periods.

3.4.2. Regression models

To examine the relationship between biodiversity disclosure and stock price crash risk, multivariate panel regressions are estimated using the three crash-risk measures as dependent variables. The primary explanatory variable is the lagged Biodiversity Impact Reduction indicator ($BIR_{i,t-1}$). All regressions include year fixed effects and firm-clustered standard errors to account for unobserved heterogeneity and within-firm dependence over time. Additional specifications further incorporate industry fixed effects and interaction terms to analyze regional heterogeneity and biodiversity-intensive industries.

The empirical analysis is conducted separately for firms from Europe, the United States and Asia in order to account for differences in institutional environments, regulatory frameworks and sustainability reporting practices across regions. Further interaction models are estimated to test whether the relationship between biodiversity disclosure and crash risk differs systematically between Western (Dummy 1 if a firm is in the european and U.S. sample and Dummy 0 if it is in the asian sample) and Asian firms as well as between biodiversity-intensive and non-intensive industries. Firms are classified as belonging to biodiversity high-impact industries based on two-digit SIC codes capturing sectors whose operations are typically associated with deforestation, habitat loss, excessive water consumption, land-use change, pollution, or toxic emissions. High-impact industries include agriculture, forestry and fisheries (SIC 01–09), mining and resource extraction (SIC 10–14), construction and infrastructure (SIC 15–17), chemicals and related products (SIC 20), lumber, wood and furniture products (SIC 24), paper and pulp manufacturing (SIC 26), petroleum refining (SIC 29), and utilities such as energy and water supply (SIC 40–49).

To address potential endogeneity concerns and the persistence of crash risk over time, the analysis additionally employs dynamic panel regressions (Arellano and Bond, 1991). The dynamic specifications include lagged dependent variables and are estimated separately for Europe, the United States and Asia. Further models incorporate ESG measures and regional interaction effects to examine whether biodiversity disclosure provides explanatory power beyond broader ESG performance.

4. Results

4.1. Descriptive statistics and correlation matrix

Descriptive statistics

This section presents the descriptive statistics and preliminary analyses for the variables used in the empirical models. The analysis covers firms from Europe, the United States and Asia over the period 2013–2024. Observations with missing values for the biodiversity reporting indicator (*BIR*) are excluded from the baseline sample. The treatment of missing observations is addressed later within the robustness analyses.

Table 1 reports the descriptive statistics for all variables across the three regional samples. Overall, the crash-risk measures (*COUNT*, *NCSKEW* and *DUVOL*) remain relatively close to zero across regions, although noticeable regional differences emerge. US firms exhibit the highest average crash-risk values, while the Asian sample shows comparatively lower and partially negative values, indicating a less pronounced left-skewness in firm-specific return distributions.

Substantial regional variation is also observable for biodiversity reporting and ESG performance. The average *BIR* value equals 0.385 in Europe, 0.240 in the United States and 0.402 in Asia. This suggests that biodiversity-related reporting is least common among US firms, whereas Asian and European firms disclose biodiversity-related activities more frequently. ESG scores follow a similar pattern, with Europe showing the highest average ESG performance.

The descriptive statistics further indicate that larger firms tend to report higher ESG scores and are more likely to disclose biodiversity-related information. Across all regions, the distributions of the financial control variables are broadly consistent with previous international crash-risk studies.

Additionally, Augmented Dickey-Fuller (ADF) tests are conducted to assess the stationarity of the variables. The corresponding results are reported in Table A2 in the Appendix. For all variables across all regional samples, the null hypothesis of a unit root can be rejected at the 1% significance level, indicating stationarity throughout the observation period.

Correlation analysis

Pearson correlation matrices for Europe, the United States and Asia are reported in Tables A3 to A5. Overall, the three crash-risk measures (*NCSKEW*, *DUVOL* and *COUNT*) exhibit strong positive correlations across all regions, confirming that the measures capture related dimensions of stock price crash risk. In particular, the correlation between *NCSKEW* and *DUVOL* exceeds 0.86 in all samples.

The correlations between biodiversity reporting (*BIR*) and the crash-risk measures remain relatively weak. In Europe and the United States, the coefficients are close to zero and mostly statistically insignificant. In contrast, the Asian sample shows small but positive and statistically significant correlations between *BIR* and all three crash-risk measures, providing initial evidence of potential regional differences in the relationship between biodiversity reporting and stock price crash risk.

A consistent positive relationship is observed between *BIR* and ESG scores across all regions. The corresponding correlation coefficients amount to 0.386 for Europe, 0.372 for the United States and 0.417 for Asia, all significant at the 1% level. This finding suggests that biodiversity reporting is closely related to broader ESG performance, while still representing a distinct sustainability dimension.

Table 1: Descriptive statistics by region

Europe (N = 7295)

Variable	Mean	Median	SD	P25	P75
COUNT	-0.050	0.000	1.720	-1.000	1.000
NCSKEW	0.050	-0.033	1.428	-0.466	0.452
DUVOL	-0.022	-0.032	0.412	-0.250	0.189
SIZE	15.489	15.400	1.366	14.540	16.380
MTBV	2.852	1.930	6.260	1.110	3.340
LEV	0.601	0.606	0.208	0.468	0.744
ROA	5.398	4.670	9.042	1.735	8.100
ROE	12.487	11.800	36.263	5.770	18.790
SIGMA	0.019	0.017	0.008	0.014	0.022
RET	0.000	0.000	0.001	-0.000	0.001
SKEW	0.026	0.004	1.196	-0.361	0.376
KURT	8.936	5.848	11.362	4.400	9.155
BIR	0.385	0.000	0.487	0.000	1.000
ESG_ Score	62.501	65.010	17.737	51.275	75.965

USA (N = 7524)

Variable	Mean	Median	SD	P25	P75
COUNT	0.172	0.000	1.664	-1.000	1.000
NCSKEW	0.196	0.090	1.578	-0.444	0.681
DUVOL	0.056	0.043	0.443	-0.200	0.289
SIZE	16.322	16.172	1.292	15.375	17.128
MTBV	5.295	2.810	31.171	1.670	5.020
LEV	0.624	0.632	0.196	0.497	0.766
ROA	6.620	5.900	7.602	2.890	9.990
ROE	37.422	14.130	552.621	7.948	24.905
SIGMA	0.019	0.017	0.009	0.014	0.022
RET	0.001	0.001	0.001	0.000	0.001
SKEW	-0.033	-0.064	1.120	-0.414	0.306
KURT	8.878	5.770	10.146	4.371	9.497
BIR	0.240	0.000	0.427	0.000	0.000
ESG_ Score	55.347	57.170	18.251	41.860	69.742

Asia (N = 9599)

Variable	Mean	Median	SD	P25	P75
COUNT	-0.332	0.000	1.633	-1.000	1.000
NCSKEW	-0.098	-0.124	0.976	-0.471	0.210
DUVOL	-0.088	-0.094	0.356	-0.286	0.096
SIZE	15.630	15.512	1.098	14.859	16.291
MTBV	2.398	1.380	4.669	0.880	2.440
LEV	0.536	0.520	0.230	0.361	0.701
ROA	5.391	4.170	6.550	1.950	7.280
ROE	10.996	9.560	29.947	5.730	14.550
SIGMA	0.021	0.019	0.010	0.015	0.023
RET	0.000	0.000	0.001	-0.000	0.001
SKEW	0.199	0.164	0.840	-0.137	0.484
KURT	7.267	5.273	7.638	4.221	7.529
BIR	0.402	0.000	0.490	0.000	1.000
ESG_ Score	52.924	55.600	20.214	39.410	68.430

Notes: SD = standard deviation; P25/P75 = 25th and 75th percentiles. *BIR* is a binary indicator (1 = biodiversity reporter, 0 = non-reporter). Observations with missing BIR values are excluded from the baseline sample.

The correlation analysis further indicates no severe multicollinearity concerns among the explanatory variables. Nevertheless, due to the positive association between ESG performance and biodiversity reporting, ESG measures are included as control variables in the subsequent regression models.

4.2. Regression results

Initially, Hypothesis 1 is examined by analysing whether the relationship between biodiversity reporting and firm-specific stock price crash risk differs across regions. To test for potential regional heterogeneity, separate panel regressions are estimated for Europe, the United States and Asia (Table 2). In addition, the interaction model including a *WEST* dummy variable is implemented to formally test whether the association between biodiversity reporting and crash risk differs systematically between Western countries and Asian markets (Table 3).

For European firms, the coefficients of BIR_{t-1} are negative across all three crash-risk measures. The negative effects are statistically significant at the 5 %-level for *COUNT* and *NCSKEW* and at the 1 %-level for *DUVOL*. If a firm reports biodiversity-related information in the previous year, the crash frequency decreases by 0.0978 units per year compared to a non-reporting firm, ceteris paribus. Likewise, both negative return skewness and down-to-up volatility decline. These findings suggest that biodiversity reporting in Europe is associated with a lower likelihood of managers withholding adverse information, thereby reducing the probability of abrupt stock price corrections.

For U.S. firms, the relationship is considerably weaker. Only the coefficient of BIR_{t-1} for *NCSKEW* is marginally significant and negative, whereas the remaining crash-risk measures remain statistically insignificant.

The interaction models formally confirm these regional differences. The interaction term $\mathrm{BIR}_{t-1} \times \mathrm{WEST}$ is significantly negative across all crash-risk measures, indicating that biodiversity reporting is associated with a stronger reduction in crash risk in Western countries than in Asian markets. However, the separate regional regressions demonstrate that this effect is primarily driven by the European sample rather than by the United States.

One possible explanation relates to the varying importance of sustainable investments across regions. In 2022, sustainable investments accounted for approximately 38 % of total assets under management in Europe, compared to only 13 % in the United States (Global Sustainable Investment Alliance, 2022). This suggests that sustainability-related information, including biodiversity disclosures, is more strongly integrated into investment decisions in Europe. As a result, firms may face stronger pressure from investors and stakeholders to provide transparent and credible biodiversity-related information (Bollen, 2007). In environments where environmental issues are perceived as particularly relevant, sustainability engagement is more likely to be rewarded by capital market participants (Di Marco et al., 2015).

Moreover, prior studies demonstrate that firms with stronger governance structures, independent boards and more effective monitoring mechanisms are less likely to withhold negative information opportunistically (Al Mamun et al., 2020; Bae et al., 2006). Dai et al. (2019) further show that the crash-reducing effect of CSR disclosure is observable primarily in regulated disclosure environments, whereas voluntary disclosure alone does not significantly reduce crash risk. The authors argue that regulation activates institutional investors as external monitoring mechanisms capable of identifying and sanctioning the concealment of adverse information.

This mechanism is further supported by Ning and Yasuda (2026) in the context of biodiversity reporting. The introduction of the TNFD framework in Japan is associated with a significant reduction in firm-specific crash risk, particularly among firms with high biodiversity exposure and strong governance structures. Although this finding initially appears inconsistent with the positive association observed within the broader Asian sample, the studies differ substantially in both sample composition and institutional setting. In particular, given the increasing strengthening of TNFD-related regulatory measures in Europe in recent years, firms are likely facing growing pressure to disclose more information. This may reduce the withholding of negative information and, consequently, limit bad news hoarding.

For Asian firms, the relationship reverses completely. The coefficients of BIR_{t-1} are positive and statistically significant at the 1 %-level across all crash-risk measures. If an Asian firm reports biodiversity-related activities in the previous year, negative return skewness increases by 0.0810 units and down-to-up volatility rises by 0.0318 units, ceteris paribus. Biodiversity reporting is therefore associated with significantly higher crash risk within the Asian sample.

This contrasting pattern is consistent with the overinvestment hypothesis and mirrors the findings of Utz (2018) for CSR disclosure in the Asia-Pacific region. In line with Li and Wu (2025), increasing pressure to adopt Western sustainability standards may simultaneously create incentives for firms to strategically manage biodiversity disclosures and obscure adverse environmental impacts. Investors may interpret biodiversity-related activities as inefficient resource allocation or potential greenwashing, thereby increasing uncertainty and triggering coordinated sell-offs.

Overall, the findings provide evidence of regional heterogeneity in the relationship between biodiversity reporting and firm-specific stock price crash risk and therefore support Hypothesis 1.

Importantly, these results differ from the global evidence documented in Bassen et al. (2024), who report an overall negative association between biodiversity reporting and crash risk. This divergence can be explained by differences in sample composition. In particular, the sample in Bassen et al. (2024) contains a substantially lower weight of Asian observations compared to the present study. In their sample, Asian firms account for only a limited share of total observations (e.g., Japan 5.78%, Hong Kong 4.56%, China 3.42%), while Western markets dominate the sample composition. Given that the present study finds a positive relationship between biodiversity reporting and crash risk in Asia and a negative relationship in Europe, the predominance of Western firms in global samples is likely to drive the overall negative effect reported in prior research.

As a result, the global average effect documented by Bassen et al. (2024) may mask substantial regional heterogeneity, which becomes visible only in a disaggregated setting. In contrast, Yang et al. (2025) focus exclusively on the U.S. market and examine biodiversity risk exposure rather than biodiversity reporting, thereby capturing a related but conceptually distinct dimension of environmental risk.

These findings give rise to a new empirical puzzle: why does the biodiversity disclosure–crash risk relationship differ across regions? Prior literature on CSR and related disclosure practices has already documented that ESG-related effects are often regionally contingent (e.g., Utz, 2018), suggesting that institutional environments play a crucial role in shaping how non-financial information is interpreted by markets. Against this background, an important question emerges as to whether the observed biodiversity disclosure effect is truly specific to biodiversity-related information, or whether it reflects a broader ESG disclosure mechanism.

To examine whether the observed biodiversity reporting effect merely reflects general ESG performance,

Table 2: Regression: Biodiversity reporting and stock price crash risk by region

	Europe			USA			Asia		
	COUNT	**NCSKEW**	**DUVOL**	**COUNT**	**NCSKEW**	**DUVOL**	**COUNT**	**NCSKEW**	**DUVOL**
BIR_{t-1}	-0.0978^{**}	-0.1112^{**}	-0.0330^{***}	0.0292	-0.0812^{*}	-0.0127	0.1492^{***}	0.0810^{***}	0.0318^{***}
	(-1.99)	(-2.55)	(-2.59)	(0.56)	(-1.90)	(-1.04)	(3.53)	(3.40)	(3.70)
$SIZE_{t-1}$	0.1197^{***}	0.0950^{***}	0.0371^{***}	0.0293	0.0245	0.0058	-0.0153	0.0093	0.0061
	(6.25)	(5.85)	(7.76)	(1.45)	(1.54)	(1.15)	(-0.74)	(0.58)	(0.69)
$MTBV_{t-1}$	-0.0020^{*}	0.0001	0.0002	-0.0004	-0.0003	-0.0001	0.0002^{***}	0.0001^{***}	0.0000^{***}
	(-1.95)	(0.10)	(0.61)	(-0.81)	(-0.91)	(-1.38)	(10.99)	(3.97)	(4.20)
LEV_{t-1}	-0.1878	-0.0177	-0.0195	-0.2314^{**}	-0.0508	-0.0333	-0.1446	-0.0687	-0.0599^{**}
	(-1.50)	(-0.17)	(-0.65)	(-2.11)	(-0.47)	(-1.09)	(-1.33)	(-1.05)	(-2.42)
ROE_t	-0.0011^{**}	-0.0017^{*}	-0.0005^{**}	0.0000	0.0000	0.0000	0.0007	-0.0002	0.0002
	(-2.47)	(-1.91)	(-2.22)	(0.60)	(0.80)	(0.49)	(1.02)	(-0.36)	(0.71)
ROA_t	0.0020	-0.0024	-0.0006	-0.0045	-0.0134^{***}	-0.0034^{***}	0.0045	0.0069^{*}	0.0021
	(1.01)	(-0.70)	(-0.74)	(-1.52)	(-4.23)	(-3.64)	(1.12)	(1.67)	(1.13)
$SIGMA_{t-1}$	-8.6974^{**}	-0.1019	-2.2578^{**}	-11.5077^{***}	-6.6747^{**}	-3.6811^{***}	-4.6665^{*}	1.1300	1.5879
	(-2.07)	(-0.03)	(-2.25)	(-2.75)	(-2.20)	(-3.10)	(-1.77)	(0.18)	(0.45)
RET_{t-1}	115.4756^{***}	58.2471^{***}	29.3863^{***}	140.0901^{***}	104.1457^{***}	44.2470^{***}	75.6443^{***}	-55.9107	-30.2581
	(4.93)	(2.89)	(5.28)	(5.26)	(4.44)	(6.48)	(2.92)	(-0.91)	(-0.80)
$SKEW_{t-1}$	-0.0710^{***}	-0.0131	-0.0090	-0.0327	-0.0799^{***}	-0.0211^{***}	-0.0600^{**}	-0.0201	-0.0096
	(-3.51)	(-0.56)	(-1.50)	(-1.53)	(-2.95)	(-3.17)	(-2.41)	(-0.97)	(-1.41)
$KURT_{t-1}$	0.0000	0.0012	0.0010	0.0000	0.0005	0.0005	0.0033	0.0017	0.0008
	(0.00)	(0.46)	(1.55)	(0.01)	(0.15)	(0.62)	(1.28)	(0.64)	(0.74)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (N)	6,706	6,706	6,706	7,041	7,041	7,041	8,889	8,889	8,889
R^2	0.0362	0.0203	0.0438	0.0196	0.0176	0.0363	0.0290	0.0236	0.0461
Within R^2	0.0184	0.0092	0.0215	0.0103	0.0075	0.0126	0.0064	0.0077	0.0154

Notes: This table presents the results of panel regressions for Europe, the USA and Asia. BIR_{t-1} is the lagged Biodiversity Impact Reduction Score (1 = reporter, 0 = non-reporter; NA values excluded). All variables used are presented in Table A1 in the appendix. Observations N are reduced due to the use of lagged variables. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. t-statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: Regression: Biodiversity reporting and crash risk with WEST-Interaction

	COUNT	**NCSKEW**	**DUVOL**
BIR_{t-1}	0.0965^{**}	0.0428^{*}	0.0163^{*}
	(2.38)	(1.80)	(1.92)
$WEST$	0.4172^{***}	0.2252^{***}	0.1091^{***}
	(12.80)	(9.40)	(13.39)
$BIR_{t-1} \times WEST$	-0.1320^{***}	-0.1452^{***}	-0.0442^{***}
	(−2.59)	(−4.09)	(−3.83)
$SIZE_{t-1}$	0.0633^{***}	0.0583^{***}	0.0251^{***}
	(5.45)	(5.14)	(4.52)
$MTBV_{t-1}$	0.0001	0.0000	0.0000
	(0.67)	(0.30)	(0.31)
LEV_{t-1}	-0.1950^{***}	−0.0591	-0.0390^{**}
	(−2.93)	(−1.15)	(−2.45)
ROE_{t}	0.0000	0.0000	0.0000
	(0.84)	(0.97)	(1.00)
ROA_{t}	0.0000	-0.0043^{*}	−0.0007
	(−0.02)	(−1.82)	(−0.74)
$SIGMA_{t-1}$	-5.8207^{***}	−0.8702	−0.4873
	(−3.01)	(−0.23)	(−0.24)
RET_{t-1}	105.8082^{***}	12.4080	4.7583
	(6.05)	(0.34)	(0.22)
$SKEW_{t-1}$	-0.0565^{***}	-0.0346^{**}	-0.0113^{**}
	(−4.43)	(−2.21)	(−2.14)
$KURT_{t-1}$	0.0000	0.0007	0.0004
	(−0.03)	(0.36)	(0.68)
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Firm-clustered SE	Yes	Yes	Yes
Observations (N)	22,636	22,636	22,636
R^2	0.0358	0.0179	0.0425
Within R^2	0.0236	0.0088	0.0222

Notes: This table reports panel regression results for the full sample using a WEST interaction specification. *WEST* equals one for firms located in Europe and the United States and zero for Asian firms. BIR_{t-1} is the lagged Biodiversity Impact Reduction Score (1 = reporter, 0 = non-reporter; NA values excluded). All variables are defined in Table A1 in the appendix. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. t-statistics are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

or whether biodiversity reporting provides incremental explanatory power beyond ESG, dynamic panel regressions are estimated separately for Europe, the United States and Asia. For each region, three specifications are considered: (i) a model including only the lagged biodiversity reporting indicator (*BIR*), (ii) a model including only the lagged ESG score and (iii) a joint specification including both variables simultaneously.

Europe. The results for Europe (Table 4) indicate a robust and economically meaningful association between biodiversity reporting and stock price crash risk, whereas the ESG score does not exhibit independent explanatory power. Across all crash risk measures, the coefficient on BIR_{t-1} is negative and statistically significant. In the isolated specification, the effect is significant at the 10% level for *COUNT* and at the 5% level in the joint specification. For *NCSKEW*, the coefficient remains significantly negative in both specifications, while for *DUVOL* the effect is also consistently significant at the 5% level.

In contrast, the coefficient on ESG_{t-1} is statistically insignificant across all specifications and risk measures. These findings suggest that biodiversity reporting captures information relevant for crash risk that is not subsumed by broader ESG performance measures. In other words, the risk-reducing effect appears to be driven by biodiversity-specific disclosure rather than general sustainability engagement.

A plausible explanation for this divergence is the increasing granularity of sustainability disclosure over time. While earlier studies predominantly rely on broad CSR or ESG indicators, biodiversity reporting may represent a more specific and decision-relevant dimension of environmental disclosure. Consistent with Hassan et al. (2020), biodiversity information can be interpreted as a refined component of CSR that has gained increasing relevance for capital market participants in recent years.

USA. For the U.S. market (Table 5), the results are considerably weaker and provide no evidence of a systematic relation between either biodiversity reporting or ESG performance and crash risk. The coefficients on both BIR_{t-1} and ESG_{t-1} are statistically insignificant for *COUNT* across all specifications. For *NCSKEW*, only a weakly significant negative coefficient for biodiversity reporting appears in the univariate specification, which becomes insignificant once ESG is included. ESG exhibits a similarly fragile pattern, losing significance in the joint specification.

For *DUVOL*, neither variable is statistically significant in any specification. Overall, the U.S. evidence suggests that neither biodiversity reporting nor general ESG performance is systematically priced in terms of crash risk. This may reflect lower disclosure intensity and weaker investor sensitivity to biodiversity-related information compared to Europe.

Asia. The results for Asia (Table 6) reveal a markedly different pattern. Both biodiversity reporting and ESG scores are positively associated with crash risk. However, biodiversity reporting emerges as the dominant and more robust predictor. For all crash risk measures, BIR_{t-1} is positive and highly significant in both the isolated and joint specifications. For instance, for *COUNT*, the coefficient remains significant at the 1% level in both the univariate and joint model. A similar pattern holds for *NCSKEW* and *DUVOL*, where the magnitude and significance of BIR_{t-1} remain stable across specifications.

By contrast, the ESG coefficient loses statistical significance once biodiversity reporting is included in the model. This indicates that ESG captures no incremental variation in crash risk beyond what is already explained by biodiversity disclosure. Moreover, model fit measures such as the within-R^2 decline when ESG replaces biodiversity reporting, further supporting the superior explanatory power of biodiversity-related information.

Further regressions separating the environmental, social and governance pillars confirm that the results are not attributable to any single ESG dimension. In particular, the biodiversity reporting indicator remains robust across all specifications, suggesting that the documented relationship cannot be explained exclusively by governance-related effects.

Taken together, the evidence does not support the interpretation that biodiversity disclosure merely reflects general ESG performance. Instead, the results point to a more nuanced picture. While ESG does not exhibit robust or consistent explanatory power once biodiversity reporting is included, biodiversity disclosure itself remains significant in Europe and Asia, albeit with opposite signs, and shows no systematic effect in the United States. Importantly, neither variable fully subsumes the other, suggesting that biodiversity reporting captures dimensions of firm-level risk that are not entirely reflected in aggregate ESG measures.

At the same time, the heterogeneous regional patterns remain only partially explained. In particular, the question of why biodiversity disclosure is informative in some institutional settings but not in others is still unresolved. This leaves an open empirical puzzle regarding the underlying drivers of these differences.

One potential explanation for this heterogeneity relates to differences in the biodiversity materiality of firms' industries. If biodiversity risks are financially more material in certain sectors, the informational content and market relevance of biodiversity reporting may vary accordingly. This motivates a closer examination of whether industry-level biodiversity exposure shapes the relationship between biodiversity disclosure and firm-specific crash risk.

To examine whether the effect of biodiversity reporting varies with industry-level environmental exposure, separate regressions are estimated for Europe, the United States and Asia (Table 7). Each specification includes the Biodiversity Impact Reporting Score (BIR), a high-impact industry indicator and their interaction term BIR $\times$ HIGH IMPACT. The interaction term captures whether the capital market response to biodiversity disclosure is systematically stronger in environmentally sensitive sectors.

Europe. In the European sample, BIR_{t-1} enters significantly negative across all crash risk measures, indicating a robust crash-reducing effect of biodiversity reporting. However, the interaction term is statistically insignificant in all specifications. This suggests that the effect of biodiversity disclosure is economically and statistically homogeneous across high- and low-impact industries. In other words, the marginal information content of biodiversity reporting does not appear to depend on sectoral environmental exposure.

USA. For the US sample, neither the main effect of BIR nor its interaction with high-impact industries shows a consistent and statistically robust pattern. While isolated weak significance appears for NCSKEW, the overall results fail to indicate a systematic relationship. Importantly, the absence of both a stable main effect and a meaningful interaction suggests that biodiversity reporting is not yet a salient pricing factor in US capital markets. Moreover, there is no evidence that industry-level environmental sensitivity amplifies or mitigates this relationship.

Asia. In contrast, the Asian sample exhibits a statistically significant positive association between BIR and all crash risk measures. However, consistent with the other regions, the interaction term remains insignificant across all specifications. This implies that the higher crash risk associated with biodiversity reporting is uniform across industry types. The calculated total effects for high-impact industries closely mirror the main effects, confirming the absence of any economically meaningful moderation by environmental exposure.

Across all three regions, a consistent pattern emerges: the interaction term BIR $\times$ HIGH IMPACT is

Table 4: Dynamic panel regression europe: BIR and ESG

	COUNT			NCSKEW			DUVOL		
	(1) BIR	**(2) ESG**	**(3) BIR+ESG**	**(4) BIR**	**(5) ESG**	**(6) BIR+ESG**	**(7) BIR**	**(8) ESG**	**(9) BIR+ESG**
BIR_{t-1}	-0.0914^{*}		-0.1028^{**}	-0.0968^{**}		-0.1195^{**}	-0.0256^{**}		-0.0324^{**}
	(-1.86)		(-2.07)	(-2.11)		(-2.46)	(-1.98)		(-2.41)
ESG_{t-1}		0.0006	0.0014		0.0018	0.0028		0.0006	0.0008
		(0.34)	(0.83)		(1.25)	(1.35)		(1.40)	(1.49)
$COUNT_{t-1}$	0.0601^{***}	0.0601^{***}	0.0600^{***}						
	(4.04)	(4.04)	(4.04)						
$NCSKEW_{t-1}$				0.1219^{***}	0.1218^{***}	0.1212^{***}			
				(2.79)	(2.79)	(2.78)			
$DUVOL_{t-1}$							0.1192^{***}	0.1187^{***}	0.1184^{***}
							(4.64)	(4.61)	(4.60)
$SIZE_{t-1}$	0.1053^{***}	0.0947^{***}	0.0979^{***}	0.0898^{***}	0.0713^{***}	0.0750^{***}	0.0314^{***}	0.0260^{***}	0.0270^{***}
	(5.44)	(4.48)	(4.62)	(5.25)	(3.90)	(4.12)	(6.40)	(4.97)	(5.18)
$MTBV_{t-1}$	-0.0021	-0.0019	-0.0019	0.0006	0.0009	0.0008	0.0003	0.0004	0.0003
	(-1.38)	(-1.16)	(-1.27)	(0.47)	(0.61)	(0.59)	(0.68)	(0.80)	(0.80)
LEV_{t-1}	-0.1583	-0.1678	-0.1820	-0.0324	-0.0632	-0.0798	-0.0150	-0.0247	-0.0292
	(-1.24)	(-1.29)	(-1.40)	(-0.29)	(-0.57)	(-0.70)	(-0.48)	(-0.79)	(-0.93)
ROE_{t}	-0.0008	-0.0008	-0.0008	-0.0011^{*}	-0.0011^{*}	-0.0011^{*}	-0.0004^{**}	-0.0004^{**}	-0.0004^{**}
	(-1.60)	(-1.56)	(-1.59)	(-1.83)	(-1.76)	(-1.83)	(-2.18)	(-2.11)	(-2.18)
ROA_{t}	0.0007	0.0011	0.0008	-0.0028	-0.0023	-0.0026	-0.0007	-0.0006	-0.0006
	(0.35)	(0.54)	(0.40)	(-0.85)	(-0.70)	(-0.80)	(-0.91)	(-0.73)	(-0.84)
$SIGMA_{t-1}$	-10.1461^{**}	-9.8285^{**}	-10.2743^{**}	-2.9547	-2.6902	-3.1982	-3.0640^{***}	-2.9983^{***}	-3.1377^{***}
	(-2.55)	(-2.48)	(-2.58)	(-0.82)	(-0.75)	(-0.89)	(-3.11)	(-3.06)	(-3.19)
RET_{t-1}	144.0040^{***}	144.7052^{***}	145.2441^{***}	73.6450^{***}	75.4806^{***}	76.1175^{***}	42.2878^{***}	42.8280^{***}	42.9880^{***}
	(5.59)	(5.59)	(5.62)	(3.38)	(3.47)	(3.51)	(6.64)	(6.71)	(6.76)
$SKEW_{t-1}$	-0.0400^{*}	-0.0401^{*}	-0.0397^{*}	0.1260^{**}	0.1262^{**}	0.1261^{**}	0.0230^{**}	0.0230^{**}	0.0230^{**}
	(-1.79)	(-1.79)	(-1.77)	(2.38)	(2.38)	(2.39)	(2.50)	(2.49)	(2.50)
$KURT_{t-1}$	-0.0001	-0.0001	-0.0001	-0.0012	-0.0011	-0.0011	0.0005	0.0005	0.0005
	(-0.05)	(-0.05)	(-0.04)	(-0.40)	(-0.39)	(-0.38)	(0.64)	(0.66)	(0.66)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (N)	5,977	5,977	5,977	5,977	5,977	5,977	5,977	5,977	5,977
R^2	0.0396	0.0390	0.0396	0.0218	0.0213	0.0224	0.0485	0.0482	0.0492
Within R^2	0.0214	0.0209	0.0215	0.0101	0.0097	0.0108	0.0253	0.0249	0.0259

Notes: This table presents panel regression results for the Europe sample (BIR = 0 or 1). Models (1), (4), (7) include BIR only; models (2), (5), (8) include ESG only; models (3), (6), (9) include both variables jointly. All variables are defined in Table A1 in the appendix. Observations N are reduced due to the use of lagged crash risk measures and the remaining independent variables. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. t-statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Dynamic panel regression USA: BIR and ESG

	COUNT			NCSKEW			DUVOL		
	(1) BIR	**(2) ESG**	**(3) BIR+ESG**	**(4) BIR**	**(5) ESG**	**(6) BIR+ESG**	**(7) BIR**	**(8) ESG**	**(9) BIR+ESG**
BIR_{t-1}	0.0304		0.0071	−0.0833*		−0.0626	−0.0140		−0.0126
	(0.58)		(0.13)	(−1.83)		(−1.35)	(−1.10)		(−0.94)
ESG_{t-1}		0.0022	0.0021		−0.0024*	−0.0019		−0.0002	−0.0001
		(1.54)	(1.44)		(−1.72)	(−1.35)		(−0.58)	(−0.33)
$COUNT_{t-1}$	0.0415***	0.0411***	0.0411***						
	(2.96)	(2.94)	(2.94)						
$NCSKEW_{t-1}$				0.0303	0.0308	0.0304			
				(0.89)	(0.91)	(0.90)			
$DUVOL_{t-1}$							0.0669***	0.0670***	0.0669***
							(2.79)	(2.80)	(2.80)
$SIZE_{t-1}$	0.0189	0.0083	0.0081	0.0213	0.0288	0.0309*	0.0028	0.0030	0.0035
	(0.92)	(0.38)	(0.37)	(1.29)	(1.55)	(1.66)	(0.54)	(0.53)	(0.60)
$MTBV_{t-1}$	−0.0007	−0.0007	−0.0007	−0.0005	−0.0005	−0.0005	−0.0002**	−0.0002**	−0.0002**
	(−1.54)	(−1.50)	(−1.50)	(−1.26)	(−1.30)	(−1.30)	(−2.02)	(−2.03)	(−2.03)
LEV_{t-1}	−0.1520	−0.1748	−0.1742	−0.1011	−0.0757	−0.0815	−0.0354	−0.0328	−0.0340
	(−1.33)	(−1.53)	(−1.53)	(−0.90)	(−0.66)	(−0.71)	(−1.13)	(−1.04)	(−1.08)
ROE_t	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.43)	(0.44)	(0.43)	(0.40)	(0.30)	(0.38)	(0.21)	(0.17)	(0.20)
ROA_t	−0.0045	−0.0045	−0.0044	−0.0137***	−0.0135***	−0.0137***	−0.0034***	−0.0033***	−0.0034***
	(−1.45)	(−1.45)	(−1.43)	(−4.07)	(−4.02)	(−4.07)	(−3.40)	(−3.36)	(−3.39)
$SIGMA_{t-1}$	−14.0395***	−14.1099***	−14.1044***	−9.1730***	−9.0792***	−9.1135***	−4.6477***	−4.6352***	−4.6436***
	(−3.38)	(−3.43)	(−3.43)	(−2.88)	(−2.82)	(−2.83)	(−4.13)	(−4.11)	(−4.11)
RET_{t-1}	175.0577***	177.5183***	177.5084***	102.1006***	99.8695***	99.8421***	51.5746***	51.4216***	51.4169***
	(5.84)	(5.95)	(5.95)	(4.25)	(4.16)	(4.16)	(6.96)	(6.95)	(6.96)
$SKEW_{t-1}$	−0.0055	−0.0058	−0.0058	−0.0222	−0.0214	−0.0220	0.0022	0.0022	0.0022
	(−0.24)	(−0.25)	(−0.25)	(−0.41)	(−0.39)	(−0.40)	(0.20)	(0.21)	(0.20)
$KURT_{t-1}$	0.0023	0.0023	0.0024	0.0031	0.0031	0.0031	0.0010	0.0010	0.0010
	(0.92)	(0.94)	(0.95)	(0.80)	(0.81)	(0.79)	(1.10)	(1.11)	(1.09)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (N)	6,250	6,250	6,250	6,250	6,250	6,250	6,250	6,250	6,250
R^2	0.0223	0.0227	0.0227	0.0172	0.0172	0.0174	0.0361	0.0360	0.0361
Within R^2	0.0139	0.0143	0.0143	0.0077	0.0078	0.0080	0.0156	0.0155	0.0156

Notes: This table presents panel regression results for the USA sample (BIR = 0 or 1). Models (1), (4), (7) include BIR only; models (2), (5), (8) include ESG only; models (3), (6), (9) include both variables jointly. All variables are defined in Table A1 in the appendix. Observations N are reduced due to the use of lagged crash risk measures and the remaining independent variables. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. t-statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Dynamic panel regression Asia: BIR and ESG

	COUNT			NCSKEW			DUVOL		
	(1) BIR	(2) ESG	(3) BIR+ESG	(4) BIR	(5) ESG	(6) BIR+ESG	(7) BIR	(8) ESG	(9) BIR+ESG
BIR_{t-1}	0.1474***		0.1255***	0.0807***		0.0730***	0.0313***		0.0304***
	(3.51)		(2.81)	(3.25)		(2.93)	(3.65)		(3.46)
ESG_{t-1}		0.0028**	0.0017		0.0012*	0.0006		0.0003	0.0001
		(2.47)	(1.41)		(1.77)	(0.84)		(1.36)	(0.27)
$COUNT_{t-1}$	0.0675***	0.0686***	0.0673***						
	(5.11)	(5.17)	(5.08)						
$NCSKEW_{t-1}$				0.0760**	0.0778**	0.0762**			
				(2.18)	(2.23)	(2.18)			
$DUVOL_{t-1}$							0.1710***	0.1736***	0.1710***
							(7.05)	(7.13)	(7.05)
$SIZE_{t-1}$	−0.0316	−0.0391*	−0.0407*	−0.0101	−0.0124	−0.0132	−0.0074*	−0.0074*	−0.0077*
	(−1.55)	(−1.80)	(−1.88)	(−0.90)	(−1.07)	(−1.15)	(−1.72)	(−1.69)	(−1.78)
$MTBV_{t-1}$	0.0002***	0.0002***	0.0002***	0.0001***	0.0001***	0.0001***	0.0000***	0.0000***	0.0000***
	(10.24)	(9.05)	(10.07)	(3.73)	(3.23)	(3.71)	(4.98)	(4.24)	(4.97)
LEV_{t-1}	−0.0972	−0.1333	−0.1211	−0.0461	−0.0615	−0.0544	−0.0395	−0.0433	−0.0404
	(−0.86)	(−1.16)	(−1.06)	(−0.62)	(−0.82)	(−0.73)	(−1.45)	(−1.56)	(−1.47)
ROE_t	0.0005	0.0004	0.0005	−0.0005	−0.0005	−0.0005	0.0000	−0.0001	0.0000
	(0.53)	(0.43)	(0.51)	(−0.60)	(−0.64)	(−0.61)	(−0.12)	(−0.16)	(−0.12)
ROA_t	0.0044	0.0038	0.0045	0.0061	0.0057	0.0061	0.0017	0.0015	0.0017
	(0.97)	(0.83)	(0.99)	(1.21)	(1.12)	(1.22)	(0.77)	(0.69)	(0.78)
$SIGMA_{t-1}$	−7.9313***	−8.0929***	−7.9609***	−7.6148*	−7.7294*	−7.6314*	−3.9907***	−4.0362***	−3.9923***
	(−3.78)	(−3.87)	(−3.77)	(−1.88)	(−1.91)	(−1.88)	(−3.22)	(−3.26)	(−3.22)
RET_{t-1}	119.6490***	120.8233***	119.8122***	29.0117	29.6393	29.0915	29.9376***	30.2786***	29.9479***
	(6.51)	(6.57)	(6.52)	(1.36)	(1.40)	(1.37)	(3.98)	(4.03)	(3.99)
$SKEW_{t-1}$	0.0028	0.0039	0.0040	0.0608	0.0626	0.0616	0.0437***	0.0442***	0.0438***
	(0.11)	(0.15)	(0.16)	(1.39)	(1.43)	(1.41)	(5.00)	(5.08)	(5.01)
$KURT_{t-1}$	0.0008	0.0006	0.0007	0.0014	0.0013	0.0014	0.0003	0.0003	0.0003
	(0.31)	(0.25)	(0.28)	(0.52)	(0.48)	(0.51)	(0.32)	(0.29)	(0.32)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (N)	8,000	8,000	8,000	8,000	8,000	8,000	8,000	8,000	8,000
R^2	0.0354	0.0346	0.0357	0.0240	0.0232	0.0241	0.0555	0.0540	0.0555
Within R^2	0.0116	0.0108	0.0119	0.0073	0.0064	0.0074	0.0225	0.0210	0.0225

Notes: This table presents panel regression results for the Asia sample (BIR = 0 or 1). Models (1), (4), (7) include BIR only; models (2), (5), (8) include ESG only; models (3), (6), (9) include both variables jointly. All variables are defined in Table A1 in the appendix. Observations N are reduced due to the use of lagged crash risk measures and the remaining independent variables. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. t-statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

statistically insignificant. This finding has important implications for the interpretation of biodiversity disclosure in capital markets. If investors perceived biodiversity reporting as a direct proxy for industry-specific environmental risk, one would expect stronger effects in high-impact sectors where such risks are more material and more likely to be priced.

The absence of such differential pricing suggests that biodiversity reporting is not primarily interpreted as a granular, sector-specific risk signal. Instead, the evidence points toward a more generalized information channel. Biodiversity disclosure appears to function as a broad indicator of transparency, governance quality, or managerial disclosure behavior rather than as a precise measure of environmental exposure.

In this sense, biodiversity reporting may reduce information asymmetry in a general way but does not appear to embed sufficient variation in content quality or specificity to allow investors to distinguish between high- and low-impact industries.

From a theoretical perspective, this aligns with an extended stakeholder-agency framework. While institutional investors increasingly demand sustainability-related disclosure (Aibar-Guzmán et al., 2023; Velte, 2023), this pressure appears to operate uniformly across firms rather than through industry-specific monitoring intensity.

Overall, the results provide no empirical support for the hypothesis 2 that biodiversity reporting effects are systematically stronger in high-impact industries. This suggests that biodiversity disclosure does not primarily function as a sector-specific risk signal in capital markets. At the same time, the absence of differential effects across industries leaves the underlying transmission mechanism of biodiversity reporting only partially explained, reinforcing the broader empirical puzzle regarding how biodiversity information is interpreted by investors.

5. Robustness

The baseline regressions rely on the implicit assumption that firms' decisions to disclose biodiversity-related information are random. However, this assumption is unlikely to hold in practice, as disclosure decisions are potentially driven by both observable and unobservable firm characteristics that may also affect future stock price crash risk. If such selection is systematic, restricting the analysis to firms with available biodiversity information may introduce a self-selection bias, leading to inconsistent coefficient estimates.

To address this concern, a *Heckman two-stage selection model* (Heckman, 1979) is employed as a robustness check.

First-stage results and exclusion restriction. The identification strategy relies on $PEER\_BIR_{i,t-1}$ as an exclusion restriction, which measures the share of firms within the same industry (based on SIC codes) and year that issued a biodiversity report one year prior to the observation period. Additionally, a new dependent variable, $BIR\_Rep.$, is constructed to capture whether firms disclose any biodiversity-related information at all. This variable represents a recoding of the original biodiversity reporting score. Specifically, all observations with original values of 1 or 0 are recoded as 1, while missing observations (NA) are coded as 0. The first-stage probit results confirm that $PEER\_BIR_{t-1}$ is highly significant across all three regional samples, documenting strong instrument relevance. With respect to exogeneity, a firm's own crash risk is unlikely to be directly affected by the average biodiversity reporting behavior of its industry peers in the prior year. While industry-level trends may influence both disclosure behavior and financial outcomes, the peer

Table 7: Regression: BIR, High-Impact-Industry-Interaction and stock price crash risk by region

	Europe			USA			Asia		
	COUNT	**NCSKEW**	**DUVOL**	**COUNT**	**NCSKEW**	**DUVOL**	**COUNT**	**NCSKEW**	**DUVOL**
BIR_{t-1}	-0.1383^{**}	-0.1183^{**}	-0.0381^{***}	0.0167	−0.0360	−0.0092	0.1150^{**}	0.0709^{**}	0.0251^{**}
	(−2.44)	(−2.37)	(−2.66)	(0.25)	(−0.64)	(−0.56)	(2.45)	(2.58)	(2.52)
HIGH IMPACT	−0.0747	−0.0283	−0.0098	0.0690	0.0787	0.0197	−0.0399	−0.0314	−0.0062
	(−0.82)	(−0.38)	(−0.42)	(1.02)	(1.23)	(1.15)	(−0.64)	(−0.88)	(−0.48)
BIR_{t-1} × *HIGH IMPACT*	0.1542	0.0748	0.0261	−0.0446	-0.1545^{*}	−0.0265	0.0055	0.0078	−0.0089
	(1.38)	(0.80)	(0.92)	(−0.42)	(−1.78)	(−1.07)	(0.06)	(0.16)	(−0.49)
$SIZE_{t-1}$	0.1152^{***}	0.0962^{***}	0.0370^{***}	0.0247	0.0205	0.0043	−0.0173	0.0100	0.0073
	(6.11)	(5.88)	(7.77)	(1.24)	(1.31)	(0.85)	(−0.84)	(0.62)	(0.81)
$MTBV_{t-1}$	-0.0022^{**}	0.0002	0.0001	−0.0004	−0.0003	−0.0001	0.0002^{***}	0.0001^{***}	0.0000^{***}
	(−2.24)	(0.16)	(0.52)	(−0.87)	(−0.82)	(−1.40)	(11.10)	(3.78)	(3.77)
LEV_{t-1}	−0.1422	−0.0626	−0.0249	−0.1623	−0.0520	−0.0233	−0.0954	−0.0487	−0.0299
	(−1.22)	(−0.62)	(−0.86)	(−1.54)	(−0.50)	(−0.80)	(−1.00)	(−0.82)	(−1.26)
ROE_{t}	-0.0011^{**}	-0.0017^{*}	-0.0005^{**}	0.0000	0.0000	0.0000	0.0006	−0.0002	0.0002
	(−2.40)	(−1.88)	(−2.20)	(0.65)	(1.29)	(0.82)	(0.94)	(−0.39)	(0.67)
ROA_{t}	0.0018	−0.0021	−0.0006	-0.0053^{*}	-0.0125^{***}	-0.0034^{***}	0.0046	0.0070^{*}	0.0020
	(0.91)	(−0.63)	(−0.74)	(−1.84)	(−4.24)	(−3.96)	(1.16)	(1.71)	(1.09)
$SIGMA_{t-1}$	-8.4202^{**}	1.2365	-1.7887^{*}	-13.0745^{***}	-6.9252^{**}	-3.8852^{***}	-5.1767^{*}	0.9224	1.4133
	(−2.08)	(0.38)	(−1.84)	(−3.21)	(−2.56)	(−3.48)	(−1.96)	(0.15)	(0.40)
RET_{t-1}	113.6266^{***}	57.1637^{***}	28.9188^{***}	142.8689^{***}	105.9665^{***}	44.9079^{***}	75.6720^{***}	−56.1193	−30.2591
	(4.85)	(2.84)	(5.19)	(5.40)	(4.54)	(6.62)	(2.89)	(−0.91)	(−0.79)
$SKEW_{t-1}$	-0.0694^{***}	−0.0123	−0.0087	−0.0344	-0.0825^{***}	-0.0218^{***}	-0.0616^{**}	−0.0206	−0.0100
	(−3.43)	(−0.53)	(−1.45)	(−1.61)	(−3.05)	(−3.28)	(−2.46)	(−0.99)	(−1.47)
$KURT_{t-1}$	0.0001	0.0010	0.0009	0.0001	0.0013	0.0006	0.0036	0.0019	0.0009
	(0.07)	(0.38)	(1.41)	(0.06)	(0.38)	(0.75)	(1.40)	(0.69)	(0.81)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (N)	6,706	6,706	6,706	7,041	7,041	7,041	8,889	8,889	8,889
R^2	0.0355	0.0200	0.0433	0.0185	0.0163	0.0346	0.0260	0.0230	0.0432
Within R^2	0.0183	0.0092	0.0214	0.0108	0.0078	0.0136	0.0062	0.0080	0.0144

Notes: This table presents panel regression results for Europe, the USA and Asia, including a High-Impact industry dummy and the interaction term BIR_{t-1} × *HIGH IMPACT*. High-impact industries include agriculture, mining, chemicals, wood/paper, construction, and energy and water supply. The high-impact dummy covers 1,845 observations in Europe, 1,681 in the USA, and 2,045 in Asia. All variables are defined in Table A1 in the appendix. All regressions include year and industry fixed effects. Standard errors are clustered at the firm level. t-statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

reporting rate reflects collective disclosure norms and institutional pressures at the industry level rather than firm-specific information environments. Furthermore, $PEER\_BIR_{t-1}$ is not significantly associated with any of the three crash risk measures when included directly in the outcome equations, consistent with the exclusion restriction.

Second-stage results and interpretation of the IMR. Across all regions, the IMR coefficients are generally insignificant, indicating that selection effects do not systematically distort the estimated relationship between biodiversity reporting and stock price crash risk. The coefficients of BIR remain largely unchanged compared to the main regression results.

Accordingly, the baseline results can be considered robust with respect to potential sample selection concerns. The findings therefore support the conclusion that the observed relationships are not driven by non-random disclosure behavior but instead reflect underlying economic effects in the data.

6. Conclusion

This study examines the relationship between biodiversity reporting and firm-specific stock price crash risk across three major regions, using established crash risk measures and a dynamic panel framework. The findings establish a new biodiversity reporting puzzle that emerges from the heterogeneous empirical patterns observed throughout the study and provide first insights into its underlying mechanisms.

The results provide a clear but heterogeneous picture. In Europe, biodiversity reporting is consistently associated with a statistically significant reduction in crash risk across all three measures. This effect remains robust in the dynamic panel specification, whereas general ESG engagement does not exhibit comparable explanatory power. In the United States, the estimated relationship is negative but mostly statistically insignificant, indicating no stable evidence that biodiversity disclosure affects crash risk in this market. In contrast, the Asian subsample reveals a statistically significant positive relationship, suggesting that biodiversity reporting is associated with higher crash risk.

Regarding Hypothesis 1, the evidence therefore confirms meaningful regional heterogeneity. Biodiversity reporting appears to function differently across institutional environments, consistent with variation in market structures, disclosure incentives and investor interpretation of non-financial information.

This finding gives rise to the central empirical puzzle of this study. Contrary to the pattern documented in prior literature, most notably the global evidence reported in Bassen et al. (2024), biodiversity reporting does not exhibit a uniform effect on crash risk. Instead, its impact varies substantially across regions. This raises the question of whether biodiversity reporting is merely another component of broader ESG disclosure or whether it reflects a distinct informational dimension.

The results suggest that biodiversity reporting possesses incremental explanatory power for stock price crash risk beyond overall and seperate ESG performance, indicating that biodiversity disclosure represents a distinct informational dimension rather than merely reflecting general ESG quality. However, this does not fully resolve the underlying mechanism, as the observed heterogeneity persists even when controlling for ESG effects.

Moreover, no evidence is found in support of Hypothesis 2. The interaction between biodiversity reporting and high-impact industries is statistically insignificant across all regions. This suggests that capital market participants do not systematically differentiate between industries with high and low environmental exposure

Table 8: Heckman Two-Stage model: Europe, USA and Asia

	Stage 1: Probit			Stage 2: OLS Panel with IMR								
	Europe	USA	Asia	Europe			USA			Asia		
	BIR_Rep.	BIR_Rep.	BIR_Rep.	COUNT	NCSKEW	DUVOL	COUNT	NCSKEW	DUVOL	COUNT	NCSKEW	DUVOL
$PEER\_BIR_{t-1}$	2.6161***	1.0949***	2.4808***									
	(11.886)	(6.094)	(11.567)									
BIR_{t-1}				−0.0923**	−0.0933**	−0.0291**	0.0185	−0.0891**	−0.0162	0.1086***	0.0676***	0.0217**
				(−1.972)	(−2.251)	(−2.444)	(0.376)	(−2.235)	(−1.393)	(2.691)	(2.919)	(2.575)
$SIZE_{t-1}$	0.4803***	0.2471***	0.6335***	0.1149***	0.0979***	0.0376***	0.0095	0.0073	−0.0009	−0.0377	0.0006	0.0083
	(9.125)	(7.264)	(12.717)	(4.821)	(5.065)	(6.574)	(0.388)	(0.350)	(−0.135)	(−1.443)	(0.023)	(0.533)
$MTBV_{t-1}$	0.0032	−0.0002	−0.0062	−0.0022**	0.0002	0.0001	−0.0004	−0.0002	−0.0001	0.0002***	0.0001***	0.0000***
	(0.787)	(−0.613)	(−0.782)	(−2.319)	(0.166)	(0.532)	(−0.857)	(−0.776)	(−1.352)	(11.155)	(4.084)	(4.144)
LEV_{t-1}	−0.5882**	−0.2172	−0.1492	−0.1298	−0.0591	−0.0238	−0.1475	−0.0490	−0.0203	−0.0885	−0.0462	−0.0315
	(−2.193)	(−1.320)	(−0.746)	(−1.098)	(−0.579)	(−0.809)	(−1.413)	(−0.466)	(−0.695)	(−0.933)	(−0.792)	(−1.373)
ROE_t	0.0011	0.0004	0.0012	−0.0011**	−0.0017*	−0.0005**	0.0000	0.0000	0.0000	0.0005	−0.0003	0.0002
	(0.763)	(1.236)	(0.854)	(−2.494)	(−1.892)	(−2.214)	(0.593)	(1.392)	(0.790)	(0.746)	(−0.450)	(0.641)
ROA_t	−0.0068	0.0021	−0.0112	0.0018	−0.0021	−0.0006	−0.0054*	−0.0126***	−0.0035***	0.0056	0.0074*	0.0020
	(−1.185)	(0.290)	(−1.632)	(0.938)	(−0.635)	(−0.744)	(−1.881)	(−4.280)	(−4.038)	(1.358)	(1.828)	(1.143)
$SIGMA_{t-1}$	21.8129***	9.4748**	10.8190**	−8.6110**	1.2303	−1.8123*	−13.1450***	−7.2002***	−3.9640***	−5.2702*	0.8534	1.4584
	(2.874)	(2.157)	(2.477)	(−2.066)	(0.361)	(−1.792)	(−3.230)	(−2.632)	(−3.562)	(−1.929)	(0.132)	(0.404)
RET_{t-1}	−72.2809***	−56.8607	−131.2300***	111.6400***	56.3306***	28.6400***	141.5800***	106.8700***	45.0630***	78.1240***	−54.5790	−30.5450
	(−2.726)	(−1.626)	(−4.468)	(4.728)	(2.792)	(5.098)	(5.294)	(4.614)	(6.651)	(2.845)	(−0.865)	(−0.782)
$SKEW_{t-1}$	−0.0699***	−0.0176	−0.0999***	−0.0679***	−0.0120	−0.0086	−0.0331	−0.0812***	−0.0212***	−0.0566**	−0.0187	−0.0106
	(−3.158)	(−0.612)	(−2.690)	(−3.307)	(−0.507)	(−1.402)	(−1.549)	(−3.019)	(−3.209)	(−2.245)	(−0.857)	(−1.505)
$KURT_{t-1}$	−0.0096***	−0.0045	−0.0017	−0.0000	0.0008	0.0009	0.0005	0.0017	0.0007	0.0039	0.0021	0.0009
	(−3.249)	(−1.490)	(−0.430)	(−0.008)	(0.314)	(1.286)	(0.219)	(0.502)	(0.915)	(1.501)	(0.717)	(0.754)
IMR				−0.0416	0.0092	0.0036	−0.4375	−0.4081	−0.1532	−0.2691	−0.1226	0.0091
				(−0.186)	(0.052)	(0.069)	(−1.254)	(−1.088)	(−1.457)	(−1.308)	(−0.587)	(0.093)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm-clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (N)	7,355	7,328	9,636	6,702	6,702	6,702	7,041	7,041	7,041	8,889	8,889	8,889
Pseudo R^2 / R^2	0.3154	0.2899	0.2781	0.0352	0.0199	0.0434	0.0185	0.0162	0.0346	0.0263	0.0231	0.0434

Notes: This table presents results from a Heckman two-stage model for Europe, the USA, and Asia. Stage 1 estimates the probability of biodiversity reporting via probit regression; *PEER_BIR_LAG1* serves as the exclusion restriction. Stage 2 includes the Inverse Mills Ratio (IMR) to correct for selection bias. *BIR_REG_L1* is the lagged biodiversity reporting indicator. All variables are defined in the appendix. All regressions include year fixed effects. Standard errors are clustered at the firm level. t-statistics/z-statistics in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

when processing biodiversity disclosure. Instead, the effect appears to operate independently of sectoral environmental materiality, implying that biodiversity reporting is not yet interpreted as a finely grained, industry-specific risk signal.

Nor can selection effects explain these patterns. The robustness analysis using a Heckman two-stage model confirms that the findings are not driven by self-selection bias, as the IMR is insignificant in all sample regions.

Taken together, these results reinforce the central puzzle of this study: biodiversity reporting exhibits systematic effects on crash risk, but these effects are neither fully explained by ESG performance, nor by industry-level materiality, nor by selection bias corrections. This implies that biodiversity reporting must capture a different underlying firm characteristic than those traditionally considered in the literature.

Despite these robust findings, some limitations should be acknowledged. First, unobserved heterogeneity, such as differences in governance quality or internal sustainability culture, may still introduce residual endogeneity despite the applied econometric controls. Second, regional aggregation may conceal heterogeneity within regions, particularly in Asia and the European Union.

Notwithstanding these limitations, the empirical strategy—including dynamic panel estimation, extensive controls, fixed effects and selection correction—provides a strong identification framework and enhances confidence in the results. The findings are therefore informative for both academic research and policy discussions.

Future research could extend this work in several directions to solve the puzzle. A more granular regulatory perspective at the country level would help disentangle institutional effects. In addition, applying text-based methods such as natural language processing could improve measurement by capturing the quality and credibility of biodiversity disclosures. Further, future studies may explore underlying mechanisms more directly, particularly the role of corporate governance, managerial incentives, and legitimacy-driven disclosure strategies (e.g., Minnick et al., 2025).

Overall, the pieces of the biodiversity reporting puzzle, while not yet fully assembled, point toward a coherent conclusion. Biodiversity reporting is neither universally beneficial nor universally harmful for capital market stability. Its effect is institutionally contingent and not fully explained by ESG performance, sectoral biodiversity materiality, or selection effects. This suggests that biodiversity disclosure captures a distinct and still not fully understood informational dimension, calling for more context-sensitive approaches to sustainability disclosure research and regulation.

Appendix

Table A1: Variable Definitions

Variable	Definition
NCSKEW	Negative conditional skewness of stock returns; measures asymmetric distribution and crash risk
DUVOL	Down-to-up volatility; ratio of negative to positive return volatility
COUNT	Number of extreme negative returns (crash events)
BIR	Dummy = 1 if firm discloses biodiversity information (Y), otherwise 0 (N); NA excluded
BIR Report	Dummy = 1 if biodiversity data available (Y or N), otherwise 0 (NA)
WEST	Dummy = 1 for Europe/USA, 0 for Asia
High Impact	Dummy = 1 for high-risk industries (e.g., energy, mining, chemicals)
$PEER\_BIR_{t-1}$	Share of firms in the same industry (SIC) and year that issued a biodiversity report in $t-1$; used as exclusion restriction in Stage 1
SIZE	Logarithm of market value of equity
MTBV	Market-to-book ratio of equity
LEV	Total liabilities / Total assets
ROE	Net income / Shareholders' equity
ROA	Net income / Total assets
SIGMA	Standard deviation of daily stock returns
RET	Average daily return
SKEW	Skewness of return distribution
KURT	Kurtosis of return distribution
ESG Score	Aggregated overall ESG score

Notes: All variables are defined as presented above.

Table A2: ADF test statistics across regions

Variable	Europe	USA	Asia
COUNT	-20.734***	-21.639***	-21.178***
NCSKEW	-21.325***	-21.770***	-21.412***
DUVOL	-21.176***	-21.943***	-21.583***
RET	-21.651***	-21.278***	-22.554***
SIGMA	-17.721***	-21.317***	-17.813***
SKEW	-21.186***	-21.789***	-20.534***
KURT	-20.372***	-20.943***	-21.473***
SIZE	-16.792***	-16.823***	-19.358***
LEV	-17.367***	-17.188***	-18.836***
MTBV	-18.420***	-21.157***	-22.152***
ROE	-19.423***	-19.961***	-20.278***
ROA	-19.015***	-17.968***	-19.510***
ESG_Score	-17.269***	-16.014***	-16.004***
BIR	-19.373***	-18.860***	-18.296***

Notes: Augmented Dickey-Fuller tests for stationarity. The null hypothesis assumes a unit root process (non-stationarity). All variables reject the null hypothesis at the 1% significance level. $^{***}p < 0.01$.

Table A3: Pearson correlation matrix: Europe

	NCSKEW	*DUVOL*	*COUNT*	*BIR*	*SIZE*	*MTBV*	*LEV*	*SIGMA*	*RET*	*SKEW*	*KURT*	*ROE*	*ROA*	*ESG*
NCSKEW	1.000													
DUVOL	0.903***	1.000												
COUNT	0.493***	0.658***	1.000											
BIR	-0.007	0.011	0.013	1.000										
SIZE	-0.007	0.032***	0.048***	0.232***	1.000									
MTBV	0.006	0.010	0.018	-0.040***	0.047***	1.000								
LEV	0.001	0.005	-0.006	0.004	0.115***	0.032***	1.000							
SIGMA	0.019	-0.001	-0.016	-0.052***	-0.334***	0.026**	0.037***	1.000						
RET	-0.342***	-0.427***	-0.297***	-0.008	0.142***	0.009	0.003	-0.107***	1.000					
SKEW	-0.906***	-0.807***	-0.419***	-0.006	-0.053***	0.005	-0.020*	0.074***	0.324***	1.000				
KURT	-0.097***	-0.067***	-0.016	-0.041***	-0.114***	0.005	-0.005	0.264***	0.010	0.281***	1.000			
ROE	-0.035***	-0.018	0.006	-0.043***	0.136***	0.087***	-0.011	-0.207***	0.115***	0.010	-0.024**	1.000		
ROA	-0.018	-0.000	0.024**	-0.040***	0.135***	0.135***	-0.259***	-0.233***	0.137***	-0.004	-0.024**	0.496***	1.000	
ESG	0.039***	0.070***	0.052***	0.386***	0.465***	-0.029**	0.222***	-0.049***	-0.031***	-0.056***	-0.049***	0.012	-0.035***	1.000

Notes: Pearson correlation matrix for the Europe sample (N = 7295). Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A4: Pearson correlation matrix: USA

	NCSKEW	*DUVOL*	*COUNT*	*BIR*	*SIZE*	*MTBV*	*LEV*	*SIGMA*	*RET*	*SKEW*	*KURT*	*ROE*	*ROA*	*ESG*
NCSKEW	1.000													
DUVOL	0.913***	1.000												
COUNT	0.501***	0.650***	1.000											
BIR	-0.021*	-0.016	0.011	1.000										
SIZE	-0.069***	-0.067***	-0.029**	0.258***	1.000									
MTBV	-0.007	-0.005	0.001	0.021*	0.058***	1.000								
LEV	0.013	0.015	0.001	-0.004	0.038***	0.076***	1.000							
SIGMA	0.005	-0.020*	-0.025**	-0.014	-0.254***	-0.007	0.012	1.000						
RET	-0.366***	-0.455***	-0.303***	-0.027**	0.150***	-0.013	-0.005	0.007	1.000					
SKEW	-0.890***	-0.799***	-0.406***	0.005	0.030***	0.003	-0.023**	0.112***	0.358***	1.000				
KURT	-0.036***	-0.023**	-0.008	-0.059***	-0.077***	0.000	-0.035***	0.246***	0.027**	0.239***	1.000			
ROE	0.003	0.006	0.006	0.022*	0.042***	0.107***	0.069***	-0.030***	0.014	-0.011	-0.009	1.000		
ROA	-0.013	-0.001	0.017	-0.020*	0.262***	0.098***	-0.249***	-0.269***	0.143***	-0.006	-0.017	0.078***	1.000	
ESG	0.005	0.019	0.025**	0.372***	0.462***	0.014	0.127***	-0.027**	-0.043***	-0.024**	-0.067***	0.031***	0.089***	1.000

Notes: Pearson correlation matrix for the USA sample (N = 7524). Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A5: Pearson correlation matrix: Asia

	NCSKEW	*DUVOL*	*COUNT*	*BIR*	*SIZE*	*MTBV*	*LEV*	*SIGMA*	*RET*	*SKEW*	*KURT*	*ROE*	*ROA*	*ESG*
NCSKEW	1.000													
DUVOL	0.866***	1.000												
COUNT	0.535***	0.627***	1.000											
BIR	0.026**	0.026**	0.034***	1.000										
SIZE	-0.045***	-0.051***	-0.037***	0.131***	1.000									
MTBV	0.020**	0.024**	0.027***	-0.073***	0.086***	1.000								
LEV	-0.032***	-0.033***	-0.029***	-0.098***	0.047***	-0.019*	1.000							
SIGMA	-0.023**	-0.009	-0.037***	-0.023**	-0.130***	0.005	0.030***	1.000						
RET	-0.272***	-0.393***	-0.219***	-0.016	0.120***	-0.028***	0.001	0.261***	1.000					
SKEW	-0.849***	-0.732***	-0.433***	-0.028***	0.004	-0.008	0.011	0.251***	0.312***	1.000				
KURT	-0.045***	0.037***	-0.002	0.007	-0.078***	0.003	-0.034***	0.290***	0.062***	0.264***	1.000			
ROE	0.010	0.022**	0.025**	-0.049***	0.100***	0.396***	-0.035***	-0.075***	0.016	-0.015	-0.003	1.000		
ROA	0.039***	0.039***	0.039***	-0.029***	0.158***	0.430***	-0.383***	-0.027***	0.082***	-0.028***	0.013	0.485***	1.000	
ESG	0.013	0.015	0.013	0.417***	0.339***	0.010	0.085***	-0.025**	-0.015	-0.024**	0.018*	0.002	-0.025**	1.000

Notes: Pearson correlation matrix for the Asia sample (N = 9599). Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

References

Adler, R., Mansi, M. & Pandey, R. (2018). Biodiversity and threatened species reporting by the top Fortune Global companies. *Accounting, Auditing & Accountability Journal*, 31(3), 787–825.

Addoum, J. M., Ng, D. T. & Ortiz-Bobea, A. (2020). Temperature Shocks and Establishment Sales. *Review of Financial Studies*, 33, 1331–1366.

Aibar-Guzmán, B., Aibar-Guzmán, C., Piñeiro-Chousa, J. R., Hussain, N., & García-Sánchez, I. M. (2023). The benefits of climate tech: Do institutional investors affect these impacts? *Technological Forecasting and Social Change*, 21(1), 192, 122536.

Al Mamun, M., Balachandran, B. & Duong, H. (2020). Powerful CEOs and stock-price crash risk. *Journal of Corporate Finance*, 62, 101582.

An, H. & Zhang, T. (2013). Stock price synchronicity, crash risk, and institutional investors. *Journal of Corporate Finance*, 21, 1–15.

Arellano, M. & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, 58, 277–297.

Bach, T. N., Hoang, K. & Le, T. (2025). Biodiversity risk and firm performance: evidence from US firms. *Business Strategy and the Environment*, 34(1), 1113–1132.

Bae, K.H., Lim, C. & Wei, K. C. J. (2006). Corporate governance and conditional skewness in the world's stock markets. *Journal of Business*, 79(6), 2999–3028.

Bassen, A., Buchholz D., Lopatta K., Rudolf A. R. (2024). Biodiversity management and stock price crash risk. *Business Strategy and the Environment*, 33(5), 4788–4805.

Bergmann, A., Stechemesser, K., & Guenther, E. (2016). Natural resource dependence theory: Impacts of extreme weather events on organizations. *Journal of Business Research*, 69(4), 1361–1366.

Boiral, O. (2016). Accounting for the unaccountable: Biodiversity reporting and impression management. *Journal of Business Ethics*, 135(4), 751–768.

Bollen, N. P. B. (2007). Mutual fund attributes and investor behavior. *Journal of Financial and Quantitative Analysis*, 42, 683–708.

Callen, J. L. & Fang, X. (2015a). Religion and stock price crash risk. *Journal of Financial and Quantitative Analysis*, 50, 169–195.

Callen, J. L. & Fang, X. (2015b). Short interest and stock price crash risk. *Journal of Banking & Finance*, 60, 181–194.

Cao, H., Coval, D. & Hirshleifer, D. (2002). Sidelined investors, trading-generated news, and security returns. *Review of Financial Studies*, 15, 615–648.

Carvalho, S. H. C. d., Cojoianu, T. & Ascui, F. (2023). From impacts to dependencies: A first global assessment of corporate biodiversity risk exposure and responses. *Business Strategy and the Environment*, 32(5), 2600–2614.

CBD (2026). 2030 Targets (with Guidance Notes). https://www.cbd.int/gbf/targets, last accessed 25.04.2026.

Chen, J., Hong, H. & Stein, J. (2001). Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices. *Journal of Financial Economics*, 61, 345–381.

Cooper, S. & Michelon, G. (2022). Conceptions of materiality in sustainability reporting frameworks: Commonalities, differences and possibilities. *Handbook of accounting and sustainability*, 44–66.

Dai, J., Lu, C. & Qi, J. (2019). Corporate social responsibility disclosure and stock price crash risk: Evidence from China. *Sustainability*, 11(2), 448.

Di Marco, M., Ferrier, S., Harwood, T.D. et al. (2015). Sustainable development must account for biodiversity. *Science*, 347(6226), 1256–1257.

Di Tommaso, C., Foglia, M., & Pacelli, V. (2025). The impact of biodiversity score on the European firm's performance. *International Review of Financial Analysis*, 106, 104460.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, 7(2), 197–226.

Dorfleitner, G. & Zhang, R. (2024). ESG news sentiment and stock price reactions: a comprehensive investigation via BERT. *Schmalenbach Journal of Business Research*, 76(2), 197–244.

Edmans, A. (2011). Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics*, 101, 621–640.

El Ghoul, S., Guedhami, O. & Kim, H. (2017). Country-level institutions, firm value, and the role of corporate social responsibility initiatives. *Journal of International Business Studies*, 48, 360—385.

El Ouadghiri, I., Kaabia, O., Peillex, J., Platania, F. & Toscano Hernandez, C. (2025). Attention to biodiversity and stock returns. *International Review of Finance*, 97, 103855.

Elliot, V., Jonäll, K., Paananen, M., Bebbington, J. & Michelon, G. (2024). Biodiversity reporting: Standardization, materiality, and assurance. *Current Opinion in Environmental Sustainability*, 68, 101435.

Elsbach, K. D. & Sutton, R. I. (1992). Acquiring organizational legitimacy through illegitimate actions: A marriage of institutional and impression management theories. *Academy of Management Journal*, 35(4), 699–738.

European Union (2023c): Commission Delegated Regulation (EU) 2023/2772 of 31 July 2023 supplementing Directive 2013/34/EU of the European Parliament and of the Council as regards sustainability reporting standards. https://bfn.bsz-bw.de/frontdoor/deliver/index/docId/1949/file/NuL2024-06-04.pdf, 133–151, last accessed 22.04.2026.

Fabrizio, K. R. & Kim, E. H. (2019). Reluctant disclosure and transparency: Evidence from environmental disclosures. *Organization Science*, 30(6), 1207–1231.

Flammer, C., Giroux, T. & Heal, G. M. (2025). Biodiversity finance. *Journal of Financial Economics*, 164, 103987.

Freeman, R. E. (2010). Strategic management: A stakeholder approach. *Cambridge University Press.*

Friedman, M. (1970). The social responsibility of business is to increase its profits. *New York Times*, 13, 122–126.

Garel A., Romec A., Sautner Z., Wagner A. F. (2024). Do investors care about biodiversity? *Review of Finance*, 28(4), 1151–1186.

Gelb, D. S. & Strawser, J. A. (2001). Corporate social responsibility and financial disclosures: An alternative explanation for increased disclosure. *Journal of Business Ethics*, 33, 1–13.

Giglio, S., Kuchler, T., Stroebel, J. & Zeng, X. (2026). Biodiversity risk. *Review of Finance*, 30(1), 131–161.

Global Sustainable Investment Alliance. (2022). *Global Sustainable Investment Review 2022*, https://www.gsi-alliance.org/wp-content/uploads/2023/12/GSIA-Report-2022.pdf, last accessed 01.04.2026.

Habib, A. & Hasan, M. M. (2017). Business strategy, overvalued equities, and stock price crash risk. *Research in International Business and Finance*, 39, 389–405.

Hassan, A. M., Roberts, L. & Atkins, J. (2020). Exploring factors relating to extinction disclosures: What motivates companies to report on biodiversity and species protection? *Business Strategy and the Environment*, 29, 1419–1436.

Heckman, J. J. (1979). Sample selection bias as a specification error. *Journal of the Econometric Society*, 153–161.

Hemingway, C. & Maclagan, P. (2004). Managers' personal values as drivers of corporate social responsibility. *Journal of Business Ethics*, 50(1), 33–44.

Hong, H. & Stein, J. (2003). Differences of opinion, short-sales constraints, and market crashes. *Review of Financial Studies*, 16, 487–525.

Hutton, A. P., Marcus, A. J. & Tehranian, H. (2009). Opaque financial reports, R^2, and crash risk. *Journal of Financial Economics*, 94, 67–86.

Jensen, M. C. & Meckling, W. H. (1976). Theory of the Firm. *Managerial behavior, agency costs and ownership structure* 3(4), 305–360.

Jin, L. & Myers, S. (2006). R^2 around the world: New theory and new tests. *Journal of Financial Economics*, 79, 257–292.

Kim, J.-B., Li, Y. & Zhang, L. (2011a). CFOs versus CEOs: Equity incentives and crashes. *Journal of Financial Economics*, 101, 713–730.

Kim, J.-B., Li, Y. & Zhang, L. (2011b). Corporate tax avoidance and stock price crash risk: Firm-level evidence. *Journal of Financial Economics*, 100, 639–662.

Kim, Y., Li, H. & Li, S. (2014). Corporate social responsibility and stock price crash risk. *Journal of Banking & Finance*, 43, 1–13.

Kim, J.-B. & Zhang, L. (2014). Financial reporting opacity and expected crash risk: evidence from implied volatility smirks. *Contemporary Accounting Research*, 31, 851–875.

Kim, J.-B., Si, Y., Xia, C. & Zhang, L. (2021). Corporate derivatives usage, information environment, and stock price crash risk. *The European Accounting Review*, 30(5), 1263–1297.

Kothari, S. P., Shu, S. & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research*, 47(1), 241–276.

Lashitew, A. A. (2021). Corporate uptake of the sustainable development goals: Mere greenwashing or an advent of institutional change? *Journal of International Business Policy*, 4, 184–200.

Li, Z. & Wu, C. (2025). Corporate social responsibility, market business environment and stock price crash risk: An analysis from the perspective of stakeholders. *International Review of Economics & Finance*, 104439.

LSEG (2026). https://www.lseg.com/en/about-us#what-we-do, last accessed 02.04.2026.

Ma, D., Ji, Q., Zhang, D., Zhao, W. (2025). Spillover among biodiversity attention, climate policy uncertainty and global stock markets. *Finance Research Letters*, 73, 106627.

McWilliams, A., Siegel, D. & Wright, P. (2006). Guest editors' introduction corporate social responsibility: strategic implications. *Journal of Management Studies*, 43(1), 1–18.

Minnick, K., Bose, S., Lim, E., Rivolta, Mia L. & Shams, S. (2025). From Biodiversity Conservation to Stock Price Stability: International Evidence of Biodiversity Impact Reduction in Mitigating Stock Price Crash Risk. *SSRN Electronic Journal*, https://ssrn.com/abstract=5797724, last accessed 31.03.2026.

Morck, R., Yeung, B. & Yu, W. (2000). The information content of stock markets: Why do emerging markets have synchronous stock price movements? *Journal of Financial Economics*, 58, 215–260.

Morton, S., Hill, R. (2014). What is Biodiversity, and Why is it Important. *Biodiversity, Science and Solutions for Australia*, 1–12.

Ning, D. & Yasuda, Y. (2026). Biodiversity Risk Disclosures and Stock Price Crash Risk. *Journal of Behavioral and Experimental Finance*, 101146.

Oikonomou, I., Brooks, C. & Pavelin, S. (2014). The effects of corporate social performance on the cost of corporate debt and credit ratings. *Financial Review*, 49, 49–75.

Pokharel, P. R. (2025). Unpacking the role of biodiversity impact reduction in ESG performance. *Corporate Social Responsibility and Environmental Management*, 32(6), 8094–8110.

Rimmel, G. & Jonäll, K. (2013). Biodiversity reporting in Sweden: Corporate disclosure and preparers' views. *Accounting, Auditing & Accountability Journal*, 26(5), 746–778.

Roll, R. (1988). R^2. *Journal of Finance*, 43, 541–566.

Senanayake, M., Harymawan, I., Dorfleitner, G., Lee, S., Rhee, J. H. & Ok, Y. S. (2024). Toward more nature-positive outcomes: A review of corporate disclosure and decision making on biodiversity. *Sustainability*, 16, 8110.

Suchman, M. C. (1995). Managing legitimacy: Strategic and institutional approaches. *Academy of Management Review*, 20(3), 571–610.

Surroca, J., Tribó, J. A. & Waddock, S. (2010). Corporate responsibility and financial performance: The role of intangible resources. *Strategic Management Journal*, 31, 463–490.

TNFD (2021). Interim Report: The Road to Meaningful Nature-Related Financial Disclosures. *TNFD Website*.

Utz, S. (2018). Over-investment or risk mitigation? Corporate social responsibility in Asia-Pacific, Europe, Japan, and the United States. *Review of Financial Economics*, 36(2), 167–193.

Velte, P. (2023). Sustainable institutional investors and corporate biodiversity disclosure: Does sustainable board governance matter? *Corporate Social Responsibility and Environmental Management.*

Walker, K. & Wan, F. (2012). The harm of symbolic actions and greenwashing: Corporate actions and communications on environmental performance and their financial implications. *Journal of business ethics*, 109(2), 227–242.

WEF (2020). Nature risk rising: Why the crisis engulfing nature matters for business and the economy. https://www3.weforum.org/docs/WEF_New_Nature_Economy_Report_2020.pdf, last accessed 14.04.2026.

WWF (2024). Living Planet Report 2024 – A System in Peril. www.wwf.org.uk/living-planet-report-2024.pdf, last accessed 14.04.2026.

Yang, J., Liang, C. & Shen, L. (2025). Biodiversity risk exposure and corporate risk-taking. *International Review of Financial Analysis*, 104844.

Zhu, W. (2016). Accruals and price crashes. *Review of Accounting Studies*, 21, 349–399.