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Essays on Nature-Related Risk Premia in Equity Markets

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Dissertation

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Introduction

1.1 Motivation and context

Biodiversity loss has emerged as a critical challenge for the global economy and financial systems. The degradation of ecosystems - from deforestation and pollinator loss to depletion of fisheries - can disrupt supply chains, reduce asset values, and undermine long-term business viability. Reports have estimated that approximately 7.2 trillion USD of enterprise value is exposed to unmanaged biodiversity risk (Carvalho et al., 2023). Consequently, biodiversity loss represents a major risk for individual and institutional investors. And as over 44 trillion USD economic value generation (over half of global GDP) is moderately or highly dependent on nature and ecosystem services, it is increasingly recognized as a systemic financial risk (GSIA, 2024).

Financial institutions are increasingly recognizing biodiversity loss as a critical factor affecting long-term business sustainability and have already started moving toward mitigation, e.g., by considering it in investment guidelines. Regulatory bodies are also increasingly focused on the economic risks posed by biodiversity loss (Hutchinson & Lucey, 2024). Multiple central banks have highlighted the systemic risks associated with biodiversity decline, noting that financial institutions must account for biodiversity risks within their lending and investment activities (Hutchinson & Lucey, 2024; MNB, 2024). This recognition by regulators marks an important step towards mainstreaming biodiversity considerations within economic and financial policy frameworks. Biodiversity protection has become a key component of EU policy as well; it is included in the EU Biodiversity Strategy for 2030, a central pillar of the European Green Deal, and the Sustainable Finance

Disclosure Regulation (SFDR) mandates that financial market participants and financial advisers disclose sustainability-related risks, impacts, and opportunities in their investment decision-making processes, including biodiversity-related Principal Adverse Impact (PAI) indicators (EU, 2019a).

The IPBES (2019) reports that "75 per cent of the land surface is significantly altered, 66 per cent of the ocean area is experiencing increasing cumulative impacts", and that current trends in biodiversity loss "will undermine progress towards 80 per cent (35 out of 44) of the targets of the Sustainable Development Goals" - underscoring the system-wide, non-diversifiable nature of these risks. Therefore, from an asset-pricing perspective, biodiversity risk also qualifies as a systematic risk: because ecosystem dependencies are concentrated in sectors that together account for a substantial fraction of global value added, and because regulatory shocks such as the Kunming-Montreal Framework affect all exposed firms simultaneously, the risk cannot be diversified away within an equity portfolio (see Section 2.7 for the formal argument).

To efficiently manage biodiversity risks (both individual and systemic levels), it is crucial to understand how financial markets perceive and price these risks. If markets efficiently price biodiversity risk, companies with high nature-related risks should face a higher cost of capital, reflecting a “biodiversity risk premium” demanded by investors. Conversely, if such risks are mispriced or ignored, a risk premium cannot be observed, and this poses a threat to both financial stability and sustainability goals. This dissertation is motivated by the urgent need to investigate whether and how financial markets are pricing biodiversity risk, and to develop tools to estimate the biodiversity risk premium.

An important concept in nature-related risk management is “double materiality”. Double materiality extends the traditional view of risk management of estimating how environmental, social, and governance (ESG) issues affect a company’s financial performance (financial materiality) by recognizing that a company’s impacts on nature and society are also material (impact materiality) (Mezzanotte, 2023). This means that firms’ contributions to ecosystem degradation can translate into financial risks to the firm and the broader system. For example, a company causing deforestation may face regulatory fines, reputational damage, or resource scarcity that harm its profitability, affecting investors as well.

1.2 Research objective and questions

The primary objective of this PhD dissertation is to estimate the biodiversity risk premium and the broader nature risk premium and assess how financial markets perceive these types of risks. This includes a progression from general biodiversity risk considerations to the more specific financial implications of biodiversity loss and ecosystem degradation. The dissertation introduces the Biodiversity Risk Premium (BRP), focusing on biodiversity-specific exposures, and then advances to estimate the Nature Risk Premium (NRP), which incorporates both biodiversity and climate-related risks. The NRP framework also distinguishes between firms' impacts on nature and their dependencies on ecosystem services, reflecting double materiality. This progression allows a more complete understanding of how nature risk is internalized into financial asset pricing.

This dissertation addresses the following research questions:

1. Is there evidence of a Biodiversity Risk Premium in global equity markets? Specifically, do biodiversity-screened portfolios experience lower risk-adjusted returns compared to conventional portfolios, suggesting that biodiversity risk is priced by investors?

2. Can the biodiversity risk premium be attributed to particular sources of biodiversity risk?

3. Do investors demand a nature risk premium that includes both climate and biodiversity-related risks? How do market prices reflect double materiality, e.g., firms' impact on ecosystems and their dependencies on ecosystem services?

4. Are EU-mandated sustainability metrics, such as the Principal Adverse Impact (PAI) indicators, effective signals of priced nature-related risks?

1.3 Overview of chapters and contributions

The author contributed to multiple research projects during the PhD program, each addressing one or more components of the research problem. Together, these studies progress from broad biodiversity risk exposure and management considerations to a focused analysis of biodiversity risk pricing, moving from foundational portfolio tests to highly granular risk factor modeling.

The remainder of this dissertation is organized into four self-contained chapters. Their sequence and primary contributions are as follows:

1. "Key concepts and current state of research in biodiversity finance" introduces biodiversity finance and defines key terms and concepts that form the foundation for subsequent chapters. This section establishes the current research priorities and emerging topics in biodiversity finance, and introduces the theory of risk-premia estimation, and whether nature-related risk premia should exist, and if so, at what sign.

2. "Biodiversity Risk Premium" heavily builds on an earlier version of Naffa and Czupy (2024). This work introduces the concept of a Biodiversity Risk Premium (BRP) as the financial cost of managing biodiversity risk. Using MSCI biodiversity scores and innovative portfolio optimization methods, the study constructs biodiversity-screened portfolios from MSCI All Country World Index constituents and assesses their performance between 2013-2023. Results show that biodiversity-screened portfolios exhibit lower risk-adjusted returns (lower Sharpe ratios) compared to otherwise similar portfolios without such screening (yielding Sharpe ratios that are, on average, approximately 1.1% to 3.4% lower than the maximum attainable Sharpe in the investment universe, or a return loss of 1, 5, and 11 basis points.). This performance gap is interpreted as evidence of a market-priced biodiversity risk premium: investors require higher returns (a premium) to hold assets with greater biodiversity risk, whereas portfolios that reduce biodiversity risk come at the cost of slightly lower risk-adjusted returns. Thus, the BRP estimate shows that biodiversity considerations influence market pricing. However, the BRP framework does not incorporate double materiality into the analysis due to the nature of MSCI biodiversity scores.

3. "Return trade-offs between biodiversity physical and transition risk in global equity markets" has been co-authored with Anita Lovas and Helena Naffa and slightly builds on the working paper of Lovas et al. (2026). This study extends the BRP concept by introducing and estimating a broader Nature Risk Premium (NRP). Unlike the previous studies, this study captures both biodiversity and climate-related risks together, referred to as nature-related

risks, and explicitly integrates the concept of double materiality. Using cross-sectional regression on the global constituents of the iShares MSCI ACWI ETF, the study incorporates Principal Adverse Impact (PAI) indicators, reflecting firms' impacts on ecosystems, and ENCORE Nature data, estimating firms' impacts and dependencies on ecosystem services. Climate-related transition risks are significantly priced at the firm level: the Carbon footprint and Scope 3 GHG emissions carry positive and significant risk premia, consistent with the carbon premium documented in the literature. However, the biodiversity-specific PAI indicator and most ENCORE pressure variables are statistically insignificant, suggesting that biodiversity transition risks are not yet systematically priced in the cross-section of global equity returns (or the sample size is too small to draw significant conclusion). Ecosystem service dependencies are priced, but in the opposite direction to what a standard risk-compensation framework would predict: firms with high dependencies on certain ecosystem services earn significantly lower subsequent returns. This pattern is more consistent with investor taste premia (Pastor et al., 2021) or market mispricing Huang et al. (2024) than with compensation for physical risk exposure. At the portfolio level, a composite long-short strategy based on ENCORE pressure and dependency scores does not generate significant adjusted returns after controlling for standard risk factors, although the EU subsample comes closest to marginal significance, consistent with the SFDR regulatory environment.

4. "Answering the research questions & Future research directions" argues that the incorporation of Earth observation data can be the next step to understanding how firms impact and depend on biodiversity, and presents important questions to investigate. It also demonstrates basic calculations that aggregate spatial biodiversity data to illustrate potential starting points for future research projects.

Chapters 3 and 4 employ diverse portfolio construction methodologies to investigate the research questions. In the first study, we designed a new method to estimate the BRP from the perspective of real-world sustainable investors. The traditional factor premium analysis approach is usually used for performance attribution and understanding risk drivers, while our method, in contrast, estimates the applicable cost of biodiversity risk mitigation (hedging), the cost that is likely to be realized by practitioners and can be used as a benchmark. The methodology formulates biodiversity risk-reduced portfolios by randomly screening companies in the investment universe by their biodiversity scores, and compares them to a portfolio with the same number of randomly selected firms. The approach separates the cost of screening (shrinking the investment universe) and biodiversity risk mitigation. Later, we also control for industry, market, size, liquidity, and other factors. We found this method computationally highly demanding. The second study employs traditional risk premium analysis methods due to the large number of PAI indicators, ENCORE dependency, and pressure categories considered. Instead of practical applicability, we concentrate on drawing general trends and patterns that emerge from the risk premium estimates. The total return of firms is used in regression models as a dependent variable; our main dependent variable (e.g., PAI indicator) and other control variables (size, liquidity, risk, market, industry, and so on) are used in the regression models.

The two studies also show well how the assessment and understanding of nature-related risks have evolved in recent years, moving from a broad to a narrow focus. The first is based on the MSCI Biodiversity score, which zooms in on biodiversity-related risks but does not separate the two sides of double materiality. The second solves this issue by distinguishing between impacts and dependencies, and uses forward-looking impact and dependency measures (PAI indicators, ENCORE dependency, and pressure scores). At the end of the dissertation, I argue that the next step in nature risk assessment is to incorporate Earth observation data into financial analysis.

Together, Chapters 3 and 4 advance our understanding of the pricing and perception of biodiversity and nature risks in general by financial markets. Without a better understanding, we are unable to solve the current global challenges, biodiversity degradation, and climate change. The studies also help future conceptualization and discussion by introducing and defining the Biodiversity Risk Premium (BRP) and Nature Risk Premium (NRP) terms. The most important result is that the studies provide empirical evidence that biodiversity risk is becoming internalized into market prices through lower risk-adjusted returns for biodiversity risk-managed portfolios and higher required returns for nature-exposed firms. This has important implications for investors and policymakers: it underscores that ignoring biodiversity risk can carry financial costs.

Another key finding is that not all nature-related risk sources are reflected in market pricing. While risks indicated by the MSCI Biodiversity score and several PAI indicators, as well as ENCORE ecosystem service dependencies and pressures, can be associated with a positive equity risk premium during certain periods, financial markets often overlook other factors. Well-known risk sources, such as greenhouse gas (GHG) emissions and exposure to biodiversity-sensitive areas, are generally perceived as material. This underscores the argument that financial markets are aware of these risks and highlights the need for standardized, publicly available forward-looking indicators linked to established disclosure frameworks.

Conversely, lesser-known or difficult-to-measure risk sources do not display clear risk premiums. The reasons for this fall outside the scope of this dissertation and may involve unaware market participants or systemic risks that cannot be diversified. For this reason, regulatory actions are crucial to help markets recognize these risks and mitigate systemic impacts. Notably, one result from the second paper indicates that firms with greater dependencies on ecosystem services tend to exert higher pressures on those services.

1.4 Structure

The dissertation is organized in the following fashion. The introduction outlined the motivation, objectives, and contributions of subsequent studies. A short literature review is presented next in Chapter 2; the two main studies follow in Chapters 3 and 4 respectively. Then I go on and present future research directions and argue why incorporating Earth observation data could be the next step in biodiversity risk estimation in Chapter 5. A summary of the dissertation concludes in Chapter 6.

Chapter 2

Key concepts and current state of research in biodiversity finance

In this section, I summarize the major trends in the biodiversity finance literature. More detailed and in-depth literature reviews can be found in the subsequent chapters. The theoretical foundations of the calculation of equity risk premia are also presented.

2.1 Key concepts in biodiversity finance

The rapid decline of biodiversity has emerged as one of the critical global challenges of the 21st century, posing significant threats to ecological stability and economic sustainability. Observing the approximately 7.2 trillion USD of enterprise value exposed to unmanaged biodiversity risk (Carvalho et al., 2023), and the gap between the $700 billion per year biodiversity restoration costs and 150 billion USD financing (Karolyi & Tobin-de La Puente, 2023), the finance sector recognizes biodiversity loss as a material risk, intertwined closely with climate-related risks (Carvalho et al., 2023).

Redford and Richter (1999, p. 1247) defines biodiversity (biological diversity) as “the natural variety and variability among living organisms, the ecological complexes in which they naturally occur, and the ways in which they interact with each other and with the physical environment”. Biodiversity finance encompasses mechanisms to generate and direct financial resources toward biodiversity conservation and sustainable use (Hutchinson & Lucey, 2024). It is a highly interdisciplinary field, building on tools and concepts originated in other fields, like accounting, ecology, and computational science. This reflects the complexity of the problem well. The field is fragmented yet growing, spread across numerous journals and institutions worldwide. Despite increasing attention, significant gaps exist, particularly regarding finance-driven solutions (Hutchinson & Lucey, 2024).

Biodiversity conservation is defined as “the management of human use of the biosphere so that it may yield the greatest sustainable benefit to current generations while maintaining its potential to meet the needs and aspirations of future generations: thus conservation is positive, embracing preservation, maintenance, sustainable utilization, restoration, and enhancement of the natural environment” (Redford & Richter, 1999, p. 1247).

A central concept of biodiversity finance is the “ecosystem”. One definition of ecosystems is “all the organisms and the abiotic [non-biological, e.g., soil, water] pools with which they interact” (Chapin et al., 2011, p. 5). Ecosystem services are defined as the contributions of ecosystems to the benefits that are used in economic and other human activities (UN, 2024). Ecosystem services include, e.g., pollination (servicing agriculture) and a good-looking forest (servicing the tourism industry).

Natural capital is the stock of natural materials in an ecosystem. When it is used, it yields a flow of goods and services (Parker et al., 2012).

Ecosystem assets are contiguous spaces of a specific ecosystem type, e.g., forests, wetlands, and agricultural areas (UN, 2024). One or multiple of these assets supply ecosystem services in an area. Ecosystem assets have two major attributes: extent (area) and condition.

Ecosystem accounting is a systematic approach to measuring and valuing the contributions of ecosystems to the economy and human well-being. It integrates ecological data with economic and social statistics to assess the stocks and flows of ecosystem services, biodiversity, and natural resources (UN, 2024). The framework defines multiple ecosystem accounts: ecosystem extent account (area of different ecosystem types), ecosystem condition account (ecological integrity and health of the ecosystem), ecosystem service flows (supply of ecosystem services, and use of those services in households), monetary ecosystem account (stocks and changes in monetary terms), thematic account (organize data on by specific policies, e.g., climate change) (UN, 2024).

2.2 Thematic areas and current state of research

Their bibliometric analysis indicates research on biodiversity finance is fragmented yet growing, spread across numerous journals and institutions worldwide (Hutchinson & Lucey, 2024).

Tan et al. (2023) identifies three main points in biodiversity research:

1. Biodiversity: species richness, species diversity, and ecosystem.
2. Biodiversity loss mechanisms
   a) Biodiversity loss drivers
   b) Climate change
3. Conservation (mainly about e.g., biodiversity conservation, designing a decision-making process to reduce impacts on biodiversity)

Multiple sources have attempted to identify the major trends in biodiversity finance, usually by bibliometric analysis, see e.g., (Hutchinson & Lucey, 2024) as an example: Restoration, Projects and impacts, Ecosystem finance, Conservation finance, Conservation, and Climate change. Among these categories, conservation remains prominent but has declined slightly, whereas Conservation Finance has gained attention, highlighting increased practical financial interventions.

2.2.1 ESG pillar trade-offs and return differentials

Yusifzada et al. (2025) investigates the relationship between environmental and social performance in stock returns, using the constituents of the MSCI All Country World Index constituents, portfolio analysis, and asset pricing models over the period 2013-2022. It finds evidence of a negative correlation between E and S scores of firms, suggesting that there exists a trade-off between these ESG dimensions. We observed significant return differentials in the earlier years of the sample: “green” companies (high E scores) outperformed “brown” companies (low E scores) from 2013 to 2016, while firms excelling in social performance saw negative relative returns compared to social laggards. These patterns imply that in the mid-2010s, investors placing emphasis on environmental issues earned excess returns, whereas those favoring social issues faced a return penalty. However, these excess return opportunities diminished over time, and by the late 2010s, the differences mostly disappeared. This suggests that markets became more efficient in pricing ESG factors:

as investor awareness and integration of sustainability grew, arbitrage opportunities between the E and S pillars were eroded.

This study provides context for the present dissertation by demonstrating that financial markets distinguish between ESG pillars and that environmental attributes are incorporated into financial returns.

2.3 Biodiversity loss as a source of financial risk

Before reviewing the regulatory and institutional responses to biodiversity risk, it is important to understand why biodiversity loss poses a threat to the financial system and whether it should be priced by financial markets. This section presents the ecological and economic evidence and introduces the distinction between systemic and systematic risk, which is formalized within the asset-pricing framework in Section 2.7.

2.3.1 The scale of biodiversity loss

The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) provides the most comprehensive scientific assessment of the state of global biodiversity at the moment. According to the IPBES Global Assessment, the global rate of species extinction is already at tens to hundreds of times higher than the average rate over the past 10 million years, and is accelerating (IPBES, 2019). Around 1 million animal and plant species are now threatened with extinction, many within decades (IPBES, 2019). At the ecosystem level, 75% of the terrestrial environment and 66% of the marine environment have been significantly altered by human actions; over 85% of wetland area has been lost (IPBES, 2019). The average abundance of native species in most major terrestrial biomes has fallen by at least 20% (IPBES, 2019).

The drivers of this decline are well identified. IPBES (2019) ranks the five direct drivers of biodiversity loss in order of global impact: (1) changes in land and sea use, (2) direct exploitation of organisms, (3) climate change, (4) pollution, and (5) invasion of alien species. These drivers are largely the by-products of economic activity: in the past 50 years, the human population has doubled, the global economy has grown nearly fourfold, and global trade has grown tenfold (IPBES, 2019). Importantly, these drivers interact and compound, and current negative trends in biodiversity are projected to continue to 2050 and beyond under all scenarios except those involving transformative change (IPBES, 2019).

2.3.2 Systemic risk: transmission to the financial system

Systemic risk in finance refers to the risk that a shock originating in one part of the system propagates through interconnections and triggers instability across the system as a whole (ECB, 2023). Biodiversity loss can generate systemic financial risk through several transmission channels.

First, nature supports economic production at a fundamental level. Approximately 50% of global GDP is moderately or highly dependent on ecosystem services, including pollination, water purification, soil fertility, and climate regulation (GSIA, 2024; WEF, 2020). The economic values at risk are substantial: the IPBES Global Assessment estimates that between \$235 billion and \$577 billion in annual global crop output is at risk from pollinator loss alone, and that land degradation has already reduced productivity in 23% of the global terrestrial area (IPBES, 2019). Because ecosystem services are difficult to substitute with manufactured products (Dasgupta, 2021; Dietz & Neumayer, 2007), their degradation can translate into significant reductions in output across multiple sectors simultaneously.

Second, biodiversity loss exhibits non-linear dynamics and tipping points. Coral reef ecosystems, for instance, are projected to decline by 70–90% at 1.5C of warming and by more than 99% at 2C (IPBES, 2019). Around 9% of the world's estimated 5.9 million terrestrial species lack sufficient habitat for long-term survival and are at risk of extinction within decades (IPBES, 2019). Such threshold effects mean that the financial consequences of biodiversity loss may materialise abruptly rather than gradually, creating tail risks that are difficult to hedge with standard instruments. Ilhan et al. (2021) document a similar pattern for carbon risk, where high-emitting firms exhibit larger tail risk in option prices.

Third, the interconnected nature of ecosystems creates contagion-like dynamics. The degradation of one ecosystem service (e.g., pollination) can cascade into others (e.g., food production, water quality), affecting firms across multiple sectors and geographies simultaneously. This cross-sectoral co-movement is the financial definition of systemic risk, and it distinguishes biodiversity risk from idiosyncratic environmental incidents such as a localized oil spill accidents.

2.3.3 Systematic risk: non-diversifiability

From an asset-pricing perspective, a distinct but related question is whether biodiversity risk is systematic, i.e., whether it is non-diversifiable and therefore commands a risk premium in equilibrium. While systemic risk refers to the potential for cascading failures across the financial system, systematic risk refers to the component of an asset's return variation that is correlated with the market-wide pricing kernel and cannot be eliminated through portfolio diversification (Cochrane, 2009).

Three features suggest that biodiversity risk is non-diversifiable:

1. Ecosystem dependencies are concentrated in sectors (such as agriculture, energy, materials, utilities) that together account for a substantial fraction of global value added (ENCORE, 2025a; WEF, 2020). Cross-sectoral diversification within an equity index does not eliminate the aggregate exposure to ecosystem degradation.

2. Regulatory and political transition risks, such as the Kunming-Montreal Global Biodiversity Framework and the SFDR PAI indicators, are common shocks that re-price all exposed firms simultaneously. E.g., Garel et al. (2024) document precisely this effect: high-biodiversity-footprint stocks lost value in the trading days following the Kunming Declaration.

3. Biosphere integrity has already breached the planetary boundary identified (Richardson et al., 2023). Crossing such a boundary triggers correlated, system-wide consequences that no individual investor can eliminate through asset selection alone.

Section 2.7 formalizes these observations within the stochastic discount factor framework and derives the conditions under which nature risk leads to a non-zero premium.

2.4 Regulatory and institutional efforts

Given the evidence that biodiversity loss constitutes both a systemic and a systematic financial risk (see Section 2.3), regulators have started to put effort into biodiversity-related research, goals, and regulations. Institutions, like the European Central Bank (ECB), form international networks like the Network for Greening the Financial

System (NGFS) and publish reports highlighting the system-wide consequences of collapsing ecosystems (and potential solutions) (NGFS, 2022). This approach is a shift from the view that treats biodiversity solely as an environmental concern and idiosyncratic risk.

The conceptualization of biodiversity-related financial risk parallels climate-related risk; it is usually broken down into "physical risks" and "transition risks" (ECB, 2023). Bua et al. (2024) defines these terms for climate, but the definition can be adopted to biodiversity: physical risks represent losses or costs due to chronic or acute hazards, e.g., falling crop yields. Transition risks refer to costly adjustments towards nature protection, like policies, technological advances, shifts in public preferences, e.g., limiting the exploitation of natural resources or banning certain products that trigger degradation (ECB, 2023).

Central banks and supervisors are organizing through international forums to better understand biodiversity physical and transition risks. More than 130 joined voluntarily the NGFS coalition to support transition to a sustainable economy and declared that addressing nature-related financial risks falls within their mandates and requires a unified response (NGFS, 2022). Another organization, the Financial Stability Board (FSB), whose goal is to assess vulnerabilities affecting the global financial system, reports that while a growing number of regulators acknowledge biodiversity as a material financial risk, most are still in early stages of analysis and policy response (FSB, 2024b). The FSB report highlights substantial data and modeling challenges in linking biodiversity loss to financial exposures, and notes that many authorities are initially focusing on improving disclosures and building capacity. These efforts reflect a recognition that better tools and information are needed for regulators to estimate nature-related exposures and potential transmission channels in the financial system (FSB, 2024a).

High-quality data, and therefore, disclosures are important inputs to mitigate biodiversity-related financial risks. The Taskforce on Nature-related Financial Disclosures (TNFD), supported by global institutions, published its recommendations in 2023, which are designed help organizations to report and act on nature-related issues (TNFD, 2023). The TNFD guidelines position nature risk alongside traditional financial and climate risks in corporate reporting, aiming to enable investors and regulators to systematically evaluate biodiversity-related vulnerabilities. For example, to disclose metrics used to assess and manage dependencies and impacts on nature, describe processes regarding nature-related risk management, locations of assets and activities across the whole value chain, where possible (TNFD, 2023).

The European Union is embedding biodiversity risk into its sustainable finance regulations. Under the Corporate Sustainability Reporting Directive (CSRD), companies are required to disclose their principal impacts and dependencies on biodiversity and ecosystems, along with the associated financial risks and opportunities from 2024 (and publish the first reports in 2025) (EU, 2022). The European Sustainability Reporting Standards (ESRS), which were developed under CSRD, require firms to report on the short, medium, and long-term financial effects that biodiversity-related risks could have on their business. This includes detailing how they manage these risks and any mitigation plans (such as biodiversity transition strategies or targets). Moreover, the EU Taxonomy for Sustainable Activities classifies which economic activities are sustainable to prevent greenwashing and help investors make more informed decisions (EU, 2023).

Other international organizations also take action. OECD has launched research projects into the economic costs of ecosystem loss, often in collaboration with central banks and the EU (OECD, 2023a).

National authorities and central banks usually perform stress testing, and start programs (like green bonds, green loans) to enhance national nature restoration. For example, the Hungarian Central Bank (MNB) evaluated nature-related transition and physical risks across portfolios and found that portfolios still fall short of Paris Agreement targets (MNB, 2024).

Despite these regulatory efforts, substantial challenges remain. Current biodiversity disclosures are inconsistent and inadequate, complicating accurate risk assessments. Improved transparency, standardized metrics, and rigorous reporting requirements are essential next steps for strengthening biodiversity finance frameworks (Carvalho et al., 2023).

2.5 Corporate biodiversity risk exposure and responses

In the corporate sector, particularly among financial institutions and firms in biodiversity-exposed industries, there is a growing trend to identify, assess, and mitigate biodiversity-related risks. Until recently, corporate action was limited: a global review of 11,812 companies found that only 29% had adopted a biodiversity policy by 2018, leaving an estimated 7.2 trillion USD in enterprise value exposed to unmanaged nature-related risks (Carvalho et al., 2023). This gap is now narrowing as firms adopt new frameworks and tools to account for nature in risk management. The recommendations by TNFD (2023) have been adopted by more than 500 companies and financial institutions, representing 17 trillion USD assets under management, and over 6.5 trillion USD in market capitalization.

Corporate risk models are also evolving to incorporate biodiversity considerations. Banks and asset managers are mapping their portfolios' dependencies on ecosystem services to find out where biodiversity loss could threaten future cash flows. Suggested approaches have also appeared, see PwC (2024) as an example. Interestingly, while the largest share of biodiversity restoration and payments in exchange for the yields of natural resources is still in the hands of governments (Parker et al., 2012), new ventures and startups have appeared to tackle biodiversity restoration and conservation challenges (Cao et al., 2025).

2.6 The evolution of firms' biodiversity impact and dependency assessment

2.6.1 Corporate disclosure-based ESG ratings

Corporate disclosure-based ESG ratings have been the most widely used approach in sustainable investing, primarily relying on self-reported data from companies regarding climate and nature-related policies, commitments, and risks (GSIA, 2024). These ratings standardize the calculation of environmental scores, aiming for comparability across industries and integration with broader ESG frameworks.

However, they face significant criticism for lacking robust verification processes, as they depend on self-disclosed information that companies may selectively present to the public (greenwashing). Extensive literature examines the implications of ESG ratings, highlighting mixed financial performance outcomes among financial issuers that are considered ESG leaders or laggards (Naffa & Fain, 2022). Studies also highlight discrepancies among rating providers, with significant disagreements in scoring methodologies and outcomes even when the same publicly available information is used as input (Berg et al., 2022).

Another issue with the classical ESG rating methodology is related to "double materiality". Double materiality is a key concept in ESG ratings, which refers to the dual perspective of how firms and the environment impact each other (Mezzanotte, 2023). Financial materiality considers how environmental and social factors affect the financial performance of a firm (e.g., how climate change impacts a firm's operations). Impact materiality looks at how a firm's activities impact society and the environment (e.g., how carbon emission contributes to global warming). Failing to take double materiality into account is problematic for multiple reasons, e.g., ESG investors might want to invest according to impact materiality only.

2.6.2 Species-level indicators

The Mean Species Abundance (MSA) indicator quantifies the mean abundance of originally occurring species relative to their abundances in an undisturbed reference situation. It was originally developed for GLOBIO, a global assessment of biodiversity change in response to socio-economic development scenarios and environmental changes (Kuipers et al., 2025; Schipper et al., 2020). The indicator has been adopted by rating firms to provide biodiversity risk assessment for investment portfolios, see, e.g., Lab (2025) and also used by frameworks like GLOBIO (Schipper et al., 2020). Formally, the MSA indicator is defined as

$$\mathrm{MSA} = \frac{1}{N} \sum_{i=1}^{N} \frac{A_{i,\text{disturbed}}}{A_{i,\text{reference}}} \tag{2.1}$$

where $A_{i,\text{disturbed}}$ is the mean abundance of originally occurring species, $A_{i,\text{reference}}$ is the abundance in an undisturbed reference space, and N is the number of species. The value can range from 0 (intact) to 1 (local extension). Advantages of the MSA indicator include its sensitivity to biodiversity change and its ability to forecast local extension (forward-looking). The main disadvantages of MSA are that it has data requirements (estimation needs data from both the target and the reference sites) and is sensitive to factors other than human pressure (Kuipers et al., 2025; Schipper et al., 2020). Similar indicators tend to suffer from uncertainties during estimation (Bromwich et al., 2024).

2.6.3 ENCORE Nature

The next step in the evolution of biodiversity risk assessment is the ENCORE Nature database, which estimates impacts and dependencies of firm economic activities on ecosystem services. Unfortunately, the ENCORE Nature database lacks geospatial information, analysis, and modeling.

2.6.4 Spatial finance

Spatial finance integrates geospatial data, including satellite imagery and habitat maps, to evaluate physical asset-related biodiversity risks (Caldecott et al., 2022). Earth observation (EO) technologies enhance environmental risk assessments by identifying deforestation, wetland loss, and habitat fragmentation at scale (Rapach et al., 2024). However, medium-resolution satellite maps often overlook small-scale habitats or endemic species without design-based area estimation and accuracy assessments, introducing spatial biases (Venter et al., 2024).

Existing frameworks predominantly rely on the ENCORE platform to connect industrial processes with ecosystem services, but this lacks precise geospatial modeling, resulting in unclear linkages between metrics and biodiversity outcomes.

2.7 Theoretical foundations of risk premia in equity markets

Before estimating risk premiums empirically, it is important to ask a fundamental question: should a nature-related risk premium exist at all, and if so, what sign does asset pricing theory predict? This section answers that question by introducing the theoretical framework for estimating risk premiums. It builds on the consumption-based asset pricing framework of Cochrane (2009), the equilibrium model of sustainable investing of Pastor et al. (2021), and the ex-ante/ex-post decomposition of Pastor et al. (2022), and applies them to nature-related risks.

2.7.1 The basic pricing equation and the stochastic discount factor

Modern asset pricing relies on a simple relationship (Cochrane, 2009). For any traded asset i with price p_t^i and payoff x_{t+1}^i, equilibrium requires that

$$p_t^i = E_t\left[m_{t+1}\, x_{t+1}^i\right] \tag{2.2}$$

where m_{t+1} is the stochastic discount factor (SDF), also called the pricing kernel (Cochrane, 2009). Under standard assumptions, m_{t+1} is proportional to an investor's intertemporal marginal rate of substitution,

$$m_{t+1} = \beta \frac{u'(c_{t+1})}{u'(c_t)} \tag{2.3}$$

where $u(\cdot)$ is the period utility function, c_t is consumption at time t, and $\beta \in (0, 1)$ is the subjective discount factor.

Equation (2.2) is the consequence of assuming that the representative investor optimizes consumption and savings while taking asset prices as given. If a positive SDF satisfying Equation (2.2) exists, prices are arbitrage-free; if no arbitrage exists, a positive SDF exists (Cochrane, 2009).

This has three consequences which we can use later:

1. First, dividing both sides of Equation (2.2) by p_t^i and defining the gross return as

$$R_{t+1}^i = \frac{x_{t+1}^i}{p_t^i} \tag{2.4}$$

we obtain

$$1 = E_t\left[m_{t+1}\, R_{t+1}^i\right] \tag{2.5}$$

2. Second, for a risk-free asset with a certain gross return R_t^f,

$$R_t^f = \frac{1}{E_t[m_{t+1}]} \tag{2.6}$$

In other words, the risk-free rate is high when investors are impatient, when expected consumption growth is high, and when consumption risk is low (Cochrane, 2009).

3. Third, by applying the covariance decomposition[1], we obtain the central expression for the expected excess return on any risky asset:

$$E_t\left[R_{t+1}^i\right] - R_t^f = -R_t^f \operatorname{Cov}_t\left(m_{t+1}, R_{t+1}^i\right). \tag{2.7}$$

Substituting (2.3) into (2.7) gives the version that is most useful for explanation:

[1]The covariance decomposition means $E[XY] = E[X]\,E[Y] + \operatorname{Cov}(X, Y)$. Applying it to Equation (2.2) gives $1 = E_t[m_{t+1}]\,E_t[R_{t+1}^i] + \operatorname{Cov}_t(m_{t+1}, R_{t+1}^i)$. Substituting $E_t[m_{t+1}] = 1/R_t^f$ from Equation (2.6) and rearranging the terms (2.7).

$$E_t\left[R^i_{t+1}\right] - R^f_t = -\frac{\mathrm{Cov}_t\left(u'(c_{t+1}), R^i_{t+1}\right)}{E_t[u'(c_{t+1})]}. \tag{2.8}$$

Equation (2.8) can be interpreted as

1. An asset whose return correlates positively with marginal utility, e.g., an asset that pays off well when investors are already poor, and consumption is low, pushes an expected return below the risk-free rate. Such an asset is useful because it smooths consumption, providing insurance-like benefits. We can think about a fire insurance: the insurance company pays when the house owner's house has burned down and marginal utility is high, so investors accept a negative net expected return (the insurance premium exceeds the expected payoff).

2. Conversely, an asset whose return correlates negatively with marginal utility and pays off well in good states and poorly in bad ones - must offer a positive risk premium to motivate investors to hold it.

The premium is therefore not compensation for variance. It is compensation for the direction and magnitude of an asset's covariance with the marginal utility of consumption.

2.7.2 The two necessary conditions for a priced risk factor

Equation (2.8) implies two necessary conditions for any factor to exhibit a non-zero risk premium:

1. The factor must correlate with the marginal utility. We can decompose any asset's payoff into a component perfectly correlated with the SDF and an orthogonal idiosyncratic component:

$$x^i_{t+1} = \mathrm{proj}\left(x^i_{t+1} \mid m_{t+1}\right) + \varepsilon^i_{t+1}, \quad \text{with} \quad E_t\left[m_{t+1}\, \varepsilon^i_{t+1}\right] = 0. \tag{2.9}$$

   Substituting into (2.2), the price of the idiosyncratic component is exactly zero. Equivalently, if $\mathrm{Cov}_t(m_{t+1}, R^i_{t+1}) = 0$, then by (2.6) the asset should earn the risk-free rate (as expected value). The intuition is that an asset whose payoff is uncorrelated with the investor's marginal utility affects the variance of consumption: a small additional holding of it neither protects nor exposes the investor to consumption fluctuations (Cochrane, 2009). Variance is therefore not the price-relevant quantity; only covariance with the SDF is.

2. The risk must be non-diversifiable. Even if a payoff covaries with one investor's marginal utility, the equilibrium SDF is the marginal rate of substitution of the representative investor - that is, of the marginal investor who clears the market. If a source of risk can be diversified away within the universe of traded assets, no representative investor bears it in equilibrium, and it cannot exhibit a premium.

   Non-diversifiability is therefore a property of the cross-section as a whole, not of any individual asset. A risk that is large for one firm but uncorrelated across firms - for example, a factory fire at a single paper factory - is idiosyncratic in the asset-pricing sense and is not priced, despite its potentially catastrophic firm-level consequences. A risk that is small for any given firm but correlated across many firms - e.g., the COP15 Kunming-Montreal commitment, which raised expected regulatory costs across multiple industries simultaneously - is systematic and is priced. Garel et al. (2024) document precisely this asymmetry: high-biodiversity-footprint stocks lost value in the trading days following the Kunming announcement, which is the empirical signature of a systematic, priced risk.

2.7.3 From the SDF to numerical estimations

Equation (2.2) is theoretically simple but empirically problematic, as m_{t+1} is unobservable. A standard solution is to assume that the SDF is linear in a small number of observable factors F_{t+1},

$$m_{t+1} = a + b' F_{t+1} \tag{2.10}$$

which, when substituted into (2.7) and solved, produces the expected return-beta representation

$$E\left[R^i_{t+1}\right] - R^f = \beta_i' \lambda, \tag{2.11}$$

where β_i is the vector of regression coefficients of R^i on the factors, and λ is the vector of factor risk premia. The relationship between the SDF representation (2.10) and the beta representation (2.11) is exact and bidirectional: given any factor structure of the SDF a beta representation exists, and given any beta representation an SDF can be constructed (Cochrane, 2009).

The simplest case is a simple CAPM, where the single factor is the excess return of the market portfolio, $F_{t+1} = R^m_{t+1} - R^f$, so that

$$E\left[R^i_{t+1}\right] - R^f = \beta_{i,m}\left(E[R^m_{t+1}] - R^f\right). \tag{2.12}$$

Empirical extensions add more factors that proxy for omitted parts of marginal utility: e.g., the size, value, profitability and investment factors of Fama and French (2015), the momentum factor of Carhart (1997), and the traded liquidity factor of Pastor and Stambaugh (2003).

2.7.4 Investor preferences as a pricing channel

Pastor et al. (2021) incorporate ESG preferences into asset pricing models. They extend the standard exponential utility function so that investors care not only about their end-of-period wealth ($\tilde{W}_{1i}$) but also about the ESG characteristics of their portfolio (X_i):

$$V(\tilde{W}_{1i}, X_i) = -e^{(-A_i\tilde{W}_{1i} - b_i' X_i)} \tag{2.13}$$

where A_i is the investor's absolute risk aversion, and $b_i = d_i g$, where the scalar $d_i \geq 0$ represents investor i's personal "ESG taste" and g is the vector of firms' ESG characteristics (positive for green, negative for brown).

By solving the utility maximization problem and aggregating across all investors to clear the market, Pastor et al. (2021) derive the equilibrium expected excess returns (μ) for the assets:

$$\mu = \mu_m \beta_m - \frac{\bar{d}}{a} g \tag{2.14}$$

where $\mu_m \beta_m$ is the standard Capital Asset Pricing Model (CAPM) expectation, $\bar{d}$ is the wealth-weighted average of all investors' ESG taste, and a is the (common) relative risk aversion.

The CAPM alpha for a stock is, therefore,

$$\alpha_n = -\frac{\bar{d}}{a} g_n \tag{2.15}$$

This result leads to that green assets have lower expected returns and negative CAPM alphas whenever the firm is green ($g_n > 0$) and at least some investors care about ESG ($\bar{d} > 0$). A concrete illustration is the German "twin" bond market: since

2020, Germany has issued green bonds that are identical to conventional bonds except for the green label, and the green twins trade at consistently lower yields than their non-green counterparts (Pastor et al., 2022). The yield spread (the "greenium") is the bond-market value of $-\bar{d}/a$ in Equation (2.15).

When we solve for the optimal portfolio weights, the result shows that every investor holds the risk-free asset, the market portfolio, and an "ESG portfolio" whose weights are proportional to $\Sigma^{-1}g$,

$$X_i = w_m + \frac{\delta_i}{a^2}\Sigma^{-1}g \qquad \delta_i = d_i - \bar{d}, \tag{2.16}$$

where w_m is the vector of market portfolio weights and Σ is the covariance matrix of returns. Investors whose ESG taste exceeds the wealth-weighted average ($\delta_i > 0$) tilt toward green stocks; investors with weaker-than-average tastes ($\delta_i < 0$) tilt toward brown stocks in exchange for higher expected returns; investors with average tastes simply hold the market portfolio.

Pastor et al. (2021) further extend the model to climate risk by adding a climate shock $\tilde{C}$ to the utility function. Expected returns then become:

$$\mu = \mu_m\beta_m - \frac{\bar{d}}{a}g + \bar{c}\,(1 - \rho_{mC}^2)\,\psi \tag{2.17}$$

where $\bar{c}$ is the wealth-weighted average sensitivity to climate shocks, ψ is the vector of firms' climate betas (slope coefficients on $\tilde{C}$ after controlling for the market), and ρ_{mC} is the correlation between market returns and the climate shock.

If a brown firm performs poorly during climate disasters (positive ψ), the last term raises its expected return to compensate investors for the added risk. Green firms typically have negative climate betas (their returns rise when bad climate news arrives), so they act as climate hedges and accept even lower expected returns. The taste-channel discount and the risk-channel discount for green firms therefore reinforce each other.

It is worth mentioning that a complementary equilibrium framework is developed by Pedersen et al. (2021), who consider three investor types, ESG-aware, ESG-motivated, and ESG-unaware. Both models share the central prediction that, in equilibrium, expected returns on green assets are weakly lower than on otherwise comparable brown assets whenever some investors have ESG preferences.

2.7.5 Realized versus expected returns

As we have seen in the previous section, the Pastor et al. (2021) framework predicts that green assets have lower expected returns than brown. Meanwhile, in academic literature, including Ardia et al. (2023), Bauer et al. (2022), Eskildsen et al. (2024), Karolyi and Tobin-de La Puente (2023), and Pastor et al. (2022) documents that green assets have outperformed brown ones in realized returns over various sample windows. Conflicting results can be resolved by a distinction between ex-ante and ex-post returns.

The Pastor et al. (2022) argues that realized returns can temporarily deviate from expected returns whenever there are unexpected shifts in ESG concerns. This can happen either through investors suddenly increasing their demand for green holdings or through consumers suddenly increasing their demand for green products. Formally, the realized excess return on stock n can be decomposed as

$$R_{n,t+1} - R_f = \underbrace{E_t[R_{n,t+1} - R_f]}_{\text{ex-ante (expected) premium}} + \underbrace{b_n \, \Delta C_{t+1}}_{\text{loading on the taste/concern shock}} + \underbrace{\eta_{n,t+1}}_{\text{idiosyncratic innovation}}, \tag{2.18}$$

where ΔC_{t+1} is the unexpected change in ESG concerns (with $E[\Delta C_{t+1}] = 0$) and b_n is the firm n's loading on that shock. Because the second term has zero expectation ex ante but a non-zero sample mean ex post whenever ΔC_{t+1} swings in one direction, the realized average return $\bar{R}_n$ is only a biased estimator of $E[R_n]$ in finite samples. The simplest illustration is again the German twin bond: although the green bond's expected return is lower (by the greenium), its realized return has exceeded its non-green twin's since 2020 because the greenium has widened (Pastor et al., 2022). The realized outperformance is entirely a shock-related effect; the expected return still remains lower.

2.7.6 Should a nature risk premium exist?

The question of whether the nature risk premium exists and, if so, its sign (positive or negative) depends on whether the two necessary conditions of Section 2.7.2 are satisfied, and on the dominant channel.

2.7.6.1 Conditions for a risk premium

The first condition requires that the nature risk premium should correlate with the marginal utility (and consequently, the SDF). There are multiple channels through which nature-related shocks can impact the SDF:

1. Biodiversity loss reduces the supply of ecosystem services that are inputs to production (e.g., pollination, water filtration, soil fertility, climate regulation, fisheries, timber, pharmaceutical materials) (Daily et al., 1997; Costanza et al., 1997; Dasgupta, 2021; Giglio et al., 2025). Because ecosystem services are difficult to substitute with capital and labor (Dietz & Neumayer, 2007), losses in biodiversity translate into permanent or persistent reductions in consumption. Pollinator collapse is a good example: 35% of global crop production by volume depends on animal pollinators (IPBES, 2020), so a sustained decline in pollinator populations directly lowers food output and consumption.

2. Even if nature shocks have no immediate consumption impact, they may alter the future investment opportunities, e.g., through stricter regulations. The EU Deforestation Regulation (EUDR), which requires importers of cattle, cocoa, and coffee to verify deforestation-free supply chains, is a recent example. The announcement of the regulations re-priced the cost structure of an entire set of brown business models simultaneously. Pastor and Veronesi (2012) make this argument for political/regulatory uncertainty.

3. Nature-related shocks (e.g., COP15 commitments) move marginal utility through investor wealth and through expected regulatory actions. Firms whose returns correlates positively with such shocks hedge against them and command lower expected returns; firms whose returns correlates negatively are riskier and command higher expected returns. Empirically, Giglio et al. (2026) build a news-based biodiversity risk index from New York Times articles and show that returns on portfolios sorted on biodiversity-risk exposure correlates with innovations in the index. This is a direct empirical evidence of $b_n \Delta C_{t+1}$ in Equation (2.18).

4. Biodiversity collapse exhibits non-linearities and potential tipping points (IPBES, 2020), which raise the probability of large-magnitude disasters. Ilhan

et al. (2021) document the same effect for carbon risk - high-emitting firms exhibit larger tail risk in option prices.

The second condition requires that the nature risk should be non-diversifiable. It is true that idiosyncratic biodiversity risk, e.g., a single firm's exposure to a specific natural habitat, can be diversified away in a properly constructed portfolio. However, it is important to determine whether biodiversity risk has a common factor structure across all firms. Based on the academic literature, the answer is yes:

1. Ecosystem dependencies are mainly concentrated in a small number of sectors (agriculture, fishing, food, etc.) that together account for a substantial fraction of global value added (ENCORE, 2025a; WEF, 2020). Cross-sectoral diversification within an equity index does not eliminate the exposure of the portfolio's dependencies on nature.

2. The regulatory and political transition risks (e.g., COP15, SFDR PAI indicators) are shocks that hit all exposed firms simultaneously.

3. Biosphere integrity is one of the planetary boundaries identified by Rockström et al. (2009) and Steffen et al. (2015) as having already been transgressed. Crossing such a boundary triggers correlated, system-wide consequences that no individual investor can hedge through asset selection alone. This is the definition of systemic, non-diversifiable risk.

2.7.6.2 The sign

Given that a nature premium exists, what sign (positive or negative) should it have? The framework described in Sections 2.7.4 and 2.7.5 implies a three-term decomposition of any observed expected excess return on a nature-exposed stock. First, the excess return is explained by traditional (such as Fama-French) risk factors. Second, the "risk channel" increases the expected excess return for brown companies, as these assets lose value in bad environmental states and must therefore compensate investors, and decreases it for green companies. Third, the "taste channel" further decreases the excess return for green stocks, since investors derive non-pecuniary utility from holding them, and increases it for brown stocks. Both the risk channel and the taste channel therefore predict lower expected returns for green assets and higher expected returns for brown assets in equilibrium (Pastor et al., 2021, 2022).

However, the realized return in any period (and sample) reflects the impact of the shock (innovation) term as well. When environmental concerns strengthen unexpectedly - happened during 2012–2020 - green assets can outperform brown assets in realized terms even though their expected returns remain lower (Pastor et al., 2022). This distinction between expected and realized returns is essential for interpreting the empirical literature on the sign of the nature premium.

The empirical evidence from recent studies is usually consistent with this theoretical framework.

Pastor et al. (2021) predict that green assets have lower expected returns than brown assets, due to both the taste and risk channels. Coqueret et al. (2025) provide additional support: using option-implied expected returns for US stocks in biodiversity-exposed sectors, they estimate a negative expected return premium for green firms (approximately -1.5% to -1.7% annually), which materialised strongly from 2021 onward. Garel et al. (2024) find that after the Kunming Declaration in October 2021, the implied cost of capital for high-biodiversity-footprint firms increased, consistent with a positive brown premium in expected returns.

Regarding realized returns, Pastor et al. (2022) argues that green stocks outperformed brown stocks between November 2012 and December 2020, but this outperformance was entirely driven by the unexpected climate concerns. When the climate concern shock is removed, the green-minus-brown factor's performance becomes flat or slightly negative. Coqueret et al. (2025) document a similar pattern for biodiversity: a positive realized return premium for green firms in double-material sectors, due to the rising biodiversity attention and risk aversion (explaining approximately 40% of the premium's variation). Garel et al. (2024) report that large-biodiversity-footprint stocks lost approximately 1.14% relative to small-footprint stocks in the three trading days following the Kunming Declaration, a typical pattern when transition risk devalues assets.

Not all studies find a significant premium. For example, Xin et al. (2025) find no significant relationship between ESG-based biodiversity ratings and stock returns, and concludes that these ratings are too noisy to capture meaningful biodiversity risk. This highlights the dependence of the estimated sign on the quality of the biodiversity risk measure used. Science-based metrics, such as the Corporate Biodiversity Footprint used by Garel et al. (2024), and news-based indices, such as the biodiversity risk index of Giglio et al. (2026), detect significant pricing, while ESG-derived sub-scores do not.

Some of the literature focus on physical risk. Huang et al. (2024) show that firms with low biodiversity physical risk outperform high-risk firms by 2–5% annually in risk-adjusted terms. They interpret this as market mispricing rather than risk compensation, because financial analysts potentially fail to recognise the operational resilience of low-risk firms, and neither institutional nor retail investors adjust portfolios for biodiversity physical risk. Ma et al. (2024) document a similar pattern in China: their news-based Biodiversity Risk Index negatively predicts aggregate stock returns, especially through the physical risk channel.

In summary, the theoretical prediction is unambiguous: in expected-return terms, brown assets should earn more than green assets due to both risk and taste channels. The empirical evidence is largely consistent with this for biodiversity, although the effect is often masked in realized returns by unexpected shocks of environmental concerns. Additionally, whether the premium is detectable at all depends critically on the quality and specificity of the biodiversity risk measure.

Chapter 3

Biodiversity Risk Premium

Helena Naffa, Gergely Czupy

Abstract: We identify a biodiversity risk premium (BRP) in investment strategies designed to mitigate biodiversity risks. To capture this premium, we construct optimised portfolios by reweighing approximately 3,000 constituents of the MSCI All Country World Index, using their MSCI biodiversity risk scores as a key screening criterion. Analysing data from 2013 to 2023, we find that biodiversity-screened portfolios exhibit lower risk-adjusted returns compared to randomly selected portfolios. This suggests the presence of a biodiversity risk premium, ranging from 1.1% to 3.4% of the maximum attainable Sharpe ratios within the investment universe, or a return loss of 1 to 11 basis points (both refers to the biodiversity-specific component, excluding the universe-shrinking cost). Our findings provide valuable insights into the pricing dynamics of biodiversity risk, enhancing the understanding of how natural capital considerations impact financial markets and investment strategies.

The first version of this chapter has been published in Naffa and Czupy (2024).

3.1 Introduction

Investors prioritise financially material risks in portfolio construction. Yet biodiversity loss, an emerging sustainability threat, remains unknown to most investors, despite posing a financially material risk to companies operating in exposed sectors. As environmental challenges intensify, understanding how biodiversity risk is priced in financial markets is critical. However, investor awareness and integration of biodiversity risk into financial decision-making remain limited.

Even though a growing number of papers examine whether biodiversity risk is priced in financial markets, they remain limited in practical applicability for Sustainable and Responsible Investment (SRI) professionals. Existing studies primarily adopt factor-based approaches or news-based indices to identify risk premia (Coqueret et al., 2025; Garel et al., 2024; Giglio et al., 2026), return predictability regressions (Ma et al., 2024), or cash-flow mispricing channels (Huang et al., 2024). While these methodologies provide valuable insights into market-wide pricing, they do not directly capture the inherent trade-offs and costs that investors face when implementing specific biodiversity-driven investment strategies in practice.

Our study fills this gap by adopting a portfolio optimisation framework that mirrors actual SRI strategies. Our approach accounts for stock interactions overlooked by factor portfolios, avoiding the reliance on short positions excluded by market convention from sustainability performance metrics. We also use the MSCI ESG dataset, a common choice among industry professionals. In doing so, we complement the theoretical predictions of Pastor et al. (2022) and the empirical evidence on green-versus-brown return differentials documented by (Ilhan et al., 2021; Pastor et al., 2021) providing a practical, global-scope estimate of the returns investors sacrifice to achieve biodiversity risk mitigation at varying intensities.

Investors integrate Environmental, Social, and Governance (ESG) factors into their investment processes through established SRI strategies (Eurosif, 2018). Investors can use one or a combination of SRI strategies in portfolio construction for various purposes, including financial and sustainability risk mitigation, enhanced financial performance, adherence to international norms on good governance principles, and alignment with discretionary investor values, and, in some cases, to pursue positive impacts that help solve real-world challenges[1] (Busch et al., 2022, 2024). Busch et al. (2022, 2024) provide a list of the main approaches: (1) exclusions (sectors with the highest adverse impact are excluded from the investment universe), (2) norms-based screening (companies are excluded based on their compliance with international norms), (3) ESG integration (systematic integration of ESG factors into traditional financial analyses), and (4) best-in-class[2] (companies' ESG attributes are rated on a relative scale within their industry subset), (5) sustainability-themed

[1]Impact investment themes commonly aligned with the UN Sustainable Development Goals (UN, 2023) or to garner the satisfaction of making an attempt at said objectives (Amel-Zadeh & Serafeim, 2018; Busch et al., 2022).

[2]Best-in-progress is based on ESG improvement over time. The best-in-universe are the best companies in an investment universe according to predetermined ESG attributes.

investments (assets are linked to specific ESG issues, such as climate change, biodiversity loss, or social issues, gender equality).

A key aspect of our methodology involves estimating the risk premium associated with biodiversity-related screening. Unlike traditional factor models that isolate a specific risk factor by going long on "green" and short on "brown" assets, our screening approach reflects the ex-ante constraints faced by institutional investors. Screening inherently reduces the number of investable constituents, potentially decreasing diversification opportunities. By constructing optimized portfolios that exclude the worst-performing biodiversity laggards, we identify the "Biodiversity Risk Premium" as the difference in risk-adjusted performance between a biodiversity-screened portfolio and a randomly selected benchmark of equal size. This approach allows us to capture the inherent cost of biodiversity screening, the sacrifice in the maximum attainable Sharpe ratios, while accounting for the "double materiality" of biodiversity risk, which encompasses both transition risks (e.g., regulatory shifts after the Kunming-Montreal Global Biodiversity Framework) and physical risks (e.g., degradation of ecosystem services) (Coqueret et al., 2025; Huang et al., 2024).

It is worth clarifying how our approach differs from the traditional multi-factor model framework commonly used in the asset-pricing literature. A multi-factor model constructs a long-short factor portfolio, e.g., long green firms and short brown firms, and tests whether the resulting return series carries a significant alpha after controlling for known factors. This approach is well-suited for identifying whether a characteristic is priced, but it does not correspond to any implementable investment strategy, since most institutional rules prohibit short selling of sustainability laggards. Our screening-based method, by contrast, starts from the constraints that real investors face: it excludes laggards from a long-only universe and measures the cost of this exclusion in terms of reduced Sharpe ratios and return loss.

Our objectives are to

1. Investigate the existence of a Biodiversity Risk Premium (BRP) using an optimization-based screening framework.

2. Examine how different levels of risk mitigation intensity influence the BRP.

3. Analyse whether the BRP varies in time.

It is important to note that our analysis does not focus on investing in companies that provide direct solutions to biodiversity loss.

Our findings have significant implications for both investors and financial institutions. Investors benefit from increased awareness and effective mitigation strategies to address biodiversity risk, while financial institutions can use the BRP estimation to develop biodiversity risk-hedging products. More broadly, we aim to raise awareness in academic discourse by spotlighting biodiversity loss in the finance sector. By doing so, we aim to build more sustainable, resilient portfolios that integrate biodiversity considerations into investment decision-making.

The remainder of this paper is organised as follows: we introduce biodiversity finance and related literature in Section 3.2, present our dataset and biodiversity risk premium estimation approach in Section 3.3 and 3.4. Results and discussion follow in Section 3.5, while Section 3.6 concludes.

3.2 Literature review

Biological diversity, or biodiversity, encompasses the variety of living organisms across all habitats and is currently deteriorating at an unprecedented, alarming pace. Between 1970 and 2016, the world witnessed a staggering 68% loss of monitored wildlife (WWF, 2020). Biodiversity loss is one of the six (out of nine) planetary boundaries breached by 2023, signaling a major ecological imbalance and an approach toward crucial tipping points (Richardson et al., 2023).

Beyond its ecological implications, the collapse of biodiversity carries profound economic consequences. Approximately 50% of global GDP is estimated to depend on nature and its services, including food, clean water, air, and a stable atmosphere (WEF, 2020). The loss of these ecosystem services compromises societal resilience and has been linked to potential pandemics (IPBES, 2020). As environmental challenges intensify, understanding how biodiversity risk is priced in financial markets is critical. However, investor awareness and the integration of biodiversity risk into financial decision-making remain limited compared to climate-related efforts.

3.2.1 Global biodiversity frameworks and the financial sector

The adoption of the Kunming-Montreal Global Biodiversity Framework at COP15 in 2022 established ambitious targets for biodiversity preservation (CBD, 2020). In alignment, the finance sector established the Task Force on Nature-related Financial Disclosure (TNFD) in 2023 to provide a framework for assessing and disclosing impacts on biodiversity (TNFD, 2023). Central banks and supervisors, through the Network for Greening the Financial System (NGFS), have highlighted that biodiversity loss imposes economic costs via physical and transition risk channels, potentially affecting financial stability (DNB, 2020; OECD, 2023b).

Despite this recognition, a large disparity persists between current investments (approximately 124-143 billion USD per year) and the estimated annual funding gap of 722-967 billion USD needed to halt biodiversity decline (Deutz et al., 2020). This underscores the need for substantial shifts in financial strategies and the involvement of private capital (Flammer et al., 2025; Hudson, 2024; Karolyi & Tobin-de La Puente, 2023).

3.2.2 Biodiversity risk and climate risk

Before the emergence of biodiversity-specific research, the sustainable finance literature focused predominantly on climate and carbon risks.

It has been shown that climate risks are already priced in financial markets via carbon premiums and downside tail risk costs (Bolton & Kacperczyk, 2023; Ilhan et al., 2021). However, biodiversity risk appears to be a distinct dimension. For example, Giglio et al. (2026) find that biodiversity exposure is only weakly correlated with climate risk at the firm level, and climate-hedging portfolios do not necessarily mitigate biodiversity risk.

3.2.3 ESG portfolio construction methodologies

Academic literature has widely investigated the link between general ESG attributes and financial performance (Friede et al., 2015). However, application in portfolio construction remains relatively new. Some studies demonstrate positive or neutral impacts (Alessandrini & Jondeau, 2020b; L. Chen et al., 2021; Utz et al., 2015; Xidonas & Essner, 2022), while others report mixed results attributed to regional differences or specific time periods (Cesarone et al., 2022; De Spiegeleer et al., 2021; Giese et al., 2019; Nagy et al., 2013). Other studies conclude that there is a trade-off among ESG performance, financial risk, and returns, and that only two of the three can be improved simultaneously. Liagkouras et al. (2020) explain this constraint by limited investment choices, whereas Alessandrini and Jondeau (2020a) and Branch et al. (2019) cite unintended risk exposures and sectoral biases. Theoretical models by Pedersen et al. (2021) and Ahmed et al. (2021) reconcile these disparities by assuming different investor types and utility functions.

The selection of the ESG rating agency and the selected ESG attributes used for ESG integration also impact portfolio selection and performance, according to Bender et al. (2018), De Spiegeleer et al. (2021), and Feifei Li and Ari Polychronopoulos (2020). This is especially noteworthy, as the low correlation among ESG rating agencies is well documented (Capizzi et al., 2021; Zumente & Lāce, 2021).

Empirical research uses different approaches to construct SRI portfolios. Following the Eurosif SRI classification proposed by Busch et al. (2022), the papers of Alessandrini and Jondeau (2020a), Branch et al. (2019), and L. Chen et al. (2021) and Liagkouras et al. (2020) used the exclusion strategy, while ESG integration is used by Branch et al. (2019), Cesarone et al. (2022), Sokolov et al. (2021), and Utz et al. (2015). We find that Alessandrini and Jondeau (2020a), Giese et al. (2019), and Nagy et al. (2013) are prime examples of best-in-class and similar strategies, while sustainability-themed investments are investigated by Naffa and Fain (2020).

The majority of published studies in this field build on the classical mean-variance portfolio optimisation framework originally developed by Markowitz (1952). A sustainability goal is usually added to the portfolio optimisation problem either as a term in the objective function or as a constraint. Other approaches we find in the literature include equally weighted portfolios in De Spiegeleer et al. (2021), and passive index-based portfolios used by Giese et al. (2019). The use of additional constraints is featured in De Spiegeleer et al. (2021) and Xidonas and Essner (2022). Machine learning approaches were used in Sokolov et al. (2021). Smart beta strategies (Alessandrini & Jondeau, 2020b) and evolutionary computing (Liagkouras et al., 2020) have also been investigated.

3.2.4 Biodiversity risk measurement and pricing

The existing academic literature on biodiversity finance is recent but expanding rapidly. Despite the growing interest, as noted by Hutchinson and Lucey (2024), we see a gap in research examining biodiversity investments from a risk-mitigation perspective.

An important theoretical work has been published by Pastor et al. (2021), who develop an equilibrium model in which agents derive non-pecuniary utility from holding green assets and disutility from holding brown assets. In their framework, green assets have lower expected returns because investors are willing to accept lower financial compensation in exchange for the satisfaction of holding environmentally friendly securities. A two-factor model comprising the market portfolio and an ESG factor emerges in equilibrium, where the ESG factor captures shifts in customers' tastes for green products and investors' tastes for green holdings. Importantly, the model shows that green assets can deliver high realized returns during periods when positive shocks to the ESG factor materialise, even though their expected returns remain low.

Pastor et al. (2022) provide direct empirical support for these predictions. They demonstrate that the strong recent performance of green assets reflects unexpectedly strong increases in environmental concerns rather than high expected returns. Additionally, they estimate that green stocks have lower expected returns than brown stocks, consistent with the equilibrium theory. Together, these two studies establish the key insight that higher realised returns for green assets should not be confused with higher expected returns: the former is a transitional phenomenon driven by the unanticipated strengthening of sustainability preferences, while the latter reflects a permanent equilibrium discount investors accept for holding green assets.

Giglio et al. (2026) provide a comprehensive framework for measuring biodiversity risk and its effect on asset values. They develop a news-based aggregate biodiversity risk index using textual analysis and a large survey of finance professionals. Their analysis demonstrates that biodiversity risk exposures are distinct from climate risk exposures. Crucially, they show that returns of portfolios sorted on biodiversity risk exposure correlate positively with innovations in the aggregate biodiversity risk index, providing evidence that biodiversity risk has been at least partially priced in U.S. equities. Their survey further indicates that market participants do not perceive the current pricing of biodiversity risks to be adequate, suggesting scope for further market adjustment.

Garel et al. (2024) find that a biodiversity footprint premium appeared after the Kunming Declaration in October 2021, while it was unobservable before this event. This can be explained by investors demanding compensation for holding firms exposed to biodiversity transition risk. An event study confirms that large biodiversity footprint stocks lost value in the days following the Kunming Declaration and the launch of the Taskforce on Nature-related Financial Disclosures (TNFD). These results suggest that investor awareness of biodiversity issues, combined with the prospect of future regulation, has begun to influence the pricing of biodiversity-exposed equities.

Coqueret et al. (2025) construct green-minus-brown biodiversity factors and show that these factors are not spanned by the Fama and French (2015) five factors or the carbon factor, indicating that biodiversity captures distinct information. Their key finding is that, while no biodiversity premium is detected across the entire universe, a significant negative premium on expected returns (approximated from option prices) emerges for companies in sectors highly exposed to the double materiality of biodiversity risks. A dynamic analysis reveals that this negative premium on expected returns materialised strongly from 2021 onward. They further demonstrate that attention to biodiversity issues and risk aversion are significant drivers of this premium.

Ma et al. (2024) contribute a complementary perspective by constructing a Biodiversity Risk (BR) Index from textual data extracted from ten mainstream Chinese news media outlets. Their BR index demonstrates robust negative predictive power for Chinese stock market returns, with the predictive relationship persisting for up to 6 months. The index also yields economically significant gains in a mean-variance asset allocation framework. The study reveals industry-level heterogeneity in biodiversity risk exposure: industries directly dependent on natural resources (e.g., agriculture, forestry) exhibit greater sensitivity, while sectors such as telecommunications exhibit lower exposure. They further decompose biodiversity risk into physical and transition components, finding that biodiversity physical risk significantly predicts stock returns, whereas transition risk has yet to materialise in the Chinese market. The predictive power of the BR index strengthened markedly after the Kunming Declaration, aligning with the post-COP15 structural shift documented by Garel et al. (2024).

Huang et al. (2024) focus specifically on the asset pricing implications of biodiversity physical risk. A long-short portfolio sorting firms by their physical risk exposure generates a significant average annual excess return after controlling for standard risk factors. The return predictability stems from market mispricing of future cash flows: firms with the lowest biodiversity physical risk outperform their peers in subsequent profitability, yet financial analysts systematically fail to recognise this resilience. The study documents that neither institutional nor retail investors adjust their portfolio allocations in response to biodiversity physical risk information.

Xin et al. (2025) examine the informativeness of the biodiversity component within ESG ratings for financial decision-making. Using MSCI's ESG biodiversity metric, which includes both management and exposure components, they test whether these scores predict stock returns, correlate with firm characteristics, or influence operating performance. Their findings are largely negative: biodiversity ratings do not predict future returns, are uncorrelated with firm characteristics beyond firm size, and have no detectable effect on returns on assets or profit margins. Institutional investors and sell-side analysts appear to ignore biodiversity ratings in their portfolio allocation and earnings forecast activities. The results are heterogeneous across industries: biodiversity ratings predict negative returns in metals and mining but positive returns in utilities.

3.2.5 Marginal contribution to the literature

Our paper makes the following distinct contributions to the already existing literature:

1. A practitioner-oriented portfolio optimization framework. Unlike factor-based approaches that construct long-short portfolios (Coqueret et al., 2025; Garel et al., 2024; Huang et al., 2024) or news-based risk indices (Giglio et al., 2026; Ma et al., 2024), we adopt an optimization-based screening framework that mirrors the actual constraints faced by institutional SRI investors. This makes the results directly actionable for asset managers who employ exclusion strategies.

2. Quantification of the biodiversity screening cost at varying risk mitigation levels. We provide granular estimates of the Biodiversity Risk Premium (BRP) at three distinct mitigation levels (25%, 50%, 75% exclusion). We show that the BRP is non-linear: at low-to-moderate intensities it is statistically indistinguishable from zero (i.e., biodiversity screening is nearly "free"), while a statistically and economically significant residual cost emerges only at the strictest screening level. No prior study has mapped this cost-intensity curve.

3. Decomposition of biodiversity risk from climate and social risk. Our orthogonalization analysis reveals that biodiversity performance in exposed sectors is overwhelmingly correlated with carbon intensity and social quality. The "pure" biodiversity component, once cleaned of these confounders, is not

independently priced. This identification challenge is a novel empirical finding that extends the theoretical predictions of Pastor et al. (2021) and the carbon-biodiversity interaction noted by Coqueret et al. (2025).

4. Use of MSCI's practitioner-grade dataset with global scope. While much of the prior literature uses Iceberg Data Lab's CBF metric (Coqueret et al., 2025; Garel et al., 2025), news-based indices (Giglio et al., 2026; Ma et al., 2024), or physical risk indices (Huang et al., 2024), we use MSCI's Biodiversity and Land Use Score - the metric most widely used by institutional investors - applied to the global MSCI ACWI universe (3,000 stocks). This complements prior US- or EU-focused findings with a global perspective.

3.3 Data and data processing

Our dataset comprises time series spanning from 2013 to 2023. Our decision to focus on this period was based on data availability and aimed to encompass the broadest possible range of market conditions, from normal market conditions to downturn. We utilise the components of the MSCI All Country World Index (ACWI) as our investment universe. The ACWI typically consists of approximately 3000 members, with the number of constituents fluctuating over time due to regular updates to the constituent list. We update the list of constituents annually on January 1st.

3.3.1 Biodiversity

In this paper, we examine biodiversity from a risk-management standpoint and proxy biodiversity- and land-use-related ESG risk using MSCI's "Biodiversity and Land Use" Key Issue Score (Natural Capital theme, Environmental pillar). In MSCI's framework, this Key Issue evaluates (1) the potential impact of a company's operations on biodiversity in its areas of operation and (2) the company's efforts to manage that environmental impact (MSCI, 2023). Importantly, the reported Key Issue Score is designed as a risk-based metric: it combines an Exposure Score (0-10, where 10 indicates highest risk) with a Management Score (0-10, where 10 indicates best practice) such that companies with higher exposure must demonstrate stronger management capability to achieve the same overall score (MSCI, 2023). Hence, a higher BIODIV_LAND_USE_SCORE should be interpreted primarily as stronger management measures relative to exposure (e.g., MSCI assesses the firm as better positioned to manage biodiversity/land-use risk given its exposure), rather than as "more biodiversity impact" per se. MSCI highlights several channels through which biodiversity and land-use issues can translate into financially relevant risks, including loss of formal and social licence to operate, litigation by affected parties, and increased costs related to land protection and reclamation (MSCI, 2023). Within the Exposure Score, MSCI combines (1) business exposure linked to business-activity "biodiversity impacts" and controversies with (2) geographic exposure that reflects conditions in countries/regions of operation (e.g., forest area loss and threatened species), which acts as a multiplier on business exposure (MSCI, 2023).

ESG scoring is based on a materiality assessment, meaning that if a particular issue is not material for a specific company, no score is assigned (MSCI, 2024). As a result, not all constituents of the MSCI ACWI index have a biodiversity score. However, companies in the energy (primarily oil and gas), materials (mining), industrials (airports, marine ports, highways), consumer (agricultural products), and utilities (gas and water utilities) sectors typically do. This accounts for approximately 400-500 firms in the index.

A higher BIODIV_LAND_USE_SCORE indicates very strong management measures relative to the company's exposure to biodiversity/land-use risk, while lower scores indicate weaker management relative to exposure (MSCI, 2023). Consistent with MSCI's score interpretation, companies with very high scores typically do not have very high risk exposure, whereas companies with very low scores are often characterised by very high exposure and poor mitigation (MSCI, 2023). Examples for companies with low/high biodiversity exposure and management scores are presented in Table 3.1.

Accordingly, using higher score thresholds in screening corresponds to selecting firms that appear more resilient/better positioned to manage biodiversity- and land-use-related ESG risks (rather than selecting firms with higher "biodiversity risk").

3.3.2 Carbon emission

To address the concern that biodiversity-screening effects may partly reflect climate (carbon) risk premia - given that several biodiversity-exposed sectors are also carbon-intensive - we additionally control for the MSCI Carbon Emissions Key Issue Score. MSCI evaluates this Key Issue based on the carbon intensity of a company's operations and the company's efforts to manage climate-related risks and opportunities (MSCI, 2025). Similar to other risk-based Key Issues, the score combines an Exposure Score (0-10, where 10 indicates highest risk) with a Management Score (0-10, where 10 indicates best practice) and combines them such that higher exposure requires stronger management capability to achieve the same overall Key Issue Score (MSCI, 2025). The management component includes inputs such as the aggressiveness and track record of emissions-reduction targets, mitigation actions (e.g., cleaner energy use, carbon capture, and other reduction efforts), and disclosure (e.g., CDP), while performance is assessed via peer-relative emissions-intensity metrics such as Scope 1+2 GHG emissions intensity and its trend (MSCI, 2025). The exposure component reflects business and geographic exposure (with geographic exposure acting as a multiplier on business exposure), where business exposure is anchored in (normalised) GHG emissions intensity for relevant business activities and supported by a range of data sources, including company disclosures and sector/regional datasets (MSCI, 2025).

Including the Carbon Emissions Key Issue Score helps separate biodiversity/land-use risk management effects from climate-risk-related effects in the cross-section of portfolio outcomes.

3.3.3 Social and governance attributes

We additionally control for MSCI's Social Pillar Score and Governance Pillar Score. For the Environmental and Social pillars, MSCI constructs Pillar Scores as the weighted average of the underlying Key Issue Scores (each on a 0-10 scale), normalised by the total sum of weights within the pillar (MSCI, 2024). Key Issue selection and weights are industry-specific: MSCI begins with an in-depth assessment of ESG risks and opportunities relevant to each industry and evaluates companies on a subset of two to seven Environmental and Social Key Issues (MSCI, 2024). Each Environmental and Social Key Issue typically represents 5% to 30% of the total ESG Rating, with weights informed by the level of contribution to the relevant externality and the expected time horizon for the risk/opportunity to materialise (MSCI, 2024).

Governance is assessed for all companies via a deduction-based scoring model that quantifies the gap between best practice and a company's governance practices (MSCI, 2024). The Governance Pillar Score is derived from converting Governance Pillar Points into a 0-10 score; MSCI notes this holistic conversion prevents strengths in one Governance Theme from offsetting deficiencies in another (MSCI, 2024).

Finally, MSCI ESG Ratings follow a "best-in-class", industry-relative approach: MSCI computes a company's Weighted Average Key Issue Score (WAKIS) and then normalises WAKIS within its ESG Ratings Industry peer group to obtain an Industry-Adjusted Score (IAS), which is subsequently mapped to the global AAA-CCC letter rating scale (MSCI, 2024). MSCI also reports percentile rankings and interprets the top tail as "Best in class" (96-100 percentile) and the bottom tail as "Worst in class" (0-5 percentile) (MSCI, 2024).

3.3.4 Closing prices, risk factors

To calculate the expected return and covariance matrix, we gathered daily adjusted closing prices from the Refinitiv Eikon database and converted them to USD using the daily exchange rate. This process assumes hedging of FX risk within investment portfolios.

The Fama-French factors for each month are sourced from the French (2023) website for both emerging markets and developed markets. Liquidity factor data has been obtained from Pastor (2026).

3.4 Methodology

3.4.1 Estimating the biodiversity risk premium

To address the research questions and evaluate whether investors pay a premium for mitigating biodiversity risk by screening, we employ a multi-step estimation approach. This involves defining the investment universe and screening criteria, constructing optimal portfolios, and finally, quantifying the efficiency costs of these screens using the Return Loss measure proposed by Calvet et al. (2007).

3.4.1.1 Investment universe and screening procedure

We begin by identifying two distinct subsets of companies within the global investment universe U, which we use the MSCI ACWI index constituents for. The first subset, $U_{\text{exposed}} \in U$, contains companies operating in GICS sectors identified as having material exposure to biodiversity risk under the MSCI materiality framework. These sectors include Energy, Materials, Industrials, Consumer Staples, and Utilities. Consequently, companies in U_{exposed} have a defined biodiversity score.

The second subset, $U_{\text{unexposed}} \in U$includes companies considered immaterial to biodiversity risk, for which no biodiversity score is defined.

We construct biodiversity-screened investment universes by excluding companies with poor biodiversity risk management. A risk mitigation level controls exclusion as:

$$U_{\text{bio}}(\alpha) = U_{\text{unexposed}} \cup \left\{ i \in U_{\text{exposed}} \mid B_i \geq \epsilon_\alpha(B) \right\} \tag{3.1}$$

where α represents the percentage of companies excluded from U_{exposed} during the screening process, i denotes an individual company, B_i is the biodiversity score of company i, and B is a column vector containing biodiversity scores for all companies in U_{exposed}. $\epsilon_\alpha(B)$ is the screening threshold corresponding to the α percentile of biodiversity scores. Effectively, investors hold all biodiversity-unexposed firms and a selection of biodiversity-exposed firms. We examine performance from the perspective of a global, diversified investor that holds broad market exposure to the MSCI ACWI index constituents.

We examine three distinct risk mitigation levels: $\alpha \in \{0.25, 0.50, 0.75\}$ corresponding to the exclusion of the bottom 25%, 50%, and 75% of performers among biodiversity-exposed firms. We refer to these levels as "low", "moderate", and "high" risk mitigation levels from now on.

To separate the specific impact of biodiversity screening from the effect of reducing the investment universe, we employ a randomized bootstrapping procedure. We define random screening as the process of selecting assets from the universe U such that the number of firms selected into the portfolio equals the number in the biodiversity-screened portfolio. Formally, for each mitigation level α, we generate J random portfolios where the j-th random universe $U^j_{\text{rnd}}(\alpha)$ satisfies:

$$\left| U^j_{\text{rnd}}(\alpha) \right| = \left| U_{\text{bio}}(\alpha) \right| \tag{3.2}$$

3.4.1.2 Portfolio optimization

Our analysis spans the period from 2013 to 2023 and is divided into overlapping three-month windows with a one-month step size (we handle issues coming from overlapping windows later). The MSCI ACWI index constituent list, the broad investment universe, is updated annually on January 1 or at the first trading day of each year.

In each window t, we calculate the annualized stock returns and the covariance matrix using daily logarithmic return data calculated from adjusted closing prices denominated in USD. We then construct ex-post optimal long-only portfolios by maximizing the Sharpe ratio within both the screened universe $U_{\text{bio}}(\alpha)$ and within each random universe $U^j_{\text{rnd}}(\alpha)$. To ensure the portfolios remain representative of the broader market structure, we constrain GICS industry weights to match those of the MSCI ACWI index and impose a 5% maximum weight limit for individual stocks.

The optimization model is formulated as follows:

$$\max_{w} \frac{w^T r - r_f}{\sqrt{w^T \Sigma w}} \tag{3.3}$$

s.t.

$$\begin{aligned} w^T 1 &= 1 \\ 0 \leq w_i &\leq 0.05 \\ \sum_{i \in \text{GICS}_k} w_i &= W_k \end{aligned} \tag{3.4}$$

where w_i represents the weight of asset i, r is the vector of annualized logarithmic returns, and $\Sigma$is the annualized variance-covariance matrix estimated using the Ledoit-Wolf shrinkage estimator (Ledoit & Wolf, 2014). r_f denotes the risk-free rate, GICS_k represents the set of companies belonging to the sector k, and W_k is the corresponding GICS sector weight in the MSCI ACWI index.

Since the Sharpe ratio maximization is a non-convex optimization problem, we transformed it into a convex quadratic one using the transformation described by (Schaible, 1974), which can be solved efficiently using mathematical solver packages. We used the Gurobi Optimizer for this purpose (Gurobi Optimization, LLC, 2022).

3.4.1.3 Measuring the Return Loss

To quantify the implications of biodiversity screening, we adopt the framework developed by Calvet et al. (2007) and compare the performance of the biodiversity-screened universe $U_{\text{bio}}(\alpha)$, the randomly screened universes $U^j_{\text{rnd}}(\alpha)$, and the original unrestricted universe U.

First, the Relative Sharpe Ratio Loss (RSRL) is defined. For a given portfolio p (screened or random), with a Sharpe ratio S_p and a benchmark index B with a Sharpe ratio S_B, the RSRL is defined as:

$$RSRL_p = 1 - \frac{S_p}{S_B} \tag{3.5}$$

This ratio has a specific interpretation: Calvet et al. (2007) show that when the benchmark portfolio is mean-variance efficient, the ratio of the portfolio's Sharpe ratio to the benchmark's Sharpe ratio equals the correlation between the portfolio's return and the benchmark's return. Therefore, this ratio measures the diversification limit of the screened portfolio; a lower ratio implies a lower correlation with the efficient frontier and, consequently, a higher loss of diversification potential.

To translate this efficiency loss into return units, we calculate the Return Loss (RL) as defined by Calvet et al. (2007). The Return Loss represents the average return an investor sacrifices by choosing a constrained portfolio rather than a position combining the benchmark portfolio with cash to achieve the same risk level. (In this study, investors do not hold cash; the whole position is invested in risky assets.) Geometrically, this is the vertical distance between the portfolio and the efficient frontier in the mean-standard deviation plane.

The Return Loss is linked to the RSRL measure and the total risk taken by the portfolio:

$$RL_p = S_B \times \sigma_p \times RSRL_p \tag{3.6}$$

where σ_p is the standard deviation of the portfolio's returns. This decomposition highlights that the return cost is the product of the benchmark's Sharpe ratio, the portfolio's volatility, and inefficiency.

In each time window, we estimate the maximum attainable Sharpe ratio, RL, and RSRL for the biodiversity screened portfolios (S_{bio}, RL_{bio}, $RSRL_{\text{bio}}$), and the average metrics of the randomly screened portfolios (S_{rnd}, RL_{rnd}, $RSRL_{\text{rnd}}$).

By comparing RL_{bio} to RL_{rnd}, we can isolate the efficiency impact of biodiversity screening from random screening and filter out the effect of shrinking the investment universe. RL_{rnd} is the mean loss from shrinking the universe (investing in fewer stocks than in the original universe). RL_{bio} represents the loss of shrinking the universe through biodiversity screening. When $RL_{\text{bio}} - RL_{\text{rnd}} > 0$, biodiversity screening results in greater losses than random screening, and investors who employ this screening strategy sacrifice larger returns than the loss of randomly shrinking the universe. When the difference is negative, investors gain an extra return via biodiversity screening.

3.4.1.4 Estimation of the Biodiversity Risk Premium

The differences in the Sharpe ratios and Return Losses between the biodiversity-screened portfolios and their randomly screened counterparts cannot be attributed solely to the impact of biodiversity considerations as a screening criterion, even after fixing industry weights. Differences in factor exposure, liquidity, or geographical allocation may drive performance differentials. Therefore, to estimate the actual Biodiversity Risk Premium, we employ a linear regression model and control for the effects of many well-known factors.

We calculate the difference between the RL_{bio} and RL_{rnd} and use it as the dependent variable in a regression model. Next, we control for the main known risk factors and portfolio-level attributes. The linear model is specified as follows:

$$RL_{\text{bio,t}}(\alpha) - RL_{\text{rnd,t}}(\alpha) = c + \beta^T \left[F_t, \Delta ESG_t, \Delta Port_t, \Delta Loc_t\right] + \epsilon_t \qquad (3.7)$$

where $RL_{\text{bio,t}}(\alpha)$ is the Return Loss of the portfolio created in the biodiversity screened universe at time t, and$RL_{\text{rnd,t}}(\alpha)$ is the average Return Loss across the random experiments, α is the risk mitigation level. The intercept c represents the adjusted Biodiversity Risk Premium, and ϵ_t is the random error. The vector of control variables includes:

1. Risk factors (F_t): This vector includes the five Fama-French factors plus the momentum factor from French (2023). Rm-Rf stands for the market risk premium; SMB represents the size factor (e.g., the excess return of small-cap stocks minus that of high-cap stocks); RMW is the excess return of highly profitable stocks and weakly profitable stocks; and CMA is the excess return of low- and high-investment firms. HML denotes the excess return of high vs. low book-to-market ratio companies. MOM denotes the momentum factor. We add another factor, LIQ, representing the liquidity premium, as in Pastor and Stambaugh (2003).

   Since the MSCI ACWI constituents cover global investment opportunities, and the Fama-French factors are available for Developed and Emerging markets separately, we follow Griffin (2002) and construct global factor values by calculating their weighted average as

$$F_{\text{global}} = w_{EM} F_{\text{EM}} + (1 - w_{EM})\, F_{\text{DM}} \tag{3.8}$$

where F_{global} is the weighted average, F_{EM} is the Fama-French factor publicised for Emerging Markets, F_{DM} is the value of the factor for Developed Markets, and w_{EM} is the weight of the Emerging Markets factor in the global factor. We employ equal weighting ($w_{EM} = 0.5$) since the Sharpe ratio maximization approach can allocate any weight to Emerging Markets (so that the Emerging Market weight can differ from its weight in the MSCI ACWI index.[3]

2. ESG attributes (ΔESG_t): This vector denotes a difference in portfolio-level ESG characteristics between the biodiversity-screened portfolio and the average of portfolios formulated in random universes. We consider the difference in the MSCI Social Pillar score (S), the MSCI Governance Pillar score (G), and the MSCI Carbon Emission score (C). The MSCI Environmental Pillar score has been excluded as it is a composite value containing both the Biodiversity and Land Use and Carbon Emission scores.

3. Portfolio-level attributes ($\Delta Port_t$): Here, we control for the difference in annualized portfolio return standard deviation.

4. Location/market attributes (ΔLoc_t): This vector controls for market and location bias. "EM weight" denotes the aggregated weight of Emerging Market firms in the portfolio following MSCI's categorization. "US weight" is the aggregated weight of US-based firms in the portfolio.

As a reminder, we do not control for sector bias as it is kept identical between the biodiversity-screened and random portfolios during optimization.

Based on this specification, a positive intercept ($c > 0$) implies that biodiversity screening yields a larger adjusted return loss than random screening, after controlling for known risk factors; in other words, return is sacrificed to mitigate biodiversity risk. Conversely, a negative intercept ($c < 0$) indicates that biodiversity risk mitigation by screening comes at a reward.

[3]We note that the weight of Emerging Market companies in the MSCI ACWI index is around 10-15%. Setting $w_{EM} = 0.1$ yielded similar results and conclusions.

3.4.2 Robustness check: normal and crisis periods

For robustness testing, we distinguish between crisis and normal market conditions, given the market resilience behaviour exemplified during the COVID-19 pandemic. Market resilience has been observed to differ from normal-period patterns, with one contributing factor being governmental responses to these crises (Berlinger et al., 2024). We utilise the maximum drawdown as an indicator to differentiate between these conditions, given its effectiveness at capturing the largest potential portfolio loss, particularly during market downturns (Harvey et al., 2019).

Within each time window, we define the maximum drawdown as:

$$a_j = \sum_{i}^{j} r_i b_i = max\{a_j \mid j = 1 \ldots i\} D_{\max} = min\{\frac{a_i}{b_i} \mid i = 1 \ldots n\} - 1 \qquad (3.9)$$

where r_i is the daily logarithmic return on day i in the period and $D_{\max}$ is the maximum drawdown in the period.

We designate a period a crisis period if its maximum drawdown is at least 20%, which aligns with the five lowest drawdowns observed within the analysed 10-year-long period. We note that the subsequent largest drawdowns in our sample were much smaller, below 10%. The identified quarters meeting this criterion, in order of drawdown value consecutively, are the following: 2020Q1 (during the COVID-19 pandemic), 2022Q2 (related to the natural gas price rally), 2018Q4 (global market sell-off), 2022Q3 (continued energy price spikes), and 2015Q3 (stock market sell-off).

3.4.3 Robustness check: factor-adjusted return difference

To validate our primary findings, we compare the results of the Return Loss approach with a traditional factor-based risk-adjusted return estimation. Specifically, we analyse the performance differential between "leaders" (high performers) and "laggards" (low performers) based on the MSCI Biodiversity and Land Use score. Since this score is only defined for five GICS sectors with material exposure to biodiversity risk in the MSCI ESG framework, this analysis is limited to this subset of the investment universe.

Two portfolios are constructed on the first day of each month. The Leader Biodiversity Portfolio consists of firms with the top third of biodiversity scores. The Laggard Biodiversity Portfolio contains companies in the bottom third. Constituents in both portfolios are equally weighted to prevent large-cap bias. For each portfolio, we calculate and record the aggregated GICS sector weights, risk characteristics (portfolio standard deviation), and market/location exposure (aggregated weights of US and the weight of Emerging Market firms).

Next, in each period, we construct a long-short hedging portfolio that goes long in the Leader Portfolio and shorts the Laggard Portfolio. This strategy represents a zero-cost investment that captures the return premium associated with high biodiversity risk mitigation quality. We record the monthly return differential, as well as the differences in sector weights, diversification, and other attributes between the long and short legs.

As the return differential may be driven by sector imbalances, style factors, or geographical exposures, we control for these effects explicitly to isolate the impact of biodiversity characteristics from other risk factors and portfolio-level attributes using a regression model. In practice, we regress the long-short return difference on the Fama-French five factors and the momentum factor from (French, 2023), the liquidity factor from (Pastor, 2026), and differences in portfolio-level characteristics listed earlier (sector bias, risk, location, market). This allows us to test whether the unexplained return differential (intercept) is statistically different from zero, which would indicate a risk premium unexplained by standard factors.

The regression model is defined as:

$$R_{\text{leader},t} - R_{\text{laggard},t} = c + \beta^T \left[F_t, \Delta GICS_t, \Delta ESG_t, \Delta Port_t, \Delta Loc_t\right] + \epsilon_t \tag{3.10}$$

where $R_{\text{leader},t} - R_{\text{laggard},t}$ is the return of the hedge portfolio at month t, F_t represents Fama-French factors, the momentum and the liquidity factor, ΔESG_t, $\Delta Port_t$, ΔLoc_t are the differences between the portfolio-level weighted ESG, portfolio-level and market/location attributes between the Leader and Laggard portfolio respectively, which we have defined in the previous section. $\Delta GICS_t$ is a vector of GICS sector weight differences.

To prevent perfect collinearity, we do not include the Utilities sector in the regression model.

We have also found that across the five biodiversity-exposed GICS sectors, there is a strong correlation between portfolio-level social, carbon-emission, and US-firm weights and the difference between the Leader and Logger portfolios. E.g., when the Leader portfolio has a high Social Pillar score, it is likely to have a high

Biodiversity and Land Use score as well. To address this collinearity and test for a "pure" biodiversity premium, we orthogonalize the biodiversity score difference by regressing it on the difference in Carbon, Social, and US-location metrics. The resulting residual ("Pure Biodiv. Score") captures the unique variation in biodiversity performance that is uncorrelated with the other three attributes.

3.5 Results

3.5.1 Descriptive statistics

3.5.1.1 Characteristics of the investment universe and biodiversity scores

In our 10-year dataset, the number of firms in the universe ranges from 2431 to 3051. Within that, the number of firms across the five biodiversity-exposed sectors ranges from 304 to 385.

Table 3.4 reports ESG-related summary statistics for the cross-section of firms as of December 1, 2021. This sample contains 2833 firms with available ESG scores. On this day, the Biodiversity and Land Use score is available for a subset of 346 firms. Due to MSCI's standardization procedure, the scores range from 0 to 10. Within the sample, Utilities and Industrials exhibit the highest average Biodiversity and Land Use scores (6.54 and 6.51, respectively), while Consumer Staples has the lowest average (2.36). Figure 3.1 visualizes the distribution in each sector.

Across the sample, Carbon Emission scores have a notably higher mean (7.95) compared to Social (4.76) and Governance (4.49) scores. The standard deviations for all scores generally range from 1.0 to 2.7, indicating moderate variation across sectors. We can also observe that the Financials and the Industrials sectors have the highest number of firms in the MSCI ACWI index.

We present the pairwise correlation between some MSCI ESG scores in Table 3.3. The strong, significant correlation between the Biodiversity and Land Use score and the Environmental Pillar score is readily apparent, but not surprising, as the biodiversity metric is part of the composite environmental score. The Social Pillar score and the Carbon Emission score also appear to be more directly correlated with the Biodiversity and Land Use score. Interestingly, Giglio et al. (2026) suggest that the overlap between the Biodiversity and Carbon Exposure may be metric-dependent.

Given that the Environmental Pillar is a composite value containing both the Biodiversity and Carbon Emission scores, to ensure the internal validity of our

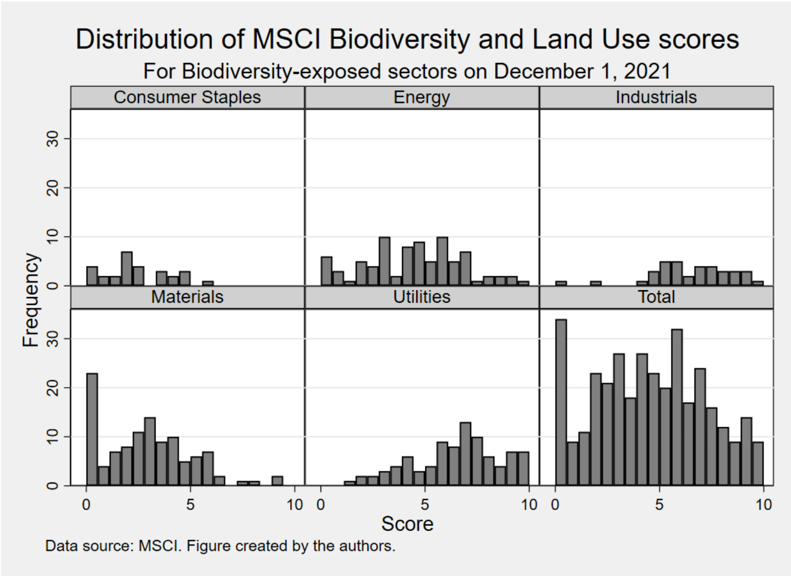

Figure 3.1: Distribution of MSCI Biodiversity and Land Use scores in five biodiversity risk-exposed GICS sectors on December 1, 2021. Higher scores indicate stronger management measures relative to biodiversity risk exposure.

models and mitigate the risk of mechanical correlation, we excluded it from our investigation.

3.5.1.2 Association between biodiversity scores and other company-level attributes

Next, we investigate how the biodiversity score is associated with other company-level characteristics using a cross-sectional linear regression model based on the dataset collected as of December 1, 2021. Several attributes are used for the analysis, Table 3.2 contains the list with details.Table 3.5 presents regression results. The model fits the data well (R2 = 0.499), and we can also report relatively low VIF values ($VIF < 4.45$).

We find that firm-level analyst attention and location are correlated with biodiversity risk management performance. Specifically, analyst coverage has a positive coefficient (0.037, $p = 0.009$), indicating that firms subject to greater public interest exhibit higher biodiversity scores. Interestingly, we observe a "US discount": US-domiciled firms show significantly lower biodiversity scores than their international peers (-0.821, $p = 0.037$).

Regarding other ESG characteristics, the results indicate a strong association with carbon emission and social performance. The Social Pillar score (0.236, $p =$ 0.007) and Carbon Emissions score (0.273, $p < 0.001$) are both positively and significantly related to biodiversity scores. This suggests that firms with robust carbon management and social policies also tend to achieve higher biodiversity metrics, potentially reflecting an integrated sustainability strategy. The Governance Pillar score is not statistically significant (p = 0.967).

Financial controls show mixed results. Market risk, proxied by the market beta, has a negative and marginally significant relationship with biodiversity scores (-0.779, p = 0.065), while capital efficiency (ROIC/WACC) is also negatively associated at marginal significance (p = 0.090). Other financial characteristics, including firm size, leverage, and profitability, do not have a statistically significant relationship with the biodiversity score in this analysis.

Our findings differ from Xin et al. (2025) who concludes that biodiversity ratings are largely uncorrelated with firm characteristics beyond firm size. The different outcomes might be explained by the different scopes of the analyses.

3.5.1.3 Comparison of firms operating in biodiversity-exposed and unexposed sectors

We continue our investigation by examining whether there is a difference between firms operating in the five biodiversity-exposed sectors and those in other sectors. Table 3.6 reports the results of a logistic regression estimating the likelihood that a firm has a defined Biodiversity and Land Use score, or, equivalently, operates in a biodiversity-exposed sector, according to the MSCI ESG framework. The dependent variable is a binary indicator equal to "1" if the firm has a non-missing biodiversity score and 0 otherwise. We used the same set of independent variables as in the previous section (see Table 3.2 for details), except for the sector dummies, which perfectly predict whether a company has a biodiversity score. The sample consists of 2,528 firms and represents the cross-section of the dataset as of December 1, 2021, as in the previous case.

The results indicate that the presence of a biodiversity score is strongly associated with a firm's environmental characteristics and valuation. We observe a negative and statistically significant coefficient for the Carbon Emissions score (-0.370, $p <$ 0.001). Since lower carbon scores typically indicate a low level of carbon-emission management, this result confirms that biodiversity scoring is systematically targeted at environmentally sensitive sectors (e.g., Energy, Materials, Utilities) rather than "cleaner" sectors like Technology or Financials. Consistent with this, the Price-to-Book ratio is negatively associated with exposure to biodiversity risk (-0.215, $p < 0.001$), suggesting that "value" firms are more likely to be scored than high-growth firms.

Geographically, the "US discount" observed in the cross-sectional linear regression persists in this logistic regression model as well. US-domiciled firms (-0.612, $p < 0.001$) and firms in emerging markets (-0.590, $p < 0.001$) are significantly less likely to have a biodiversity score compared to their counterparts in other developed markets.

In terms of financial characteristics, leverage and risk appear to be negatively associated with coverage. Firms with higher Financial Leverage (-0.386, $p < 0.001$) and return standard deviation (-0.022, $p < 0.001$) are less likely to have a Biodiversity score. The low-risk anomaly described, e.g., by Traut (2023) can be an explanation for that. In contrast, profitability is a positive predictor, with ROE showing a significant positive association (0.028, $p < 0.001$). Interestingly, firm size is not a statistically significant signal of coverage in this model (0.008, $p = 0.14$). This implies that firm size is equally distributed in sectors.

Finally, we find evidence of a correlation between ESG characteristics. The Social Pillar score is positively associated with the likelihood of having a biodiversity score (0.095, $p < 0.01$), suggesting that firms with higher social qualities are also more likely to fall within the scope of biodiversity assessments and to be in biodiversity-exposed sectors.

3.5.2 The Biodiversity Risk Premium in screened portfolios

To determine if investors face a biodiversity premium when mitigating biodiversity risk, or if biodiversity risk aversion can be carried out free of charge, we build a linear regression model following the approach outlined in Section 3.4.

3.5.2.1 Descriptive statistics of biodiversity portfolio return loss and other metrics

Table 3.7 reports the summary statistics for the biodiversity screening thresholds, Relative Sharpe Ratio Loss (RSRL), and Return Loss (RL) across the three risk mitigation levels (0.25, 0.50, 0.75). It is expected to see a direct, monotonic relationship between screening threshold and portfolio inefficiency. As the biodiversity screening becomes more rigorous, moving from excluding the bottom 25% of exposed

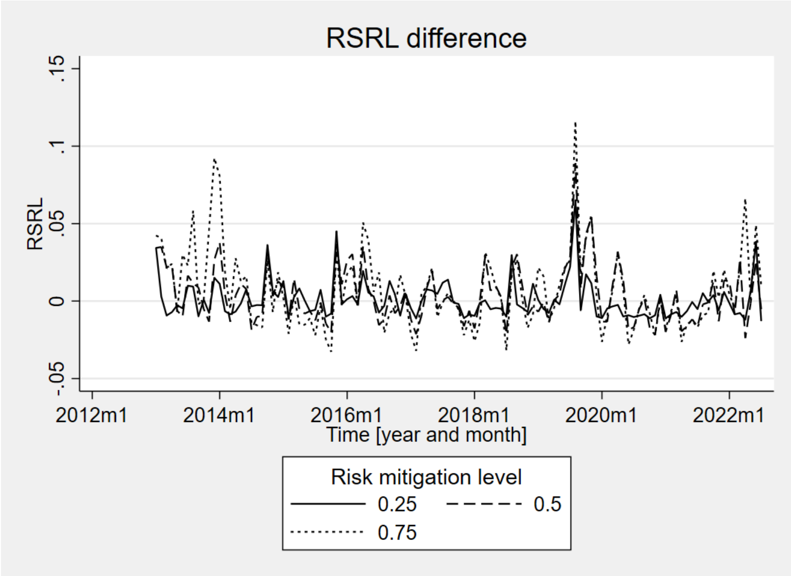

Figure 3.2: Temporal evolution of the difference in Relative Sharpe Ratio Loss (RSRL) between biodiversity-screened and randomly screened portfolios at three risk mitigation levels (25%, 50%, 75%). A positive difference indicates that biodiversity screening reduces risk-adjusted performance more than random screening of equal intensity.

firms to the bottom 75%, the average biodiversity score threshold rises from 2.12 to 5.69. This stricter inclusion criterion mechanically narrows the eligible investment universe, thereby increasing efficiency costs.

The Relative Sharpe Ratio Loss for the biodiversity-screened portfolios increases substantially with risk mitigation, rising from an average of 1.19% at the 25% level to 4.14% at the 75% level. This indicates that as investors prioritize higher biodiversity quality, the correlation between their portfolio and the efficient frontier decreases. Crucially, the biodiversity portfolios consistently exhibit higher inefficiencies than their randomly screened counterparts. The gap between the two widens from 0.09% at 0.25 to 0.71% at 0.75 risk mitigation level, suggesting that the specific exclusion of biodiversity laggards imposes a diversification penalty beyond that of simple universe reduction. The temporal evolution of the difference between the biodiversity-screened RSRL and randomly screened RSRL is visualized in Figure 3.2.

The Return Loss, which quantifies the annualized return lost to maintain the biodiversity constraint, shows a similar pattern. At the lowest mitigation level (0.25), the average return loss is approximately 16 basis points (bps) per year. This cost more than doubles to 37 bps at the moderate level (0.50) and reaches nearly 60 bps at the highest level.

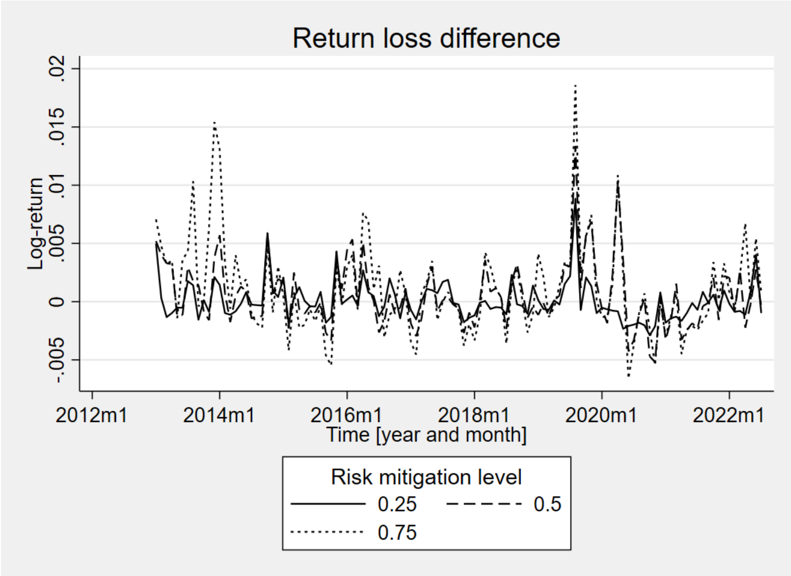

Figure 3.3: Return Loss difference between the biodiversity-screened and randomly screened portfolios. A positive value indicates the biodiversity-specific cost of screening beyond the cost of reducing the investment universe. The three lines correspond to the 25%, 50%, and 75% exclusion levels.

Comparing this to the random selection yields the excess cost of the biodiversity filter. The difference in return loss is positive across all scenarios, averaging 0.6 bps, 5.4 bps, and 10.9 bps for the three mitigation levels, respectively. While these raw differences appear modest on average, the standard deviations (ranging from 17 bps to 41 bps) indicate significant temporal variation. The temporal evolution of the RL difference is visualized in Figure 3.3.

While the average efficiency cost of biodiversity screening is economically small at low ambition levels, it becomes increasingly tangible for stricter strategies. The positive spread over random screening implies that high-biodiversity firms cannot perfectly replicate the risk-return profile of the excluded laggards, potentially signalling a unique risk factor or a distinct lack of diversification substitutes within the "green" universe.

3.5.2.2 Regression analysis of biodiversity portfolio efficiency

As we have described in Section 3.4, the Return Loss can be attributed not just to choosing biodiversity as a screening criterion, but to several other risk factors. To control for these effects, we include them in a regression model. Models in Table 3.8, 3.9, and 3.10 present the results of the regression analysis explaining the excess Return Loss of biodiversity-screened portfolios across three risk mitigation levels.

The dependent variable is the difference in Return Loss, where a positive value indicates that the biodiversity-screened portfolio incurs a higher efficiency cost than the random portfolio.

Variance Inflation Factor (VIF) tests were conducted to check for multicollinearity among the independent variables. The mean VIF is low (ranging from 2.32 to 2.42 across models), and no individual variable exceeds a VIF of 10 (the highest being HML at 7.0). This confirms that the regression coefficients are stable and not significantly distorted by correlations among the control variables in these models.

The intercept represents the adjusted biodiversity efficiency cost, which is the portion of the return-loss differential that cannot be explained by standard risk factors, volatility differences, market factors, or ESG attributes.

At the 25% and 50% screening levels, the intercept is generally statistically insignificant in the full model (Model 3), with p-values of 0.071 and 0.283, respectively. This suggests that for low-to-moderate screening intensities, the efficiency gap between biodiversity and random portfolios is almost entirely explained by mechanical factors, primarily differences in volatility and factor exposure. There is no statistically distinct "cost" to biodiversity screening at these levels once risk is controlled for.

At the highest screening intensity, a distinct cost emerges. The intercept in the full model (Model 3) is positive and statistically significant (0.000891, $p < 0.05$). This indicates a residual annualized efficiency cost of approximately 1.07% (roughly 9 basis points per month), unique to the biodiversity screen. This implies that high biodiversity risk mitigation imposes a welfare cost on investors that exceeds what would be expected solely from the reduction in diversification or style factor tilts.

Across all specifications, the difference in standard deviation is the dominant driver of the efficiency gap, with highly significant positive coefficients. This confirms the theoretical prediction of Calvet et al. (2007): the primary source of welfare loss in screened portfolios is the mechanical increase in idiosyncratic risk (under-diversification). The negative coefficient can be explained by the low-risk anomaly (Traut, 2023).

Looking at other control variables, the momentum factor shows a significant positive relationship with the return loss differential at lower ambition levels (0.25 and 0.50). This suggests that biodiversity portfolios may have different momentum exposures than the random universe. Interestingly, the Social Pillar score difference is negative and significant at the 0.50 mitigation level (-0.00831), suggesting that better social performance in the biodiversity portfolio partially mitigates the efficiency loss. However, this effect is not consistent across all screening levels. Liquidity is generally insignificant, though it shows a marginal negative value at the high-ambition level ($p < 0.10$), suggesting that the biodiversity-screened universe might benefit slightly from a liquidity premium relative to random selection. This observation is supported by the association between the number of analysts and the biodiversity scores in Section 3.5.1. A higher number of analyses tend to track more liquid stocks as well.

The regression results demonstrate that the efficiency cost of biodiversity screening is non-linear. At lower thresholds, the "cost" seems to be a function of lost diversification (volatility). However, at strict thresholds (0.75), a true, statistically significant factor emerges, indicating that the most biodiversity-risk-proof firms offer inferior risk-adjusted returns relative to the broader market, even after accounting for their risk profiles. Our results are consistent with Pastor et al. (2021, 2022) who predict green assets have lower expected returns because investors derive non-pecuniary utility from holding them.

3.5.2.3 Sub-period analysis

To investigate the temporal stability of the biodiversity risk premium, first, we partition the sample into two distinct sub-periods: pre-2020 ($N = 84$) and post-2020 ($N = 31$). This split is motivated by the structural break associated with the COVID-19 pandemic and the concurrent acceleration of capital flows into ESG strategies. The results for these sub-periods are reported in Models (4) and (5) of 3.8, 3.9, and 3.10.

Consistent with the full-sample analysis, the adjusted biodiversity premium (the intercept) for the low (0.25) and moderate (0.50) mitigation levels remains statistically indistinguishable from zero in both sub-periods. The difference in portfolio standard deviation remains the primary driver of the return loss differential, particularly in the pre-2020 period. Interestingly, at the moderate ambition level (0.50), the post-2020 period reveals a sensitivity to US market weight (0.119, $p < 0.05$), suggesting that geographic allocation played a larger role in efficiency differentials during the post-COVID market recovery phase.

The most interesting results emerge at high screening intensity. While the full-sample model indicated a statistically significant efficiency cost, the sub-period analysis reveals that the drivers of this cost have fundamentally shifted. In the pre-

2020 period, the intercept is positive (0.000689) but loses statistical significance (p=0.161), potentially due to the reduced sample size. The efficiency loss during this period is overwhelmingly explained by the increase in risk (2.96, $p < 0.001$).

Additionally, we observe a significant negative coefficient for liquidity (-0.0174, $p < 0.01$), implying that prior to the ESG boom, biodiversity-screened portfolios benefited from a liquidity premium that partially offset their diversification costs.

In the post-2020 period, the intercept drops to near zero (0.00006, $p = 0.95$), indicating that no residual biodiversity premium exists once appropriate controls are applied. Crucially, the explanatory power shifts from generic volatility to specific ESG characteristics, which aligns well with the findings of Garel et al. (2024) who realizes that the biodiversity footprint premium only appeared after the Kunming Declaration (October 2021). The difference in Social Pillar score becomes a significant negative predictor (-0.0124, $p < 0.01$). This implies that in the modern ESG regime, the high social performance of biodiversity-compliant firms actively reduces the return loss, acting as a "quality" hedge. Conversely, the Carbon Emission score difference becomes significant and positive (0.0120,$p < 0.05$), indicating that a higher score in the screened portfolio is associated with a higher return loss during the second sub-period.

3.5.2.4 Time-varying nature of BRP

To further investigate the time-varying nature of the biodiversity risk premium, we estimate the adjusted return-loss model using a rolling window approach. Given the extensive set of control variables (factor, ESG, and portfolio attributes), we employ a 36-month rolling window to ensure sufficient degrees of freedom for stable parameter estimation. Figure 3.4 plots the evolution of the adjusted biodiversity risk premium and its 95% confidence interval for the three mitigation levels.

The results reveal a distinct regime shift in the pricing of biodiversity risk. In the earlier part of the sample (2015-2019), the biodiversity premium hovers near zero or remains slightly positive, particularly for the high-ambition portfolios. This suggests that during this period, the efficiency loss from biodiversity screening was greater than that from random screening.

Interestingly, a structural break appears around the COVID-19 pandemic and the Kunming agreement, which is aligned with the results of Coqueret et al. (2025), Garel et al. (2025), and Ma et al. (2024), though the mechanisms differ. The sub-

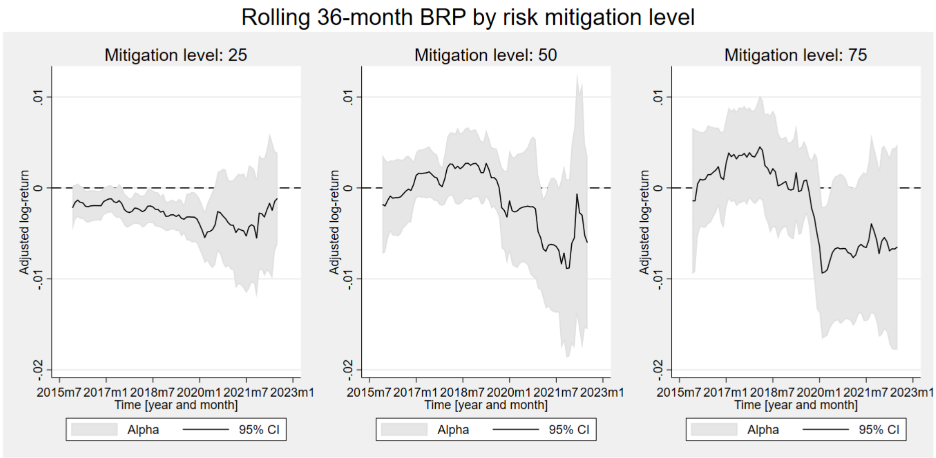

Figure 3.4: Temporal evolution of the adjusted return-loss of biodiversity-screened portfolios at three risk-mitigation levels. The adjusted return loss is the residual of regression model (3.7), representing the biodiversity-specific component after controlling for Fama-French factors, momentum, liquidity, ESG attributes, and portfolio characteristics.

period regression models robustly support the temporal dynamics observed in the 36-month rolling regressions. Post-2020, the premium for the moderate and high mitigation levels turns negative (therefore, biodiversity screening led to smaller losses). For the high-risk-mitigation portfolio, the annualized adjusted premium ranges from approximately -1.5% to -2.0%. This indicates that in the recent market regime, the cost of biodiversity risk protection has decreased. Investors excluding biodiversity laggards during this volatile period incurred a statistically significant efficiency gain that could not be explained by standard risk factors, liquidity, or broad ESG traits. Conversely, the low-ambition strategy remains relatively immune to these fluctuations, with the premium remaining statistically indistinguishable from zero throughout the sample period.

3.5.3 Analysis of biodiversity leader-laggard return differentials

As an alternative to the Sharpe-ratio-based estimation approach, we evaluate whether biodiversity risk has a distinct risk premium by estimating regression models that explain the return differential between biodiversity leaders and laggards.

We find that cumulative biodiversity leader and laggard portfolio returns varied significantly in the 10-year period of the analysis (Figure 3.5). While the cumulative performance of the top and bottom portfolios remained negative for most of the

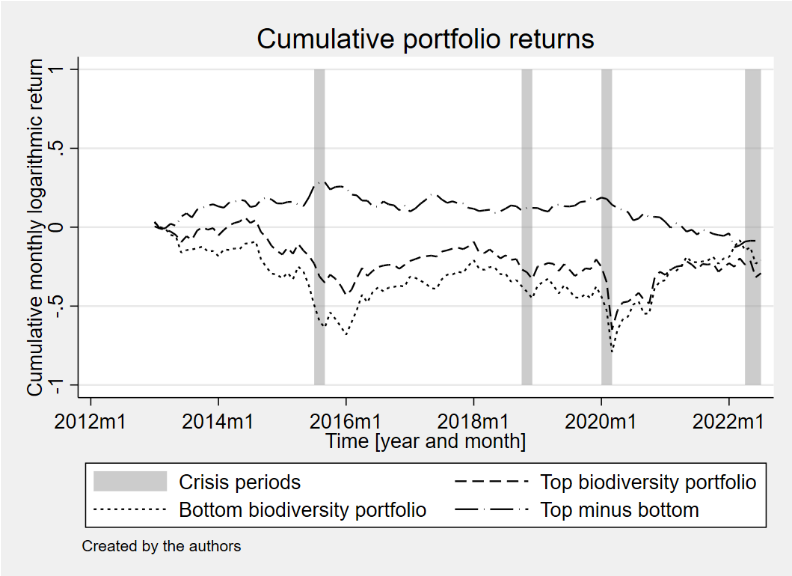

Figure 3.5: Cumulative returns of the Leader and Laggard Biodiversity portfolio, and the hedge portfolio. Leader portfolio: top third of MSCI Biodiversity and Land Use scores among biodiversity-exposed firms; Laggard portfolio: bottom third. Both portfolios are equally weighted and rebalanced monthly. Hedge portfolio: long Leader, short Laggard.

period, the hedge portfolio (long the biodiversity leader portfolio, short the biodiversity laggard portfolio) yielded positive performance, which seemed to diminish towards the end of the period.

Since hedge portfolio returns can be attributed to many factors, we control for the well-known Fama-French five factors (Market, SMB, HML, RMW, CMA), momentum (WML), and liquidity (LIQ) factors to isolate the marginal contribution of biodiversity characteristics. We also use portfolio-level controls to consider industry allocation, market exposure, risk, and ESG characteristics.

A significant challenge in isolating a biodiversity premium is the high correlation between biodiversity scores and carbon-emission-related and social metrics. As shown in Table 3.12, a cross-sectional regression of the difference in biodiversity scores between the leader and laggard portfolios on differences in Social, Carbon, and US-firm weight variables yields an R2 of 0.89. The difference in the Carbon Emission score (0.198, $p < 0.001$) and Social Pillar scores (0.771, $p < 0.001$) are dominant predictors. This multicollinearity manifests in the estimation models including both scores as extreme Variance Inflation Factors (VIFs), with Carbon and Social score differentials exhibiting $VIF > 50$ in unadjusted regression models.

This evidence supports the argument that biodiversity risk performance is strongly associated with better carbon-emission management and with social characteristics of firms in biodiversity-exposed GICS sectors. This problem did not emerge in the previous optimization-based investigation, as the investment universe included many firms with carbon emissions data but without biodiversity information, which broke the collinearity (carbon emission information is available for all companies).

To address this collinearity and test for a "pure" biodiversity premium, we orthogonalize the biodiversity score by regressing it on Carbon, Social, and US-location metrics. The resulting residual ("Pure Biodiv. Score") captures the unique variation in biodiversity performance that is uncorrelated with the other three attributes.

Table 3.11 reports regression results for the full sample period (Models 1-4) and sub-periods (Models 5-6). In the full-sample model (Model 4), the intercept (0.000347), which represents the risk-adjusted return differential, is statistically indistinguishable from zero (0.0003, $p = 0.90$). This indicates that, on average, the raw performance gap between biodiversity leaders and laggards is fully explained by their exposure to standard equity risk factors and sector tilts.

Consistent with our Sharpe-ratio-based analysis, portfolio volatility emerges as the most robust predictor of returns. The coefficient is negative and highly significant across all models (-6.049, $p < 0.01$). This relationship implies that the "outperformance" of leaders can be partly attributed to the low-volatility anomaly (Traut, 2023) rather than a nature-specific premium.

Looking at the full sample period, the coefficient on the pure biodiversity residual is statistically insignificant (0.0236, $p = 0.41$), confirming that the unique "pure" component of biodiversity risk is not priced by the market in the five biodiversity risk-exposed sectors. In the pre-2020 sub-period (Model 5), the intercept becomes positive and statistically significant (0.0018, $p < 0.01$), while the coefficient for the pure biodiversity score remains insignificant. This means that the leader portfolio showed superior performance, but this cannot be explained by biodiversity quality. In the post-2020 period (Model 6), neither the intercept nor the biodiversity residual is significant, suggesting that the excess return dissipated.

To sum up, these findings indicate that biodiversity risk does not currently carry a risk premium across the five selected sectors. The performance of biodiversity-screened portfolios is attributable to three primary drivers: (1) a structural tilt toward low-volatility stocks, (2) a significant overlap with Carbon Emission, and (3) a strong correlation with Social metrics.

We also note that Coqueret et al. (2025) show that their ex-GHG biodiversity factor captures information independently of the GHG factor, suggesting that the identification challenge is at least partly data-dependent.

3.5.4 Discussion

Our analysis provides evidence of a biodiversity risk premium in global equity markets. Yet, its identification is complicated by its entanglement with established risk factors and its sensitivity to market regimes. We summarise the three central findings before discussing each in detail.

1. A relatively small biodiversity risk premium exists but is economically significant only at high screening intensities. At low and moderate levels of biodiversity risk mitigation, the adjusted BRP is statistically indistinguishable from zero; a distinct residual cost emerges only under the strictest screens.

2. The premium is regime dependent. A structural break around the COVID-19 pandemic and the Kunming-Montreal Global Biodiversity Framework altered the pricing dynamics, shifting drivers from pure diversification loss to ESG-characteristic-mediated channels.

3. In biodiversity-exposed sectors, the premium is difficult to separate from carbon and social risk factors in our dataset. The "pure" biodiversity component orthogonal to carbon intensity and social quality is not independently priced, suggesting that what markets currently label as biodiversity risk correlates with a composite of climate transition risk and social capital.

Our results confirm that biodiversity screening imposes a Sharpe ratio reduction relative to random portfolios of comparable size, consistent with a biodiversity risk premium. However, the premium's magnitude depends critically on screening strength. At the two lower mitigation levels (0.25, 0.50), the adjusted intercept is not statistically different from zero; the efficiency gap is almost entirely absorbed by the difference in portfolio standard deviation, identifying under-diversification as the primary cost channel, consistent with Calvet et al. (2007). A statistically significant residual cost appears only at 0.75 mitigation level, which is approximately 9 basis points per month. This nonlinearity arises because firms with low biodiversity scores can be replaced by substitutes. In contrast, at stricter thresholds, the remaining firms cannot replicate the risk-return profiles of the excluded laggards, consistent with Pedersen et al. (2021).

The BRP is not stationary. Sub-period regressions and rolling-window estimates reveal a structural break around 2020. Pre-2020, the premium is positive and driven by volatility differentials, partially offset by a liquidity channel. Post-2020, it compresses to near zero and at moderate-to-high screening levels turns negative, meaning biodiversity-screened portfolios outperformed random counterparts. We attribute this shift to heightened investor attention to systemic risks following COVID-19, the COP15 policy signal that catalysed revaluation of nature-exposed assets (Garel et al., 2024), and accelerating ESG capital flows that compressed the green-brown return differential. Post-2020, the Social Pillar score differential becomes a significant negative predictor of return losses and an implicit quality hedge, while the Carbon Emission score differential turns positive and significant, pointing to a distinct climate-biodiversity interaction channel. These dynamics are consistent with Coqueret et al. (2025). Also, the structural break around the Kunming-Montreal agreement is already supported in the literature (Garel et al., 2024; Y. Li et al., 2025).

Geographic composition also matters. At low screening levels, relatively more emerging-market firms remain in the portfolio, and their higher expected returns contribute positively to portfolio returns. At higher mitigation levels, exclusions disproportionately remove emerging-market firms, which tend to lag on ESG scores, introducing regional/market biases that Alessandrini and Jondeau (2020b), De Spiegeleer et al. (2021), and Giese et al. (2019) also identify as drivers of SRI performance differences. Additionally, we document a persistent "US discount": US-domiciled firms exhibit significantly lower biodiversity scores than international peers, and their portfolio weight influences efficiency differentials, particularly in the post-2020 period, where the US weight variable gains significance at the moderate screening level. Garel et al. (2024) also supports this observation as their international sample also exhibits cross-country variation.

While the portfolio-optimisation analysis establishes the existence of a BRP, the leader-laggard robustness check exposes a fundamental identification problem. When we orthogonalize the biodiversity score against Carbon Emission, Social Pillar, and US-location metrics, the residual "pure" biodiversity component is not priced in any specification in the five biodiversity-exposed sectors. A cross-sectional regression of the biodiversity score differential on these three attributes yields R2=0.89, confirming that biodiversity performance in the five exposed GICS sectors is overwhelmingly linked to carbon intensity and social quality. This does not negate the premium's existence but reveals that it is difficult to isolate from other sustainability dimensions within these sectors. The industries flagged by MSCI's materiality framework are Energy, Materials, Industrials, Consumer Staples, and Utilities, which are also those with the highest carbon intensity (Ilhan et al., 2021).

We note that the overlap between the biodiversity and carbon emission scores might be a characteristic of our dataset, as the biodiversity measures of Giglio et al. (2026) have been shown to differ from climate risk exposures at the firm level. Another explanation is that the MSCI scores contain double materiality, with only risk significantly predicting returns, whereas transition risk does not (in the Chinese market). Ma et al. (2024) argues that financial analysts systematically fail to recognise biodiversity resilience. This supports our finding that the "pure" biodiversity component is not priced - if analysts ignore it, price discovery can be impaired.

For investors, the identification challenge carries a dual message. Portfolios already positioned for low carbon intensity and strong social performance may carry implicit biodiversity hedges, reducing the incremental cost of explicit screens. Conversely, investors seeking to manage pure biodiversity exposure will need more granular, impact-oriented data beyond current ESG rating frameworks. As biodiversity-specific disclosures mature through the TNFD (2024a) and spatially resolved data become available, conditions for a separable biodiversity factor may emerge.

Our findings are subject to several limitations. We rely on MSCI's proprietary Biodiversity and Land Use score; alternative providers may yield different assessments (Berg et al., 2022; Gibson Brandon et al., 2021). Mean-variance optimisation is sensitive to estimation error (Fabozzi et al., 2007), though the Ledoit-Wolf shrinkage and sector-weight constraints mitigate this. We abstract from transaction costs and liquidity frictions (Hevér & Csóka, 2025), so reported costs represent lower bounds. Future research should incorporate alternative, spatially explicit biodiversity data, explore broader SRI strategies, such as tilting and engagement, and investigate how mandatory TNFD disclosures reshape the market's ability to price biodiversity risk independently.

Finally, our findings carry several practical implications. For asset managers, the BRP estimates provide a benchmark for pricing biodiversity-risk-hedging financial products, complementing emerging instruments such as the S&P Biodiversity indexes. Given that the BRP at low-to-moderate screening intensities is statistically indistinguishable from zero, investors can substantially reduce biodiversity risk exposure at negligible cost. This is a finding that should encourage wider adoption of biodiversity screening in sustainable investment strategies. For regulators and policymakers, the temporal variability of the BRP, and particularly its structural change around the COVID-19 period, underscores the need for consistent monitoring of how biodiversity risks are priced. Regulators should consider harmonizing biodiversity disclosure frameworks to reduce the measurement noise documented in earlier studies (Xin et al., 2025) and to ensure that material biodiversity risks are visible to market participants. For authorities overseeing financial stability, the finding that the BRP is non-zero at the highest screening level suggests that biodiversity risk cannot be fully diversified away, consistent with its classification as a systemic risk. This strengthens the case for integrating biodiversity risk into macro-level stress testing and scenario analyses.

3.6 Conclusion

This study examines the financial implications of biodiversity risk mitigation within investment portfolios, emphasising the practical application of the biodiversity risk premium (BRP). By analysing almost 3,000 constituents of the MSCI All Country World Index over a decade, spanning 2013 to 2023, we implemented a screening strategy similar to socially responsible investing (SRI), excluding firms with the lowest biodiversity risk scores at various levels.

Our research findings show that the biodiversity risk premium exists, indicating that it represents a cost to the investor that is both statistically and economically significant. Specifically, we observed decreases of 1.19%, 2.62%, and 4.14% in the maximum attainable Sharpe ratio across the universe for low, moderate, and high levels of biodiversity risk mitigation by screening, corresponding to 16, 37, and 60 basis points, respectively, which contains the loss incurred from reducing the size of the investment universe. The cost of choosing biodiversity as the screening attribute, compared to any other criterion, results in an additional return loss of 1, 5, and 11 basis points. These figures can serve as inputs for product pricing, client communication, and performance attribution of biodiversity-focused investment vehicles.

Our study also highlights the added benefit of biodiversity alignment on ESG scores, revealing unintended consequences that improve the social pillar and carbon-intensity management metrics, alongside a reduction in the Sharpe ratio.

We find temporal fluctuation of the biodiversity risk premium and a structural change around the COVID-19 period.

However, it is imperative to recognise that biodiversity risk mitigation via portfolio screening offers only short-term benefits at the individual investor level. To effectively address the global biodiversity crisis, collective action is required to avoid breaching critical planetary boundaries. Global asset owners must acknowledge biodiversity risk as a systemic risk, understanding that portfolio-level diversification alone cannot mitigate its far-reaching consequences. We need sustainable solutions on a systemic scale to safeguard the integrity of our planet's biosphere for future generations.

3.7 Appendix

ESG Profile	Company	Description
Low exposure, low management	Pason Systems Inc. Exp: 0.6, Mgmt: 1.7, B&L use: 6.7 pason.com	Pason Systems Inc. operates primarily as a software and data management provider, resulting in a minimal direct physical footprint on natural habitats. Consequently, its corporate governance lacks specialized biodiversity mitigation targets, as ecological preservation is not a material financial risk for its business model.
High exposure, low management	Guanghui Energy Co., Ltd. Exp: 9.4, Mgmt: 2.5, B&L use: 0.1 xjguanghui.com	Guanghui Energy Co., Ltd. is an energy conglomerate engaged in large-scale coal mining and oil extraction. These operations cause extensive habitat fragmentation and ecosystem disruption. Despite the physical exposure to biodiversity risks, the company seems to be lacking of biodiversity risk mitigation plan.
High exposure, high management	Woodside Energy Group Ltd. Exp: 9.0, Mgmt: 7.4, B&L use: 5.4 woodside.com	Woodside Energy Group Ltd. operates oil and gas developments close to highly sensitive marine ecosystems, presenting a structurally high inherent exposure to biodiversity degradation risks. To mitigate these critical ecological risks, the corporation implements sophisticated management frameworks, including real-time acoustic monitoring for marine mammals.
Low exposure, high management	Sydney Airport Finance Company Pty Limited Exp: 3.8, Mgmt: 7.1, B&L use: 10 sydneyairport.com.au	Sydney Airport Finance Company Pty Limited functions as a centralized financing vehicle, meaning its direct, office-bound operations have small physical exposure to biodiversity risks. However, as the financial supporter of Sydney Airport, it inherits the parent company's comprehensive environmental management plans.

Table 3.1: Examples for companies with low and high biodiversity exposure and management scores (as of 2022) in the MSCI ESG framework. Data source: MSCI (score), company information collected from company websites.

Variable	Source	Description
Logarithm of Market Capitalization in USD	Bloomberg. Key: CUR_MKT_CAP	The natural logarithm of the firm's market capitalization is measured as the product of shares outstanding and the closing stock price on the analysis date. The logarithmic transformation mitigates the influence of extreme values and the right skewness inherent in the cross-sectional distribution of firm size.
Logarithm of Financial Leverage	Bloomberg. Key: FNCL_LVRG	The natural logarithm of the firm's financial leverage ratio, defined as total debt divided by total equity. This variable captures the degree to which a firm relies on debt financing relative to equity. The logarithmic transformation addresses the skewed distribution of leverage ratios across firms.
Price to Book ratio	Bloomberg. Key: PX_TO_BOOK_RATIO	The ratio of the firm's market value of equity to its book value of equity. This variable serves as a proxy for growth opportunities and market expectations of future profitability, with higher values indicating that the market assigns a premium relative to the firm's accounting net worth.
Return on Equity (ROE)	Bloomberg. Key: RETURN_TOT_EQY	Net income divided by the book value of shareholders' equity. ROE measures the rate of return earned on the equity capital deployed by the firm and captures profitability from the perspective of equity holders.
Capital efficiency (ROIC/WACC)	Bloomberg. Key: ROC_WACC_RATIO	The ratio of the firm's return on invested capital (ROIC) to its weighted average cost of capital (WACC). This variable measures the extent to which a firm generates economic value beyond its cost of capital, with values exceeding unity indicating positive economic value creation.
Asset return standard deviation	Bloomberg. Key: INTERVAL_VOLATILITY	The standard deviation of the firm's asset returns, estimated over a trailing 1-year window. This variable captures total firm-level risk and reflects the volatility of the underlying business operations, independent of capital structure effects.
Market Beta	Bloomberg. Key: BETA_ADJ_OVERRIDABLE	The firm's systematic risk exposure is estimated as the slope coefficient from a regression of the firm's stock returns on market returns. Beta captures the sensitivity of a firm's equity to broad market movements and serves as a measure of non-diversifiable risk.
Total analysts	Bloomberg. Key: BEST_SALES_NUMEST	The number of sell-side equity analysts issuing earnings forecasts for the firm. Analyst coverage proxies for the richness of the firm's information environment, as greater coverage is associated with enhanced price discovery and reduced information asymmetry. Additionally, companies followed by more analysts are generally more liquid.
Emerging Market indicator	MSCI. If the firm is part of the MECI Emerging Markets Index.	A binary variable equal to one if the firm is domiciled in a country classified as an emerging market, and zero otherwise.
US indicator	Bloomberg. If the key COUNTRY_FULL_NAME equals "UNITED STATES".	A binary variable equal to one if the firm is headquartered in the United States, and zero otherwise.
Social Pillar, Governance Pillar, and Carbon Emission scores	MSCI. Keys: BIODIV_LAND_USE_SCORE, ENVIRONMENTAL_PILLAR_SCORE, SOCIAL_PILLAR_SCORE, GOVERNANCE_PILLAR_SCORE, CARBON_EMISSIONS_EXP_SCORE	Scores from the MSCI dataset.
GICS sector	Bloomberg. Key: GICS_SECTOR_NAME	We created indicator dummies equal to "1" if a firm operates in a specific GICS sector and "0" otherwise.

Table 3.2: Company-level attributes, their respective data sources, access keys, and short description.

Scores	(1)	(2)	(3)	(4)	(5)
(1) Biodiversity and Land Use	1.000				
(2) Environmental Pillar	0.824*	1.000			
(3) Social Pillar	0.456*	0.245*	1.000		
(4) Governance Pillar	0.117*	0.192*	0.150*	1.000	
(5) Carbon Emission	0.496*	0.454*	0.230*	0.304*	1.000

Note: *** p<0.01, ** p<0.05, * p<0.1.

Table 3.3: Pairwise correlations for some MSCI ESG scores calculated between the members of the MSCI ACWI index on December 1, 2021.

Score	BIODIV_LAND_USE	SOCIAL_PILLAR	GOVERNANCE_PILLAR	CARBON_EMISSIONS
Communication Services				
Mean	.	5.095977	3.852874	8.592529
Standard deviation	.	1.564097	1.592783	1.4233
N	0	174	174	174
Consumer Discretionary				
Mean	.	4.524138	4.334138	8.357586
Standard deviation	.	1.394268	1.664791	1.64166
N	0	290	290	290
Consumer Staples				
Mean	2.360714	4.776613	4.666935	8.38629
Standard deviation	1.596139	1.351239	1.416743	1.804126
N	28	248	248	248
Energy				
Mean	4.49759	5.85	3.904082	5.385714
Standard deviation	2.344479	1.993145	1.935183	2.391005
N	83	98	98	98
Financials				
Mean	.	4.352183	4.901747	8.84978
Standard deviation	.	1.248354	1.442022	1.337698
N	0	458	458	454
Health Care				
Mean	.	5.051111	4.697407	8.296926
Standard deviation	.	1.123515	1.393704	1.540644
N	0	270	270	270
Industrials				
Mean	6.511389	4.922738	4.300244	8.120098
Standard deviation	2.044096	1.730393	1.776322	2.009887
N	36	409	409	408
Information Technology				
Mean	.	4.860119	4.546726	8.070238
Standard deviation	.	1.396697	1.308841	1.783308
N	0	336	336	336
Materials				
Mean	2.885455	4.019455	4.365759	5.240467
Standard deviation	2.168745	1.861223	1.893408	2.545722
N	110	257	257	257
Real Estate				
Mean	.	4.607006	4.657325	8.128662
Standard deviation	.	2.009149	1.654101	1.554607
N	0	157	157	157
Utilities				
Mean	6.535169	5.557353	4.492647	7.642794
Standard deviation	2.120792	1.761087	1.954506	2.345561
N	89	136	136	136

Table 3.4: Summary statistics for some selected MSCI ESG ratings by GICS sector on December 1, 2021.

Variable	Model (1) (Biodiversity and Land Use Score)
Ln Market Cap	-0.226
	[0.129]
Ln Financial Leverage	0.334
	[0.259]
Ln Price to Book Ratio	-0.109
	[0.578]
ROE	-0.002
	[0.895]
ROIC/WACC	-0.394
	[0.090]
Std	-0.002
	[0.854]
Market beta	-0.779
	[0.065]
Total Analysts	0.037**
	[0.009]
Is_EM	-0.378
	[0.285]
Is_US	-0.821*
	[0.037]
Social Pillar Score	0.236**
	[0.007]
Governance Pillar Score	0.003
	[0.967]
Carbon Emission Score	0.273***
	[0.000]
Consumer Staples	1.925***
	[0.000]
Energy	3.368***
	[0.000]
Industrials	1.270**
	[0.006]
GICS	2.900***
	[0.000]
Constant	2.493
	[0.116]
N	311
R^2	0.499

Table 3.5: Regression results explaining the MSCI Biodiversity and Land Use score with multiple sector and company-level attributes.

Variable	Model (1) (Does it have a Biodiversity and Land Use score?)
Ln Market Cap	0.008
	[0.886]
Ln Financial Leverage	-0.386***
	[0.000]
Ln Price to Book Ratio	-0.215***
	[0.000]
ROE	0.028***
	[0.000]
ROIC/WACC	-0.116
	[0.159]
Std	-0.022***
	[0.000]
Market beta	-0.322*
	[0.040]
Total Analysts	-0.006
	[0.306]
Is_EM	-0.590***
	[0.000]
Is_US	-0.612***
	[0.000]
Social Pillar Score	0.095**
	[0.002]
Governance Pillar Score	-0.004
	[0.902]
Carbon Emission Score	-0.370***
	[0.000]
Constant	3.824***
	[0.000]
N	2528
R^2	

Table 3.6: Logit model estimated coefficients. The model investigates the difference between companies with and without MSCI biodiversity scores.

	Screening threshold	RSRL_bio	RSRL_rnd	Delta RSRL	RL_bio	RL_rnd	Delta RL
Risk mitigation level							
.25							
Mean	2.1234	0.0119	0.0110	0.0009	0.0016	0.0015	0.0001
Standard deviation	0.2624	0.0129	0.0019	0.0126	0.0017	0.0005	0.0017
.5							
Mean	3.8855	0.0262	0.0225	0.0037	0.0037	0.0032	0.0005
Standard deviation	0.3704	0.0195	0.0037	0.0187	0.0030	0.0010	0.0029
.75							
Mean	5.6854	0.0414	0.0343	0.0071	0.0060	0.0049	0.0011
Standard deviation	0.4740	0.0273	0.0055	0.0259	0.0043	0.0015	0.0041

Table 3.7: Descriptive statistics (mean, standard deviation) for the Relative Sharpe Ratio Loss (RSRL) and Return Loss (RL) for each risk mitigation level.

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
MktRF	-0.003	-0.001	-0.001	0.002	-0.003
	[0.369]	[0.630]	[0.508]	[0.394]	[0.216]
SMB	0.000	0.000	0.000	0.005	-0.003
	[0.956]	[0.912]	[0.966]	[0.263]	[0.788]
HML	-0.004	-0.001	-0.001	0.003	0.003
	[0.668]	[0.835]	[0.833]	[0.643]	[0.683]
RMW	-0.002	-0.007	-0.008	-0.006	0.013
	[0.855]	[0.168]	[0.137]	[0.416]	[0.263]
CMA	0.002	-0.001	-0.001	-0.004	0.005
	[0.895]	[0.887]	[0.868]	[0.702]	[0.548]
WML	0.003	0.008**	0.008**	0.009**	0.004
	[0.594]	[0.008]	[0.005]	[0.005]	[0.426]
LIQ	-0.004	-0.003	-0.003	-0.002	0.003
	[0.307]	[0.172]	[0.115]	[0.361]	[0.326]
Delta EM weight		0.006	0.007	0.005	0.007
		[0.642]	[0.637]	[0.708]	[0.890]
Delta US weight		0.010	0.011	0.010	0.082
		[0.431]	[0.383]	[0.482]	[0.319]
Delta Std		2.197***	2.160***	2.400***	0.775
		[0.000]	[0.000]	[0.000]	[0.233]
Delta Social Pillar Score			0.000	0.000	0.010
			[0.911]	[0.982]	[0.509]
Delta Governance Pillar Score			0.003	0.002	0.000
			[0.195]	[0.452]	[0.994]
Delta Carbon Emission Score			-0.002	-0.002	0.005
			[0.375]	[0.393]	[0.703]
Constant	0.000	0.000*	0.000	0.000	-0.000
	[0.745]	[0.038]	[0.071]	[0.234]	[0.540]
N	115	115	115	84	31
R^2					

Note: p-values in brackets. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 3.8: Model variations for the adjusted return loss (RL) at 25% ambition level.

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
MktRF	0.003	0.003	0.002	0.004	-0.006
	[0.729]	[0.375]	[0.565]	[0.374]	[0.329]
SMB	-0.000	0.011	0.013	0.010	-0.012
	[0.990]	[0.207]	[0.135]	[0.310]	[0.633]
HML	-0.016	-0.004	-0.003	-0.011	0.009
	[0.472]	[0.731]	[0.813]	[0.338]	[0.346]
RMW	-0.009	-0.013	-0.012	-0.042*	0.009
	[0.639]	[0.329]	[0.357]	[0.015]	[0.743]
CMA	0.021	0.005	0.005	-0.012	-0.001
	[0.547]	[0.782]	[0.763]	[0.628]	[0.924]
WML	0.006	0.012*	0.012*	0.014*	0.005
	[0.567]	[0.033]	[0.035]	[0.010]	[0.706]
LIQ	-0.000	-0.004	-0.004	-0.011*	0.001
	[0.977]	[0.371]	[0.342]	[0.036]	[0.954]
Delta EM weight		0.028	0.024	0.006	0.033
		[0.130]	[0.119]	[0.615]	[0.466]
Delta US weight		0.040	0.018	-0.003	0.119*
		[0.158]	[0.384]	[0.866]	[0.029]
Delta Std		2.451***	2.381***	2.550***	1.187*
		[0.000]	[0.000]	[0.000]	[0.010]
Delta Social Pillar Score			-0.008**	-0.006**	-0.013*
			[0.001]	[0.009]	[0.040]
Delta Governance Pillar Score			0.001	0.003	-0.004
			[0.712]	[0.437]	[0.641]
Delta Carbon Emission Score			0.004	0.000	0.014*
			[0.135]	[0.900]	[0.019]
Constant	0.000	0.000	0.000	0.000	-0.001
	[0.334]	[0.210]	[0.283]	[0.258]	[0.183]
N	115	115	115	84	31
R^2					

Note: p-values in brackets. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 3.9: Model variations for the adjusted return loss (RL) at 50% ambition level.

Variable	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)
MktRF	0.000	-0.003	-0.002	-0.001	-0.013
	[0.966]	[0.619]	[0.654]	[0.928]	[0.093]
SMB	0.025	0.011	0.008	0.022	-0.034
	[0.424]	[0.413]	[0.544]	[0.172]	[0.288]
HML	-0.016	-0.009	-0.009	0.003	0.007
	[0.504]	[0.438]	[0.407]	[0.861]	[0.633]
RMW	-0.000	-0.012	-0.014	-0.032	0.021
	[0.989]	[0.543]	[0.485]	[0.227]	[0.511]
CMA	0.025	-0.004	-0.002	-0.036	0.003
	[0.489]	[0.839]	[0.934]	[0.265]	[0.883]
WML	0.003	0.005	0.005	0.012	-0.008
	[0.793]	[0.540]	[0.548]	[0.145]	[0.640]
LIQ	-0.002	-0.010	-0.010	-0.017**	0.016
	[0.856]	[0.088]	[0.086]	[0.005]	[0.125]
Delta EM weight		0.023	0.019	0.001	0.031
		[0.192]	[0.270]	[0.929]	[0.450]
Delta US weight		0.056*	0.047	0.019	0.083
		[0.031]	[0.054]	[0.351]	[0.166]
Delta Std		2.658***	2.559***	2.957***	1.291*
		[0.000]	[0.000]	[0.000]	[0.050]
Delta Social Pillar Score			-0.005	-0.003	-0.012**
			[0.160]	[0.452]	[0.006]
Delta Governance Pillar Score			0.003	0.003	-0.001
			[0.426]	[0.468]	[0.855]
Delta Carbon Emission Score			0.002	0.001	0.012*
			[0.420]	[0.834]	[0.025]
Constant	0.001	0.001*	0.001*	0.001	-0.000
	[0.099]	[0.015]	[0.029]	[0.161]	[0.952]
N	115	115	115	84	31
R^2					

Note: p-values in brackets. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 3.10: Model variations for the adjusted return loss (RL) at 75% ambition level.

Variable	(1) Delta Biodiversity and Land Use score
Delta Social Pillar Score	0.771***
	[0.000]
Delta Carbon Emission Score	0.198***
	[0.000]
Delta US weight	3.476***
	[0.000]
Constant	0.000
	[1.000]
N	115
R^2	0.892

Note: p-values in brackets. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 3.11: OLS regression results decomposing the portfolio-level biodiversity score differential between the biodiversity-screened and randomly screened portfolios into Social Pillar Score, Carbon Emission Score, and US weight components. $R^2 = 0.892$ indicates that 89.2% of the biodiversity score differential variation can be explained by these three variables.

Variable	Model (1) Hedge port. return	Model (2) Hedge port. return	Model (3) Hedge port. return	Model (4) Hedge port. return	Model (5) Hedge port. return	Model (6) Hedge port. return
MktRF	-0.017	-0.028	0.001	-0.002	-0.014	0.069
	[0.812]	[0.690]	[0.990]	[0.984]	[0.905]	[0.539]
SMB	-0.026	-0.078	-0.070	-0.086	-0.019	-0.190
	[0.907]	[0.742]	[0.759]	[0.714]	[0.941]	[0.792]
HML	-0.266	-0.230	-0.320	-0.360	-0.294	-0.392
	[0.340]	[0.387]	[0.230]	[0.194]	[0.485]	[0.413]
RMW	0.271	0.306	0.289	0.231	0.363	-0.103
	[0.403]	[0.335]	[0.321]	[0.434]	[0.415]	[0.810]
CMA	0.149	0.100	0.359	0.372	0.178	0.722
	[0.611]	[0.735]	[0.212]	[0.206]	[0.728]	[0.269]
WML	-0.242	-0.258	-0.226	-0.245	-0.126	-0.300
	[0.125]	[0.103]	[0.143]	[0.113]	[0.484]	[0.238]
LIQ	-0.031	-0.011	0.064	0.066	0.028	0.064
	[0.781]	[0.921]	[0.546]	[0.541]	[0.856]	[0.656]
Delta Consumer Staples		0.006	0.196	0.279	-0.284	-0.598
		[0.964]	[0.224]	[0.151]	[0.300]	[0.499]
Delta Energy		0.012	0.062	0.039	-0.348*	-0.154
		[0.752]	[0.273]	[0.547]	[0.014]	[0.654]
Delta Materials		0.001	0.037	0.048	-0.278*	1.117
		[0.985]	[0.453]	[0.380]	[0.020]	[0.267]
Delta Industrials		-0.118	-0.011	-0.065	-0.653**	0.785
		[0.279]	[0.923]	[0.623]	[0.003]	[0.463]
Delta Std			-6.210**	-6.049**	-5.013*	-8.714
			[0.006]	[0.007]	[0.036]	[0.064]
Delta EM weight			-0.121	-0.166	-0.367*	0.512
			[0.215]	[0.162]	[0.014]	[0.476]
Delta Governance Pillar Score				-0.005	-0.021	0.151
				[0.662]	[0.092]	[0.073]
Pure Biodiv. score				0.024	0.045	0.156
				[0.407]	[0.195]	[0.158]
Constant	0.000	0.001	0.000	0.000	0.018**	0.129
	[0.865]	[0.845]	[0.990]	[0.904]	[0.007]	[0.166]
N	115	115	115	115	84	31
R^2	0.053	0.083	0.187	0.196	0.260	0.510

Note: p-values in brackets. * p < 0.05, ** p < 0.01, *** p < 0.001.

Table 3.12: Factor-based premium estimates. Dependent variable: monthly return of the Leader–Laggard hedge portfolio (long top-third, short bottom-third biodiversity score). Models (1)-(4) progressively add risk factors, sector deltas, portfolio characteristics, and ESG/governance attributes. Models (5) and (6) restrict the sample to normal and crisis periods, respectively.

Chapter 4

Return trade-offs between biodiversity physical and transition risk in global equity markets

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Abstract: This paper tests whether biodiversity-related physical and transition risks exhibit distinct risk premia in global equity markets. We utilize a panel of over 2,000 constituents of the MSCI All Country World Index covering the 2019 to 2024 period. By combining ENCORE ecosystem service dependency and pressure scores with EU Principal Adverse Impact (PAI) indicators, we estimate biodiversity risk premia through Fama-MacBeth cross-sectional regressions and long-short portfolio analysis. We document three main findings. First, climate-related transition risks are significantly priced. Second, some ecosystem service dependencies carry significant but negative premia and earn lower subsequent returns. Third, a composite long-short strategy based on ENCORE pressure and dependency scores yields no significant adjusted returns. Our results also indicate that the EU's Sustainable Finance Disclosure Regulation enhances the market's capacity to price nature-related risks.[1,2]

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4.1 Introduction

In recent years, the financial sector has faced increasing pressure to account for environmental risks. Among these, biodiversity loss has emerged as one of the most critical threats to society and the economy. The reduction of nature has long been a concern among biologists, who warn of its severe implications for ecosystems and human societies (Cardoso et al., 2020; Folke et al., 1996; Oliver et al., 2015). Despite its systemic relevance, biodiversity remains insufficiently embedded in the financial decision-making framework (Karolyi et al., 2023; Nedopil, 2023). Biodiversity can pose significant risks to companies through two primary channels: physical and transition risks. Physical risks arise from the degradation of ecosystems and the associated loss of ecosystem services on which economic activities depend, potentially undermining firms' operational continuity and asset values (Campiglio et al., 2023; Kulionis et al., 2024; Migliorelli, 2023). In parallel, transition risks emerge from the financial consequences of evolving regulatory frameworks, policy shifts, and changing market expectations as economies move toward more sustainable and nature-positive pathways. These may include the introduction of stricter environmental regulations, mandatory disclosure requirements, or shifts in consumer preferences, all of which can have material implications for firms' strategic positioning and financial performance (Giglio et al., 2024; OECD, 2023a; Pastor & Veronesi, 2012).

The interaction between firms' financial performance and environmental, social, and governance (ESG) factors has been studied extensively (Atz et al., 2023; Friede et al., 2015). Still, very little is known about the connection between ecological consequences, biodiversity, and the company's risk and performance (Berg et al., 2022; Billio et al., 2024). Furthermore, as corporate incentives to disclose ESG-related information increase, the risk of greenwashing practices becomes more pronounced (Lublóy et al., 2025; Yu et al., 2020).

Growing awareness of biodiversity loss has spurred both academic research and policy initiatives. Policymakers and financial authorities are creating frameworks to measure and manage biodiversity risks within financial risk management. Notably, the European Commission et al. (2024) developed a methodological framework to assess financial risks from biodiversity loss. The Finance for Biodiversity Foundation (FfB) and the Taskforce on Nature-related Financial Disclosures (TNFD) provide practical guidance for financial institutions on assessing and disclosing biodiversity risks (FfB, 2025; TNFD, 2024b). Additionally, the OECD (2023a) offers supervisory guidance for integrating these risks into central bank operations and financial stability assessments, emphasizing cross-sectoral coordination.

Measuring nature-related impact and dependencies is complex and requires consideration of multiple factors beyond simple techniques (e.g., species counts) due to the dynamic and interconnected nature of the ecosystems. Therefore, approaches of impact measurement should incorporate ecosystem resilience (Kennedy et al., 2023; Mandle et al., 2024), address the cumulative effects of habitat loss (Teckentrup et al., 2019; Thrush et al., 2008), and reflect both ecological and economic perspectives (S. Baumgärtner et al., 2006; Drechsler, 2020). Measuring biodiversity dependency involves understanding how various factors influence biodiversity (Marshall et al., 2020), including environmental variables, species interactions, and human activities (Etienne & Haegeman, 2012).

The recent emergence and public availability of new datasets, like the ENCORE tool, developed by the ENCORE Partnership, and PAI indicators mandated by EU Regulations (EU, 2019b), make it possible to measure and attribute nature-related risks in a forward-looking and more objective way. The academic community and the financial market participants are currently assessing these databases and discovering their attributes.

Despite increasing recognition of biodiversity's role in corporate risk, empirical evidence on how biodiversity metrics influence firm performance and risk pricing remains limited. Our study addresses this gap by systematically examining the relationship between biodiversity indicators and corporate financial outcomes.

Specifically, we focus on the following research questions:

1. How do various biodiversity metrics, including Principal Adverse Impact (PAI) indicators and ENCORE's pressure and dependency scores, affect firms' performance?

2. How are biodiversity-related physical and transition risks, proxied respectively by dependency and impact scores, priced by investors?

To answer these questions, we first conduct cross-sectional regression analyses with control variables to assess the impact of biodiversity metrics on firm total returns, with regional restrictions and temporal subsamples. This analysis reveals the presence of a biodiversity premium. We then extend our study by constructing long-short portfolios based on firms' biodiversity dependencies and impacts using monthly data over a six-year period, consistent with the portfolio construction procedures commonly used in the asset-pricing literature and applied, among others, by Pastor et al. (2022). This dynamic approach captures both physical risks (dependency-related) and transition risks (impact-related).

Our findings provide novel empirical evidence on how biodiversity-related risks are priced in financial markets and their implications for corporate financial performance and risk management. This contributes to the growing field of biodiversity finance and informs investors, policymakers, and corporate governance frameworks.

The remainder of this study is organized as follows. We provide a literature review in Section 4.2 and describe our methodology and dataset in Section 4.3. Results are presented in Section 4.4, discussed in Section 4.5, while Section 4.6 concludes.

4.2 Literature and hypotheses development

The integration of environmental factors into asset pricing models has evolved from a niche ethical consideration to a fundamental component of risk management. Central to this discourse is the "carbon risk premium" hypothesis, which posits that investors demand higher expected returns for holding assets exposed to non-diversifiable climate transition risks (Bolton & Kacperczyk, 2021). Empirical studies have largely confirmed this, identifying a statistically significant return spread between "brown" and "green" firms across various jurisdictions (Liu & You, 2023). On the other hand, growing climate awareness can at times invert this pattern: recent work finds that surges in climate concern have led green assets to outperform (as investors bid them up), even though ex ante their expected returns were lower (a "greenium") (Ilhan et al., 2021). In practice, markets are learning to hedge climate news and risks. (Engle et al., 2020) construct dynamic hedge portfolios that respond to climate change news, showing that investors increasingly seek protection against climate risk exposures. Overall, top-tier studies indicate that climate-related characteristics (e.g. carbon intensity, climate news exposure) carry return premium, reflecting a mix of risk compensation and shifts in investor preferences.

The pricing of environmental risks in financial markets has garnered increasing scholarly attention, particularly in the domains of climate change and biodiversity

(Friede et al., 2015; Hutchinson & Lucey, 2024; Kouwenberg & Zheng, 2023; X. Li & Naffa, 2025). While climate-related financial risks are well-documented and increasingly integrated into company valuations and risk assessments (Giglio et al., 2021; Rosella Carè & Olaf Weber, 2023; Zhang, 2022), biodiversity-related risks remain comparatively underexplored. Empirical evidence suggests that climate risks, including greenhouse gas emissions and associated physical and transition risks, are partially priced into financial instruments (Gong et al., 2023; Huynh et al., 2020; Venturini, 2022). Accurate measurement of these risks critically depends on the selection of appropriate metrics, a challenge well recognized in climate finance (Cherief et al., 2025; Pescaroli & Alexander, 2018; Venturini, 2022), yet biodiversity risks differ fundamentally due to their often irreversible nature and complex ecological interdependencies, requiring distinct approaches beyond those used for climate risk (Cao et al., 2025).

The development of biodiversity-specific metrics has advanced, aiming to capture firms' exposure to both biodiversity dependency and impact (Carvalho et al., 2023; Coqueret et al., 2025; Schrapffer et al., 2022). Tools such as ENCORE (Exploring Natural Capital Opportunities, Risks and Exposure) enable quantification of sectoral and firm-level dependencies on ecosystem services (EEA, 2025), revealing substantial biodiversity exposures within financial portfolios.

Using ENCORE data, analysts can quantify, for instance, a bank's reliance on pollination or water purification services in its loan book. For example, studies report that 36% of Dutch and 42% of French financial institutions' portfolios exhibit high or very high biodiversity dependencies (DNB, 2020; Svartzman et al., 2021). At the corporate level, approximately 10% of the largest publicly listed companies faced significant biodiversity impact risks as early as 2018, with around 21% exposed to material dependency risks (Carvalho et al., 2023). Schrapffer et al. (2022) estimated that within a portfolio based on the Stoxx 600 index, about 60% of assets have high or very high dependency on biodiversity, and nearly 80% exhibit high or very high impact on biodiversity. Sectors such as integrated oil and gas, clothing, and electricity demonstrate particularly high biodiversity dependencies alongside significant negative impacts. Despite these insights, the direct linkage between biodiversity impacts and dependencies and corporate financial performance remains insufficiently examined.

Despite the conceptual clarity of these risks, survey evidence from Gjerde et al. (2026) reveals a significant perception gap: while nearly half of corporate managers view nature risks as financially material, fewer than 25% believe that investors have successfully integrated them into cash flow projections or the cost of capital. This "valuation lag" underscores the need for more objective, quantitative metrics to bridge the gap between perceived materiality and market pricing.

A significant strand of the literature employs firm-level biodiversity risk measures derived from textual analysis of corporate disclosures, such as the framework introduced by Giglio et al. (2026). This approach captures biodiversity risk exposure by analysing U.S. firms' 10-K filings and has been extended to other markets, including China (Z.-H. Chen et al., 2025; He et al., 2024). Findings indicate that biodiversity hedge portfolios outperform in response to biodiversity-related news, and greater biodiversity disclosure correlates positively with market valuation, especially for smaller and high-pollution firms (Giglio et al., 2026; Xi, 2024). This indicates that such risks are partially reflected in market prices. Furthermore, firms with elevated biodiversity risk exposure face increased downside tail risk (Liang et al., 2024), while proactive biodiversity risk management is associated with positive cumulative abnormal returns preceding relevant events (Kalhoro & Kyaw, 2024). Empirical evidence also suggests a negative relationship between biodiversity degradation and firm profitability (Bach et al., 2025), although stronger biodiversity disclosures may enhance profitability (Elsayed, 2023). In the Chinese context, firms with higher biodiversity risk exposure exhibit significantly lower stock returns, a pattern amplified during periods of heightened public awareness China (Z.-H. Chen et al., 2025).

Most existing studies rely on aggregated biodiversity risk measures derived from corporate disclosures, without explicitly distinguishing between physical and transition risks. While Garel et al. (2024) identify a delayed market response to biodiversity impact metrics (Corporate Biodiversity Footprint), and Coqueret et al. (2025) highlight sector-specific biodiversity risk premiums, these analyses do not account for firms' dependencies on natural capital. Similarly, (Cosma et al., 2024) report negative associations between biodiversity exposure and firm valuation, particularly in tangible goods industries, but without disentangling risk types. Other studies (Adamolekun, 2024; Ahmad & Karpuz, 2024) discuss the financial consequences of biodiversity degradation, such as increased bankruptcy risk, yet lack firm-level ecological linkage data. Strong biodiversity governance has been linked to reduced stock price crash risk, likely through improved information environments (Bassen et al., 2024).

This literature review identifies a significant gap regarding the different pricing of physical risk, related to firm dependence on ecosystem services, and transition risk, related to a firm's negative impacts on biodiversity, in equity markets. Many climate finance studies identify a "carbon premium" or difference between green and brown stocks; however, biodiversity risk and natural capital dependency are just beginning to be recognized as separate and measurable risk factors. This study fills the existing gap by utilizing cross-sectional regressions and long-short portfolio analyses. It employs ENCORE dependency/pressure scores, PAI pressure measures, and subsample restrictions based on region (EU versus global) and time (pre- versus post-2022) to evaluate the relationship between these distinct risk components and returns. The hypotheses presented are as follows:

- Hypothesis I. (Pressure/Impact Risk Premium). Firms with higher biodiversity pressure (high PAI score or ENCORE pressure) will generate higher expected returns than firms with lower pressure.
- Hypothesis II. (Dependency Risk Premium). Firms more dependent on ecosystem services (as per ENCORE dependency) will earn higher returns than those less dependent, because physical risks from ecosystem degradation threaten their operations.
- Hypothesis III. (Composite Biodiversity Strategy). A strategy that combines the two dimensions, long low-pressure/high-dependency firms, short high-pressure/low-dependency ones, will produce a statistically significant return spread, indicating that markets reward firms that both minimize impact and retain dependency on nature.

Each hypothesis is associated with a specific test in our empirical analysis: firm-level return regressions for H1 and H2, and portfolio sorting using long–short spreads for H3. Confirming H1 and/or H2 aligns with a growing body of literature suggesting that nature-related risks are priced, similar to carbon risk premiums. In contrast, rejecting them, shown by the lack of return differences, implies that biodiversity factors are not yet incorporated into market pricing. The hypotheses aim to assess whether investors think of biodiversity loss as a significant risk that implies higher expected returns, or if, conversely, investor preferences for preserving biodiversity are already leading to lower returns for high-impact firms. These tests will shed light on the primary question: do biodiversity pressures and dependencies appear in asset prices?

4.3 Data and methodology

Our analysis is based on a multi-source dataset that includes the components of the iShares MSCI All Country World Index ETF, using the index composition as of December 31, 2024. The index includes 2,258 constituents from large- and mid-cap companies across 23 developed and 24 emerging markets. The dataset combines financial information at both firm and country levels with PAI indicators and ENCORE ecosystem service dependency and pressure levels. Company-level data were obtained over a six-year period, from 2019 to 2024.

In this study, the Finance sector is not excluded, as none of the data sources has portfolio-level look-through capabilities; i.e., the biodiversity attributes describe only the firm's direct environmental impacts, not the investment portfolio's environmental impacts.

To evaluate the adverse sustainability impacts, we utilize the Principal Adverse Impact (PAI) indicators dataset obtained from LSEG Data & Analytics. While the SFDR framework (EU 2019/2088) mandates 14 indicators (9 environmental and 5 social/governance), see EU (2019b), our final model utilizes 12 metrics. We excluded Indicator 4 (fossil fuel exposure) due to its limited granularity as a sectoral flag in the dataset, and Indicator 14 (controversial weapons) due to a lack of statistical variation within our sample. The included indicators represent a diverse range of metrics, including greenhouse gas (GHG) emissions (measured in tonnes of CO2e or intensity ratios), energy efficiency (GWh), and social metrics such as the unadjusted gender pay gap and board gender diversity (expressed in percentages). PAI indicator field access codes in the LSEG database are presented in Table 1.

To assess the double materiality of biodiversity, this paper uses ENCORE data, which is a web-based tool developed by the Natural Capital Finance Alliance in partnership with UNEP-WCMC and UNEP Finance Initiative (ENCORE, 2025b). It helps understand and visualize the impact of environmental changes on economic sectors by linking ecosystem services to business production processes. The database covers 167 economic sectors and 21 ecosystem services. The ENCORE quantifies, for each production process, the level of impact and dependency on biodiversity on an ordinal scale, which is then also translated into a numerical scale from 0 to 5: (0) absent, (1) very low, (2) low, (3) moderate, (4) high, (5) very high. Even though a firm can operate in multiple industries or sub-sectors, we assign ENCORE values based on its most representative sub-sector, indicated in the LSEG database.

4.3.1 Regression models for risk premium estimation

In this section, we describe the empirical strategy used to investigate the pricing of biodiversity-related risks in global equity markets.

We employ the Fama-MacBeth cross-sectional regression procedure to estimate biodiversity risk premia from our panel data (Cochrane, 2009). Following common practice in the asset pricing literature, we proxy risk exposures with observable firm attributes rather than estimated factor loadings. This approach aligns with Fama and French (1992) for size and value, Bolton and Kacperczyk (2024) for carbon emissions, and Pastor et al. (2022) for ESG characteristics. Consequently, we regress firm-level excess returns directly on lagged biodiversity risk characteristics and control variables in yearly cross-sections. Specifically, we estimate separate regression specifications for the ENCORE scores and the individual PAI indicators to isolate their respective impact on the cross-section of returns.

This approach has two advantages over the classical two-pass method in our setting. First, since no established biodiversity factor return series exists, our biodiversity risk proxies are observed characteristics (ENCORE scores and PAI indicators), making a first-pass time-series beta estimation infeasible. Second, using observable characteristics rather than estimated betas avoids the errors-in-variables problem that necessitates the Shanken correction in the two-pass framework (Cochrane, 2009). The risk premium is then estimated as the time-series average of the yearly cross-sectional coefficients, with standard errors computed using the Newey-West correction with one lag to account for potential autocorrelation, following Cochrane (2009). We used STATA 19 for the statistical analysis. Following the Fama-MacBeth procedure, we estimate the risk premium in two steps. In the first step, we run a cross-sectional regression for each year t in our sample period (2019-2024):

$$R_{i,t} - R_{f,t} = \alpha_t + \lambda_t d_{i,t-1} + \gamma_t' X_{i,t-1} + \epsilon_{i,t} \tag{4.1}$$

where $R_{i,t} - R_{f,t}$ is the excess return of firm i in year t, computed as the difference between the logarithmic adjusted total return (including capital gains and dividends) and the risk-free rate; α_t is the intercept; $d_{i,t-1}$ is the lagged value of the biodiversity risk variable of interest (e.g., an ENCORE dummy or PAI indicator); λ_t is its estimated coefficient; $X_{i,t-1}$ is a vector of lagged control variables; γ_t is the corresponding coefficient vector; and $\epsilon_{i,t}$ is the error term.

When ENCORE ecosystem dependency and pressure levels are in focus, we create dummy variables defined as

$$d_i = \begin{cases} 1, & \text{if the level is 'HIGH' or 'VERY HIGH'}, \\ 0, & \text{otherwise.} \end{cases} \tag{4.2}$$

in other words, $d_i = 1$ when the given pressure or dependency is categorized as "high" or "very high", and 0 in all other cases. For these model variations, a non-zero λ_t is regarded as evidence that the risk coming from these ecosystem service dependencies or pressures are priced by financial markets.

All model specifications incorporate a comprehensive set of control variables $X_{i,t-1}$ to ensure that the estimated effects of biodiversity-related measures are independent of established financial determinants. Following the asset pricing and corporate finance literature (Jegadeesh & Titman, 2001; Naffa & Fain, 2020), we control for firm characteristics such as size, valuation, profitability, operating performance, and capital structure. To capture market risk and volatility, we include the annualized standard deviation of daily log returns, while liquidity is proxied by the Amihud measure.

We further account for regional heterogeneity by including dummy variables for MSCI-developed market-categorized and EU firms, and US-based firms. Industry effects are included through GICS sector dummies in PAI regressions, but are excluded from the ENCORE regression models to prevent collinearity with ENCORE subsector-level exposures. Finally, to absorb broader ESG dimensions, we add LSEG D&A Governance and Social pillar scores as additional controls. These scores provide a relative industry-benchmarked measure of corporate performance (LSEG, 2024), ensuring that our biodiversity-specific findings are not driven by broader social or governance quality. This rich set of covariates minimizes omitted-variable bias and aligns with established empirical asset-pricing practices.

To address skewness in the distribution of firm characteristics, we applied variable-specific transformations guided by Box-Cox diagnostics. Market capitalization was transformed using the natural logarithm. For the price-to-earnings ratio, return on assets, and continuous PAI indicators (GHG emissions scope 1-3, carbon footprint, GHG intensity, energy intensity, water emissions, and hazardous waste), we applied the inverse hyperbolic sine (IHS) transformation. The IHS transformation is approximately equal to $\ln(2x)$ for large positive values, but, unlike the natural logarithm, accommodates zero and negative observations, making it well-suited for environmental metrics that frequently take the value zero (Bellemare & Wichman, 2020). We also winsorized all continuous variables at the 5th and 95th percentiles to mitigate the influence of outliers.

In the second step of the Fama-MacBeth procedure, we estimate the risk premium as the time-series average of the yearly cross-sectional coefficient estimates:

$$\hat{\lambda} = \frac{1}{T}\sum_{t=1}^{T}\hat{\lambda}_t \tag{4.3}$$

As noted by Cochrane (2009), the Fama-MacBeth procedure is numerically equivalent to a pooled OLS regression when the right-hand variables do not vary over time, but in our setting, the lagged firm characteristics vary across years, making the period-by-period estimation essential. The procedure provides a correction for cross-sectional dependence in the residuals, since the standard errors of $\hat{\lambda}$ are derived from the time-series variation of the $\hat{\lambda}_t$ estimates rather than from a single pooled regression. To account for potential autocorrelation in the estimated coefficients, we apply the Newey-West correction with one lag to the time series of $\hat{\lambda}_t$.

The coefficient $\hat{\lambda}$ represents the estimated risk premium associated with the biodiversity risk metric. A statistically significant coefficient indicates that the market prices the specific risk component. We test the null hypothesis $H_0 : \lambda = 0$ using t-statistics derived from the Newey-West adjusted standard errors.

4.3.2 Estimating the trade-off between physical and transition risk premiums

To analyze how financial markets compare biodiversity physical risk to transition risk, we use a different methodology. First, we aggregate ecosystem service dependencies and pressures following (Schrapffer et al., 2022):

$$PS = 0.2N_{VL} + 0.4N_L + 0.6N_M + 0.8N_H + 1.0N_{VH} \tag{4.4}$$

where PS refers to the calculated pressure score, $N\ldots$ denotes the number of very low (N_{VL}), low (N_L), medium (N_M), high (N_H) and very high (N_{VH}) pressures exerted by any single firm. A firm's dependency score (DS) is calculated similarly by summing the number of dependencies from very low to very high. We then construct two portfolios based on the firms' pressure and dependency scores. The LPHD (low pressure high dependency) portfolio contains firms with equal weights with pressure scores below the 0.33rd quantile of pressure scores, and with a dependency score above the 0.67th quantile of dependency scores in the sample, formally

$$LPHD = \{i \mid P_i \leq Q_p(0.33) \wedge D_i \geq Q_d(0.66)\} \tag{4.5}$$

where P_i is the pressure score of firm i, $Q_p\ (\tau)$ is the τ-th quantile of pressure scores in the sample, $D_p\ (\tau)$ is the τ-th quantile of dependency scores in the sample.

The HPLD (high pressure low dependency) portfolio is defined in a similar way, containing equally weighted firms with high pressure scores and low dependency scores:

$$HPLD = \{i \mid P_i \geq Q_p(0.66) \wedge D_i \leq Q_d(0.33)\} \tag{4.6}$$

We estimate the coefficients of a linear model in the form of

$$\begin{aligned} R_{HPLD} - R_{LPHD} =& \alpha + \beta_{RM-Rf}\,(R_M - Rf) + \\ & \beta_{SMB} SMB + \beta_{HML} HML + \\ & \beta_{RMW} RMW + \beta_{CMA} CMA + \\ & \beta_{WML} WML + \beta_{LIQ} LIQ + \epsilon_i \end{aligned} \tag{4.7}$$

where $R_{HPLD} - R_{LPHD}$ is the monthly logarithmic return difference between the HPLD and LPHD portfolios in each month between January 1st 2019 to December 31st 2024, α is the intercept, $R_M - R_f$, SMB, HML, RWM and CMA represent the monthly Fama-French five factors from (Fama & French, 2015), WML is the momentum factor from Carhart (1997) that we calculated as the weighted averages of the factors for Emerging Markets and Developed Markets:

$$FF_i = w * FF_{i,\ EM} + (1 - w) * FF_{i,DM} \tag{4.8}$$

where FF_i is a global factor, w is the weight of Emerging Market factors ($FF_{i,EM}$) in the global factor, and $FF_{i,DM}$ is the Developed Markets factor following (Griffin, 2002). We assign equal weights ($w = 0.5$) to Emerging and Developed Market factors rather than market-capitalization weights. This choice gives equal importance to both market segments and avoids the dominance of U.S. equities in the global factor, which could obscure biodiversity risk dynamics in emerging markets.

In this model, the primary parameter of interest is the intercept (α). A statistically significant α (tested using robust standard errors) indicates that the tradeoff between biodiversity-related transition and physical risks constitutes a distinct source of risk and return in global equity markets, independent of traditional factor exposures.

In addition to the baseline specification, where pressure and dependency scores are directly computed from the ENCORE database as described above, we also implemented two alternative portfolio constructions to test robustness. First, we rescaled pressure and dependency scores by firm size, weighting exposures with market capitalization so that larger firms carry proportionally higher scores. LIQ is a liquidity factor obtained from Pastor et al. (2022). Second, we filter the dataset for European companies.

4.4 Empirical analysis

In this section, we present the empirical analysis of how PAI indicators and ENCORE-based biodiversity metrics affect firm-level stock returns, and whether return differences emerge across portfolios sorted by ENCORE biodiversity measures. The results are first derived from the Fama-MacBeth cross-sectional regressions described in Section 4.4.2 and 4.4.3, followed by the portfolio-level analysis of Section 4.4.4.

4.4.1 Descriptive statistics

4.4.1.1 Control variables

Table 4.3 presents the descriptive statistics for the control variables utilized in this study over the five-year sample period. The firm-size proxy, Market Capitalization, exhibits a relatively tight distribution with a mean of 16.48 and a median of 16.4, suggesting that the log-transformation successfully mitigated the skewness typically found in market valuation data. In contrast, liquidity, as measured by the Amihud measure, shows significant right skewness, with a mean of 20.12 vastly exceeding the median of 8.7, indicating a subset of observations with notably lower liquidity. Profitability and leverage measures, specifically ROA and Leverage Ratio, demonstrate sufficient variation for econometric identification.

Table 4.4 reports the pairwise correlation matrix among the control variables. Annualized daily return volatility is negatively correlated with firm size (-0.168, $p < 0.01$). The leverage ratio exhibits strong negative associations with the price-to-earnings ratio (-0.426, $p < 0.01$) and return on assets (-0.391, $p < 0.01$). The Amihud liquidity measure is positively correlated with the price-to-earnings ratio (0.223, $p < 0.01$) and negatively correlated with leverage (-0.205, $p < 0.01$).

Among the regional indicators, US-listed firms are associated with larger market capitalization (0.355, $p < 0.01$) and higher PE ratios (0.238, $p < 0.01$), while EU membership is positively correlated with the Amihud liquidity proxy (0.152, $p < 0.01$). The MSCI developed market dummy correlates positively with firm size (0.245, $p < 0.01$) and the PE ratio (0.219, $p < 0.01$), consistent with the concentration of larger, more highly valued firms in developed markets.

The governance and social pillar scores are moderately correlated with firm size (0.199 and 0.276, respectively, both $p < 0.01$), indicating that larger firms tend to score higher on these ESG dimensions.

4.4.1.2 PAI indicators

Table 4.2 presents descriptive statistics for the PAI indicators used in the cross-sectional regressions. Coverage varies substantially across indicators, which can be explained by the fact that disclosure of PAI indicators is mandatory only for EU firms and is often only estimated by the data vendor for others. The governance-related binary indicators, UNGC and OECD violations, and lack of UNGC/OECD compliance monitoring, have the broadest coverage, consistent with the relatively standardized nature of governance reporting. In contrast, water emissions and gender pay gap are reported by a substantially smaller subset of firms, suggesting that disclosure of these metrics remains limited.

Among the climate-related indicators, all GHG emission variables are reported in natural logarithm form. Scope 3 emissions exhibit the highest mean (4.64) and median (4.94) among the three scopes. Scope 1 emissions have the lowest mean (2.31), while scope 2 emissions fall in between (mean = 2.48). The carbon footprint has a mean of 15.28 (on a log scale) and a relatively narrow interquartile range, suggesting moderate cross-sectional dispersion. Hazardous waste and water emissions, also reported in logarithmic form, exhibit wide ranges (0-22.16 and 0-15.16, respectively), reflecting substantial heterogeneity in these dimensions.

The non-renewable energy share has a mean of 0.73 and a median of 0.84, suggesting that the typical firm in the sample draws a large majority of its energy from non-renewable sources.

Among the governance and social indicators, both UNGC/OECD violations and the lack of monitoring thereof are binary variables with low means (0.12 and 0.19, respectively) and medians of zero, indicating that the majority of firms are not flagged for violations or monitoring deficiencies. Board gender diversity has a mean and median of 25%, consistent with global observations of moderate female board representation. The gender pay gap ranges from approximately 20 to 172, reflecting wide cross-country variation in pay equity.

4.4.2 Risk premium of nature transition risks

4.4.2.1 PAI indicators

The estimated risk premia for the collected set of PAI indicators are illustrated in Figure 4.1 and presented in Table 4.5. In the figure, dots denote the Fama-MacBeth coefficient estimates (the time-series average of yearly cross-sectional coefficients), and vertical bars indicate 95% confidence intervals based on Newey-West standard errors with one lag, see Section 4.3 for details.

Looking at the figure, we can observe a consistent pattern for climate-related risks. The carbon footprint is the most robustly priced PAI indicator, with a coefficient of 0.006 ($p = 0.019$). GHG Emissions scope 3 also carries a significant positive premium of 0.005 ($p = 0.038$). GHG Emissions scope 2 is marginally significant (0.006, $p = 0.082$), while scope 1 and total GHG emissions show positive but statistically insignificant coefficients of similar magnitude (0.006 and 0.005, respectively).

The governance and social indicators present a mixed picture. UNGC and OECD violations carry a positive and significant coefficient of 0.020 ($p = 0.043$), indicating that firms involved in violations of global governance standards earn higher subsequent returns, consistent with a risk-compensation mechanism. The lack of UNGC/OECD monitoring also shows a positive coefficient (0.014), but it does not reach statistical significance ($p = 0.170$). The gender pay gap shows a small negative coefficient (-0.001, $p = 0.067$). Board gender diversity is statistically insignificant in this analysis.

The only directly biodiversity-specific indicator is economically negligible and statistically insignificant (0.000, $p = 0.748$), suggesting limited pricing power for this metric over the 2019-2024 period. Likewise, non-renewable energy share, energy intensity, water emissions, and hazardous waste do not yield statistically significant premia in the estimation. These results may reflect measurement limitations of these

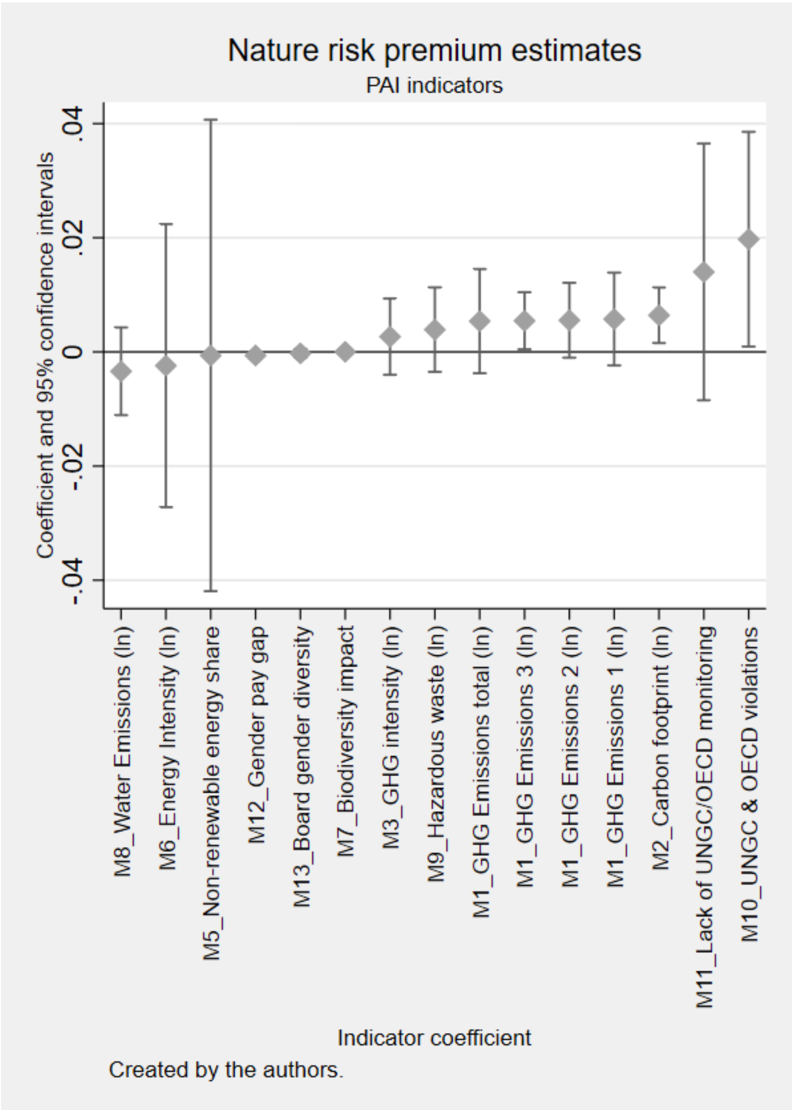


Figure 4.1: Equity premium estimates for the PAI indicators. Dots represent coefficient estimates, vertical bars represent 95% confidence intervals. Coefficients estimated using the Fama-MacBeth two-pass procedure. Standard errors computed with Newey-West correction (1 lag). Sample: 2,258 MSCI ACWI constituents, 2019–2024 (T = 6 annual cross-sections).

indicators or insufficient time-series data within the six-year sample window (T = 6 cross-sections for the Newey-West second-stage), which limits statistical power.

For all model specifications, we present VIF statistics for 2022 and for yearly models (2019-2024) in the supplementary document, due to the large number of models built for the analysis. We report low VIF values across all models, all below 5.92, which is below the usual 10.0 VIF threshold.

We also note that excluding firms with 0.0 PAI indicators does not materially change the result and does not lead to substantially different conclusions.

4.4.2.2 ENCORE ecosystem service dependencies

ENCORE ecosystem service dependency premium estimates are visualized in Figure 4.2 and presented in Table 4.6.

Among the ENCORE dependency variables examined, three yield statistically significant premia at the 5% level, all with negative signs. These are Solid waste remediation (-0.083, p = 0.014), visual amenity (-0.045, p = 0.014), and soil and sediment retention (-0.051, p = 0.036). The negative coefficients indicate that firms highly dependent on these ecosystem services earned lower subsequent returns, after controlling for standard financial characteristics.

An additional group of dependency variables shows marginal significance at the 10% level, including spiritual, artistic, and symbolic services (-0.039, p = 0.068), and biological control, biomass provisioning, local climate regulation, and soil quality regulation (each with a coefficient of approximately -0.114, p = 0.082). These share the same coefficient because they correspond to the same set of firms in the ENCORE classification (as the indicator variable identifies the same group of companies).

Several dependencies, such as flood mitigation (0.025, p = 0.447), global climate regulation (0.020, p = 0.635), and water supply (-0.002, p = 0.959), do not achieve statistical significance in our analysis. This may reflect the limited time series available (T = 6 annual cross-sections) or indicate that markets do not yet systematically price these dependencies at the firm level.

Similarly to the PAI premium estimates, we present VIF statistics for all model specifications in the supplementary document. All VIF values for all models are below 2.5.

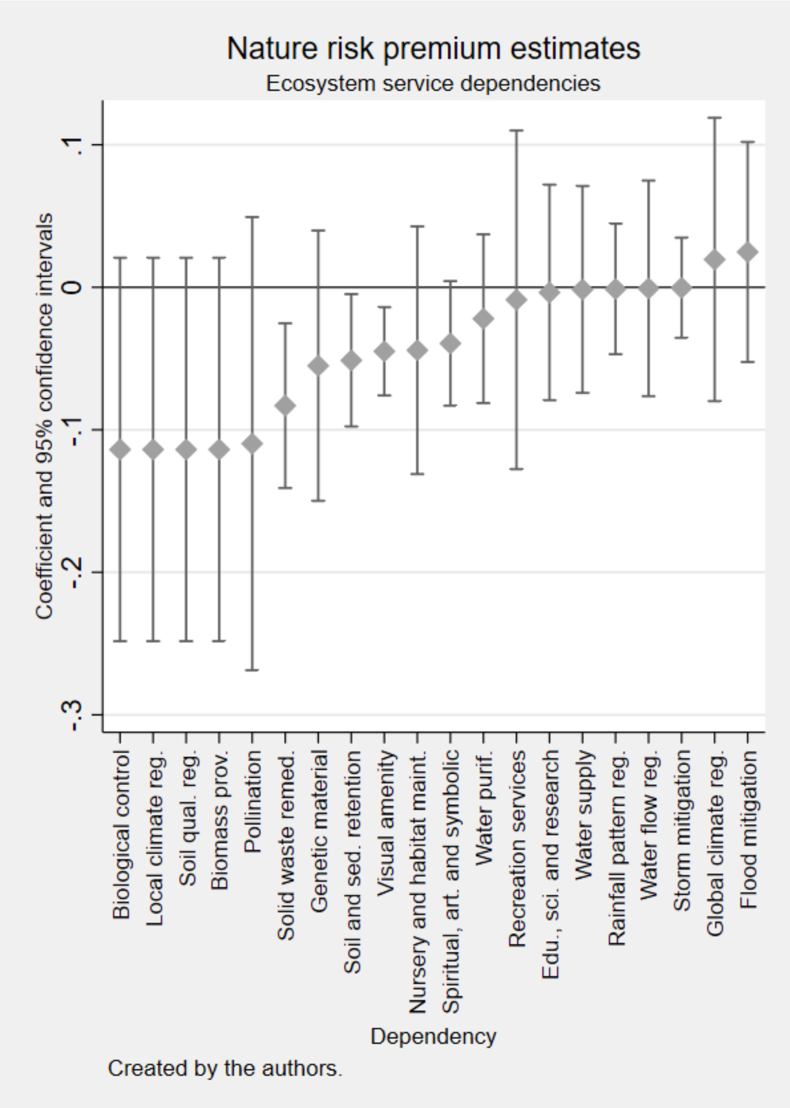


Figure 4.2: Equity premium estimates for the ENCORE ecosystem service dependencies. Dots represent coefficient estimates, vertical bars represent 95% confidence intervals. Dependent variable: firm-level excess return. The biodiversity risk variable is a dummy equal to 1 if the ENCORE dependency level is HIGH or VERY HIGH. Control variables include size, valuation, profitability, leverage, liquidity, volatility, ESG scores, and regional dummies (see Table 4.3).

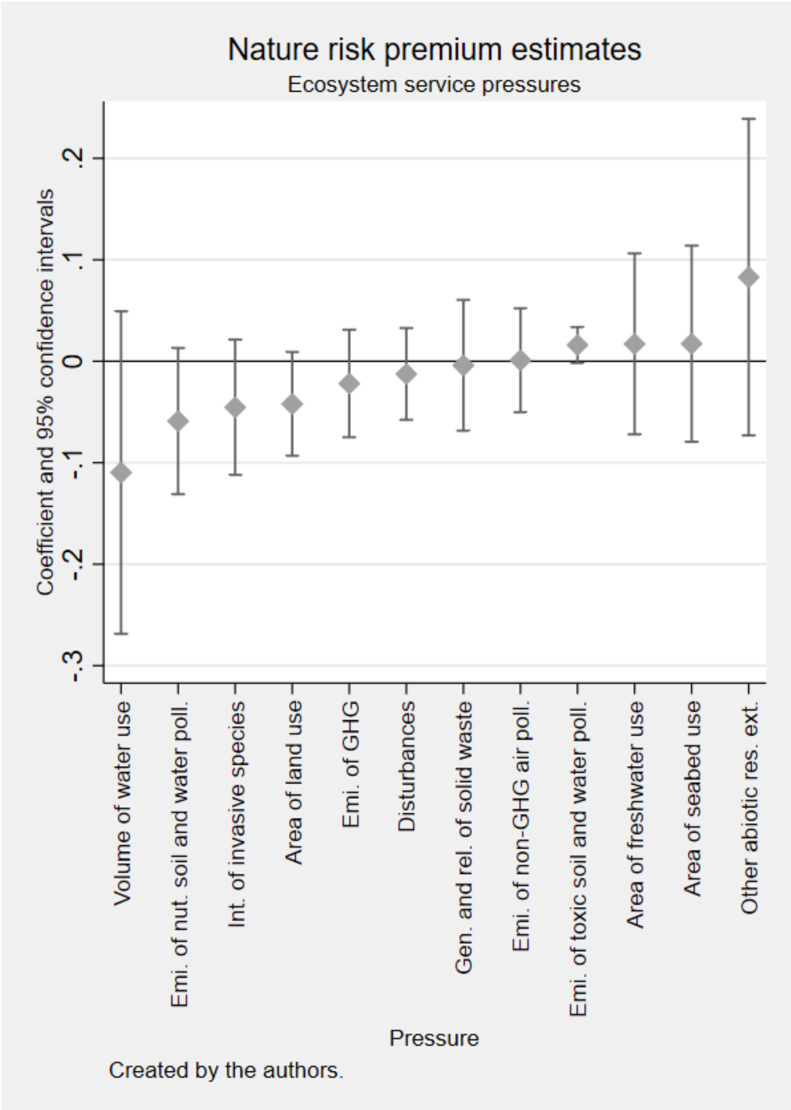


Figure 4.3: Equity premium estimates for the ENCORE ecosystem service pressures. Dots represent coefficient estimates, vertical bars represent 95% confidence intervals. Dependent variable: firm-level excess return. The biodiversity risk variable is a dummy equal to 1 if the ENCORE pressure level is HIGH or VERY HIGH. Control variables include size, valuation, profitability, leverage, liquidity, volatility, ESG scores, and regional dummies (see Table 4.3).

4.4.3 Risk premium of nature physical risks

ENCORE ecosystem service pressure premium estimates are visualized in Figure 4.3 and presented in Table 4.3. Among the pressure variables, only emissions of toxic soil and water pollutants are significant (0.016, $p = 0.068$), with a positive coefficient suggesting that firms that generate higher levels of toxic pollutants exhibit a marginally higher return premium. Area of land use (-0.042, $p = 0.088$) and emissions of nutrient soil and water pollutants (-0.059, $p = 0.089$) are also significant at the 10% level but carry negative signs, indicating, interestingly, that firms with high land or nutrient-pollution pressures earned slightly lower returns. The remaining pressure variables are statistically insignificant. This suggests that, based on the ENCORE classification alone, most individual ecosystem-level pressure channels are not reflected in the cross-section of firm returns during our sample period.

Similarly to the previous regression models, we present VIF statistics for all models in the supplementary documents. All VIF values are below 2.5.

4.4.4 Trade-off between physical and transition risk

The cumulative returns of the HPLD (high-pressure low-dependency) and the LPHD (low-pressure high-dependency) portfolios, and their long-short hedge portfolio, are visualized in Figure 4.4. Even though both portfolios yielded positive returns by the end of the analysed period, their hedge portfolio (long HPLD and short LPHD) showed negative cumulative return.

The regression estimates of the HPLD-LPHD return differentials across four portfolio construction approaches are shown in Table 4.8. The dependent variable is the monthly logarithmic return of the HPLD (high-pressure low-dependency) portfolio minus that of the LPHD (low-pressure high-dependency) portfolio, as described in Section 4.3.

In the baseline specification (Model 1) using ENCORE pressure and dependency scores according to Equation 4, the intercept is -0.004 and statistically insignificant ($p = 0.397$). This indicates that when biodiversity exposure is measured via the ENCORE dataset, firms under higher ecological pressure do not systematically earn different risk-adjusted returns than their low-pressure, high-dependency counterparts. The strategy, however, exhibits a significant negative market beta (-0.294, $p = 0.004$).

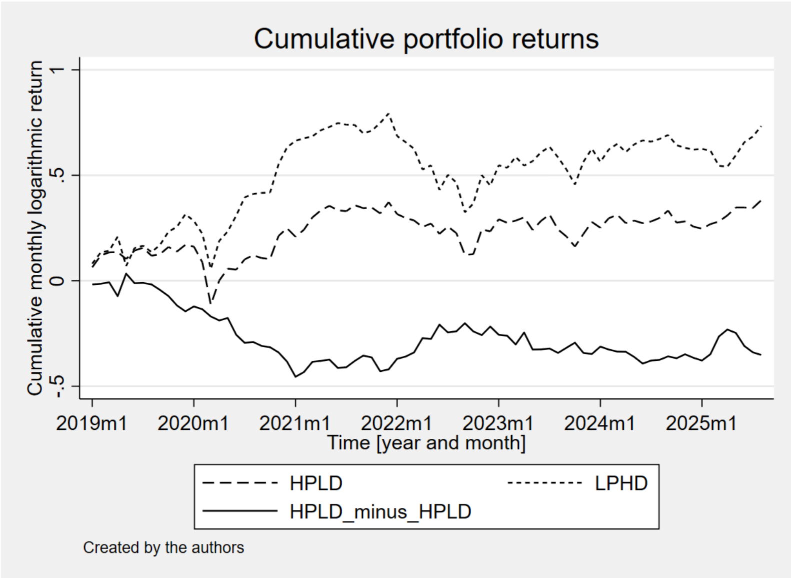


Figure 4.4: Cumulative portfolio returns of the HPLD (high-pressure low-dependency), LPHD (low-pressure and high-dependency), and HPLD-LPHD hedge portfolios over the period of the analysis.

When the ENCORE scores are rescaled by market capitalization (Model 2), the intercept turns positive (0.003) but remains statistically insignificant (p = 0.412). This specification reveals a stronger factor structure: the HML factor is positive and highly significant (1.050, p < 0.001), indicating that the return spread tilts toward value: high-pressure low-dependency firms tend to be more value-oriented when scaled by size. The CMA loading is negative and significant (-0.821, p = 0.020), and the liquidity factor is positive and significant (0.269, p = 0.003), suggesting that the return differential in this specification is partly attributable to investment and liquidity characteristics.

When restricting the sample to EU-headquartered firms (Model 3), the intercept is negative (-0.006, p = 0.109). While not reaching conventional significance thresholds, this is the closest to a significant alpha among the four specifications, consistent with the SFDR's regulatory goal, under which PAI reporting is mandatory for EU-domiciled financial market participants. The RMW loading is negative and marginally significant (-0.584, p = 0.060), while the liquidity factor is negative and significant (-0.179, p = 0.022), indicating that the return differential in Europe is partly associated with profitability and liquidity characteristics.

In the post-2022 subsample (Model 4), the intercept remains negative (-0.007) and insignificant (p = 0.320), but the overall model fit increases substantially (R2 = 0.686 versus 0.395 in Model 1). The CMA factor loading is positive and significant

(1.327, p = 0.046), pointing to stronger explanatory power of standard risk factors in the period following the introduction of key biodiversity disclosure frameworks. This increase in R2, accompanied by the simultaneous absence of alpha, suggests that standard factors absorb a larger share of biodiversity-related return variation in the more recent period, consistent with the greater incorporation of nature-related information into market prices.

Across all four specifications, the HPLD-LPHD return differential does not yield a statistically significant intercept, indicating that ENCORE-based measures alone do not generate a priced trade-off between biodiversity physical and transition risks after controlling for standard asset pricing factors.

Table 4.9 presents VIF statistics for Model 1. The largest value is 4.215 for the HML factor, indicating low multicollinearity among the regression variables.

4.5 Discussion

4.5.1 Pricing of transition risks

Our results provide partial support for Hypothesis 1, which states that firms with higher biodiversity pressure earn higher expected returns. Among the PAI indicators, climate-related metrics yield the strongest evidence: the carbon footprint carries a significant positive premium of 0.006 (p = 0.019), and scope 3 GHG emissions are also significant (0.005, p = 0.038). These findings align with the carbon risk premium documented by Bolton and Kacperczyk (2021) and with the greenium estimates of Eskildsen et al. (2024), who report a cost-of-capital advantage for greener firms globally.

However, Atilgan et al. (2025) show that a substantial portion of the U.S. carbon premium reflects systematic positive earnings surprises rather than compensation for priced risks. Pastor et al. (2022) further demonstrate that green stocks' realized outperformance during 2012-2020 was driven by unexpected increases in climate concern, not higher expected returns. Our finding of a positive carbon footprint premium is therefore consistent with both a risk-compensation and a transition-repricing interpretation.

The biodiversity-specific PAI indicator is insignificant in our analysis, as are most ENCORE pressure variables. This is consistent with Xin et al. (2025), who find that ESG-based biodiversity ratings do not predict stock returns, and with

Coqueret et al. (2025), who report no full-sample biodiversity premium in U.S. equities. Garel et al. (2024) find that the corporate biodiversity footprint premium emerged only after the Kunming Declaration in October 2021, suggesting that the insignificance of the biodiversity-specific PAI indicator in our full-sample estimation may mask a time-varying effect. Among ENCORE pressures, only toxic soil and water pollutant emissions reach marginal significance (0.016, $p = 0.068$), while the remaining pressure sources show no significant pricing effects.

We therefore partially accept H1: climate-related transition risks, as captured by standardized PAI indicators, are significantly priced in global equity markets, but biodiversity-specific transition risk measures do not yield significant premia over the full sample period.

4.5.2 Pricing of physical risks

Hypothesis 2 claims that firms more dependent on ecosystem services earn higher returns as compensation for the physical risks posed by ecosystem degradation. Our results reject this hypothesis in its stated form. Three dependency variables yield significant premia at the 5% level - solid waste remediation (-0.083), visual amenity (-0.045), and soil and sediment retention (-0.051) - but all carry negative signs. An additional cluster of dependencies (biological control, biomass provisioning, local climate regulation, soil quality regulation) shows negative coefficients at the 10% level (-0.114, $p = 0.082$). Firms highly dependent on these ecosystem services earned lower, not higher, subsequent returns.

The negative direction is more consistent with the equilibrium framework of Pastor et al. (2021), in which green assets earn lower expected returns because investors derive non-pecuniary utility from holding environmentally aligned assets and because such assets hedge against environmental risks. Eskildsen et al. (2024) formalize this mechanism, estimating a greenium driven by investor demand rather than fundamentals. Ma et al. (2024) document a related pattern in China, where biodiversity physical risk negatively predicts aggregate stock returns, particularly in resource-dependent industries.

An alternative interpretation is offered by Huang et al. (2024), who find that low-biodiversity physical risk firms outperform high-risk firms due to market mispricing: financial analysts fail to recognize the operational resilience of firms with lower physical risk exposure. Under this view, the negative dependency premia we document could partly reflect mispricing rather than investor preferences alone.

In general, we reject H2: ecosystem service dependencies are significantly priced, but with a negative sign: the opposite of the hypothesized risk-compensation effect. The evidence is more consistent with investor taste premia or mispricing than with compensation for physical risk exposure.

4.5.3 Physical vs transition risks

Hypothesis 3 claims that a composite long-short strategy (long low-pressure, high-dependency firms; short high-pressure, low-dependency firms) yields a significant return spread. Our portfolio-level analysis does not support this hypothesis when biodiversity exposure is measured through ENCORE scores. Across all four ENCORE-based specifications (baseline, size-scaled, EU-only, and post-2022), the adjusted return (model intercept) is statistically insignificant, indicating that the trade-off between physical and transition biodiversity risks does not constitute a distinct source of abnormal returns beyond standard factor exposures.

The EU subsample (Model 3) comes closest to marginal significance ($p = 0.109$), consistent with the regulatory scope of the SFDR and with Eskildsen et al. (2024), who show that the greenium is more negative in countries with stronger sustainable investor presence. The post-2022 subsample (Model 4) shows a substantially higher R2 (0.686 versus 0.395 in Model 1), suggesting that standard risk factors absorb an increasing share of biodiversity-related return variation over time. This is consistent with the increased integration of nature-related information into asset prices following the Kunming Declaration (Coqueret et al., 2025; Garel et al., 2024).

The absence of a significant ENCORE-based portfolio adjusted return contrasts with the significant firm-level premia found in the cross-sectional regressions for individual dependency and PAI variables. We offer two potential explanations for this difference. First, ENCORE scores are assigned at the process level (sub-sectors) and do not vary across firms within the same sub-sector, limiting the ability to capture firm-specific biodiversity risk. Xin et al. (2025) show that sector-level biodiversity ratings are largely uninformative for return prediction, consistent with this limitation. Second, the aggregate pressure and dependency scores used for portfolio construction compress detailed ecosystem exposures into single indices. Tang et al. (2025) warn that apparent green premia can be confounded by non-environmental firm characteristics, a concern that applies to any composite score that correlates with size or industry.

Therefore, we do not find support for H3 using the ENCORE dataset. While some ecosystem service dependencies and climate-related PAI indicators are priced at the firm level, their combined score does not show a statistically significant trade-off after controlling for standard risk factors. The evidence suggests that biodiversity risk pricing, while detectable in the cross-section, has not yet consolidated into a distinct and investable return factor. This is consistent with (Giglio et al., 2026), who show that biodiversity risk pricing is a recent and still-evolving phenomenon.

4.6 Conclusion

This study examines whether biodiversity-related physical and transition risks are priced in global equity markets. Using firm-level data for over 2,000 constituents of the MSCI All Country World Index from 2019 to 2024, we combine ENCORE ecosystem service dependency and pressure scores with Principal Adverse Impact (PAI) indicators to test for biodiversity risk premia through Fama-MacBeth cross-sectional regressions and long-short portfolio analysis. Our findings yield three main results. First, climate-related transition risks are significantly priced at the firm level. The carbon footprint and scope 3 GHG emissions carry positive and significant risk premia, consistent with the carbon premium documented by Bolton and Kacperczyk (2024). UNGC and OECD violations also command a significant positive premium, indicating that governance-related transition risks are reflected in expected returns. However, the biodiversity-specific PAI indicator and most ENCORE pressure variables are statistically insignificant, suggesting that biodiversity transition risks are not yet systematically priced in the cross-section of global equity returns.

Second, ecosystem service dependencies are priced, but in the opposite direction to what a standard risk-compensation framework would predict. Firms with high dependencies on solid waste remediation, visual amenity, and soil and sediment retention earn significantly lower subsequent returns. This finding is more consistent with investor taste premia, as modeled by Pastor et al. (2021), or with market mispricing of operational resilience, as documented by Huang et al. (2024), than with compensation for physical risk exposure.

Third, at the portfolio level, the ENCORE-based long-short strategy contrasting high-pressure low-dependency firms with low-pressure high-dependency firms does not generate significant adjusted returns after controlling for standard risk factors.

The EU subsample comes closest to marginal significance, consistent with the regulatory environment created by the SFDR. The post-2022 period shows a substantial increase in model explanatory power, suggesting that standard factors increasingly absorb biodiversity-related return variation as nature-related disclosure frameworks mature.

These results carry several implications. For policymakers, the significance of PAI-based climate metrics (but not of ENCORE-based biodiversity measures) highlights the informational advantage of firm-level, standardized disclosure over sector-level classification systems. Mandatory reporting frameworks such as the SFDR appear to enhance the market's ability to price environmental risks. For investors, the negative dependency risk premia suggest that firms aligned with ecosystem services may already be subject to preference-driven demand that impacts their expected returns, a pattern that may intensify as biodiversity awareness grows.

Our study is subject to several limitations. The short sample period (T = 6 annual cross-sections) constrains the statistical power of the Fama-MacBeth second-stage inference. ENCORE scores do not vary within sub-industries, limiting firm-level differentiation. The use of a fixed index constituent list introduces potential survivorship bias. Future research should extend the sample as longer time series become available, employ time-varying index compositions, and explore firm-level biodiversity metrics, such as the Corporate Biodiversity Footprint, that offer greater cross-sectional variation.

4.7 Appendix

	Indicator Name	Source	Access key / Function
1	GHG emissions (Scope 1, 2, and 3, and total GHG emissions)	LSEG DataStream	Scope 1: ENERO112V Scope 2: ENERO114V Scope 3: ENERO47V Total: ENERO116V
2	GHG intensity of investee companies	LSEG DataStream	X(ENERDP0961) + X(ENERO03V)
3	Share of investment in companies active in the fossil fuel sector	Bloomberg	FOSSIL_FUEL_OPERATIONS_REV_PCT
4	Share on non-renewable energy consumption and production	LSEG DataStream	Renewable energy use: 1 − X(ENRRO06V) Renewable energy supply: 1 − X(ENPIO11V) We use the larger between the two quantities.
5	Energy consumption intensity per high-impact climate sector	LSEG DataStream	X(ENRRO04V)/3600
6	Activities negatively affecting biodiversity-sensitive areas	LSEG DataStream	ENERDP019 [Y/N]
7	Emissions to water	LSEG DataStream	ENERDP058
8	Hazardous waste ratio	LSEG DataStream	ENERDP056
9	Violations of UN Global Compact Principles and OECD guidelines for multinational enterprises	Bloomberg	EBK_UNGC_OECD_VIOLATIONS
10	Lack of processes and compliance mechanisms to monitor compliance with UN Global Compact Principles and OECD Guidelines for Multinational Enterprises	Bloomberg	UNGC_COMPLIANCE_SCORE
11	Unadjusted gender pay gap	LSEG DataStream	SODODP016
12	Board gender diversity	LSEG DataStream	CGBSO03V
13	Exposure to controversial weapons (anti-personnel mines, cluster munitions, chemical weapons, and biological weapons)	Bloomberg	EBK_CONTRVERSL_WEAPONS_INVOLVMNT

Table 4.1: PAI indicator access codes in the LSEG (earlier Refinitiv Eikon) database.

Variable	N	Min	Max	Mean	Median	Original LSEG Unit
M5 Non-renewable energy share	5727	0	1.00	0.73	0.84	Percentage (%)
M7 Biodiversity impact	10746	0	98.61	45.04	66.32	Percentage (%)
M10 UNGC & OECD violations	14738	0	1.00	0.12	0	Binary (Yes/No)
M11 Lack of UNGC/OECD monitoring	12482	0	1.00	0.19	0	Binary (Yes/No)
M12 Gender pay gap	3327	19.7	172.41	88.96	93	Percentage (%)
M13 Board gender diversity	13167	0	77.78	25	25	Female ratio (%)
M1 GHG Emissions 1 (ln)	12105	0	14.27	2.31	1.58	Tonnes CO_2e
M1 GHG Emissions 2 (ln)	12105	0	13.02	2.48	2.34	Tonnes CO_2e
M1 GHG Emissions 3 (ln)	8419	0	13.97	4.64	4.94	Tonnes CO_2e
M1 GHG Emissions total (ln)	12105	0	14.32	3.25	3.01	Tonnes CO_2e
M2 Carbon footprint (ln)	8738	4.82	23.06	15.28	15.48	tCO_2e / EURM invested
M3 GHG intensity (ln)	8888	0.02	13.78	6.16	6.42	tCO_2e / EURM revenue
M6 Energy Intensity (ln)	10568	0	7.93	0.38	0.08	GWh / EURM revenue
M8 Water Emissions (ln)	1617	0	15.16	5.95	6.19	Tonnes / EURM invested
M9 Hazardous waste (ln)	6117	0	22.16	7.86	8.29	Tonnes / EURM invested

Table 4.2: Descriptive statistics of selected Principal Adverse Impact (PAI) indicators over the analysis period. N refers to the total number of firm-year observations with non-missing values. Variables with (ln) suffix have been transformed using the natural logarithm or inverse hyperbolic sine.

Variable	N	Min.	Max.	Mean	Median
Std. log return	8902	0.17	0.57	0.32	0.30
Market Cap. (ln)	12337	14.60	18.67	16.48	16.40
Amihud measure	8902	0.37	101.86	20.12	8.70
Operating income growth	11099	-0.48	1.18	0.13	0.07
Leverage ratio	12337	0.02	4.05	0.76	0.34
P/E ratio (ln)	11095	2.33	5.06	3.61	3.59
ROA (ln)	12273	-1.66	3.62	1.94	2.25
Is MSCI developed	12790	0	1.00	0.69	1
Is EU	12790	0	1.00	0.16	0
Is US	12790	0	1.00	0.26	0
Governance pillar score	12477	22.91	90.19	61.33	64.45
Social pillar score	12445	28.06	91.79	66.28	69.29

Table 4.3: Descriptive statistics of control variables.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Std. log return	1.00											
Market Cap. (ln)	−0.168*	1.00										
Amihud measure	0.078*	−0.134*	1.00									
Operating income growth	0.02	0.056*	0.01	1.00								
Leverage ratio	0.01	−0.175*	−0.205*	−0.036*	1.00							
P/E ratio (ln)	0.037*	0.197*	0.223*	−0.01	−0.426*	1.00						
ROA (ln)	−0.170*	0.224*	0.125*	0.180*	−0.391*	0.115*	1.00					
Is MSCI developed	−0.158*	0.245*	0.125*	−0.024*	−0.139*	0.219*	0.037*	1.00				
Is EU	−0.041*	0.081*	0.152*	0.01	0.048*	0.021*	−0.023*	0.213*	1.00			
Is US	−0.024*	0.355*	0.189*	0.01	−0.198*	0.238*	0.104*	0.394*	−0.259*	1.00		
Governance pillar score	−0.044*	0.199*	−0.113*	0.01	0.042*	−0.024*	0.01	0.132*	0.102*	0.083*	1.00	
Social pillar score	−0.051*	0.276*	−0.095*	0.00	−0.01	0.026*	0.038*	0.110*	0.256*	0.028*	0.352*	1.00

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4.4: Correlation between control variables.

Variable	Coefficient	p-value	Lower 95% CI	Upper 95% CI
M10_UNGC & OECD violations	0.020	0.043	0.001	0.039
M11_Lack of UNGC/OECD monitoring	0.014	0.170	−0.008	0.036
M12_Gender pay gap	−0.001	0.067	−0.001	0.000
M13_Board gender diversity	−0.000	0.437	−0.001	0.001
M1_GHG Emissions 1 (ln)	0.006	0.129	−0.002	0.014
M1_GHG Emissions 2 (ln)	0.006	0.082	−0.001	0.012
M1_GHG Emissions 3 (ln)	0.005	0.038	0.000	0.010
M1_GHG Emissions total (ln)	0.005	0.190	−0.004	0.015
M2_Carbon footprint (ln)	0.006	0.019	0.002	0.011
M3_GHG intensity (ln)	0.003	0.351	−0.004	0.009
M5_Non-renewable energy share	−0.001	0.970	−0.042	0.041
M6_Energy Intensity (ln)	−0.002	0.813	−0.027	0.022
M7_Biodiversity impact	0.000	0.748	−0.000	0.000
M8_Water Emissions (ln)	−0.003	0.308	−0.011	0.004
M9_Hazardous waste (ln)	0.004	0.233	−0.003	0.011

Table 4.5: Fama-MacBeth coefficients representing the estimated annual risk premium associated with each PAI indicator after controlling for firm size, valuation, profitability, leverage, liquidity, volatility, ESG scores, regional dummies, and GICS sector dummies. Standard errors corrected using Newey-West (1 lag).

Variable	Coefficient	p-value	Lower 95% CI	Upper 95% CI
Biological control	−0.114	0.082	−0.248	0.021
Biomass prov.	−0.114	0.082	−0.248	0.021
Edu., sci. and research	−0.004	0.907	−0.079	0.072
Flood mitigation	0.025	0.447	−0.052	0.102
Genetic material	−0.055	0.196	−0.150	0.040
Global climate reg.	0.020	0.635	−0.080	0.119
Local climate reg.	−0.114	0.082	−0.248	0.021
Nursery and habitat maint.	−0.044	0.248	−0.131	0.043
Pollination	−0.110	0.136	−0.269	0.049
Rainfall pattern reg.	−0.001	0.950	−0.047	0.045
Recreation services	−0.009	0.857	−0.128	0.110
Soil and sed. retention	−0.051	0.036	−0.098	−0.005
Soil qual. reg.	−0.114	0.082	−0.248	0.021
Solid waste remed.	−0.083	0.014	−0.141	−0.025
Spiritual, art. and symbolic	−0.039	0.068	−0.083	0.004
Storm mitigation	−0.000	0.982	−0.035	0.035
Visual amenity	−0.045	0.014	−0.076	−0.014
Water flow reg.	−0.001	0.980	−0.076	0.075
Water purif.	−0.022	0.383	−0.081	0.037
Water supply	−0.002	0.959	−0.074	0.071

Table 4.6: Fama-MacBeth coefficients representing the estimated annual risk premium associated with each ENCORE ecosystem service dependency indicator (high or very high) after controlling for firm size, valuation, profitability, leverage, liquidity, volatility, ESG scores, regional dummies, and GICS sector dummies. Standard errors corrected using Newey-West (1 lag). Note that biological control, biomass provisioning, local climate regulation, and soil quality regulation share the same coefficient (0.114) because the dummy variable identifies the same set of firms in the ENCORE classification.

Variable	Coefficient	p-value	Lower 95% CI	Upper 95% CI
Area of freshwater use	0.017	0.643	−0.072	0.106
Area of land use	−0.042	0.088	−0.093	0.009
Area of seabed use	0.017	0.664	−0.079	0.114
Disturbances	−0.013	0.508	−0.058	0.033
Emi. of GHG	−0.022	0.336	−0.075	0.031
Emi. of non-GHG air poll.	0.001	0.962	−0.050	0.052
Emi. of nut. soil and water poll.	−0.059	0.089	−0.131	0.013
Emi. of toxic soil and water poll.	0.016	0.068	−0.002	0.034
Gen. and rel. of solid waste	−0.004	0.878	−0.068	0.060
Int. of invasive species	−0.045	0.141	−0.112	0.021
Other abiotic res. ext.	0.083	0.230	−0.073	0.239
Volume of water use	−0.110	0.136	−0.269	0.049

Table 4.7: Fama-MacBeth coefficients representing the estimated annual risk premium associated with each ENCORE ecosystem service pressure indicator (high or very high) after controlling for firm size, valuation, profitability, leverage, liquidity, volatility, ESG scores, regional dummies, and GICS sector dummies. Standard errors corrected using Newey-West (1 lag).

Variable	(1) Model 1 (base)	(2) Model 2 (scaled)	(3) Model 3 (EU)	(4) Model 4 (post-2022)
MktRF	-0.294^{**}	-0.250^{**}	0.0177	0.0673
	(0.004)	(0.005)	(0.821)	(0.767)
SMB	0.359	−0.564	−0.0429	−0.347
	(0.231)	(0.067)	(0.905)	(0.602)
HML	0.434	1.050^{***}	−0.00607	0.404
	(0.055)	(0.000)	(0.978)	(0.337)
RMW	−0.129	−0.184	−0.584	0.0630
	(0.701)	(0.579)	(0.060)	(0.937)
CMA	0.239	-0.821^{*}	0.620	1.327^{*}
	(0.502)	(0.020)	(0.055)	(0.046)
WML	0.0162	−0.0858	−0.168	0.00928
	(0.931)	(0.640)	(0.268)	(0.969)
LIQ	0.0285	0.269^{**}	-0.179^{*}	−0.222
	(0.778)	(0.003)	(0.022)	(0.103)
Constant	−0.00369	0.00333	−0.00553	−0.00683
	(0.397)	(0.412)	(0.109)	(0.320)
Observations	72	72	72	24
R^2	0.395	0.363	0.327	0.686

Table 4.8: Trade-off regression result estimates. Dependent variable: monthly logarithmic return of HPLD minus LPHD portfolio. Independent variables: Fama-French 5 factors, momentum, and liquidity. Model 1: baseline ENCORE scores; Model 2: market-cap-scaled ENCORE scores; Model 3: EU firms only; Model 4: post-2022 subsample. p-values in parentheses. A significant intercept would indicate a priced trade-off between physical and transition biodiversity risks beyond standard factor exposures.

Variable	**VIF**
MktRF	1.635873
SMB	1.335114
HML	4.215492
RMW	1.416649
CMA	3.890026
WML	1.576695
LIQ	1.337863

Table 4.9: VIF statistics for Model 1.

Chapter 5

Answering the research questions & Future research directions

The empirical results in Chapters 3 and 4 reveal a fundamental measurement challenge: the biodiversity risk premium is detectable at the portfolio level but difficult to isolate from climate and social factors at the firm level, largely because current measures (whether disclosure-based ESG scores or sector-level ENCORE classifications) lack the spatial granularity needed to capture firm-specific biodiversity exposure.

This chapter argues that Earth Observation (EO) data, combined with ecosystem accounting frameworks such as the SEEA-EA, can overcome these limitations by providing spatially explicit, forward-looking, and verifiable measures of ecosystem condition at the asset-location level. With the new dataset, future research will be able to extend the analysis in the dissertation and answer important research questions.

5.1 Answering the research questions

This section provides a concise answer to each of the research questions posed in Section 1.2, based on the empirical evidence presented in this dissertation.

- Research Question 1: Is there evidence of a Biodiversity Risk Premium (BRP) in global equity markets?

  It depends on the biodiversity risk mitigation level. Chapter 3 provides empirical evidence that biodiversity-screened portfolios exhibit lower risk-adjusted returns compared to randomly screened portfolios of equal size. The total Relative Sharpe Ratio Loss associated with biodiversity screening ranges from 1.19% to 4.14% of the maximum attainable Sharpe ratio across low, moderate, and high screening levels. After controlling for Fama-French factors, momentum, liquidity, ESG attributes, portfolio risk, and geographical composition, the biodiversity-specific additional return loss (the BRP) amounts to approximately 1, 5, and 11 basis points for the three levels, respectively. The BRP is non-linear: it is statistically indistinguishable from zero at low-to-moderate screening intensities and becomes statistically significant only at the strictest (75%) screening level.

- Research Question 2: Can the biodiversity risk premium be attributed to particular sources of biodiversity risk?

  Partially. Chapter 3 shows that the biodiversity component of MSCI scores, once orthogonalized against the carbon emission score and social pillar score, is no longer independently priced. This suggests that the observed BRP is largely explained by correlations with climate risk and social quality, rather than representing a pure biodiversity factor. Additionally, Chapter 4 shows that among individual risk sources, climate-related transition risks (carbon footprint, scope 3 GHG emissions) are the most robustly priced components. Biodiversity-specific indicators (MSCI biodiversity impact PAI indicator, ENCORE pressures) do not yield significant risk premia in the cross-section of equity returns; even though the small sample size might be the cause for that.

- Research Question 3: Do investors demand a nature risk premium that includes both climate and biodiversity-related risks? How do market prices reflect double materiality?

  The evidence is mixed. Chapter 4 documents that climate-related transition risks are significantly priced: the carbon footprint carries a positive premium of 0.6% per unit ($p = 0.019$), and scope 3 GHG emissions also carry a significant positive premium. However, biodiversity-specific transition risk measures (the biodiversity-sensitive areas PAI indicator, most ENCORE pressures) are not statistically significant. Regarding double materiality, ecosystem service dependencies (reflecting physical risk) are priced but with negative signs - firms more dependent on ecosystem services earn lower subsequent returns.

This finding is more consistent with investor taste premia (Pastor et al., 2021) or market mispricing (Huang et al., 2024) than with risk compensation. In general, we find evidence that financial markets are beginning to price nature-related risks, but the pricing is inconsistent: climate-related dimensions are better recognized than biodiversity-specific ones, and physical risk is not yet priced in the direction predicted by standard risk-compensation models.

- Research Question 4: Are EU-mandated sustainability metrics, such as the PAI indicators, effective signals of priced nature-related risks?

  Partially. Chapter 4 shows that certain PAI indicators, such as the carbon footprint, scope 3 GHG emissions, and UNGC/OECD violations, are significantly associated with equity risk premia. However, most other PAI indicators (e.g., non-renewable energy share, energy intensity, water emissions, biodiversity impact) are not statistically significant. We assume that PAI indicators works well for well-known and easily quantifiable risk sources but are less informative for risks that are harder to measure or less known to investors. The EU regulatory subsample in our portfolio analysis comes closest to significance, and the post-2022 period shows substantially higher model explanatory power, indicating that the SFDR framework is enhancing market pricing of nature-related risks over time.

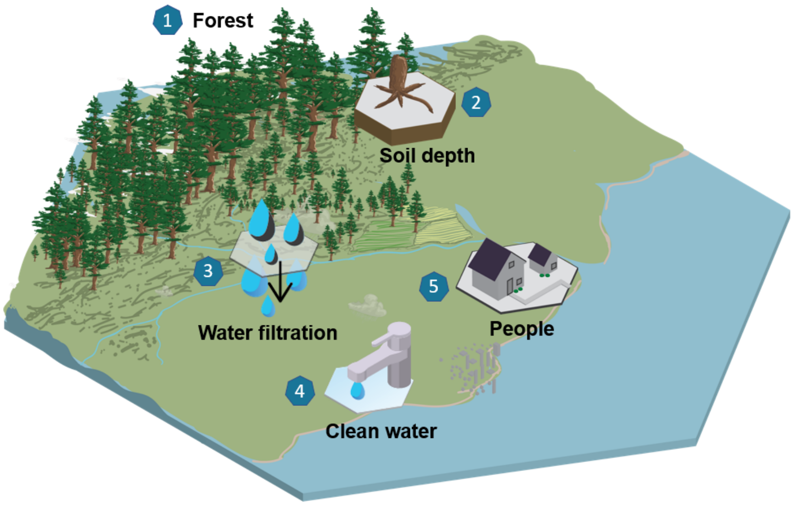
5.2 The SEEA-EA model

Spatial finance integrates geospatial information with financial analysis to evaluate physical asset-related risks within companies (Caldecott et al., 2022). Earth observation (EO) data, particularly satellite imagery, opens the opportunity for environmental risk assessment (Rapach et al., 2024).

A logical next step in improving biodiversity risk estimation is to combine spatial finance and the direct measurement of firms' dependencies and pressures on the environment. The process requires a link between the condition of the environment and the firm, and the collection and linking of large, multi-disciplinary datasets.

The System of Environmental-Economic Accounting - Ecosystem Accounting (SEEA-EA) model, which has been developed by the Department of Economic and Social Affairs of the United Nations, can be a building block in connecting firms

Figure 5.1: How ecosystem assets generate ecosystem services in the SEEA-EA model.



Source: UN (2024).

to the natural environment. Before I describe the model, some concepts must be defined first.

Ecosystem services are defined as the contributions of ecosystems to the benefits that are used in economic and other human activities (UN, 2024). Ecosystem services include, e.g., pollination (servicing agriculture) and a good-looking forest (servicing the tourism industry).

Ecosystem assets are contiguous spaces of a specific ecosystem type, e.g., forests, wetlands, and agricultural areas (UN, 2024). One or multiple of these assets supply ecosystem services in an area. Ecosystem assets have two major attributes: extent (area) and condition. Figure 5.1 illustrates how ecosystem assets generate services for humans. For example, a forest as an ecosystem asset has both an extent (1) and a condition (2), which can be captured by an indicator, like the soil depth. The forest collects and filters rainwater before it reaches rivers, providing an ecosystem service called “water filtration” (3). The benefit of this service for the human population is clean water and reduced water cleaning costs (4) for the beneficiaries, humans (5) (UN, 2024).

Ecosystem accounting is a systematic approach to measuring and valuing the contributions of ecosystems to the economy and human well-being. It integrates ecological data with economic and social statistics to assess the stocks and flows of ecosystem services, biodiversity, and natural resources (UN, 2024). The framework defines multiple ecosystem accounts: ecosystem extent account (area of different ecosystem types), ecosystem condition account (ecological integrity and health of the ecosystem), ecosystem service flows (supply of ecosystem services, and use of those services in households), monetary ecosystem account (stocks and changes in monetary terms), thematic account (organize data on by specific policies, e.g., climate change) (UN, 2024).

5.3 Future research questions

One can assess ecosystem assets, their extent, and their condition based on the SEEA-EA model, provided that proper indicators are available. By using company asset location databases, researchers are capable of associating a company's asset locations with the surrounding ecosystem services. Exposure and impact on ecosystem services can be estimated using the ENCORE Nature database. This approach makes it possible to provide unbiased, forward-looking biodiversity risk assessment at a company level.

Based on my work and limitations in Chapters 3 and 4, future biodiversity finance research should answer the following, methodology-related questions:

1. Which are the best indicators to assess ecosystem service conditions?

   Chapter 4 relies on ENCORE pressure and dependency levels, which are ordinal (five levels from very low to very high) and assigned at the sub-sector level rather than the firm level. As a consequence, all firms within the same ENCORE sub-sector receive identical scores, hiding the cross-sectional differences between companies. This limitation can contribute to the statistical insignificance of most ENCORE pressure variables. At the same time, Xin et al. (2025) demonstrate that ESG-derived biodiversity sub-scores are too noisy to predict stock returns. Earth observation data could be the solution that overcome both limitations. Finding out which EO indicators best proxy specific ecosystem service conditions is required for all subsequent investigations. Can we find a single indicator, or do we need composite scores?

2. How to map firms' economic activities and revenue to regions?

   The analysis in Chapter 4 connects ENCORE data based on each firm's most representative sub-sector (as indicated in the LSEG database). This hides the differences between a firm's operations: a large company, which works in multiple sectors, gets the scores of only one sub-sector. Similarly, the MSCI biodiversity score used in Chapter 3 aggregates all of a firm's activities into a single score, so that the BRP estimation cannot distinguish between firms whose biodiversity risk is concentrated in a single region and those whose risk is spread across multiple ones. Building an asset-location-revenue map, i.e., linking physical asset locations (factories, plantations, offices) to revenue and to regional ecosystem condition indicators, is a prerequisite for translating EO data into firm-level pressure and dependency metrics.

Without progress on these items, the asset-pricing related questions cannot be answered at the required granularity. Once the methodology has been established, future research can concentrate on the following questions:

1. What are the biodiversity risk premiums for the impacts and dependencies based on the new, unbiased dataset?

   Chapter 3 estimates the BRP using MSCI's Biodiversity and Land Use score, a disclosure-based metric that combines exposure and management capabilities. The BRP at the strictest screening level is statistically significant, but the biodiversity component of the score is highly correlated with carbon intensity and social quality. This raises the question of whether the estimated BRP reflects genuine biodiversity risk or only proxies for climate and social factors. Chapter 4 adds more details to this observation: the biodiversity-specific PAI indicator is statistically insignificant, while climate-related indicators such as the carbon footprint are robustly priced. Re-estimating the BRP and NRP using EO-based metrics would help determine whether the currently estimated premia reflect biodiversity risk only, or whether they are connected to other environmental and social factors.

2. How do the premiums compare to the premiums calculated from classical ESG ratings?

   The divergence between the results obtained e.g., by Garel et al. (2024) and the results reported by Xin et al. (2025) demonstrates that the choice of the biodiversity risk measure hugely affects the results about pricing. Chapter 3 uses an intermediate metric (MSCI's proprietary score), and Chapter 4 combines firm-level PAI indicators with sector-level ENCORE data. Yusifzada et al. (2025) also illustrates the measurement problem, as the environmental pillar score used in the study contains climate, pollution, and biodiversity-related information (among others). A firm can reach a high E score by excelling climate risk management, while being more neglecting in biodiversity. A systematic comparison of premium estimates across different measurement approaches could inform regulators about which metrics are most informative for capital allocation.

3. Is there any mechanism to allocate biodiversity risk between regions, and does regional differences in ecosystem conditions affect risk premia?

   Chapter 4 provides evidence that geography matters for biodiversity risk pricing as the EU subsample comes closest to a significant adjusted return, while the global model version is "even more" insignificant. This regional difference likely reflects the SFDR regulatory environment, under which PAI disclosure is mandatory for EU financial market participants. Additionally, the post-2022 subsample shows a substantially higher R^2, suggesting that the aging of disclosure frameworks enhances the ability of standard factors to absorb biodiversity-related return variation. Future research should exploit firm-level location-based revenue data and spatial ecosystem condition indicators to test whether firms operating in regions with degraded ecosystems face higher risk premia than firms in ecologically intact regions.

4. Is there a gap between perceived and actual biodiversity risk, and how does it evolve over time?

   The results of Chapter 4 indicate an asymmetry: well-known risk sources, like carbon footprint and scope 3 GHG emissions, carry significant risk premia, while lesser-known or harder-to-measure biodiversity indicators (like water emissions, hazardous waste, biodiversity impact) do not. This pattern suggests that markets price risks that are easily quantifiable but overlook risks that are less visible. Studies that investigate how the public views these risk sources could verify whether these risk sources are actually overlooked, or the insignificance has been rather caused by the dataset or other factors. If biodiversity risk follows a similar trajectory as the environmental return differentials in Yusifzada et al. (2025), the currently insignificant biodiversity-specific indicators may become priced as disclosure frameworks mature and investor attention increases.

5.4 Preliminary results – Tree Cover Density estimates

It is yet to be determined which is a good measure of each ecosystem service's condition. Rendon et al. (2019) provide an overview of ecosystem service condition measures in Europe and finds that there are large gaps in this field. Examples among the few studies are Olander et al. (2018) who develop new indicators showing human benefits of wetlands, and Hernández-Morcillo et al. (2013) who describe indicators for cultural services.

Tree Cover Density (TCD) could be one of the widely used indicators that measures ecosystem extent and condition in future financial analysis. It is measured as the percentage of land area covered by the vertical projection of tree crowns (McDonald et al., 2021). Tree cover provides a variety of ecosystem service benefits, like reducing air pollutant concentration, mitigating stormwater runoff, maintaining water quality, encouraging physical recreation, and improving mental health (McDonald et al., 2021). Higher TCD in school surroundings correlates with improved cognitive function and academic achievement among students, likely due to stress reduction and enhanced attentional restoration (D. Li et al., 2019). Additionally, TCD's role in modulating microclimates and reducing respiratory ailments highlights its public health significance, particularly in marginalized communities with lower canopy coverage in the past (Jennings et al., 2019).

Another appealing attribute of TCD is that it has been estimated for Europe based on the Sentinel22 missions and made available for analysis for the public free of charge for 2012, 2015, and between 2018-2021, see ESA (2025) for details. The high resolution (10/pixel) images make it possible to study change and condition for small surroundings, but require aggregation for the regions in the scope of analysis.

The TCD can be an ecosystem health condition indicator for many ecosystem services; some has been collected in Table 5.1 with explanation and references.

Before using TCD as a financial-risk metric, three important limitations should be acknowledged. The Copernicus TCD product began only in 2012, so there is no long historical time series that we can use to assess long-run ecosystem change. Additionally, it is difficult to compare the TCD in different areas, as the quality of vegetation might significantly differ; studying the change is, therefore, recommended. The application I show should be interpreted as a proof of concept for the

Table 5.1: Ecosystem services for which the TCD measure can be used to estimate ecosystem service health

Category	Ecosystem service	Reference
Climate regulation	Carbon storage	Zhao and Sander (2015)
	Urban heat island mitigation	Nowak et al. (2022) and Salmond et al. (2016)
	Microclimate stabilization	Jim and Chen (2009) and Salmond et al. (2016)
Air quality regulation	Pollutant removal	Jim and Chen (2009) and Nowak et al. (2022)
	Oxygen production	Jim and Chen (2009)
Water regulation	Stormwater runoff regulation	Berland et al. (2017)
	Water quality improvement	Nowak et al. (2022)
Biodiversity support	Habitat provision	J. Baumgärtner and Bieri (2006) and Brockerhoff et al. (2017)
	Ecological connectivity	Henry et al. (2017)
Human social and cultural benefits	Human health	Jim and Chen (2009) and Salmond et al. (2016)

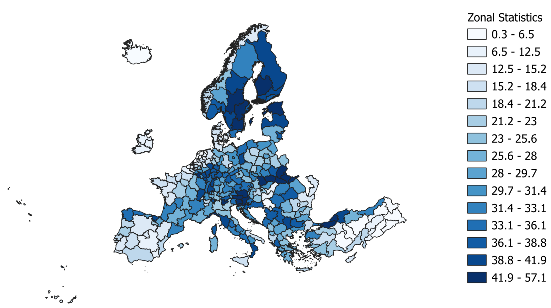
analysis, not as a ready-to-use firm-level risk metric.

I calculate the average Tree Cover Density for the European NUTS2 regions for 2019 and 2021 to show an example of ecosystem service condition assessment. The analysis is based on the 100m/pixel resolution TCD raster maps, which have been collected by the European Space Agency during the Sentinel-2 missions and made available in (ESA, 2025). I used the QGIS 3.38 GIS software for the analysis, and NUTS2 region boundaries from (Eurostat, 2025). Tree Cover Density data points are visualized in Figure 5.2 while the average values for NUS2 regions are presented in Figure 5.3.

Figure 5.2: Tree Cover Density statistics for 2018.

Source: Copernicus (2025).

Figure 5.3: Tree Cover Density averaged for each NUTS2 region in Europe. Created based on the calculations of the author using data from Copernicus (2025).



Chapter 6

Summary

This dissertation aims to explore whether and how financial markets internalize biodiversity and broader nature-related risks into equity pricing, and to develop tools for estimating the associated premiums. Motivated by the increasing recognition of biodiversity loss as a systemic economic and financial risk (Carvalho et al., 2023; GSIA, 2024), the research addressed the urgent need for empirical evidence on whether market participants price these risks, and if so, through what mechanisms. Across two empirical studies, the dissertation introduced and quantified the Biodiversity Risk Premium (BRP) and the Nature Risk Premium (NRP), providing new conceptual and empirical contributions to the emerging field of biodiversity finance.

The dissertation comprises two empirical chapters that estimate the BRP and the NRP, and two accompanying chapters (one to introduce the topic, define important terms in biodiversity finance, and present the current state of the art in this field, and one to discuss future research directions).

The first study introduces the Biodiversity Risk Premium (BRP) measure, using biodiversity-screened portfolios to assess the financial implications of biodiversity exposure. Results demonstrate that portfolios with reduced biodiversity risk achieve lower risk-adjusted returns. This indicates that investors demand a premium for biodiversity-exposed assets (Naffa & Czupy, 2024). This study provides one of the first pieces of empirical evidence that biodiversity risk is priced in global equity markets, even though it does not account for double materiality.

Building on these findings, the second study defines and estimates the Nature Risk Premium (NRP), which captures both biodiversity and climate risks and integrates firms' impacts on and dependencies of ecosystems. Using Principal Adverse Impact (PAI) indicators and ENCORE data, the study confirms the existence of a

nature-related risk premium at the firm level. It shows that companies more exposed to ecosystem degradation and climate risks deliver higher realized returns, consistent with investor compensation for nature-related risks (EU, 2019a; Hutchinson & Lucey, 2024). This broader and more granular framework demonstrates that both dependencies and impacts on ecosystems are relevant for pricing.

Altogether, these studies provide evidence that biodiversity and nature risks are not only ecologically important but also financially material, with quantifiable implications for equity pricing. By conceptualizing and estimating the BRP and NRP, the dissertation advances the methodological toolkit available to researchers and practitioners. The results also carry significant implications for regulators and policymakers because while markets do recognize and price most biodiversity-related risks, others remain overlooked, in our opinion, particularly those that are harder to measure or less well-known. This selective pricing highlights the importance of standardized, forward-looking, and geospatial indicators to ensure that material risks are properly reflected in investment decisions and regulatory frameworks.

The dissertation also highlights the importance of the double materiality perspective, which can now be properly considered due to the increasingly available datasets. Firms' impacts on biodiversity, such as deforestation or pollution, are not only ethical concerns but can generate direct financial consequences through regulatory sanctions, reputational damage, and supply chain disruptions (Mezzanotte, 2023). Conversely, firms' dependencies on ecosystem services, such as water availability, pollination, or soil fertility, can threaten their long-term success if ecosystems degrade (UN, 2024). Integrating both sides of this materiality is essential for a comprehensive understanding of financial exposure. The two studies included in this dissertation also illustrate how financial analysis has evolved in recent years, from biodiversity-specific ratings to double materiality-aligned indicators.

On top of the important findings, this dissertation explores and suggests future research directions. A key recommendation is the integration of Earth Observation (EO) data into financial risk assessment, enabling forward-looking, spatial measurement of impacts and dependencies of firms. This approach will overcome many limitations of disclosure-based ESG ratings, which often suffer from inconsistency, subjectivity, and greenwashing (Berg et al., 2022). EO-based metrics, with ecosystem accounting frameworks such as the SEEA-EA, could provide unbiased, verifiable, and comparable measures of biodiversity risk across firms and regions. This would allow financial markets and regulators to more accurately identify, price, and manage firm-level and systemic risks arising from biodiversity loss.

To sum it up, the dissertation makes four key contributions. First, it empirically demonstrates that biodiversity and nature-related risks are beginning to be priced in equity markets. Second, it introduces the concepts of BRP and NRP, providing a structured way to quantify these risks. Third, it establishes the importance of distinguishing between firms' impacts and dependencies, highlighting the importance of double materiality. Fourth, it identifies future research directions, particularly the use of Earth Observation data to build more precise and actionable measures of biodiversity risk.

The broader implication is: biodiversity loss is not only an ecological threat but also a financial one. As over half of global GDP is dependent on nature (GSIA, 2024), the continued degradation of ecosystems will increasingly threaten economic stability. For investors, integrating biodiversity risk into portfolio construction is not merely a matter of sustainability preferences but a correct response to internalize such exposures. For regulators, ensuring consistent, transparent, and forward-looking disclosure of biodiversity risks is essential to preserve financial stability.

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