Return to Nature:
Biodiversity Loss and Global Stock Returns

Marloes Hagens[†] Mathijs van Dijk[‡]

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Abstract

We examine whether biodiversity risk is priced in global equity markets using two new firm-level biodiversity risk measures: an environmental cost data based measure grounded in the IPBES drivers of biodiversity loss and a geospatial measure that links firms' asset locations to key biodiversity areas. Our study encompasses a larger sample than prior research: 12,288 firms across 58 countries over 2009-2022. We find that biodiversity risk matters, but pricing depends on the level of variation in biodiversity risk. Within firms, higher biodiversity risk is associated with lower returns and profitability, consistent with negative cash flow effects. Within industries, higher biodiversity risk predicts higher returns. Our analysis of the geospatial measure reveals that firms with risky assets in biodiversity-sensitive areas earn higher returns. Thus, our results are consistent with a between-firm biodiversity risk premium. Our study contributes to a more nuanced understanding of biodiversity risk in asset pricing and offers new directions for climate and nature finance research.

Keywords: biodiversity loss, biodiversity risk, asset pricing, global stock returns, nature finance, spatial finance

JEL classification: G12, G18, Q57, Q51, Q57

[†]Rotterdam School of Management, Erasmus University. E-mail: hagens@rsm.nl

[‡]Rotterdam School of Management, Erasmus University & Netspar. E-mail: madijk@rsm.nl

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1 Introduction

In June 2025, authorities in Indonesia revoked the permits of four out of five nickel mining firms operating in Raja Ampat—an archipelago often described as "the last paradise on earth" (Financial Times, 2025). This decision, motivated by biodiversity protection, wipes out projects worth several hundred million dollars and thereby illustrates how environmental risks can translate into immediate financial consequences for firms and investors. With scientists warning us that roughly one million species face extinction within decades under business-as-usual scenarios (Convention on Biological Diversity, 2021; IPBES, 2019a), and the World Economic Forum ranking biodiversity loss and ecosystem collapse as the second-greatest long-term global risk (Elsner, Atkinson, & Zahidi, 2025), it is little wonder that biodiversity loss is increasingly recognized as a material risk to the economy (Dasgupta, 2021; Johnson et al., 2021; Karolyi & Tobin, 2022).

A small but growing literature provides initial evidence suggesting that physical and transition risks stemming from biodiversity loss are priced in financial markets (Coqueret, Giroux, & Zerbib, 2025; Garel, Romec, Sautner, & Wagner, 2024; Giglio, Kuchler, Stroebel, & Zeng, 2025). Yet, this research is still in its infancy: most studies focus on U.S. data, cover relatively short periods, and rely on coarse or indirect measures of biodiversity risk. As a result, it remains unclear whether and how biodiversity risk is priced in global equity markets, and what constitutes an appropriate measure of firm-level biodiversity risk.

In this paper, we build upon prior studies in three key ways. First, we introduce two new firm-level measures of biodiversity risk: (i) a risk measure that is grounded in the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) framework for drivers of biodiversity loss and uses the S&P Trucost Environmental costs database on firm-level environmental costs, and (ii) a geospatial biodiversity risk measure that links the location of firms' assets with potential biodiversity risk exposure to detailed geographic data on key biodiversity areas. Second, we considerably extend the cross-sectional and time-series dimensions by studying the stock returns of 12,288 firms from 58 countries over 14 years, from 2009 to 2022. Third, we demonstrate the importance of disentangling the pricing of biodiversity risk across different levels of variation: within firms, within industries, and across industries.

In summary, our results suggest that biodiversity risk may be transmitted to financial markets through multiple channels. At the within-firm level, higher biodiversity risk is associated with lower returns and profitability, consistent with unexpected negative cash flow effects. In contrast, within-industry variation shows a positive association with both returns and profitability, which we interpret as evidence largely in favor of a biodiversity risk premium. Our asset- and geospatial biodiversity data-based measure corroborates the existence of a between-firm biodiversity risk premium: firms with risky assets in biodiversity-sensitive locations earn higher returns, providing direct evidence that local biodiversity risk is financially material and priced

by investors. Both transition and physical biodiversity risks are associated with returns, but transition risk emerges as the dominant effect. Furthermore, tests of nations' environmental policy characteristics and time variation provide some support for a risk premium, but magnitudes remain economically small. Taken together, these findings suggest that both cash flow effects and risk premia play a role, with their relative importance depending on the level of aggregation. Before explaining the results in more detail, we will first outline how we define and measure a firm's exposure to biodiversity risk and link this to returns data and what our empirical strategy looks like.

We define biodiversity risk as a firm's material financial risk arising from potential hindrances to its economic activities due to biodiversity loss, thus encompassing both transition and physical risk. For our first measure of biodiversity risk, we utilize the Trucost Environmental Dataset (S&P Global Sustainable1, n.d.-b), which provides environmental cost variables and covers more than 18,000 firms from 2002 onwards (S&P Global Sustainable1, n.d.-b) We link these environmental cost to direct drivers of biodiversity loss identified by the IPBES. The IPBES is an independent body established by governments, in response to the Conference of the Parties of the Convention on Biological Diversity (CBD), and it provides authoritative global assessments based on peer-reviewed science of the state of global biodiversity, ecosystems, and the services they provide to people. It plays a role analogous to the IPCC for climate that inform international biodiversity policy. In the context of biodiversity loss risk for firms and financial markets, IPBES is therefore a valid reference because it provides the most widely accepted synthesis of what drives biodiversity changes and how people depend on biodiversity. Specifically, the direct drivers of biodiversity loss we aim to measure on a firm level are changes in land and sea use, direct exploitation of organisms, climate change, and pollution (IPBES, 2019a). So, for each firm, we measure the sum of these drivers as the the sum of specific environmental cost data items from the Trucost: air pollutants, land and water pollutants, waste, greenhouse gas emissions, natural resource use, and water use. By using the IPBES framework to operationalize our Trucost-based biodiversity risk measure, we aim to enhance its construct validity and root it in environmental science.

Although we believe the above-described measure is informative on biodiversity risk, it might be too broad; it could capture 'general' environmental risk, or risks associated with it, such as climate and pollution risks (as is the nature of measuring something system-wide like biodiversity loss risk). Therefore, we complement it with a second measure designed to capture biodiversity-loss risk more precisely and to address these concerns. Our second measure of biodiversity risk is based on firms' static asset location data, which we extract from the Physical Risk dataset (S&P Global Sustainable1, n.d.-a), combined with different biodiversity-sensitive regions: Key Biodiversity Areas (BirdLife International, 2024), Protected Areas (UNEP-WCMC & IUCN, 2025), and Critical Natural Assets areas (Chaplin-Kramer et al., 2023). We operationalize spatial

biodiversity risk as the count of "risky" assets inside the biodiversity-sensitive regions scaled by the firm's accounting total assets. By linking firms' physical assets to biodiversity-sensitive areas, this spatial measure both complements our initial proxy and identifies biodiversity-loss risk more specifically, rather than general environmental risk.

We combine our biodiversity risk measures with standard return and accounting data to build our empirical panel. For monthly stock returns, we use the CRSP, Compustat North America, and Compustat Global security price databases. The set of control variables includes market-based and accounting firm characteristics originating from the Compustat North America and Compustat Global Fundamental Annual databases. After combining the Trucost-based biodiversity risk with monthly returns and firm characteristics data, we obtain a total of 874,052 firm–month observations for our panel data regressions (12,288 firms distributed across the globe, for 14 years). When we merge the asset- and geospatial-based biodiversity risk with returns and controls data, we retain a smaller yet still economically significant dataset: 335,037 firm-month observations (1,685 unique firms, based on 739,309 assets globally).

We investigate the possible existence of a biodiversity risk premium by assessing whether our measures of biodiversity risk are related to the cross-section of stock returns. We run panel regressions of stock returns on the Trucost-based biodiversity risk measure, along with a host of control variables and fixed effects. Specifically, we test our cross-sectional returns using month–year, industry, and country fixed effects, as well as month–year–industry and month–year–country fixed effects, to absorb sector- and country-specific dynamics, such as macroeconomic conditions, policy developments, or industry cycles. Next, we also test the relationship between returns and biodiversity risk, controlling for firm and time fixed effects to account for unobserved, time-invariant firm characteristics and global shocks that affect all firms simultaneously. This structure ensures that the estimated relation reflects changes in biodiversity risk within firms, industries, and countries over time, rather than differences between them. This establishes the empirical foundation for our analysis of the link between biodiversity risk and stock returns. In our baseline panel regressions, we find a positive but insignificant effect of biodiversity risk on returns when we include the combinations of industry, country, and month-year fixed effects. Interestingly, the impact of biodiversity risk on returns switches to negative and highly significant once firm and time fixed effects are included. The switch from positive to negative effect indicates that the relationship between biodiversity risk and returns seems to depend on the lens through which we view biodiversity risk.

Our findings show that the choice of fixed effects matters for the direction and strength of the relation between stock returns and biodiversity risk, suggesting that it is vital to consider the level of variance at which one examines the data. Hence, drawing inspiration from Pástor, Stambaugh, and Taylor (2022), we set up within-industry, across-industry and within-firm analyses alongside each other. When allowing for these different dimensions of variance, we find that within-

firm biodiversity risk has a significantly negative relation with returns, whereas within-industry biodiversity risk has a significantly positive relation with returns. A one standard deviation increase in within-firm and within-industry biodiversity risk causes a 1.96 pp decrease and 1.56 pp increase in returns annually. This pattern suggests that biodiversity risk may be priced differently when investors observe firm-specific changes versus industry-level differences. Furthermore, these findings underscore the importance of empirical design: standard asset pricing tests based on between-firm variation may yield misleading conclusions if within-firm variation drives pricing effects, potentially even exhibiting effects of the opposite sign. These results are robust to a range of specifications and controls, including standard firm characteristics and different fixed effects structures.

Our analysis thus far is all based on our biodiversity measure, grounded in the IPBES framework and based on Trucost firm-level environmental cost data. This biodiversity risk measure consists of multiple components. To better understand the source of the effects of biodiversity risk on returns, we explore the relation between these components and stock returns. We find considerable heterogeneity in the relation between returns and the individual drivers of our biodiversity risk measure: air pollutants, water use, natural resource use, waste, GHG emissions, and land/water pollutants. Within firms, air pollutants and waste show robust negative associations with returns, while natural resource use is positively related to returns. Within industries, air pollutants and waste exhibit positive return effects, while water use has a negative effect. Across industries, only weak evidence emerges, with limited significance for land/water pollutants and water use. These patterns suggest that different drivers may reflect distinct pricing channels—some may be linked to realized cash flow effects, others may be perceived as transition or physical risk. We observe notable differences across environmental policy areas in the OECD's PINE (Policy Instruments for the Environment) database, which records countries' use of environmental taxes, fees, and other regulatory instruments. These differences broadly correspond to the varying degrees of risk exposure or opportunities for exploitation across environmental domains (OECD, 2024). Notably, we observe that the overall biodiversity risk-return relation is not simply driven by more climate risk components such as GHG emissions, a result that is consistent with the empirical evidence from Coqueret et al. (2025).

Our baseline result shows that biodiversity risk correlates with returns, but it is unclear whether this is a priced risk factor or cash-flow shocks. Looking at country- and region-level environmental (policy) performance can help us test whether we are observing a risk premium. Thus, we investigate whether differences in country-level general environmental policies, as well as biodiversity loss-specific government policies, are relevant to the biodiversity risk-return relation. To this end, we interact our firm-level biodiversity risk measures with measures of country-level policies in these areas. We find that a country's environmental performance, when measured as SDG14 or SDG15, exhibits a significant positive interaction effect with the within-

firm biodiversity risk on returns. A plausible mechanism could be that there is better policy quality and clarity: if regulation is credible, gradual, and well-communicated, firms can adapt, and cash-flow shocks caused by biodiversity risk are less severe. Moreover, we observe a positive interaction effect of environmental performance, when measured as SDG14 with biodiversity risk on returns. In case of a risk premium, the interaction between SDG14 or SDG15 and firm-level biodiversity risk can plausibly take two distinct forms. One could argue that that firms headquartered in countries with high SDG14 and SDG15 performance would be exposed to less transition and physical risk than those in countries with low SDG14 and SDG15 performance, because these nations have low policy uncertainty and are better on track with preserving biodiversity goals. At the same time, there might be an expectation that high SDG countries are expected to introduce new but unknown regulations in the future, hence introducing more transition risk (but still a low physical risk). The observed interaction effect of the within-industry interactions with SDG14 and SDG15 on returns are, directionally speaking, in line with the latter explanation. Yet the observed effect size is small, hence, we refrain from drawing strong conclusions regarding a risk premium based on the environmental (policy) performance results.

Next, we complement the cross-country environmental (policy) performance analysis with a broader regional perspective, since regions encompass meaningful institutional, regulatory, and cultural commonalities. We examine the relation between biodiversity risk and returns across global regions, similar to Bolton and Kacperczyk (2023), and we observe a pattern consistent with a biodiversity risk premium: the within-industry biodiversity risk premium is higher for regions where we assume future environmental regulations to be more uncertain (such as North America, Asia, and the Southern Hemisphere), relative to regions where environmental policy is already more established (such as in Europe). We show that the results on returns are consistent in sign across global regions, with similar patterns emerging in North America, Europe, Asia, and the Southern Hemisphere. Nonetheless, some regions show more pronounced effect sizes than others. We find that the positive effect of within-industry biodiversity risk on returns is larger for firms headquartered in North America than for firms headquartered in Europe, Asia, and the Southern Hemisphere. These results suggest that biodiversity risk pricing is not particularly confined to a single larger region or setting. Moreover, the results are similar to the results shown by Bolton and Kacperczyk (2023), where the authors showed that a carbon premium is most pronounced for firms headquartered in North America.

Our results so far are based on regressions of realized stock returns on firm-level biodiversity measures. A challenge in the literature on the role of climate and nature-related effects in asset pricing is that these effects may be of relatively recent origin and may thus not purely reflect equilibrium effects. In other words, effects on realized returns may be driven by a risk premium (equilibrium effect) or by temporary cash flow or discount rate shocks. To disentangle possible risk premia from cash flow effects, we examine the relation between biodiversity risk and

firm-level profitability. We find that the negative within-firm return relation is mirrored by a negative association between biodiversity risk and profitability. This consistency across market- and accounting-based outcomes suggests that at least part of the within-firm return effect may be due to a negative cash flow effect by firm-level biodiversity risk exposure. In contrast, we observe a positive within-industry relation between biodiversity risk and profitability, mirroring the positive relation with returns. Thus, this empirical result regarding within-industry biodiversity risk can either be a positive risk premium, but can also still be a positive cash flow effect. Taken together, our findings suggest the coexistence of both equilibrium risk premium and cash flow effects, depending on the level of aggregation considered for biodiversity risk. The findings imply that firms with increasing within-firm biodiversity risk tend to underperform, showing negative profitability. At the same time, investors appear to demand higher returns for holding biodiversity risk-exposed firms relative to their peers, or these firms perform better than their peers in terms of profitability. Therefore, we cannot reject either the cash flow channel or the risk premium channel for within-industry biodiversity risk. These findings were consistent across different geographic areas.

In light of the possibility that the pricing of biodiversity risk is still developing in global financial markets, we are interested in whether the pricing effects we document vary over the course of our sample period. We explore whether the relationship between biodiversity risk and returns changes following biodiversity loss attention-grabbing events: the launch of the Taskforce on Nature-related Financial Disclosures and the COP 15 Kunming conference on biodiversity. We find a positive interaction effect of several event-grabbing for within-firm and within-industry biodiversity risk The negative baseline relation between within-firm risk and returns became smaller (less negative) after these events, which could indicate that investors began paying more attention to biodiversity risk after these milestones. As attention and policy initiatives rose, investors may have started to price biodiversity risk, demanding compensation for holding riskier firms — hence the relationship between risk and returns shifts toward positive. The positive interaction between the within-industry biodiversity risk and the Kunming/TNFD dummies is consistent with results in Garel et al. (2024), and this effect is consistent with a biodiversity risk premium. Nonetheless, the effect size we document is economically small, so we do not overinterpret this result.

We then turn to the analysis based on the second firm-level biodiversity measure: a geospatial measure that links firms' asset locations to key biodiversity areas. We find that the asset- and geospatial-based biodiversity risk measure is positively related to returns. This effect is robust across various definitions of "risky" assets (transition, physical, or both) and across different spatial biodiversity metrics (Key Biodiversity Areas, Protected Areas, and Critical Natural Assets). A one standard deviation increase in our spatial biodiversity risky asset measure corresponds with a 0.5 to 1.2 percentage point increase in annual returns. The largest effects occur for assets

near or inside Key Biodiversity Areas; for Protected Areas, significance arises only for transition-risk-relevant assets; for Critical Natural Assets, the effect is smaller overall but highly significant. The specific risk classification of the asset (whether the economic activity is relevant in terms of transition risk, physical risk, or both) does not matter for the magnitude of the effect. Hence, both transition and physical risk type of combinations of assets and locations load positively on returns, but the transition risk type of locations exposures generally exhibit larger and more robust effects than physical risk exposures. Nonetheless, when the physical risk asset type is combined with the Protected Area, a transition risk type of region, then the effect is no longer significant, suggesting that transition and physical risk exposures are more cleanly identified when asset and region types are conceptually aligned. Overall, the asset- and geospatial-based biodiversity risk measure complements the Trucost-based biodiversity risk measure and shows that where a risky asset is located materially affects stock returns. Because this analysis exploits within-industry (and within-country) variation in asset- and geospatial-based biodiversity risk, it provides complementary evidence in favor of a between-firm biodiversity risk premium.[1].

This paper fits in the growing biodiversity finance literature. Despite its material importance to many firms, biodiversity remains a relatively new topic in finance. While climate-related risk premia are now well-documented (Bolton & Kacperczyk, 2021, 2023; Witkowski, Adamczyk, & Franek, 2021; Zhang, 2025), top journals have, until recently, been largely silent on biodiversity risk (Guer, Mueller, & Schiereck, 2024; Karolyi & Tobin, 2022), and biodiversity finance papers attracted far fewer citations than climate finance papers (Nedopil, 2022). Nowadays, research examining the role of biodiversity (loss) within finance is starting to pick up (Ali, García-Sánchez, Aibar-Guzmán, & Rehman, 2024; Bahrami, Gustafson, & Steiner, 2024; Chen, Chen, Cong, Gao, & Ponticelli, 2023; Chenet, 2021; Coqueret et al., 2025; Flammer, Giroux, & Heal, 2023; Garel et al., 2024; Giglio et al., 2025; Schrapffer, Estran, Delzant, Paturel, & Ferron, 2022; Xin, Grant, Groom, & Zhang, 2025; Zhou & Almond, n.d.).

More specifically, we present evidence on whether biodiversity risk is priced in assets, a topical discussion. Garel et al. (2024) show that firms with large biodiversity footprints had higher realized stock returns after the Kunming Declaration (2019–2022). Giglio et al. (2025) construct an aggregate biodiversity news index and demonstrate that portfolio returns sorted on biodiversity exposure covary with this news factor, indicating that biodiversity shocks are priced at the aggregate level. Coqueret et al. (2025) takes a forward-looking perspective by using option-implied expected returns and documents higher costs of capital for firms with larger biodiversity footprints, particularly in sectors where double materiality is most salient, but they do not find a significant biodiversity risk pricing in realized returns or in expected returns in the market. Interestingly, a possible biodiversity risk premium seems to be distinct

[1]Unfortunately, as we do not have time variation within-firm, we cannot complement the earlier within-firm biodiversity risk results with evidence from the asset- and geospatial-based biodiversity risk.

from a carbon premium (Coqueret et al., 2025; Garel et al., 2024; Giglio et al., 2025). Moreover, a survey among financial professionals indicates that people think the current pricing of transition and physical risk is inadequate (Giglio et al., 2025). Taken together, these studies suggest the emergence of a biodiversity risk premium across firms, with somewhat stronger support for a transition risk premium than for a physical risk premium.

At the same time, collectively, the results remain somewhat inconclusive: evidence in favor of an unconditional cross-sectional biodiversity risk premiums remains weak, since only recently has biodiversity risk premium become visible and it appears to be strongest in highly exposed sectors. The current studies on biodiversity risk pricing have their limitations. Namely, the studies rely on relatively short and recent sample time windows, focusing mainly on the US firms or a small international panel of firms, making it difficult to assess if biodiversity risk has been priced over longer horizons globally. Moreover, the studies mainly examine biodiversity risk exposure at the between-firm level, possibly ignoring the different risk assessments by investors. What is more, the studies offer limited insights into the underlying drivers of biodiversity risk exposure and focus primarily on transition risk. The literature has not integrated any spatial-based measures, even though biodiversity risk is primarily a local problem. Finally, the biodiversity pricing literature has so far focused mainly on transition risk or on combined transition and physical risk, with little separate attention to physical risk.

Our study aims to address these limitations by combining a long international firm-level panel with two transparent and decomposable biodiversity risk measures (one based on Trucost environmental costs mapped to the IPBES driver framework and one based on asset-level risk exposure to local biodiversity risks), and by explicitly decomposing the biodiversity–return relation into within-firm, within-industry, and across-industry components, which we then further relate to profitability, policy, and geography. Our asset- and geospatial biodiversity risk measure will help distinguish between transition and physical risk: by matching transition- and physical-risk assets to areas that are primarily transition- or physical-risk relevant, we can distinguish between the two risks. Moreover, by decomposing the Trucost based biodiversity risk, we can also disentangle transition risk and physical risk better.

We have three main contributions to the climate and nature finance literature. First, we introduce two new firm-level measures of biodiversity risk. Biodiversity loss is a highly complex concept that is difficult to measure and quantify, which is probably the reason why financial economists have shied away from the topic for a long time (Giglio et al., 2025). We aim to make a comprehensible and applicable measure for biodiversity risk. Our first measure of biodiversity risk, based on firm-level environmental cost data, aims to pick up impact and dependency on biodiversity, thereby covering the double materiality of both transition and physical risk. Nonetheless, we also try to pick apart transition and physical risk effects by examining underlying components that are relatively more transition or physical risk. We utilize the biodiversity

driver framework developed by the IPBES and manage to build a firm-specific score bottom-up using digestible components. We complement the firm-level biodiversity risk measure with a second measure: the asset- and geospatial-based biodiversity risk. Because biodiversity loss is inherently a local problem (more so than for example climate change), this approach increases construct validity by linking firms' risky assets to biodiversity-sensitive areas. This is new in the biodiversity risk pricing literature: to the best of our knowledge, we are the first to introduce an asset and geospatial-based firm-level measure of biodiversity risk exposure. The results using both the Trucost-based measure and the asset-and geospatial show that not only the scale of a firm's biodiversity risk exposure but also its spatial risk exposure through assets locations positively affect stock returns. This appears to hold for both transition risk and physical risk. This novel, asset- and geospatial-based approach to measuring how investors perceive biodiversity risk enables us to better identify biodiversity risk (as opposed to other types of environmental risk) and to validate our findings using firm-level data.

Second, by utilizing the S&P Global Trucost Environmental Dataset (S&P Global Sustainable1, n.d.-b), we substantially expand both the N (cross-sectional) and T (time-series) dimensions, compared to recent biodiversity risk asset pricing papers (Coqueret et al., 2025; Garel et al., 2024; Giglio et al., 2025). After combining the Trucost environmental database with monthly returns and firm characteristics data from CRSP and Compustat, we obtained a total of 874,052 firm–month observations in our panel data regressions (12,288 firms distributed across the globe, for 14 years), creating a larger firm-panel dataset and allowing us to compare different dimensions of variance in biodiversity risk.

Third, we demonstrate the importance of disentangling the pricing of biodiversity risk across different levels of variation: within firms, within industries, and across industries. While many existing papers investigate various fixed effects, they predominantly focus on between-firm variance. Our results are consistent with the evidence of a positive between-firm premium (Coqueret et al., 2025; Garel et al., 2024; Giglio et al., 2025), while also introducing a within-firm dimension, where biodiversity risk predicts lower returns and profitability. We find that the relation between returns (or profitability) and biodiversity risk depends on how biodiversity risk is measured. Thus, by allowing for the possibility that investors assess "biodiversity risk" at different levels, we provide a more nuanced presentation of how biodiversity risk is potentially priced, shedding light on potential underlying mechanisms.

2 Hypothesis Development

Before defining our hypotheses, let us first define biodiversity loss risk (or simply biodiversity risk) for a firm. *Biodiversity risk* is defined as the firm-specific risk that can be attributed to biodiversity loss that hinders economic activities. Typically, biodiversity risk comprises of tran-

sition risk and physical risk[2]. *Transition risk* arises when firms impose damage on biodiversity through their operations and may face regulatory or market pressures to change, complicating the operations that potentially lead to reduced profitability or stranded assets (Van Toor, Piljic, Schellekens, Van Oorschot, & Kok, 2020). *Physical risk* arises when firms depend on ecosystem services and these services deteriorate due to biodiversity loss, threatening production processes and potentially jeopardizing financial performance (N. C. F. A. UNEP-WCMC, 2021; Van Toor et al., 2020). These two risks are interdependent and may even reinforce each other: delaying the transition exacerbates future physical risks, which, in turn, make the transition more urgent.

Building on the literature on environmental risk premia (e.g., (Bolton & Kacperczyk, 2021, 2023; Coqueret et al., 2025; Garel et al., 2024; Giglio et al., 2025)), we test the following hypotheses:

1. **Biodiversity Risk hypothesis:** Firm-level biodiversity risk is associated with a premium in the cross-section of stock returns.
2. **Spatial biodiversity risk hypothesis:** Firms with assets located in biodiversity-sensitive areas (e.g., Key Biodiversity Areas, Protected Areas, Critical Natural Assets) earn higher returns, consistent with a biodiversity risk premium.

3 Data and Methods

To test our hypotheses, we first need to quantify the biodiversity risk that investors face when investing in a firm. In this section, we define and operationalize our biodiversity risk measure, provide a detailed explanation of our data collection and variable measurements, and explain the empirical asset pricing strategy to test our hypotheses. Note that we construct two different measures of biodiversity risk: one is based on firm-level environmental cost data and the other is based on asset- and geospatial data.

3.1 Firm-level Biodiversity Risk

Our first measure of biodiversity risk is based on firm-level environmental cost data from the Trucost Environmental dataset (S&P Global Sustainable1, n.d.-b). The Trucost Environmental Data helps to assess the environmental impact of a company's operations. They calculate environmental costs using their 'Environmentally Extended Input-Output Model'. The Trucost Environmental dataset covers over 15,000 of the world's largest listed firms (representing 95% of the global market capitalization). The historical coverage for large-cap firms dates back to 2005,

[2]Note that "reputational risk"and "litigation risk" are also identified in the literature as well, but it will not be the focus of this research paper.

and for small- and mid-cap firms it dates back to 2016. The complete dataset contains over 100 environmental key performance indicator variables, encompassing hundreds of environmental issues, including carbon and other pollutants, water dependency, natural resource efficiency, and waste disposal. Trucost carbon emissions data, from the same Environmental dataset, is adopted and widely used in the finance literature - for example, see Bolton and Kacperczyk (2021, 2023), Garel et al. (2024), Bolton, Halem, and Kacperczyk (2022), and Bolton and Kacperczyk (2025).

We will measure biodiversity risk by linking the environmental data to both transition risk and physical risk. These two risks are inherently intertwined—firms that damage biodiversity often depend on it as well. Separating the two is conceptually appealing, but in practice, it proves to be a complex task. Thus, measure total biodiversity risk as the sum of these two risks. First, to proxy transition risk, we start by linking the main drivers of biodiversity loss (IPBES, 2019a) to variables in the S&P Global Trucost Environmental dataset. Second, we recognize that two of these environmental data items that we link to drivers of biodiversity loss could also serve as proxies for dependency on biodiversity. Thus, our final measure of biodiversity risk is the sum of impact on biodiversity loss and dependency on biodiversity, but without double measurements of the variables that could fit under both transition and physical risk.

All variables we selected are direct (scope 1) external environmental costs. The external costs are estimated by Trucost, where the external cost is the value of a service based on the cost of damage that results from its loss. Trucost bases these estimates on the assumption that the cost of maintaining an environmental benefit is a reasonable estimate of its value. In most cases, Trucost only provides estimated environmental costs; neither the underlying quantity level data in original units nor the cost coefficient per quantity unit (with which they calculate the environmental costs) is published by Trucost. For more information, we refer to the methodological guide provided by Trucost (S&P Global Sustainable1, n.d.-b). All the environmental costs variables were provided in million US$ (short: $M), therefore, we can aggregate variables to construct a biodiversity risk variable that is measured in $M.

3.1.1 Impact on Biodiversity Loss: Transition Risk

A proxy for a firm's transition risk would be a firm's impact, or footprint, on biodiversity. Note that it is not possible to link any aggregate biodiversity loss *directly* back to a firm, because the aggregate multiple pressure factors are what drive the aggregate biodiversity loss[3]. Additionally, biodiversity cannot be accurately captured by a single variable or indicator, as it is fundamentally a multidimensional concept Purvis and Hector (2000). Thus, aggregate measures of biodiversity loss should not be linked to short-term firm activity Wilting and van Oorschot (2017).

[3]For example, the following statement would be tough to argue: firm X caused a Y% decrease in biodiversity.

We deem it more instructive to analyze the drivers of biodiversity, because firms, through economic activity, are inseparably linked to the main drivers of species depletion IPBES (2019b). We follow a science-based approach, as outlined in the IPBES' drivers of biodiversity loss (IPBES, 2019a). To capture biodiversity transition risk in this paper, a variable is constructed that reflects the firm's impact on biodiversity. According to the IPBES, the direct drivers of nature and biodiversity loss, ordered from most to least impactful, are:

1. Changes in land and sea use
2. Direct exploitation of organisms
3. climate change
4. Pollution
5. Invasion of alien species

In this paper, a firm's impact on biodiversity loss is defined as the sum of the quantified impacts of the five constituent biodiversity loss drivers in dollars ($M). Therefore, a firm's impact on biodiversity loss refers to a comprehensive assessment of the environmental and economic costs associated with biodiversity loss. A positive impact on biodiversity loss means a firm is driving biodiversity loss. A negative effect on biodiversity would suggest a firm is contributing towards the restoration of biodiversity; nevertheless, as the data we will be using are environmental cost data items, we only measure *positive* impacts on biodiversity loss. A greater impact on biodiversity loss translates to a higher risk of biodiversity transition.

The selection of data items from the Trucost Environmental Database that are matched to biodiversity loss drivers are *Natural Resource Use*, *Water*, *GHG*, *Air Pollutants*, *Land and Water Pollutants*, *Waste*. Natural Resource Use and Water proxy for changes in land and sea use and direct exploitation of organisms drivers, GHG proxies for the climate change driver, and finally, Air Pollutants, Land and Water Pollutants, and Waste proxy for the pollution driver. Therefore, for each firm i and at time t, we operationalize transition biodiversity risk as the sum of Air Pollutants$_{i,t}$, Land and Water Pollutants$_{i,t}$, Waste$_{i,t}$, GHG$_{i,t}$, Natural Resource Use$_{i,t}$ and Water$_{i,t}$. Each constituent is matched to environmental variables provided by Trucost, except for the invasion of alien species. Unfortunately, no specific firm-level variable in the Trucost database could be linked to the invasion of alien species. A firm can be responsible for introducing alien species (for example, a transport firm), but the Trucost environmental dataset does not provide any information on this. Thus, the invasion of alien species falls outside the scope of our measure. In the Appendix Section I.A.1 we list the set of data items we used from the S&P Global Trucost Environmental Dataset, including their respective definitions provided by Trucost.

3.1.2 Dependency on Biodiversity: Physical Risk

A firm's dependency on biodiversity is defined as the extent to which the firm utilizes the ecosystem services that nature and biodiversity provide in its economic activities. Nature offers four types of ecosystem services: provisioning, regulating, cultural, and supporting (Millennium Ecosystem Assessment, 2001). Provisioning ecosystem services means that a well-functioning ecosystem, which relies on biodiversity, provides material and tangible natural resources that firms utilize in their production processes.The other ecosystem services (regulating, cultural, and supporting) do not involve material and extractable resources, but rather involve non-material benefits and services (IPBES, 2019a). The non-material ecosystem services are just as essential as material natural resources to a healthy and stable environment, and consequently, a stable economic climate. This might be a feasible exercise at the sector level; however, it is not straightforward to measure non-material services at the firm level. Therefore, we make a distinction between the extractable natural resources and the use of non-material ecosystem services for our measure of a firm's dependency on biodiversity, and limit the scope of our physical risk measure to material provisioning services only. Measuring the other three main ecosystem service dependencies on a firm level is outside the scope of this research.

We define a firm i's dependency on biodiversity as the economic dependency on biodiversity through the use of provisioning services, or natural resources, used by that firm i. We quantify the use of provisioning services as the sum of a firm's economic input in a production process that came from ecosystem services in million US$. Therefore, for each firm i at time t we measure physical biodiversity risk as the sum of Natural Resource Use$_{i,t}$ and Water$_{i,t}$, where Natural Resource Use$_{i,t}$ and Water$_{i,t}$ are the data items in Trucost that measure environmental costs of natural resource use and water use, therefore corresponding with provisioning ecosystem service. A greater reliance on provisioning natural resources, and thus a higher total economic dependency, translates into a higher physical risk to biodiversity.

3.1.3 Constructing the total firm-level Biodiversity Risk

Thus, we quantify a firm's total biodiversity risk, the sum of transition and physical risk, as follows:

$$\begin{aligned} \text{Biodiversity Risk}_{i,t} = {} & \text{Air Pollutants}_{i,t} \\ & + \text{Land and Water Pollutants}_{i,t} \\ & + \text{Waste}_{i,t} \\ & + \text{GHG}_{i,t} \\ & + \text{Natural Resource Use}_{i,t} \\ & + \text{Water}_{i,t}, \end{aligned} \tag{1}$$

where we do not double count Natural Resource Use$_{i,t}$ nor Water$_{i,t}$. Thus, Biodiversity Risk$_{i,t}$ is the \$M exposure to the external environmental costs, associated with impact on biodiversity loss and dependency on biodiversity of a firm i and time t. Note that this measure of total biodiversity risk is thus equal to our initial definition of transition risk, illustrating the challenge of truly disentangling transition risk from physical risk. In an attempt to isolate transition risk from physical risk and vice versa, we will perform additional analyses with the biodiversity risk measure, where we first exclude Natural Resource Use$_{i,t}$ + Water Use$_{i,t}$ (in an attempt to isolate and measure only transition risk), and then exclude Air Pollutants$_{i,t}$ + Land and Water Pollutants$_{i,t}$ + Waste$_{i,t}$ + GHG$_{i,t}$ (in an attempt to isolate and measure only physical risk).

To normalize the environmental data, we take the natural logarithm of our biodiversity risk, so that our variable of interest in the analysis is ln(Biodiversity Risk). All the variables originating from the Trucost Environmental data were winsorized at 1% and 99% within each fiscal year, following Bolton and Kacperczyk (2023). Specifically, we winsorize ln(Biodiversity Risk) after taking the natural logarithm of the sum of the separate constituents. Moreover, as we will also perform analyses on the individual constituents, we will also take the natural logarithm of these constituent drivers, and then winsorize these at 1% and 99% within each fiscal year.

The summary statistics of all variables, including the ln(Biodiversity Risk), are given in the Data Appendix I.B.1. To illustrate our biodiversity risk measure, Figure 1 shows the mean Biodiversity Risk scores across industries. We report the highest biodiversity risk scores in Global Industry Classification Standard (GICS) industries (1) Utilities, (2) Energy, (3) Materials, (4) Transportation, (5) Food, Bev. & Tobacco. These environmental data may heavily rely on a firm's specific industry or sector; therefore, it is relevant to examine within-industry differences explicitly. Next, Figure 2 plots the ranks of the mean biodiversity impact of firms in each country (averaged over all time). (1) Mauritius, (2) Russia, (3) Luxembourg, (4) Colombia, and (5) Germany are the five highest-ranked countries in terms of average biodiversity risk of firms headquartered in these countries.

When comparing our firm-level biodiversity risk measures to other papers, we identify key similarities and differences, which are summarized in the Appendix I.C. First, our definition of biodiversity risk follows Coqueret et al. (2025) in addressing the concept of double materiality. However, unlike their approach, which averages transition and physical risk scores into a composite measure, we sum the two components—without double-counting—to capture the total risk exposure. Second, compared to Giglio et al. (2025), our biodiversity risk measure is more grounded in environmental science and actual firm operations, whereas their method is based on sentiment and firms' (voluntary) disclosure. Third, the biodiversity risk method proposed by Garel et al. (2024) is closely related to our method because we also employ a footprint logic. Nonetheless, their measure uses a km^2 MSA damage unit, whereas our measure is in million US\$ cost units, since Trucost's damage function is communicated in monetary terms. However, we

extend the literature by modeling spatial dependencies, disaggregating biodiversity risk into separate drivers (a bottom-up approach), and attempt to separate impact and dependency instead of aggregating them.

Comparing our measure of biodiversity risk with the industry distributions of the actual output of biodiversity risk measures in the nascent biodiversity risk premium literature, we find that it is most consistent with Giglio et al. (2025) and Coqueret et al. (2025), and also comparable to Garel et al. (2024). Namely, our biodiversity risk measure has the highest scores for Utilities, Energy, Materials, Transportation, Food, and Beverage. Giglio et al. (2025) report the highest biodiversity risk exposure scores in (1) Energy, (2) Utilities, (3) Food, Bev. & Tobacco, (4) Pharma, Biotech. & Life Sciences and (5) Materials[4]. Coqueret et al. (2025) report their highest double materiality biodiversity risk scores for (1) Materials, (2) Consumer staples, (3) Utilities, (4) Energy, and (5) Real estate[5]. Our biodiversity risk measure is most consistent with these two previous papers, in terms of the industries Utilities, Energies, and Materials. Garel et al. (2024) report the highest corporate biodiversity footprint for the industries (1) Retail and wholesale, (2) Paper and forest, (3) Food, (4) Asset Management, and (5) Oil and Gas[6]. We also pick up Food (Food, Bev & Tobacco) and Oil and Gas (Energy) with our measure, but the rest of the industry rankings are mostly different. Probably, this is because Garel et al. (2024) uses a more land-use change-based measure. Notably, we do not seem to pick up either Real Estate or Pharmaceuticals as an overall risky industry in terms of biodiversity, which these two other papers with which our measure is most consistent do pick up Coqueret et al. (2025); Giglio et al. (2025). Moreover, our measure appears to capture fewer 'consumer staples' or 'retail and wholesale' industries, as identified in Coqueret et al. (2025) and Garel et al. (2024). These differences in biodiversity risk, when compared to industry averages, are essential when considering the construct validity of the various measures. Moreover, given the industry average differences, focusing on within-industry effects instead of across-industry effects is preferred when comparing the results with other biodiversity risk pricing studies.

To situate our measure within the broader literature, it is essential to highlight its differences from other prominent approaches. Our measure differs from other notable approaches in measuring biodiversity risk. Our measure of biodiversity risk differs from the general equilibrium model approach, which models a firm's nature dependency (Johnson et al., 2021). This study, however, examines estimates of environmental costs associated with a firm's economic activity. Moreover, as it is a firm-level measure of biodiversity risk, the empirical approach differs from sectoral approaches in measuring biodiversity risk (Arlt, Berg, Hut, & Streitz, 2024; Van Toor et al., 2020). Taken together, these distinctions highlight that our methodology offers a com-

[4]In Giglio et al. (2025), see *Figure 4: Industry-Level Biodiversity Risk Exposure.*
[5]In Coqueret et al. (2025), see *Table 7: Double materiality GICS ranking.*
[6]In (Garel et al., 2024), see *Table 2. The CBF: rankings by industry and country.*

plementary, bottom-up perspective on firm-specific biodiversity risk, which is both empirically tractable and directly linked to realized environmental outcomes.

3.2 Spatial Biodiversity Risk measure

A valid critique to our first measure of biodiversity risk is whether it specifically measures biodiversity loss risk, and not more generally environmental risk, or risks associated with it such as climate and pollution risk. Moreover, biodiversity impacts and dependencies are, first and foremost, local problems, as biodiversity loss is caused by local drivers rather than global ones (such as global greenhouse gas emissions, which drive global climate change). Local changes do not imply global changes, per se, and the provision of natural capital is also local. Thus, our first measure of biodiversity risk based on firm-level data is an inherently blunter instrument for addressing the problem at hand, as it is prone to spatial and dilution effects (as high- and low-risk assets may cancel each other out at the aggregate). Moreover, firm-level data may overlook the broader context of biodiversity, local regulations, and community conflicts. Thus, measuring biodiversity risk with geospatial and asset-level data to measure biodiversity loss may lead to alternative firm-level metrics, as it

Therefore, we aim to complement our Trucost firm-level biodiversity risk measure with an asset- and geospatial-based measure of biodiversity risk. This measure is more specific to biodiversity loss risk and less so to other environmental risks; therefore, we address concerns that the Trucost firm-level measure, on its own, could be too general. Moreover, we offer a new perspective on the biodiversity risk pricing literature, as spatial analyses have not yet been incorporated (Coqueret et al., 2025; Garel et al., 2024; Giglio et al., 2025). Of course, an asset- and geospatial-based measure is not without its disadvantages: it is data intensive, data coverage and quality may be lacking (especially if there are no time series), and even though we aim to gauge what is going on "on the ground", it is based on a lot of subjective assumptions about the asset types and the relevance of certain areas to conclude something about biodiversity risk (can we truly know what is happening "on the ground" at each asset?). Having said that, combining both approaches, we aim to gain a better understanding of biodiversity risk.

To create an asset- and geospatial-based biodiversity risk representation for each firm i, we examine the types of assets owned by the firm and their global asset locations. Namely, certain types of assets will be more relevant than others when considering transition and physical biodiversity risk, and the location of the asset determines whether the asset is truly at risk. For example, an asset that typically pollutes a lot, such as a mining project, is more at transition risk than a retail store, and even at transition risk when it is located inside an area that aims to protect the local biodiversity. Similarly, when an asset is highly dependent on the provisions of natural resources, such as forestry, it is more physically at risk than a headquarters, and it

is even more at risk if it is located inside an area where a lot of natural resources are being extracted (high depletion). We define certain assets as being of transition and physical risk, intending to exclude clearly less salient asset types, such as office locations. These risks become most relevant when such assets are located in biodiversity-sensitive regions.

To capture this asset- and geospatial biodiversity risk, or in short Spatial Biodiversity Risk$_i$, we count the number of "risky" assets a firm holds—i.e., assets of a risk-relevant type that fall within these sensitive biodiversity risk regions—and scale this count by the firm's total assets (book value). This gives us a firm-level spatial sensitivity of biodiversity risk:

$$\text{Spatial Biodiversity Risk}_i = \frac{\text{Risky assets of firm } i}{\text{Total assets of firm } i}.$$

The measure can be constructed for transition risk asset types, physical risk asset types, or both combined, and across different biodiversity risk regions. This provides a comparable, asset- and geospatial-based indicator of biodiversity loss exposure across firms. Note that the only time variation in Spatial Biodiversity Risk$_i$ comes from Total Assets of firm i, as total assets vary over time, but we do not have time variation in the asset locations. In the Appendix I.A.6 we provide a more formal definition of the asset- and geospatial-based biodiversity risk.

The asset locations were retrieved from the Trucost Physical Risk Asset datasets, where we obtained ∼739,309 assets globally matched to ∼13,152 firms, where the asset locations linked to firms are static. After merging the biodiversity risk data with stock returns and firm characteristics, we retain 1,685 unique firms (335,037 firm-month observations). Although the sample size is smaller than the Trucost-based sample, it is comparable to other large-scale asset-pricing studies (e.g., (Bolton & Kacperczyk, 2021); (Garel et al., 2024)).

The descriptive statistics for (non-)scaled count variables are displayed in Panel C of summary statistics table, Table 11 in the Appendix.

The assets in our dataset are various in types: for example, the dataset includes offices, headquarters, retail stores, and other types of property, but also mining facilities, power plants, sites, agriculture, and exploration, to name a few. Whether an asset is considered "risky", so that $r \in \{\text{TR}, \text{PR}, \text{TR}|\text{PR}\}$, depends on its asset type. An overview of all transition and physical risky asset types is presented in the Data Appendix I.A.6.

To measure Spatial Biodiversity Risk, we will consider three main spatial biodiversity datasets: Key Biodiversity Areas, Protected Areas, and Critical Natural Assets Areas[7]. We explain these biodiversity areas and their relevance for transition and physical in more detail below. The Key Biodiversity Areas, Protected Areas, and Critical Natural Assets areas data are plotted with and without asset locations in Figures 3, 4, and 5, respectively.

[7]Note that, of course, these areas may overlap; we report correlations between assets inside different regions of the Appendix section I.B.2

The first spatial biodiversity data, Key Biodiversity Areas (henceforth: KBA), are defined as "the most critical places in the world for species and their habitats ", thus where conservation efforts would matter the most and would need to be focused on (BirdLife International, 2024). The KBA data is included in the Integrated Biodiversity Assessment Tool (IBAT Alliance, 2024). These areas could therefore serve as proxy transition risk areas, as there is a clear push to conserve nature within them.

The second spatial biodiversity dataset, Protected Areas (henceforth: PA), from the World Database on Protected Areas (UNEP-WCMC & IUCN, 2025) is a comprehensive global dataset of marine and terrestrial protected areas, and its data are also included in the Integrated Biodiversity Assessment Tool (IBAT Alliance, 2024). The database is a joint project between the UN Environment Programme and the International Union for Conservation of Nature (IUCN). The database is managed by the UN Environment Programme World Conservation Monitoring Centre (UNEP-WCMC), in collaboration with governments, non-governmental organisations, academia, and industry. Similar to the KBA data, the PA data could therefore proxy as spatial transition risk areas. The transition risk could be either materialized or not yet materialized, because the fact that an area is protected does not mean the protection is also enforced. Nonetheless, these areas are at a higher risk of transition risk than any other area, similarly to the KBA data.

The third spatial biodiversity data, to proxy for physical biodiversity risk, is the Critical Natural Assets (CNA) data Chaplin-Kramer and Kennedy (2022), published by Chaplin-Kramer et al. (2023) in Nature Ecology & Evolution. CNA are defined as the natural and semi-natural terrestrial and aquatic ecosystems that provide 90% of the total current magnitude of nature's contributions to people, mapped at 2 km resolution, and cover around 30% of total global land area (excluding Antarctica) and 24% of national territorial waters (marine Exclusive Economic Zones, or EEZs) (Chaplin-Kramer et al., 2023). With the CNA data, we aim to identify areas of spatial physical biodiversity risk.

Therefore, the asset is flagged as having transition risk or physical risk when the type of asset is relevant to transition or physical risk, and if it is inside a biodiversity risk-relevant region $j \in \{KBA, PA, CNA\}$. We note that for transition risk, region type $g \in \{\text{KBA}, \text{PA}\}$ has a better theoretical fit, and for transition risk and region type $g = \{\text{CNA}\}$) has a better fit with physical risk.

3.3 Global stock returns, profitability, and firm characteristics

For monthly stock returns, we will use price and return data from the following data files: CRSP Monthly Stock File, Compustat Global Security Daily, Compustat North America Security Daily, and Compustat North America Security Monthly. We compute stock returns following the data

handling strategy of empirical asset pricing literature (Alves, Krüger, & Van Dijk, 2025; Bali, Engle, & Murray, 2016; Beaver, McNichols, & Price, 2007; Bessembinder, Chen, Choi, & Wei, 2023; Chaieb, Langlois, & Scaillet, 2021; Fama & French, 1992). The set of control variables include market-based and accounting firm characteristics, namely $\text{Beta}_{i,t}$, $\text{Size}_{i,t}$, $\text{B/M}_{i,t}$, $\text{Investments}_{i,t}$, $\text{Momentum}_{i,t}$, $\text{Volatility}_{i,t}$, $\text{Leverage}_{i,t}$, $\text{Tangibility}_{i,t}$, $\text{R\&D}_{i,t}$, $\text{INV/A}_{i,t}$, $\text{Sales Growth}_{i,t}$, $\text{ROE}_{i,t}$, similar to Bolton and Kacperczyk (2021, 2023). To construct these control variables, we extract data from the following data files: Compustat North America Fundamentals Annual and the Compustat Global Fundamentals Annual. The exact definitions of the stock returns and firm-level control variables are described in more detail in Section I.A.1, and see Section I.A.2 in the Appendix for a detailed description of how we compute and filter price and returns data.

We merge the stock returns, market data, company characteristics and Trucost environmental data as follows. To merge the firm characteristics data originating from Compustat with the price and returns data from CRSP and Compustat, we again use the 'gvkey' identifier, and we match the dates so that the fundamentals data are lagged; that is, we match the fundamentals data in year t to the returns in the month June in calendar year $t+1$. To merge the Trucost data onto the returns and controls dataset, we match the firm's SNL 'institutionid' to 'companyid', and then to 'gvkey' again. We match the Trucost data using the effective publishing date, following the methodology by Zhang (2025). The final monthly dataset used for the asset pricing analyses spans from 2009 to 2022. Note that if we could opt to include data before 2009, it would involve backfilled data. See Appendix Section I.A.5 for a more detailed methodological note on how we matched the dates. After merging all the datasets, 12,288 unique firms remain. Then, after dragging values down the biodiversity measures as monthly observations until the following new information becomes available, we obtain 874,052 monthly observations of returns, fiscal year-end biodiversity values, and control variables in the complete dataset that will be used for analyses.

To mitigate the impact of outliers, we winsorize returns from Compustat (Global and North America at 0.1% and 99.9% within each month based on the sample of CRSP returns of the corresponding, and the CRSP returns remains untouched; here, we follow Jensen, Kelly, and Pedersen (2023) and assume the CRSP data is reliable. All matched control variables are winsorized at the 1% and 99% levels within each month, following the winsorization strategy by Bolton and Kacperczyk (2023). In the Appendix Section I.B.1 in Table 11 in Panel A, we present the descriptive statistics of all the variables used in the analyses on returns.

For the profitability analysis, we again take Fundamentals Annual from Compustat Global and North America Fundamentals Annual, and we create market-based variables originating from security price data from CRSP and Compustat. Then, for each firm, we merge the fiscal year values of the Trucost data with the fiscal year values of the profitability and controls dataset. After merging, we have 12,814 unique firms for 14 years. We winsorize different ROA values,

independent variables, and all control variables at 1% and 99%, following the methodology of Hsu, Li, and Tsou (2023). After winsorization, we normalize all independent variables so that they have zero mean and unit standard deviation, to facilitate the interpretation of economic magnitudes. In the Appendix Section I.B.1 in Table 11 in Panel C, we present the descriptive statistics of all the variables used in the analyses on profitability.

3.4 Environmental performance countries

Countries will differ in their degree of policy strictness and effectiveness in addressing biodiversity loss. For each country c and time t, we aim to measure 'environmental (policy) performance'. By including this variable in our analyses, we can determine whether these country characteristics influence any potential biodiversity risk pricing effect. We explore two different measures of a nation's environmental (policy) performance, namely the countries' Sustainable Development Goals (SDG) scores[8], and SDG goal 14 Life Below Water subscore, SDG goal 15 Life on Land subscore. Environmental Policy Index (EPI) score by Yale Block et al. (2024)[9], the EPI Biodiversity Habitat subscore, and the EPI Ecosystem Vitality subscore.

Note that EPI and SDG (sub)scores may capture different aspects of environmental (policy) performance. Namely, the EPI score evaluates policy effectiveness and current environmental outcomes, whereas the SDG score assesses how close a country is to achieving a long-term development goal, including intentions as well as outcomes. Therefore, a country's EPI score may be high, but its SDG score may be low, or vice versa. For example, Costa Rica's EPI ranking is relatively lower, positioned at 68th globally. This suggests room for improvement in its policy effectiveness, for instance, in areas such as air quality and waste management. Conversely, Costa Rica excels in environmental SDGs, particularly in SDG 13 (Climate Action) and SDG15 (Life on Land). The country is renowned for its commitment to renewable energy and biodiversity conservation, with significant portions of its territory designated as protected areas. Thus, when we aim to measure policy environmental performance, SDG and EPI could both be correct measures, but at the same time, pick up some different aspects. We posit that the EPI scores proxy transition risk more closely than the SDG scores do, whereas the SDG scores would capture both transition and physical risk. All scores range from 0–100, with higher scores indicating better (environmental) performance. More information about the scores can be found in the Appendix section I.A.1 Table 8.

[8]SDG scores Sachs, Lafortune, and Fuller (2024) were accessed via the Sustainable Development Report website: https://dashboards.sdgindex.org/downloads

[9]The EPI score aims to provide a scale on how close countries are to established environmental policy targets, measuring different indicators on climate change performance, environmental health. The EPI scores were accessed via https://epi.yale.edu/downloads, where the ZIP file of the 2024 Indicator scores was downloaded.

3.5 Empirical Strategy

The first regression model we run to test the relation between biodiversity risk and returns is based on the transitional carbon risk models by Bolton and Kacperczyk (2021, 2023). In accordance with the methodology adopted in Alves et al. (2025), this paper utilizes panel regression as an alternative to the Fama-MacBeth (Fama & MacBeth, 1973) regressions[10].

Let $\ln(\text{Biodiversity Risk})_{i,t}$ be the natural logarithm of the biodiversity risk of firm i at time t (as explained in section 3.1). Then, to evaluate whether biodiversity risk is priced in assets, we run the following panel regressions:

$$\text{Ret}_{i,t} = a_0 + a_1 \ln(\text{Biodiversity Risk})_{i,t} + \gamma \text{Controls}_{i,t} + \mu_{i,j,c,t} + \varepsilon_{i,t}, \tag{2}$$

with the coefficient of interest a_1. $\text{Controls}_{i,t}$ is a vector firm-month-year specific variables control variables, including $\text{Beta}_{i,t}$, $\text{Size}_{i,t}$, $\text{B/M}_{i,t}$, $\text{Investments}_{i,t}$, $\text{Momentum}_{i,t}$, $\text{Volatility}_{i,t}$, $\text{Leverage}_{i,t}$, $\text{Tangibility}_{i,t}$, $\text{R\&D}_{i,t}$, $\text{INV/A}_{i,t}$, $\text{Sales Growth}_{i,t}$, $\text{ROE}_{i,t}$, similar to Bolton and Kacperczyk (2021, 2023).

$\mu_{i,t}$ captures different fixed effects specifications. Because unobserved factors at the firm (i), industry (j), country (c), and time (t) levels that are likely to influence stock returns, we include corresponding fixed effects to absorb these sources of variation. Moreover, note that, ex ante, it is not straightforward to determine what investors are explicitly looking for when considering biodiversity risk exposure: do investors deem the differences between firms relevant, or even different exposures over time within the same firm? Therefore, we include several fixed effects combinations to explore various interpretations of biodiversity risk pricing. First, we include the sum of industries, countries, and time fixed effects. Second, there may be specific effects on returns within an industry or a country in a particular month. Therefore, we include a version of fixed effects that interacts the industry and country dummies with the time dummies. Third, returns are, of course, firm-specific (stock-specific) and time-specific. Therefore, we include the sum of firm and time fixed effects. For industry fixed effects, we use Compustat's industry code 'gind', linked to the firm (third level in the GICS hierarchy). For country fixed effects, we use the country where the firm's headquarters are located, identified by Compustat's 'loc'. The time fixed effects are created as the unique month-year combination factor related to the monthly returns data. The 'gvkey' firm identifiers tie in the firm fixed effect. Standard errors

[10]Using panel data regressions allow for a more nuanced examination of the data, as opposed to the equal weighting of time periods in Fama-MacBeth regressions (Fama & MacBeth, 1973). Specifically, panel regressions tend to assign a higher weight to time periods with a greater number of observations. This is particularly useful the current paper, because the environmental data coverage increases over time (see Figure 6 in the Appendix). Using the standard Fama-MacBeth regression method may under-weigh data in time periods where the estimation of the relation could be more accurately determined (Alves et al., 2025).

are clustered at the firm and year levels to deal with dependencies among residuals.

Next, inspired by the empirical set-up of Pástor et al. (2022), where the authors assess the within- and across-industry variation of their measure of greenness alongside each other, we explicitly examine within-firm, within-industry, and across-industry variation alongside each other, to explore whether pricing potentially differs over the different levels of variation. Specifically, we define the within-across variations for firm i nested in industry j for month t as follows:

$$\begin{aligned}\ln(\text{Biodiversity Risk})_{i,t}^{within\ firm} =& \ln(\text{Biodiversity Risk})_{i,t} \\ &- \frac{\sum_t^{T_i} \ln(\text{Biodiversity Risk})_{i,t}}{T_i},\end{aligned} \tag{3}$$

$$\begin{aligned}\ln(\text{Biodiversity Risk})_{i,j,t}^{within\ industry} =& \ln(\text{Biodiversity Risk})_{i,t} \\ &- \ln(\text{Biodiversity Risk})_{t,j}^{across\ industry},\end{aligned} \tag{4}$$

$$\ln(\text{Biodiversity Risk})_{t,j}^{across\ industry} = \frac{\sum_{i \in I_{j,t}} \ln(\text{Biodiversity Risk})_{i,t}}{N_{j,t}}, \tag{5}$$

where $I_{j,t}$ represents the collection of all firms in industry j at time t and $N_{j,t}$ represents the number of firms in that set. With these variables, we run the following regression:

$$\begin{aligned}\text{Ret}_{i,t} = b_0 &+ b_1\ \ln(\text{Biodiversity Risk})_{i,t}^{within\ firm} \\ &+ b_2\ \ln(\text{Biodiversity Risk})_{i,j,t}^{within\ industry} \\ &+ b_3\ \ln(\text{Biodiversity Risk})_{j,t}^{across\ industry} \\ &+ \gamma \text{Controls}_{i,t} + \mu_{c,t} + \varepsilon_{i,t},\end{aligned} \tag{6}$$

where $\text{Controls}_{i,t}$ denotes the same collection of control variables as in equation 2, γ is the vector of the coefficients on control variables, $\mu_{c,t}$ denotes different fixed effects capturing unobserved heterogeneity. Since we have already controlled for within- and across-firm and industry variation, we only add country and time (additive or interaction) fixed effects. $\varepsilon_{i,t}$ is the error term. Our coefficients of interest are b_1, b_2, and b_3.

Next, in an exploratory analysis, we examine whether the separate constituents of our biodiversity measure have different effects on returns. The distinct components of biodiversity risk could exert heterogeneous effects on financial performance; hence, nuanced effects may be obscured in the aggregate biodiversity risk measure. Additionally, examining the effects of the different drivers can help disentangle the mechanisms behind the aggregate relation. If the coefficient of biodiversity risk on returns is negative, this would be consistent with a story of gradual pricing-in of transition risk, suggesting that current price adjustments anticipate a future positive risk premium, or with a story of in sample cash flow shows of the materialization of transition risk, by means of introduction of regulations such as taxes, fees, and production

restrictions. Analyzing the drivers could shed light on the possibility of materializing transition risks, as there may be differences in the number of regulations in place across various environmental domains, such as the different drivers of biodiversity risk. If the coefficient is positive, this would be consistent with a biodiversity risk premium, or short-term cash flow advantages from the exploitation of natural resources or the absence of effective regulation, which allows high-risk firms to generate excess returns in the present. Analyzing the separate drivers can shed light on whether such positive effects are concentrated in specific environmental domains, such as areas where regulatory coverage is weak or enforcement is limited.

So, we first analyze the effects of the separate drivers on returns. We decompose the aggregated ln(Biodiversity Risk) into its constituent components (e.g., the drivers ln(Natural Resource Use), ln(Water), ln(Land/Water Pollutants), ln(Air Pollutants), ln(Waste), ln(GHG)). We run a regression model that uses the decomposition of the natural logarithm of the biodiversity risk measure into these six distinct components, where we decompose each of the drivers into its own within-firm, within-industry, and across-industry variation.

Next, we examine whether the results are driven by specific heterogeneity between nations' environmental (policy) performance. Specifically, we will run a regression to determine whether there is an interaction effect between a nation's environmental (policy) performance and the firm level's biodiversity risk. We match the firms' headquarters locations to their respective countries' environmental (policy) performance scores. This cross-country environmental policy analysis can provide us with insights into biodiversity risks, as policies may be enforced at the headquarters level.

In addition to nations' environmental (policy) performance, it is also helpful to examine larger geographic regions. Different regions worldwide may face varying transition and physical biodiversity risks due to various policies, attitudes, and institutions in place. Although using regions as a sample split is a much coarser method, regions could capture relevant commonalities and reduce the dimensionality of the analysis. Moreover, examining the relation between biodiversity risk and returns by region allows us to investigate whether any particular region drives the relation or whether there are heterogeneous effects that may counteract each other. Therefore, we assess the regional effects by categorizing the headquarters location of each firm into the regions of North America, Europe, Asia, and the Southern Hemisphere (or the "rest" of the world), following the regional classification of Bolton and Kacperczyk (2023). Then, we continue analyzing the within-across specification from equation 6, but now perform this analysis for each region.

In exploratory analysis, we will investigate whether a biodiversity risk premium might emerge only in a later subset of our sample, as investors may not have been paying attention to biodiversity risk previously. Still, professionals now seem to acknowledge the issue, as recently noted (Giglio et al., 2025). For example, Garel et al. (2024) found that a biodiversity footprint

premium might be emerging in the months following the Kunming Declaration (the first part of COP15) and the launch of the TNFD. Bolton and Kacperczyk (2021, 2023) also include a Dummy to identify the period after the Paris agreement, and they show a more substantial carbon premium in the latter part of their sample. We therefore run regressions of returns on interactions between decomposed biodiversity risk (within-firm, within-industry, across-industry) and time-variant dummies indicating attention-grabbing events. Specifically, we focus on the Kunming Declaration (October 2021, arguably the most critical UN event of the decade related to biodiversity, and also used in previous literature (Coqueret et al., 2025; Garel et al., 2024)), the TNFD launch (June 2021), and the Paris Agreement for comparison. Finally, we interact biodiversity risk with the monthly "NYT Biodiversity News Index" of Giglio et al. (2025), where higher values indicate more negative biodiversity news, and also test the average "NYT Climate News Index" to examine whether macro biodiversity (or climate) attention in news spills is relevant in the relation between biodiversity risk and returns.

A key challenge is to disentangle whether the return effects of biodiversity risk reflect variation in discount rates or in realized cash flows. To address this, we complement the return regressions with firm-year panel regressions of profitability, measured as $\text{ROA}_{i,t}$, on $\ln(\text{Biodiversity Risk})_{i,t}$ (decomposed into within-firm, within-industry, and across-industry variation). This allows us to test whether biodiversity risk proxies for expected changes in profitability (cash flow channel) or instead reflects variation in required returns unrelated to fundamentals (discount rate channel). Following Hsu et al., we estimate the effect of biodiversity risk on contemporaneous profitability, short-term changes in profitability (forward one-year differences), and long-term growth in profitability (forward-looking ten-year averages). The set of controls in year t includes Size, B/M, INV/A, Leverage, Tangibility, R&D, Sales Growth, and Operational Profitability. Moreover, a lagged ROA_{t-1} is added as a control in the specification with $\overline{\text{ROA}}_t$ as a dependent variable, and the ROA_t and ΔROA_{t+1} are added as control variables for the specification with $\overline{\text{ROA}}_{i,t+10:t+1}$ as an dependent variable. We again test for different fixed effects specifications, namely, fiscal year, country, and the interaction of the two.

Finally, we complement the use of firm-level information with biodiversity risk information at firms' asset and production sites, since a firm's exposure to biodiversity risk mostly occurs on-site at production locations, rather than at the headquarters location per se. Thus, we regress the monthly returns data with the asset- and geospatial-based Spatial Biodiversity $\text{Risk}^{r,g}_{i,t}$. We again test for different fixed effects specifications $\mu_{j,t,c}$, namely, the addition of industry (j), month (t), and country (c) fixed effects, and the interaction of industry (j) and month (t) combined with the interaction of country (c) and month (t).

4 Results

4.1 Do firms with higher biodiversity risk earn higher returns?

We start our analysis with analyzing the results of the panel data regressions of firm i's excess returns in month $t+1$ on the natural logarithm of firm i's ln(Biodiversity Risk)$_{i,t}$. In Table 1, the results of these panel data regressions are given controlling for several firm characteristics (a short and long version of control variables, alternating one another), and fixed effects (no fixed effects in column (1) and (2), industry + time (year-month) + country fixed effects in columns (3) and (4), industry × time (year-month) + country × (year-month) fixed effects in columns (5) and (6), and firm + time (year-month) fixed effects in columns (7) and (8)). Firstly, we observe a positive loading of ln(Biodiversity Risk)$_{i,t}$ on excess returns for all specifications with no fixed effects and different industry, country, and time combinations of fixed effects, albeit it is almost always insignificant (apart from model (4)). Interestingly, when we move to firm + month-year fixed effects, we observe a *negative* and highly significant loading of ln(Biodiversity Risk)$_{i,t}$ on excess returns; namely, in the model with the most control variables, we observe a coefficient for ln(Biodiversity Risk)$_{i,t}$ of $\beta = -0.164$ ($SE = 0.043$), $p < 0.001$, where β represents the change in monthly excess returns for a 1% change in Biodiversity Risk$_{i,t}$ in million USD. A one-standard-deviation increase in the impact of log-transformed biodiversity was associated with a -0.164×0.523 [11] $= -0.086$ percentage point change in excess monthly returns, suggesting a -1.032 percentage point change in a year. This result indicates an economically meaningful effect of the within-firm and time variation of biodiversity risk on stock returns.

4.1.1 Context matters: within- and across-firm and industry variation

Having established that biodiversity risk is related to returns, we next examine how this relation differs across levels of variation. To make the impacts of different levels of variance explicit, we decompose ln(Biodiversity Risk) into within-firm, within-industry, and across-industry terms. Table 2 shows the results of the regressions specified in equation 6, suppressing the results for the estimates for the control variables[12]. Firstly, we observe that the negative within-firm effect remains visible in this specification, alongside the within-industry and across-industry effects. This negative loading persists and is consistent across different fixed effects specifications. Namely, in the country × month-year fixed effects model in the last column (5), The estimated coefficient on ln(Biodiversity Risk)$^{within\ firm}$ is $\beta = \breve{}0.314$ ($SE = 0.057$), $p < 0.001$. Hence, a

[11] The standard deviation of the log-transformed biodiversity risk measure is 0.523, with firm + month-year fixed effects, is 0.523. See Table 14 in the Appendix for the summary statistics for all the within standard deviations across all the fixed effects specifications.

[12] The complete set of estimates for all variables, including the control variables, can be provided upon request.

one standard deviation increase in ln(Biodiversity Risk)$^{within\ firm}$ is associated with a decrease in monthly returns of $\breve{}0.314 \times 0.518^{13} \approx -0.163$ percentage points per month, translating to a 1.956 percentage points decrease in returns per year.

Secondly, we observe a positive *within-industry* effect which is consistent with the signs of specifications (3) to (6), but now is also significant. The coefficient on ln(Biodiversity Risk)$^{within\ industry}$ is $\beta = 0.070$ ($SE = 0.008$), $p < 0.001$. Therefore, a one standard deviation increase in ln(Biodiversity Risk)$^{within\ industry}$ is associated with an increase in monthly returns of $0.070 \times 1.856^{14} \approx +0.130$ percentage points per month, translating to a 1.56 percentage points increase in returns per year.

Thirdly, ln(Biodiversity Risk)$^{across\ industry}$ had a positive coefficient estimate, but was not found to be significantly different than zero. Thus, the across-industry variation in biodiversity risk does not appear to be a significant factor in explaining the variation in returns.

In summary, the within-firm, within-industry, and across-industry specifications enabled us to control for within-firm effects while observing the within-industry effects and vice versa, consistent with the earlier results in Table 1. This approach also yielded significant coefficient estimates for the within-industry effects. Given the magnitudes of these effects, the impact of within-firm and within-industry variation on returns is considered economically important. Several asset-pricing mechanisms could be at play. The adverse within-firm effect may reflect realized cash flow shocks, consistent with biodiversity risk materializing through higher costs or operational disruptions. By contrast, the positive within-industry relation is more consistent with an equilibrium effect: firms with higher biodiversity risk may be perceived as riskier, resulting in a biodiversity risk premium. These two patterns are not mutually exclusive. They may coexist, alongside the gradual pricing-in of biodiversity risk in discount rates, and cannot be fully disentangled from residual noise or mispricing. Taken together, the findings suggest that biodiversity risk is financially material, but its transmission into returns depends on whether risk is measured within firms or across industries: context matters.

4.1.2 Exploring sources of biodiversity risk effects

To better understand the sources of baseline effects, we decompose our biodiversity risk measure into its underlying components and examine their individual relations with returns. We dissect the aggregate measure and we run regressions of returns on the separate constituents of our biodiversity risk measure, each again with a within-firm, within-industry and across-industry specification. The results of these regressions are summarized in Table 3, where the control

[13]The within standard deviation of $\sigma = 0.518$ is specific to the fixed effect specification country $\times$ time, see Table 12.

[14]The standard deviation for ln(Biodiversity Risk)$^{within\ industry}$ with the country $\times$ time fixed effects is 1.856, see Table 12

variables were included in the model but suppressed from the results for readability. We will take the country × time fixed effect specification in the last column as our baseline result[15]

Firstly, for the within-firm effects, we observe both positive and negative loadings across the biodiversity risk drivers on returns. On the one hand, for Land/Water Pollutants, Air Pollutants, Waste, and GHG emissions, we observe a negative loading on returns, although the significance of this negative effect is most prominent for Air Pollutants ($p < 0.001$, and consistent across different fixed effects specifications), and significant for Waste ($p < 0.05$), weakly significant Land/Water Pollutants ($p < 0.10$), and not significant for GHG. These negative loadings have the same direction as the effect observed for the aggregate biodiversity risk measure. On the other hand, we observe a positive coefficient for Natural Resource Use and Water, with strong significance for Natural Resource Use ($p < 0.01$), and not significant for Water. Thus, there is reasonable evidence to believe that within-firm variation of Natural Resource Use is positively related to returns, whereas the within-firm variation on Air Pollutants, Waste and Land/Water Pollutants seems to be negatively related to returns.

Secondly, for the within-industry effects, we again observe both positive and negative effects. We observe negative effects for Water and GHG, but the negative effect on returns is only significant for Water ($p < 0.01$). Then, we observe positive effects for Natural Resource Use, Land/Water Pollutants and Waste, although these positive loadings on returns are only significant for Air Pollutants ($p < 0.001$) and for Waste ($p < 0.05$). Hence, we concluce the

Thirdly, for the across industry effects, for Natural Resource Use, Land/Water Pollutants, and Waste we observe a positive effect on returns, and for Water and Air Pollutants we observe a negative effect on returns, but only the for Land and Water Pollutants is the effect weakly significant ($p < 0.10$). For other fixed effects specifications, we do observe some significance for Water and Land/Water Pollutants, but the significance is not consistent across all specifications. Hence, we find at most limited evidence of positive associations of industry effects of Land/Water Pollutants and and negative associations of industry effects of Water.

Summing up the results from Table 3, we observe heterogeneity across the different drivers for the within-firm, the within-industry and the across industry effects. Interestingly, we observe that the effects by several biodiversity loss risk components that are different than the effects by GHG emissions, a result also found by Coqueret et al. (2025). How can these results help explain the effects observed in Table 2? In an attempt to investigate whether the negative within-firm effect of the aggregated biodiversity risk measure could have been materialization of transition risks, we now turn to analyzing the differences in policies that are in place for these drivers and examine theoretical implications of transition or physical risk.

One possible mechanism behind these heterogeneous effects of the biodiversity risk constituents is the extent to which each driver is subject to existing policy intervention. We in-

[15]The full set of coefficient estimate results and fit statistics can be provided upon request.

deed observe that policies extensively target some biodiversity loss drivers, while others remain largely unregulated. In the OECD PINE database, the domains “Mitigation”, “GHG”, “Fossil Fuels” (matching the GHG driver), “Air Pollution”, and “Waste” (matching the Waste driver) have substantially more policies globally. By contrast, the domains “Fresh water” (matching the Water driver), "Soil Pollution”, “Water Pollution” (matching the Land/Water Pollutants driver) and “Forests” and “Minerals” (matching the Natural Resource Use driver) (OECD, 2024)[16]. Therefore, exposures to air pollution, waste, and GHG transition risks may, on average, have already materialized, whereas natural resource use, land/water pollutants, and water appear less affected. The relative lack of policies in these domains suggests that firms may still be able to exploit natural resources at a minimal cost. Such exploitation could translate into positive cash flow shocks, consistent with the within- and across-firm effects we observe.

As a robustness check, we group the constituents into a transition risk versus physical risk category. We find that transition-related components (air and land/water pollutants, waste, GHG) replicate the main pattern of negative within-firm and positive within-industry effects (Table 16 in the Appendix). By contrast, physical-risk components (natural resource use and water) show only negative within-firm relations (Table 17 in the Appendix). These results suggest that the observed biodiversity risk premium is primarily driven by transition-related exposures, whereas physical risk is more consistently associated with cash flow effects.

While these decompositions shed light on where the effects originate, they do not address whether the strength of these relations depends on institutional or temporal context. We therefore next examine environmental policy and regional heterogeneity.

4.1.3 The moderating role of environmental policy

Understanding how national policies interact with firm-level biodiversity risk can shed light on whether these risks are priced and whether they depend on a firm’s headquarters location. In particular, stronger environmental policies might either mitigate biodiversity-related risks—by reducing the likelihood of disruptive regulatory changes—or amplify their relevance for investors, for example, when policy frameworks make biodiversity outcomes more transparent or enforceable. We assess whether measures of a country’s environmental performance moderate the relation between biodiversity risk and stock returns, focusing on the widely used Sustainable Development Goals (SDGs) and the Environmental Performance Index (EPI).

We start by analyzing the results of regressing returns on the countries’ SDG, the SDG14, and the SDG15 scores in relation to biodiversity risk, presented in Table 4 panels A, B, and C, respectively. We found no main effects of the SDG scores on the returns, except for SDG15, but this was not robust after controlling for time fixed effects. We observe significant and positive

[16]For each driver, we summed up the all (in)active instrument types of the relevant domains in the OECD PINE database.

interactions with SDG14 within-firm ($p < 0.01$) and within-industry ($p < 0.10$) contexts, as well as a positive significant interaction between SDG15 performance and the within-firm variance of biodiversity ($p < 0.05$). In contrast, we do not observe a significant interaction effect for the general SDG score. This makes sense: a nation's relative SDG performance is only relevant to the relation between biodiversity risk and returns, provided that the SDG score is specific to topics related to biodiversity.

After testing it with the SDG measures, we tried to disentangle transition risk from physical risk by using a different measure that is, supposedly, a more direct measure of (biodiversity) transition risk: the Environmental Policy Index (EPI) and its subscores Biodiversity Habitat and Ecosystem vitality Block et al. (2024). We included the results in the Appendix I.B in Table 15: we find positive signs for the interaction between the within-firm biodiversity risk and a country's EPI and negative (but effectively zero) signs for the interaction between the within-industry biodiversity risk and a country's EPI, but all of the interaction effects are not significant at at least 5% significance level.

How do we interpret these empirical results in light of a possible biodiversity risk premium for within-industry biodiversity risk? A risk premium hypothesis would pose that the coefficient on the interaction between the risk measure and the policy performance is negative, not positive. Namely, suppose SDG14 and SDG15 are suitable indicators of a nation's current performance and action on biodiversity-relevant goals. Then, firms headquartered in high SDG14 and SDG15 countries would be exposed to less transition and physical biodiversity risk than those in low SDG14 and SDG15 performance countries, because there is less policy uncertainty (transition risk) and, since the SDGs are also outcome-based, less damage to biodiversity (physical risk). Therefore, a biodiversity risk premium predicts lower returns for high biodiversity risk firms in countries that perform well on SDG14 and SDG15. Garel et al. (2024) observed evidence in favor of this mechanism, namely, they find that the risk premium is higher in countries with lower biodiversity protection, hence where higher uncertainty about future regulations is highest. We observe the opposite: a positive interaction effect, albeit small[17]. On the other hand, one could argue that the transition risk is actually *higher* in high SDG countries: maybe the expectation is that well-performing SDG countries will also impose more regulations in the future, too. In this scenario, one would expect a positive interaction effect between a country's SDG score and the firm's biodiversity risk - which is what we observe. Nonetheless, since the effect sizes are small, we cannot draw any definitive conclusions.

If the within-firm biodiversity risk effects on returns were indeed unexpected adverse cash flow effects, then within countries with high SDG scores, we see that negative cash flow effects are lower for firms. Intuitively speaking, this makes sense: in countries with high SDG scores,

[17]Nonetheless, different results may arise because Garel et al. (2024) uses a single time-invariant dummy for a country's EPI, whereas we use a time series of the EPI scores.

negative physical cash flow effects would be lower because biodiversity has not deteriorated to a critical level, dampening the negative financial costs. Negative transition cash flow effects would be lower because a firm knows what to expect in terms of shocks for a country with high SDG performance; lower SDG performance may indicate vague rules and inefficient regulation. Hence, SDG performance seems to mediate the negative unexpected cash flow. Since the effect sizes are larger than those for the within-industry effects, we interpret this result as corroborating the negative cash flow channel for within-firm biodiversity in risky firms.

Finally, we investigate whether policy heterogeneity becomes more pronounced when we transition from the national to the regional level. Using regions is admittedly a coarser approach, but it reduces dimensionality while still capturing meaningful institutional, regulatory, and cultural commonalities. Examining regions allows us to test whether differences in the biodiversity risk premium are systematically driven by regions where we assume that future regulation is more uncertain (such as North America, Asia, and the Southern Hemisphere) relative to regions where environmental policy is already more established (such as Europe). We therefore re-estimate the within- and across-firm and industry specifications by region. The results, presented in Table 5, indicate that the overall directional effects are consistent across regions and consistent with the results presented in Table 2. Nonetheless, the significance and size of the within-industry variation coefficients differ across regions, with larger coefficients in North America, Asia, and the Southern Hemisphere compared to Europe, for both within-industry and within-firm biodiversity risk. These findings provide evidence that regional policy contexts shape the extent to which biodiversity risk is reflected in returns. Moreover, the fact that a possible within-industry biodiversity risk premium is more pronounced outside of Europe is consistent with the idea that higher policy uncertainty strengthens the pricing of biodiversity risks. See the Appendix section I.B.5 for a more detailed discussion about the geographic distribution of the results.

4.1.4 Investor attention and biodiversity policy events

In addition to cross-sectional policy and regional factors, shifts in global attention to biodiversity may also influence how investors price biodiversity risk. We investigate whether the results in Table 2 depend on attention toward biodiversity loss or on a specific time period within our sample, further examining the risk premium and cash flow channels, as well as a potential attention shift channel. The results are displayed in Table 18 in Appendix section I.B.7. We find that in the latter part of our sample, returns are higher across all aggregat ion levels of biodiversity risk. Thus, these results are consistent with a biodiversity risk premium. After key attention-shifting events such as the Kunming Declaration, the TNFD launch, and the Paris Agreement, high-biodiversity-risk firms earn higher returns, suggesting that investors demand compensation for this risk. These patterns are difficult to reconcile with a pure cash-flow channel, which would predict lower—not higher—returns post-event. While we cannot fully rule out cash-

flow effects, our evidence aligns more strongly with a biodiversity risk premium. Moreover, the results of does not support the thesis of a shift in investors' preferences over time. If investors shift their funds to firms with less biodiversity risk, one would expect to observe lower returns over time for firms with a larger biodiversity risk; we observe higher returns over time.

4.1.5 Biodiversity risk and profitability (unexpected cash flow channel)

The preceding analyses focus on return patterns. To assess whether these effects on returns reflect pricing effects or realized cash-flow shocks, we next analyze biodiversity risk in relation to firm-level profitability. The results of specifications in profitability regressions are summarized in Table 6. The control variables are suppressed to provide a concise summary[18]. We will first investigate the within-firm biodiversity risk variation, then the within-industry biodiversity risk, and then finally the across industry biodiversity risk.

The within-firm variance effect of ln(Biodiversity Risk) on ROA_t, ΔROA_{t+1}, $\overline{ROA}_{t+10:t+1}$ are found the first rows of each block in Table 6. We find that the within-firm variance on biodiversity risk loads *negatively* on contemporaneous profitability ($p < 0.05$, although the significance disappears in the country × year fixed effects specification). Moreover, the biodiversity risk also loads negatively on the short-term future and long-term future ROA ($p < 0.001$). This could mean that the within-firm increase in biodiversity risk causes a negative cash flow effect, possibly through materialization of the biodiversity risk. This effect is powerful for the short-term future: a one-standard deviation in ln(Biodiversity Risk)$_t^{within-firm}$ decreases the ROA by -0.007.[19] This effect is consistent with the results from Table 2, and suggests that there is not a within-firm biodiversity risk premium pricing in effect, but rather a within-firm realized cash flow effect of biodiversity risk.

Next, we analyze the within-industry variation. Each second row of each block in Table 6 shows the effect of the within-industry variation on biodiversity risk on the different ROA variables. We observe a positive loading of the within-industry variation of biodiversity risk on ROA_t, ΔROA_{t+1}, $\overline{ROA}_{t+10:t+1}$, all $p < 0.001$. This result is robust across all fixed effects specifications. For example, for the contemporaneous ROA_t, a one standard deviation in $ln(Biodiversity\ Risk)^{within\ ind}$ increases the ROA_t ratio by 0.006. Moreover, a one standard deviation in $ln(Biodiversity\ Risk)^{within\ ind}$ increases the difference in ROA ratio of year *t+1* compared to *t*, ΔROA_{t+1}, by 0.009. These results suggest that if a firm i has a higher biodiversity risk in year t compared to another firm j in the same industry, that it is more profitable in the current period, short term future and long term future, possibly through a positive cash flow effect in the short term. This is a puzzling result, since we did not expect *ex-ante* that a

[18]The full Tables with all coefficient estimates and regression results can be provided upon request.

[19]Since we normalized the independent variables, the coefficients show the change in ROA per one standard deviation change in the independent variable.

firm would have been more profitable if the biodiversity risk was higher. A possible explanation of these results is that these firms could *exploit* the natural resources more than others to their advantage, pointing towards a positive cash flow effect rather than a risk premium. It is important to notice the difference between the within-firm and within-industry variation here: when these firms have a within-firm increase, that they would still feel the impacts of the realization of the costs of policies, but could still have a relative advantage compared to other firms in the same industry. Possibly, policies would then be effective for within-firm changes, but would not motivate a firm to become more efficient in terms of biodiversity risk compared to peers.

Finally, we analyze the effects of across industry variation of biodiversity risk on ROA. In every third row of each block in Table 6 we see that an industry with an on average higher biodiversity risk has a positive effect on contemporaneous and short term ROA, and a negative long future ROA, although only the the effects on the contemporaneous ROA are consistently significant ($p < 0.001$). This result suggests that the across industry variation in biodiversity risk is positively related to profitability, but only in the short term and not long term profitability. This short term positive cash flow effect suggests that some industries on average might profit from exploiting nature, but this does not seem to hold on the long run.

We also split this ROA analysis for separate geographic regions. The results for these separate geographic regions can be found in the Internet Appendix Section I.B.9. In short, we find heterogeneous results across regions for the within-firm and within-industry effects on contemporaneous, short-term future and long-term future ROA. Although the effects are consistent in terms of sign when comparing them to the main effects on profitability as in Table 6, the coefficient sizes does differ across regions. The biodiversity risk of European firms exhibit more muted and often insignificant effects compared to firms from other regions. North America is an outlier in terms of its within-firm effects being *positive* rather than negative. Moreover, North American firms exhibit the strongest negative short- and long-term within-firm effects on ROA compared to other regions, and has a generally large within-industry positive effects all ROA horizons. The Southern Hemisphere firms generally have larger magnitudes than the general effects, especially in within-industry effects. Lastly, firms in Asia show the strongest negative contemporaneous within-firm effects, such that the difference between North America and Asia is largest. Therefore, only for North America is the negative within-firm biodiversity risk effect on returns not explained by the direction of the contemporaneous cash-flow effects; for all other regions, this would still be a possible economic channel. The positive return effects are still consistent with short term and long term future cash flow effects across all regions, but some regions are more pronounced than others.

4.2 Does spatial biodiversity risk lead to higher returns?

The previous analyses rely on firm-level Trucost data based on headquarters location. We complement these findings by running regressions of returns on the asset- and geospatial-based biodiversity risk scores. By doing so, we aim to directly capture local biodiversity exposure. Different specifications and combinations for r and g in Spatial Biodiversity Risk^{r,g} were tested, and summarized in Table 7. The coefficients reported in this table represent the marginal effect of increasing the count of that asset type per million USD of total assets on the firm's monthly return, holding other factors and fixed effects constant[20].

We first examine the biodiversity risk based on assets that could either be transition risk or physical risk, or both (namely, $r = TR|PR$), and that are located inside relevant biodiversity loss risk areas ($g = \{KBA, PA, CNA\}$). The results are displayed in the first three rows of Table 7. Across different fixed effects specifications in columns (1)-(6), we show that the asset- and geospatial-based biodiversity risk has a positive and significant relation with returns. For example, taking the industry × month-year and country × month-year fixed effects specification in column (6), a 1-unit increase in the number of risky assets inside KBA regions per \$1 million in total assets is associated with a $\beta = 1.126$ percentage points higher monthly stock return, ceteris paribus ($p < 0.01$). The corresponding one standard deviation increase in the Spatial Biodiversity Risk measure corresponds with a 0.103 percentage point increase in monthly returns, hence a 1.236 percentage point increase in annualized returns[21].

For the PA and CNA areas, the effects are smaller, but still positive and significant. For either transition or physical risky assets, a 1-unit increase in risky assets per 1 million total assets in a PA region would translate to a $\beta = 0.342$ percentage points higher monthly stock return, ceteris paribus ($p < 0.05$); a one standard deviation increase in risky assets per 1 million total assets in a PA region would translate to a 0.546 annualized effect on returns[22]. Again for either transition or physical risky assets, a 1-unit increase in risky assets per 1 million total assets in a CNA region would translate to a $\beta = 0.322$ percentage points higher monthly stock return, ceteris paribus ($p < 0.05$); a one standard deviation increase in risky assets per 1 million total assets in a CNA region would translate to a 1.164 annualized effect on returns. Notably, we observe that the effects of risky assets within PA areas are overall less significant than in the other areas, also for transition risk type assets, and both (although still significant and positive). The strongest effects in terms of significance come from the KBA and CNA areas, regardless of

[20]The full set of results, including all the coefficients for the controls and all the fit statistics, can be provided upon request.

[21]See Table 12 in the Internet Appendix I.B.3 for all within fixed effects standard deviations of Spatial Biodiversity Risk^{r,g} , that are then multiplied by the corresponding β to create the 1 standard deviation effect.

[22]See Table 12 in the Internet Appendix I.B.3 the within standard deviations of Spatial Biodiversity Risk^{r,g}.

the asset type r. Moreover, compared to other areas, $g = KBA$ areas have the *largest* coefficient, irrespective of the asset type r[23].

Comparing the results across the different asset risk types ($r = TR$ transition risk in the second block of rows, $r = PR$ physical risk in the third block of rows, or both $r = TR|PR$ in the first block of rows) for the same biodiversity risk relevant areas ($g = KBA$, $g = PA$, or $g = CNA$), the coefficients and their significance are very similar; the only notable difference is that for the physical risk asset type $r = PR$ and $g = PA$ combination, where the coefficient estimates are no longer significant. This result matches the intuition that PA areas are mostly transition risk relevant, since they denote protected areas specifically, and are less physical risk relevant. Overall, combined with any area g, risk types $r = TR|PR$ and $r = TR$ produce the larger effects than risk type $r = PR$.

Overall, the evidence suggests that an asset- and geospatial-based biodiversity risk is positively correlated with stock returns. The strongest and most pronounced effects are observed for risky assets located within Key Biodiversity Areas, followed by those in Critical Natural Assets areas, where the effects remain highly significant but smaller in magnitude. Results for Protected Areas are weaker and seem to be confined to transition-risk relevant assets. Transition risk exposures generally exhibit stronger and more robust effects than physical risk exposures, although both dimensions are relevant. Taken together, these findings indicate that investors demand compensation for holding risky assets exposed to biodiversity-risky areas, with effect sizes that are economically meaningful and robust across specifications, thereby providing evidence in favor of a biodiversity risk premium. Importantly, these results demonstrate that a *local* biodiversity risk measure—aggregated from the asset and geospatial levels to the firm level—provides meaningful explanatory power in addition to the biodiversity firm-level risk measures.

5 Conclusion

We investigate whether firm-level biodiversity risk is priced in global equity markets by examining stock returns in relation to biodiversity risk exposures for a large sample of firms worldwide. We measure firm-level biodiversity risk exposure in two ways. First, we use environmental data

[23]We also run several modifications to the asset- and geospatial-based biodiversity-returns regressions to test robustness. For instance, when we define a risky asset as being *near* the biodiversity risk relevant areas instead of inside (so within 1 km of the biodiversity risk areas), then the results of these regressions have the same directional effect, but have generally smaller effects. The total effect size is smaller for KBA and CNA, and the results for PA stay the same, although the significance disappears. Moreover, if we take the log of the normalized count variable instead of the level variable, then the results observe that the direction of the results are still positive, yet the coefficients are overall slightly smaller in size and less significant. Possibly, the effects of the level regressions could be driven by some outliers, but the conclusions we draw from them are the same in terms of direction and significance. Tables with these robustness tests can be reviewed in Internet Appendix I.B.10.

by S&P Trucost and use the IPBES framework to create a firm-level biodiversity risk measure, covering 12,288 firms across 58 countries over 2009–2022. Second, we construct an asset- and geospatial biodiversity data measure for each firm. Our analysis highlights four central findings.

Our results yield four main insights. First, within-firm increases in biodiversity risk are associated with lower returns and profitability, consistent with negative cash-flow effects, while within-industry variation is positively related to both returns and profitability, consistent with a biodiversity risk premium among peers. Second, the spatially sensitive measures confirm that firms with assets exposed to biodiversity-risky areas earn higher returns, reinforcing that spatial context matters and providing additional support for a between-firm biodiversity risk premium. Third, in the context of a country's environmental (policy) performance, we find weak evidence in favor of a risk premium. Regional patterns in the relationship between biodiversity risk and returns show stronger within-industry effects outside Europe, consistent with higher policy uncertainty driving pricing. Fourth, analyses of the individual drivers indicate heterogeneous effects, suggesting distinct regulatory exposures and risk materialization across the transition and physical risk components. Fifth, biodiversity risk appears more priced in periods of heightened investor attention—returns to within-industry risk exposures are stronger after salient biodiversity events, although magnitudes are small.

These results contribute to the emerging literature on biodiversity asset pricing. According to Garel et al. (2024), while no significant impact of biodiversity on asset returns was observed between 2019 and 2022, firms with substantial biodiversity footprints following the Kunming Declaration in October 2021 experienced higher realized returns. Giglio et al. (2025) found that the returns of portfolios categorized by firms' exposure to biodiversity risk covary with an aggregate measure of biodiversity risk news. Coqueret et al. (2025) show that firms with higher biodiversity footprints experience an increased cost of capital, especially within sectors that are significantly exposed to the double materiality of biodiversity risks. Compared to these studies, our results provide a more differentiated picture. We find that biodiversity risk is associated with lower returns and profitability when measured within firms, but with higher returns and profitability when measured within industries. Thus, while earlier work suggests a possible biodiversity premium between firms, albeit under certain conditions, our analysis reveals that the sign of the relation depends on how biodiversity risk is defined and measured. Moreover, our analysis with the spatial biodiversity risk measure corroborates the existence of a between-firm biodiversity risk premium.

Furthermore, our study contributes to the literature in four ways. First, we introduce multiple dimensions of variance, allowing for a more nuanced assessment of how investors may price biodiversity risk. This approach demonstrates that conclusions depend on whether variation is measured within firms, within industries, or across industries, providing a different perspective than the current literature, which primarily focuses on between-firm differences. Second,

we propose a biodiversity risk measure based on the IPBES framework that is both tractable and grounded in environmental science, capturing firms' impact and dependency. This measure is also decomposable into its different components, and we show how different constituents of biodiversity risk can have heterogeneous financial effects. Third, our large global panel enables broader generalization than previous studies, with greater cross-sectional and temporal coverage. Fourth, we add a spatial dimension by linking firms' assets to Key Biodiversity Areas, Protected Areas, and Critical Natural Assets. While our asset- and geospatial-based measure lacks time-series variation in asset exposures, it provides novel evidence that complements firm-level measurements and identifies biodiversity loss risk more specifically.

In conclusion, our evidence suggests that biodiversity risk influences financial markets through a combination of realized cash flow impacts and risk premiums, with the relation depending on how biodiversity risk is measured. Future research should disentangle these mechanisms more precisely. Promising directions include analyses of earnings calls and disclosures to separate cash flow from pricing channels, case studies with asset-level data and local biodiversity conditions, and comparisons across alternative biodiversity risk metrics such as commercial biodiversity datasets. Given the complexity of biodiversity loss, further research at multiple levels of variance—within firms, across industries, within and across regions— and spatial measures can improve our understanding of how nature-related risks are transmitted to financial markets.

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Table 1—*Results of panel regressions of monthly stock returns on ln(Biodiversity Risk), the natural logarithm of firm-level environmental costs (in million USD) linked to biodiversity risk. Columns (1)–(2) report results without fixed effects; Columns (3)–(4) add industry, month–year, and country fixed effects; Columns (5)–(6) include interactions of industry or country with month–year fixed effects. Columns (7)-(8) include the firm + month-year fixed effects. Odd-numbered columns control for Beta, Size, B/M, Investments, and Momentum; even-numbered columns add Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE. Standard errors are clustered by firm and year.*

Dependent Variable:	Returns (%)							
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables								
ln(Biodiversity Risk)	0.029	0.036	0.042	0.048	0.027	0.026	-0.150**	-0.164**
	(0.041)	(0.033)	(0.032)	(0.024)	(0.033)	(0.024)	(0.038)	(0.043)
Beta	0.458	0.097	0.201	0.119	0.221	0.241	0.241	0.136
	(0.394)	(0.262)	(0.391)	(0.363)	(0.405)	(0.403)	(0.406)	(0.420)
Size	0.011	0.106	-0.047	-0.022	-0.022	-0.024	-1.969***	-1.799***
	(0.096)	(0.072)	(0.040)	(0.034)	(0.046)	(0.039)	(0.183)	(0.157)
B/M	0.119	0.221	0.105	0.130	0.080	0.083	0.396**	0.496**
	(0.183)	(0.135)	(0.105)	(0.088)	(0.102)	(0.087)	(0.122)	(0.150)
Investments	-1.046*	-0.938*	-0.717*	-0.539	-0.502	-0.377	-0.716**	-0.403**
	(0.401)	(0.426)	(0.321)	(0.312)	(0.246)	(0.248)	(0.194)	(0.117)
Momentum	0.156	-0.138	0.046	-0.030	0.117	0.139	-0.911*	-1.064**
	(0.310)	(0.415)	(0.153)	(0.193)	(0.138)	(0.145)	(0.310)	(0.304)
Volatility		10.866		2.429		-0.791		3.605
		(6.449)		(2.308)		(1.690)		(2.391)
Leverage		-0.199		-0.219		-0.124		0.169
		(0.224)		(0.136)		(0.148)		(0.518)
Tangibility		-0.242		0.280		0.247		0.706
		(0.296)		(0.153)		(0.145)		(0.432)
R&D		1.216		1.577		1.111		9.308*
		(2.308)		(1.641)		(1.387)		(3.110)
INV/A		1.711		-0.838		0.010		-2.125
		(1.697)		(0.899)		(0.560)		(1.509)
Sales Growth		-0.558		-0.313		-0.212*		-0.307
		(0.313)		(0.154)		(0.097)		(0.169)
Return On Equity (ROE)		0.680		-0.317		-0.312		-1.291***
		(0.348)		(0.212)		(0.173)		(0.292)
Fixed-effects								
Industry			Yes	Yes				
Month			Yes	Yes			Yes	Yes
Country			Yes	Yes				
Industry-Month					Yes	Yes		
Country-Month					Yes	Yes		
Firm							Yes	Yes
Fit statistics								
Observations	880,255	874,052	880,255	874,052	880,255	874,052	880,255	874,052
R^2	0.002	0.004	0.155	0.155	0.293	0.294	0.173	0.173
Within R^2			0.001	0.001	0.000	0.001	0.007	0.008

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

Table 2—*Results of panel regressions of monthly stock returns on the within-firm, within-industry, and across-industry variation of ln(Biodiversity Risk), the natural logarithm of firm-level costs (in million USD) linked to biodiversity risk. For the across- and within-firm variation, we define ln(Biodiversity Risk)$^{across\ industry}_{t,j}$ as the average of ln(Biodiversity Risk) of all firms in industry extitj in time extitt, and ln(Biodiversity Risk)$^{within\ industry}_{i,j,t}$ = ln(Biodiversity Risk)$_{i,t}$ − ln(Biodiversity Risk)$^{across\ industry}_{t,j}$. Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) includes interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.269*	-0.300***	-0.282*	-0.309***	-0.314***
	(0.114)	(0.068)	(0.108)	(0.062)	(0.057)
ln(Biodiversity Risk)$^{within\ ind}$	0.033	0.066***	0.050	0.077***	0.070***
	(0.056)	(0.009)	(0.047)	(0.005)	(0.008)
ln(Biodiversity Risk)$^{across\ ind}$	0.068	0.010	0.090	0.030	0.029
	(0.070)	(0.033)	(0.065)	(0.027)	(0.026)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Month-Year		Yes		Yes	
Country			Yes	Yes	
Country-Month-Year					Yes
Fit statistics					
R-squared	0.004	0.155	0.004	0.155	0.253
Within R-squared	NA	0.001	0.004	0.001	0.001
Observations	874052	874052	874052	874052	874052

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

Table 3— *Results of panel regressions of monthly stock returns on the within-firm, within-industry, and across-industry variation of the separate drivers of ln(Biodiversity Risk), the natural logarithm of firm-level costs (in million USD) linked to biodiversity risk. The drivers are Natural Resource Use, Water, Land/Water Pollutants, Air Pollutants, Waste, and GHG. Each driver is given as the natural logarithm of firm-level environmental costs (in million USD). Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) includes interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Variable	(1)	(2)	(3)	(4)	(5)
ln(Natural Resource Use)$^{within\ firm}$	0.042	0.051*	0.041·	0.049**	0.048**
	(0.025)	(0.017)	(0.023)	(0.015)	(0.016)
ln(Natural Resource Use)$^{within\ ind}$	0.002	0.007	0.004	0.008	0.008
	(0.015)	(0.015)	(0.014)	(0.014)	(0.014)
ln(Natural Resource Use)$^{across\ ind}$	-0.026	0.010	-0.037	-0.004	0.007
	(0.063)	(0.056)	(0.058)	(0.053)	(0.051)
ln(Water)$^{within\ firm}$	0.029	0.018	0.022	0.013	0.008
	(0.017)	(0.010)	(0.017)	(0.012)	(0.011)
ln(Water)$^{within\ ind}$	-0.020**	-0.018**	-0.013**	-0.013**	-0.012**
	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)
ln(Water)$^{across\ ind}$	-0.078*	-0.037*	-0.069*	-0.035*	-0.029
	(0.027)	(0.015)	(0.028)	(0.016)	(0.016)
ln(Land/Water pollutants)$^{within\ firm}$	-0.027	-0.022·	-0.029	-0.024*	-0.021
	(0.020)	(0.011)	(0.021)	(0.011)	(0.013)
ln(Land/Water pollutants)$^{within\ ind}$	0.001	-0.002	0.004	0.000	0.000
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
ln(Land/Water pollutants)$^{across\ ind}$	0.073**	0.044·	0.066**	0.041*	0.034·
	(0.019)	(0.021)	(0.019)	(0.018)	(0.017)
ln(Air pollutants)$^{within\ firm}$	-0.156**	-0.214***	-0.153**	-0.214***	-0.210***
	(0.044)	(0.034)	(0.044)	(0.034)	(0.023)
ln(Air pollutants)$^{within\ ind}$	0.071**	0.091***	0.068**	0.092***	0.093***
	(0.019)	(0.016)	(0.021)	(0.018)	(0.015)
ln(Air pollutants)$^{across\ ind}$	-0.036	-0.087	-0.006	-0.054	-0.069

Table 3 (continued)

Variable	(1)	(2)	(3)	(4)	(5)
	(0.106)	(0.086)	(0.107)	(0.089)	(0.085)
$\ln(\text{Waste})^{within\ firm}$	-0.039	-0.044	-0.043·	-0.047·	-0.047*
	(0.029)	(0.026)	(0.023)	(0.022)	(0.021)
$\ln(\text{Waste})^{within\ ind}$	0.029	0.033*	0.034·	0.036*	0.031*
	(0.023)	(0.013)	(0.017)	(0.013)	(0.011)
$\ln(\text{Waste})^{across\ ind}$	0.199	-0.004	0.211	0.024	0.015
	(0.152)	(0.044)	(0.149)	(0.045)	(0.043)
$\ln(\text{GHG})^{within\ firm}$	-0.087	-0.068	-0.083	-0.062	-0.066
	(0.062)	(0.044)	(0.055)	(0.049)	(0.045)
$\ln(\text{GHG})^{within\ ind}$	-0.023	-0.025	-0.026	-0.031	-0.035·
	(0.034)	(0.016)	(0.030)	(0.022)	(0.019)
$\ln(\text{GHG})^{across\ ind}$	0.054	0.111	0.032	0.084	0.098
	(0.109)	(0.083)	(0.114)	(0.090)	(0.084)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Month-Year		Yes		Yes	
Country			Yes	Yes	
Country-Month-Year					Yes
Fit statistics					
R-squared	0.004	0.155	0.005	0.155	0.254
Within R-squared	NA	0.001	0.004	0.001	0.001
Observations	874008	874008	874008	874008	874008

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

Table 4— *Results of panel regressions of monthly stock returns on the within-firm, within-industry and across-industry variation of ln(Biodiversity Risk), the natural logarithm of firm-level costs (in million USD) linked to biodiversity risk. We interact ln(Biodiversity Risk) with three alternative time-varying measures of the firm's headquarters country environmental (policy) performance: Sustainable Development Goal (SDG) index (panel A), SDG 14 Life Below Water (panel B), and SDG 15 Life on Land (panel C). Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) includes interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Panel A: SDG (general)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-1.022	-0.391	-0.566	-0.571	-0.690
	(0.904)	(0.602)	(0.713)	(0.550)	(0.450)
ln(Biodiversity Risk)$^{within\ ind}$	0.172	0.203	0.079	0.056	0.129
	(0.221)	(0.227)	(0.250)	(0.236)	(0.234)
ln(Biodiversity Risk)$^{across\ ind}$	-0.283	-0.414	-0.284	-0.137	0.112
	(0.281)	(0.252)	(0.357)	(0.202)	(0.150)
Country SDG	-0.018	-0.025	-0.117	0.136	0.016
	(0.025)	(0.023)	(0.247)	(0.101)	(0.015)
ln(Biodiversity Risk)$^{within\ firm}\times$ SDG	0.011	0.002	0.004	0.004	0.005
	(0.012)	(0.008)	(0.010)	(0.007)	(0.006)
ln(Biodiversity Risk)$^{within\ ind}\times$ SDG	-0.002	-0.002	-0.000	0.000	-0.001
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)
ln(Biodiversity Risk)$^{across\ ind}\times$ SDG	0.005	0.006	0.005	0.002	-0.001
	(0.004)	(0.003)	(0.005)	(0.003)	(0.002)

Panel B: SDG 14 Life Below Water

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.770	-0.673*	-0.758*	-0.608*	-0.892***
	(0.489)	(0.240)	(0.349)	(0.221)	(0.204)

Table 4 (continued)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ ind}$	-0.064	-0.032	-0.047	-0.046	-0.085
	(0.054)	(0.066)	(0.113)	(0.110)	(0.085)
ln(Biodiversity Risk)$^{across\ ind}$	0.196	-0.019	0.070	-0.170	-0.117
	(0.184)	(0.188)	(0.184)	(0.168)	(0.107)
Country SDG14	0.021	0.010	0.036	0.010	-0.001
	(0.018)	(0.009)	(0.116)	(0.038)	(0.033)
ln(Biodiversity Risk)$^{within\ firm}\times$ SDG14	0.008	0.006·	0.008	0.005	0.010**
	(0.006)	(0.003)	(0.005)	(0.003)	(0.003)
ln(Biodiversity Risk)$^{within\ ind}\times$ SDG14	0.001	0.002	0.001	0.002	0.003·
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
ln(Biodiversity Risk)$^{across\ ind}\times$ SDG14	-0.002	0.000	0.000	0.003	0.002
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)

Panel C: SDG 15 Life on Land

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.636·	-0.505*	-0.581	-0.453*	-0.545**
	(0.350)	(0.174)	(0.342)	(0.179)	(0.141)
ln(Biodiversity Risk)$^{within\ ind}$	0.187**	0.179**	0.169·	0.122	0.117
	(0.051)	(0.046)	(0.082)	(0.075)	(0.074)
ln(Biodiversity Risk)$^{across\ ind}$	-0.073	-0.114	-0.000	-0.057	0.046
	(0.097)	(0.078)	(0.094)	(0.080)	(0.067)
Country SDG15	-0.008	-0.009	-0.195*	-0.021	-0.004
	(0.008)	(0.007)	(0.086)	(0.018)	(0.013)
ln(Biodiversity Risk)$^{within\ firm}\times$ SDG15	0.007	0.004	0.005	0.003	0.004*
	(0.005)	(0.002)	(0.004)	(0.002)	(0.002)
ln(Biodiversity Risk)$^{within\ ind}\times$ SDG15	-0.003*	-0.002*	-0.002	-0.001	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
ln(Biodiversity Risk)$^{across\ ind}\times$ SDG15	0.002·	0.002	0.001	0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

Table 5—*Results of panel regressions of monthly stock returns on the within-firm, within-industry, and across-industry variation of ln(Biodiversity Risk), the natural logarithm of firm-level costs (in million USD) linked to biodiversity risk, using different samples of our data based on geographic regions. Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) include interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Region	Variable	(1)	(2)	(3)	(4)	(5)
North America	ln(Biodiversity Risk)$^{within\ firm}$	-0.425·	-0.404**	-0.422·	-0.402**	-0.403**
		(0.200)	(0.121)	(0.201)	(0.122)	(0.122)
	ln(Biodiversity Risk)$^{within\ ind}$	0.081	0.125*	0.079	0.123*	0.122*
		(0.055)	(0.046)	(0.056)	(0.048)	(0.048)
	ln(Biodiversity Risk)$^{across\ ind}$	0.138·	0.060·	0.142*	0.064·	0.064·
		(0.065)	(0.032)	(0.064)	(0.033)	(0.033)
Europe	ln(Biodiversity Risk)$^{within\ firm}$	-0.145	-0.199*	-0.158	-0.208**	-0.223**
		(0.118)	(0.069)	(0.116)	(0.066)	(0.071)
	ln(Biodiversity Risk)$^{within\ ind}$	-0.010	0.021	0.005	0.031	0.024
		(0.060)	(0.032)	(0.059)	(0.031)	(0.030)
	ln(Biodiversity Risk)$^{across\ ind}$	0.079	0.004	0.090	0.012	0.007
		(0.081)	(0.037)	(0.081)	(0.036)	(0.034)
Asia	ln(Biodiversity Risk)$^{within\ firm}$	-0.290·	-0.336**	-0.285·	-0.329***	-0.342***
		(0.157)	(0.082)	(0.145)	(0.072)	(0.071)
	ln(Biodiversity Risk)$^{within\ ind}$	0.034	0.063*	0.028	0.057*	0.053*
		(0.063)	(0.026)	(0.055)	(0.024)	(0.025)
	ln(Biodiversity Risk)$^{across\ ind}$	0.084	0.041	0.068	0.019	0.019
		(0.054)	(0.039)	(0.050)	(0.034)	(0.036)
Southern Hemisphere	ln(Biodiversity Risk)$^{within\ firm}$	-0.292*	-0.155	-0.336*	-0.189·	-0.170
		(0.128)	(0.107)	(0.126)	(0.105)	(0.124)
	ln(Biodiversity Risk)$^{within\ ind}$	0.038	0.035	0.070	0.054*	0.056·
		(0.057)	(0.038)	(0.058)	(0.025)	(0.027)
	ln(Biodiversity Risk)$^{across\ ind}$	-0.014	-0.007	0.026	0.016	0.023
		(0.057)	(0.041)	(0.055)	(0.041)	(0.038)
	Controls	Yes	Yes	Yes	Yes	Yes
	Fixed-effects					
	Month-Year		Yes		Yes	
	Country			Yes	Yes	
	Country-Month-Year					Yes

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

Table 6—*Overview of Regression Results for Different specifications Profitability (ROA) analysis on within firm and within and across industry ln(Biodiversity Risk), the natural logarithm of firm-level costs (in million USD) linked to biodiversity risk. In the first three rows, we use contemporaneous ROA_t as the dependent variable; in the next three rows, we use ΔROA_{t+1} as the dependent variable; in the last rows, we use the moving average $\overline{ROA}_{t+10:t+1}$ as the dependent variable. Column (1) reports results without fixed effects; Column (2) adds fiscal year fixed effects; Column (3) adds fiscal year and country fixed effects; Column (4) includes interactions of country with fiscal year fixed effects. All the regressions control for Size, B/M, Leverage, Tangibility, R&D, INV/A, Sales Growth, and Operating Profitability, but the coefficients for these control variables were suppressed in the table for brevity. For the regressions with ROA_t we also include the persistence of the dependent variable as a control variable, namely, ROA_{t-1}. For the regressions with $\overline{ROA}_{t+10:t+1}$ as the dependent variable we also include the ROA_t and ΔROA_{t+1} as control variables. Standard errors are clustered by firm.*

Dep. Variable	Independent Variables	(1)	(2)	(3)	(4)
ROA_t	ln(Biodiversity Risk)$^{within\ firm}$	-0.000	-0.001·	-0.001	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)
	ln(Biodiversity Risk)$^{within\ ind}$	0.007***	0.007***	0.006***	0.006***
		(0.001)	(0.001)	(0.001)	(0.001)
	ln(Biodiversity Risk)$^{across\ ind}$	0.004***	0.004***	0.004***	0.004***
		(0.000)	(0.000)	(0.000)	(0.000)
ΔROA_{t+1}	ln(Biodiversity Risk)$^{within\ firm}$	-0.008***	-0.007***	-0.007***	-0.007***
		(0.000)	(0.000)	(0.000)	(0.000)
	ln(Biodiversity Risk)$^{within\ ind}$	0.009***	0.008***	0.009***	0.009***
		(0.000)	(0.000)	(0.000)	(0.000)
	ln(Biodiversity Risk)$^{across\ ind}$	0.003***	0.002***	0.002***	0.002***
		(0.000)	(0.000)	(0.000)	(0.000)
$\overline{ROA}_{t+10:t+1}$	ln(Biodiversity Risk)$^{within\ firm}$	-0.005***	-0.005***	-0.005***	-0.005***
		(0.001)	(0.001)	(0.001)	(0.001)
	ln(Biodiversity Risk)$^{within\ ind}$	0.006***	0.006***	0.006***	0.006***
		(0.002)	(0.002)	(0.002)	(0.002)
	ln(Biodiversity Risk)$^{across\ ind}$	-0.002**	-0.002**	-0.002*	-0.002*
		(0.001)	(0.001)	(0.001)	(0.001)
Controls		Yes	Yes	Yes	Yes
Fixed-effects					
Fiscal Year			Yes	Yes	
Country				Yes	
Fiscal Year - Country					Yes

Note 1: Clustered (gvkey) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

Table 7—*Asset-geospatial Biodiversity Risk and Returns. This table summarizes the results of panel regressions of firm-level monthly returns (%) on Spatial Biodiversity Risk*$^{r,g}_{i,t}$*, the asset- and geospatial-based measure of biodiversity risk for firm i at time t, for different fixed effects and controls specifications. Each horizontal block (row) reflects a separate regression using a different measure of spatial biodiversity risk. Within each row, the six columns report coefficient estimates from six distinct model specifications that differ in their fixed effects and control-variable sets. Columns (1)–(2) report results without fixed effects; Columns (3)–(4) add industry, month–year, and country fixed effects; Columns (5)–(6) include interactions of industry or country with month–year fixed effects. Odd-numbered columns control for Beta, Size, B/M, Investments, and Momentum; even-numbered columns add Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE. The coefficients of these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Dependent Variable:			Returns (%)			
Indep. Var: Spatial Biodiversity Risk^{r,g}	(1)	(2)	(3)	(4)	(5)	(6)
Spatial Biodiversity Risk$^{TR\|PR,\ KBA}$	1.438***	1.030***	1.290**	1.110***	1.287**	1.126**
	(0.370)	(0.166)	(0.346)	(0.288)	(0.353)	(0.333)
Spatial Biodiversity Risk$^{TR\|PR,\ PA}$	0.701*	0.364***	0.587*	0.346	0.534*	0.342*
	(0.255)	(0.085)	(0.210)	(0.174)	(0.197)	(0.161)
Spatial Biodiversity Risk$^{TR\|PR,\ CNA}$	0.411**	0.281***	0.372**	0.328***	0.352**	0.322**
	(0.126)	(0.047)	(0.100)	(0.064)	(0.102)	(0.096)
Spatial Biodiversity Risk$^{TR,\ KBA}$	1.438***	1.030***	1.290**	1.110***	1.287**	1.126**
	(0.370)	(0.166)	(0.346)	(0.288)	(0.353)	(0.333)
Spatial Biodiversity Risk$^{TR,\ PA}$	0.701*	0.364***	0.587*	0.346	0.534*	0.342*
	(0.255)	(0.085)	(0.210)	(0.174)	(0.197)	(0.161)
Spatial Biodiversity Risk$^{TR,\ CNA}$	0.411**	0.281***	0.372**	0.328***	0.352**	0.322**
	(0.126)	(0.047)	(0.100)	(0.064)	(0.102)	(0.096)
Spatial Biodiversity Risk$^{PR,\ KBA}$	1.406***	1.003***	1.226***	1.033***	1.202***	1.026**
	(0.342)	(0.204)	(0.296)	(0.247)	(0.306)	(0.303)
Spatial Biodiversity Risk$^{PR,\ PA}$	0.711*	0.372***	0.592*	0.350	0.534*	0.339
	(0.258)	(0.083)	(0.211)	(0.173)	(0.199)	(0.166)
Spatial Biodiversity Risk$^{PR,\ CNA}$	0.391**	0.256**	0.345**	0.292***	0.326**	0.286**
	(0.137)	(0.088)	(0.104)	(0.063)	(0.105)	(0.097)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Industry			Yes	Yes		
Month			Yes	Yes		
Country			Yes	Yes		
Industry-Month					Yes	Yes
Country-Month					Yes	Yes

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

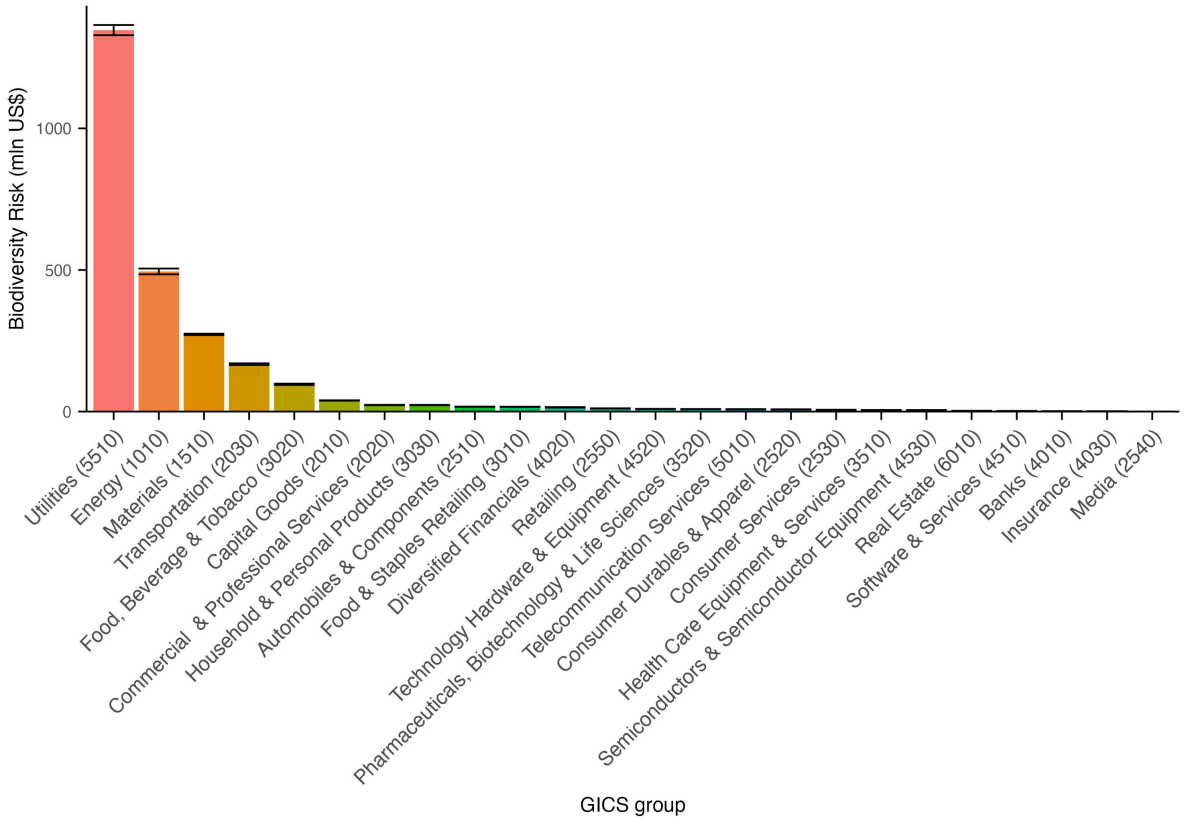


Figure 1—*The average firm-level Biodiversity Risk (mln USD) based on Trucost Environmental data, before log transformation and winsorization, and for GICS industry groups, averaged over all years (2009 to 2022). Standard error bars are plotted in black.*

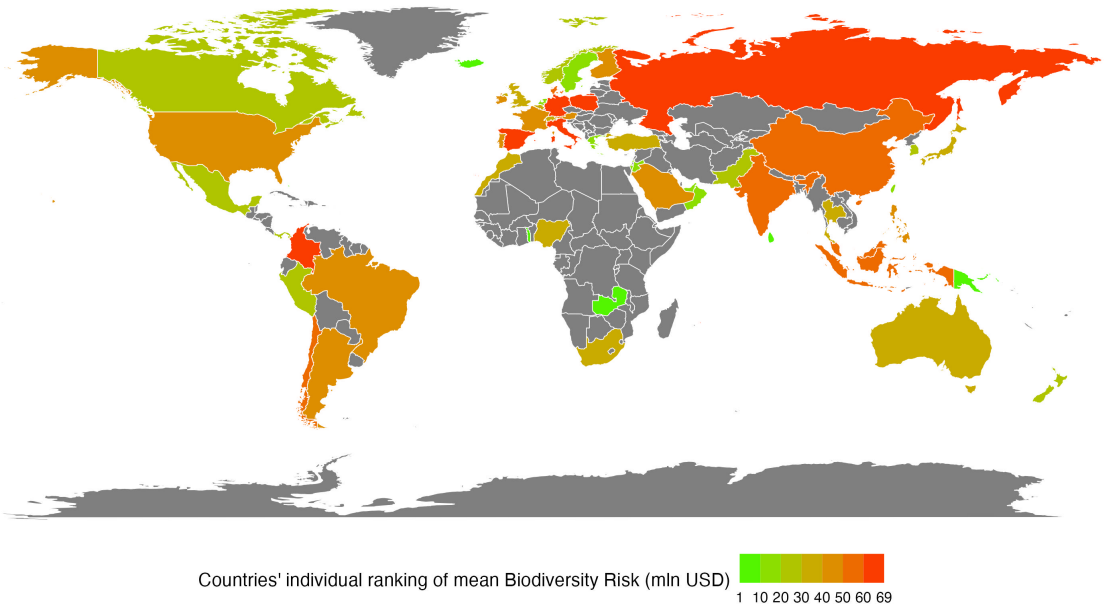
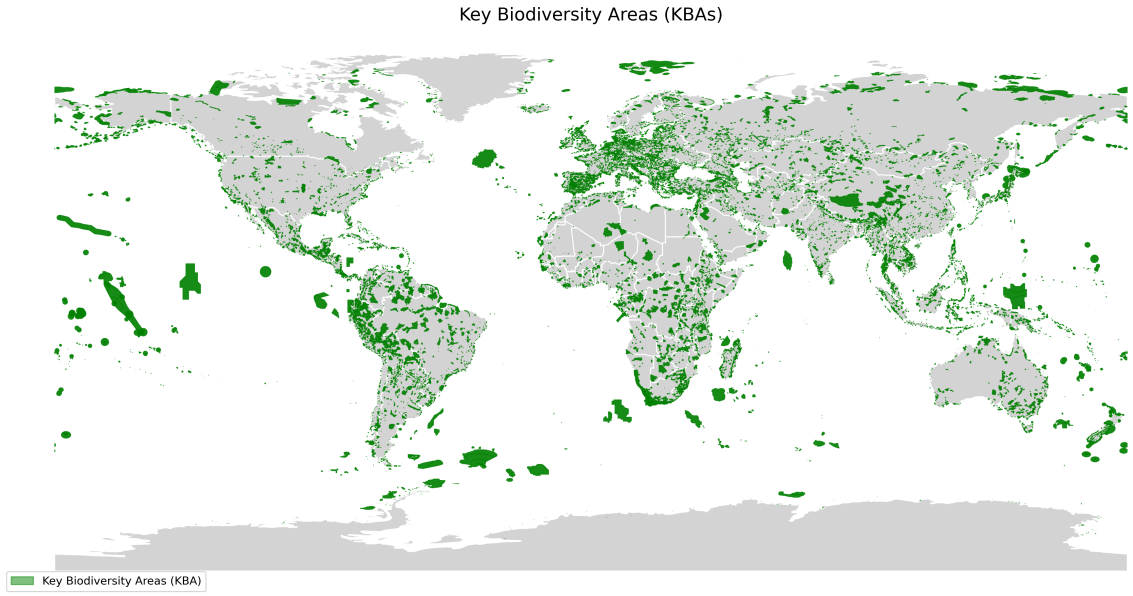
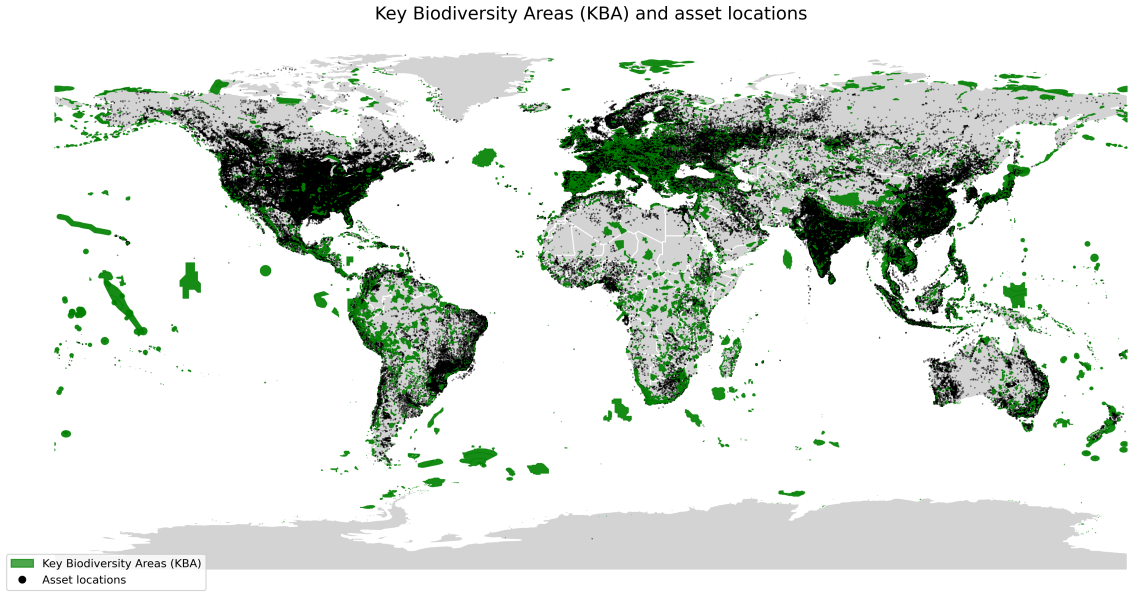


Figure 2—*Countries' ranking of their mean biodiversity risk (log mln US dollars environmental costs equivalent, before winsorization) of all firms in a country over all years in the data. Those countries for which we do not have data are coloured grey.*

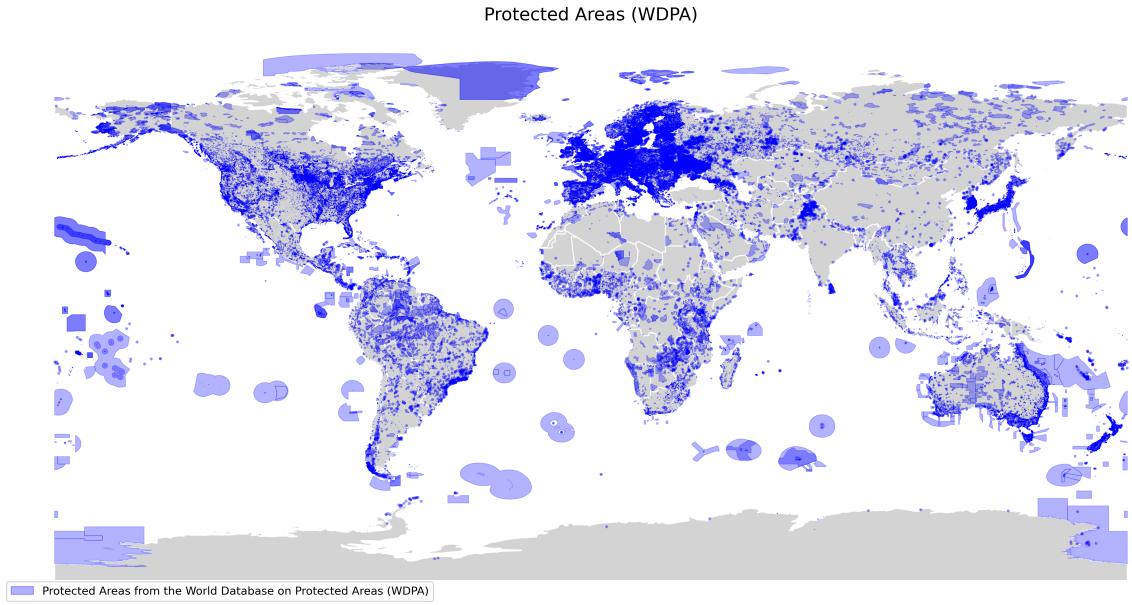


(a) *Key Biodiversity Areas (in green).*

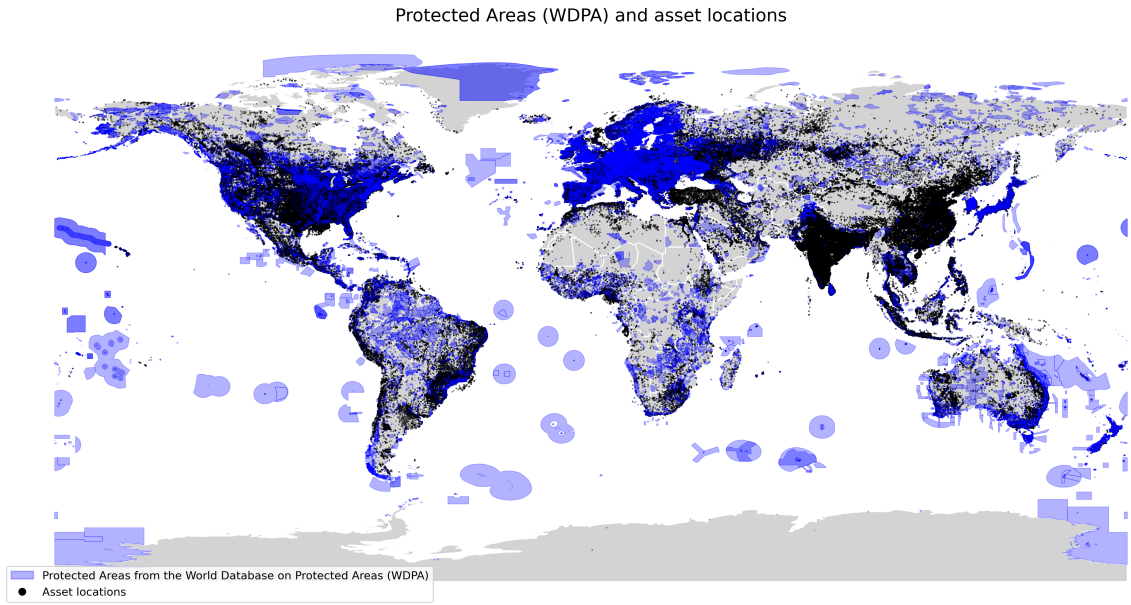


(b) *Key Biodiversity Areas (in green) together with Asset Locations (in black).*

Figure 3—*Key Biodiversity Areas polygons and all firm assets locations.*

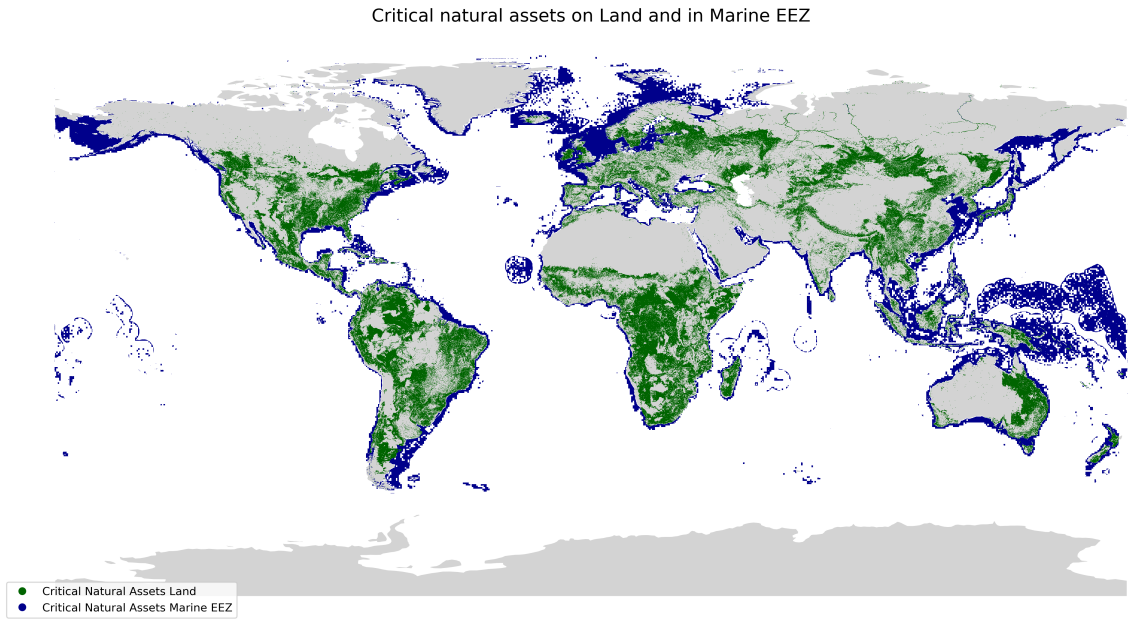


(a) *Protected Areas (in blue).*

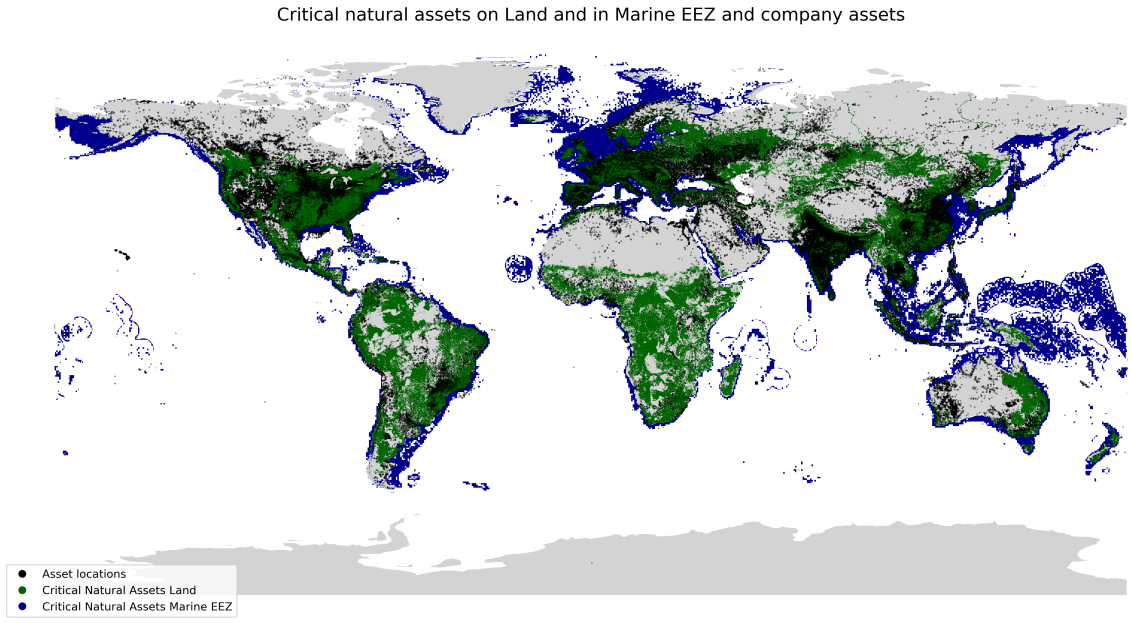


(b) *Protected Areas (in blue) together with Asset Locations (in black).*

Figure 4—*Protected Areas polygons and all firm assets locations.*



(a) *Critical Natural Assets Areas (in green and blue).*



(b) *Critical Natural Assets Areas (in green and blue) together with Asset Locations (in black).*

Figure 5—*Critical Natural Assets polygons and all firm assets locations.*

Internet Appendix

I.A Data Appendix

I.A.1 All variables definitions and sources

Table 8—*Variable names, definitions, and their respective data sources.*

Variable	Definition	Source
Stock returns and firm-level variables		
Returns	Returns are the monthly changes in the total value of an investment in a common stock per dollar of initial investment, in percentages (%). For U.S. stocks, the monthly returns are sourced from CRSP Monthly Stock File, where they use the following formula to compute the monthly returns: $ret_t = [(p_t f_t + d_t)/p_{t-1})] - 1$. For non-U.S. and non-Canada firms, the monthly stock returns are computed using the Compustat Global Security Daily. For Canadian firms, the monthly stock returns are computed using the Compustat North America Security Daily and the Compustat North America Security Monthly files.	CRSP: Monthly Stock File. Compustat Global/North America: Security Daily; Security Monthly.

Table continues on the next page

Variable	Definition	Source
Beta	Beta is computed as the regression slope of a regression of monthly excess stock returns on market excess returns over the previous 24 months. At least 12 months of valid excess returns data must be available during these 24 months. The one-month Treasury bill rates are taken as the risk-free rate, and were used to calculate the excess returns for all stocks. Moreover, market excess returns are country-specific. The non-U.S. market returns are provided by the Monthly WRDS World Indices dataset, a dataset with market-capitalization weighted indices that provide a broad measure of equity-market performance throughout 39 countries/areas, or computed manually using the same methodology for countries that are not covered by WRDS Monthly WRDS World Indices dataset using the from Compustat Global's Index Daily Price data. The U.S. market returns and the Treasury bill rates were retrieved from Kenneth French's data library.	CRSP: Monthly Stock File. Compustat North America: Security Daily; Security Monthly; Compustat Global: Security Daily; Index Daily Prices. WRDS: Monthly World Indices. Kenneth French's data library.
Size	Following Fama and French (1992), Size is computed as the natural logarithm of market capitalization as of June of each year and held that value constant until May of the following year.	CRSP: Monthly Stock File. Compustat Global/North America: Security Daily; Security Monthly.

Table continues on the next page

Variable	Definition	Source
Book-to-Market (B/M)	Following Fama and French (1992), B/M is computed every June of each year t, using the last Book Equity value of the previous calendar year and the market capitalization value of December of the previous year, and then we take the natural logarithm of the ratio of book equity of equity to market capitalization.	CRSP: Monthly Stock File. Compustat Global/North America: Security Daily; Security Monthly; Fundamentals Annual.
Investments	Investment, or asset growth, is defined as the percentage change in total assets (Compustat item `at`). That is, ($\texttt{at}_t$ - $\texttt{at}_{t-1}$) / $\texttt{at}_{t-1}$.	Compustat Global/North America: Fundamentals Annual.
Momentum	Momentum is defined as the cumulative return during a 11-month period between months t-1 and t-11, following Bali et al. (2016). We require at least 9 months of return data during the 11-month period.	CRSP: Monthly Stock File. Compustat Global/North America: Security Daily; Security Monthly.

Table continues on the next page

Variable	Definition	Source
Volatility	Following Bolton and Kacperczyk (2023), volatility is defined as the standard deviation over a 12-month period ($ret_{t-12}, ret_{t-11}, ..., ret_{t-1}$, measured at the end of month t, excluding the current period's ret_t). We require at least non-NA 9 months of returns data during the 12-month period to compute the volatility.	CRSP: Monthly Stock File. Compustat Global/North America: Security Daily; Security Monthly.
Leverage	Leverage is defined as the ratio of debt (the sum of items `dltt` and `dlc` in Compustat) to book value of assets (Compustat item `at`), where we allow dltt OR dlc to be missing, but not both. If leverage is negative, it is set to missing.	Compustat Global/North America: Fundamentals Annual.
Tangibility	Tangibility is defined as taking the Property, Plant and Equipment - Total (Net) (Compustat item `ppent`) divided by the book value of total assets (Compustat item `at`).	Compustat Global/North America: Fundamentals Annual.
R&D	R&D is defined as research and development spending expenses (Compustat item `xrd`) divided by the book value of total assets (Compustat item `at`). If `xrd` is missing, then R&D is set to 0.	Compustat Global/North America: Fundamentals Annual.
Invest/Assets (INV/A)	INV/A is defined as the ratio of capital expenditures (Compustat item `capx`) to the book value of total assets (Compustat item `at`).	Compustat Global/North America: Fundamentals Annual.

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Variable	Definition	Source
Sales Growth	Sales Growth is defined as the percentage change in net sales (Compustat item `sale`). That is, (`sale`$_t$ - `sale`$_{t-1}$) / `sale`$_{t-1}$.	Compustat Global/North America: Fundamentals Annual
Return on Equity (ROE)	ROE is defined as the net income (`ni`) divided by the market capitalization.	CRSP: Monthly Stock File. Compustat Global/North America: Security Daily; Security Monthly; Fundamentals Annual
Market Capitalization	Market Capitalization was taken from CRSP directly for US firms, and for non-US firms using Compustat data, it was calculated as outstanding shares (cshoc) times the simple price: Hence, `cshoc` × `(prccd / qunit)` × `(fxrate / ajexdi) /1000`, where we divide by 1000 to express the market capitalization in mln USD (since shares outstanding is already in thousands).	CRSP: Monthly Stock File. Compustat Global/North America: Security Daily; Security Monthly; Fundamentals Annual
Book Equity	Book Equity is defined as the book value of stockholders' equity + balance sheet deferred taxes + investment tax credit (if available) - book value of preferred stock, where non-positive book equity values were treated as missing.	Compustat Global/North America Fundamentals Annual
Firm-level Trucost Biodiversity Risk Variables		

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Variable	Definition	Source
Biodiversity Risk	Biodiversity Risk is defined as the exposure to biodiversity loss measured as external costs associated with impact on biodiversity loss and dependency on biodiversity for a firm ($M). Biodiversity Risk is constructed from items that were extracted from the Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely as the sum of *Natural Resource Use*, *Water*, *GHG*, *Land and Water Pollutants*, *Air Pollutants*, and *Waste*.	S&P Global Trucost Environmental
Transition Biodiversity Risk	Transition Biodiversity Risk is defined as the exposure to biodiversity loss, isolating the transition risk component, measured as external costs associated with impact on biodiversity loss for a firm ($M). We isolate transition risk by excluding the environmental variables that are arguably more related to physical risk. Transition Biodiversity Risk is constructed from items that were extracted from the Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely as the sum of *GHG*, *Land and Water Pollutants*, *Air Pollutants*, and *Waste*.	S&P Global Trucost Environmental
Physical Biodiversity Risk	Physical Biodiversity Risk is defined as the exposure to biodiversity loss, isolating the transition risk component, costs associated with dependency on biodiversity for a firm ($M). We isolate physical risk by excluding the environmental variables that are arguably more related transition physical risk. Physical Biodiversity Risk is constructed from items that were extracted from the Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely as the sum of *Natural Resource Use*, and *Water*.	S&P Global Trucost Environmental

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Variable	Definition	Source
Air Pollutants	Air Pollutants is defined as the external cost of pollutants released to air by the consumption of fossil fuels and production processes which are owned or controlled by a firm. The external cost is an estimate of the value of a service based on the cost of damage that results from its loss. It is based on the assumption that the cost of maintaining an environmental benefit is a reasonable estimate of its value. This variable is extracted from the Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely Absolute: 'Air Pollutants Direct Cost'($M) (`dataItemId = 319380`).	S&P Global Trucost Environmental
GHG	GHG is defined as the external cost of greenhouse gas (GHG) emissions released to air by the consumption of fossil fuels and production processes which are owned or controlled by a firm. The external cost is an estimate of the value of a service based on the cost of damage that results from its loss. It is based on the assumption that the cost of maintaining an environmental benefit is a reasonable estimate of its value. This variable is extracted from the Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely: 'Absolute: GHG Direct Cost'($M) (`dataItemId=319437`).	S&P Global Trucost Environmental
Land and Water Pollutants	Land and Water Pollutants is defined as the external cost of pollutants released to land and water by a firm due to its own activities. The external cost is an estimate of the value of a service based on the cost of damage that results from its loss. It is based on the assumption that the cost of maintaining an environmental benefit is a reasonable estimate of its value. This variable was extracted from the Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely: 'Absolute: LWP Direct Cost '($M) (`dataItemId=319445`).	S&P Global Trucost Environmental

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Variable	Definition	Source
Natural Resource Use	Natural Resource Use is defined as the external cost of the direct extraction of minerals, metals, natural gas, oil, coal, forestry, agriculture and aggregates by a firm. The external cost is an estimate of the value of a service based on the cost of damage that results from its loss. It is based on the assumption that the cost of maintaining an environmental benefit is a reasonable estimate of its value. This variable was extracted from the Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely: 'Absolute: Natural Resources Direct Cost' ($M) (`dataItemId=319469`).	S&P Global Trucost Environmental
Waste	Waste is defined as the external cost of hazardous and non-hazardous waste produced by a firm. The external cost is an estimate of the value of a service based on the cost of damage that results from its loss. It is based on the assumption that the cost of maintaining an environmental benefit is a reasonable estimate of its value. This variable was extracted from the Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely 'Absolute: Waste Direct Cost '($M) (`dataItemId=319545`).	S&P Global Trucost Environmental
Water	Water is defined as the external cost of water consumed by the company from natural sources. The external cost is an estimate of the value of a service based on the cost of damage that results from its loss. It is based on the assumption that the cost of maintaining an environmental benefit is a reasonable estimate of its value. This variable is extracted from Trucost Environmental Database offered by S&P Global Sustainable1 (n.d.-b), namely 'Absolute: Water Direct Cost '($M) (`dataItemId=319560`).	S&P Global Trucost Environmental

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Variable	Definition	Source
Asset- and geospatial Biodiversity Risk (BR)	We define Asset- and geospatial Biodiversity Risk (BR) for firm i as the ratio of the number of "risky" assets firm i holds—i.e., assets of a risk-relevant type that fall within sensitive biodiversity risk regions—and the firm i total assets (book value, Compustat's `at`). This gives us a firm-level biodiversity risk score: $$\text{Spatial Biodiversity Risk}_i = \frac{\text{Risky assets of firm } i}{\text{Total assets of firm } i}.$$ The measure is constructed for transition risk asset types, physical risk asset types, or both combined, and across different biodiversity risk regions. The asset types we deem as transition risk or physical risk (or both) are listed in Table 10. The asset locations are taken form Trucost Physical Risk database S&P Global Sustainable1 (n.d.-a). Biodiversity risky areas are Key Biodiversity Areas (KBA), Protected Areas (PA), and Critical Natural Assets (CNA) areas. Each asset location is flagged as a "Risky Asset of firm i" if its location is inside the polynomial of the biodiversity risk areas and if it is of one of the asset types listed in Table 10. The spatial biodiversity data we used are provided by BirdLife International (2024) (KBA), UNEP-WCMC and IUCN (2025) (PA), and Chaplin-Kramer and Kennedy (2022) (CNA).	BirdLife International (KBA), UNEP-WCMC and IUCN (PA), Open Science Framework page of Chaplin-Kramer and Kennedy (2022) (CNA), S&P Global Trucost Physical Risk, Compustat Global/North America: Fundamentals Annual
Country-level environmental performance variables		

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Variable	Definition	Source
Environmental Performance Index (EPI)	The Environmental Performance Index (EPI) score aims to provide a scale on how close nations are to established environmental policy targets, measuring different indicators on climate change performance, environmental health (Block et al., 2024). The score ranges from 0–100, so that higher means better EPI performance. The 2024 EPI integrates 58 metrics across 11 categories, which include areas such as climate change mitigation, air quality, waste management, as well as the sustainability of fisheries and agriculture, deforestation, and the protection of biodiversity. The EPI scores were accessed via https://epi.yale.edu/downloads, where the ZIP file of the 2024 Indicator scores was downloaded.	`yale.epi`
EPI Biodiversity Habitat (BH)	The Biodiversity and Habitat (BH) issue category is a subscore of the EPI and it measures the efforts of nations to preserve natural ecosystems and safeguard the full range of biodiversity within their borders. The EPI BH index ranges from 0-100, so that a higher score means a better performance on protecting biodiversity and natural ecosystems. The EPI BH is constructed with 12 indicators: protection of marine key biodiversity areas, protection of important marine and coastal habitats, stringency of marine protection, Protected Areas Representativeness Index, Species Habitat Index, Species Protection Index, terrestrial biome protection, protection of terrestrial key biodiversity areas, protected area effectiveness, cropland and building inside protected areas, Red List Index, Species Habitat Index, and Bioclimatic Ecosystem Resilience Index. For more information, see https://epi.yale.edu/measure/2024/BDH. Download available at https://epi.yale.edu/downloads.	Yale

Table continues on the next page

Variable	Definition	Source
EPI Ecosystem Vitality (EV) subscore	The EPI Ecosystem Vitality (EV) policy objective assesses how effectively nations are preserving, protecting, and enhancing ecosystems and the services they provide. This EPI EV score accounts for 60% of the overall EPI score. The score ranges from 0–100, so that higher means better EPI EV performance. The EPI EV is divided into seven categories: Biodiversity & Habitat, Ecosystem Services, Fisheries, Climate Change, Pollution Emissions, Agriculture, and Water Resources. For more information, see https://epi.yale.edu/epi-results/2020/component/eco. Download available at https://epi.yale.edu/downloads.	Yale
Sustainable Development Goals (SDG) score	Sustainable Development Goals (SDG) scores measure the total progress towards achieving all 17 SDGs. The score can be interpreted as a percentage of SDG achievement. A score of 100 indicates that all SDGs have been achieved. The SDG Index score represents a nation's position between the worst (0) and the best or target (100) outcomes. The SDG scores are focused on absolute country performance and not relative to other countries performance, so that 100 corresponds to the nation's "technical optimums". Therefore, the SDG score aims to measure a nation's distance to achieving sustainability. Each nation's SDG score is based on the Sustainable Development Report (SDR), which reviews progress made each year on the SDGs for each nation (Sachs et al., 2024). The data accessed via the (SDR) website and can be downloaded here: https://dashboards.sdgindex.org/downloads	Sustainable Development Report (SDR)

Table continues on the next page

Variable	Definition	Source
SDG Goal 14: Life Below Water score	The SDG Goal 14 Life Below Water is to conserve and sustainably use the oceans, seas and marine resources. The score is computed normalizing the performance on relevant measured targets, namely (i) Mean area that is protected in marine sites important to biodiversity, (ii) Ocean Health Index: Clean Waters score, (iii) Fish caught from overexploited or collpased stocks, (iv) Fish caught by trawling or dredging, (v) Fish caught that are then discarded, (vi) Marine biodiversity threats embodied in imports. The score ranges from 0–100, where higher means better absolute performance on the SDG 14 goal. The data accessed via the (SDR) website and can be downloaded here: https://dashboards.sdgindex.org/downloads	Sustainable Development Report (SDR)
Sub Pillars SDG Goal 15 Life on Land score	The SDG Goal 15 Life on Land goal is to protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss. The score is computed normalizing the performance on relevant measured targets, namely (i) Mean area that is protected in terrestrial sites important to biodiversity, (ii) Mean area that is protected in freshwater sites important to biodiversity, (iii) Red List Index of species survival, (iv) Permanent deforestation, (v) Imported deforestation. The score ranges from 0–100, where higher means better absolute performance on the SDG 15 goal. The data accessed via the (SDR) website and can be downloaded here: https://dashboards.sdgindex.org/downloads	Sustainable Development Report (SDR)

I.A.2 Price data and the computation of returns

We rely on CRSP, Compustat Global and Compustat North America for the price data to compute stock returns. Firms and securities (stocks) are identified via *permco* and *permno* in CRSP data and via *gvkey* and the *gvkey-iid* combination in Compustat data. For Compustat price data (covering all countries except the U.S.), we also apply a multitude of filters to fix data

errors and decimal errors and apply some manual corrections, following Chaieb et al. (2021) and Bessembinder et al. (2023). Our sample is restricted to stocks whose `gvkey` can be matched to the S&P Global Trucost Environmental Data firm list, obtained by mapping Trucost's SNL `institutionId` through Capital IQ's `companyId` back to the `gvkey` firm identifiers.

U.S. stock data

. For U.S. stocks, the CRSP monthly stock file is used to gather monthly returns and the daily stock file is used to create aggregated monthly variables. Firms and securities (stocks) are identified via `permco` and `permno` in CRSP data. For the monthly U.S. stock returns, we combine the (i) the CRSP monthly security in `crsp.msf`, (ii) the CRSP identifying information in `msenames` and (iii) the CRSP delisting information in `msedelist`, nmatching the datasets on `permno`. We filter CRSP `crsp.msf`, following the textbook of Bali et al. (2016): see this textbook for an extensive discussion on the filters. We select US stocks by keeping only United States exchanges: NYSE, AMEX and the Nasdaq (from CRSP `msenames`: `exchcd IN '1', '2', '3'` respectively), and only keep Ordinary Common Shares (from CRSP `msenames`: `shrcd IN ('10', '11')`).

The CRSP `permno` values are matched with `gvkey` values, using the CRSP-Compustat linking table available in the CRSP library. The specified linking between CRSP and Compustat follows Bali et al. (2016). We set `linktype in ('LU', 'LC')`, where a value of `LU` indicates that the link is established by comparing CUSIP values in the Compustat and CRSP databases and a value of `LC` indicates that the link has been researched and that the research has verified that the link is correct. Next, we set `usedflag = '1'`, meaning that the `gvkey` represents a direct link to the corresponding `permno`, and `linkprim IN ('P', 'C)`, where `P` indicates a primary link marker, as identified by Compustat in monthly security data, and where `C` indicates a primary link marker, as identified by CRSP to resolve ranges of overlapping or missing primary markers from Compustat in order to produce one primary security throughout the company history. For more information on the exact meanings of the different values in the `linktype`, `linkprim`, and `usedflag` fields, please consult the CRSP/Compustat merged database documentation.

We follow Beaver et al. (2007) in delisting the data, following the steps in the script on Richard Price's webpage: https://sites.google.com/site/richardaprice3/research/delistings. Rather than using a single replacement value for missing delisting returns Beaver et al. (2007) suggest using multiple replacement values depending on the nature of the delisting. As for the replacement values, they use the average daily delisting return for the corresponding three-digit delisting code, because average delisting returns vary significantly for different delisting codes. Note that, although the use of multiple replacement values is arguably better than the use of a single replacement value, the use of any replacement value is an estimate of an unknown return.

The market capitalization (in million USD) for each security is defined as the product of the number of outstanding shares `shrout` and the last traded price in a month `altprc`. Then, the market capitalization is aggregated to a firm level by summing the security market capitalizations for each `permco` in each month. Zero market capitalization are replaced by N/A values.

We apply some basic filters to the U.S. stock return data, following Bessembinder et al. (2023).

- We set returns to missing when there is no data for trading volume in the entire month (in daily stock data files).
- A stock-month observation requires at least five daily observations with positive closing prices. This is equivalent to saying that the return data is missing for months with less than 5 trading days and for the month immediately after. We delete those stock-months with less than 5 trading days with positive prices and set the next month return to missing.
- We delete stocks from the data with coverage of less than 6 months in total (measured as non N/A returns).
- We filter out stocks whoms NAICS industry codes start with 525 (Funds, Trusts, and Other Financial Vehicles).
- For (delisting) returns, we set special returns with special missing value codes as N/A[24].

Global stock data (excluding U.S. and Canada)

For Global stock data, excluding the U.S. and Canada, we combine the Compustat Global Security Daily data file `g_secd` with the Compustat Global Security data `g_security`, Compustat Global Exchange Rate Daily data `g_exrt_dly`, Compustat Global Company data `g_company` to compute monthly returns and to create aggregated monthly variables.

We match `g_company` data with `g_secd` by the unique firm `gvkey` and `g_security` with `g_secd` on the unique gvkey and iid combination. Exchange rates data is matched with `g_secd` on the monthly dates.

We filter out carried forward prices and bid/ask/average prices, following Chaieb et al. (2021). So, we filter `g_secd` data so that `prcstd IN ('3', '10')` (High, Low and Close, or Prices as reported).

We compute several monthly variables using the daily trading data in `g_secd`. For each unique month-year-gvkey-iid combination, we compute...

- the number of positive closing prices (`prccd > 0`).

[24]See the missing code values in the Data Description guide provided by CRSP (page 132 for returns and page 63 for delisting returns): https://fbe.unimelb.edu.au/__data/assets/pdf_file/0008/547685/stock_indices_data_descriptions.pdf

- the number of positive trading volume days (`cshtrd > 0`). When the trading volume is missing (N/A) every day of the month, we set the number of positive trading volume days for that month to missing (N/A(as opposed to zero.
- the total number of NA trading volume days as, where we define a NA trading volume day when `cshtrd < 0 OR cshtrd IS NULL` .
- the monthly average trading volume in local currency (`AVG(a.cshtrd * a.prccd / a.qunit / 1e6)`) and USD (`AVG((a.cshtrd * a.prccd / a.qunit / 1e6) * (c.fxrate))`). We also compute this on a yearly base by using the unique year-gvkey-iid combination.

We filter such that we...

- Use only the end-of-month observations
- Select common stock only (`tpci='0'`), or select preferred stocks and special stocks (`tpci in ('Q', '1')`) provided they are the primary issues (`iid = prirow`).
- Include specified stock exchange codes, thus excluding US and CAN exchange codes, hence `!exchg IN ('11', '12', '14', '7', '9')` . For the full list of exchanges, see Table 9.
- Exclude securities that contain '%', as they are likely preferred stocks with a fixed dividend (Bessembinder et al., 2023), so `dsci NOT LIKE '%!%%'ESCAPE '!'` .
- Delete rows where price data is N/A, hence `prccd IS NOT NULL AND prccd > 0` .

Canadian stock data

For Canadian stocks, we follow the exact same steps as for the Global (non-U.S. and non-Canada) stock returns described above, but instead of drawing from the Compustat Global database, we draw from the Compustat North America. We combine the Compustat North America Security Daily data file `comp.secd` with the Compustat North America Security data `security` , Compustat Global Exchange Rate Daily data `g_exrt_dly` , Compustat Company data `company` to compute monthly returns and to create aggregated monthly variables. Of course, we apply different filters for the stock exchanges for Canada, namely we select stock returns data from `comp.secd` where `exchg IN ('11', '12', '14', '7', '9')` , `prcstd IN ('3', '10', '4')` Moreover, we complement `comp.secd` dataset with `comp.secm` observations where `comp.secd` observations are missing, to increase coverage if possible.

Computing, cleaning and additional filtering of returns based on Compustat data

For non-U.S. stock returns, that are based on either Compustat Global or Compustat North America data, we compute the returns using the price data. Moreover, we rigoriously clean the

data and apply additional filters.

First, we compute the adjusted end-of-month stock price (USD), so that `prc = [ [ (prccd / qunit) * fxrate ] / ajexdi ] * trfd`. Then we compute the market capitalization (mln USD) as `mktcap = cshocadj * (prccd / qunit * fxrate / ajexdi) / 1000`. Note that we have to divide by 1000 since in Compustat `cshocadj` is presented in thousands.

We apply the following data cleaning and filtering steps to the price data from Compustat Global and Compustat North America:

1. We delete depositary receipts (`iid = 90`).
2. Following Chaieb et al. (2021), we use common shares only (but we filtered for this already in our data selection).
3. We filter out stocks whose industries start with NAICS 525 (Funds, Trusts, and Other Financial Vehicles).
4. We exclude non-common equity by checking keywords in the issue description (`dsci`) (Griffin, Kelly, & Nardari, 2010) following the appendix B, 3 "Refining the common stock universe, of Chaieb et al. (2021).
5. We do several manual data corrections to solve several errors in Compustat data that would otherwise might not have been captured. See Table 2 in appendix of Chaieb et al. (2021) for the explanation of the errors for Compustat data not captured by the filters above.
6. We apply filters on the business description (`busdec`), following Bessembinder et al. (2023). Namely, we aim to filter out (i) securities that are likely to be real estate investment trusts; (ii) securities that are likely to be fund or trusts; (iii) securities that are likely to be funds, trust, reits, etf, hedge funds.
7. We fix potential decimal errors, that pertain only a single date (immediate reversal) or that persist up to three period (see appendices §6.a and §6.b. of Bessembinder et al. (2023)).

After following these steps, we reconstruct price and market capitalization data using the corrected data. Then, we recompute the returns and apply the majority of the adjustments of Bessembinder et al. (2019 2023) as final filters to the Compustat data, among which taking care of delisting returns. So we proceed with the following filters:

7. When there is no data for trading volume in the entire month (in daily security files `g_secd` or `comp.secd`), then returns are set to missing.

8. To retain a stock-month in our sample, a stock-month observation requires to have at least five daily observations with positive closing prices. This is equivalent to saying that the return data is missing for months with less than 5 trading days and for the month immediately after. We delete those stock-month observations with less than 5 trading days with positive prices and set the next month return to missing, following §1 of the data appendix of Bessembinder et al. (2023).

9. We compute the average number of daily observations of positive trading volume for each stock in each month. Then, stocks in the lowest 3% cross-month average are deleted from the sample. See §8.a. of the data appendix of Bessembinder et al. (2023)

10. Stocks are dropped if `ajex` ever takes value of 0 are dropped and stocks with changes in `qunit` and without corresponding changes in currency (`curccd`) and corresponding contemporaneous changes in `simplepriceusdadj` of more than 50% in absolute value; see §8.b. of the data appendix of Bessembinder et al. (2023).

11. We delete the remaining history (t+1, t+2, ... T) for any stock, if its market capitalization drops below $US 1 million, or if its share price drops below $US 0.01 at a time t; see §8.c. of the data appendix of Bessembinder et al. (2023). Exceptions to this rule are stocks from Brazil, Indonesia, Nigeria and Turkey, where many active stocks on those markets have very low share prices. Hence, for stocks from these countries, we drop the stock if its share price drops below $US 0.001.

12. In cases where the returns data contains gaps of more than 11 months, we set the first month AFTER the data resumes to be missing; see §8.d. of the data appendix of Bessembinder et al. (2023). In cases where the data contains gaps of 11 months or fewer, we measure the return by RET (t) = adjPRCFX(t) / adjPRCFX(tlag) x TRF(t) / TRF(tlag) - 1 (as normal) where trfd is the Compustat adjustment factor (Bessembinder et al., 2023) state that if `trfd` is missing, it should be filled with the value within the past one year if available, or the value within the future one year if available. If there are missing `trfd` values, hence replace those values with the closest available `trfd` (within one year, before and after). If no `trfd` observation is available within one year, the return is set to be missing.

13. We deem the monthly changes in adjusted shares outstanding (`cshocadj`) and market capitalization in USD by a factor of more than 5 for `cshocadj` and 2.5 for `mktcap` to be indicative of likely data errors. The exception is China, where reverse mergers are common. In China deem the monthly changes in adjusted shares outstanding (`cshocadj`) and market capitalization in USD (`mktcap`) by a factor of more than 50 for `cshocadj`

and 25 for `mktcap` to be indicative of likely data errors. We clean the data following §8.e. of the data appendix of Bessembinder et al. (2023).

14. We identify cases in which market capitalization jumps in a manner that is not supported by reported returns or changes in shares outstanding. We delete all observations up to and including the jump, if any jump appears during the first 24 months or when it is in first 20% of observations for that firm; see the explanation of the procedure in §8.f. of the data appendix of Bessembinder et al. (2023).

15. We fix erroneous observations that were not captured by the earlier filters following the procedure in §8.g. and §8.h. of the data appendix of Bessembinder et al. (2023).

16. For the treatment of inactive returns, delisting returns, and short-lived stocks, we follow the steps listed in §8.i. of the data appendix of Bessembinder et al. (2023). That is, (i) we treat effectively inactive stocks (those stocks that are indicated to be active but the stock price data identical for 12 or more months before the end of the sample) as effectively delisted, and the identical share price observations should be deleted, following Shumway (1997); (ii) we set final return for non-U.S. stocks that were delisted with bankruptcy or liquidation reasons (code `dlrsn = ('02', '03')`) to -30%; (iii) we delete stocks with less than six monthly observations in total.

Merging CRSP and Compustat

After collecting all the stock price and returns data from Compustat Global, Compustat North America and CRSP, we check whether each gvkey-iid-month-year observation is covered by only one unique dataset, or whether there are duplicates across datasets. If there are two primary securities with overlapping listing period, we retain only the stock-months observations during the overlapping period of the security with the longest listing period. We apply this first *within* each dataset originating from CRSP and Compustat, and then *across*. Only after doing so do we merge the datasets.

I.A.3 Additional firm identifiers

We link firm identifiers to our dataset, using the WRDS Capital IQ `wrds_gvkey` cross-reference table (linking gvkey-companyid) and the S&P Capital IQ cross-reference table (linking companyid-institutionid). We link these identifiers in two steps.

First, we link the `gvkey` identifiers to Compustat Capital IQ `companyId`, using the WRDS Capital IQ cross-reference table `wrds_gvkey` (in the `ciq` library). Firm i with a `gvkey` on date t `datadate` in our returns dataset (`df`) is linked to a `companyId` from `wrds_gvkey` when and only when there is a `gvkey` match and the date intervals overlap, with missing bounds

in `wrds_gvkey` are interpreted as open-ended (`wrds_gvkey.startdate IS NULL` $\rightarrow -\infty$ and `wrds_gvkey.enddate IS NULL` $\rightarrow +\infty$). Formally, `companyId` identifiers from `wrds_gvkey` are joined on the our stock returns dataset (`df`) if they satisfy:

```
wrds_gvkey.gvkey = df.gvkey
AND (
    (wrds_gvkey.startdate <= df.datadate AND df.datadate <= wrds_gvkey.enddate)
    OR (wrds_gvkey.startdate <= df.datadate AND wrds_gvkey.enddate IS NULL)
    OR (df.datadate <= wrds_gvkey.enddate AND wrds_gvkey.startdate IS NULL)
    OR (wrds_gvkey.startdate IS NULL AND wrds_gvkey.enddate IS NULL)
) .
```

Next, we map Capital IQ `companyId` to Trucost's `institutionId` identifier using S&P Global's `CompanyCrossRef` table. Firm i with a `companyId` in our dataset `df` is matched to a `institutionId` from `CompanyCrossRef` in timepoint t when and only when there is a `companyId` match and the date intervals overlap, with missing bounds in `CompanyCrossRef` are interpreted as open-ended (`CompanyCrossRef.startdate IS NULL` $\rightarrow -\infty$ and `CompanyCrossRef.enddate IS` $\rightarrow +\infty$). Formally, `institutionId` identifiers from `CompanyCrossRef` are joined on the our stock returns dataset (`df`) if they satisfy:

```
CompanyCrossRef.companyId = df.companyid
AND (
    (CompanyCrossRef.startDate <= df.datadate AND df.datadate <= CompanyCrossRef.endDate)
    OR (CompanyCrossRef.startDate <= df.datadate AND CompanyCrossRef.endDate IS NULL)
    OR (df.datadate <= CompanyCrossRef.endDate AND CompanyCrossRef.startDate IS NULL)
    OR (CompanyCrossRef.startDate IS NULL AND CompanyCrossRef.endDate IS NULL)
)
AND CompanyCrossRef.primaryFlag = 1
AND CompanyCrossRef.identifierTypeId = 9458 ,
```

where `primaryFlag=1` indicates whether the link is the primary vendor identfier relating back to the companyId, and where (`identifierTypeId = 9458` refers to the unique value of the type of identifier being SNL `institutionId`).

Table 9—*Stock Exchanges and Compustat Exchange Codes*

Country	**Stock Exchange**	**Code**
Argentina	Bolsa De Comercio De Buenos Aires	135
Australia	ASX All Markets	106
Austria	Wiener Boerse AG	273
Belgium	NYSE Euronext Brussels	132
Brazil	BM and F Bovespa SA Bolsa De Valores Mercadorias E Futuros	243

Country	Stock Exchange	Code
Brazil	Rio de Janeiro	238
Canada	Toronto Stock Exchange	7
Canada	TSX Venture Exchange	9
Chile	Santiago Stock Exchange	242
China	Shanghai Stock Exchange	249
China	Shenzhen Stock Exchange	250
Colombia	Bolsa De Valores De Colombia	118
Denmark	OMX Nordic Exchange Copenhagen AS	144
Finland	NASDAQ OMX Helsinki Ltd	167
France	Paris	231
France	NYSE Euronext Paris	286
Germany	Deutsche Boerse AG	154
Germany	XETRA	171
Greece	Athens Exchange SA Cash Market	107
Hong Kong	Hong Kong Exchanges and Clearing Ltd	170
India	BSE Ltd	120
India	National Stock Exchange of India	219
Indonesia	Indonesia Stock Exchange	175
Ireland	Irish Stock Exchange All Market (Euronext Dublin)	172
Israel	Tel Aviv Stock Exchange	262
Italy	Borsa Italiana Electronic Share Market	209
Japan	Tokyo Stock Exchange	264
Japan	Osaka Securities Exchange	227
Jordan	Amman Stock Exchange	103
Malaysia	Bursa Malaysia	181
Mexico	Bolsa Mexicana de Valores Mexican Stock Exchange	208
Morocco	Casablanca Stock Exchange	139
Netherlands	NYSE Euronext Amsterdam	104
New Zealand	New Zealand Exchange Ltd	225
New Zealand	Wellington	277
Nigeria	Nigerian Stock Exchange	185
Norway	Oslo Bors ASA	228
Oman	Muscat Securities Market	301
Pakistan	Karachi Stock Exchange Guarantee Limited	178
Peru	Bolsa De Valores De Lima	191
Philippines	Philippine Stock Exchange Inc	203

Country	Stock Exchange	Code
Poland	Warsaw Stock Exchange	276
Portugal	NYSE Euronext Lisbon	192
Russia	MICEX Stock Exchange	332
Russia	Moscow Stock Exchange	211
Saudi Arabia	Saudi Stock Exchange	306
Singapore	Singapore Exchange	251
South Africa	Johannesburg Stock Exchange	177
South Korea	Korea Exchange KOSDAQ	298
South Korea	Korea Exchange Stock Market	248
Spain	Bolsa De Madrid	201
Sri Lanka	Colombo Stock Exchange	142
Sweden	NASDAQ OMX Nordic	256
Switzerland	Swiss Exchange	151
Switzerland	Zurich	280
Taiwan	TAIPEI EXCHANGE	245
Taiwan	Taiwan Stock Exchange	260
Thailand	Stock Exchange of Thailand	110
Turkey	Istanbul Stock Exchange	174
UAE	Abu Dhabi Securities Exchange	318
UAE	Dubai Financial Market	323
United Kingdom	London Stock Exchange	194
USA	NYSE	11
USA	Amex	12
USA	Nasdaq Stock Market	14

I.A.4 Coverage plot of Trucost data over time

The coverage of the Trucost data over time is plotted in Figure 6, which shows that the coverage of our biodiversity risk measure increases over time, as Trucost's coverage also rises, particularly since 2016.

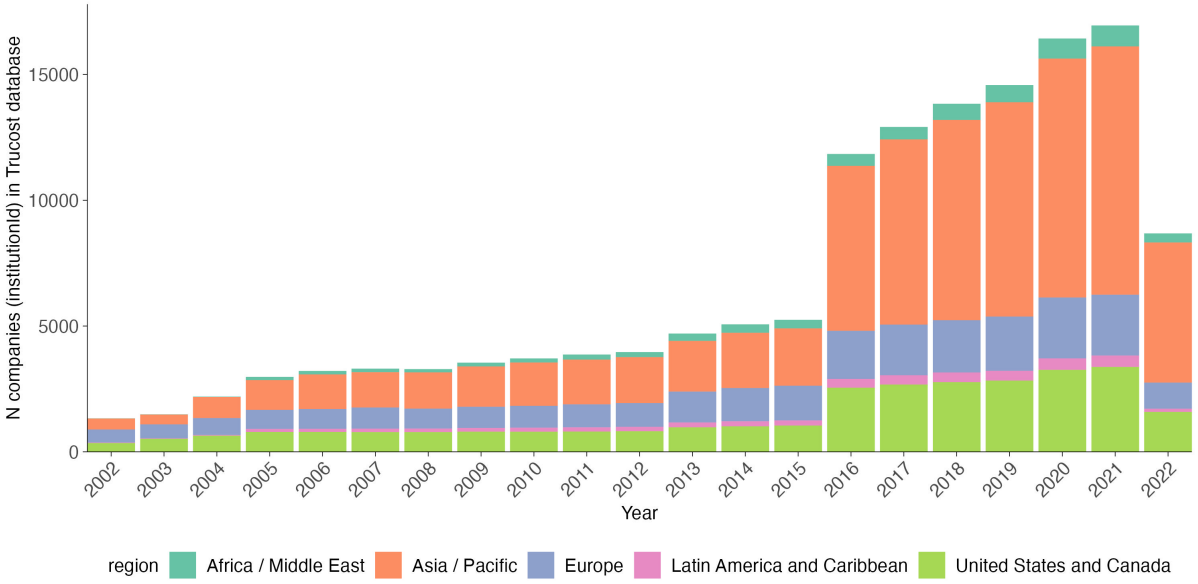


Figure 6—*Coverage of the unique companies that have data in the Trucost environmental database for each fiscal year, as provided by Trucost across different regions (where the region of a company is identified through 'countryId').*

I.A.5 Methodological note on matching Trucost data to financial data: using the effective publishing date of the Trucost data

A common problem in using environmental data is the fact that most data providers backfill their data, especially before 2008 Zhang (2025). Hence, data of a certain environmental variable (such as greenhouse gas emitted in a year) may have become public much later than the reporting lag of accounting variables. Zhang (2025) describes how failure to take this into account can cause forward-looking bias. When lagging the carbon emissions like an accounting variable, as done by Bolton and Kacperczyk (2021, 2023), as in one might measure forward-looking firm performance information contained in emissions rather than risk premium. After accounting for the data release lag, negative carbon returns were measured in the U.S. and insignificant carbon returns globally (Zhang, 2025), hence not replicating the "carbon premium" results by Bolton and Kacperczyk (2021, 2023). Therefore, if one wants to measure an environmental variable to measure transition risk or physical risk, one should lag the data sufficiently (Zhang, 2025).

The main date matching method we use follows Zhang (2025) to prevent forward-looking bias. Specifically, we take the effective release dates of the Trucost environmental data, and then take the first day of the subsequent month. That is, for an effective date on a day in month m, we take the first day of month $m+1$ to match with the return data to. The effective

reporting dates lags for all Trucost data were computed plotted in Figure 7. As one can see, there are some serious data release lags present in the data. On the one hand, we can be strict and match on the effective release date as specified in our Trucost database, to strictly prevent any forward-looking bias. On the other hand, if we match using the effective reporting dates from Trucost, there are some serious lags in the data, and then this 'old' information may even no longer be deemed relevant for an investor. Also, we could assume investors may have had some other way to gather environmental information about firms they may be interested in, for example via a yearly report. To test robustness of our results we will try to use different matching date options, ranging from the most strict to more lenient data matching.

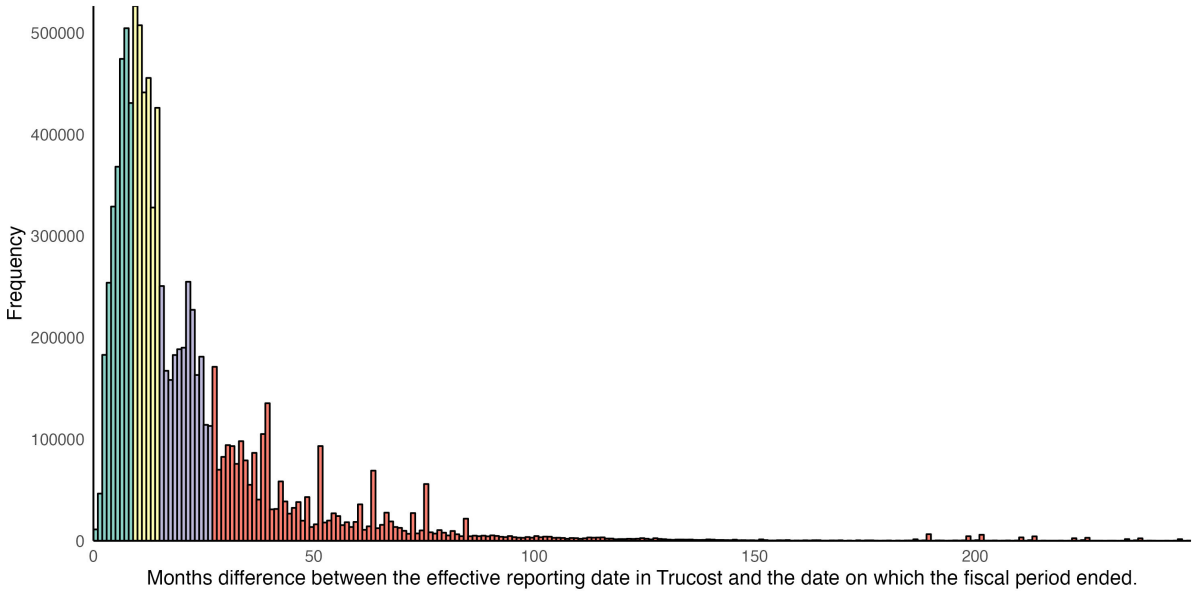


Figure 7—*Data release lags (in months) for all Trucost Emission data variables. On the x-axis are all the possible time differences (in months) between the effective reporting date in Trucost and the date on which the fiscal period ended.*

I.A.6 Formal definition Asset- and Geospatial Biodiversity Risk

Next to the biodiversity risk based on firm-level data (Trucost), we also compute a asset- and geospatial-based biodiversity risk measure for firms. When we define a firm's biodiversity risk based on assets, we do not do so based on headquarter location but based on production and industrial locations with clear transition and physical risks[25]. Next, the assets with potential transition or physical biodiversity risk would particularly risky if they are inside areas where

[25]See Table 10 in the appendix for the classification of the transition and physical risk relevant asset types

either the transition or physical risk is higher. Certain locations might be protected, are deemed important to be protect, to conserve biodiversity and nature, such that these locations would provide additional transition risk. On the other hand, we can distinguish areas where physical biodiversity risk is high, namely by defining where we extract a lot of resources (focusing only provisioning ecosystem services).

Combining the asset type and asset location arguments above, we classify an asset as being exposed to transition (physical) biodiversity risk if its type belongs to the corresponding set of risk-relevant asset types and its location satisfies the appropriate spatial criterion with a risk region. Formally, let let $a \in \mathcal{A}_i$ denote asset a inside the set of assets of firm i. Let $t(a)$ denote the asset type of a, $\ell(a) \subset \mathbb{R}^2$ its point or polygon geometry, $\mathcal{T}^{TR}$ and $\mathcal{T}^{PR}$ the sets of transition- and physical-risk-relevant asset types, and $\mathcal{R}^g \subset \mathbb{R}^2$ the union of polygons for geospatial region type g (e.g., KBA, PA, CNA). We define exact matches as $\mathcal{R}^{g,\text{in}} := \mathcal{R}^g$. Using the intersection operator $\cap$, we define the spatial predicate $\Omega(\ell(a), \mathcal{R}^g)$ to be true if $\ell(a) \cap \mathcal{R}^g \neq \emptyset$, hence when asset a is "in" geospatial region g. Using the indicator function $\mathbf{1}\{\cdot\}$, the asset-level risk flag is

$$R_a^{r,g} \;=\; \mathbf{1}\big\{\, t(a) \in \mathcal{T}^r \,\big\}\, \mathbf{1}\big\{\, \Omega\big(\ell(a), \mathcal{R}^g\big) \,\big\},$$

with $r \in \{\text{TR}, \text{PR}, \text{TR|PR}\}$ - indexing transition, physical, or their union. Therefore, the asset is flagged as having transition risk or physical risk when the type (r) of the asset is relevant to transition or physical and when it is inside a region (g) that is relevant for transition risk (region type $g \in \{\text{KBA}, \text{PA}\}$) or physical risk (region type $g = \{\text{CNA}\}$). Then, for every firm i in set $\mathcal{I}$, we construct a firm-level, asset- and geospatial-based biodiversity risk measure Spatial Biodiversity $\text{Risk}_i^{r,g}$ by summing the number of risky assets per firm and scaling by the firm's total assets TA_i (book value from Compustat):

$$\text{Spatial Biodiversity Risk}_{i,t}^{r,g} \;=\; \frac{1}{TA_{i,t}} \sum_{a \in \mathcal{A}_i} R_a^{r,g}, \qquad i \in \mathcal{I}.$$

This single generic formulation nests all variants used in the analysis (all combinations of asset risk types r and geospatial region g). More simply put, a firm's biodiversity risk is defined as:

$$\text{Spatial Biodiversity Risk}_i = \frac{\text{Risky assets of firm } i}{\text{Total assets of firm } i}.$$

Note that the only time variation in Spatial Biodiversity $\text{Risk}_{i,t}^{r,g}$ comes from $TA_{i,t}$, as total assets vary over time. We do not have time variation in the asset-based information.

All biodiversity-region geometries, containing both polygons and points, are first reprojected from geographic coordinates (degrees; e.g., EPSG:4326) to a projected coordinate reference system in meters (EPSG:3857) to ensure that distance-based operations are metric-consistent. The reprojected polygons and points are merged into a single geometry set. For each asset geometry

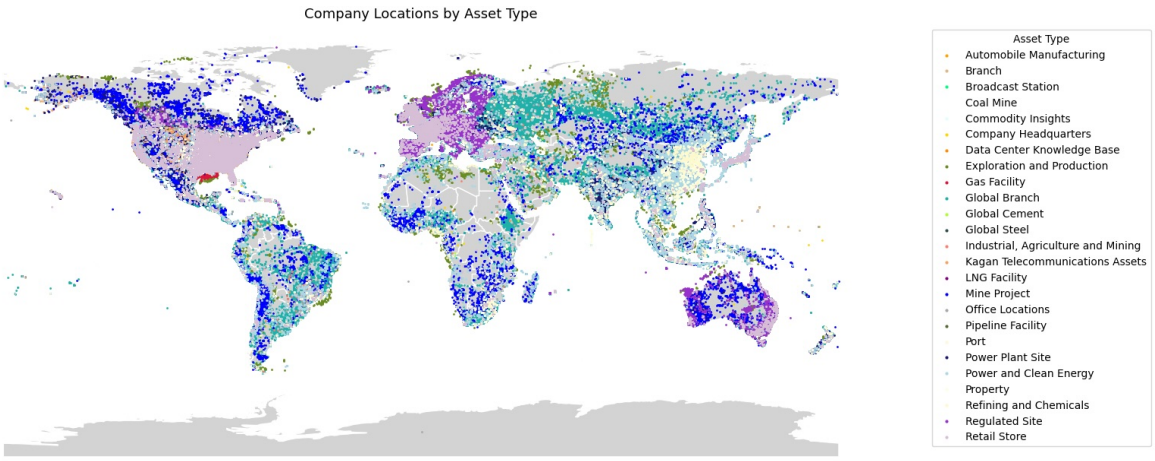


Figure 8—*All the assets in the S&P Global database, color coded by asset type.*

$\ell(a)$, we test for a spatial intersection with this set to construct an "inside" indicator. The resulting Boolean values are cast to dummy variables (1/0), corresponding to $\mathbf{1}\{\ell(a) \cap \mathcal{R}^{\mathrm{g,in}} \neq \emptyset\}$ in our notation[26].

The definition transition and physical risky asset types are presented in 10.

[26]We also offer a more lenient, buffered match, such that we measure assets *near* instead of inside a region j: $\mathcal{R}^{j,\mathrm{near}} := \mathrm{buf}_{d_0}(\mathcal{R}^j)$, where $\mathrm{buf}_{d_0}(\cdot)$ expands a polygon by a buffer of radius d_0 (e.g., $d_0 = 1$ km). To capture "near" relationships, every region geometry is buffered by 1,000 meters and the intersection test is repeated, corresponding to $\mathbf{1}\{\ell(a) \cap \mathcal{R}^{\mathrm{j,near}} \neq \emptyset\}$ in our notation.

Table 10—*Asset types with transition risk and physical risk flags. The Asset Type Id and the Asset Type Name information originate from the Trucost Physical Risk Database, and the categorization of these asset types into transition risk and physical risk is done by the authors.*

Asset Type Id	Asset Type Name	Transition Risk	Physical Risk
0	Branch	0	0
1	Power Plant Site	1	0
2	Coal Mine	1	1
3	Broadcast Station	0	0
4	Global Branch	0	0
5	Gas Facility	1	1
6	LNG Facility	1	1
7	Pipeline Facility	1	1
8	Mine Project	1	1
9	Pipeline Development	1	0
10	Property	0	0
11	Transmission Line	0	0
12	TV Network	0	0
13	Retail Store	0	0
14	Regulated Site	0	0
15	Automobile Manufacturing	1	1
16	Exploration and Production	1	1
17	Industrial, Agriculture and Mining	1	1
18	Port	1	0
19	Power and Clean Energy	0	0
20	Refining and Chemicals	1	1
21	Commodity Insights	0	0
22	World Electric Power Plants	0	0
23	Company Headquarters	0	0
24	Data Center Knowledge Base	0	0
25	Kagan Telecommunications Assets	0	0
26	Office Locations	0	0
27	Global Cement	1	1
28	Global Steel	1	1

I.B Results Appendix

I.B.1 Descriptive statistics

Table 11—*Summary statistics for all variables used in regressions. Panel A reports the summary statistics for the returns regression variables. Panel B reports the summary statistics for the profitability regression variables. Panel C reports the summary statistics of the asset- and geolocation based biodiversity risk count variables (levels and scaled by Total Assets), that are also used in the returns regressions. The summary statistics were performed on the data with only complete cases of dependent, independent, and all control variables used in the respective regressions. For the returns regressions, the monthly returns from Compustat were winsorized at 0.1% and 99.9% each month based on the sample of CRSP returns of the same month, CRSP returns are not winsorized. The ln(Biodiversity Risk) and all the control variables were winsorized at 1th and 99th percentile. For the profitability regressions, all variables are winsorized at 1th and 99th percentile, to reduce the impact of outliers.*

Panel A: Returns regression (with Trucost Biodiversity Risk)

	N^{obs}	Mean	Median	Min	Max	StDev
Returns (%)	874,052	0.665	0.139	-89.033	1625.043	13.017
Beta	874,052	1.173	1.112	-1.947	4.552	0.745
Size	874,052	7.233	7.226	2.332	10.979	1.592
B/M	874,052	-0.585	-0.496	-4.179	1.879	0.991
Investments	874,052	0.108	0.054	-0.495	3.331	0.304
Momentum	874,052	0.099	0.023	-0.862	7.108	0.498
Volatility	874,052	0.109	0.094	0.024	0.582	0.063
Leverage	874,052	0.228	0.207	0.000	0.863	0.181
Tangibility	874,052	0.274	0.229	0.001	0.862	0.216
R&D	874,052	0.021	0.001	0.000	0.432	0.049
INV/A	874,052	0.042	0.030	0.000	0.307	0.042
Sales Growth	874,052	0.091	0.046	-0.785	3.624	0.353
Return On Equity (ROE)	874,052	0.040	0.049	-1.421	0.736	0.156
ln(Biodiversity Risk)	874,052	1.040	0.915	-8.897	8.405	2.834
ln(Biodiversity Risk)$^{across\ ind}$	874,052	0.977	0.772	-5.515	7.007	2.086
ln(Biodiversity Risk)$^{within\ ind}$	874,052	0.064	0.047	-12.707	10.249	1.924

Table 11—*(continued)*

	N^{obs}	Mean	Median	Min	Max	StDev
ln(Biodiversity Risk)$^{within\ firm}$	874,052	0.002	0.003	-11.139	8.085	0.528
ln(Natural Resource Use)	874,052	-12.973	-13.816	-13.816	6.112	3.407
ln(Natural Resource Use)$^{across\ ind}$	874,052	-12.989	-13.778	-13.816	-2.929	1.953
ln(Natural Resource Use)$^{within\ ind}$	874,052	0.016	-0.008	-10.886	19.379	2.776
ln(Natural Resource Use)$^{within\ firm}$	874,052	-0.001	0.000	-18.594	16.703	1.031
ln(Water)	874,052	-5.092	-2.275	-13.816	6.604	6.859
ln(Water)$^{across\ ind}$	874,052	-5.159	-2.961	-13.816	5.814	5.564
ln(Water)$^{within\ ind}$	874,052	0.067	-0.172	-17.295	18.309	4.002
ln(Water)$^{within\ firm}$	874,052	0.001	0.000	-17.215	19.918	1.588
ln(Land/Water pollutants)	874,052	-6.516	-4.116	-13.816	4.585	6.287
ln(Land/Water pollutants)$^{across\ ind}$	874,052	-6.595	-4.520	-13.816	3.806	5.148
ln(Land/Water pollutants)$^{within\ ind}$	874,052	0.079	-0.227	-15.577	17.092	3.586
ln(Land/Water pollutants)$^{within\ firm}$	874,052	0.001	0.000	-17.622	17.677	1.085
ln(Air pollutants)	874,052	-1.039	-1.065	-13.816	6.723	3.026
ln(Air pollutants)$^{across\ ind}$	874,052	-1.106	-1.208	-7.871	4.998	2.234
ln(Air pollutants)$^{within\ ind}$	874,052	0.067	0.078	-15.842	10.785	2.055
ln(Air pollutants)$^{within\ firm}$	874,052	0.002	0.007	-10.541	11.292	0.681
ln(Waste)	874008	-1.800	-1.679	-13.816	5.590	2.533
ln(Waste)$^{across\ ind}$	874,052	-1.861	-1.797	-6.945	2.410	1.362
ln(Waste)$^{within\ ind}$	874008	0.062	0.107	-14.153	8.706	2.148
ln(Waste)$^{within\ firm}$	874008	0.001	0.009	-15.242	13.917	0.929
ln(GHG)	874,052	0.119	-0.035	-13.816	7.695	2.850
ln(GHG)$^{across\ ind}$	874,052	0.052	-0.098	-6.214	6.062	2.056
ln(GHG)$^{within\ ind}$	874,052	0.067	0.062	-16.002	10.345	1.988
ln(GHG)$^{within\ firm}$	874,052	0.002	0.007	-12.621	7.692	0.581

Table 11—*(continued)*

	N^{obs}	Mean	Median	Min	Max	StDev
Country Environmental Policy Index (EPI)	873,889	50.593	55.698	5.759	72.632	12.953
Country EPI biodiversity habitat	873,889	38.703	39.792	3.310	82.534	17.475
Country EPI ecosystem vitality	873,889	49.928	51.614	10.434	75.963	11.427
Country SDG	783,325	74.665	74.453	52.514	86.418	5.539
Country SDG14 subscore	767,266	60.607	60.166	30.973	88.068	6.884
Country SDG15 subscore	783,325	58.812	55.905	24.477	91.038	11.061

Panel B: Asset-and geospatial biodiversity risk data, where asset type $r \in$ {TR, PR, TR\|PR}, region $g \in$ {KBA, PA, CNA} and Spatial Biodiversity Risk$_i^{g,r} = \frac{\text{Count Risky Assets}_i(g,\, r)}{\text{Total Assets}_i}$

	N^{obs}	Mean	Median	Min	Max	StDev
Count Assets(KBA & TR|PR)	335,037	3.233	0.000	0	156.000	11.919
Count Assets(KBA & TR)	335,037	3.233	0.000	0	156.000	11.919
Count Assets(KBA & PR)	335,037	1.162	0.000	0	76.000	4.561
$\frac{\text{Count Assets(KBA \& TR\|PR)}}{\text{Total Assets}}$	335,037	0.004	0.000	0	6.902	0.095
$\frac{\text{Count Assets(KBA \& TR)}}{\text{Total Assets}}$	335,037	0.004	0.000	0	6.902	0.095
$\frac{\text{Count Assets(KBA \& PR)}}{\text{Total Assets}}$	335,037	0.003	0.000	0	6.902	0.093
Count Assets(CNA & TR|PR)	335,037	18.742	4.000	0	448.000	49.422
Count Assets(CNA & TR)	335,037	18.742	4.000	0	448.000	49.422
Count Assets(CNA & PR)	335,037	10.211	0.000	0	432.000	36.916
$\frac{\text{Count Assets(CNA \& TR\|PR)}}{\text{Total Assets}}$	335,037	0.021	0.001	0	20.707	0.314
$\frac{\text{Count Assets(CNA \& TR)}}{\text{Total Assets}}$	335,037	0.021	0.001	0	20.707	0.314
$\frac{\text{Count Assets(CNA \& PR)}}{\text{Total Assets}}$	335,037	0.017	0.000	0	20.707	0.300

Panel C: Profitability regression variables

	N^{obs}	Mean	Median	Min	Max	StDev
ROA_t	97,718	0.035	0.040	-1.095	0.350	0.109
ΔROA_{t+1}	90,953	-0.003	0.000	-0.678	0.814	0.087
$\overline{ROA}_{t+1:t+10}$	21,595	0.045	0.040	-0.700	0.235	0.060
ln(Biodiversity Risk)$^{across\ ind}$	97,718	1.102	0.893	-5.653	7.274	2.155

Table 11—*(continued)*

	N^{obs}	Mean	Median	Min	Max	StDev
ln(Biodiversity Risk)$^{within\ ind}$	97,718	0.027	0.012	-12.643	9.715	1.940
ln(Biodiversity Risk)$^{within\ firm}$	97,718	0.007	0.008	-9.146	7.599	0.631
Size$_t$	97,718	7.247	7.237	2.141	10.993	1.568
B/M$_t$	97,718	-0.606	-0.536	-3.966	2.009	0.954
INV/A$_t$	97,718	0.044	0.031	0.000	0.356	0.045
Leverage$_t$	97,718	0.222	0.203	0.000	0.954	0.173
ln(PPE)$_t$	97,718	5.756	5.832	-6.656	10.382	2.219
R&D$_t$	97,718	0.021	0.001	0.000	0.513	0.050
Sales Growth$_t$	97,718	0.194	0.061	-0.876	3701.467	11.979
Op. Profitability$_t$	97,718	0.257	0.212	-1.979	7.328	0.382

I.B.2 Correlation plots

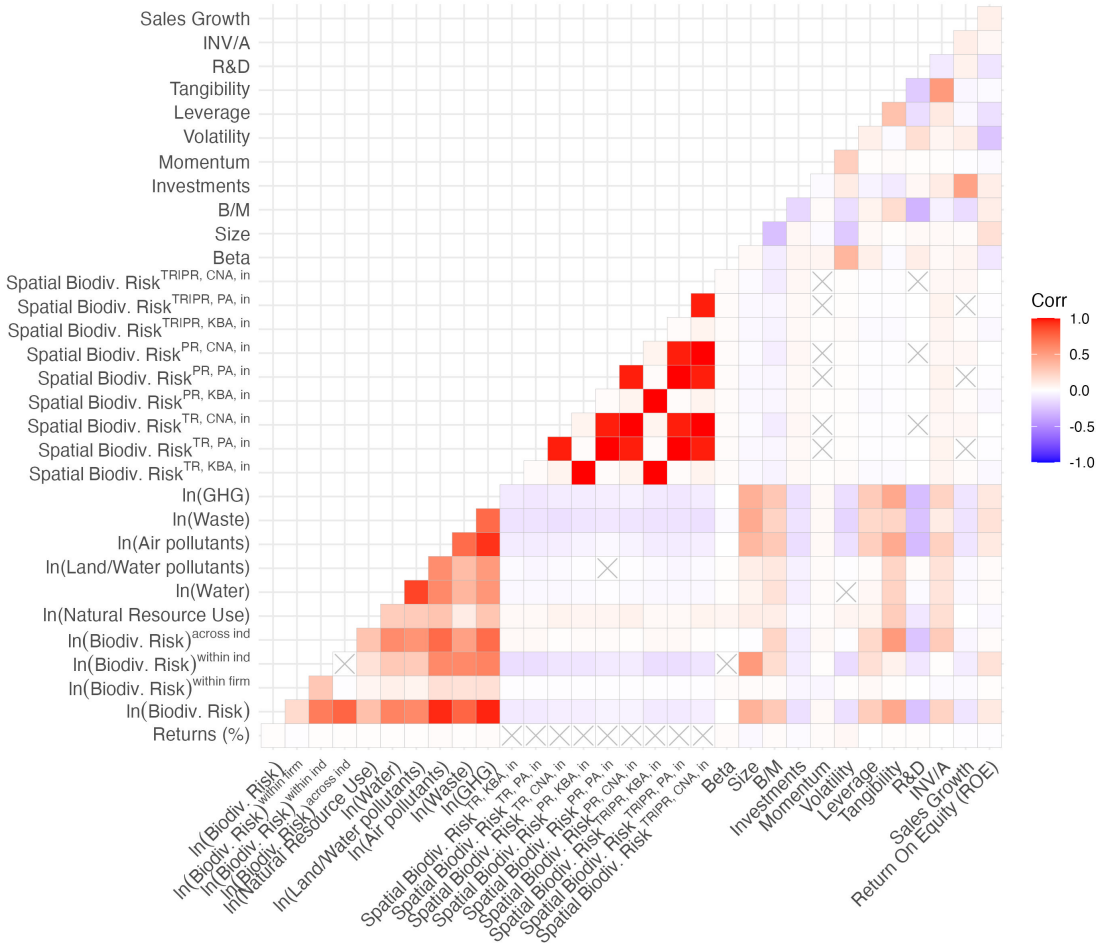


Figure 9—*Correlation plot between all firm-level variables.*

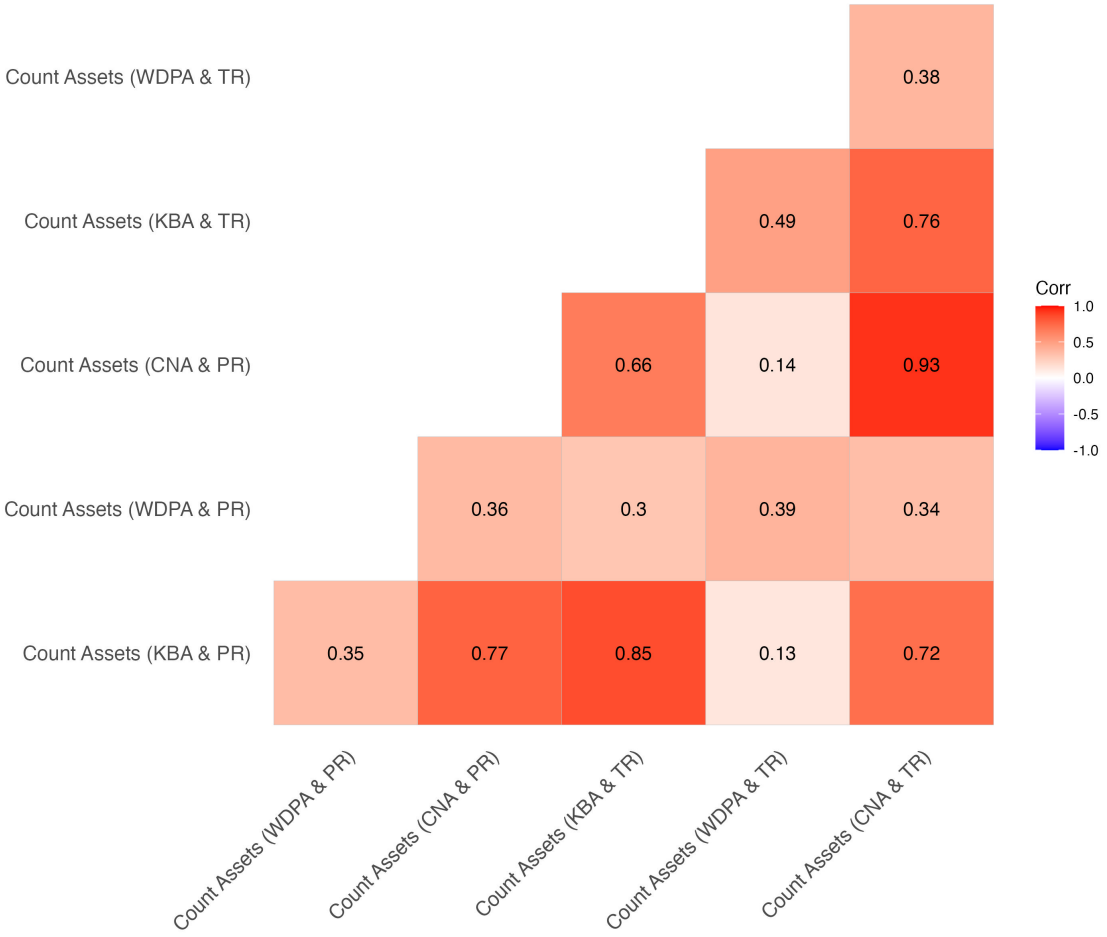


Figure 10—*Correlations across of transition risk type assets ($r = TR$) or of physical risk type assets ($r = TR$) inside different areas ($g = \{KBA, PA, CNA\}$. Note that the counts are not scaled, as opposed to the actual used measure in the analysis that is scaled by total assets.*

I.B.3 Within Standard Deviations for Biodiversity Risk measures

Table 12—*All within standard deviations (Within StDev) for the normalized Spatial Biodiversity Risk^{r,j} in the fixed effects specifications in the third, fourth and fifth column, namely the no fixed effects (no FE), industry + month-year + country fixed effects (j + c + t) and the interactions of industry with month-year and country with month-year fixed effects (j×t + c×t). All use the estimation sample of $N^{obs} = 335,037$.*

	Within StDev		
Variable	*(no FE)*	*(j + c + t)*	*(j × t + c × t)*
Spatial Biodiversity Risk$^{r=TR,\ j=PA}$	0.136	0.135	0.133
Spatial Biodiversity Risk$^{r=PR,\ j=PA}$	0.136	0.134	0.133
Spatial Biodiversity Risk$^{r=TR\|PR,\ j=PA}$	0.136	0.135	0.133
Spatial Biodiversity Risk$^{r=TR,\ j=KBA}$	0.095	0.094	0.092
Spatial Biodiversity Risk$^{r=PR,\ j=KBA}$	0.093	0.092	0.090
Spatial Biodiversity Risk$^{r=TR\|PR,\ j=KBA}$	0.095	0.094	0.092
Spatial Biodiversity Risk$^{r=TR,\ j=CNA}$	0.314	0.308	0.301
Spatial Biodiversity Risk$^{r=PR,\ j=CNA}$	0.300	0.294	0.288
Spatial Biodiversity Risk$^{r=TR\|PR,\ j=CNA}$	0.314	0.308	0.301

Table 13—*All within standard deviations (Within StDev) for the firm-level Trucost biodiversity risk measure under the fixed-effect specifications in columns two to six: no fixed effects (no FE), time (t), country (c), country + time (c + t), and country × time (c×t). All use the estimation sample of $N^{obs} = 874,052$.*

	Within StDev				
Variable	*(no FE)*	*(t)*	*(c)*	*(c + t)*	*(c × t)*
ln(Biodiversity Risk)$^{\text{within-firm}}$	0.528	0.525	0.528	0.525	0.518
ln(Biodiversity Risk)$^{\text{within-ind}}$	1.924	1.924	1.870	1.870	1.856
ln(Biodiversity Risk)$^{\text{across-ind}}$	2.086	1.971	2.005	1.885	1.880

Table 14—*Within standard deviations (Within StDev) of ln(Biodiversity Risk) under four fixed-effect specifications: no fixed effects (no FE), industry + time + country (j + t + c), industry × time + country × time (j×t + c×t), and firm + time (i + t). Estimation sample size* $N^{obs} = 874,052$.

	Within StDev			
Variable	*(no FE)*	*(j + t + c)*	*(j × t + c × t)*	*(i + t)*
ln(Biodiversity Risk)	2.834	1.876	1.845	0.523

I.B.4 Additional analysis: Environmental (policy) performance measured with EPI instead of the SDG

We analyze the results of regressing returns on the countries' EPI general score, the EPI biodiversity habitat, and the EPI ecosystem vitality score in relation to biodiversity risk, presented in Table 15 panels A, B, and C, respectively. First, the country's EPI Biodiversity Habitat and EPI Ecosystem Vitality scores have a significant positive effect ($p < 0.05$ and $p < 0.001$, respectively), indicating that higher policy index scores related to biodiversity are associated with higher returns. Note that the general EPI score does not have any main effect on returns, Hence, only the EPI scores specific to biodiversity risk are positively related to returns. One could argue that these effects of EPI Biodiversity Habitat and EPI Ecosystem Vitality scores on returns could also reflect other country characteristics (such as GDP), since these are correlated (Block et al., 2024). Nonetheless, this effect is not observed for the general EPI. Second, when examining the interaction effects, we find no significant effects for the interaction between biodiversity risk and the overall EPI score or the EPI score with the Ecoystem Vitality score. We found a small positive and weakly significant effect for the EPI Biodiversity Habitat score interacting with the within-firm biodiversity risk, $p < 0.10$. Thus, we find at most weak evidence that a nation's environmental policy strictness, measured by the EPI, is relevant in the relation between a firm's biodiversity risk and stock returns. The fact that we do not find a significant result for the national environmental policy performance measure, as measured by EPI scores, differs from the previous results in the biodiversity risk pricing literature. The supposed biodiversity risk premium was found in countries with lower biodiversity protection, hence where higher uncertainty about future regulations is highest (Garel et al., 2024). Nonetheless, the difference in these environmental policy performance results may arise because Garel et al. (2024) uses a single time-invariant dummy for a country's EPI. In contrast, we use a time series of the EPI scores.

Table 15— *Results of panel regressions of monthly stock returns on the within-firm, within-industry, and across-industry variation of ln(Biodiversity Risk), the natural logarithm of firm-level environmental costs (in million USD). We interact biodiversity risk with alternative measures of the firm's headquarters country environmental performance: Environmental Policy Index (EPI) overall score (Panel A), EPI Biodiversity Habitat (B), and EPI Ecosystem Vitality (C). Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) includes interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Panel A: EPI (general)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.548*	-0.474·	-0.537*	-0.445*	-0.545**
	(0.228)	(0.221)	(0.220)	(0.203)	(0.170)
ln(Biodiversity Risk)$^{within\ ind}$	0.103	0.121·	0.102·	0.093	0.081
	(0.078)	(0.058)	(0.055)	(0.058)	(0.057)
ln(Biodiversity Risk)$^{across\ ind}$	0.101	0.020	0.100	0.019	0.099
	(0.080)	(0.066)	(0.067)	(0.069)	(0.059)
Country Environmental Policy Index (EPI)	0.007	-0.000	0.002	0.007	0.008
	(0.008)	(0.008)	(0.033)	(0.008)	(0.009)
ln(Biodiversity Risk)$^{within\ firm}\times$ EPI	0.006	0.004	0.005	0.003	0.005
	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)
ln(Biodiversity Risk)$^{within\ ind}\times$ EPI	-0.001	-0.001	-0.001	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(Biodiversity Risk)$^{across\ ind}\times$ EPI	-0.001	-0.000	-0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Panel B: EPI Biodiversity Habitat (BH)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.436*	-0.391*	-0.423*	-0.376*	-0.443***
	(0.186)	(0.143)	(0.177)	(0.129)	(0.098)

Table 15 (continued)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ ind}$	0.108·	0.119**	0.101*	0.104**	0.092**
	(0.059)	(0.036)	(0.042)	(0.031)	(0.028)
ln(Biodiversity Risk)$^{across\ ind}$	0.093	0.024	0.104	0.037	0.076
	(0.076)	(0.044)	(0.065)	(0.041)	(0.047)
EPI BH	0.004	-0.002	0.009	0.003	0.012*
	(0.006)	(0.005)	(0.012)	(0.008)	(0.005)
ln(Biodiversity Risk)$^{within\ firm}\times$ EPI BH	0.004	0.002	0.004	0.002	0.003·
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
ln(Biodiversity Risk)$^{within\ ind}\times$ EPI BH	-0.002·	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(Biodiversity Risk)$^{across\ ind}\times$ EPI BH	-0.001	-0.000	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Panel C: EPI Ecosystem Vitality (EV)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.480*	-0.388·	-0.455·	-0.336·	-0.443**
	(0.217)	(0.195)	(0.218)	(0.176)	(0.138)
ln(Biodiversity Risk)$^{within\ ind}$	0.156·	0.161*	0.139*	0.108·	0.091
	(0.076)	(0.058)	(0.056)	(0.056)	(0.054)
ln(Biodiversity Risk)$^{across\ ind}$	0.072	0.007	0.077	0.018	0.102
	(0.078)	(0.056)	(0.062)	(0.062)	(0.067)
EPI EV	0.004	-0.002	-0.006	0.009	0.016***
	(0.009)	(0.009)	(0.023)	(0.007)	(0.003)
ln(Biodiversity Risk)$^{within\ firm}\times$ EPI EV	0.004	0.002	0.004	0.001	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
ln(Biodiversity Risk)$^{within\ ind}\times$ EPI EV	-0.003·	-0.002	-0.002	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(Biodiversity Risk)$^{across\ ind}\times$ EPI EV	-0.000	0.000	0.000	0.000	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

I.B.5 Additional analysis: Geographic distribution: Biodiversity risk around the world

Having established that biodiversity risk and the context in which we measure it matter for returns, an important next step is to examine whether these relationships differ across regions. Table 5 reports the regional results for the regressions of $ln(Biodiversity)^{within\ firm}$, $ln(Biodiversity)^{within\ industry}$, and $ln(Biodiversity)^{across\ industry}$ on excess returns for different fixed effects specifications. The analysis was run for each region separately, as indicated by the horizontal lines in the table. Note that the control variables were again suppressed; the complete set of results and fit statistics can be provided upon request. Examining the coefficient estimates, we first observe that the negative coefficient for the within-firm variation observed in Tables 1 and 2 is still present for different regions across several different fixed effects specifications, although the significance may sometimes drop (especially for Southern Hemisphere we do not observe significant effects anymore, although this may be due to the substantially smaller sample[27]. Next, we observe that the within-industry variation effect observed in Tables 1 and 2 is still present in terms of sign, but only remains significant for some, not all, specifications. However, looking at fixed effects specifications with *at least* country + time or country × time fixed effects (columns (2), (3) and (4)), it is clear that the within-industry effect is still significantly present for North America, Asia and the Southern Hemisphere, $p < 0.05$, but *not* significant for Europe. This is a striking and puzzling result, as Europe is typically regarded as a region with stricter environmental regulations. Nonetheless, the results have some parallels with those from Bolton and Kacperczyk (2023), where the authors find geographic variation in the carbon premium worldwide.

Although we observe positive within-industry effects, which is more in line with Bolton and Kacperczyk; Bolton and Kacperczyk (2021; 2023), the negative effect in the within-firm variation for the Asia subsample is bigger in absolute terms than for the Europe sample, and similarly large as the North America sample, and even has a stronger significance. The fact that the results of these papers and the results presented in this paper show differences between geographical locations of firms is interesting and puzzling. Finally, similar to before, we find no across industry variation effects across the different regions for different model specifications.

All in all, our unconditional results seem to not have been driven by any particular region, since all the regions show similar directional effects. Although the within-firm variation coefficient estimates are equally significant across regions, the significance of the within-industry variation estimates does differ across regions.

[27]In Table 5, the respective number of observations for the Southern Hemisphere is almost a quarter of the size of the North American sample size across all specifications. Full sample sizes and the rest of the results for each specification can be provided upon request.

I.B.6 Additional analysis: Transition Risk vs Physical Risk drivers

We decompose the biodiversity risk measure into two sums of components, with one more closely associated with transition risk than with physical risk. We proxy transition risk by the log of the sum of land and water pollutants, air pollutants, waste, and greenhouse-gas emissions, and physical risk by the log of the sum of natural resource use and water. The regressions of the transition biodiversity risk sum on the physical biodiversity risk sum indicate that the transition-risk dimension primarily accounts for the baseline results.

For within-firm variation, the coefficients of the transition-risk components in Table 16 exhibit a strong and statistically significant negative association with returns, with coefficient magnitudes comparable to those in the baseline specification results in Table 2. In contrast, the coefficients for the within-firm physical-risk components in Table 17 remain negatively related to returns, yet they are substantially smaller in magnitude (approximately one-tenth) of the baseline effect and statistically weaker compared to the within-firm coefficients in Table 2. A similar pattern emerges for within-industry variation. The coefficients for the within-industry transition-risk components in Table 16 display positive and statistically significant within-industry effects, almost precisely similar to the results in Table 2, whereas the coefficients for the within-industry effects of physical-risk components in Table 17 are markedly smaller and lose statistical significance.

These results form an interesting extension to 3. At the same time, because transition and physical risk are difficult to disentangle empirically, we exercise caution in interpreting these results. Nonetheless, the results indicate that the sum of the transition risk components is a stronger driver of the main biodiversity risk results than the sum of the physical risk components.

Table 16—*Results of panel regressions of monthly stock returns on the within-firm, within-industry and across-industry variation of ln(Land/Water Pol. + Air Pol + Waste + GHG), the natural logarithm of firm-level environmental costs (in million USD). For the across- and within-firm variation, we define* $ln(Land/WaterPol. + AirPol + Waste + GHG)_i^{across}$ *as the average of* $ln(Land/WaterPol. + AirPol + Waste + GHG)$ *for firm i, and* $ln(Land/WaterPol. + AirPol + Waste + GHG)_{i,t}^{within} = ln(Land/WaterPol. + AirPol + Waste + GHG)_{i,t} - ln(Land/WaterPol. + AirPol + Waste + GHG)_i^{across}$. *Next, for the across- and within-industry variation, we define* $ln(Land/WaterPol. + AirPol + Waste + GHG)_{j,t}^{across}$ *as the average of* $ln(Land/WaterPol. + AirPol + Waste + GHG)$ *for in industry j in time t, and* $ln(Land/WaterPol. + AirPol + Waste + GHG)_{i,t,j}^{within} = ln(Land/WaterPol. + AirPol + Waste + GHG)_{i,t} - ln(Land/WaterPol. + AirPol + Waste + GHG)_{j,t}^{across}$. *Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) include interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Variable	(1)	(2)	(3)	(4)	(5)
ln(Land/Water Pol. + Air Pol + Waste + GHG)$^{within\ firm}$	-0.296*	-0.320***	-0.305*	-0.327***	-0.330***
	(0.123)	(0.075)	(0.116)	(0.070)	(0.065)
ln(Land/Water Pol. + Air Pol + Waste + GHG)$^{within\ ind}$	0.038	0.070***	0.051	0.078***	0.072***
	(0.059)	(0.011)	(0.051)	(0.008)	(0.011)
ln(Land/Water Pol. + Air Pol + Waste + GHG)$^{across\ ind}$	0.076	0.012	0.096	0.032	0.031
	(0.073)	(0.032)	(0.068)	(0.027)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Month-Year		Yes		Yes	
Country			Yes	Yes	
Country-Month-Year					Yes
Fit statistics					
R-squared	0.004	0.155	0.004	0.155	0.253
Within R-squared	NA	0.001	0.004	0.001	0.001
Observations	874052	874052	874052	874052	874052

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

Table 17—*Results of panel regressions of monthly stock returns on the within-firm, within-industry and across-industry variation of ln(Natural Resource Use + Water), the natural logarithm of firm-level environmental costs (in million USD). For the across- and within-firm variation, we define* $ln(NaturalResourceUse + Water)_{i}^{across}$ *as the average of* $ln(NaturalResourceUse + Water)$ *for firm i, and* $ln(NaturalResourceUse + Water)_{i,t}^{within} = ln(NaturalResourceUse + Water)_{i,t} - ln(NaturalResourceUse + Water)_{i}^{across}$. *Next, for the across- and within-industry variation, we define* $ln(NaturalResourceUse + Water)_{j,t}^{across}$ *as the average of* $ln(NaturalResourceUse + Water)$ *for in industry j in time t, and* $ln(NaturalResourceUse + Water)_{i,t,j}^{within} = ln(NaturalResourceUse + Water)_{i,t} - ln(NaturalResourceUse + Water)_{j,t}^{across}$. *Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) include interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Variable	(1)	(2)	(3)	(4)	(5)
ln(Natural Resource Use + Water)$^{within\ firm}$	-0.003	-0.021·	-0.011	-0.027*	-0.031**
	(0.019)	(0.011)	(0.018)	(0.011)	(0.009)
ln(Natural Resource Use + Water)$^{within\ ind}$	-0.010	-0.001	-0.002	0.004	0.004
	(0.010)	(0.004)	(0.008)	(0.003)	(0.003)
ln(Natural Resource Use + Water)$^{across\ ind}$	0.003	0.002	0.008	0.005	0.005
	(0.010)	(0.009)	(0.010)	(0.008)	(0.007)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Month-Year		Yes		Yes	
Country			Yes	Yes	
Country-Month-Year					Yes
Fit statistics					
R-squared	0.004	0.155	0.004	0.155	0.253
Within R-squared	NA	0.001	0.004	0.001	0.001
Observations	874052	874052	874052	874052	874052

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

I.B.7 Additional analysis: Do returns depend on important biodiversity events and news?

Having established the baseline relation between biodiversity risk and returns, we next examine whether this relation changes when investor attention to biodiversity risk is heightened by major events or news shocks. The results of these news and attention towards biodiversity loss specifications are summarized in Table 18. Note that the control variables were again suppressed; the complete set of results and fit statistics can be provided upon request. We will remain cautious with any conclusions, given the limited, approximately two-year post-event data following the biodiversity loss attention-grabbing events.

Firstly, the biodiversity macro news index constructed by Giglio et al. (2025) did not significantly interact with our biodiversity risk measures, and neither did the climate macro news index. Secondly, splitting the sample before and after biodiversity loss "attention-grabbing events", namely the launch of the TNFD, the Kunming Conference, did have significant interactions, but so did the more "climate change "grabbing event, the Paris conference. Namely, we observe a positive interaction effect for within-firm biodiversity risk after the Paris Agreement, $p < 0.05$, after the Kunming Agreement, $p < 0.10$, and after the TNFD Agreement, $p < 0.05$. Therefore, the adverse effect on returns by within-firm biodiversity risk is *smaller* after these recent attention-grabbing events. This could mean either that we are observing the pricing effect of a biodiversity risk premium at the within-firm level, or that the adverse cash flow effects are smaller after these events, or both. Next, we observe a positive interaction effect for within-industry after the Paris Agreement $p < 0.10$, after the Kunming Agreement $p < 0.01$, and after the TNFD Agreement $p < 0.01$. Thus, the positive effect on returns by within-industry biodiversity risk is *larger* after these events. This could mean that a potential biodiversity risk premium is more pronounced during this period, that the positive cash flow effects are larger, or both. Finally, we also observe positive interaction effects for the across-industry effects after the Paris Agreement, $p < 0.10$, after the Kunming Agreement, $p < 0.01$, and after the TNFD Agreement, $p < 0.01$. That is, industries with higher biodiversity risks had higher returns after these events. However, this effect might pick up "general" industry-specific events at the end of the sample. Notably, the direction of the effect and the statistical significance of the within-firm variance effect of *ln(Biodiversity Risk)* on returns is robust in all these attention specifications, but for the within-industry variance, the statistical significance disappears.

The results from Table 18 are consistent up with the transition and physical risk premium channel. We find *higher* returns for high biodiversity risk firms, on every level we measure, after the Kunming Declaration, the launch of the TNFD, but also the Paris agreement. These are key events around which investors' beliefs around biodiversity risk (or environmental risks in general) might have changed. After these events, stock prices of firms with high biodiversity

impact and dependency go down with higher implied expected (and realized) returns for large biodiversity risk firms.

At the same time, the cash flow channel could still also exist alongside evidence for a biodiversity risk premium, but we observe that the results in Table 18 support the biodiversity risk premium channel more than the cash flow channel. Following the logic of the cash flow channel, Pre-Kunming, - TNFD and -Paris, there would have been more scope for unanticipated upside in cash flows from biodiversity-intensive activity than after. Overall, our results show *higher*, not *lower*, returns for any type of biodiversity risk in the period after these biodiversity-relevant events. Therefore, these results do not seem to be consistent with a possible cash flow channel, a similar conclusion as drawn by Garel et al. (2024). Having said that, cash flow effects could still exist *alongside* the biodiversity risk premium; we cannot disentangle the two completely.

The results of this analysis do not support the shifts in investors' preferences over time. If investors shift away their funds from firms with a lot of biodiversity impact, one would expect to observe lower returns over time for firms with larger biodiversity impact. However, we find that in the latter part of our sample, we find *higher* returns across all aggregation levels of biodiversity risk. Thus, the results from Table 18 does not seem to support attention or preferences shifts channels.

Table 18—*Results of panel regressions of monthly stock returns on the within-firm, within-industry, and across-industry variation of ln(Biodiversity Risk) interacted with different time-varying measures. Panel A uses Bio. News$_t$, the monthly mean NYT Biodiversity News Index. Panel B uses Clim. News$_t$, the monthly mean NYT Climate News Index. Panel C uses TNFD$_t$, a dummy equal to one for observations in the months after the launch of the TNFD, and zero otherwise. Panel D uses Kunming$_t$, a dummy equal to one for observations in months after the Kunming Biodiversity Conference, and zero otherwise. Panel E uses Paris$_t$, a dummy equal to one for observations in months after the Paris Climate Conference, and zero otherwise. Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) includes interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Panel A: Mean NYT Biodiversity News Index (Bio. News$_t$)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.226·	-0.354***	-0.235·	-0.358***	-0.373***
	(0.122)	(0.074)	(0.124)	(0.074)	(0.071)
ln(Biodiversity Risk)$^{within\ ind}$	0.064	0.084**	0.079	0.097**	0.056
	(0.057)	(0.025)	(0.053)	(0.031)	(0.045)
ln(Biodiversity Risk)$^{across\ ind}$	-0.048	-0.042	-0.027	-0.022	-0.037
	(0.108)	(0.052)	(0.106)	(0.054)	(0.068)
Bio. News	-2.872		-2.844		
	(2.753)		(2.753)		
ln(Biodiversity Risk)$^{within\ firm}$× Bio. News	-0.134	0.166	-0.141	0.150	0.189
	(0.480)	(0.288)	(0.474)	(0.274)	(0.210)
ln(Biodiversity Risk)$^{within\ ind}$× Bio. News	-0.036	-0.054	-0.038	-0.059	0.046
	(0.090)	(0.082)	(0.094)	(0.086)	(0.122)
ln(Biodiversity Risk)$^{across\ ind}$× Bio. News	0.284	0.162	0.287	0.159	0.204
	(0.297)	(0.169)	(0.296)	(0.168)	(0.209)

Panel B: Mean NYT Climate News Index (Clim. News$_t$)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.282·	-0.434***	-0.280·	-0.434***	-0.415***
	(0.158)	(0.089)	(0.156)	(0.086)	(0.092)
ln(Biodiversity Risk)$^{within\ ind}$	0.022	0.014	0.031	0.025	0.029

Table 18 (continued)

Variable	(1)	(2)	(3)	(4)	(5)
	(0.045)	(0.035)	(0.038)	(0.038)	(0.042)
ln(Biodiversity Risk)$^{across\ ind}$	-0.059	-0.011	-0.038	0.011	0.025
	(0.134)	(0.065)	(0.132)	(0.059)	(0.057)
Clim. News	-2.155		-2.143		
	(1.353)		(1.376)		
ln(Biodiversity Risk)$^{within\ firm}\times$ Clim. News	0.098	0.268	0.081	0.251	0.203
	(0.244)	(0.186)	(0.237)	(0.174)	(0.203)
ln(Biodiversity Risk)$^{within\ ind}\times$ Clim. News	0.109	0.094	0.111	0.092	0.074
	(0.078)	(0.070)	(0.079)	(0.069)	(0.078)
ln(Biodiversity Risk)$^{across\ ind}\times$ Clim. News	0.105	0.039	0.104	0.037	0.008
	(0.148)	(0.070)	(0.142)	(0.069)	(0.066)

Panel C: Time dummy post TNFD introduction (TNFD$_t$)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.235	-0.355***	-0.239·	-0.360***	-0.363***
	(0.140)	(0.061)	(0.133)	(0.055)	(0.041)
ln(Biodiversity Risk)$^{within\ ind}$	0.018	0.026	0.028	0.037	0.032
	(0.052)	(0.023)	(0.042)	(0.023)	(0.021)
ln(Biodiversity Risk)$^{across\ ind}$	-0.067	-0.067·	-0.048	-0.046	-0.026
	(0.057)	(0.036)	(0.058)	(0.039)	(0.034)
Dummy Post TNFD	-2.194**		-2.185*		
	(0.721)		(0.735)		
ln(Biodiversity Risk)$^{within\ firm}\times$ TNFD	0.145	0.202·	0.134	0.189·	0.185*
	(0.168)	(0.095)	(0.165)	(0.090)	(0.079)
ln(Biodiversity Risk)$^{within\ ind}\times$ TNFD	0.161**	0.159**	0.162**	0.159**	0.151**
	(0.048)	(0.045)	(0.048)	(0.045)	(0.044)
ln(Biodiversity Risk)$^{across\ ind}\times$ TNFD	0.310**	0.318***	0.312**	0.318***	0.235**
	(0.086)	(0.065)	(0.083)	(0.065)	(0.063)

Panel D: Time dummy post Kunming Biodiversity Conference (Kunming$_t$)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.250·	-0.341***	-0.256·	-0.347***	-0.352***
	(0.133)	(0.065)	(0.126)	(0.059)	(0.044)
ln(Biodiversity Risk)$^{within\ ind}$	0.030	0.037·	0.042	0.047*	0.042·
	(0.054)	(0.020)	(0.046)	(0.021)	(0.021)
ln(Biodiversity Risk)$^{across\ ind}$	-0.043	-0.051	-0.023	-0.030	-0.015
	(0.050)	(0.038)	(0.052)	(0.042)	(0.037)
Dummy Post Kunming	-2.372**		-2.369**		
	(0.661)		(0.671)		

Table 18 (continued)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}\times$ Kunming	0.172	0.178	0.160	0.164	0.167·
	(0.156)	(0.105)	(0.153)	(0.100)	(0.086)
ln(Biodiversity Risk)$^{within\ ind}\times$ Kunming	0.146**	0.149**	0.148**	0.150**	0.145**
	(0.045)	(0.044)	(0.046)	(0.045)	(0.045)
ln(Biodiversity Risk)$^{across\ ind}\times$ Kunming	0.302**	0.317***	0.304**	0.317***	0.235**
	(0.088)	(0.072)	(0.086)	(0.071)	(0.068)

Panel E: Time dummy post Paris Climate Conference (Paris$_t$)

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiversity Risk)$^{within\ firm}$	-0.560***	-0.504***	-0.571***	-0.502***	-0.467***
	(0.094)	(0.081)	(0.089)	(0.074)	(0.064)
ln(Biodiversity Risk)$^{within\ ind}$	-0.006	0.007	0.008	0.020	0.005
	(0.062)	(0.050)	(0.057)	(0.048)	(0.038)
ln(Biodiversity Risk)$^{across\ ind}$	-0.104	-0.115·	-0.077	-0.093	-0.085
	(0.063)	(0.063)	(0.060)	(0.061)	(0.052)
Dummy Post Paris	-0.721		-0.663		
	(0.764)		(0.746)		
ln(Biodiversity Risk)$^{within\ firm}\times$ Paris	0.402*	0.288*	0.403*	0.272*	0.219*
	(0.170)	(0.112)	(0.166)	(0.095)	(0.094)
ln(Biodiversity Risk)$^{within\ ind}\times$ Paris	0.072	0.076	0.070	0.072	0.084·
	(0.053)	(0.057)	(0.052)	(0.056)	(0.046)
ln(Biodiversity Risk)$^{across\ ind}\times$ Paris	0.199·	0.163·	0.196·	0.161·	0.150·
	(0.099)	(0.084)	(0.098)	(0.082)	(0.070)

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

I.B.8 Additional analysis: Trucost-based biodiversity risk, excluding GHG

In Table 19, we show the results for the regression when we exclude the environmental costs associated with GHG emissions from a firm's total sum of environmental costs associated with biodiversity risk. By doing so, we aim to disentangle the climate risks from the biodiversity risk. The results in 19 show that the results in Table 2 are robust against removing the GHG environmental costs from the measure, although the effect size is slightly smaller for the within-firm variance.

Table 19—*Results of panel regressions of monthly stock returns on the within-firm, within-industry, and across-industry variation of ln(Biodiversity Risk - GHG), the natural logarithm of firm-level costs (in million USD) linked to biodiversity risk, excluding GHG emissions from the sum of environmental costs. Column (1) reports results without fixed effects; Column (2) adds month–year fixed effects; Column (3) adds country fixed effects; Column (4) adds month–year and country fixed effects; Column (5) includes interactions of country with month–year fixed effects. All the regressions control for Beta, Size, B/M, Investments, Momentum, Volatility, Leverage, Tangibility, R&D, INV/A, Sales Growth, and ROE, but the coefficients for these control variables were suppressed in the table for brevity. Standard errors are clustered by firm and year.*

Variable	(1)	(2)	(3)	(4)	(5)
ln(Biodiv. Risk - GHG)$^{within\ firm}$	-0.232*	-0.270***	-0.248*	-0.281***	-0.284***
	(0.098)	(0.056)	(0.092)	(0.050)	(0.044)
ln(Biodiv. Risk - GHG)$^{within\ ind}$	0.032	0.065***	0.051	0.078***	0.072***
	(0.052)	(0.009)	(0.043)	(0.005)	(0.007)
ln(Biodiv. Risk - GHG)$^{across\ ind}$	0.065	0.006	0.089	0.028	0.027
	(0.069)	(0.034)	(0.066)	(0.029)	(0.028)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed-effects					
Month-Year		Yes		Yes	
Country			Yes	Yes	
Country-Month-Year					Yes
Fit statistics					
R-squared	0.004	0.155	0.004	0.155	0.253
Within R-squared	NA	0.001	0.004	0.001	0.001
Observations	874052	874052	874052	874052	874052

Clustered (Firm & Year) standard-errors in parentheses
*Signif. Codes: ***: 0.001,**: 0.01, *: 0.05, ·: 0.1*

I.B.9 Additional analysis: ROA regional analysis

In Tables 20, 21, 22, 23, we rerun the ROA analyses from Table 6, but then for different regions, as briefly discussed in Section 4.1.5.

Table 20—*Overview of Regression Results for Different specifications Profitability (ROA) analysis on within firm and within and across industry log biodiversity impact, for the North America region only In the first few rows, we use contemporaneous ROA_t as the dependent variable, then in the next few rows, we use ΔROA_{t+1} as the dependent variable, and then in the last rows we use the moving average $\overline{ROA}_{t+10:t+1}$ as the dependent variable.*

Dep. Variable	Independent Variables	(1)	(2)	(3)	(4)
ROA_t	ln(Biodiversity Risk)$^{within\ firm}$	0.012*	0.011*	0.011*	0.012*
		(0.005)	(0.005)	(0.005)	(0.005)
	ln(Biodiversity Risk)$^{within\ ind}$	0.010***	0.009***	0.009***	0.009***
		(0.002)	(0.002)	(0.002)	(0.002)
	ln(Biodiversity Risk)$^{across\ ind}$	0.012***	0.012***	0.012***	0.012***
		(0.001)	(0.001)	(0.001)	(0.001)
ΔROA_{t+1}	ln(Biodiversity Risk)$^{within\ firm}$	-0.062***	-0.053***	-0.053***	-0.053***
		(0.006)	(0.006)	(0.006)	(0.006)
	ln(Biodiversity Risk)$^{within\ ind}$	0.019***	0.018***	0.018***	0.018***
		(0.002)	(0.002)	(0.002)	(0.002)
	ln(Biodiversity Risk)$^{across\ ind}$	0.006***	0.004***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)
$\overline{ROA}_{t+10:t+1}$	ln(Biodiversity Risk)$^{within\ firm}$	-0.026**	-0.028**	-0.027**	-0.028**
		(0.009)	(0.009)	(0.009)	(0.009)
	ln(Biodiversity Risk)$^{within\ ind}$	0.007·	0.007*	0.007*	0.007*
		(0.004)	(0.004)	(0.004)	(0.004)
	ln(Biodiversity Risk)$^{across\ ind}$	0.003	0.003	0.003	0.003
		(0.002)	(0.002)	(0.002)	(0.002)
Controls		Yes	Yes	Yes	Yes
Fixed-effects					
Fiscal Year			Yes	Yes	
Country				Yes	
Fiscal Year - Country					Yes

Note 1: Clustered (gvkey) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

Table 21—*Overview of Regression Results for Different specifications Profitability (ROA) analysis on within firm and within and across industry log biodiversity impact, for the Europe region only In the first few rows, we use contemporaneous ROA_t as the dependent variable, then in the next few rows, we use ΔROA_{t+1} as the dependent variable, and then in the last rows we use the moving average $\overline{ROA}_{t+10:t+1}$ as the dependent variable.*

Dep. Variable	Independent Variables	(1)	(2)	(3)	(4)
ROA_t	ln(Biodiversity Risk)$^{within\ firm}$	-0.002	-0.004	-0.004	-0.003
		(0.004)	(0.004)	(0.004)	(0.004)
	ln(Biodiversity Risk)$^{within\ ind}$	0.006***	0.007***	0.007***	0.007***
		(0.002)	(0.002)	(0.002)	(0.002)
	ln(Biodiversity Risk)$^{across\ ind}$	0.001	0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)	(0.001)
ΔROA_{t+1}	ln(Biodiversity Risk)$^{within\ firm}$	-0.036***	-0.032***	-0.032***	-0.032***
		(0.004)	(0.004)	(0.004)	(0.004)
	ln(Biodiversity Risk)$^{within\ ind}$	0.010***	0.009***	0.010***	0.009***
		(0.002)	(0.002)	(0.002)	(0.002)
	ln(Biodiversity Risk)$^{across\ ind}$	0.008***	0.007***	0.007***	0.007***
		(0.001)	(0.001)	(0.001)	(0.001)
$\overline{ROA}_{t+10:t+1}$	ln(Biodiversity Risk)$^{within\ firm}$	-0.012	-0.013·	-0.015*	-0.015·
		(0.008)	(0.008)	(0.007)	(0.008)
	ln(Biodiversity Risk)$^{within\ ind}$	0.005	0.005	0.005	0.004
		(0.004)	(0.004)	(0.004)	(0.004)
	ln(Biodiversity Risk)$^{across\ ind}$	-0.004	-0.003	-0.003	-0.003
		(0.003)	(0.003)	(0.003)	(0.003)
Controls		Yes	Yes	Yes	Yes
Fixed-effects					
Fiscal Year			Yes	Yes	
Country				Yes	
Fiscal Year - Country					Yes

Note 1: Clustered (gvkey) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

Table 22—*Overview of Regression Results for Different specifications Profitability (ROA) analysis on within firm and within and across industry log biodiversity impact, for the Asia region only In the first few rows, we use contemporaneous ROA_t as the dependent variable, then in the next few rows, we use ΔROA_{t+1} as the dependent variable, and then in the last rows we use the moving average $\overline{ROA}_{t+10:t+1}$ as the dependent variable.*

Dep. Variable	Independent Variables	(1)	(2)	(3)	(4)
ROA_t	ln(Biodiversity Risk)$^{within\ firm}$	-0.009***	-0.011***	-0.011***	-0.009***
		(0.002)	(0.002)	(0.002)	(0.002)
	ln(Biodiversity Risk)$^{within\ ind}$	0.008***	0.007***	0.007***	0.007***
		(0.001)	(0.001)	(0.001)	(0.001)
	ln(Biodiversity Risk)$^{across\ ind}$	0.009***	0.010***	0.009***	0.009***
		(0.001)	(0.001)	(0.001)	(0.001)
ΔROA_{t+1}	ln(Biodiversity Risk)$^{within\ firm}$	-0.026***	-0.023***	-0.024***	-0.023***
		(0.002)	(0.003)	(0.003)	(0.003)
	ln(Biodiversity Risk)$^{within\ ind}$	0.012***	0.012***	0.012***	0.012***
		(0.001)	(0.001)	(0.001)	(0.001)
	ln(Biodiversity Risk)$^{across\ ind}$	0.005***	0.004***	0.004***	0.004***
		(0.001)	(0.001)	(0.001)	(0.001)
$\overline{ROA}_{t+10:t+1}$	ln(Biodiversity Risk)$^{within\ firm}$	-0.019*	-0.021*	-0.022*	-0.019·
		(0.009)	(0.009)	(0.010)	(0.010)
	ln(Biodiversity Risk)$^{within\ ind}$	0.005	0.007	0.007	0.007
		(0.005)	(0.005)	(0.005)	(0.005)
	ln(Biodiversity Risk)$^{across\ ind}$	-0.002	-0.002	-0.002	-0.002
		(0.002)	(0.002)	(0.002)	(0.001)
Controls		Yes	Yes	Yes	Yes
Fixed-effects					
Fiscal Year			Yes	Yes	
Country				Yes	
Fiscal Year - Country					Yes

Note 1: Clustered (gvkey) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

Table 23—*Overview of Regression Results for Different specifications Profitability (ROA) analysis on within firm and within and across industry log biodiversity impact, for the Southern Hemisphere region only In the first few rows, we use contemporaneous ROA_t as the dependent variable, then in the next few rows, we use ΔROA_{t+1} as the dependent variable, and then in the last rows we use the moving average $\overline{ROA}_{t+10:t+1}$ as the dependent variable.*

Dep. Variable	Independent Variables	(1)	(2)	(3)	(4)
ROA_t	ln(Biodiversity Risk)$^{within\ firm}$	-0.008	-0.007	-0.006	-0.005
		(0.006)	(0.006)	(0.006)	(0.007)
	ln(Biodiversity Risk)$^{within\ ind}$	0.019***	0.020***	0.020***	0.019***
		(0.004)	(0.004)	(0.004)	(0.004)
	ln(Biodiversity Risk)$^{across\ ind}$	0.009***	0.008***	0.006**	0.006*
		(0.002)	(0.002)	(0.002)	(0.002)
ΔROA_{t+1}	ln(Biodiversity Risk)$^{within\ firm}$	-0.034***	-0.029***	-0.028***	-0.028***
		(0.008)	(0.008)	(0.008)	(0.008)
	ln(Biodiversity Risk)$^{within\ ind}$	0.017***	0.015***	0.014***	0.014***
		(0.003)	(0.003)	(0.003)	(0.003)
	ln(Biodiversity Risk)$^{across\ ind}$	0.008***	0.008***	0.008***	0.008***
		(0.002)	(0.002)	(0.002)	(0.002)
$\overline{ROA}_{t+10:t+1}$	ln(Biodiversity Risk)$^{within\ firm}$	-0.028**	-0.024*	-0.025*	-0.026*
		(0.010)	(0.010)	(0.010)	(0.011)
	ln(Biodiversity Risk)$^{within\ ind}$	0.024**	0.022**	0.020**	0.021**
		(0.007)	(0.007)	(0.007)	(0.007)
	ln(Biodiversity Risk)$^{across\ ind}$	0.007	0.006	0.006	0.006
		(0.004)	(0.004)	(0.004)	(0.004)
Controls		Yes	Yes	Yes	Yes
Fixed-effects					
Fiscal Year			Yes	Yes	
Country				Yes	
Fiscal Year - Country					Yes

Note 1: Clustered (gvkey) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

I.B.10 Additional analysis: Robustness check asset-geospatial biodiversity risk: ln(Spatial Biodiversity Risk) and $s = near$ (<1km)

To accommodate the non-normality of the distribution of the scaled count variables, and subsequently, the impacts by extreme outliers, we also run the regressions with the $log(1+X)-log(TA)$ version of the risky asset count data (where $-log(TA)$ scaled the data). This log transformation enables us to test the robustness of our baseline results, where we use the level version of the scaled count variable. Therefore, we transform our asset- and geospatial based biodiversity risk variable as such:

$$\text{Spatial Biodiversity Risk}_{i,t}^{r,g,s} \;=\; log(\sum_{a \in \mathcal{A}_i} R_a^{r,j,s} + 1) - log(TA_{i,t}) \qquad i \in \mathcal{I}.$$

The results of the log specifications are displayed in Table 25 In each row, the coefficient for the log version of the BR measure represents the βpp change in return for a 1% increase in the count–to-TA ratio. Across the different risk types $r = TR|PR$, TR, PR and different areas $g = KBA, PA, CNA$, we see that the results are still positive, but the significance is less strong. For example, in Table 25, examining the transition risky asset types $r = TR$ inside $s = in$ Protected areas $g = PA$, a 1% increase in the count–to-TA ratio results in a monthly $\beta = 0.072$ pp effect on returns, which is economically very small, yet statistically significant ($p < 0.01$). However, if we observe a 100% increase in the ratio (doubling), then we would expect a 0.60 percentage point (pp) effect on annualized returns. Thus, only large swings in risky assets relative to total assets are economically meaningful, yet still relatively small. It is questionable whether this is a game-changer for most investment or operational decisions. Moving to the Key Biodiversity Areas $g = KBA$, the effect is larger: a 1% increase in the count–to-TA ratio results in a monthly $\beta = 0.132$ pp effect on returns, an economically more significant effect than $g = PA$ and significant ($p < 0.05$). If one doubles the ratio, then we would observe a 1.098 pp effect on annualized returns. Finally, when looking at the Critical Natural Assets areas $g = CNA$, combined with the physical risk asset types $r = PR$, we observe that a 1% increase in the count–to-TA ratio results in a monthly $\beta = 0.143$ pp effect on returns ($p < 0.05$). Therefore, a higher density of assets inside $g = KBA$ and $g = CNA$ has similar economic effects on returns. Although these effects of the $BR^{r,j,s}$ variable are not significant for the fixed effects combination of industry + month + country, it is significant for the stricter version of the fixed effects, industry × month + country × month. Thus, controlling for industry- and country-specific shocks in each month, a high density of risky assets within the $g = KBA$ and $g = CNA$ areas yields moderately economic effects on returns. In contrast, within the $g = PA$ areas, it yields more minor effects. Lastly, comparing these results with

Table 24—*Asset-geolocation Biodiversity Risk and Returns. This table summarizes the results of panel regressions of firm-level monthly returns (%) on asset- and geospatial-based biodiversity risk measure (Spatial Biodiversity Risk^{r,g}), where we use a near rather than inside definition, for different fixed effects and controls specifications. The regressions include controls, but are suppressed for brevity. Columns (1), (3), and (5) include the smaller set of control variables, whereas columns (2), (4), and (6) include the larger set of control variables. The full sets of results, including the coefficients for the control variables and the fit statistics for each regression, can be provided upon request.*

Dependent Variable:	Returns (%)					
Model: $X = BR^{r,g}$	(1)	(2)	(3)	(4)	(5)	(6)
Spatial Biodiversity Risk$^{TR\|PR,KBA,near}$	1.322***	0.902***	1.151**	0.960**	1.148***	0.980**
	(0.344)	(0.134)	(0.308)	(0.256)	(0.305)	(0.301)
Spatial Biodiversity Risk$^{TR\|PR,PA,near}$	0.594*	0.306**	0.507**	0.312	0.476*	0.322*
	(0.222)	(0.091)	(0.178)	(0.158)	(0.178)	(0.155)
Spatial Biodiversity Risk$^{TR\|PR,CNA,near}$	0.319**	0.220*	0.290***	0.260***	0.281***	0.260***
	(0.088)	(0.098)	(0.069)	(0.035)	(0.067)	(0.058)
Spatial Biodiversity Risk^{TR,KBA,near}	1.322***	0.902***	1.151**	0.960**	1.148***	0.980**
	(0.344)	(0.134)	(0.308)	(0.256)	(0.305)	(0.301)
Spatial Biodiversity Risk^{TR,PA,near}	0.594*	0.306**	0.507**	0.312	0.476*	0.322*
	(0.222)	(0.091)	(0.178)	(0.158)	(0.178)	(0.155)
Spatial Biodiversity Risk^{TR,CNA,near}	0.319**	0.220*	0.290***	0.260***	0.281***	0.260***
	(0.088)	(0.098)	(0.069)	(0.035)	(0.067)	(0.058)
Spatial Biodiversity Risk^{PR,KBA,near}	1.351***	0.937***	1.151***	0.944***	1.105***	0.923**
	(0.319)	(0.177)	(0.270)	(0.221)	(0.263)	(0.275)
Spatial Biodiversity Risk^{PR,PA,near}	0.640*	0.343**	0.545**	0.340	0.497*	0.334
	(0.232)	(0.092)	(0.187)	(0.165)	(0.190)	(0.171)
Spatial Biodiversity Risk^{PR,CNA,near}	0.335**	0.218**	0.293***	0.246***	0.275***	0.243***
	(0.108)	(0.065)	(0.076)	(0.034)	(0.073)	(0.062)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Industry			Yes	Yes		
Month			Yes	Yes		
Country			Yes	Yes		
Industry-Month					Yes	Yes
Country-Month					Yes	Yes

Clustered (Firm & year) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

Table 25—*Asset-geolocation Biodiversity Risk and Returns. This table summarizes the results of panel regressions of firm-level monthly returns (%) on asset- and geospatial-based Biodiversity Risk (ln(Spatial Biodiversity Risk)^{r,g}), for different fixed effects and controls specifications. The regressions include controls, but are suppressed for brevity. Columns (1), (3), and (5) include the smaller set of control variables, whereas columns (2), (4), and (6) include the larger set of control variables. The full sets of results, including the coefficients for the control variables and the fit statistics for each regression, can be provided upon request.*

Dependent Variable:	Returns (%)					
Model: X = *ln(Spatial Biodiversity Risk)*^{r,g}	(1)	(2)	(3)	(4)	(5)	(6)
ln(Spatial Biodiversity Risk)$^{TR\|PR,KBA}$	-0.015	-0.070	0.005	0.038	0.105	0.132*
	(0.132)	(0.135)	(0.067)	(0.067)	(0.053)	(0.051)
ln(Spatial Biodiversity Risk)$^{TR\|PR,PA}$	-0.016	-0.074	0.003	0.032	0.102	0.126*
	(0.133)	(0.134)	(0.067)	(0.067)	(0.054)	(0.052)
ln(Spatial Biodiversity Risk)$^{TR\|PR,CNA}$	0.002	-0.052	0.025	0.062	0.119*	0.151*
	(0.132)	(0.136)	(0.067)	(0.067)	(0.054)	(0.054)
ln(Spatial Biodiversity Risk)^{TR,KBA}	-0.015	-0.070	0.005	0.038	0.105	0.132*
	(0.132)	(0.135)	(0.067)	(0.067)	(0.053)	(0.051)
ln(Spatial Biodiversity Risk)^{TR,PA}	0.012	-0.007	0.062	0.066*	0.075**	0.072**
	(0.059)	(0.054)	(0.033)	(0.029)	(0.025)	(0.024)
ln(Spatial Biodiversity Risk)^{TR,CNA}	0.002	-0.052	0.025	0.062	0.119*	0.151*
	(0.132)	(0.136)	(0.067)	(0.067)	(0.054)	(0.054)
ln(Spatial Biodiversity Risk)^{PR,KBA}	-0.015	-0.071	0.004	0.036	0.103	0.130*
	(0.131)	(0.134)	(0.066)	(0.066)	(0.052)	(0.049)
ln(Spatial Biodiversity Risk)^{PR,PA}	-0.016	-0.074	0.003	0.032	0.102	0.126*
	(0.133)	(0.134)	(0.067)	(0.068)	(0.054)	(0.053)
ln(Spatial Biodiversity Risk)^{PR,CNA}	-0.001	-0.057	0.020	0.054	0.113*	0.143*
	(0.132)	(0.136)	(0.066)	(0.065)	(0.053)	(0.052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Industry			Yes	Yes		
Month			Yes	Yes		
Country			Yes	Yes		
Industry-Month					Yes	Yes
Country-Month					Yes	Yes

Clustered (Firm & year) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

Table 26—*Asset-geolocation Biodiversity Risk and Returns. This table summarizes the results of panel regressions of firm-level monthly returns (%) on asset- and geospatial-based Biodiversity Risk (ln(Spatial Biodiversity Risk)$^{r,\ g}$), for different fixed effects and controls specifications. The regressions include controls, but are suppressed for brevity. Columns (1), (3), and (5) include the smaller set of control variables, whereas columns (2), (4), and (6) include the larger set of control variables. The full sets of results, including the coefficients for the control variables and the fit statistics for each regression, can be provided upon request.*

Dependent Variable:	Returns (%)					
Model: X = *ln(Spatial Biodiversity Risk)*^{r,g}	(1)	(2)	(3)	(4)	(5)	(6)
ln(Spatial Biodiversity Risk)$^{TR\|PR,KBA,near}$	-0.015	-0.071	0.004	0.035	0.103	0.130*
	(0.132)	(0.135)	(0.067)	(0.068)	(0.053)	(0.050)
ln(Spatial Biodiversity Risk)$^{TR\|PR,PA,near}$	-0.015	-0.073	0.005	0.034	0.104	0.129*
	(0.133)	(0.135)	(0.067)	(0.067)	(0.054)	(0.052)
ln(Spatial Biodiversity Risk)$^{TR\|PR,CNA,near}$	0.006	-0.046	0.029	0.067	0.121*	0.155**
	(0.133)	(0.136)	(0.068)	(0.067)	(0.055)	(0.055)
ln(Spatial Biodiversity Risk)^{TR,KBA,near}	-0.015	-0.071	0.004	0.035	0.103	0.130*
	(0.132)	(0.135)	(0.067)	(0.068)	(0.053)	(0.050)
ln(Spatial Biodiversity Risk)^{TR,PA,near}	-0.015	-0.073	0.005	0.034	0.104	0.129*
	(0.133)	(0.135)	(0.067)	(0.067)	(0.054)	(0.052)
ln(Spatial Biodiversity Risk)^{TR,CNA,near}	0.006	-0.046	0.029	0.067	0.121*	0.155**
	(0.133)	(0.136)	(0.068)	(0.067)	(0.055)	(0.055)
ln(Spatial Biodiversity Risk)^{PR,KBA,near}	-0.015	-0.071	0.004	0.035	0.102	0.129*
	(0.131)	(0.135)	(0.066)	(0.066)	(0.052)	(0.049)
ln(Spatial Biodiversity Risk)^{PR,PA,near}	-0.014	-0.072	0.006	0.035	0.104	0.129*
	(0.133)	(0.134)	(0.067)	(0.067)	(0.054)	(0.053)
ln(Spatial Biodiversity Risk)^{PR,CNA,near}	0.002	-0.054	0.022	0.057	0.115*	0.144*
	(0.132)	(0.136)	(0.066)	(0.065)	(0.053)	(0.052)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects						
Industry			Yes	Yes		
Month			Yes	Yes		
Country			Yes	Yes		
Industry-Month					Yes	Yes
Country-Month					Yes	Yes

Clustered (Firm & year) standard-errors in parentheses
*Signif. Codes: ***: 0.001, **: 0.01, *: 0.05, ·: 0.1*

regression results from the level version of the count, the effects are overall smaller in economic terms and less significant; therefore, the effects of the level regressions were most likely driven by outliers.

I.C Literature Appendix

In this appendix section, we present a comparison with other studies in the nascent biodiversity risk pricing literature. Table 27 presents an overview of methodological differences between the studies, mainly focused on how each paper intends to measure firm-level biodiversity risk exposure.

Table 27—*Comparative analysis of Biodiversity Risk Measures across papers.*

Aspect	**This Research Paper**	**Giglio et al. (2024)**	**Garel et al. (2024)**	**Coqueret et al. (2025)**
Metric(s) Type(s)	Sum of cost-equivalent impacts from 5 IPBES biodiversity drivers + firm's dependence on provisioning ecosystem services, and an asset- and geospatial-based measure of biodiversity risk exposure.	Multifaceted, also incorporating perception and sentiment. Exposure to biodiversity-related news innovations; text mentions (10-Ks); survey ratings; and CDP disclosures.	Ecological footprint measure: physical degradation caused by firms (damage in km^2 MSA), normalized by firm scale.	Double materiality combining intensity-adjusted footprint score and a dependency materiality score.
Granularity	Firm-level data and asset-and geospatial biodiversity data aggregated to firm-level	Macro news risk, Sector/industry and firm-level. No spatial granularity.	Firm-level. No spatial granularity.	Firm-level. No spatial granularity.

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Aspect	This Research Paper	Giglio et al. (2024)	Garel et al. (2024)	Coqueret et al. (2025)
Spatial Measure	Explicitly modeled with a complementary biodiversity risk measure, that is based on production (asset) sites locations for assets that are salient in terms of transition and physical risk. Acknowledges protected areas and biodiversity-rich zones.	Not modeled.	Not modeled.	Not modeled.

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Aspect	This Research Paper	Giglio et al. (2024)	Garel et al. (2024)	Coqueret et al. (2025)
Transition Risk operationalization	Sum of Trucost Environmental Costs of environmental variables that match IPBES driver-based damages caused by firm activity (e.g., pollution) in million US$; Transition risk specific assets in transition risk specific biodiversity sensitive areas.	Firm disclosure via 10-K mentions (counts measures); CDP environmental impact reports; investor perception (survey).	Corporate Biodiversity Footprint in Mean Species Abundance loss per km^2, from a firm's annual activities in land use, greenhouse gas (GHG) emissions, water pollution, and air pollution.	Corporate Biodiversity Footprint (in Mean Species Abundance loss per km^2 from a firm's annual activities in land use, greenhouse gas (GHG) emissions, water pollution, and air pollution. Limited distinction between Transition vs Physical Risk, they take double materiality as main measure.

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Aspect	This Research Paper	Giglio et al. (2024)	Garel et al. (2024)	Coqueret et al. (2025)
Physical Risk operationalization	Sum of Trucost Environmental Costs of environmental variables that match provisioning ecosystem services used by firm in production, thereby proxy for economic dependency. Focuses on material, measurable resource flows. Physical risk specific assets in a physical risk specific biodiversity sensitive area.	Survey-based dependency ratings; 10-K mentions (e.g., references to natural resource reliance). Limited distinction between Transition vs Physical Risk.	Not measured.	Implied TNFD and SBTN industry level materiality ranking. Limited distinction between Transition vs Physical Risk, they take double materiality as main measure.

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Aspect	This Research Paper	Giglio et al. (2024)	Garel et al. (2024)	Coqueret et al. (2025)
Aggregation Method	Sum of physical and transition risks, and normalized count of risky assets in geospatially relevant biodiversity loss areas.	Aggregated industry level as a value-weighted average of firm-level scores. Asset-level spatial scores are averaged to a firm level.	Corporate Biodiversity Footprint firm level measure as is, no aggregation.	Corporate Biodiversity Footprint (and subcomponents) on firm level measure as is, and sector level double materiality score as the **average** of dependency and impact scores.

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Aspect	This Research Paper	Giglio et al. (2024)	Garel et al. (2024)	Coqueret et al. (2025)
Forward- / Backward-Looking	Backward-looking (using realized returns and realized biodiversity risk).	Forward-looking (news shocks, 10-Ks, survey expectations).	Backward-looking footprint and returns.	Both: realized returns + expected returns from options. Transition risk backward looking since it is measured by biodiversity footprint, but the dependency risk measure is arguably more forward-looking in nature. Authors do not explicitly discuss.

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Aspect	This Research Paper	Giglio et al. (2024)	Garel et al. (2024)	Coqueret et al. (2025)
Empirical Strategy (asset pricing)	Panel regressions with firm, industry, and/or country fixed effects. Separate inclusion of physical and transition risks.	Examining the hedging performance of a biodiversity risk-sorted portfolio compared to an aggregate news measure.	Panel regressions and event studies linking Corporate Biodiversity Footprint to (abnormal) returns.	Fama-MacBeth regressions, long-short portfolio returns, expected return decomposition using option-implied premiums. Biodiversity risk factor creation.
Sample Coverage	Global panel of 12,288 firms from 58 countries, from 2009-2022.	5,984 U.S. firms, from 2000 to 2023.	International panel with 2,106 firms from 34 countries, from 2019–2022.	522 "global" firms from 2012–2022 (but keep only U.S. firms, implied by CRSP).

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Aspect	This Research Paper	Giglio et al. (2024)	Garel et al. (2024)	Coqueret et al. (2025)
Data Source Biodiversity Risk Measure	Trucost Environmental Dataset (firm-level)	10-K statements (firm level aggregated to industry level), survey (industry); Bloomberg: biodiversity ETF portfolio holdings (industry); CDP: firms' responses to the CDP Climate Change Questionnaire (firm level aggregated to industry level)	Iceberg DataLab: Corporate Biodiversity Footprint (CBF)	Iceberg DataLab: Corporate Biodiversity Footprint (CBF); Sectorial Materiality Tool by TNFD and SBTN: sectoral dependency scores.
Data Source Prices and Returns	Compustat and CRSP	CRSP	CRSP	CRSP