Master Thesis U.S.E.

Biodiversity risk and its pricing in European stock markets

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Abstract

This study contributes to the emerging biodiversity finance literature by examining how biodiversity risks are reflected in the pricing of European stock markets and the impact of biodiversity-related policies on this risk premium. Using a panel data set of 4093 European companies from 2019 to 2023, biodiversity risk levels are measured at the company level and integrated into the asset pricing model with a new high-minus-low biodiversity risk factor (HLBR). The Carhart 4-factor style panel regressions on individual companies and decile portfolios sorted by biodiversity risk show that higher biodiversity risks necessitate compensation, leading to higher excess returns. The Difference-in-Difference model results indicate that following the Kunming Declaration and the launch of the TNFD, biodiversity risk pricing increased more steeply for high-risk companies than for low-risk ones. However, heterogeneous effects are observed in quantile portfolios sorted by industry and biodiversity risk level, indicating variability in how biodiversity risks impact returns across different industries.

JEL-codes: G12, Q51, Q57

Keywords: Biodiversity risk, Factor models, Asset pricing, Europe, Kunming Declaration, TNFD

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1. INTRODUCTION

"Destroy nature, and you destroy the economy," stated Frank Elderson, member of the ECB's Executive Board, during an interview with the Financial Times (Arnold, 2023). In an era where the interconnection between ecological health and economic stability is becoming increasingly clear, the direct risks of climate change are no longer the only threats we face. Biodiversity, the variety of living species within ecosystems, is declining at an alarming rate (Garel et al., 2023). Given that more than half of the world's GDP depends on nature's services, this degradation emerges as a global economic crisis with far-reaching implications for human well-being (United Nations, 2022; World Bank, 2020). The biodiversity loss is evident in the observed 69% decrease in wildlife populations between 1970 and 2018, ranging from large mammals and birds to insects and amphibians (WWF, 2022). Simultaneously degrading soil and land quality further exacerbates these negative environmental trends (UNCCD, 2022). These events are a direct result of our ongoing human activities, such as habitat destruction, resource overexploitation, pollution, and land usage (Calice et al., 2023). Consequently, the urgency of these environmental changes has now pushed us beyond the planetary boundary for biodiversity loss (Rockström et al., 2009; Steffen et al., 2015).

As a response to these challenges posed by biodiversity loss, new regulations on biodiversity are being introduced. Notably, the Kunming-Montreal Global Biodiversity Framework, launched in December 2022 following the United Nations Biodiversity Conference (COP15), seeks to reverse biodiversity degradation. The commitment to this policy requires businesses to evaluate their impact on biodiversity and set ambitious targets, including protecting 30% of land and marine ecosystems by 2030 (United Nations Environment Programme, 2022). Also, in September 2023, the first version of the Taskforce on Nature-related Financial Disclosures (TNFD) was formed to provide a framework for businesses and financial institutions to disclose nature-related risks and opportunities. Therefore, it is no longer possible to ignore how companies' core operations are affecting, and being affected by, biodiversity loss and the accompanying consequences of stricter climate policies. The behaviour of businesses is under increasing scrutiny, and investors must pay closer attention to the additional biodiversity risks that may impact asset valuation in their portfolios. However, climate change risks have received comparatively more attention in sustainable finance studies than the risks directly connected with biodiversity loss and ecosystem degradation, despite their interrelation.

A wide range of research has already enhanced our understanding of climate risks within financial markets, particularly highlighting how risks associated with carbon emissions are priced differently between carbon-intensive and low-carbon companies (Alessi et al., 2021; Bolton & Kacperczyk, 2021b; Choi et al., 2020; Görgen et al., 2020; Hsu et al., 2023; In et al., 2019). Moreover, it is suggested by empirical evidence that polluting stocks react more negatively than clean stocks to climate policies, implying a possible carbon risk premium (Hsu et al., 2023; Monasterolo & De Angelis, 2020; Nguyen, 2020). Finally, it has been suggested that the impact of climate change news on stock prices primarily reflects rising investor concerns about climate issues, which supports the evidence of the growing market sensitivity to environmental risks (Engle et al., 2020; Pástor et al., 2022; Pedersen et al., 2021).

Despite biodiversity loss being increasingly recognised as a potential source of financial risk (NGFS-INSPIRE, 2022), the connection between biodiversity risk and financial markets has long been overlooked by researchers in economics and finance. This might be due to the complex nature of biodiversity, which derives from a variety of sources and processes, making it hard to fully catch the relationships between species, ecosystems, and humans. Therefore, compared to the more straightforward measurable climate risks through carbon emissions, the value of biodiversity is too multifaceted to be captured by a single metric (Cherief et al., 2022).

Nevertheless, there has been a modest emergence of biodiversity finance literature attributed to studies by the Dutch and French Central Banks, which have sparked interest in how the financial sector handles risks associated with biodiversity loss (Svartzman et al., 2021; Van Toor et al., 2020). More recently, several studies have responded to Karolyi and Tobin-de la Puente's (2022) call for research by exploring how biodiversity loss risks are framed and priced, highlighting their significance as a new dimension of risk (Becker et al., 2023; Cherief et al., 2022; Conqueret et al., 2024; Garel et al., 2023; Giglio et al., 2023; Hoepner et al., 2023; Soylemezgil & Uzmanoglu, 2024; Xin et al., 2023, Xiong et al., 2023). This has resulted in the first developments of new measures to quantify biodiversity risks and the identification of a biodiversity risk premium, particularly evident in the US market since 2021 (Conqueret et al., 2024; Giglio et al., 2023). Despite a lack of impact on global stock returns between 2019 and 2022, stocks with significant biodiversity risk saw a notable decrease in asset values directly following the Kunming Declaration in October 2021 (Coqueret et al., 2024; Garel et al., 2023). Over the longer term, these riskier stocks yield higher returns, indicating a positive biodiversity risk premium driven by increasing investor awareness and regulatory risks.

Given that existing studies have primarily focused on global or US stock markets, this study will specifically contribute to the expanding field of biodiversity asset pricing by focusing on the European stock market. There is an increase in biodiversity-related regulations in Europe, exemplified by the European Commission's 2022 Nature Restoration Law, a key component of the EU Biodiversity Strategy 2020 with binding restoration targets. This law reflects heightened concern for biodiversity loss in Europe and underscores a relevant research opportunity in this geographical area. Additionally, this study addresses the need for more precise methodologies to measure company-level biodiversity risks, moving beyond sector-based analyses that often overlook location-specific factors (Cherief et al., 2022). In conclusion, the asset pricing approach has never been used to examine the pricing of biodiversity risks in the European market using a company-level methodology, leading to a highly interesting literature gap. This sets the fundamentals for formulating the following research question: "How is biodiversity risk reflected in the pricing of European stock markets, and to what extent do biodiversity-related policies influence this risk premium?".

This study uses a data set of 4,093 European companies from 2019 to 2023 to comprehensively review the entire European market. A multi-step approach is employed to estimate the biodiversity risk premium, allowing the research question to be divided and addressed in various stages. First, a long-short portfolio is created by incorporating the high-minus-low biodiversity risk factor (HLBR) into the CAPM, Fama-French, and Carhart 4-factor models. Next, panel regressions are conducted using data from individual companies across the different asset pricing models, including the HLBR factor. This analysis is further refined using the Fama-Macbeth procedure to evaluate investor perception of biodiversity as an investment risk and to identify evidence for the biodiversity risk premium. Subsequently, decile and quantile portfolios are constructed based on high and low biodiversity risks, considering company-specific dependency and impact on biodiversity, as well as industry classifications. These portfolios are analyzed using a Carhart 4-factor model regression. Finally, a Difference-In-Difference (DID) approach is employed to assess shifts in the biodiversity risk premium following the October 2021 Kunming Declaration and the Taskforce on Nature-related Financial Disclosures (TNFD) in June 2021.

The findings show that higher biodiversity risks lead to higher excess returns, as demonstrated in Carhart 4-factor style regressions on individual companies and decile portfolios. Following the Kunming Declaration and the TNFD launch, biodiversity risk pricing increased for high-risk companies. However, quantile portfolios sorted by industry and biodiversity risk level show heterogeneous effects across industries. Finally, no significant abnormal returns were found, indicating no evidence of a standalone biodiversity risk premium.

The remainder of this study is structured as follows. In Section 2, the most critical literature is reviewed. Next, Section 3 discusses the theoretical framework. Section 4 consists of two parts: a description of the data and the different methodological approaches. Section 5 presents the results and interpretation. Finally, Section 6 contains the discussion and conclusion.

2. LITERATURE REVIEW

This section first explores the concept of biodiversity risks and their components, followed by an overview of biodiversity-related regulations. It concludes with a review of the existing literature on how biodiversity risk is priced in the financial markets.

2.1 Biodiversity risks

Ecosystem services serve as a starting point to define and understand the relationship between biodiversity risks and financial markets. It emphasises the essential role that biodiversity plays in maintaining the health and productivity of ecosystems (Flammer et al., 2023). These ecosystems provide crucial services such as nutrient cycling, animal pollination, water filtration, climate regulation, and the production of food and nature-based materials, which are vital for sustaining economic activities and human prosperity (Giglio et al., 2023; Van Toor et al., 2020). In addition to the negative impact of biodiversity degradation on these ecosystems' functionality, the economic and financial sectors must also recognise biodiversity loss as a serious cost (Becker et al., 2023).

Biodiversity loss creates a twofold financial risk for companies. There is a risk associated with their dependency on ecosystem services, also referred to as physical risk, and a risk associated with their impact on biodiversity, known as transition risk (Conqueret et al., 2024; Giglio et al., 2023; NGFS- INSPIRE, 2022; Van Toor et al., 2020). In literature, this two-way relationship is known as the double materiality principle of biodiversity (Becker et al., 2023; Schrapffer et al., 2022). In other words, companies whose activities depend on ecosystem services might, through their operations, inadvertently contribute to the degradation of those services (Calice et al., 2023).

First, as indicated by various studies, there is financial risk associated with physical dependencies on nature (Becker et al., 2023; Calice et al., 2023; Giglio et al., 2023; Soylemezgil & Uzmanoglu, 2024; Van Toor et al., 2020; Xin et al., 2023). When firms cannot rely on ecosystem services, their operational costs may rise, their production process efficiency may suffer, and their overall ability to generate revenue may be compromised (Van Toor et al., 2020). For instance, a disruption in natural pest control could increase crop damage and reduce agricultural output, necessitating costly chemical alternatives. This increase in operational costs and reduction in productivity can lower the company's value and impact its ability to meet financial obligations (Cherief et al., 2022). As a result, the overall financial condition of the firm can degrade, highlighting the interdependence between businesses, biodiversity and the services they rely on (Van Toor et al., 2020).

In addition to these physical risks for businesses, corporate activities also conversely pose a threat to biodiversity. Interestingly, the companies that depend most heavily on biodiversity for their production do not necessarily have the greatest impact on it. However, the agricultural and forestry products industry is an exception, noted for being both one of the most dependent industries and one with the highest impact on biodiversity (Cherief et al., 2022). Intensive agriculture and forestry in Europe have led to a significant decline in ecosystem services like water purification, pest control, and pollination over the past 50 years (Becker et al., 2023). Practices such as heavy tillage and burning crop residues have further degraded biodiversity by destroying habitats and soil life, impacting the ecosystem's functionality (Cherief et al., 2022). Therefore, it is essential to mitigate this ecosystem damage to maintain the services they provide for businesses. These impacts on biodiversity can lead to transition risks as businesses face new regulatory changes and shifting societal expectations that force them to adjust. The literature indicates that such risks intensify as regulators implement stricter laws to prevent further disruption of biodiversity (Calice et al., 2023; Giglio et al., 2023; Van Toor et al., 2020). New policies, including sustainable forestry and land-use regulations, have been introduced to safeguard biodiversity in newly designated protected areas. Consequently, businesses that harm biodiversity within these areas may encounter higher costs or face outright prohibitions, requiring them to adapt or relocate their operations (Giglio et al., 2023; Van Toor et al., 2020). Additionally, regulations will mandate legally binding biodiversity targets and disclosure of companies' environmental impacts, which potentially increase costs (Becker et al., 2023; Soylemezgil & Uzmanoglu, 2024). Technological advancements and shifting consumer preferences toward lower biodiversity impact also create transition risks, challenging companies to transform (Calice et al., 2023; Giglio et al., 2023; Van Toor et al., 2020). In conclusion, businesses that significantly impact biodiversity will need to confront a new reality.

The two risks—physical and transition—merge into a company's overall biodiversity risk. These risks are intertwined; higher physical risks necessitate a more urgent transition to mitigate ecosystem decline. Delaying this transition increases physical risks, leading to the need for a shorter, more abrupt transition period, heightening the transition risks (Van Toor et al., 2020).

2.2 Regulatory landscape for biodiversity

Domestic and international policies are integral to transitioning towards an economy that sustains biodiversity. As aforementioned, biodiversity loss is becoming an increasingly critical issue on global policy agendas, leading to consequences for businesses that negatively impact biodiversity (Van Toor et al., 2020).

The focus on biodiversity protection began with Agenda 21 at the 1992 Earth Summit in Rio de Janeiro, but it quickly became clear that greater urgency was required. That same year, the European Union introduced the Habitats Directive, designed to safeguard natural habitats and wild flora and fauna (Cherief et al., 2022). Additionally, in the past years, the UN Convention on Biological Diversity (CBD) has established international agreements to expand protected nature areas worldwide, mitigate the causes of biodiversity loss and encourage sustainable ecosystem use (Van Toor et al., 2020). Most recently, the Kunming-Montreal Global Biodiversity Framework was established following the 15th Conference of Parties to the UN Convention on Biological Diversity in October 2021. This framework marks a significant development within the landscape of biodiversity-related policies and sets a transformative plan to halt and reverse biodiversity loss through financial flows by 2030. Moreover, the framework enhances measurable accountability by setting both qualitative and quantifiable targets, such as protecting 30% of Earth's lands and oceans, reducing harmful biodiversity subsidies by $500 billion annually, and increasing funding for conservation (Cherief et al., 2022; Soylemezgil & Uzmanoglu, 2024). This allows for more effective monitoring, disclosure and enforcement.

Zooming in on Europe, in 2020, the European Commission launched the European Green Deal, outlining a roadmap for Europe to achieve climate neutrality by 2050. An essential component of this deal is the Biodiversity Strategy, which includes creating an extensive network of protected zones and rehabilitating degraded ecosystems via initiatives such as afforestation and pesticide reduction (Xin et al., 2023). Two years later, in 2022, an important milestone was achieved with the approval of the Corporate Sustainability Reporting Directive (CSRD) by the European Parliament and the Council of the European Union. As a component of the European Green Deal, this directive enhances the transparency of sustainability information provided by companies. It introduces 'double materiality,' mandating firms to disclose how sustainability issues affect their finances and their operations' impacts on society and the environment, including biodiversity (Becker et al., 2023). Focusing specifically on the Netherlands, the "Strengthening Biodiversity" initiative is a government program designed to improve the country's biodiversity health by reducing the ecological footprint by 50% by 2050 (Van Toor et al., 2020). The program prioritises restoring natural habitats, adopting sustainable agricultural practices, and incorporating biodiversity considerations into urban planning.

Lastly, it is important to note that reporting nature-related risks is also receiving increasing attention at a global level. Following the Task Force on Climate-related Financial Disclosures (TCFD), the Task Force on Nature-related Financial Disclosures (TNFD) was launched in June 2021. This initiative provides financial institutions, corporations, and their investors with a framework to report and act on evolving nature-related risks (Xin et al., 2023).

The literature identifies two significant policy events closely related to biodiversity, on which this study will further focus. Following research such as Garel et al. (2023) and Soylemezgil & Uzmanoglu (2024), the Kunming-Montreal agreement and the TNFD are used to strengthen the evidence of the pricing of biodiversity risk.

2.3 The pricing of biodiversity risk

The significance of the two-sided biodiversity risk is underscored by the recent survey of Giglio et al. (2023) involving finance professionals and policymakers worldwide. Findings revealed that 70% of the respondents recognised the financial materiality of both physical and transition biodiversity risks for U.S. firms. The question arises whether investors are pricing these financial risks associated with biodiversity loss and incorporating them into their capital allocation decisions. Researchers have worked along different lines to assess whether biodiversity risks are priced.

First, several studies compared firms' stock returns with high versus low biodiversity risk exposure, providing evidence of a biodiversity risk premium (Coqueret et al., 2024; Garel et al., 2023; Giglio et al., 2023; Xin et al., 2023). The study by Giglio et al. (2023) marked the beginning of quantitative analyses of news-based biodiversity risk. It used the method of forming portfolios of U.S. firms sorted by their industry-level biodiversity risk exposure. These portfolios demonstrated that returns fluctuated in response to biodiversity news; when unfavourable news about biodiversity emerged, industries with high exposure to physical and regulatory risks experienced a more substantial drop in valuations than those with less exposure. This behaviour suggested that biodiversity risks were already factored into market prices.

These findings were complemented by the work of Garel et al. (2023), who quantified biodiversity risks using the Corporate Biodiversity Footprint (CBF), a measure developed by Iceberg Data Lab (2023). This metric solely evaluated the negative impacts of corporate activities on biodiversity but excluded data on the physical risks from biodiversity loss. Using an international sample, they employed a characteristics-based approach to examine the relationship between the CBF and the associated monthly returns between 2019 and 2022. They showed that initially, stock prices of firms with a large CBF decrease following significant biodiversity-related policy announcements (Kunming, TNFD), reflecting immediate market adjustments to anticipated regulatory costs. However, over time, these stocks exhibited higher returns, indicating a positive biodiversity risk premium due to increased investor awareness and regulatory risks.

Similar to the research by Garel et al. (2023), Coqueret et al. (2024) explored the impact of biodiversity risks on asset pricing using the Corporate Biodiversity Footprint (CBF). To assess the financial implications in the US market, they created a "green-minus-brown" factor, comparing companies at the sector level with low (green) versus high (brown) biodiversity intensity. Consistently, they found a marked shift after relevant regulatory announcements, with a focus on near-term expectations. Post-2021, stocks heavily impacting biodiversity have shown a negative return premium, reflecting immediate market concerns about their future valuation due to upcoming regulatory changes (Coqueret et al., 2024).

Additionally, Xiong et al. (2023) measured biodiversity risks by linking biodiversity loss incidents to corporate actions in the global equity market. The study constructed long-short portfolios based on firms' biodiversity risk exposures. These portfolios showed a significant 'biodiversity alpha' in the US market before the Kunming Declaration in October 2021. This became negative afterwards, indicating an initial underpricing of biodiversity risks that was later corrected.

In the study by Xin et al. (2023), biodiversity risks were assessed using a composite measure derived from MSCI's ESG ratings, with their focus specifically on the critical biodiversity and land use issues. Conversely, this research found that neither the overall biodiversity scores nor the sub-components (exposure to and management of biodiversity risks) significantly predicted stock returns between 2013 and 2020.

Several significant insights stand out from the studies reviewed, which are particularly relevant to this research. Notably, there is an absence of consideration for physical risks associated with biodiversity loss in some measures. Also, there is a need to be more uniform in how biodiversity risks are measured, and there is little consensus on whether biodiversity risks positively, negatively, or negligibly impact stock values across these studies. Lastly, the studies primarily focus on U.S. firms or engage in broad global comparisons. This approach overlooks potential regional variations in how biodiversity risks are priced by markets, especially in less examined regions like Europe, where differing biodiversity concerns and regulatory frameworks could significantly influence risk profiles.

Subsequently, some studies, including Becker et al. (2023), went beyond stock prices to examine the significance of biodiversity risks in financial instruments. They explored how lenders incorporated biodiversity risks into loan pricing, using the MSCI 'Geographic Segment Exposure to Fragile Ecosystems' indicator to assess corporate operations in sensitive areas. They refined these exposure scores by adjusting for revenue from each location, which offered a clearer picture of a company's involvement in ecosystem degradation. This approach revealed a significant positive correlation between firms' biodiversity exposure and syndicated loan pricing, especially in the EU, likely due to Europe's stricter environmental regulations (Becker, 2023). Furthermore, Cherief et al. (2022) used the Mean Species Abundance (MSA) index to assess biodiversity risks and their influence on corporate bond spreads. This analysis focused on the impact of acute biodiversity incidents in biodiversity-rich countries, such as toxic spills or natural disasters. They observed that bond spreads increased significantly after these events, reflecting the market's acknowledgement of a biodiversity risk premium. Similarly, Soylemezgil et al. (2024) investigated the corporate bond market in the U.S., using the biodiversity news index by Giglio et al. (2023) to measure how biodiversity risks influenced bond yield spreads. Their findings indicated that bonds with longer maturities from companies facing greater biodiversity risks exhibited wider yield spreads, with this effect intensifying following the adoption of the Kunming-Montreal Framework.

Lastly, in the study by Hoepner et al. (2023), the researchers explored how non-climate environmental factors, including biodiversity, affected the credit risk profiles of infrastructure firms. The study employed qualitative ESG indicators, converted into numerical scores, to demonstrate that effectively managing biodiversity risks correlated with lower long-term credit risk, leading to more favourable conditions for long-term financing.

In conclusion, multiple recent studies demonstrate that biodiversity risk is consistently integrated into market valuations, often as a positive biodiversity risk premium. This premium varies with regulatory shifts and public awareness, particularly following significant events like the Kunming Declaration and the launch of the TNFD. Beyond stock prices, biodiversity risks impact pricing across various other financial instruments, including corporate bonds and syndicated loans.

3. THEORETICAL FRAMEWORK

This section outlines the underlying theories of asset pricing models and the pricing of biodiversity risks. The theories serve as a foundation for the hypotheses formulated for this study.

3.1 Asset pricing theory

The foundational theory underlying the literature review on asset pricing is the risk-return trade-off, which posits that riskier securities are priced lower and, therefore, offer higher expected returns. The Modern Portfolio Theory (MPT) by Markowitz (1952) introduces the concept of diversification and optimising the risk-return ratio within a portfolio. MPT emphasises that a portfolio's balance of risk and return should be optimised. This involves selecting a mix of assets that achieves the highest expected return for a given level of risk or the lowest risk for a given level of expected return (Markowitz, 1952). Sharpe's Capital Asset Pricing Model (CAPM), introduced in 1964, extended the MPT (1952) by formalising the relationship between expected return and risk through a single-factor model. In this model, the market risk premium is the sole factor affecting expected returns, with 'beta' representing a security's sensitivity to this premium.

However, CAPM's simplicity as a single-factor model has prompted the development of more comprehensive models that account for various other risk factors affecting asset returns. The Arbitrage Pricing Theory (APT) introduced by Ross in 1976 offers a flexible alternative to CAPM by predicting asset returns through multiple macroeconomic factors rather than a single market portfolio. Consequently, multi-factor models such as the Fama-French three-factor model (1992) include additional factors to capture the complexity of financial markets better. Specifically, it adds the size premium (small minus big companies, SMB) and the value premium (high book-to-market minus low book-to-market, HML) to the CAPM equation, significantly improving the model's explanatory power. Carhart (1997) expanded the three-factor model by adding a momentum factor, while Fama and French (2015) further extended it to include factors for profitability and investment. This multi-factor approach is especially relevant when considering the Efficient Market Hypothesis (EMH), which asserts that asset prices fully reflect all available information (Fama, 1970). It aligns with EMH by suggesting that several factors, rather than just market risk, can influence returns, which reflects the market's efficient response to diverse information sources.

Currently, factor models are extensively utilised in asset pricing literature to examine the systematic factors that influence the cross-section of stock returns. Overall, a multitude of factors contribute to explaining stock returns, suggesting that environmental risks, including biodiversity, could also serve as a significant explanatory variable.

3.2 Biodiversity risk and asset pricing

Sustainable finance studies increasingly incorporate environmental risks into asset pricing models to enhance forecasting. Driven by a growing awareness of the importance of environmental, social, and governance (ESG) information in assessing risk and potential return, Pedersen et al. (2021) have introduced the concept of the ESG-efficient frontier. This concept redefines the traditional efficient frontier by integrating ESG metrics, enabling investors to optimise portfolios by balancing financial returns with environmental risk management. Such adaptations ensure that asset prices reflect traditional financial metrics and that companies manage environmental risks effectively. By employing these refined models, investors can make more informed decisions and create 'greener' portfolios that closely align with their values and risk tolerances. Subsequently, this shift parallels the concept of an 'equity greenium' (Pástor et al., 2022). The equity greenium is supported by general equilibrium asset pricing models, which demonstrate that 'green' investors are prepared to accept lower expected returns for holding green stocks, particularly as the economy's shift towards a low-carbon future gains credibility (Alessi et al., 2021; Fama & French, 2007; Pástor et al., 2022; Pedersen et al., 2021).

In contrast, so-called 'sin stocks', associated with industries like tobacco or fossil fuels, often command higher risk-adjusted returns due to their exclusion from sustainability-focused investment portfolios (Bolton & Kacperczyk, 2021a; 2021b). This phenomenon, identified by Hong and Kacperczyk (2009), suggests that ethical concerns, future regulatory risks, climate attention and potential public backlash create a need for higher returns to attract risk-tolerant investors. Additionally, the market segmentation theory suggests that widespread divestment from these companies increases the demand for higher premiums among remaining investors to compensate for the heightened risks of exclusion (Hong & Kacperczyk, 2009).

Further, Pástor et al. (2022) explore the likelihood that green firms could outperform in the long term, especially if market trends persist in favouring sustainability and regulatory frameworks intensify their focus on environmental impacts.

In conclusion, from an investor's perspective, it is increasingly crucial to incorporate environmental risk into portfolio selection decisions, aligning with sustainable finance theories. Therefore, this study aims to document a similar phenomenon concerning the expected returns of stocks with high biodiversity risk exposure. It will explore whether growing concerns about biodiversity loss and changing investor preferences, driven by biodiversity-related regulations, impact the expected stock prices of companies with varying levels of biodiversity exposure.

3.3 Hypotheses

Based on the literature, theories, and concepts discussed in the preceding sections, this study aims to answer the main question "How is biodiversity risk reflected in the pricing of European stock markets, and to what extent do biodiversity-related policies influence this risk premium?" through the following hypothesis.

H1: Biodiversity risk is systematically priced into European stock markets.

The first hypothesis establishes a foundation for examining how biodiversity risk is generally priced across the European market. Research by Coqueret et al. (2024), Garel et al. (2023), and Giglio et al. (2023) reveals that these risks are factored into stock valuations due to changing investor behaviour and regulatory focus. This is supported by theoretical models like the Fama-French multi-factor models (Fama & French, 1992; 2015) and the ESG-efficient frontier by Pedersen et al. (2021), demonstrating market adaptation to comprehensive factors, including environmental risks. After establishing whether biodiversity risk is systematically priced into European stock markets through Hypothesis 1, Hypothesis 2 delves deeper into the nuances of how biodiversity risk impacts companies differently based on their exposure levels.

H2: Companies with higher exposure to biodiversity risks exhibit a higher biodiversity risk premium in their stock prices compared to those with lower exposure.

The second hypothesis is supported by both mature and recent literature. Earlier research on climate risks by Bolton & Kacperczyk (2021a) indicates that investors require a premium for holding shares of high-emission firms. Recently, Garel et al. (2023) found a positive premium for high biodiversity risk stocks, driven by growing investor awareness and regulatory pressures, further supporting this hypothesis. Following hypothesis 2, hypothesis 3 focuses on the differential impact of biodiversity risk across specific industries.

H3: The biodiversity risk premium is more pronounced in industries with high biodiversity risks.

The third hypothesis is supported by several studies on climate risks. Bolton & Kacperczyk (2021b) observed that high-emission industries underperformed others, indicating a smaller carbon premium in less stigmatised sectors. Görgen et al. (2020) found that transitioning to a green economy negatively impacts "brown industries", reflecting their sensitivity to environmental risks. Building on the previous hypotheses, hypothesis 4 examines how new or stricter biodiversity policies are expected to impact biodiversity risk premiums. This hypothesis explores the influence of regulatory changes on the premiums associated with biodiversity risks.

H4: The introduction or tightening of biodiversity-related policies has significantly increased the biodiversity risk premium for companies at greater risk of biodiversity loss.

The fourth hypothesis aligns with Garel et al. (2023), which observed that stocks affecting biodiversity yielded higher returns following the Kunming-Montreal agreement and the TNFD. This supports earlier findings by Nguyen (2020) and Hsu et al. (2022), showing that polluting stocks generally react negatively to climate policy changes, suggesting an emerging carbon risk premium. Monasterolo & De Angelis (2020) also noted that low-carbon assets gained appeal after the Paris Agreement, reinforcing this trend.

4. EMPIRICAL STRATEGY

4.1 Data collection and description

The European sample consists of 4,093 listed firms for which biodiversity and financial data are available over the years 2019 to 2023. Following the methodologies suggested by Cherief et al. (2022) and Garel et al. (2023), this approach adopts a shorter time frame. The lack of time series data on biodiversity necessitates limiting the study period. Additionally, the most significant recent global policy developments concerning biodiversity are included within this timeframe. The sections that follow discuss the collection and processing of biodiversity and financial data to form portfolios of the companies sorted by their biodiversity risk exposures.

4.1.1 Biodiversity risk data

Various metrics have recently been developed to assess companies' dependency and impact on biodiversity (Coqueret et al., 2024). First, the ENCORE dataset examines how economic subsectors and production processes are exposed to natural capital. Second, in 2023, the Science Based Targets Network (SBTN) launched a tool for companies to assess their impacts on nature and set nature-related targets. Third, the UN Environment Programme and S&P Global introduced the Nature & Biodiversity Risk dataset, and WWF launched the Biodiversity Risk Filter at the 2023 World Economic Forum (Flammer et al., 2023). Additionally, the IBAT alliance manages global biodiversity datasets such as the World Database on Protected Areas and the IUCN Red List of Threatened Species (Cherief et al., 2022).

This study examines the WWF Biodiversity Risk methodology, which incorporates more than 50 distinct data layers on biodiversity. It moves beyond the limited scope of sector-level biodiversity risk data used exclusively in previous studies, such as those by Toor et al. (2020) and Calice et al. (2021). It builds upon the widely used IBAT and ENCORE datasets and expands on location-specific analyses similar to those employed by S&P Global and SBTN. This approach generates a comprehensive biodiversity risk score for each European company, reflecting their physical and transition risks. The score is based on company site location, industry classification, materiality rating, and local biodiversity (WWF, 2023).

The industry-specific dependency and impact on biodiversity of WWF are assessed using the ENCORE dataset, which rates sub-industries from 'very high' to 'very low' based on their performance. ENCORE links these scores to 86 business processes and 21 ecosystem services. For example, the 'Small-scale livestock (beef and dairy)' process within the 'Agricultural Products' sub-industry is highly dependent on ecosystem services such as groundwater, soil condition, and flood and storm protection. This dependency results in a score calculated by evaluating potential disruptions and financial impacts from the loss of these ecosystem services on the sub industry. The impact score is further refined using supply chain data from SBTN and EXIOBASE, a detailed multi-regional input-output table that tracks environmental impacts from raw material extraction to production ('cradle to gate') (SBTN, 2020). This study uses the GICS industry classification to link the companies in the sample with the WWF's industry classifications and associated scores. More details on the industry classifications, risk categories, indicators, and metrics for assessing the biodiversity risks are provided in Table A1 and A2 in the Appendix.

The dependency and impact scores are adjusted based on the geographic location of the company's operations. This approach identifies whether each location faces a heightened risk of disrupting ecosystem services crucial to a specific company's business activities (Van Toor et al., 2020). WWF (2023) uses 56 global datasets to assess the biodiversity integrity of specific landscapes and seascapes. Building on Becker's research (2023), this study uses geographical revenue-based weighting to provide a location-specific view of a company's involvement in biodiversity risks, a method also recommended by WWF (2023). The Revere Geographic Revenue ("GeoRev") data, which captures the company's revenue per geography in percentages, was obtained from FactSet. A limitation of using revenue as a proxy is that it may not accurately represent the physical assets within a country (WWF, 2023).

Ultimately, the total physical and transition risk score, which assesses specific aspects of biodiversity at a particular site for a certain industry, ranges from 0 to 5. This study derives a company's overall biodiversity risk score by aggregating these scores, weighted according to their business relevance and geographic location weights. The 75th percentile method is used both in the aggregation of indicators to risk categories and from risk categories to the two risk types. This approach alerts businesses that certain sites may be particularly vulnerable to biodiversity-related risks critical to their operations. This is crucial because a single high-risk issue can significantly harm a company or its supply chain. Consequently, the total biodiversity risk score is an average of the physical and transition risk scores, according to the WWF Biodiversity Risk methodology (WWF, 2023). This score does not account for downstream dependencies and impacts, significantly underestimating the biodiversity risks due to companies lacking accurate, location-specific supply chain data (Calice et al., 2023; Van Toor et al., 2020; WWF, 2023). Additionally, a limitation of the score is that it represents a point-in-time evaluation and is only as current as the underlying datasets of the biodiversity indicators (WWF, 2023).

Table 1 shows the summary statistics of the biodiversity risks based on the year 2023. The number of companies (N) is based on the final dataset, where the companies with missing data for financial measurements have already been removed, described in the following section 3.2. Additionally, in Table A3 and A4 in the Appendix, the distribution of the number of observations of all companies across industries and geographic locations is provided.

Table 1: Summary statistics biodiversity risk scores

Note: This table presents the summary statistics for the Total Biodiversity Risk, which is composed of the Total Transition Risk and the Total Physical Risk. These components are further subdivided into Physical Risk and Transition Risk based on the industry and geographic location of the companies in the final dataset.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	N	Median	Mean	St. Dev	Min	Max	Kurtosis	Skewness
Total Biodiversity Risk	4093	2.827	2.923	0.365	1.525	3.893	-0.593	0.673
Total Transition Risk	4093	2.804	2.907	0.411	1.625	4.267	-0.046	0.812
Total Physical Risk	4093	2.837	2.939	0.373	1.425	4.085	-0.476	0.650
Physical Risk – Industry	4093	1.900	2.141	0.648	1.550	4.000	-0.753	0.778
Transition Risk – Industry	4093	2.083	2.374	0.744	1.750	3.917	-0.211	1.121
Physical Risk – Geography	4093	3.676	3.738	0.327	0.000	4.780	4.965	0.605
Transition Risk – Geography	4093	3.454	3.440	0.345	0.000	4.890	1.558	-0.150

4.1.2 Financial data

Month-end stock prices for all European companies from 2019 to 2023 are sourced from the FactSet database to calculate monthly stock returns, with adjustments for stock splits, spin-offs, and dividends. Data on common shares outstanding are also obtained from FactSet, which are used to calculate the absolute market capitalization by multiplying the total shares outstanding by the current market price per share. The relative market capitalization is necessary for calculating the new risk factor. After that, the historical month-end yields of Germany's 10-year Government Bonds, considered an appropriate risk-free rate for European data samples due to Germany's stable credit rating and economic stability, are used for calculating the monthly excess returns. To further refine the analysis, the excess returns are winsorised at the 1st and 99th percentiles. This process adjusts extreme values in the dataset to mitigate the impact of potential outliers. Winsorising at these percentiles ensures the results are not skewed by extreme observations, thereby providing a more robust and reliable assessment of the excess returns. Furthermore, the STOXX 600 historical month-end data has been employed as a benchmark to compare the performance of stock returns. The STOXX 600 is a comprehensive European equity index that represents the performance of 600 companies from 17 European countries, closely aligning with the sample used in this study. To merge all of this financial data from FactSet with the biodiversity risk scores, the company's ISIN and CUSIP identifier codes, also obtained from FactSet, are used.

Additionally, the Fama-French risk factors 'SMB' (Small Minus Big) and 'HML' (High Minus Low), along with the Carhart momentum factor 'WML' (Winners Minus Losers) are retrieved from the data library of French, K. R. (2024). Since the risk factors are calculated using excess returns in USD, it is necessary to convert the stock returns, the European market return, and the risk-free rate to USD to maintain consistency. This conversion prevents any currency mismatch that could distort the results and ensures that the creation of the new risk factor aligns with the data and methodology of French, K. R. (2024).

This study controls for firm-specific characteristics by incorporating well-established control variables, consistent with methodologies in the literature that apply asset pricing models to assess the impact of environmental risks on stock returns. In line with the studies of Görgen et al. (2020) and Bolton & Kacperczyk (2021a), the control variables include the Natural logarithm of Total Assets, Book-to-Market Ratio, Leverage Ratio, Investment-to-Asset Ratio, and Natural logarithm of Property, Plant, and Equipment. By integrating these controls, the analysis accounts for various factors known to influence stock returns, ensuring a more robust examination of biodiversity risks. Furthermore, the Book-to-Market Ratio and Leverage Ratio are winsorised at the 5^{th} and 95^{th} percentiles to mitigate the impact of outliers.

Table 2 presents the summary statistics of the input variables for the Fama-French three-factor model and the control variables. Due to missing values from the financial variables, the amount of 5715 European companies had been narrowed to the final sample of 4093 companies over the period of January 2019 to December 2023.

Table 2: Summary statistics of financial data

Note: This table presents the summary statistics of the financial input data. The Excess Return, the Market Cap and all Control Variables consist of data from 60 months of 4093 companies, resulting in 245580 observations (=N). The market return, risk-free rate, SMB, HML and WML risk factors cover the months between 2019 and 2023, consisting of 60 observations (=N). The (market) return is in excess of the risk-free rate, and the market capitalization is both in absolute and relative numbers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variables	N	Median	Mean	St. Dev	Min	Max	Kurtosis	Skewness
Financial Data								
Excess Return	245580	-0.0031	0.0044	0.1324	-0.3368	0.5032	2.3105	0.7136
Absolute Market Cap	245580	230.86	3195.93	14366.77	0.0011	473537.8	221.85	12.471
Relative Market Cap	245580	0.0018	0.0244	0.1084	7.68E-09	3.1162	198.97	11.963
Log Total Assets	245580	6.5028	6.7031	2.5994	-7.667	17.4946	0.0331	0.2832
Book-to-Market Ratio	245580	0.6537	0.8667	0.7328	0.0600	2.7671	0.5592	1.15072
Leverage Ratio	245580	0.4864	0.8432	1.0138	0	3.8435	2.2271	1.7103
Investments/Total Assets	245580	0.0061	0.1045	0.2550	-0.1182	1.4207	8.2551	3.0305
Log PPE	245580	3.7080	3.4865	3.1417	-13.8343	12.4243	0.4048	-0.3886
Risk-free Rate	60	-0.0021	0.0055	0.0130	-0.0077	0.0300	-1.1328	0.7626
Market Return	60	0.0111	0.0028	0.0537	-0.1580	0.1706	1.1994	-0.1873
Fama-French Risk Factors								
SMB	60	-0.2450	-0.1258	1.9179	-4.2200	5.0300	0.2819	0.3909
HML	60	-0.5550	0.0547	3.6867	-11.300	12.090	2.6327	0.4631
WML	60	0.7550	0.4703	3.9106	-18.390	8.5000	8.2652	-1.7548

Both absolute and relative market capitalizations show high kurtosis and skewness, indicating significant outliers and a long-tailed distribution. This study chose not to normalise the market capitalization data to maintain these outliers, as relative market capitalization is used solely for ranking companies in portfolio creation, and absolute market capitalization is provided as supplementary information.

4.2 Methodology

The methodology involves applying various models to estimate the biodiversity risk premium. First, a long-short portfolio is constructed to generate the high-minus-low biodiversity risk factor (HLBR). Next, panel regressions on individual companies are conducted, followed by applying the Fama-Macbeth procedure for further refinement. Then, decile portfolios based on biodiversity risk levels are established. Subsequently, portfolios are categorised by industry, followed by the formation of quantile portfolios based on both industry and biodiversity risk levels. Finally, a Difference-In-Difference (DID) model approach measures shifts in the biodiversity risk premium following crucial policy developments.

4.2.1 The biodiversity risk factor

Drawing on the methodologies of Coqueret et al. (2024), Giglio et al. (2023), Görgen et al. (2020), and Xin (2023), this study proposes to examine how biodiversity risks are reflected in stock prices through a biodiversity risk factor mimicking portfolio. Portfolios are constructed by sorting stocks based on their exposure to biodiversity risks, taking long positions in companies with high risk and short positions in those with low risk. The CAPM, Fama-French three-factor and Carhart four-factor model are extended by a risk factor to prove the biodiversity risk premium. The procedure used to construct the "High-minus-Low Biodiversity Risk" (HLBR) factor follows the UMD (momentum) factor methodology on the data library of French, K. R. (2024). First, six portfolios are created by sorting portfolios into two market capitalization and three biodiversity risks exposure groups. The breakpoints of the biodiversity risk exposure were the 30th and 70th percentiles and are divided by the market capitalization median. Second, the HLBR factor is calculated through high biodiversity risks (HBR) and low biodiversity risks (LBR) stocks, sorted into small (S) and big (B) stocks. This leads to a small-high risk (SHR), big-high risk (BHR), small-low risk (SLR), and a big-low risk portfolio (BLR). The biodiversity risk exposure is based on the latest available data from the WWF Biodiversity Risk dataset (2023), following the study by Gimeno & Gonzalez (2022). They indicate that this can be considered a proper approximation of the HLBR factor assuming that environmental risks remain relatively stable over a long period. Also, reducing the risks from biodiversity loss is a long-term effort, which eliminates the need to balance portfolios annually. The following formula for the High-minus-Low Biodiversity Risk (double sorted) portfolio is used:

$$HLBR = \frac{1}{2}\,(SHR + BHR) - \frac{1}{2}\,(SLR + BLR) \tag{1}$$

4.2.2 Panel Regressions

This study employs multiple asset pricing models to assess the impact of biodiversity risk on stock returns for individual European companies from 2019 to 2023. Monthly excess returns are regressed using various models; each augmented with the newly constructed biodiversity risk factor (HLBR). The analysis includes three primary asset pricing models: the Capital Asset Pricing Model (CAPM), the Fama-French 3-Factor Model, and the Carhart 4-Factor Model. Each model is extended with the HLBR factor to examine its effect on stock returns. The following formula is used for the CAPM-based multi-factor regression, expanded with the HLBR factor:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,t}\left(r_{m,t} - r_{f,t}\right) + \beta_{5,t}(HLBR)_t + \varepsilon_{i,t} \tag{2}$$

Where the dependent variable, $(r_{i,t} - r_{f,t})$, represents the excess return of stock *I* at time *t*, with Germany's 10-Year Government Bonds used as the risk-free rate. The constant, α_i, indicates the out- or underperformance of the individual stock. The independent variable, $\left(r_{m,t} - r_{f,t}\right)$, represents the Market factor, defined as the return of the EuroStoxx600 Index in excess of the risk-free rate. The biodiversity risk factor is denoted by $HLBR$ and the residual of the regression is given by $\varepsilon_{i,t}$. The beta estimates, β_1 and β_5, measure the sensitivity to the market and biodiversity risk factors, respectively.

Next, the CAPM model is expanded by including additional risk factors. The SMB factor indicates the size factor, measuring the excess return of small-capitalization stocks over large-capitalization stocks. The HML factor measures the excess return of value stocks over growth stocks. The WML factor, also known as the momentum factor, captures the phenomenon that stocks that have performed well in the past are likely to continue performing well, whereas stocks with poor past performance are likely to continue underperforming.

The Fama-French 3-Factor Model includes SMB and HML:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,t}(r_{m,t} - r_{f,t}) + \beta_{2,t}(SBM)_t + \beta_{3,t}(HML)_t + \beta_{5,t}(HLBR)_t + \varepsilon_{i,t} \quad (3)$$

The Carhart 4-Factor Model further includes WML:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,t}(r_{m,t} - r_{f,t}) + \beta_{2,t}(SBM)_t + \beta_{3,t}(HML)_t + \beta_{4,t}(WML)_t + \beta_{5,t}(HLBR)_t + \varepsilon_{i,t} \quad (4)$$

Where the added coefficients, β_3, β_4, and β_5, represent the portfolio's sensitivity to the size, value, and momentum risk factors, respectively.

The correlation matrix in Table 3 presents the relationships between the different risk factors of the asset pricing models used in the panel regressions. Notably, the biodiversity risk factor (HLBR) has a moderate negative correlation with the market factor (MRKTRf) (-0.245) and varying correlations with other factors such as SMB (-0.269) and HML (0.375). This indicates that the HLBR factor captures unique risks that are not explained by traditional market, size, and value factors. Initially, the Fama-French 6-factor model, which includes additional profitability (RMW) and investment (CMA) factors, was considered. However, high multicollinearity between HML and RMW (0.788) shown in Table A5 of the Appendix led to its exclusion. To mitigate multicollinearity and enhance robustness, the study used CAPM, Fama-French 3-Factor, and Carhart 4-Factor models. VIF values in Table 4 confirmed acceptable multicollinearity levels for the Carhart 4-Factor model with HLBR, with a mean VIF of 1.729 and a standard deviation of 0.451, ensuring reliable regression coefficients.

Table 3: Correlation matrix Carhart 4 Risk Factors + HLBR

Note: This table presents correlation coefficients between the risk factors used in the Carhart 4-Factor model and the newly introduced biodiversity risk factor (HLBR). The correlations provide insights into the relationships and potential multicollinearity issues among the factors.

Variables	MRKTRf	SMB	HML	WML	HLBR
MRKTRf	1	0.281	0.150	-0.595	-0.245
SMB	0.281	1	-0.170	0.041	-0.269
HML	0.150	-0.170	1	-0.522	0.375
WML	-0.595	0.041	-0.522	1	0.055
HLBR	-0.245	-0.269	0.375	0.055	1

Table 4: VIF values comparison asset pricing models

Note: This table presents the Variance Inflation Factor (VIF) values for the different asset pricing models. The VIF values are used to assess the degree of multicollinearity among the predictors in the regression models. Lower VIF values indicate less multicollinearity, suggesting that the factors in the model are not highly correlated.

VIF Asset Pricing Model	N	Mean	St. Dev.	Min	Max
FF 3-Factor	3	1.119	0.036	1.077	1.144
Carhart 4-Factor	4	1.700	0.477	1.183	2.276
Carhart 4-Factor + HLBR	5	1.729	0.451	1.217	2.354

Subsequently, several diagnostic tests were conducted to validate the robustness of the results. The Breusch-Pagan Test indicated significant heteroscedasticity (Appendix, Table A6), necessitating robust standard errors. The Wooldridge Test revealed significant autocorrelation (Appendix, Table A7), justifying clustered robust standard errors. Lastly, following methodologies by Görgen et al. (2020) and Xin et al. (2023), country and industry fixed effects were included to control for unobserved heterogeneity, providing a more accurate estimate of the biodiversity risk factor.

4.2.3 Fama-Macbeth Procedure

Following the panel regression analysis, the Fama and Macbeth (1973) two-step procedure is employed to investigate the robustness of the findings further and determine if excess returns are affected by risk factors, including the biodiversity risk factor, over time. This method is advantageous as it accounts for time variability in coefficients, addresses cross-sectional dependency, and provides robust average risk premium estimates. In the first step, the procedure involves estimating the factor exposures by regressing monthly excess returns against the identified risk factors, with the inclusion of the control variables:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,t}(r_{m,t} - r_{f,t}) + \beta_{2,t}(SBM)_t + \beta_{3,t}(HML)_t + \beta_{4,t}(WML)_t + \beta_{5,t}(HLBR)_t + \beta_{6t}(Controls)_t + \varepsilon_{i,t} \tag{5}$$

In the second step, the study regresses monthly excess returns against the betas estimated in the first step to directly estimate the risk premiums for each factor. This stage tests the significance of the risk factors and reveals the premiums investors require for exposure to these risks:

$$\hat{r}_{i,t} = \gamma_{0,t} + \gamma_{1,t}\hat{\beta}_{1,i} + \gamma_{2,t}\hat{\beta}_{2,i} + \gamma_{3,t}\hat{\beta}_{3,i} + \gamma_{4,t}\hat{\beta}_{4,i} + \gamma_{5,t}\hat{\beta}_{5,i} + \gamma_{6,t}\hat{\beta}_{6,i} + \varepsilon_{i,t} \tag{6}$$

To ensure robustness in the first step of the Fama-Macbeth procedure, diagnostic tests were conducted. The Durbin-Watson Test checked for autocorrelation showed mean DW statistics of 1.98793 and 1.992464 for models without and with fixed effects (Table 5), both within the acceptable range of 1.5 to 2.5. Despite these reassuring results, Newey-West standard errors were applied to correct for any potential autocorrelation and heteroscedasticity. Additionally, mean residuals were calculated every two years to check for omitted variables, with Table 6 showing residuals consistently close to zero, indicating no structural effects. This stability confirms the model's reliability and validates proceeding with the second step of the Fama-Macbeth regression.

Table 5: Summary of Durbin-Watson statistics

Note: This table presents the summary of Durbin-Watson statistics for the Fama-Macbeth models with and without fixed effects. The Durbin-Watson (DW) statistic is a measure of the presence of autocorrelation in the residuals from the regression analysis. The mean DW values for both models are within the range [1.5, 2.5], indicating no significant autocorrelation.

	Mean DW	**Percentage within range [1.5, 2.5]**
Without Fixed Effects	1.98793	100%
Fixed Effects	1.992464	100%

Table 6: Average residuals every two years

Note: This table presents the average residuals from the Fama-Macbeth models with and without fixed effects, measured over two-year intervals from 2019 to 2023. This helps in understanding the accuracy of the model predictions over time.

	2019-2020	**2021-2022**	**2023**
Mean Residuals Without Fixed Effects	1.410456^{e}-19	4.806826^{e}-19	2.603175^{e}-19
Mean Residuals Fixed Effects	3.053907^{e}-17	-3.675201^{e}-18	-3.656216^{e}-17

4.2.4 Decile Portfolio regressions

Following the panel regressions on individual companies, the effect of the biodiversity risk factor is further examined using decile portfolios constructed based on biodiversity risk exposure, in accordance with the methodology outlined by Görgen et al. (2020).

First, equally weighted stock returns are sorted into equal groups of 10%, based on their biodiversity risks exposures of the last available data of the WWF Biodiversity Risk dataset (2023). This categorization allows for an analysis of each portfolio's risk exposure, with Decile 1 containing the top 10% of companies with the highest biodiversity risk and Decile 10 containing the bottom 10% with the lowest risks. The decile portfolios and the corresponding monthly excess returns are presented in Table 7. Initially, a multi-factor regression is performed without the HLBR factor to establish a baseline for the effects of traditional risk factors (market, size, value, momentum) on the decile portfolios:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,t}(r_{m,t} - r_{f,t}) + \beta_{2,t}(SBM)_t + \beta_{3,t}(HML)_t + \beta_{4,t}(WML)_t + \varepsilon_{i,t} \quad (7)$$

Where the dependent variable, $r_{i,t} - r_{f,t}$, represents the excess return of the decile portfolio *I* at time *t*, where *t* is represented in months. The constant, α_i, indicates the out- or underperformance of the decile portfolio. The remaining independent variables and beta estimates, including the risk factors (MRKTRf, SMB, HML, WML), follow the same structure as in the previous panel regressions.

Subsequently, the HLBR factor is introduced to the Carhart four-factor model to examine its unique impact on the decile portfolios and determine whether biodiversity risk is priced alongside the traditional factors:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,t}(r_{m,t} - r_{f,t}) + \beta_{2,t}(SBM)_t + \beta_{3,t}(HML)_t + \beta_{4,t}(WML)_t + \beta_{5,t}(HLBR)_t + \varepsilon_{i,t} \quad (8)$$

Table 7: Summary statistics monthly excess returns decile portfolios

Note: This table presents the summary statistics of the excess returns of the decile portfolios The total return covers all decile portfolios combined. The data include the months between 2019 and 2023, consisting of 60 observations (=N).

Variables	(1) N	(2) Median	(3) Mean	(4) St. Dev	(5) Min	(6) Max	(7) Kurtosis	(8) Skewness
Decile 1	60	0.548	0.454	6.130	-19.488	17.613	1.595	-0.246
Decile 2	60	1.084	0.314	6.104	-18.080	19.214	1.566	-0.296
Decile 3	60	0.984	0.616	6.178	-19.324	20.475	2.079	-0.124
Decile 4	60	1.645	0.584	6.144	-14.754	17.049	0.216	-0.081
Decile 5	60	1.639	0.620	6.418	-15.947	17.815	0.301	-0.025
Decile 6	60	1.310	0.511	6.679	-16.996	19.048	0.425	-0.128
Decile 7	60	0.991	0.279	6.432	-16.238	18.601	0.544	-0.143
Decile 8	60	1.400	0.293	6.388	-18.526	17.362	0.809	-0.286
Decile 9	60	0.980	0.389	6.658	-17.719	18.883	0.576	-0.194
Decile 10	60	1.1897	0.326	6.372	-16.477	16.690	0.258	-0.206
Total return	60	1.259	0.438	6.251	-17.354	18.274	0.840	-0.178

Since linear regressions are deployed, several assumptions were tested for independence, linearity, normality, and homoscedasticity. Figures A10 and A11 in the Appendix present the diagnostic plots. The residuals are scattered without clear patterns, indicating a sufficient linear relationship. The Normal Q-Q plots show minor deviations at the tails, but most points lie close to the line, suggesting reasonable normality. Scale-Location plots indicate a fairly constant spread, implying heteroscedasticity is not significant. Residuals vs. Leverage plots identify a few influential points, but they are not overly dominant. Overall, the diagnostic plots suggest that the linear regression model assumptions are largely met.

Additionally, the Breusch-Pagan (BP) test and the Durbin-Watson (DW) test were conducted for the models with and without the HLBR factor (Tables A12 to A15 in the Appendix). The BP test p-values are above 0.05, indicating no significant heteroscedasticity. The DW statistics are close to 2, suggesting no significant autocorrelation. These tests reinforce the validity of the linear regression models used in the analysis.

4.2.5 Industry and quantile portfolio regressions

In addition to decile portfolios, the effect of biodiversity risk on excess returns is analyzed within portfolios based on industry classification, in line with Görgen et al. (2020), using the GICS industry classification linked to WWF's industry classifications. After that, quantile portfolios are formed by sorting stocks within industries and grouping them into quantiles based on biodiversity risk levels, following Giglio et al. (2023)

and Xin et al. (2023). In Table 8, the summary statistics for each industry, including the monthly excess returns, are presented. The following formula represents the multi-factor regression model applied to industry-level excess returns:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,t}(r_{m,t} - r_{f,t}) + \beta_{2,t}(SBM)_t + \beta_{3,t}(HML)_t + \beta_{4,t}(WML)_t + \beta_{5,t}(HLBR)_t + \varepsilon_{i,t} \qquad (9)$$

Where the dependent variable, $r_{i,t} - r_{f,t}$, represents the excess return of industry *I* at time *t*, where *t* is represented in months. The constant, α_i, indicates the out- or underperformance of the specific industry portfolio. The remaining independent variables and beta estimates, including the risk factors (MRKTRf, SMB, HML, WML, HLBR), follow the same structure as in the decile portfolio regressions.

Table 8: Summary statistics monthly excess returns industry portfolios

Note: This table presents summary statistics for the monthly excess returns of industry portfolios from 2019 to 2023. The statistics include the number of observations (N = 60 months), median, mean, standard deviation (St. Dev.), minimum (Min), and maximum (Max) values for each industry.

	(1)	(2)	(3)	(4)	(5)	(6)
Industry	N	Median	Mean	St. Dev	Min	Max
Water utilities /Service Providers	60	0.0063	0.0000	0.0615	-0.1707	0.1251
Transportation Services	60	0.0055	0.0036	0.0680	-0.2067	0.2368
Textiles, Apparel & Luxury Good Production	60	0.0147	0.0057	0.0711	-0.2156	0.2434
Telecommunication services	60	0.0066	0.0001	0.0564	-0.1535	0.1421
Paper & Forest Product Production	60	0.0117	0.0075	0.0626	-0.1377	0.1900
Oil, Gas & Consumable Fuels	60	0.0035	0.0006	0.0714	-0.2257	0.2210
Offices & Professional Services	60	0.0132	0.0044	0.0629	-0.1790	0.1860
Metals & Mining	60	0.0040	0.0055	0.0717	-0.2077	0.1959
Land Development & Construction	60	0.0094	0.0018	0.0598	-0.1834	0.1635
Hospitality Services	60	0.0039	0.0026	0.0679	-0.2347	0.2366
Health Care, Pharmaceuticals and Biotechnology	60	0.0030	0.0018	0.0609	-0.1501	0.1417
General or Speciality Retailing	60	0.0083	0.0059	0.0761	-0.2191	0.1880
Food Retailing	60	0.0088	0.0042	0.0496	-0.1028	0.1428
Food & Beverage Production	60	0.0082	0.0029	0.0497	-0.1119	0.1404
Fishing and aquaculture	60	-0.0002	-0.0113	0.0911	-0.2027	0.1996
Electronics & Semiconductor Manufacturing	60	0.0108	0.0054	0.0736	-0.1775	0.1663
Electric Energy Production – Solar, Wind	60	-0.0057	0.0095	0.0945	-0.2071	0.2276
Electric Energy Production – Combustion	60	0.0071	0.0089	0.0600	-0.1334	0.1702
Construction Materials	60	0.0140	0.0097	0.0716	-0.2228	0.2092
Chemicals & Other Materials Production	60	0.0111	0.0029	0.0621	-0.1371	0.1932
Automotive, Electrical Equip. & Machinery Prod.	60	0.0137	0.0059	0.0709	-0.2059	0.2069
Appliances & General Goods Manufacturing	60	0.0156	0.0080	0.0718	-0.1961	0.2057
Agriculture (animal products)	60	0.0065	0.0065	0.0668	-0.1655	0.1731
Agriculture (plant products)	60	0.0020	0.0013	0.0498	-0.1231	0.1220

Additionally, this study further delves into the effects of biodiversity risks across all industries by following the methodology of Giglio et al. (2023) and Xin et al. (2023). Through this approach, stocks are grouped into their respective industries and subsequently sorted into quantiles within each industry based on their biodiversity risk levels. The "high" portfolio includes an equally weighted selection of stocks from each industry, representing the top quintile with the highest biodiversity risk levels. On the other hand, the "low" portfolio comprises an equally weighted selection of stocks from the bottom quintile, characterised by the lowest biodiversity risk levels within each industry. Portfolios 2 to 4 consist of equally weighted terciles, each representing different levels of intermediate biodiversity risk within their respective industries. Table 9 presents a summary of the statistics for a representative sample of three industries, illustrating the key trends observed across all quantile portfolios. Detailed summary statistics for all 20 industries are provided in Appendix Table A17. The same multi-factor regression formula applied to the industry portfolios is utilised here, with the dependent variable adjusted to represent the quantile portfolios:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_{1,t}(r_{m,t} - r_{f,t}) + \beta_{2,t}(SBM)_t + \beta_{3,t}(HML)_t + \beta_{4,t}(WML)_t + \beta_{5,t}(HLBR)_t + \varepsilon_{i,t} \quad (10)$$

Where the dependent variable, $r_{i,t} - r_{f,t}$, represents the excess return of the portfolio *i* sorted by biodiversity risk within each industry at time *t*, where *t* is represented in months. The constant, α_i, indicates the out- or underperformance of the specific quantile portfolio. The remaining independent variables and beta estimates follow the same structure as in the decile and industry portfolio regressions.

Table 9: Summary statistics monthly excess returns representative quantile portfolios

Note: This table presents summary statistics for a sample of three industries, showing the effect of biodiversity risk on monthly excess returns from 2019 to 2023. Stocks are grouped into quintiles based on biodiversity risk levels. The number of observations (N = 60 months) is included.

Industry	Quantile	(1) N	(2) Median	(3) Mean	(4) St. Dev	(5) Min	(6) Max
Transportation Services	1 (High)	60	0.0113	0.0112	0.0681	-0.1882	0.2388
	2	60	0.0052	0.0028	0.0723	-0.2119	0.2628
	3	60	-0.0035	0.0013	0.0836	-0.2401	0.2821
	4	60	0.0047	0.0015	0.0756	-0.2068	0.2632
	5 (Low)	60	0.0070	0.0013	0.0623	-0.1880	0.1393
Paper & Forest Product Production	1 (High)	60	0.0095	0.0178	0.1006	-0.1655	0.2545
	2	60	0.0072	0.0020	0.0665	-0.1659	0.1976
	3	60	0.0093	0.0050	0.0600	-0.1396	0.1806
	4	60	0.0112	0.0042	0.0662	-0.1969	0.1647
	5 (Low)	60	0.0108	0.0077	0.0747	-0.1778	0.2128
General or Speciality Retailing	1 (High)	60	0.0119	0.0153	0.0854	-0.2227	0.2967
	2	60	0.0068	0.0066	0.0862	-0.2732	0.2083
	3	60	-0.0047	-0.0007	0.0742	-0.2314	0.1565
	4	60	0.0053	0.0054	0.0844	-0.1998	0.2056
	5 (Low)	60	0.0096	0.0035	0.0761	-0.1849	0.1605

4.2.6 Difference-In-Difference model

Drawing from Bolton & Kacperczyk (2021b), Garel et al. (2023), and Xiong et al. (2023), this study examines the impact of the October 2021 Kunming Declaration and the June 2021 TNFD on stock prices and risk premiums, comparing firms with high biodiversity risk to those with low risk. The Difference-In-Difference (DID) method is employed, selecting the control group subjectively, following Wooldridge's (2010) econometric approach. Companies with high biodiversity risk are deemed 'affected by the Kunming Declaration,' while those with low risk are considered 'unaffected'. A 'treatment' variable indicates this classification, assigned a value of 0 for unaffected companies and 1 for affected ones. The same classification applies to the launch of the Taskforce on Nature-related Financial Disclosures (TNFD).

For the time variable, a binary 'time effect' is established, assigning a value of 0 to data points preceding or within October 2021 and a value of 1 to those after October 2021. The interaction term is then crafted, combining the 'treatment' status of the companies with the time variable. In the context of the Kunming Declaration, this approach delineates the two groups based on high and low risk across the two time periods before and after October 2021. This will serve to validate and evaluate the magnitude of the DID effect. The DID model is specified as follows:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_1 Treatment_i + \beta_2 Time_t + \beta_3 (Treatment_i * Time_t) + \beta_{4,t}(r_{m,t} - r_{f,t}) + \beta_{5,t}(SBM)_t + \beta_{6,t}(HML)_t + \beta_{7,t}(WML)_t + \beta_{8,t}(HLBR)_t + \beta_9 (Controls)_{i,t} + \varepsilon_{i,t} \tag{11}$$

Where the dependent variable, $(r_{i,t} - r_{f,t})$, represents the excess return of stock *I* at time *t*. The constant, α_i, indicates the intercept. $Treatment_i$ is a binary variable indicating high biodiversity risk (1 if affected, 0 if unaffected), $Time_t$ is a binary time variable (1 for post-event, 0 for pre-event), and $Treatment_i * Time_t$ is the interaction term. The model also includes the market risk premium $(r_{m,t} - r_{f,t})$, and the risk factors $(SMB)_t$, $(HML)_t$, $(WML)_t$, and $(HLBR)_t$. The coefficient of interest, β_3, captures the additional effect on excess returns for high biodiversity risk firms relative to low biodiversity risk firms due to the event. The control variables are represented by $(Controls)_{i,t}$, and the residual of the regression is given by $\varepsilon_{i,t}$.

Control variables added to this model include Natural logarithm of Total Assets, Book-to-Market Ratio, Leverage Ratio, Investment-to-Asset Ratio, and Natural logarithm of Property, Plant, and Equipment. These controls are included to account for other factors that may influence stock returns, following the methodologies of Görgen et al. (2020) and Hsu et al. (2022). Also, both country and industry fixed effects are included to control for unobserved heterogeneity across countries and industries. Moreover, the study uses clustered standard errors to correct for potential issues with autocorrelation and heteroscedasticity.

To ensure the validity of the DID analysis, the parallel trends assumption is tested, which asserts that the treatment and control groups would follow the same trend over time in the absence of treatment, allowing post-treatment divergence to be attributed to the treatment effect. Additionally, a placebo treatment effect test, which involves randomly assigning placebo treatment groups, is conducted to ensure that observed post-treatment effects are not due to random chance or pre-existing trends, confirming that the observed treatment effects in the main analysis are not spurious.

5. RESULTS AND INTERPRETATION

The results of the analysis encompass several methodologies, including panel regressions, Fama-MacBeth cross-sectional regressions, decile, quantile, and industry portfolio regressions, along with the Difference-In-Difference (DID) approach. These methodologies collectively examine the impact of biodiversity risk on stock returns and assess the influence of significant biodiversity-related policy announcements.

5.1 Results Panel Regressions and Fama-Macbeth Procedure

The panel regression analysis, presented in Table 10, addresses Hypothesis 1 (H1) by examining how biodiversity risk is systematically priced into European stock markets. The analysis compares the traditional CAPM, Fama-French three-factor, and Carhart four-factor models, with and without the biodiversity risk factor (HLBR).

In the baseline CAPM model (column 1), the market factor (MRKTRf) is highly significant and positive, indicating market risk as a critical determinant of excess returns. Adding the HLBR factor to the CAPM model (column 2) initially shows a negative coefficient for biodiversity risk, suggesting lower returns; however, this result should be interpreted with caution as it changes with the addition of more comprehensive risk factors. As more risk factors are included, the explanatory power improves, reflected in higher Adjusted R^2 values. The Fama-French three-factor model (column 3) shows significant size (SMB) and value (HML) factors, with an Adjusted R^2 of 0.18516. Adding the HLBR factor (column 4) results in a significant positive coefficient, indicating that biodiversity risk positively influences excess returns after accounting for size and value. The Carhart four-factor model (column 5) includes the momentum factor (WML), further improving the Adjusted R^2 to 0.18541. The momentum factor is significant and positive. When the HLBR factor is included (column 6), it remains significant and positive, suggesting that higher biodiversity risk stocks command higher expected returns. The robustness of these results is confirmed by conducting the same analysis without fixed effects, as shown in Appendix Table A8, which presents similar patterns.

Overall, these results support the acceptance of **H1**: Biodiversity risk is systematically priced into European stock markets. The positive coefficient of the HLBR factor in the extended models indicates that investors recognise biodiversity risk and require a higher return for bearing it, reflecting the pricing of such risks. This aligns with previous research by Coqueret et al. (2024), Garel et al. (2023), and Giglio et al. (2023), highlighting the growing integration of biodiversity risks into stock valuations due to increased awareness and emphasis on biodiversity conservation. These findings also support theoretical models like the ESG-efficient frontier by Pedersen et al. (2021), illustrating the market's adaptation to comprehensive factors, including environmental risks, in this case, biodiversity risks.

Table 10: Panel Regressions CAPM, Fama-French 3-Factors, and Carhart 4-Factors

Note: This table shows panel regression results with fixed effects and company-level clustered standard errors. The dependent variable is excess return. The models include the traditional CAPM, Fama-French three-factor, and Carhart four-factor models, with and without the biodiversity risk factor (HLBR). 'Y' indicates the inclusion of country and industry fixed effects.

	Dependent variable:					
	ExcessReturn					
	CAPM	CAPM + HLBR	FF 3-Factors	FF 3-Factors + HLBR	Carhart 4-Factors	Carhart 4-Factors + HLBR
	(1)	(2)	(3)	(4)	(5)	(6)
MRKTRf	0.01034^{***}	0.01029^{***}	0.00921^{***}	0.00933^{***}	0.00932^{***}	0.00938^{***}
	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)
HLBR		-0.00058^{**}		0.00139^{***}		0.00135^{***}
		(0.00024)		(0.00026)		(0.00026)
SMB			0.01039^{***}	0.01054^{***}	0.01032^{***}	0.01051^{***}
			(0.00015)	(0.00016)	(0.00015)	(0.00016)
HML			0.00082^{***}	0.00057^{***}	0.00094^{***}	0.00063^{***}
			(0.00009)	(0.00010)	(0.00010)	(0.00010)
WML					0.00026^{***}	0.00012
					(0.00010)	(0.00010)
Country fixed effect	y	y	y	y	y	y
Industry fixed effect	y	y	y	y	y	y
Observations	245,460	245,460	245,460	245,460	245,460	245,460
R^2	0.17854	0.17859	0.19874	0.19899	0.19877	0.19900
Adjusted R^2	0.16462	0.16467	0.18516	0.18540	0.18518	0.18541
F Statistic	$52{,}459.61000^{***}$ (df = 1; 241368)	$26{,}239.41000^{***}$ (df = 2; 241367)	$19{,}956.13000^{***}$ (df = 3; 241366)	$14{,}990.26000^{***}$ (df = 4; 241365)	$14{,}969.53000^{***}$ (df = 4; 241365)	$11{,}992.56000^{***}$ (df = 5; 241364)
Note:						*p<0.1; **p<0.05; ***p<0.01

Following the panel regressions, the Fama-MacBeth procedure was employed to investigate the pricing of biodiversity risk further. Cross-sectional regressions with fixed effects were performed on monthly individual stock returns using the assigned beta values. The table reports the time-series mean coefficients over all months, along with their corresponding t-values and standard errors. The results, displayed in Table 11, show that the HLBR factor remains significant and positive (0.1632), reinforcing the panel regression findings. The market factor (MRKTRf), size (SMB), and momentum (WML) factors are also significant, while the value factor (HML) shows a negative coefficient (-0.3147), consistent with the panel regression results. This confirms that biodiversity risk is systematically priced in the European stock market, as indicated by the significant and positive HLBR coefficient. Additionally, Table A9 in the Appendix presents the Fama-MacBeth cross-sectional regression without fixed effects, which shows similar outcomes, further validating the robustness of the findings. Moreover, the significance of the control variables, such as Log Total Assets and Investment-to-Asset Ratio, further emphasises the robustness of the model, indicating that these factors are essential in understanding the dynamics of stock returns in the context of biodiversity risk.

Overall, the Fama-Macbeth results validate the panel regression findings and strengthen the evidence that biodiversity risk is a significant and systematic factor in European stock markets, thereby supporting **H1**.

Table 11: Fama-Macbeth results with fixed effects and Newey-West SE

Note: This table shows the Fama-Macbeth regression analysis results with industry fixed effects and Newey-West standard errors. The analysis uses monthly individual stock returns and includes risk factors: MRKTRf, SMB, HML, WML, and HLBR, along with control variables. Reported are the mean coefficients, standard errors, t-statistics, and p-values.

Term	Mean Coefficient	Std Error	t-statistic	P-value	R^2
MRKTRf	0.3289742	0.0689593	4.7705580	0.0000125	0.1827856
SMB	0.1140721	0.0297651	3.8324123	0.0003104	0.1827856
HML	-0.3147225	0.0476429	-6.6058599	0.0000000	0.1827856
WML	0.2070654	0.0535251	3.8685680	0.0002759	0.1827856
HLBR	0.1632135	0.0209665	7.7844843	0.0000000	0.1827856
Log Total Assets	0.0007934	0.0001483	5.3497979	0.0000015	0.1827856
Book-to-Market Ratio	0.0000056	0.0000033	1.7024041	0.0939434	0.1827856
Leverage Ratio	-0.0000202	0.0000168	-1.2012982	0.2344358	0.1827856
Investment-to-Asset Ratio	-0.0034161	0.0007518	-4.5437264	0.0000279	0.1827856
Log PPE	0.0000829	0.0001383	0.5993715	0.5512200	0.1827856

5.2 Results Decile Portfolio Regressions

Table 12 presents the Carhart four-factor model regression outputs applied to the biodiversity risk decile portfolios. This analysis focuses on the model without the HLBR factor. The dependent variables are the return-based decile portfolios, with the final column representing all stock returns combined.

First of all, the R-squared values range from 0.817 (RET5) to 0.892 (RET8), indicating a strong explanatory model. Significant F-statistic values (61.296 to 113.097) further confirm the model's accuracy. The market risk premium (MRKTRf) coefficients are consistently significant across all deciles, with values close to 1, indicating a robust correlation between market returns and portfolio returns. The SMB factor is also significant across all deciles, suggesting that smaller companies generally have higher returns regardless of biodiversity risk levels. Conversely, the HML factor is only significant in the first three deciles (RET1, RET2, and RET3) with high biodiversity risk, indicating the value premium is more relevant in portfolios with higher biodiversity risks. The WML factor shows no consistent significance across the deciles.

The constant terms (alphas) in the model are generally not significant across the decile portfolios. This aligns with the study by Xiong et al. (2023), which also found insignificant alphas in biodiversity risk-sorted portfolios. The lack of significant alphas suggests that, when controlling for the traditional risk factors, there is no evidence of a standalone biodiversity risk premium.

Ultimately, the results support **H1**, showing that biodiversity risk is systematically priced into European stock markets. The significant coefficients of the market risk premium and SMB factors across all deciles imply that biodiversity risk influences return on European stocks. The findings align with research by Coqueret et al. (2024), Garel et al. (2023), and Giglio et al. (2023), demonstrating that biodiversity risks are increasingly incorporated into stock valuations.

Table 12: Carhart 4-Factor regression on decile portfolios

Note: This table shows the regression outputs of the four-factor model. The dependent variables are the return-based decile portfolios, with the final variable all stock returns combined. The results are based on monthly excess returns from 2019-2023.

	Dependent variable:										
	RET1 High Biodiversity Risk	RET2	RET3	RET4	RET5	RET6	RET7	RET8	RET9	RET10 Low Biodiversity Risk	RET Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
MRKTRf	0.897***	0.933***	0.883***	0.935***	0.908***	0.977***	0.946***	0.888***	0.995***	0.956***	0.932***
	(0.087)	(0.050)	(0.076)	(0.065)	(0.072)	(0.070)	(0.072)	(0.054)	(0.069)	(0.059)	(0.058)
SMB	1.015***	0.897***	1.017***	0.853***	1.077***	1.103***	1.038***	1.149***	1.094***	1.077***	1.032***
	(0.228)	(0.206)	(0.199)	(0.220)	(0.217)	(0.254)	(0.257)	(0.188)	(0.237)	(0.273)	(0.220)
HML	0.344***	0.178*	0.245**	0.015	0.017	0.021	0.037	0.059	0.027	-0.003	0.094
	(0.123)	(0.095)	(0.112)	(0.091)	(0.126)	(0.126)	(0.142)	(0.067)	(0.104)	(0.098)	(0.102)
WML	0.165	0.062	0.008	0.053	0.004	0.015	-0.002	-0.112	0.005	0.066	0.026
	(0.104)	(0.058)	(0.092)	(0.078)	(0.093)	(0.082)	(0.078)	(0.086)	(0.073)	(0.048)	(0.066)
Constant	0.238	0.131	0.484	0.408	0.502	0.373	0.148	0.242	0.249	0.167	0.294
	(0.303)	(0.213)	(0.346)	(0.340)	(0.391)	(0.317)	(0.262)	(0.222)	(0.287)	(0.321)	(0.257)
Observations	60	60	60	60	60	60	60	60	60	60	60
R^2	0.821	0.871	0.859	0.831	0.817	0.850	0.862	0.892	0.884	0.865	0.878
Adjusted R^2	0.808	0.861	0.848	0.819	0.803	0.839	0.851	0.884	0.876	0.855	0.869
F Statistic (df = 4; 55)	63.143***	92.442***	83.491***	67.676***	61.296***	77.947***	85.541***	113.097***	104.999***	88.166***	98.747***
Note:											*p<0.1; **p<0.05; ***p<0.01

In Table 13, the augmented Carhart four-factor model with the HLBR factor provides new insights. First, the R-squared values in the extended model range from 0.846 to 0.899, and the adjusted R-squared values range from 0.820 to 0.888, indicating a strong explanatory model with a slight improvement when biodiversity risk is included. Also, significant F-statistic values confirm the model's accuracy.

The MRKTRf and SMB factors remain consistently significant across all deciles, indicating a robust correlation with market returns and higher returns for smaller companies, regardless of biodiversity risk levels. The HML factor becomes insignificant with the HLBR factor included, and the WML factor shows some significance only in the lowest biodiversity risk portfolio (RET10).

The inclusion of the HLBR factor provides notable findings regarding the pricing of biodiversity risk in stock returns. In high biodiversity risk portfolios (RET1 t/m RET5), the HLBR coefficients are positive and statistically significant, indicating that higher biodiversity risk is associated with higher returns. This aligns with the notion that investors demand higher risk-adjusted returns for assuming greater biodiversity-related risks to attract risk-tolerant investors, similar to the premium observed for ''sin stocks'' (Bolton & Kacperczyk, 2021a; 2021b). In contrast, the HLBR coefficients are negative and significant in certain low biodiversity risk portfolios (RET8 and RET10), indicating that lower biodiversity risk is associated with lower returns. This finding supports the ''equity greenium'' theory, where investors are willing to accept lower expected returns for holding ''green'' stocks (Pástor et al., 2022).

Furthermore, the regression models' constants are generally insignificant, indicating no abnormal returns and, therefore, no standalone biodiversity risk premium after accounting for the risk factors. This result aligns with Xiong et al. (2023) and suggests that interpreting the results should follow the study of Giglio et al. (2023), which propose focusing on the beta coefficient with respect to the biodiversity risk. They argue that estimating risk premia (alphas) requires a much longer time series, which is not available in this study.

In conclusion, regarding Hypothesis 2 **(H2)**: "Companies with higher exposure to biodiversity risks exhibit a higher biodiversity risk premium in their stock prices compared to those with lower exposure", the results from this study do not fully support this hypothesis. The results suggest that investors require higher returns to compensate for the increased biodiversity risk rather than a distinct premium associated solely with biodiversity risk. This aligns with the climate study by Görgen et al. (2020), which found no evidence of a risk premium associated with carbon risk but observed that "brown" firms are associated with higher returns. However, these findings do not fully align with Bolton & Kacperczyk (2021a) and Garel et al. (2023), who found a positive risk premium indicated by positive abnormal returns.

Table 13: Carhart 4-Factor Regression Model including HLBR on decile portfolios

Note: This table shows the regression outputs of the Fama-French three-factor model with the additional HLBR factor. The dependent variables are the return-based decile portfolios, with the final variable all stock returns combined. The results are based on monthly excess returns from 2019-2023.

	Dependent variable:										
	RET1 High Biodiversity Risk	RET2	RET3	RET4	RET5	RET6	RET7	RET8	RET9	RET10 Low Biodiversity Risk	RET Total
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
MRKTRf	0.932***	0.946***	0.913***	0.955***	0.933***	0.970***	0.934***	0.872***	0.983***	0.938***	0.938***
	(0.074)	(0.049)	(0.063)	(0.059)	(0.059)	(0.069)	(0.069)	(0.059)	(0.067)	(0.056)	(0.057)
SMB	1.129***	0.940***	1.117***	0.920***	1.161***	1.081***	0.998***	1.096***	1.053***	1.016***	1.051***
	(0.245)	(0.228)	(0.213)	(0.241)	(0.238)	(0.262)	(0.259)	(0.182)	(0.241)	(0.253)	(0.231)
HML	0.157	0.108	0.082	-0.093	-0.119	0.058	0.103	0.145	0.093	0.096	0.063
	(0.129)	(0.099)	(0.110)	(0.107)	(0.142)	(0.141)	(0.162)	(0.090)	(0.122)	(0.121)	(0.118)
WML	0.079	0.029	-0.068	0.003	-0.059	0.032	0.028	-0.072	0.036	0.111**	0.012
	(0.098)	(0.053)	(0.082)	(0.080)	(0.093)	(0.071)	(0.076)	(0.086)	(0.071)	(0.044)	(0.063)
HLBR	0.817***	0.311*	0.714***	0.473*	0.594*	-0.160	-0.288	-0.379*	-0.291	-0.434**	0.135
	(0.223)	(0.177)	(0.200)	(0.273)	(0.349)	(0.251)	(0.213)	(0.209)	(0.204)	(0.192)	(0.219)
Constant	0.208	0.119	0.457	0.390	0.480	0.379	0.159	0.256	0.259	0.184	0.289
	(0.246)	(0.191)	(0.297)	(0.313)	(0.360)	(0.311)	(0.237)	(0.208)	(0.281)	(0.309)	(0.258)
Observations	60	60	60	60	60	60	60	60	60	60	60
R^2	0.859	0.876	0.887	0.844	0.835	0.851	0.866	0.899	0.888	0.875	0.879
Adjusted R^2	0.846	0.865	0.876	0.829	0.820	0.838	0.853	0.890	0.878	0.863	0.868
F Statistic (df = 5; 54)	65.731***	76.305***	84.711***	58.298***	54.645***	61.816***	69.669***	96.220***	85.854***	75.568***	78.284***

Note: *p<0.1; **p<0.05; ***p<0.01

5.3 Results Industry and Quantile Portfolio Regressions

In Table 14, the Carhart four-factor regression model with the HLBR factor is applied to industry portfolios, revealing how biodiversity risk impacts returns across industries. Table A16 in the Appendix provides detailed industry-specific biodiversity scores, including physical and transition risks, with scores ranging from 0 to 5, representing very low to very high risk. These scores enable comparison with the outcomes of the regression model. The R-squared values range from 0.564 to 0.876, indicating varying explanatory power across industries. The MRKTRf and SMB factors remain again consistently significant, while the HML factor is generally insignificant, and the WML factor shows inconsistent significance.

Significant positive HLBR coefficients are observed in several high-risk industries. For instance, the Textiles, Apparel & Luxury Goods sector (HLBR coefficient 0.008, $p<0.01$) and the Oil, Gas & Consumable Fuels sector (HLBR coefficient 0.009, $p<0.05$) have both high physical and transition risks. These findings indicate that the biodiversity risks, where these industries specifically have a high dependency and a high impact on biodiversity loss, result in a substantial negative impact on these industries and are therefore compensated with higher stock returns. This is consistent with expectations, as most of them can be characterised as industries with high biodiversity risks and aligns with the results of Görgen et al. (2020). However, there are also industries with a relatively low to moderate dependency and impact on biodiversity loss that show significant positive HLBR coefficients. For example, despite having lower biodiversity risks, the General or Specialty Retailing and Food Retailing sectors still exhibit significant positive HLBR factors. This suggests that even industries with relatively lower biodiversity risks can show significant positive returns due to the HLBR factor, indicating a more complex relationship between biodiversity risks and stock returns within this model.

In addition to the significant HLBR coefficients, the Paper & Forest Product Production and Construction Materials industries, both with relatively high physical and transition risks, show abnormal returns beyond what is explained by traditional risk factors and the HLBR factor. On one hand, this aligns with the findings of Coqueret et al. (2024), who also found significant alphas in sectors most exposed to the double materiality of biodiversity risks. On the other hand, there are many industries with high biodiversity risk levels that do not experience abnormal returns, and therefore, do not have a biodiversity risk premium.

The findings indicate that biodiversity risk significantly Influences returns in high-risk industries, supporting the notion that investors demand higher returns to compensate for these risks. While the results partly support Hypothesis 3 (**H3**) by showing a pronounced biodiversity risk premium in some high-risk industries, the lack of abnormal returns in many other high-risk industries suggests a nuanced relationship between biodiversity risk and financial performance. Although the results support the systematic pricing of biodiversity risk (**H1**), the variability in HLBR coefficients and the significance of alphas indicate that the biodiversity risk premium is not uniformly distributed across all industries. These heterogeneous effects across industries are consistent with the findings of Xin et al. (2023).

Next, Table 16 extends the Carhart four-factor regression model by applying it to quantile portfolios within industries, categorizing them by biodiversity risk. This further analysis delves into how biodiversity risk influences stock returns across different risk levels within industries. Notably, the output table focuses on the HLBR factor and any abnormal returns (alphas), omitting the traditional risk factors (MRKTRf, SMB, HML, WML) for clarity. The quantile portfolios show highly mixed results, but a small pattern emerges. Most first quantiles (highest biodiversity risk) often have significant positive HLBR loadings; Figure 15 effectively illustrates this trend, showing the distribution of HLBR coefficients across different portfolios and industries. The figure highlights that the highest biodiversity risk portfolios generally exhibit positive coefficients, with a large and clear difference compared to the other quantiles.

Table 14: Carhart 4-Factor Regression Model including the HLBR factor on industry portfolios

Industry Portfolios - Carhart 4-Factor Model Regressions

Dependent variable:

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
MRKTRf	0.009***	0.009***	0.011***	0.008***	0.009***	0.010***	0.009***	0.010***	0.009***	0.009***	0.008***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SMB	0.004	0.008***	0.010***	0.006***	0.012***	0.011***	0.010***	0.013***	0.009***	0.012***	0.011***	0.013***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
HML	-0.002	0.003**	0.0002	0.001	-0.001	0.005***	0.001	0.002	0.001	0.003*	-0.002	0.001
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
WML	0.001	-0.002	-0.001	0.002	-0.001	0.0002	0.0001	0.0003	0.001	-0.002	0.0004	-0.0005
	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
HLBR	0.002	0.002	0.008***	-0.003	0.010***	0.009***	-0.001	0.007**	0.001	0.005*	-0.002	-0.003
	(0.004)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Constant	-0.003	0.003	0.004	-0.002	0.006*	-0.002	0.003	0.003	-0.0002	0.002	0.001	0.005
	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.003)	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)
Observations	60	60	60	60	60	60	60	60	60	60	60	60
R^2	0.564	0.853	0.840	0.760	0.840	0.795	0.876	0.791	0.854	0.826	0.817	0.841
Adjusted R^2	0.523	0.839	0.825	0.737	0.825	0.776	0.864	0.771	0.841	0.810	0.800	0.827
Residual Std. Error (df = 54)	0.042	0.027	0.030	0.029	0.026	0.034	0.023	0.034	0.024	0.030	0.027	0.032
F Statistic (df = 5; 54)	13.945***	62.509***	56.737***	34.144***	56.552***	41.803***	76.233***	40.777***	63.364***	51.359***	48.126***	57.253***

	P13	P14	P15	P16	P17	P18	P19	P20	P21	P22	P23	P24
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
MRKTRf	0.007***	0.007***	0.009***	0.011***	0.012***	0.010***	0.010***	0.008***	0.010***	0.011***	0.008***	0.007***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
SMB	0.005**	0.008***	0.010*	0.012***	0.018***	0.009***	0.014***	0.012***	0.011***	0.011***	0.015***	0.008***
	(0.002)	(0.002)	(0.005)	(0.002)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
HML	-0.004**	-0.001	-0.003	-0.001	-0.005*	-0.002	0.001	-0.002*	0.0003	0.0004	-0.0001	0.003*
	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
WML	-0.001	0.0002	-0.001	0.001	-0.0003	0.001	0.0003	0.0001	-0.001	0.001	0.001	0.004**
	(0.002)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
HLBR	0.007***	0.005**	0.002	-0.002	0.011**	0.007***	0.009***	0.001	0.002	0.001	0.015***	0.001
	(0.003)	(0.002)	(0.006)	(0.002)	(0.005)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)
Constant	0.003	0.001	-0.012	0.004	0.008	0.006	0.008*	0.002	0.005	0.006	0.004	-0.002
	(0.004)	(0.003)	(0.010)	(0.003)	(0.008)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)
Observations	60	60	60	60	60	60	60	60	60	60	60	60
R^2	0.671	0.795	0.433	0.885	0.652	0.807	0.858	0.808	0.873	0.874	0.616	0.690
Adjusted R^2	0.640	0.776	0.381	0.874	0.620	0.789	0.845	0.790	0.861	0.862	0.580	0.661
Residual Std. Error (df = 54)	0.030	0.024	0.072	0.026	0.058	0.028	0.028	0.028	0.026	0.027	0.043	0.029
F Statistic (df = 5; 54)	21.996***	41.953***	8.255***	82.963***	20.250***	45.135***	65.282***	45.308***	74.382***	74.642***	17.317***	24.035***

Note: *p<0.1; **p<0.05; ***p<0.01

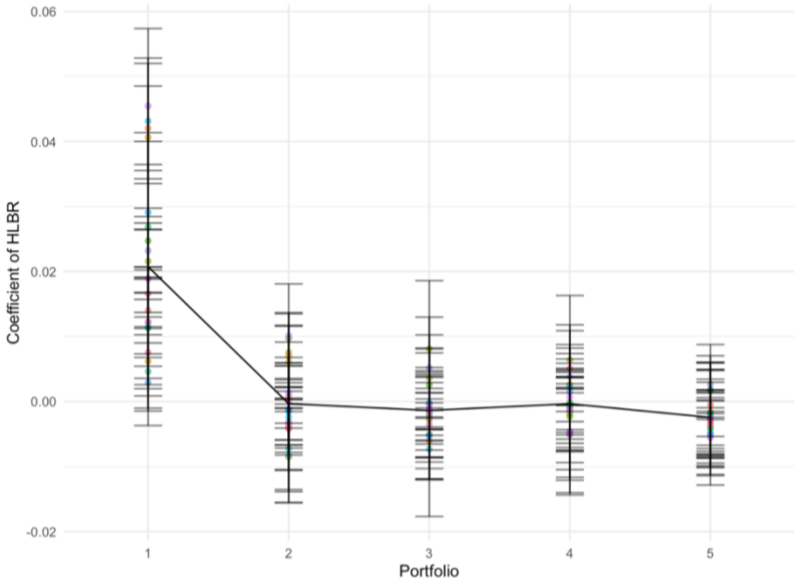
This table shows the Carhart 4-Factor regression results, including the HLBR factor, for 24 industry portfolios. The dependent variable is the average monthly excess return per industry. The industry portfolios are listed at the bottom of the table, ranging from Water Utilities/Service Providers (P1) to Agriculture (plant products) (P24). Country and industry fixed effects are included.

P1 - Water utilities /Service Providers
P2 - Transportation Services
P3 - Textiles, Apparel & Luxury Good Production
P4 - Telecommunication services
P5 - Paper & Forest Product Production
P6 - Oil, Gas & Consumable Fuels
P7 - Offices & Professional Services
P8 - Metals & Mining
P9 - Land Development & Construction
P10 - Hospitality Services
P11 - Health Care, Pharmaceuticals and Biotechnology
P12 - General or Speciality Retailing
P13 - Food Retailing
P14 - Food & Beverage Production
P15 - Fishing and aquaculture
P16 - Electronics & Semiconductor Manufacturing
P17 - Electric Energy Production - Solar, Wind
P18 - Electric Energy Production - Combustion
P19 - Construction Materials
P20 - Chemicals & Other Materials Production
P21 - Automotive, Electrical Equip. & Machinery Prod.
P22 - Appliances & General Goods Manufacturing
P23 - Agriculture (animal products)
P24 - Agriculture (plant products)

Additionally, when the HLBR factor is significant in the fifth quantile (lowest biodiversity risk), it nearly always tends to be negative. The results of quantiles 2, 3, and 4 are mixed and vary widely, indicating that moderate levels of biodiversity risk have less consistent impacts on returns. The diversity of significant HLBR coefficients in these middle quantiles suggests that the biodiversity risk-return relationship is less clear compared to the more pronounced trends observed at the extremes (highest and lowest risk levels). This pattern is well illustrated in the Offices & Professional Services sector. The first quantile exhibits a significant positive HLBR coefficient, indicating higher returns for higher biodiversity risks. Interestingly, the fifth quantile shows a significant negative HLBR coefficient, indicating that lower biodiversity risks are associated with lower returns, which aligns with the findings from Görgen et al. (2020). Additionally, the first quantile in this industry shows a significant positive alpha, suggesting abnormal returns beyond what is explained by the risk factors, further emphasising the higher compensation required for higher biodiversity risks.

Figure 15: Coefficients of HLBR Factor by Portfolio and Industry

Note: This figure shows the coefficients of the HLBR factor for quantile portfolios ranked by biodiversity risk, from Portfolio 1 (high biodiversity risk) to Portfolio 5 (low biodiversity risk) for each industry.



However, this trend is not as evident in other industries. In the Oil, Gas & Consumable Fuels sector, the first and fourth quantiles have significant positive HLBR coefficients but no significant alphas, suggesting higher returns for higher biodiversity risks without abnormal returns. Agriculture (plant products) shows no significant HLBR coefficients or alphas, indicating no clear impact of biodiversity risks on returns. In contrast, the Textiles, Apparel, and luxury Goods industry shows the opposite pattern, with a significant negative HLBR coefficient in the first quantile, indicating that higher biodiversity risk is associated with lower returns, and a positive HLBR coefficient in the third, fourth, and fifth quantiles.

In summary, these mixed results highlight the complex and varied impacts of biodiversity risks across different sectors. **H1** is supported by the presence of significant HLBR coefficients, and **H2** receives partial support, as higher biodiversity risk often correlates with higher returns in some sectors but not uniformly across all. **H3** suggests a pronounced biodiversity risk premium in high-risk industries; however, the inconsistency in significant results across different sectors and quantiles raises questions about the reliability and generalizability of this premium. Consequently, this hypothesis cannot be accepted.

Table 16: Carhart 4-Factor Regression Model including HLBR on quantile portfolios

Note: This table presents the Carhart four-factor regression model with HLBR on quantile portfolios, showing HLBR coefficients and alphas by industry. Portfolio 1 has the highest biodiversity risk, Portfolio 5 the lowest. Traditional risk factors are included but omitted here for clarity. The results are based on average excess returns from 2019-2023 and use clustered standard errors.

		High Biodiversity Risk				Low Biodiversity Risk
Industry	Variable	Portfolio 1	Portfolio 2	Portfolio 3	Portfolio 4	Portfolio 5
Transportation Services	HLBR	0.014***	0.001	-0.002	-0.0003	-0.0005
		(0.003)	(0.002)	(0.005)	(0.005)	(0.001)
	Alpha	0.009***	0.002	0.001	0.001	0.0001
		(0.003)	(0.002)	(0.005)	(0.007)	(0.004)
Textiles, Apparel & Luxury Good Production	HLBR	-0.042***	-0.007***	0.006***	0.001***	0.004***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Alpha	0.021**	0.009	-0.0002	-0.008*	-0.005
		(0.010)	(0.006)	(0.005)	(0.005)	(0.006)
Telecommunication Services	HLBR	0.006**	-0.009**	-0.005	-0.001	-0.002
		(0.003)	(0.004)	(0.004)	(0.002)	(0.003)
	Alpha	0.004***	-0.005	-0.003	0.006*	-0.008
		(0.002)	(0.007)	(0.004)	(0.003)	(0.005)
Paper & Forest Product Production	HLBR	0.041***	0.006**	0.004	0.003	-0.003
		(0.006)	(0.003)	(0.002)	(0.002)	(0.002)
	Alpha	0.012	0.003	0.005	0.004*	0.007
		(0.015)	(0.003)	(0.004)	(0.002)	(0.005)
Oil, Gas & Consumable Fuels	HLBR	0.022***	0.008***	0.008	0.006***	0.002
		(0.003)	(0.002)	(0.005)	(0.002)	(0.004)
	Alpha	-0.007	-0.003	-0.005	0.002	0.002
		(0.006)	(0.004)	(0.005)	(0.005)	(0.004)
Offices & Professional Services	HLBR	0.012***	-0.004**	-0.003*	-0.002	-0.005**
		(0.004)	(0.002)	(0.002)	(0.003)	(0.002)
	Alpha	0.009*	0.0002	0.005	0.002	0.001
		(0.005)	(0.001)	(0.003)	(0.003)	(0.005)
Metals & Mining	HLBR	0.025***	0.010***	0.003	-0.002	-0.002
		(0.006)	(0.002)	(0.004)	(0.003)	(0.003)
	Alpha	0.008	0.008*	-0.004	0.004	0.001
		(0.009)	(0.005)	(0.006)	(0.008)	(0.005)
Land Development & Construction	HLBR	0.011**	-0.001	-0.0003	-0.0001	-0.004*
		(0.005)	(0.002)	(0.002)	(0.003)	(0.002)
	Alpha	0.008**	-0.003	0.001	-0.003	-0.005**
		(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Hospitality Services	HLBR	0.027***	-0.003*	-0.002	-0.001	0.002
		(0.007)	(0.002)	(0.004)	(0.004)	(0.002
	Alpha	0.013	-0.002	0.0004	0.002	-0.002
		(0.008)	(0.002)	(0.004)	(0.003)	(0.003)
Health Care, Pharmaceuticals and Biotechnology	HLBR	0.005	-0.007**	-0.002	-0.005	-0.002
		(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
	Alpha	0.001	0.002	0.007**	-0.001	-0.003
		(0.001)	(0.002)	(0.003)	(0.005)	(0.006)
General or Speciality Retailing	HLBR	0.011**	-0.008**	-0.007***	-0.005	-0.005*
		(0.005)	(0.004)	(0.002)	(0.005)	(0.003)
	Alpha	0.012	0.007	-0.001	0.006	0.002
		(0.008)	(0.005)	(0.004)	(0.010)	(0.004)
Food Retailing	HLBR	0.043***	-0.002	-0.005	0.002	-0.003
		(0.005)	(0.006)	(0.006)	(0.007)	(0.003)

	Alpha	0.002	0.003	0.004	0.007	-0.001
		(0.007)	(0.007)	(0.005)	(0.008)	(0.007)
Food & Beverage Production	HLBR	0.029***	-0.002	-0.0002	-0.001	-0.003
		(0.006)	(0.002)	(0.002)	(0.002)	(0.003)
	Alpha	0.010	-0.002	0.001	-0.002	0.0001
		(0.007)	(0.002)	(0.002)	(0.003)	(0.004)
Electronics & Semiconductor Manufacturing	HLBR	0.003	-0.001	-0.005***	0.002	-0.005
		(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
	Alpha	0.002	0.003	0.0005	0.003	0.005
		(0.003)	(0.004)	(0.001)	(0.003)	(0.007)
Electric Energy Production – Combustion	HLBR	0.023***	0.001	0.005	0.004*	0.003
		(0.003)	(0.002)	(0.004)	(0.002)	(0.002)
	Alpha	0.010	0.003	0.004	0.008	0.006
		(0.007)	(0.004)	(0.009)	(0.006)	(0.007)
Construction Materials	HLBR	0.045***	0.010**	-0.0005	-0.005	-0.006*
		(0.006)	(0.004)	(0.002)	(0.003)	(0.003)
	Alpha	0.018	0.005	0.009*	0.006	-0.0005
		(0.012)	(0.007)	(0.005)	(0.004)	(0.004)
Chemicals & Other Materials Production	HLBR	0.012***	-0.004	-0.001	0.001	-0.003
		(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
	Alpha	0.009	0.001	0.001	-0.001	-0.001
		(0.008)	(0.004)	(0.005)	(0.004)	(0.008)
Automotive, Electrical Equipment & Machinery	HLBR	0.019***	0.00003	-0.001	-0.005	-0.003
		(0.004)	(0.003)	(0.003)	(0.004)	(0.002)
	Alpha	0.013***	0.004	0.004	0.001	0.001
		(0.004)	(0.004)	(0.003)	(0.005)	(0.003)
Appliances & General Goods Manufacturing	HLBR	0.017***	-0.003	-0.004	-0.001	-0.003
		(0.005)	(0.003)	(0.003)	(0.003)	(0.002)
	Alpha	0.009	0.005	0.007**	0.004	0.003
		(0.007)	(0.003)	(0.003)	(0.003)	(0.004)
Agriculture (plant products)	HLBR	0.008	-0.004	-0.002	0.005	-0.003
		(0.006)	(0.003)	(0.002)	(0.003)	(0.005)
	Alpha	-0.0004	0.001	-0.006	-0.001	-0.003
		(0.005)	(0.007)	(0.006)	(0.005)	(0.011)

5.4 Results Difference-in-Difference Model Regressions

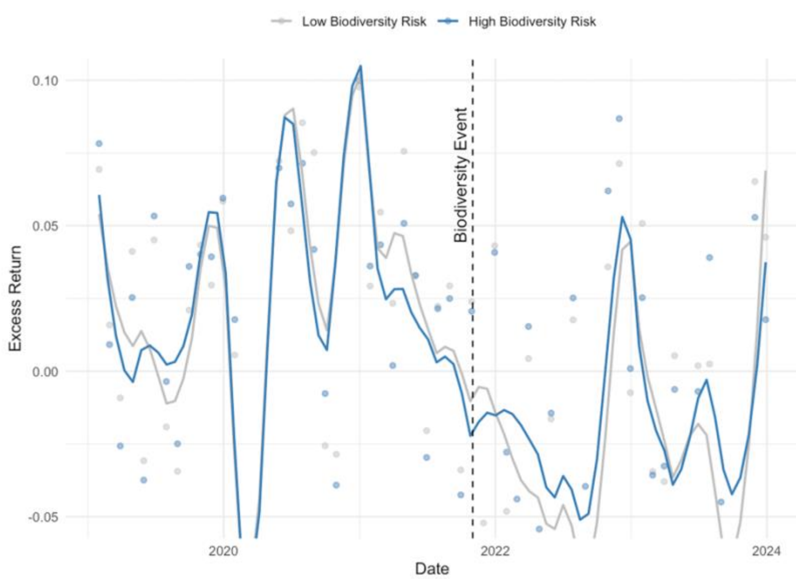
Table and Figures 17 and 18 present the Difference-in-Differences (DID) estimation results for the Kunming-Montreal Declaration and the Taskforce on Nature-related Financial Disclosures (TNFD), respectively, using clustered standard errors and fixed effects. The interaction term (Treatment * Time) in both models shows a positive and highly significant coefficient (0.010 and 0.008, $p<0.01$), indicating that these biodiversity-related policies have significantly increased the excess returns for companies at greater risk of biodiversity loss. This suggests that investors demand higher returns for holding stocks exposed to higher biodiversity risks following these policy changes, aligning with Garel et al. (2023) and Xiong et al. (2023). The including and excluding fixed effects does not significantly alter the outcomes, further supporting the findings.

Additionally, the positive coefficient for the HLBR factor (0.001 for Kunming-Montreal and 0.002 for TNFD, $p<0.01$) reinforces the idea that higher biodiversity risk is associated with higher returns, consistent with Garel et al. (2023). The graphs in Figures 17 and 18 visually support these findings, showing that companies with high biodiversity risks experienced a marked increase in excess returns compared to those with low biodiversity risks after the policy changes. Moreover, the significant negative coefficient for the time variable in the TNFD model (-0.010, $p<0.01$) indicates a general decline in excess returns over time, which could reflect broader market trends or the impact of other concurrent factors affecting the market during this period.

Table and Figure 17: DID results – Kunming Montreal Declaration

Note: This table and figure present the DID estimation results for the Kunming Montreal Declaration. The dependent variable is the monthly excess return of individual companies regressed on the risk factors and control variables. Country and industry fixed effects are included in model (2). The figure illustrates the divergence in excess returns between high and low biodiversity risk portfolios following the biodiversity event, with the dashed line representing the Kunming Declaration in October 2021.

	Dependent variable:	
	Excess Return	
	(1)	(2)
Time	-0.005***	-0.005***
	(0.001)	(0.001)
Interaction (Treatment * Time)	0.010***	0.010***
	(0.001)	(0.001)
MRKTRf	0.009***	0.009***
	(0.0001)	(0.0001)
SMB	0.010***	0.010***
	(0.0002)	(0.0002)
HML	0.001***	0.001***
	(0.0001)	(0.0001)
WML	0.00000	0.00000
	(0.0001)	(0.0001)
HLBR	0.001***	0.001***
	(0.0003)	(0.0003)
LOG Total Assets	-0.015***	-0.015***
	(0.001)	(0.001)
BM-Ratio	-0.00000***	-0.00000***
	(0.00000)	(0.00000)
Leverage Ratio	-0.00000	-0.00000
	(0.00000)	(0.00000)
Investments/Total Assets Ratio	-0.008	-0.008
	(0.005)	(0.005)
LOG PPE	-0.001	-0.001
	(0.0005)	(0.0005)
Country fixed effect	N	Y
Industry fixed effect	N	Y
Observations	245,460	245,460
R^2	0.201	0.201
Adjusted R^2	0.188	0.188
Note:	*p<0.1; **p<0.05; ***p<0.01	

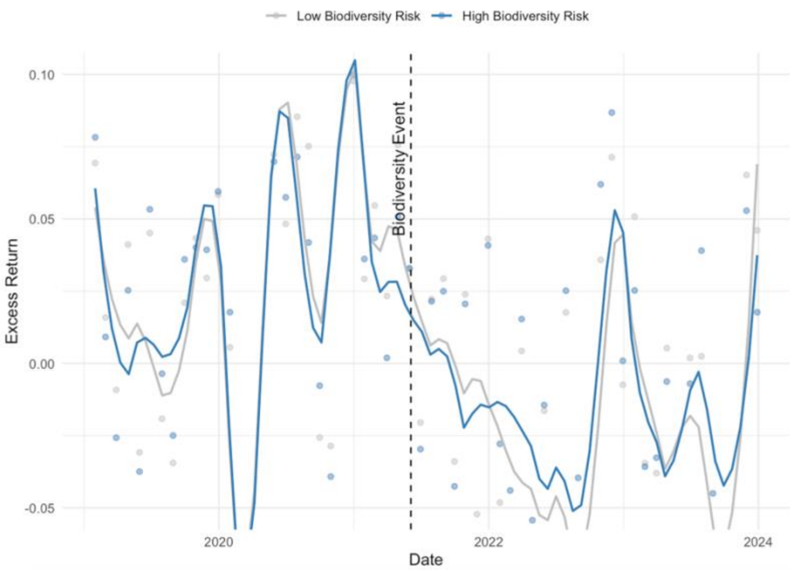


In the Appendix, various models are included to ensure robustness. Tables A18 and A21 replicate the main DID regressions without clustered standard errors, with the interaction term remaining positive and significant, confirming the robustness of the results. Furthermore, Tables A19 and A22 present the results of placebo treatment effect tests, where random groups were utilised in place of the actual treatment group. The insignificance of the placebo treatment effects suggests that the significant results observed in the primary models are not attributable to random chance but are likely due to the genuine biodiversity-related events. Lastly, Figures A20 and A23 validate the parallel trends assumption. The pre-treatment trends for both treatment and control groups are parallel, supporting the validity of the DID approach. The divergence in trends post-treatment can be attributed to the biodiversity events, as no other concurrent changes affect only the treatment group. This validation increases confidence that the observed post-treatment changes in excess returns are indeed due to the biodiversity policies and not pre-existing differences between the groups.

Table and Figure 18: DID results – TNFD

Note: This table and figure present the DID estimation results for the TNFD launch. The dependent variable is the monthly excess return of individual companies regressed on the risk factors and control variables. Country and industry fixed effects are included in model (2). The figure illustrates the divergence in excess returns between high and low biodiversity risk portfolios following the biodiversity event, with the dashed line representing the TNFD launch in June 2021

	Dependent variable:	
	Excess Return	
	(1)	(2)
Time	-0.010***	-0.010***
	(0.001)	(0.001)
Interaction (Treatment * Time)	0.008***	0.008***
	(0.001)	(0.001)
MRKTRf	0.009***	0.009***
	(0.0001)	(0.0001)
SMB	0.010***	0.010***
	(0.0002)	(0.0002)
HML	0.001***	0.001***
	(0.0001)	(0.0001)
WML	-0.0001	-0.0001
	(0.0001)	(0.0001)
HLBR	0.002***	0.002***
	(0.0003)	(0.0003)
LOG Total Assets	-0.012***	-0.012***
	(0.001)	(0.001)
BM-Ratio	-0.00000***	-0.00000***
	(0.00000)	(0.00000)
Leverage Ratio	-0.00000	-0.00000
	(0.00000)	(0.00000)
Investments/Total Assets Ratio	-0.009*	-0.009*
	(0.005)	(0.005)
LOG PPE	-0.001*	-0.001*
	(0.0005)	(0.0005)
Country fixed effect	N	Y
Industry fixed effect	N	Y
Observations	245,460	245,460
R^2	0.202	0.202
Adjusted R^2	0.188	0.188
Note:	*p<0.1; **p<0.05; ***p<0.01	



Overall, these findings support Hypothesis 4 **(H4)**, demonstrating that biodiversity-related policies significantly affect the returns of companies at higher risk of biodiversity loss. This is evident in both figures, where portfolios with the highest biodiversity risk exhibit greater excess returns than those with lower biodiversity risk following the policy events. These results underscore the substantial influence of regulatory changes on market behaviour, aligning with the anticipated impact of increased biodiversity risk on returns.

6. DISCUSSION AND CONCLUSION

Biodiversity loss represents a substantial and alarming threat to the ecological health and stability of our planet. This decline in biodiversity profoundly impacts ecosystems by disrupting processes such as pollination, water purification, and soil fertility, reducing resilience to environmental changes, and diminishing essential ecosystem services. As companies' dependence on ecosystem services and their impact on biodiversity loss grows, these biodiversity risks increasingly influence their financial assets. Despite this, there is still insufficient attention given to biodiversity risks and their implications for financial markets. To address this gap and contribute to the biodiversity finance literature, this study explores whether investors account for biodiversity risks in the European stock market and how their awareness changes following biodiversity-related policy changes.

Building on the mature research by Pedersen et al. (2021), which incorporated environmental risks into traditional asset pricing models, this study adds biodiversity risk metrics to the Carhart four-factor model by creating a new high-minus-low biodiversity risk (HLBR) factor. Integrating this HLBR factor into different asset pricing models reveals that biodiversity risks are acknowledged in the European market. Panel regressions for individual companies display a positive HLBR coefficient, demonstrating that investors demand higher returns for biodiversity-related risks. These findings align with the research of Coqueret et al. (2024) and Giglio et al. (2023), emphasising the increasing incorporation of biodiversity risks into stock valuations. The Fama-Macbeth analysis further supports the HLBR factor as a systematic risk factor within the European market.

When examining decile portfolios sorted by biodiversity risk, adding the HLBR factor significantly improves the model's explanatory power. The highest biodiversity risk portfolios exhibit significantly positive HLBR coefficients, indicating that investors demand higher returns for these risks, similar to the returns required for "sin stocks", as noted by Bolton & Kacperczyk (2021a; 2021b). Conversely, the lowest biodiversity risk portfolios display negative HLBR coefficients, aligning with the "equity greenium" theory, where investors are content with lower returns for holding "green" stocks (Pástor et al., 2022).

Industry-specific portfolios predominantly feature significant positive HLBR coefficients in high-risk sectors, while also showing positive estimates in some lower-risk industries, indicating a diverse impact of biodiversity risks across sectors. Quantile portfolio analysis further reveals that portfolios with the highest biodiversity risk typically exhibit positive coefficients, distinguishing them from other quantiles. However, the effects vary significantly across industries in terms of abnormal returns, suggesting that high biodiversity dependency and impact do not consistently lead to a more pronounced biodiversity risk premium.

Finally, the Difference-in-Difference model regressions reveal that following the Kunming Declaration and TNFD launch, investors demand higher returns for high biodiversity risk stocks. This aligns with Garel et al. (2023), who observed increased returns for stocks impacting biodiversity post-policy events. This pattern underscores market sensitivity to biodiversity policies, reflecting investor awareness and valuation adjustments in response to the Kunming Declaration's strategy to mitigate biodiversity loss through financial flows by 2030 and the TNFD's initiative to report and act on evolving nature-related risks.

These findings underscore significant implications for companies, investors and policymakers, emphasising the need for increased attention. Companies should thoroughly evaluate their dependency and impact on biodiversity, understanding how these factors affect their financial performance. Furthermore, they should integrate biodiversity risks into their standard risk management frameworks to build internal accountability and facilitate transparent disclosure of their actions. Investors should integrate biodiversity risks into their investment strategies, recognising the potential for higher returns associated with high biodiversity risk companies, especially after relevant policy changes. Evaluating the biodiversity footprint of firms can help investors avoid stranded assets and seize financial opportunities from companies with strong biodiversity practices. Policymakers should incorporate biodiversity considerations into regulatory frameworks to mitigate financial risks and promote biodiversity conservation. By doing so, they can stabilise financial markets and encourage nature-positive business practices.

The limitations of this study, consistent with other research in biodiversity finance, include several issues in data collection and biodiversity risk metrics. Firstly, a short time horizon was selected due to the lack of reliable, long-term biodiversity data, limiting the availability of time-series data. Therefore, the HLBR factor was constructed using time-invariant biodiversity risk levels, with equal-weighted long-short portfolios and without annual rebalancing, introducing additional limitations. Consequently, the current biodiversity data lacks high quality, with ongoing research still in its early stages, affecting the reliability of biodiversity risk measurements. Moreover, estimating future trends in biodiversity loss and its consequent effects on ecosystems involves considerable uncertainty. In measuring company-level biodiversity risks, this study adjusts industry-level scores based on the geographic location of operations using a geographical revenue-based weighting method. Despite its use in the WWF biodiversity risk filter method, this approach is imprecise as revenue location does not always reflect operational location and neglects supply chain activities. Lastly, the internal validity of this research could be optimised, as the adjusted R-squared values of the panel regressions indicate that most of the variance in excess returns is unexplained, suggesting that other variables influencing stock returns were not included.

These limitations provide an opportunity for further academic research. Future studies should aim to develop more accurate measures of company-specific biodiversity risks, incorporating supply chain considerations and extending the data's time horizon. With the availability of long-term biodiversity data, it will be possible to annually rebalance the biodiversity risk factor to reflect updated risk levels, improving the ability to estimate risk premia, which requires much longer time series. Consequently, improved precision in these measures will clarify the relationship between biodiversity loss and industry-specific pricing dynamics, a connection that was not clearly established in this study.

In conclusion, this study addresses the research question, "How is biodiversity risk reflected in the pricing of European stock markets, and to what extent do biodiversity-related policies influence this risk premium?". It finds that biodiversity risk is increasingly systematically reflected in stock pricing, as investors demand higher returns for high-risk stocks, particularly following relevant biodiversity-related policies. This integration of biodiversity risk into financial models indicates a broader shift in the European economy towards acknowledging and mitigating nature-related risks. As investors become more aware of biodiversity loss, they direct capital towards practices supporting biodiversity conservation. By valuing biodiversity in financial terms, the European economy can align with the urgent need to protect and restore ecosystems, striving towards a nature-positive future.

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8. APPENDIX

Table A1: WWF Biodiversity Risk industry sectors (WWF, 2023)

WWF Risk Filter Industry Sector	Associated Business Processes
Agriculture (animal products)	Large-scale livestock (beef and dairy)
	Small-scale livestock (beef and dairy)
Agriculture (plant products)	Large-scale irrigated arable crops
	Large-scale rainfed arable crops
	Small-scale irrigated arable crops
	Small-scale rainfed arable crops
Appliances and general goods manufacturing	Manufacture of machinery, parts and equipment
	Houseware and specialties production
Automotive, electrical equipment and machinery production	Manufacture of machinery, parts and equipment
	Tire and rubber production
Chemicals and other materials production	Catalytic cracking, fractional distillation, and crystallization
	Incomplete combustion
	Polymerization
	Vulcanization
	Synthetic fertiliser production
	Cryogenic air separation
	Gas adsorption
	Membrane technology
	Natural gas combustion
	Recovery and separation of carbon dioxide
	Solids processing
Construction materials	Glass making
	Construction materials production
Electric energy production – combustion (biomass, coal, gas, nuclear, oil), geothermal energy	Infrastructure holdings
	Electric/nuclear power transmission and distribution
	Nuclear and thermal power stations
	Biomass energy production
	Geothermal energy production
Electric energy production – hydropower	Infrastructure holdings
	Hydropower production
	Electric/nuclear power transmission and distribution
Electric energy production – solar, wind	Infrastructure holdings
	Solar energy provision
	Wind energy provision
	Electric/nuclear power transmission and distribution
	Electronics and hardware production

Electronics and semiconductor manufacturing	Manufacture of semiconductor equipment
Fishing and aquaculture	Aquaculture
	Freshwater wild-caught fish
	Saltwater wild-caught fish
Food and beverage production	Alcoholic fermentation and distilling
	Processed food and drink production
Food retailing	Infrastructure holdings
General or specialty retailing	Infrastructure holdings
Health care, pharmaceuticals, and biotechnology	Infrastructure holdings
	Life science, pharma and biotech manufacture
	Life science, pharma and biotech tools and services
	Provision of health care
	Managed health care
Hospitality services	Cruise line provision
	Hotels and resorts provision
	Restaurant provision
Land development and construction	Construction
	Infrastructure builds
Metals and mining	Alumina refining
	Mining
	Iron extraction
	Iron metal production
	Metal processing
	Steel production
Offices and professional services	Infrastructure maintenance contracts
	Infrastructure holdings
	Financial services
	Leisure facility provision
	Real estate activities
	Environmental and facilities services
Oil, gas and consumable fuels	Mining
	Oil and gas drilling
	Manufacture of machinery, parts and equipment
	Oil and gas services
	Oil and gas exploration surveys
	Oil and gas refining
	Oil and gas storage
	Oil and gas transportation
	Gas distribution
	Gas retail
	Large-scale forestry

Paper and forest product production	Production of forest and wood-based products
	Small-scale forestry
	Paper packaging production
	Production of paper products
Telecommunication services (including wireless)	Cable and satellite installations on land
	Fiber-optic cable installation (marine)
	Telecommunication and wireless services
Textiles, apparel, and luxury good production	Jewelry production
	Natural fiber production
	Synthetic fiber production
	Footwear production
	Production of leisure or personal products
	Tobacco production
Transportation services	Infrastructure maintenance contracts
	Distribution
	Airport services
	Marine transportation
	Marine ports and services
	Railway transportation
	Construction
Water utilities and water service providers	Water services (wastewater, treatment, and distribution)

Table A2: WWF biodiversity risk assessment framework (WWF, 2023)

Type of risk	Risk category	Risk indicator	Metrics	Dependency / Impact
Physical Risk	Provisioning Services	Water Scarcity	Water Scarcity	Dependency
		Forest Productivity and Distance to Markets	Realizable Hard and Soft Commercial Timber	
		Limited Wild Flora & Fauna Availability	Global Centers of Unsustainable Commercial Harvesting of Species	
		Limited Marine Fish Availability	Stock Status	
	Regulating & Supporting Services – Enabling	Soil Condition	Soil Organic Carbon	Dependency
		Water Condition	Freshwater Quality	
			Marine Water Quality	
		Air Condition	PM2.5 Concentrations	
		Ecosystem Condition	Ecosystem Intactness & Connectivity (Terrestrial)	
			Ecosystem Connectivity (Freshwater)	
			Ecosystem Intactness (Marine)	
		Pollination	Crop Pollination	
	Regulating Services – Mitigating	Landslides	Landslide Hazard	Dependency
		Wildfire Hazard	Wildfire Hazard	
		Plant/Forest/Aquatic Pests and Diseases	Frequency of Plant/Forest/Aquatic Pests and Diseases	
		Herbicide Resistance	Antimicrobial and Agrochemical Resistances	
		Extreme Heat	Extreme Heat Hazard	
		Tropical Cyclones	Tropical Cyclonic Wind and Storm Surge Hazard	
	Cultural Services	Tourism Attractiveness	Tourism Demand Drivers (Natural and Cultural)	Dependency
	Pressures on Biodiversity	Land, Freshwater and Sea Use Change	Cropland Expansion (Terrestrial)	Impact
			Fragmentation of Rivers (Freshwater)	
			Direct Human Impact & Fishing (Marine)	
		Tree Cover Loss	Tree Cover Loss	
		Invasives	Presence of Invasives	
		Pollution	Terrestrial Nutrient Pollution	
			Terrestrial Pesticide Pollution	
			Freshwater Nutrient Pollution	

			Marine Nutrient Pollution	
			Marine Pesticide Pollution	
			Air Pollution	
Transition Risk	Environmental Factors	Protected/Conserved Areas	Protected Areas	Impact
		Key Biodiversity Areas	Key Biodiversity Areas	
		Other Important Delineated Areas	Intact Forest Landscapes	
			WWF's Global 200	
			Ecologically or Biologically Significant Marine Areas	
			Vulnerable Marine Ecosystems	
		Ecosystem Condition	Ecosystem Intactness & Connectivity (Terrestrial)	
			Ecosystem Connectivity (Freshwater)	
			Ecosystem Intactness (Marine)	
		Range Rarity	Range Rarity	
	Socioeconomic Factors	Indigenous Peoples, Local Communities, Lands and Territories	No Data	Impact
		Resource Scarcity: Food, Water, Air	Food Security	
			Water Scarcity	
			Air Condition	
		Labor/Human Rights	Ratified International Human Rights Instruments	
			Labor Rights Violations	
		Financial Inequality	Financial Inequality	
	Additional Reputational Factors	Media Scrutiny	Media Scrutiny (Ecological Topics)	Dependency
			Media Scrutiny (Social Topics)	
		Political Situation	Violence Against Land and Environmental Defenders	
			Freedom	
			Governance	
			Corruption	
		Sites of International Interest	Natural World Heritage Sites	
			RAMSAR Sites	
		Risk Preparation	Index of Risk Preparation	

Table A3: Data composition by industry

Industries	Observations
Agriculture (animal products)	13
Agriculture (plant products)	19
Appliances & General Goods Manufacturing	252
Automotive, Electrical Equipment & Machinery Production	334
Chemicals & Other Materials Production	274
Construction Materials	79
Electric Energy Production – Combustion (Biomass, Coal, Gas, Nuclear, Oil), Geothermal Energy	92
Electric Energy Production – Solar, Wind	8
Electronics & Semiconductor Manufacturing	235
Fishing and aquaculture	3
Food & Beverage Production	168
Food Retailing	35
General or Speciality Retailing	123
Health Care, Pharmaceuticals and Biotechnology	116
Hospitality Services	109
Land Development & Construction	402
Metals & Mining	133
Offices & Professional Services	1330
Oil, Gas & Consumable Fuels	94
Paper & Forest Product Production	63
Telecommunication services (including wireless)	77
Textiles, Apparel & Luxury Good Production	79
Transportation Services	116
Water utilities / Water Service Providers	8

Table A4: Data composition by geography

Countries	Observations	Countries	Observations
Albania	2	Kazakhstan	10
Algeria	4	Kenya	2
Angola	6	Kuwait	2
Argentina	19	Latvia	17
Australia	99	Libya	3
Austria	89	Liechtenstein	2
Bahamas	2	Lithuania	33
Bangladesh	4	Luxembourg	14
Belarus	3	Malawi	1
Belgium	123	Malaysia	13
Bermuda	1	Malta	28
Bosnia and Herzegovina	10	Mauritius	1

Botswana	1	Mexico	63
Brazil	123	Moldova	1
Bulgaria	58	Monaco	1
Cameroon	2	Montenegro	1
Canada	196	Morocco	1
Cayman Islands	1	Mozambique	3
Chile	12	Namibia	3
China	675	Netherlands	186
Colombia	12	New Caledonia	1
Congo	1	New Zealand	6
Congo DRC	1	Nigeria	9
Croatia	47	North Macedonia	4
Curacao	1	Norway	263
Cyprus	26	Oman	3
Czech Republic	57	Pakistan	5
Denmark	180	Peru	8
Dominican Republic	4	Philippines	3
Egypt	15	Poland	316
Equatorial Guinea	1	Portugal	50
Estonia	16	Puerto Rico	1
Falkland Islands	1	Qatar	2
Faroe Islands	11	Romania	112
Finland	205	Russian Federation	134
France	816	Saudi Arabia	15
French Polynesia	1	Serbia	20
Gabon	4	Sierra Leone	1
Georgia	5	Singapore	23
Germany	1239	Slovakia	19
Ghana	3	Slovenia	33
Gibraltar	3	South Africa	13
Greece	90	South Korea	58
Greenland	1	Spain	309
Guernsey	4	Suriname	1
Guinea	1	Sweden	435
Guyana	2	Switzerland	206
Haiti	1	Tanzania	5
Honduras	1	Thailand	5
Hungary	49	Trinidad and Tobago	2
Iceland	14	Tunisia	4
India	102	Turkey	310
Indonesia	16	Ukraine	27
Iran	4	United Arab Emirates	18

Iraq	7	United Kingdom	1163
Ireland	83	United States	1408
Israel	9	Uruguay	3
Italy	95	Uzbekistan	1
Jamaica	2	Vietnam	6
Japan	149	Zambia	2
Jersey	4	Zimbabwe	1
Jordan	3		

Figure A5: Correlation matrix Fama-French 6 Risk Factors + Carhart Momentum + HLBR

Note: This table presents correlation coefficients between the risk factors used in the Fama-French 6-Factor model and the newly introduced biodiversity risk factor (HLBR).

Variables	MRKTRf	SMB	HML	WML	RMW	CMA	HLBR
MRKTRf	1	0.281	0.150	-0.595	0.063	-0.218	-0.245
SMB	0.281	1	-0.170	0.041	0.093	-0.483	-0.269
HML	0.150	-0.170	1	-0.522	-0.788	0.784	0.375
WML	-0.595	0.041	-0.522	1	0.321	-0.226	0.055
RMW	0.063	0.093	-0.788	0.321	1	-0.641	-0.268
CMA	-0.218	-0.483	0.784	-0.226	-0.641	1	0.480
HLBR	-0.245	-0.269	0.375	0.055	-0.268	0.480	1

Table A6: Breusch-Pagan Test for heteroscedasticity in panel data

H0: No first order autocorrelation

Asset Pricing Model	BP	df	P-value
CAPM	354.5	1	< 2.2e-16
CAPM + HLBR	398.15	2	< 2.2e-16
FF 3-Factor	514.79	3	< 2.2e-16
FF 3-Factor + HLBR	514.58	4	< 2.2e-16
Carhart 4-Factor	661.8	4	< 2.2e-16
Carhart 4-Factor + HLBR	672.32	5	< 2.2e-16

Table A7: Wooldridge Test for autocorrelation in panel data

H0: No first order serial correlation Model

Asset Pricing Model	chisq	df	P-value
CAPM	6353.9	60	< 2.2e-16
CAPM + HLBR	6319	60	< 2.2e-16
FF 3-Factor	4896.6	60	< 2.2e-16
FF 3-Factor + HLBR	4888	60	< 2.2e-16
Carhart 4-Factor	4902.6	60	< 2.2e-16
Carhart 4-Factor + HLBR	4891.7	60	< 2.2e-16

Table A8: Panel Regressions without fixed effects

Note: This table shows panel regression results with company-level clustered standard errors. The dependent variable is excess return. The models include the traditional CAPM, Fama-French three-factor, and Carhart four-factor models, with and without the biodiversity risk factor (HLBR). 'N' indicates the exclusion of country and industry fixed effects

	Dependent variable:					
	ExcessReturn					
	CAPM	CAPM + HLBR	FF 3-Factors	FF 3-Factors + HLBR	Carhart 4-Factors	Carhart 4-Factors + HLBR
	(1)	(2)	(3)	(4)	(5)	(6)
MRKTRf	0.01034^{***}	0.01029^{***}	0.00921^{***}	0.00933^{***}	0.00932^{***}	0.00938^{***}
	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)	(0.00007)
HLBR		-0.00058^{**}		0.00139^{***}		0.00135^{***}
		(0.00024)		(0.00026)		(0.00026)
SMB			0.01039^{***}	0.01054^{***}	0.01032^{***}	0.01051^{***}
			(0.00015)	(0.00016)	(0.00015)	(0.00016)
HML			0.00082^{***}	0.00057^{***}	0.00094^{***}	0.00063^{***}
			(0.00009)	(0.00010)	(0.00010)	(0.00010)
WML					0.00026^{***}	0.00012
					(0.00010)	(0.00010)
Country fixed effect	n	n	n	n	n	n
Industry fixed effect	n	n	n	n	n	n
Observations	245,460	245,460	245,460	245,460	245,460	245,460
R^2	0.17854	0.17859	0.19874	0.19899	0.19877	0.19900
Adjusted R^2	0.16462	0.16467	0.18516	0.18540	0.18518	0.18541
F Statistic	$52{,}459.61000^{***}$ (df = 1; 241368)	$26{,}239.41000^{***}$ (df = 2; 241367)	$19{,}956.13000^{***}$ (df = 3; 241366)	$14{,}990.26000^{***}$ (df = 4; 241365)	$14{,}969.53000^{***}$ (df = 4; 241365)	$11{,}992.56000^{***}$ (df = 5; 241364)
Note:						*p<0.1; **p<0.05; ***p<0.01

Table A9: Fama-Macbeth Cross-sectional regression results – No fixed effects

Note: This table presents the Fama-Macbeth regression analysis results with Newey-West standard errors, without fixed effects. The analysis uses monthly individual stock returns and includes risk factors: MRKTRf, SMB, HML, WML, and HLBR, along with control variables. Reported are the mean coefficients, standard errors, t-statistics, and p-values.

Term	Mean Coefficient	Std Error	t-statistic	P-value	R^2
MRKTRf	0.3899810	0.0591338	6.5948910	0.0000000	0.1717633
SMB	0.1225346	0.0295425	4.1477343	0.0001091	
HML	-0.3050131	0.0429496	-7.1016462	0.0000000	
WML	0.1806907	0.0472470	3.8243860	0.0003186	
HLBR	0.1551565	0.0175667	8.8324216	0.0000000	
Log_TotalAssets	0.0008249	0.0001200	6.8714689	0.0000000	
BM_Ratio	0.0000058	0.0000032	1.8058282	0.0760471	
Leverage_Ratio	-0.0000190	0.0000177	-1.0752048	0.2866605	
Invest_TotalAssets	-0.0037185	0.0007362	-5.0505858	0.0000045	
Log_PPE	-0.0000083	0.0001095	-0.0758242	0.9398155	

Figure A10: Linearity Assumptions Carhart 4-Factors Decile Portfolios

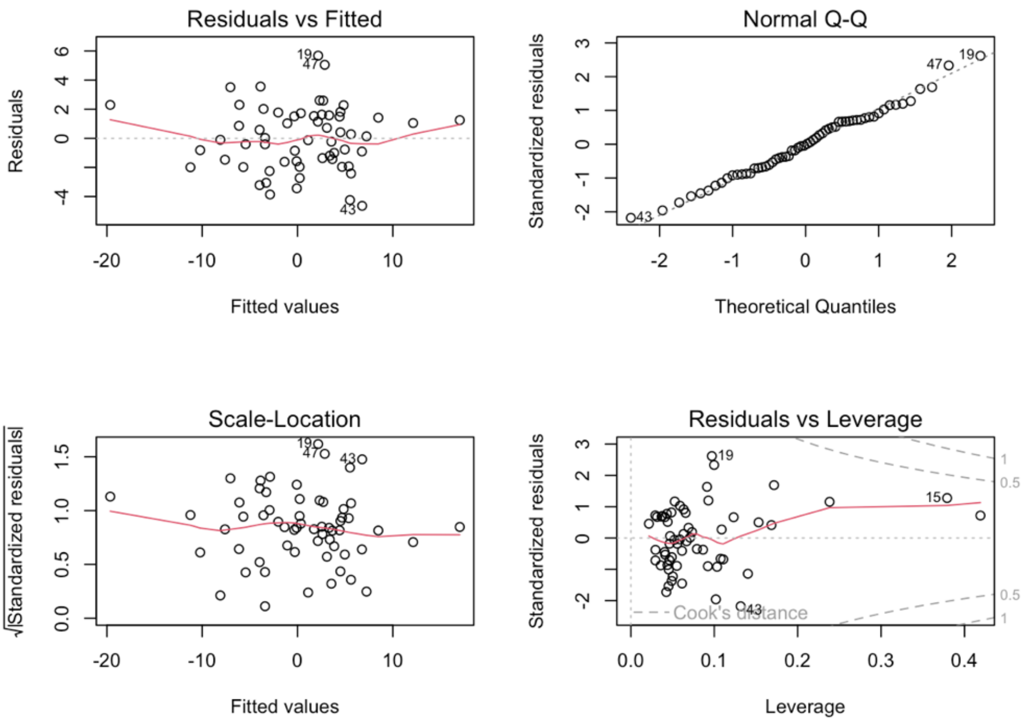

Figure A11: Linearity Assumptions Carhart 4-Factors +HLBR Decile Portfolios

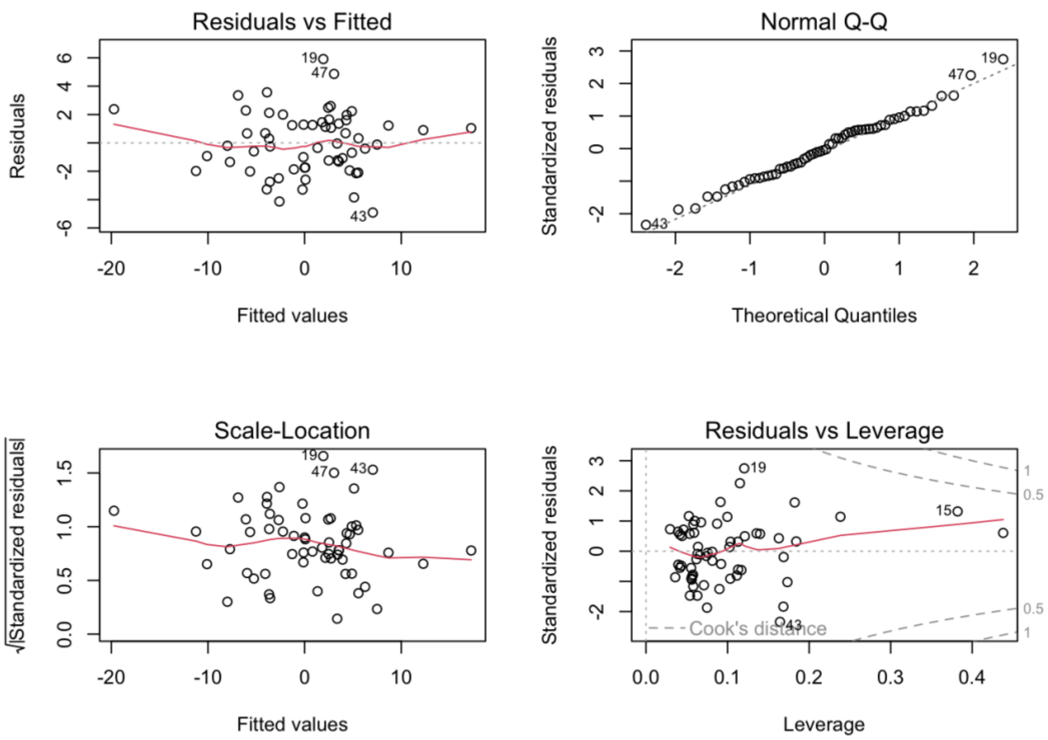

Table A12: Breusch-Pagan Test results for Carhart 4-Factor Model Regressions

Portfolio	BP	df	P-value
RET1	5.4371	4	0.2453
RET2	0.7905	4	0.9397
RET3	5.6794	4	0.2244
RET4	3.1827	4	0.5277
RET5	3.2137	4	0.5227
RET6	4.1956	4	0.3802
RET7	3.8966	4	0.4202
RET8	3.5794	4	0.4659
RET9	2.2721	4	0.6859
RET10	3.6923	4	0.4492
Total Portfolio (RET)	3.6529	4	0.4550

Table A13: Breusch-Pagan Test results for Carhart 4-Factor + HLBR Model Regressions

Portfolio	BP	df	P-value
RET1	6.2026	5	0.2870
RET2	2.0540	5	0.8416
RET3	4.3989	5	0.4935
RET4	2.8441	5	0.7240
RET5	3.9549	5	0.5559
RET6	4.8494	5	0.4345
RET7	4.8862	5	0.4299
RET8	3.7496	5	0.5860
RET9	3.3684	5	0.6434
RET10	2.9412	5	0.7090
Total Portfolio (RET)	3.5162	5	0.6209

Table A14: Wooldridge Test for autocorrelation in Carhart 4-Factor Model Regressions

Portfolio	DW Statistic	P-value
RET1	1.8107	0.2348
RET2	2.1827	0.7678
RET3	1.7193	0.1391
RET4	1.6399	0.08057
RET5	1.5904	0.05477
RET6	1.8655	0.3056
RET7	2.1457	0.7212
RET8	1.9723	0.4639
RET9	1.994	0.4977
RET10	1.9091	0.3678
Total Portfolio (RET)	1.8988	0.3527

Table A15: Wooldridge Test for autocorrelation in Carhart 4-Factor + HLBR Model Regressions

Portfolio	DW Statistic	P-value
RET1	2.0413	0.5559
RET2	2.1932	0.7701
RET3	1.7039	0.1192
RET4	1.6601	0.08798
RET5	1.5983	0.05468
RET6	1.8704	0.3004
RET7	2.1827	0.7573
RET8	1.9864	0.4688
RET9	2.0073	0.5021
RET10	1.9146	0.3547
Total Portfolio (RET)	1.9036	0.3375

Table A16: Industry-specific biodiversity scores

Note: This table presents detailed industry-specific biodiversity scores, including physical and transition risks, with scores ranging from 0 to 5, representing very low to very high risk.

Industry	Physical Risk Score	Transition Risk Score
Fishing and aquaculture	4	3.25
Agriculture (plant products)	3.2	3.92
Agriculture (animal products)	3.2	3.92
Paper & Forest Product Production	3.8	3.25
Metals & Mining	3.05	3.92
Land Development & Construction	3.05	3.83
Oil, Gas & Consumable Fuels	3	3.83
Transportation Services	2.85	3.25
Electric Energy Production Geothermal Energy	2.9	3.08
Hospitality Services	3.5	2.42
Construction Materials	3	2.25
Textiles, Apparel & Luxury Good Production	2.55	2.50
Food & Beverage Production	2.4	2.58
Water utilities / Water Service Providers	2.05	2.33
Electric Energy Production - Solar, Wind	1.95	2.42
Automotive, Electrical Equip. & Machinery Production	2.2	2.08
Chemicals & Other Materials Production	1.9	2.25
Health Care, Pharmaceuticals and Biotechnology	2.05	2.08
Telecommunication services	1.85	2.08
Appliances & General Goods Manufacturing	1.75	2.17
Electronics & Semiconductor Manufacturing	1.75	2.08
Offices & Professional Services	1.55	1.75
General or Speciality Retailing	1.55	1.75
Food Retailing	1.55	1.75

Table A17: Detailed summary statistics for all quantile portfolios

Note: This table presents detailed summary statistics for all industries, each divided into five portfolios based on biodiversity risk levels from 2019 to 2023. The number of observations (N = 60 months) is included.

Industry	Quantile	(1) N	(2) Median	(3) Mean	(4) St. Dev	(5) Min	(6) Max
Transportation Services	1 (High)	60	0.0113	0.0112	0.0681	-0.1882	0.2388
	2	60	0.0052	0.0028	0.0723	-0.2119	0.2628
	3	60	-0.0035	0.0013	0.0836	-0.2401	0.2821
	4	60	0.0047	0.0015	0.0756	-0.2068	0.2632
	5 (Low)	60	0.0070	0.0013	0.0623	-0.1880	0.1393
Textiles, Apparel & Luxury Good Production	1 (High)	60	0.0318	0.0267	0.1041	-0.2347	0.2354
	2	60	0.0179	0.0118	0.0807	-0.1985	0.2748
	3	60	-0.0003	-0.0002	0.0823	-0.2286	0.2829
	4	60	0.0018	-0.0062	0.0707	-0.1939	0.1988
	5 (Low)	60	-0.0061	-0.0042	0.0701	-0.2198	0.2252
Telecommunication services	1 (High)	60	0.0030	0.0058	0.0615	-0.1214	0.1852
	2	60	0.0020	-0.0027	0.0660	-0.1629	0.1264
	3	60	0.0108	-0.0017	0.0592	-0.1607	0.1680
	4	60	0.0037	0.0068	0.0587	-0.1382	0.1720
	5 (Low)	60	0.0026	-0.0047	0.0634	-0.1697	0.1414
Paper & Forest Product Production	1 (High)	60	0.0095	0.0178	0.1006	-0.1655	0.2545
	2	60	0.0072	0.0020	0.0665	-0.1659	0.1976
	3	60	0.0093	0.0050	0.0600	-0.1396	0.1806
	4	60	0.0112	0.0042	0.0662	-0.1969	0.1647
	5 (Low)	60	0.0108	0.0077	0.0747	-0.1778	0.2128
Oil, Gas & Consumable Fuels	1 (High)	60	-0.0006	-0.0026	0.0868	-0.2711	0.2266
	2	60	-0.0024	-0.0002	0.0790	-0.1957	0.2589
	3	60	0.0064	-0.0021	0.0849	-0.2654	0.2041
	4	60	0.0174	0.0042	0.0732	-0.2385	0.2170
	5 (Low)	60	0.0082	0.0028	0.0594	-0.1658	0.1860
Offices & Professional Services	1 (High)	60	0.0176	0.0111	0.0672	-0.1817	0.2046
	2	60	0.0070	0.0005	0.0636	-0.2055	0.1801
	3	60	0.0130	0.0056	0.0633	-0.1600	0.1802
	4	60	0.0130	0.0032	0.0623	-0.1768	0.1980
	5 (Low)	60	0.0116	0.0030	0.0674	-0.1673	0.1709
Metals & Mining	1 (High)	60	0.0211	0.0138	0.0844	-0.1741	0.2384
	2	60	0.0081	0.0105	0.0783	-0.2082	0.2261
	3	60	-0.0100	-0.0028	0.0733	-0.2291	0.2003
	4	60	0.0084	0.0045	0.0794	-0.1892	0.2417
	5 (Low)	60	0.0103	0.0014	0.0779	-0.2380	0.2018
Land Development & Construction	1 (High)	60	0.0133	0.0115	0.0646	-0.1940	0.1681
	2	60	0.0015	-0.0009	0.0539	-0.1777	0.1481

	3	60	0.0139	0.0016	0.0640	-0.1867	0.1898
	4	60	0.0069	-0.0006	0.0540	-0.1563	0.1334
	5 (Low)	60	0.0051	-0.0030	0.0723	-0.1918	0.1605
Hospitality Services	1 (High)	60	0.0127	0.0180	0.0875	-0.2280	0.1962
	2	60	-0.0020	-0.0036	0.0858	-0.3036	0.3111
	3	60	-0.0004	0.0008	0.0720	-0.2365	0.2577
	4	60	0.0059	0.0017	0.0729	-0.2406	0.2186
	5 (Low)	60	-0.0066	-0.0027	0.0589	-0.1830	0.2046
Health Care, Pharmaceuticals and Biotechnology	1 (High)	60	0.0037	0.0022	0.0617	-0.1597	0.1423
	2	60	0.0159	0.0023	0.0705	-0.1381	0.1994
	3	60	0.0131	0.0069	0.0689	-0.1412	0.1663
	4	60	0.0053	0.0001	0.0603	-0.1456	0.1432
	5 (Low)	60	-0.0049	-0.0026	0.0621	-0.1811	0.1331
General or Speciality Retailing	1 (High)	60	0.0119	0.0153	0.0854	-0.2227	0.2967
	2	60	0.0068	0.0066	0.0862	-0.2732	0.2083
	3	60	-0.0047	-0.0007	0.0742	-0.2314	0.1565
	4	60	0.0053	0.0054	0.0844	-0.1998	0.2056
	5 (Low)	60	0.0096	0.0035	0.0761	-0.1849	0.1605
Food Retailing	1 (High)	60	0.0080	0.0060	0.0917	-0.1520	0.1990
	2	60	0.0080	0.0046	0.0619	-0.1307	0.1538
	3	60	0.0161	0.0029	0.0830	-0.1905	0.2126
	4	60	0.0106	0.0054	0.0670	-0.1662	0.1680
	5 (Low)	60	0.0057	0.0020	0.0450	-0.0929	0.1014
Food & Beverage Production	1 (High)	60	0.0045	0.0135	0.0742	-0.1332	0.1912
	2	60	0.0000	-0.0009	0.0431	-0.0989	0.1092
	3	60	0.0112	0.0018	0.0562	-0.1322	0.1488
	4	60	0.0034	-0.0012	0.0503	-0.1362	0.1367
	5 (Low)	60	0.0018	0.0009	0.0530	-0.1561	0.1245
Electronics & Semiconductor Manufacturing	1 (High)	60	0.0117	0.0034	0.0601	-0.1632	0.1788
	2	60	0.0094	0.0045	0.0791	-0.1908	0.1684
	3	60	0.0092	0.0014	0.0688	-0.1694	0.1579
	4	60	0.0143	0.0053	0.0792	-0.1942	0.1734
	5 (Low)	60	0.0107	0.0065	0.0760	-0.1731	0.1849
Electric Energy Production - Combustion	1 (High)	60	0.0003	0.0139	0.0830	-0.1706	0.2229
	2	60	0.0118	0.0063	0.0555	-0.1506	0.1646
	3	60	0.0032	0.0054	0.0661	-0.1681	0.1387
	4	60	0.0190	0.0102	0.0588	-0.1422	0.1585
	5 (Low)	60	0.0063	0.0089	0.0646	-0.1353	0.1696
Construction Materials	1 (High)	60	0.0187	0.0256	0.1165	-0.1973	0.2689
	2	60	0.0093	0.0083	0.0776	-0.2232	0.2728
	3	60	0.0155	0.0074	0.0839	-0.2607	0.2366
	4	60	0.0165	0.0060	0.0831	-0.2522	0.2196

	5 (Low)	60	-0.0027	0.0011	0.0746	-0.1873	0.1355
Chemicals & Other Materials Production	1 (High)	60	0.0048	0.0120	0.0669	-0.1161	0.1935
	2	60	0.0083	0.0031	0.0602	-0.1549	0.1559
	3	60	0.0000	0.0002	0.0621	-0.1347	0.2045
	4	60	0.0033	0.0002	0.0666	-0.1456	0.1733
	5 (Low)	60	0.0075	-0.0005	0.0723	-0.1546	0.2304
Automotive, Electrical Equip. & Machinery Prod.	1 (High)	60	0.0145	0.0159	0.0765	-0.2076	0.2188
	2	60	0.0110	0.0047	0.0710	-0.2118	0.2063
	3	60	0.0159	0.0049	0.0740	-0.2183	0.2239
	4	60	0.0092	0.0017	0.0753	-0.2052	0.2102
	5 (Low)	60	0.0136	0.0022	0.0704	-0.1864	0.1747
Appliances & General Goods Manufacturing	1 (High)	60	0.0073	0.0142	0.0764	-0.1999	0.1957
	2	60	0.0146	0.0065	0.0729	-0.1959	0.2142
	3	60	0.0174	0.0080	0.0736	-0.1841	0.1839
	4	60	0.0084	0.0059	0.0780	-0.2027	0.2471
	5 (Low)	60	0.0132	0.0052	0.0736	-0.1979	0.1889
Agriculture (plant products)	1 (High)	60	-0.0050	0.0073	0.0849	-0.2077	0.2098
	2	60	-0.0129	0.0021	0.0739	-0.1480	0.1611
	3	60	-0.0034	-0.0049	0.0535	-0.1457	0.1864
	4	60	-0.0119	0.0011	0.0613	-0.1500	0.1599
	5 (Low)	60	-0.0032	-0.0004	0.0671	-0.1423	0.1449

Table A18: DID estimation results – Kunming Montreal Declaration – No clustered SE

Note: This table presents the DID estimation results for the Kunming Montreal Declaration without clustered standard errors. The dependent variable is the monthly excess return of individual companies regressed on the risk factors and control variables. Country and industry fixed effects are included in model (2).

	Dependent variable:	
	Excess Return	
	(1)	(2)
Time	-0.005***	-0.005***
	(0.001)	(0.001)
Interaction (Treatment * Time)	0.010***	0.010***
	(0.001)	(0.001)
MRKTRf	0.009***	0.009***
	(0.0001)	(0.0001)
SMB	0.010***	0.010***
	(0.0001)	(0.0001)
HML	0.001***	0.001***
	(0.0001)	(0.0001)
WML	0.00000	0.00000
	(0.0001)	(0.0001)
HLBR	0.001***	0.001***
	(0.0002)	(0.0002)
LOG Total Assets	-0.015***	-0.015***
	(0.001)	(0.001)
BM-Ratio	-0.00000***	-0.00000***
	(0.00000)	(0.00000)
Leverage Ratio	-0.00000	-0.00000
	(0.00000)	(0.00000)
Investments/Total Assets Ratio	-0.008*	-0.008*
	(0.005)	(0.005)
LOG PPE	-0.001**	-0.001**
	(0.0004)	(0.0004)
Country fixed effect	N	Y
Industry fixed effect	N	Y
Observations	245,460	245,460
R^2	0.201	0.201
Adjusted R^2	0.188	0.188
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A19: Placebo Treatment Effect – DID Kunming Montreal Declaration

Note: This table presents the placebo treatment effect results for the DID analysis of the Kunming-Montreal Declaration, using random groups instead of the actual treatment group. The results include models with and without fixed effects, showing the placebo treatment effect, time, and control variables.

	Dependent Variable:	
	Model without Fixed Effects	Model with Fixed Effects
	(1)	(2)
Placebo Treatment Effect	-0.0002528	-0.0003086
	(0.0004822)	(0.0004821)
Time	0.0003626	0.0003625
	(0.0006027)	(0.0006026)
MRKTRf	0.009219***	0.009219***
	(0.0000648)	(0.0000648)
SMB	0.010449***	0.010449***
	(0.0001388)	(0.0001388)
HML	0.0007441***	0.0007440***
	(0.0000874)	(0.0000874)
WML	-0.0000002	-0.0000002
	(0.0000963)	(0.0000963)
HLBR	0.0014378***	0.001438***
	(0.0001672)	(0.0001671)
Log Total Assets	-0.014651***	-0.014649***
	(0.0007267)	(0.0007266)
BM Ratio	-0.0000012***	-0.0000012***
	(0.0000002)	(0.0000002)
Leverage Ratio	-0.0000022	-0.0000022
	(0.0000017)	(0.0000017)
Invest Total Assets	-0.0087405	-0.0087440
	(0.0047447)	(0.0047447)
Log PPE	-0.0010252**	-0.001025**
	(0.0003609)	(0.0003609)
Country fixed effect	N	Y
Industry fixed effect	N	Y
Observations	245,460	245,460
R^2	0.20098	0.20098
Adjusted R^2	0.1874	0.1874
F-statistic	5059.02***	5059.04***
Note:		*p<0.1; **p<0.05; ***p<0.0

Figure A20: Parallel Trends Assumption – DID Kunming Montreal Declaration

Note: This figure presents the parallel trends assumption for the DID analysis of the Kunming-Montreal Declaration. It shows the average excess return trends for high and low biodiversity risk portfolios. The dashed line represents the date of the Kunming Declaration in October 2021.

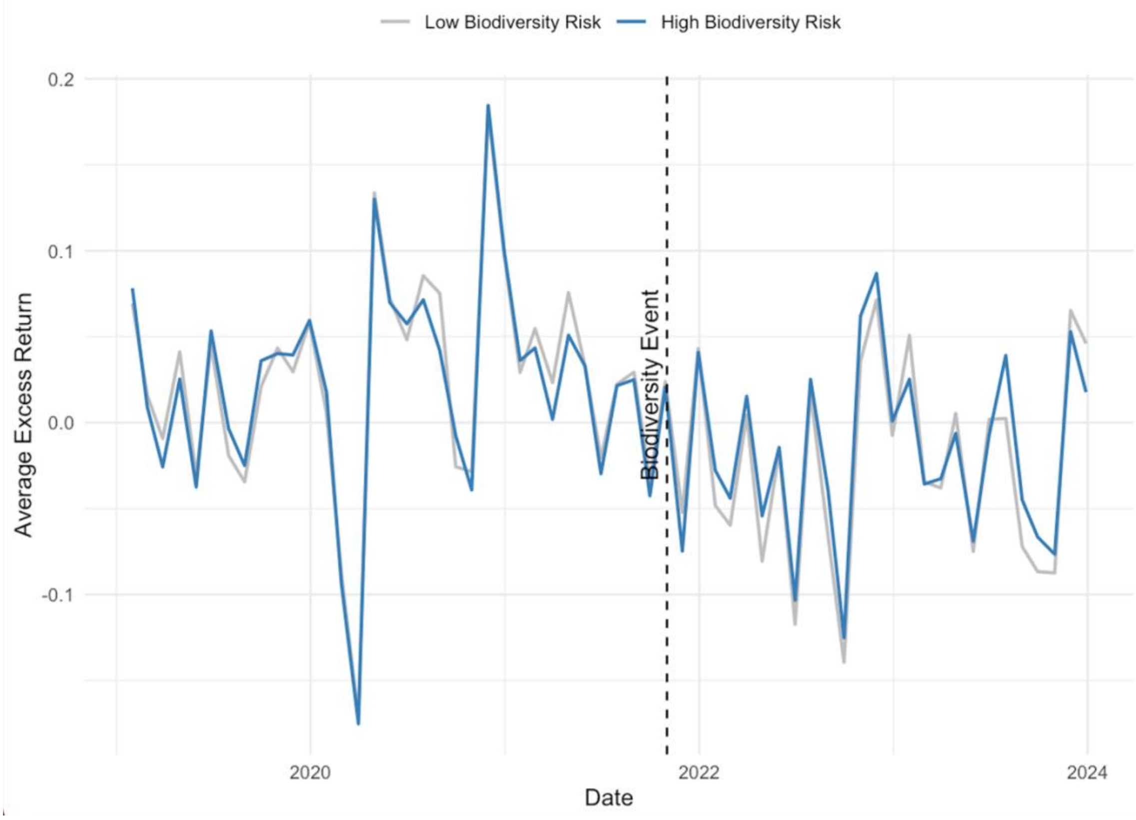

Table A21: DID estimation results – TNFD – No clustered SE

Note: This table presents the DID estimation results for the TNFD launch without clustered standard errors. The dependent variable is the monthly excess return of individual companies regressed on the risk factors and control variables. Country and industry fixed effects are included in model (2).

	Dependent variable:	
	Excess Return	
	(1)	(2)
Time	-0.010***	-0.010***
	(0.001)	(0.001)
Interaction (Treatment * Time)	0.008***	0.008***
	(0.001)	(0.001)
MRKTRf	0.009***	0.009***
	(0.0001)	(0.0001)
SMB	0.010***	0.010***
	(0.0001)	(0.0001)
HML	0.001***	0.001***
	(0.0001)	(0.0001)
WML	-0.0001	-0.0001
	(0.0001)	(0.0001)
LHBR	0.002***	0.002***
	(0.0002)	(0.0002)
LOG Total Assets	-0.012***	-0.012***
	(0.001)	(0.001)
BM-Ratio	-0.00000***	-0.00000***
	(0.00000)	(0.00000)
Leverage Ratio	-0.00000	-0.00000
	(0.00000)	(0.00000)
Investments/Total Assets Ratio	-0.009*	-0.009*
	(0.005)	(0.005)
LOG PPE	-0.001***	-0.001***
	(0.0004)	(0.0004)
Country fixed effect	N	Y
Industry fixed effect	N	Y
Observations	245,460	245,460
R^2	0.202	0.202
Adjusted R^2	0.188	0.188
Note:	*p<0.1; **p<0.05; ***p<0.01	

Table A22: Placebo Treatment Effect – DiD TNFD

Note: This table presents the placebo treatment effect results for the DID analysis of the TNFD launch, using random groups instead of the actual treatment group. The results include models with and without fixed effects, showing the placebo treatment effect, time, and control variables.

	Dependent Variable:	
	Model without Fixed Effects	Model with Fixed Effects
	(1)	(2)
Placebo Treatment Effect	-0.0002449	-0.0003185
(0.0004821)	(0.0004820)	
Time	-0.0062950***	-0.0062962***
	(0.0005712)	(0.0005712)
MRKTRf	0.0090611***	0.0090611***
	(0.0000632)	(0.0000632)
SMB	0.010158***	0.010158***
	(0.0001400)	(0.0001400)
HML	0.0008321***	0.0008320***
	(0.0000874)	(0.0000874)
WML	-0.0001212	-0.0001212
	(0.0000952)	(0.0000952)
HLBR	0.0016397***	0.0016401***
	(0.0001651)	(0.0001651)
Log Total Assets	-0.011845***	-0.011843***
	(0.0007254)	(0.0007254)
BM Ratio	-0.0000012***	-0.0000012***
	(0.0000002)	(0.0000002)
Leverage Ratio	-0.0000023	-0.0000023
	(0.0000017)	(0.0000017)
Invest Total Assets	-0.0094507*	-0.0094546*
	(0.0047409)	(0.0047409)
Log PPE	-0.0011304**	-0.0011302**
	(0.0003604)	(0.0003604)
Country Fixed Effect	N	Y
Industry Fixed Effect	N	Y
Observations	245,460	245,460
R^2	0.20138	0.20138
Adjusted R^2	0.1878	0.18781
F-statistic	5071.65***	5071.65***
Note:		*p<0.1; **p<0.05; ***p<0.0

Figure A23: Parallel Trends Assumption – Difference-in-difference analysis – TNFD

Note: This figure presents the parallel trends assumption for the DID analysis of the TNFD launch. It shows the average excess return trends for high and low biodiversity risk portfolios. The dashed line represents the date of the TNFD launch in June 2021.