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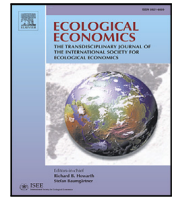


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The biodiversity premium[☆]

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ABSTRACT

Focusing on biodiversity risks, we perform an empirical asset pricing analysis and document three main results. First, the factor going long on low biodiversity intensity assets and short on high biodiversity intensity ones as well as the factors based on the biodiversity intensity subcomponents (land use, greenhouse gases—GHG, air pollution, and water pollution) have heterogeneous dynamics but are not spanned by the Fama and French (2015) and carbon factors. Second, the biodiversity factor excluding the GHG subcomponent (ex-GHG) commands a positive risk premium on realized returns and a negative one on expected returns in the sector highly exposed to the double materiality of biodiversity risks (i.e., physical and transition risks). Third, we show that the negative premium of both the biodiversity and the ex-GHG biodiversity factors on expected returns has materialized strongly from 2021 onward and that it amplifies with attention to biodiversity issues and risk aversion.

1. Introduction

Biodiversity is defined by the UN Convention on Biological Diversity¹ as “the variability among living organisms from all sources including, inter alia, terrestrial, marine and other aquatic ecosystems and the ecological complexes of which they are part.” The preservation of biodiversity is a fundamental issue, not only because of the intrinsic value of life on Earth, but also because biodiversity provides us with key direct services (such as the production of food and raw materials for medicines) and indirect services (such as pollination, water filtering, or ecosystem balance).

Yet, despite its existential value, biodiversity has collapsed with human activity, leading to a sixth mass extinction (Strona and Bradshaw, 2022), which has accelerated dramatically over the last two hundred years (IPBES, 2019). For example, between 1970 and 2016, populations of vertebrate and freshwater species declined by 68% and 84%, respectively (WWF, 2020). Today, a significant share of living species is threatened with extinction: 41% of amphibian species, 35% of reptile species, 35% of conifer species, one-third of coral species, and more than a quarter of mammal species are threatened with extinction (IPBES, 2019).

Beyond the ecological challenges, the decline in biodiversity poses a dual financial risk for businesses: a risk linked to their dependence on ecosystem services (also known as physical risk) and a risk related to their impact on biodiversity (also known as transition risk).² Are investors incorporating these financial risks into their capital allocation? In what way and with what dynamics?

We answer these questions in this paper by carrying out an empirical asset pricing study on US data, and we reach three main results. First, from a biodiversity intensity measure based on Iceberg Data-lab's biodiversity footprint scaled by company revenue, we construct a green-minus-brown factor, long of companies with low intensity (also referred to as “green”) and short of companies with high intensity (also referred to as “brown”). We show that, although this factor has not delivered a positive financial performance since 2012 (flat when constructed as equally weighted and negative when constructed as value-weighted), its dynamics conceal a strong heterogeneity in the long-short factors constructed from the biodiversity sub-components (land use, greenhouse gases, air pollution, water pollution, total excluding greenhouse gas emissions). In addition, neither the green-minus-brown carbon factor (e.g., Pástor et al., 2022) nor the Fama and French (2015) factors span these biodiversity factors.

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¹ <https://www.cbd.int/>.

² Transition risk refers to all the financial risks to which companies with a large biodiversity footprint are exposed (tightening in regulation to preserve biodiversity, change in stakeholder preferences, technological risks, etc.).

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Second, by analyzing both realized returns and expected returns estimated from option prices by Chabi-Yo et al. (2023), and controlling for Fama and French (2015) and carbon factors, we do not identify a biodiversity risk premium on the entire universe of companies between 2012 and 2022. However, by focusing our analysis on sectors with high exposure to the double materiality of biodiversity risks (transition and physical risks), we show that realized returns command a positive risk premium, while expected returns command a negative risk premium. These results suggest the following interpretations: (i) an unexpected increase in preferences for assets with a low biodiversity footprint has pushed up their realized returns relative to those with a high footprint, as documented by Pástor et al. (2022) and Bolton and Kacperczyk (2023) for climate risks; (ii) a demand by investors to compensate for holding assets with a high biodiversity footprint underpins the risk premium on expected returns (Pástor et al., 2021, 2022; Pedersen et al., 2021; Zerbib, 2022).

Third, to go beyond average risk premia, we conduct a dynamic analysis of the price of biodiversity risk on the expected returns of companies in sectors highly exposed to the double materiality of biodiversity risks. We show that the expected returns of companies with low biodiversity footprints have fallen significantly relative to those with high biodiversity footprints from 2021 onward, reaching -10% in 2022. This dynamic is true for both the biodiversity factor and the biodiversity factor excluding the channel of greenhouse gases. Furthermore, by regressing the price of risk of these two biodiversity factors on climate risk attention, biodiversity risk attention, consumer sentiment, oil price, and risk aversion, we explain 40% of its dynamics. Notably, attention to biodiversity risk and risk aversion contribute to increasing the gap between the cost of capital of assets with a high biodiversity footprint and those with a low biodiversity footprint.

This paper contributes to the literature on sustainable finance. First, to the best of our knowledge, along with Giglio et al. (2023) and Garel et al. (2024), it is one of the first three papers on biodiversity asset pricing. While also using Iceberg Datalab data, Garel et al. (2024) study the effect of biodiversity on asset prices and implied cost of capital for a sample of international firms between 2019 and 2022. Although they find no effect of biodiversity on asset returns between 2018 and 2022, they show that asset prices fell and implied cost of capital increased for companies with large biodiversity footprints following the Kunming Declaration in October 2021. By constructing a news-based measure of biodiversity risk, in the spirit of Engle et al. (2020) and Giglio et al. (2023) find that returns of portfolios sorted on companies' exposure to biodiversity risk covary positively with innovations in biodiversity risk. Our results extend this literature by showing that the cost of capital, through expected returns approximated by option prices, is increased for companies with a high biodiversity footprint compared to those with a low footprint in the sectors most exposed to the double materiality of biodiversity risks. In addition, we show that this effect has materialized from 2021 onward, and we identify biodiversity attention and risk aversion as drivers of the biodiversity risk premium. Finally, we verify that this effect is driven by biodiversity components that are different from GHG emissions. Although the literature on the interface between finance and biodiversity is still emerging (Karolyi and Tobin-de la Puente, 2023), it is worth noting that Flammer et al. (2023) shed light on the financing of biodiversity conservation and restoration by private capital.

We also contribute, more generally, to the literature on sustainable asset pricing. To date, almost all of this literature has focused on climate risks (Engle et al., 2020; Choi et al., 2020; Sautner et al., 2023) and shows that these command a risk premium that increases the cost of capital of companies with a large carbon footprint (Pástor et al., 2021; Pedersen et al., 2021; Zerbib, 2022; Bolton and Kacperczyk, 2021; De Angelis et al., 2023; Cheng et al., 2023; Ardia et al., 2023; van der Beck, 2023). We complement this literature by documenting a similar phenomenon on the expected returns of assets with a strong biodiversity footprint but on a narrower scope and a more recent

period, namely, in the sectors most exposed to the double materiality of biodiversity risks, from 2021 onward. We also show that low biodiversity footprint assets in these sectors have benefited from higher realized returns, consistent with an unexpected increase in preferences for these assets, similar to what Pástor et al. (2022) find for low climate footprint assets.

The paper is organized as follows. We present the data in Section 2 and we perform the asset pricing analysis in Section 3. Section 4 concludes this paper.

2. Data

2.1. Corporate Biodiversity Footprint (CBF)

Several metrics have recently been developed to measure the biodiversity impact of financial investments.³ In this paper, we use the Corporate Biodiversity Footprint (CBF) metric developed by Iceberg DataLab,⁴ with the support of several major institutional investors, including AXA IM, BNP Paribas AM, Mirova, and Sycomore AM. The CBF is one of the most mature available indicators across different sectors and offers multiple advantages: maturity of coverage, robustness of the methodology, transparency, scalability, granularity, and comparability across sectors and assets. In addition, its computation is supervised by a scientific committee and endorsed by several key stakeholders, notably, the asset managers supporting the development of this metric.

The CBF is a footprinting approach aiming to reflect the negative impact of corporate activities on biodiversity. It follows a science-based approach covering all the material impacts of the firms' supply chain, processes, and products.

The measure relies on the "Mean Species Abundance" (MSA) concept, which calculates the average relative abundance of native species in an ecosystem compared to an undisturbed one. The MSA scale ranges from 0%, for areas with depleted biodiversity, to 100%, for regions matching the original, undisturbed ecosystem. The indicator was introduced during the development of the open-source database version of the GLOBIO3 model (Alkemade et al., 2009) by the Netherlands Environmental Assessment Agency (PBL). The GLOBIO model aims to simulate the impact of various human pressures on biodiversity. It has been endorsed by the international scientific community and multilateral institutions (IPBES, IPCC), and its use is recommended by the United Nations for biodiversity measurement (Convention on Biological Diversity, 1997).

The CBF methodology estimates the degradation of a company's activities on biodiversity per km^2 , expressed as $\text{km}^2 \cdot \text{MSA}$. This measure makes it easy for non-experts to comprehend the footprint. For example, a value of $-1 \text{ km}^2 \cdot \text{MSA}$ represents the biodiversity equivalent found in a pristine tropical forest of 1 km^2 undisturbed by human activities. The impacts of companies are modeled based on four primary environmental pressures affecting species and habitats: changes in land use, climate change from greenhouse gas emissions, air pollution through terrestrial eutrophication and acidification, and water pollution involving the release of toxic chemicals and plastic waste into the environment. Similar to carbon dioxide accounting, all these pressures are aggregated into scopes 1, 2, and 3 (upstream and downstream) following the definition of the GHG Protocol.

The CBF calculation involves three steps. In the first step, the purchases and revenues of the company are divided along the value

³ The Finance for Biodiversity Foundation lists six main metrics: the Corporate Biodiversity Footprint (Iceberg DataLab), Biodiversity Footprint Financial Institutions (CREM and Pre Sustainability), Species Threat Abatement (IUCN), Global Biodiversity Score For Financial Institutions (CDC Biodiversity), Exploring Natural Capital Opportunities, Risk and Exposure (UNEP-WCMC, UNEP-FI & NCFI).

⁴ <https://icebergdatalab.com/>.

chain into quantities of physical goods and services, referred to as “commodities”. This is done by using the Country \times NACE Sector segmentation of revenues and mapping them into quantities through a proprietary physical input–output model called “Wunderpus”, which extends the open-source “EXIOBASE” model.

The second step involves mapping the company’s activity mix to environmental pressures, using a life-cycle analysis (LCA). Based on open-source data and scientific literature, quantities of commodities are transformed into quantified impacts on the four main environmental pressures mentioned above. Each impact is expressed in a specific unit relative to the environmental pressure; for instance, impacts on change of land use are calculated in km², while impacts on climate change are expressed in tCO₂e.

The third step translates these environmental pressures into a unique biodiversity impact unit, which is expressed in km².MSA. For a given pressure, the CBF estimate is calculated as the product of the pressure and its marginal impact on biodiversity. Pressure-impact damage functions from the GLOBIO model enable the transformation of environmental pressures expressed in physical quantities such as tCO₂e, tNO_xe, or km² into km².MSA. Importantly, the baseline MSA is not necessarily 100% per km², since areas may already be degraded on average. In the data, the loss is represented with a negative sign; hence, the larger the absolute number, the more biodiversity degradation is generated by the firm.

The CBF is available from 2011 for over 500 companies worldwide, and the coverage is increasing over the years to reach over 2600 companies by 2022.⁵ For the data up to 2018, a top-down approach is used by Iceberg DataLab to calculate the CBF: company footprints are estimated based on average sector revenues. From 2018 onward, footprints are calculated using company revenues through a bottom-up approach. Therefore, even if the type of data used changes from 2018, the method for calculating the CBF remains the same; however, from 2018 onward, the CBF is more discriminating at the intra-sector level.

Finally, to compare biodiversity footprints with carbon footprints, in particular, to isolate the biodiversity effect from that of carbon, we also retrieve carbon emissions and intensities (that is, emissions scaled by revenues) from the S&P–Trucost database. Given the coverage of companies in Trucost, we work on a final sample of 522 companies that include both biodiversity and carbon footprints from January 2012 to December 2022. This scope is sizeable given the relatively low — albeit growing — propensity of companies to disclose data; indeed, the figures are not reported by the companies themselves, but compiled by a third-party source. We refer to [Marco-Fondevila and Álvarez-Etxeberria \(2023\)](#) for an analysis of the determinants of biodiversity disclosure.

To further illustrate the nature of the data, we present use cases and provide external validation of the CBF in the following section.

2.2. CBF use cases and external validation

To exemplify the CBF score, we plot its decomposition for three large U.S. firms in [Fig. 1](#): Apple, Exxon Mobil, and Walmart.⁶ Three points are noteworthy. First, the CBF scores are substantially different: as expected, technology companies have much smaller footprints than energy or retail firms.

Second, the breakdown of intensities highlights the diversity of pressure sources between sectors, with a significantly higher footprint for retail (e.g., Walmart) and oil & gas (e.g., Exxon) than for telecommunications (e.g., Apple). Indeed, the biodiversity footprint of Walmart

⁵ In case of missing values, data are backfilled with a maximum of three years.

⁶ As there is a size effect, which we address below by using intensities, we consider here three very large companies to allow reasonable comparability of the CBF scores between them.

results mainly from the land occupied for growing vegetables and raising livestock. As for Exxon, the company is one of the top ten oil and gas companies in terms of revenues: it vertically integrates all activities in the value chain, from extraction to refining and distribution of petroleum products. Its biodiversity footprint is, therefore, mainly due to changes in land use (scope 1, for 29%) and the impact on climate change of the end use of its products (downstream scope 3, for 26%).

Third, the dynamics of the biodiversity footprints of Walmart and Exxon have diverged over the past ten years: a deterioration with an increase in the footprint for the former versus a reduction for the latter, especially for the land use and greenhouse gases dimensions. These changes in the CBF can be explained notably by the improvement in measurement accuracy over time and, in particular, the effect linked to the use of firm revenues (switch to a bottom-up approach) in the calculation of the footprint from 2018 onward. However, in the case of our asset pricing study, these evolutions do not raise major issues as we do not focus on an intra-sector analysis: we use either sector portfolios (which, by definition, average out sector-wide measures) or individual firms across sectors. In addition, in [Section 3.2](#), we perform robustness checks suggesting that our conclusions are robust to the change in methodology in 2018.

To provide external validation of the CBF, we compare it to four lists of companies with a significant impact on biodiversity: the Nature Action 100, a list of 100 companies in key sectors in terms of their impact on biodiversity, to which a coalition of investors has committed to engage as shareholders⁷; the WBA Nature Benchmark, a private initiative rating over 1000 companies according to their impact on nature⁸; the Forest 500 list, which identifies and rates 500 companies with the greatest influence on tropical deforestation, based on their exposure to forest-risk commodities or financing⁹; the Forest IQ platform, which provides a score on over 2000 companies based on their impact on deforestation.¹⁰ To compare the CBF with these lists of companies, we proceed in three different ways. First, we calculate statistics on the sectoral correlations between the CBF and the ratings of the other lists. As expected, given that the CBF has a negative score, we find negative correlations, with medians between –15% and –35% ([Fig. 9](#) in the [Appendix](#)). Second, we calculate the average CBF of the quartile of companies with the highest impact on biodiversity for each of the WBA Nature, Forest 500, and Forest IQ ratings ([Table 4](#), also in the [Appendix](#)): for all three lists, the average CBF of this quartile of companies corresponds to a CBF percentile between 23% and 48%, confirming that the CBF identifies companies with a high impact on biodiversity. Third, we calculate the percentage of companies in each of these lists belonging to the lowest quintile in terms of CBF (i.e., having the greatest impact on biodiversity; [Table 4](#)). Depending on the metric chosen, a substantial share of these lists belongs to this quintile. In particular, approximately 70% of Action 100 and WBA Nature companies have a CBF in the lowest quintile.

However, in most asset pricing studies, particularly in portfolio sorting, it is customary to normalize the CBF scores by an approximation of the company size to avoid size bias. Thus, we construct CBF intensities by dividing raw CBF scores by company revenues. The distribution of the absolute values of the intensities (also referred to as *absolute intensities*) for each sector is shown in [Fig. 2](#).

We also categorize the sectors according to what we refer to as “double materiality:” (i) their exposure to physical biodiversity risk, and (ii) their impact on biodiversity, which also captures their transition risk. To construct these categories, we use two measures. (i) First, we measure companies’ exposure to physical risk using the Sectorial Materiality Tool — developed by The Taskforce on Nature-related Financial

⁷ <https://www.natureaction100.org/>.

⁸ <https://www.worldbenchmarkingalliance.org/nature-benchmark/>.

⁹ <https://forest500.org/>.

¹⁰ <https://forestiq.org/about/>.

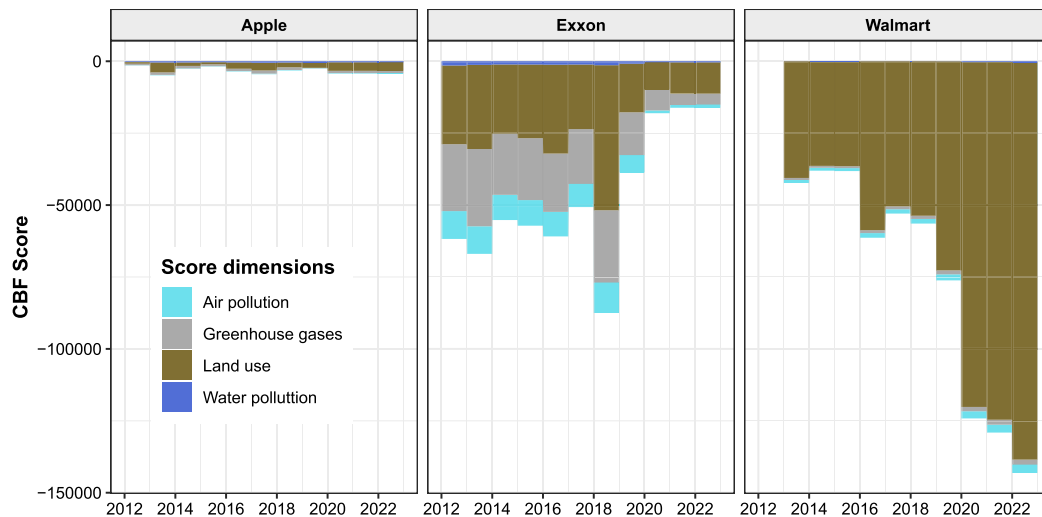


Fig. 1. Sample decomposition of CBF scores. This figure plots the evolution of the four dimensions of the Iceberg Data Lab CBF Scores for three large US corporations. Negative values mean *more* biodiversity loss.

Disclosure (TNFD) and the Science Based Targets Network (SBTN) — which provides materiality rankings at the industry level for 12 impact categories grouped by nature-related issues (land, water, and sea use change, resource exploitation, climate change, pollution, and invasive & other).¹¹ We apply a linear mapping to these ratings to translate them into a score (i.e., a percentile) ranging from 0% for no dependency to 100% for very high dependency. (ii) Second, to measure the impact on biodiversity, we proceed similarly using the ranking of each industry based on the absolute CBF intensity. We then construct an aggregated composite double materiality score as the average of the two scores. Lastly, we divide the universe into three terciles: from the tercile of companies least dependent on and impacting biodiversity to the tercile of companies most dependent on and impacting biodiversity. We refer to the latter tercile as the universe of industries “highly exposed” to the double materiality of biodiversity risks. The double materiality ranking is presented in Table 6 in Appendix. The AFOLU (agriculture, forestry, and other land uses), construction, heat and water utilities, beverages, and electrical equipment sectors are among the most exposed to the double materiality of biodiversity risks.

Fig. 2 shows the disparities between sectors according to their degree of double materiality. Intensities in the telecommunications and healthcare sectors, which have a low degree of double materiality, are significantly lower than those in the energy or industry sectors, which have a high degree of double materiality.

Finally, to analyze which dimensions of biodiversity loss are most critical, we present the absolute CBF intensities distribution for all dates and US companies in the sample in Fig. 3. Corporate land use induces the heaviest biodiversity loss, consistent with Sun et al. (2022). This effect is mainly materialized in the food consumption, manufacturing products, shelter, and clothing sectors (Bjelle et al., 2021). Conversely, water pollution is the least impactful pillar of the CBF, with many observations associated with marginal losses.

¹¹ These ratings aim to answer the following two questions: (i) How significant is the loss of functionality in the production process if the ecosystem service is disrupted? (ii) How significant is the financial loss due to the loss of functionality in the production process? The ratings are expressed as “Very High”, “High”, “Medium”, “Low”, or “Very Low” dependency, with “Very high” materiality rating meaning that both the loss of functionality and the expected financial impact are extremely severe.

2.3. Biodiversity versus carbon footprints

One of the aims of this study is to disentangle the effect of biodiversity and climate on asset returns. In this section on data, we carry out two preliminary analyses to highlight the commonalities and divergences between these two types of metrics.

First, we calculate a series of correlations between combinations of biodiversity intensity on each dimension, carbon intensity, as well as market capitalizations and asset returns. In practice, we compute cross-sectional correlation statistics over all dates of the period of interest. Fig. 4 depicts these statistics ranked according to the median correlation value. It shows two distinct blocks. The first one displays extremely positive correlations and corresponds particularly to correlations between biodiversity factors, which are strongly linked. The second block shows values concentrated around zero and corresponds to the correlations of biodiversity with carbon intensities, asset returns, or market capitalization. Notably, it shows that correlations between biodiversity and carbon intensities are weak and suggests that these two metrics capture sufficiently different information.

Second, to analyze the similarity between biodiversity intensities and carbon intensity, we study the overlap between the rankings according to the two measures. In practice, we study the proportion of companies in both the top 20% of carbon intensity and the top 20% of biodiversity intensity, for each of the dimensions. Similarly, we study the proportion of companies in both the bottom 20% of carbon intensity and the bottom 20% of biodiversity intensity, for each dimension. Fig. 5 shows that these proportions are very different according to the biodiversity intensity dimensions considered. The “sky” components (air pollution and GHGs) show the greatest overlap with carbon intensities, with up to 60% overlap for the top 20% group. Conversely, there is much less overlap when it comes to water pollution. These patterns clearly suggest that biodiversity indices, although partially correlated with carbon emission indices, also capture different effects relevant to our study.

2.4. Realized versus expected returns

The theoretical literature on sustainable asset pricing (Pástor et al., 2021; Pedersen et al., 2021; Zerbib, 2022) shows that climate risks and preferences for companies with low climate footprints affect expected returns by raising the cost of capital of companies that are the largest emitters of greenhouse gases. Testing this hypothesis empirically using realized returns is valid in equilibrium. However, unexpected changes in investors’ climate preferences and risk expectations induce

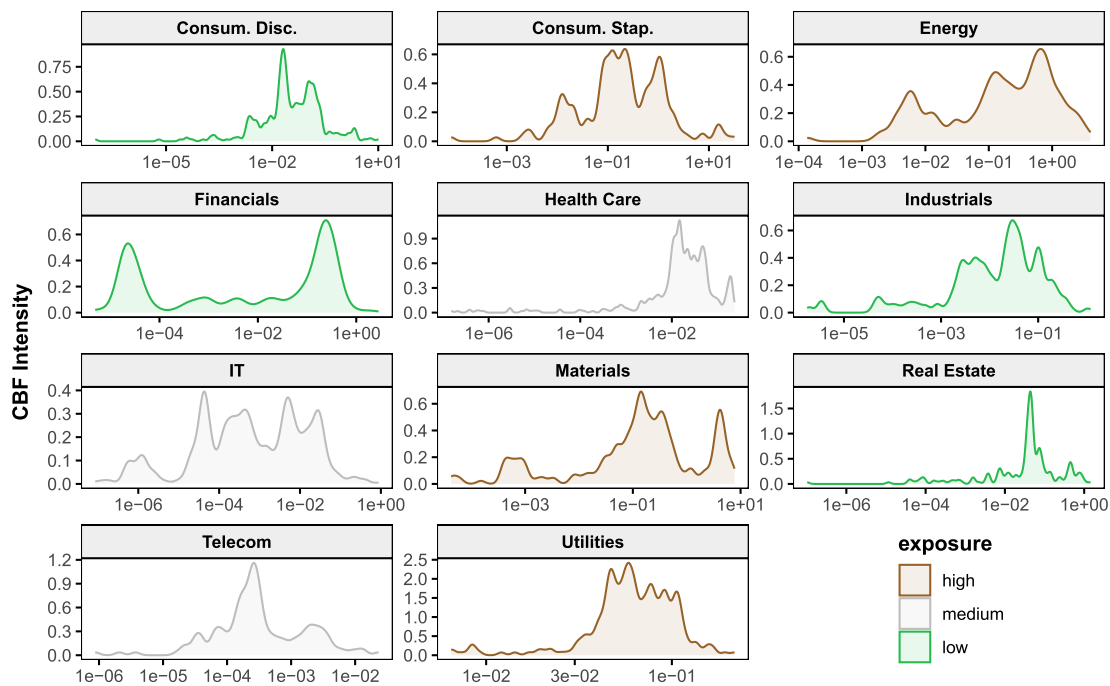


Fig. 2. Distribution of absolute CBF intensities across sectors. We show the distribution of the absolute CBF intensities across 11 sectors, depending on their double materiality exposure to biodiversity loss (defined in Table 7). High scores correspond to large biodiversity dependence and impact. The denominator of the intensity is either the revenue (solid line) or the market capitalization of the company, both expressed in million dollars (dashed density). The x-axis is in logarithmic scale.

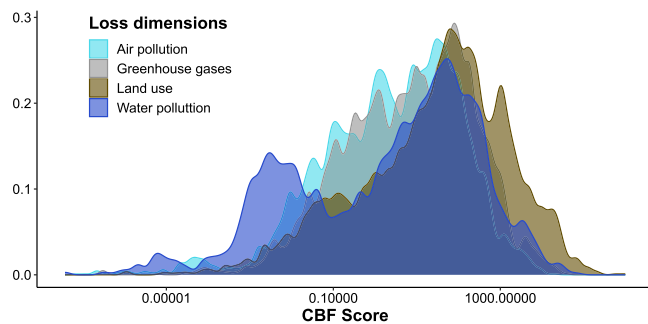


Fig. 3. Prominence of loss dimensions. This figure plots the smoothed density of the absolute CBF score across its four dimensions. High values imply larger negative footprints. The x-axis is in logarithmic scale.

an opposite effect on realized returns, favoring greener assets that benefit from inflows over browner ones (Pástor et al., 2022; Bolton and Kacperczyk, 2023). Therefore, by analogy with climate issues, we choose to analyze both realized returns and a proxy for expected returns hardly unaffected by these inflows.

To do so, we obtain daily stock realized returns from the CRSP database, and we use the proxies built from option prices by Chabi-Yo et al. (2023) to approximate expected returns.¹² For each firm, this metric is computed as the highest lower bound on average excess returns, which they obtain following a decomposition of excess returns into two components. The first one is directly quantifiable and stems from the information gathered in options prices that characterizes the risk-neutral distribution; the second term is unobservable but can be bounded. As this lower bound is tight, it serves as an unbiased proxy for unconditional expected returns.

¹² We are grateful to the authors for making the expected returns proxies available in open access.

In detail, after optimizing certain parameters (e.g., the level of risk aversion), the authors end up with two degrees of freedom. The first is the horizon of the option set: maturities range from 30 days to 365 days; the second choice concerns the approximation of the unknown utility function: the authors use a second-order and a third-order Taylor approximation, but they show that the latter adds little value compared with the former. In total, the authors obtain five maturities and two approximations, that is, ten sets of expected returns. As biodiversity risks materialize over the medium to long term, we choose the series based on the longest time horizon, that is, 365 days, with a second-order Taylor expansion (GLB2-365D). However, the correlations across dates and assets between the ten series are all above 89%.

In Fig. 6, we plot the time series of quantiles of monthly realized returns (left panel) and yearly expected returns (right panel). Oscillating around zero, and despite pronounced movements in 2011 and 2020, realized returns are more volatile in cross-section than expected returns. However, the median of expected returns is always positive, and the crash linked to the Covid-19 crisis at the beginning of 2020 generated a sharp spike in expected returns, which subsequently faded.

3. The biodiversity premia

In this section, we study the impact of biodiversity risks on asset returns as part of an asset pricing exercise: we first construct long-short biodiversity factors, and we estimate the risk premia associated with biodiversity risks. This asset pricing approach has a number of advantages, in particular enabling us to analyze the dynamics of the price of risk over time.

3.1. The biodiversity risk factors

We construct biodiversity factors defined as portfolios long of the quintiles of firms with the highest CBF intensity (i.e., the smallest biodiversity footprint) and short of the quintiles of firms with the lowest CBF intensity (i.e., the highest biodiversity footprint). We construct factors based on (i) the total CBF, (ii) the four dimensions of the CBF (land use, GHG, air pollution, water pollution), and (iii)

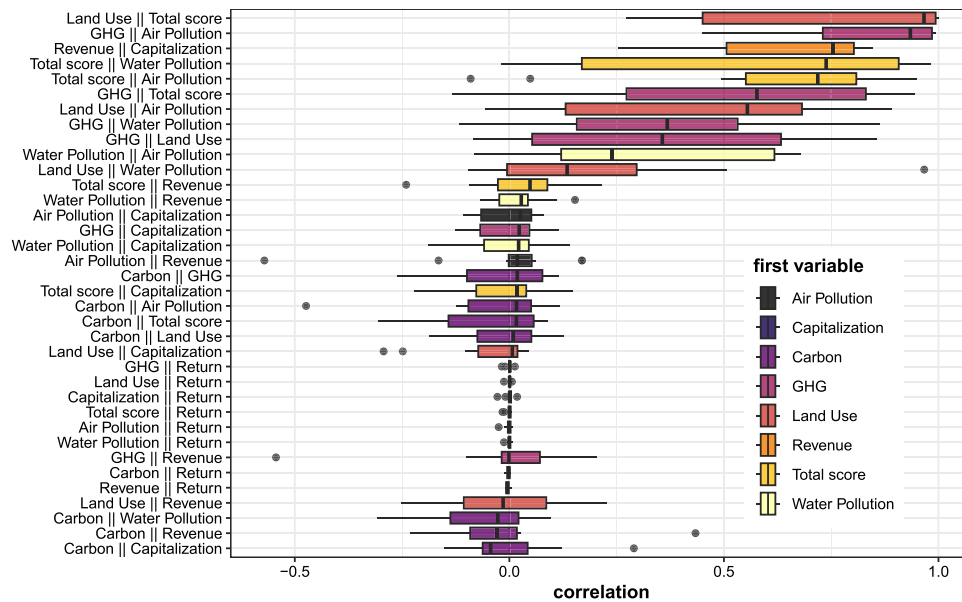


Fig. 4. Correlation between intensities, revenue, returns, and capitalization. This figure represents the box plots of cross-sectional correlations between several variables, notably carbon and biodiversity intensities. The correlations are computed each month in cross-section and their statistics are calculated across dates. The symbol || represents the separation between two variables that are used to calculate the correlation.

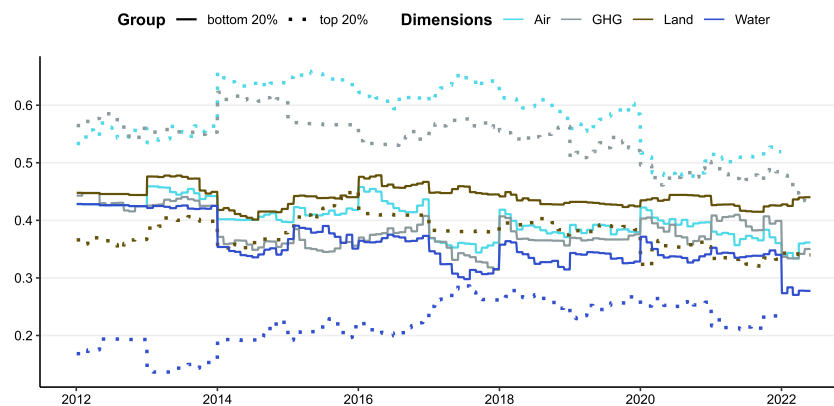


Fig. 5. Similarities in the distribution tails of the biodiversity footprint and carbon footprint. This figure plots the proportion of the bottom 20% (solid line) and top 20% (dotted line) of stocks in terms of carbon intensities that are also among the worst (bottom 20%) and best (top 20%), respectively, in terms of the biodiversity footprint across its four dimensions.

the CBF excluding GHG (“ex-GHG”). (iv) We also build similarly a green-minus-brown carbon factor, independent of biodiversity issues, constructed from S&P-Trucost data (henceforth called “total CO2”). We study market-cap weighted and equally weighted factors. The portfolios are updated monthly, and their performances are evaluated the subsequent month.¹³

Fig. 7 shows the cumulative performance of all the factors sorted on revenue-based intensity. Three comments are in order. First, the performances of equally weighted biodiversity factors have been weaker than value-weighted ones, due to a steady decline since 2020. Second, the dynamics of the biodiversity factors are very heterogeneous: the risk factors linked to greenhouse gases and air pollution have the highest performance, while the one linked to land use has a very negative performance; the factor linked to water pollution is among the best performers when equally weighted but has an intermediate performance when value-weighted. Third, in both cases, the carbon factor dominates all biodiversity factors, reflecting the continuous interest in low-carbon

assets by sustainable investors, also referred to as “unexpected shift in preferences” (Pástor et al., 2022).

The first way of comparing the various factors is to study their correlations with each other. The correlations are given in Table 5 in Appendix B.1 and lead to three conclusions. The performances of the biodiversity factors are all highly positively correlated, to varying degrees. Conversely, the biodiversity factors are only weakly correlated with the carbon factor, which underlines the interest in studying the impact of biodiversity on asset prices as a complement to existing work on carbon risk (Engle et al., 2020; Bolton and Kacperczyk, 2021, 2024; Pástor et al., 2022; Zhang, 2024). Third, biodiversity factors barely comove with the Fama and French (2015) factors, with the exception of the HML factor, which has a strongly negative correlation, suggesting proximity between the scope of companies with a low biodiversity footprint and companies with a growth profile, in line with existing findings on the carbon factor (Pástor et al., 2022).

In the second step, we investigate whether the biodiversity factors are spanned by the Fama and French (2015) and carbon factors. To do so, we regress each biodiversity factor on these factors (Table 1). In the equally weighted case, the total CBF score with and without GHG (also referred to as “ex-GHG”) has a significant alpha. This result

¹³ To mitigate the effect of outliers, the daily returns at winsorized at +150%.

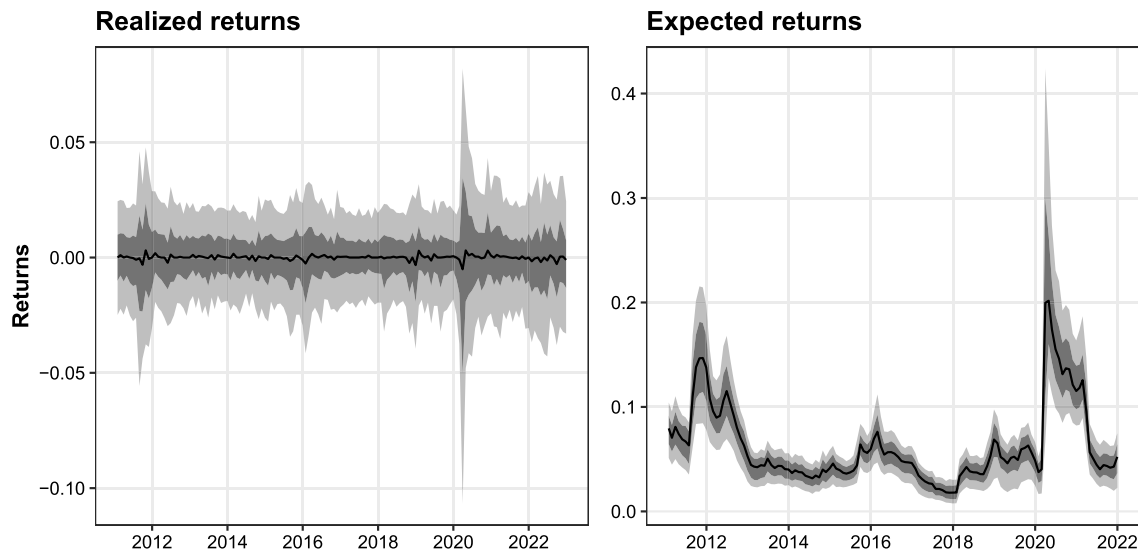


Fig. 6. Dynamics of realized and expected returns. We plot the time series of the quantiles of one-month realized (left) and one-year expected (right) returns. The black line is the median, the light gray area excludes the extreme deciles (hence, shows the 10%–90% interval) while the dark gray area represents the inter-quartile range (25%–75% quantiles). The expected returns are based on the second-order Taylor expansion described in Chabi-Yo et al. (2023) for options with one year maturity (GLB2-365D).

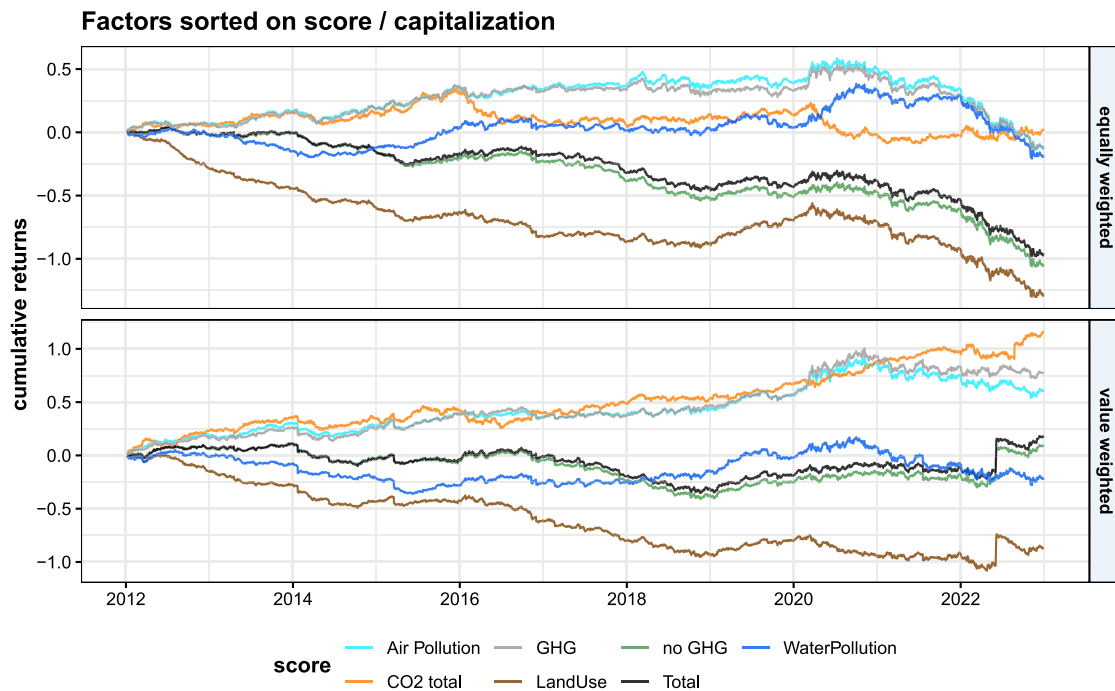


Fig. 7. Cumulative returns of the green-minus-brown biodiversity factors. We plot the cumulative returns of the biodiversity green-minus-brown factors along each dimension, across two weighting schemes: equally-weighted in the upper panel and value-weighted in the lower one. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

suggests that the biodiversity factors with and without GHG emissions have dynamics that cannot be fully explained by the Fama French and carbon factors. The fact that these alphas are insignificant in the value-weighted case suggests that small-cap companies significantly drive such an effect. Some biodiversity sub-factors are at the root of this result, notably the land use factor, which is significant in both the equally-weighted and value-weighted cases. Thus, as the biodiversity factors are not subsumed by the Fama and French (2015) and the carbon factors, we proceed with the estimation of the biodiversity risk premia in the next section.

3.2. The biodiversity premia

In this section, we estimate the biodiversity and the ex-GHG biodiversity risk premia through a two-pass regression (Fama and MacBeth, 1973). In the first pass, for each stock, at a weekly frequency, we estimate the 1-year rolling betas, which we winsorize at the 2% level to mitigate the effect of outliers; in the second pass, risk prices are estimated as the average of the loadings estimated in the cross-sectional regression of returns on betas each month. In all regressions, we control for the Fama and French (2015) five factors, and when estimating

Table 1

Factor exposure of green-minus-brown biodiversity factors. This table shows the coefficients and *t*-statistics (in brackets) of the Fama MacBeth regressions, with Newey–West standard errors, of the green-minus-brown biodiversity factors on the Fama and French (2015) factors and the green-minus-brown carbon factor. The significance levels are coded according to *p*-values as (***) < 0.001 < (**) < 0.01 < (*) < 0.1.

Sorting variable	alpha	MKT-RF	SMB	HML	RMW	CMA	Carbon
Panel A: Equally-weighted portfolios							
Total score	−0.0004*** (−4.455)	0.074*** (6.054)	−0.076*** (−4.197)	−0.506*** (−22.411)	−0.095** (−2.821)	−0.17*** (−3.581)	0.141*** (6.208)
Air pollution	−0.0001 (−0.641)	0.124*** (4.767)	−0.02 (−0.949)	−0.581*** (−22.223)	−0.24*** (−6.597)	−0.207*** (−3.701)	0.328*** (11.349)
GHG	−0.0001 (−0.594)	0.089*** (3.923)	−0.029 (−1.292)	−0.622*** (−23.836)	−0.176*** (−5.08)	−0.11* (−2.141)	0.334*** (12.531)
Land use	−0.0005*** (−5.736)	0.07*** (6.146)	−0.041* (−2.181)	−0.49*** (−23.308)	−0.184*** (−6.036)	−0.184*** (−4.798)	0.106*** (5.561)
Water pollution	0.0000 (−0.425)	−0.019 (−1.167)	−0.071* (−2.247)	−0.499*** (−19.539)	0.034 (0.981)	−0.23*** (−4.099)	0.03 (1.234)
Ex-GHG	−0.0004*** (−4.992)	0.079*** (6.106)	−0.063** (−3.307)	−0.475*** (−21.09)	−0.1** (−2.818)	−0.175*** (−3.687)	0.117*** (5.351)
Panel B: Value-weighted portfolios							
Total score	0.0000 (−0.024)	0.049* (2.033)	0.037 (1.54)	−0.391*** (−8.837)	0.09* (2.07)	0.012 (0.161)	0.097* (2.564)
Air pollution	0.0001 (0.783)	0.017 (0.956)	−0.074** (−3.105)	−0.715*** (−22.184)	−0.013 (−0.462)	−0.005 (−0.104)	0.358*** (5.812)
GHG	0.0001 (1.632)	−0.016 (−0.883)	−0.066* (−1.891)	−0.817*** (−27.383)	0.095** (2.781)	0.164** (2.945)	0.331*** (5.632)
Land use	−0.0004* (−2.498)	0.051* (2.52)	0.045* (2.002)	−0.354*** (−8.474)	0.06 (1.418)	−0.01 (−0.137)	0.085* (2.38)
Water pollution	−0.0001 (−0.903)	0.056*** (3.529)	−0.051 (−1.207)	−0.576*** (−16.896)	0.059 (1.358)	−0.133* (−1.876)	0.017 (0.477)
Ex-GHG	0.0000 (−0.205)	0.056* (2.2)	0.048* (1.997)	−0.363*** (−7.75)	0.087* (1.987)	−0.003 (−0.038)	0.085* (2.324)

the ex-GHG biodiversity risk premium, we also control for the carbon factor.

We perform the estimations on sector portfolios and consider two main cases: a first estimation based on realized returns and a second one based on a proxy for expected returns derived from option prices. The use of this proxy allows us to avoid capturing the impact of unexpected changes in preferences on asset prices (Pástor et al., 2022). The sector portfolios are those of Fama and French (2015) in the case of realized returns, while we reconstruct expected returns at the sector level from the expected returns of each stock. For each of these two cases, we consider both equally-weighted and market-cap-weighted factors.

In the first approach, we carry out the estimation for all the sectors in the universe (Panel A of Table 2). When using realized returns, in all the cases studied, neither the biodiversity factor nor the ex-GHG biodiversity factor has a significant price of risk. Similarly, analysis of the risk premium on expected returns gives non-significant results for both equally-weighted and value-weighted biodiversity factors.

Second, we focus on the sectors highly exposed to the double materiality of biodiversity risks (transition and physical risks), as described in Section 2.2. This double materiality analysis is natural and consistent with current regulatory developments, such as those of the European Commission, which require companies to disclose their impact and dependencies on ecosystem services through the Sustainable Finance Disclosure Regulation (SFDR). Therefore, we focus on companies in sectors classified as “highly exposed”. We work at the firm level because the number of sectors is too limited. Specifically, we focus on the scope of firms for which we have both realized and expected returns over the entire period, thereby ending up with 156 stocks spanning the scope of highly exposed industries.

The estimation based on realized returns shows a positive price of risk of 7.2% on the value-weighted ex-GHG biodiversity factor (Panel B of Table 2). This result highlights the financial outperformance of companies with a low biodiversity footprint in the sectors most exposed to the double materiality of biodiversity risks and echoes the results of Pástor et al. (2022) on climate issues.

Panel B of Table 2 also shows the results of the same estimation on expected returns. We document a significantly negative price of risk

of −1.7% and −1.5% for the value-weighted biodiversity and ex-GHG biodiversity factors, respectively.¹⁴ This result suggests that investors require a higher cost of capital to hold assets with a large biodiversity footprint compared to those with a smaller footprint in the highly exposed sectors. This result is in line with the theoretical work on ESG asset pricing (e.g., Pástor et al., 2021) as well as the empirical results on the climate factor (e.g., Pástor et al., 2022).

We study the robustness of this result to the change in CBF calculation methodology, which occurred in 2018, in two different ways (Appendix B.3.2). First, we show that the percentage of companies changing quintile before and after 2018 remains stable, at around 25%. The stability of this turnover rate before and after 2018 alleviates concerns about the possibility that this change in methodology might have had a significant effect on the construction of the biodiversity factor. Second, we show that, even over a different period shaped by the war in Ukraine and rising interest rates, the price of the biodiversity risk factor remains significantly negative in industries highly exposed to the double materiality of biodiversity risks.

This study, thus, contributes to the literature, notably by documenting a negative risk premium linked to the biodiversity footprint on sectors most exposed to the double materiality of biodiversity risks. This finding is consistent with the one of Garel et al. (2024), who observe a negative price shock for companies with a high biodiversity footprint following the UN Biodiversity Conference (COP15). It also echoes the finding of Giglio et al. (2023) that returns of portfolios sorted on companies’ exposure to biodiversity risk covary positively with innovations in biodiversity risk. However, this result also raises two other important questions: what are the dynamics of these premia, and can they be explained by certain factors? We answer these questions in the next section.

¹⁴ The analysis using expected returns extracted from 30-day option prices yields prices of risk with a similar order of magnitude but significance levels lower than 10% (see Table 8 in the Appendix). This result is not surprising as the horizon is too short to embed a significant pricing of biodiversity risks.

Table 2

Annual biodiversity risk premium. This table gives the estimates of annualized biodiversity risk premia via a Fama MacBeth two-pass estimation with Newey–West standard errors. In panel A, we use the returns of sector portfolios, while in panel B, we use those of single stocks in the sectors most exposed to the double materiality of biodiversity risks as dependent variables. We focus on two factors: the biodiversity factor and the ex-GHG biodiversity factor. For both panels, we consider two main cases: monthly realized returns and annual expected returns estimated from option prices (Chabi-Yo et al., 2023). Risk prices are annualized for realized returns. Finally, for each of the cases considered, we give risk prices based on green-minus-brown biodiversity factors constructed as value-weighted and equally weighted based on CBF intensities computed with firms' revenues. The t -statistics are given in brackets and significance thresholds for p -values are coded as: (***) < 0.001 < (**) < 0.01 < (*) < 0.1.

Panel A: Entire universe								
	Realized returns				Expected returns			
	EW	VW	EW	VW	EW	VW	EW	VW
Biodiv	0.047 (0.707)	-0.015 (0.132)			0.001 (0.351)	0.007 (1.141)		
BiodivExGHG			0.013 (0.209)	-0.054 (0.478)			0.001 (0.501)	0.005 (0.781)
Fama French (2015) controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carbon control	No	No	Yes	Yes	No	No	Yes	Yes
Panel B: Highly exposed industries to the double materiality biodiversity risks								
	Realized returns				Expected returns			
	EW	VW	EW	VW	EW	VW	EW	VW
Biodiv	0.016 (0.419)	0.036 (1.521)			-0.002 (1.157)	-0.017* (1.662)		
BiodivExGHG			0.017 (0.460)	0.072** (3.194)			-0.001 (0.287)	-0.015* (1.718)
Fama French (2015) controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carbon control	No	No	Yes	Yes	No	No	Yes	Yes

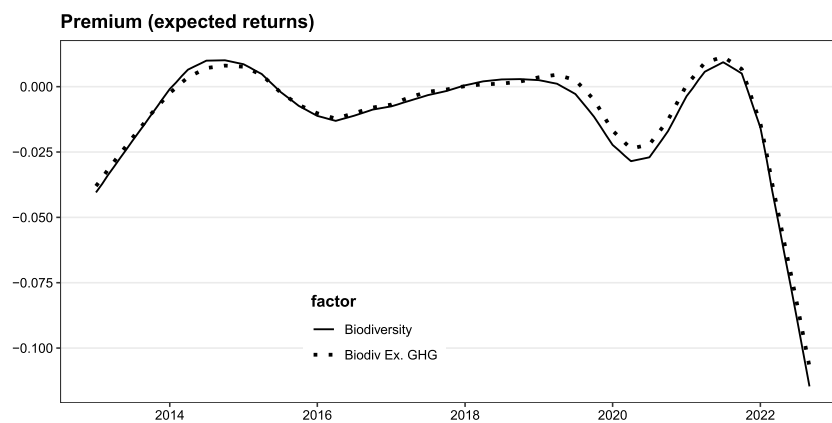


Fig. 8. Dynamics of the annual price of risk of US stocks' expected returns in industries highly exposed to the double materiality of biodiversity risks. This figure gives the dynamics of the annual price of risk of US stocks in industries highly exposed to the double materiality of biodiversity risks estimated in Table 2 from the one-year expected returns with a value-weighted factor. We plot the twelve-month additive trend decomposition for both the biodiversity and the biodiversity ex-GHG factors.

3.3. Explaining time-variations of the biodiversity premia

In this section, we study and explain the dynamics of prices of risks in the industries most exposed to the double materiality of biodiversity risks. To do so, we display, in Fig. 8, the one-year rolling price of risk estimated on expected returns using a value-weighted biodiversity factor. Both the price of biodiversity and ex-GHG biodiversity risks are fairly stable until 2021: they have been oscillating around zero since the beginning of the analysis period and have fallen sharply from 2021 to reach -10% in 2022. Thus, they reflect the recent awareness toward biodiversity risks and their impact on asset prices, which is consistent with record-high public attention to biodiversity according to the biodiversity attention index of Giglio et al. (2023). Therefore, the negative price of risk estimated in the previous section is mainly driven by its recent trend.

Next, we study the drivers of the dynamics of biodiversity risk prices. To do so, for each of the two biodiversity dimensions i (biodiversity and ex-GHG biodiversity), we consider the following linear specification:

$$\lambda_{i,t} = \phi_1 + \phi_2 \lambda_{i,t-1} + \phi_3' X_{t-1} + \epsilon_{i,t}, \quad (1)$$

where $\lambda_{i,t}$ is the one-year rolling price of risk in month t for biodiversity factor i and ϕ_2 accounts for the likely persistence of the price of risk over time. We consider the following independent variables denoted by vector X_{t-1} : a biodiversity attention index and a climate risk index, both derived from Giglio et al. (2023), the oil prices, a consumer sentiment index taken from the FRED-MD database (McCracken and Ng, 2016) and a risk aversion index provided by Bekaert et al. (2022). These variables account for different possible channels, from climate change awareness to the general state of the economy and specific market conditions.

The results are given in Table 3. The estimations explain up to 40% of the biodiversity price of risk dynamics.

First, attention to biodiversity very significantly lowers the price of risk, and thus contributes to increasing the gap between expected returns on stocks of companies with a low biodiversity footprint and those of companies with a high biodiversity footprint. This result is consistent with the impact of investor awareness of biodiversity risks on asset prices. Similarly, by significantly lowering the price of biodiversity risk, the increase in risk aversion appears to lead investors to revise their expectations on returns according to companies' biodiversity footprints. As shown in Table 10 in the Appendix, the effect is

Table 3

Drivers of the biodiversity risk premia This table gives estimates of the regression of the residuals of an AR(1) on the price of risk of biodiversity and ex-GHG biodiversity on several time series as independent variables. Significance thresholds for p -values are coded as: + $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

	Biodiversity	BiodiversityExCarbon
(Intercept)	0.000 (0.002)	0.000 (0.164)
Biodiversity attention	-0.005*** (-5.478)	-0.005*** (-5.037)
Climate attention	0.002** (2.646)	0.002** (2.784)
Consumer sentiment	0.002** (2.912)	0.002** (2.887)
Oil price	0.000 (0.132)	0.000 (-0.151)
Risk aversion	-0.002* (-2.464)	-0.001+ (-1.889)
Num.Obs.	110	110
R2	0.415	0.386
R2 Adj.	0.381	0.350

similar when we replace the risk aversion with the VIX index which captures forward-looking expectations on uncertainty.

Second, conversely, attention to climate risk has a positive impact on the price of biodiversity risk, suggesting a possible reallocation of assets within environmental issues in favor of low-carbon footprint assets (Engle et al., 2020). Finally, consumer sentiment is associated with a positive and significant coefficient. This is consistent with previous findings on carbon risk premium (e.g., Lucia et al., 2022): when investors are more confident about the future, they tend to revise their preferences and assign less importance to future risks, thereby lowering the compensation required for holding “brown” firms in their portfolios.

4. Conclusion

Our results highlight the existence of a biodiversity risk premium on expected returns, in the US, in the sectors most exposed to the double materiality of biodiversity risks. A dynamic analysis shows that this risk premium has recently materialized, notably from 2021, to reach an annual price of risk of -10% in 2022 on the factor going long on low-biodiversity intensity stocks and short on high-biodiversity intensity stocks. We also show that this biodiversity risk premium is distinct from a carbon premium, already widely studied in the literature, and that it increases with attention to biodiversity issues and risk aversion.

A natural question arising from this result concerns the impact that investors can have on companies with a high biodiversity footprint by increasing their cost of capital: do these companies have an incentive to reduce their biodiversity footprint? To what extent? (De Angelis et al., 2023) show that underweighting assets with a high carbon footprint only leads to a slight reduction in their carbon footprints. There are reasons to assume a similar hypothesis, given the similarity of the mechanisms involved, but an in-depth analysis would be an interesting avenue for future research.

In addition, there are several other major related topics worth exploring in future research. First, it would be interesting to understand which investors are most committed to investing in firms with a low biodiversity footprint, and to what extent these investment choices reflect the preferences of their clients. Second, it would be useful to learn how investors balance the biodiversity objective with the climate objective. To this end, a dynamic multi-criteria model could be developed and estimated. Finally, it would be interesting to analyze shareholder engagement in favor of biodiversity and the reaction of companies to it.

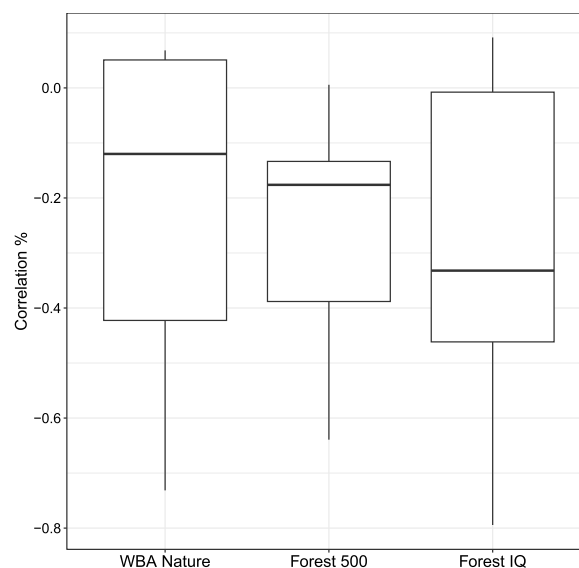


Fig. 9. Correlation of the CBF with other public biodiversity assessments. This figure shows the distribution of sector correlation between the CBF and other publicly available scores. AS the CBF has negative values, the lower the correlation the closer the two assessments are.

CRedit authorship contribution statement

Guillaume Coqueret: Writing – review & editing, Writing – original draft, Visualization, Software, Formal analysis, Data curation, Conceptualization. **Thomas Giroux:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Olivier David Zerbib:** Writing – review & editing, Methodology, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Thomas Giroux reports a relationship with Mirova that includes: employment.

Appendix A. Biodiversity corporate footprint (CBF): additional results

See Fig. 9 and Table 4.

Appendix B. The biodiversity premia: further results

B.1. Factors

See Table 5.

B.2. Materiality rankings

See Tables 6 and 7.

B.3. Robustness checks

B.3.1. Estimation of the biodiversity risk premia using expected returns extracted from 30-day option prices

See Table 8.

Table 4

Corporate Biodiversity Footprint (CBF) vs. Public biodiversity assessments For quantitative scores (denoted by *), we identify the companies belonging to the worst quartile, while we keep the total list for Action 100. For each group, we display (i) the average CBF percentile relative to the rest of the universe (upper part of the table) and (ii) the proportion of this group belonging to the worst quintile (20%) of the CBF distribution (lower part of the table).

	Action 100	WBA Nature*	Forest 500*	Forest IQ*
Average percentile CBF	23.13	23.90	30.55	40.51
Average percentile CBF/Revenues	39.13	37.60	44.18	48.69
Average percentile CBF Land Use	24.68	26.85	28.64	39.51
Average percentile CBF Land Use/Revenues	39.27	39.96	39.08	46.26
Worst 20% CBF	71%	70%	48%	36%
Worst 20% CBF/Revenues	39%	37%	26%	26%
Worst 20% CBF Land Use	69%	66%	50%	36%
Worst 20% CBF Land Use/Revenues	42%	37%	36%	26%

Table 5

Correlation between factors. This table provides the correlations between the factors sorted on the CBF intensities, the Fama and French (2015) factors, and the carbon factor. The upper right (resp. lower left) panel uses equally-weighted (resp. value-weighted) factors. The upper left and lower right panels use value-weighted factors. Total refers to all biodiversity components taken together.

	Traditional factors					Biodiversity factors						
	MKT-RF	SMB	HML	RMW	CMA	Air Poll.	GHG	Land use	Total	Water Poll.	no GHG	CO2
MKT-RF	1.000	0.202	-0.045	-0.197	-0.290	0.242	0.173	0.190	0.173	0.017	0.190	-0.101
SMB	0.202	1.000	0.209	-0.251	-0.023	-0.071	-0.114	-0.108	-0.162	-0.201	-0.141	0.001
HML	-0.045	0.209	1.000	0.317	0.615	-0.691	-0.715	-0.726	-0.721	-0.692	-0.700	0.246
RMW	-0.197	-0.251	0.317	1.000	0.305	-0.386	-0.344	-0.371	-0.300	-0.187	-0.304	0.108
CMA	-0.290	-0.023	0.615	0.305	1.000	-0.605	-0.573	-0.578	-0.566	-0.498	-0.557	-0.023
Air Pollution	0.131	-0.183	-0.713	-0.270	-0.514	1.000	0.972	0.848	0.861	0.729	0.843	0.087
GHG	0.046	-0.229	-0.747	-0.202	-0.456	0.957	1.000	0.824	0.843	0.724	0.819	0.093
LandUse	0.107	-0.029	-0.335	-0.111	-0.247	0.512	0.510	1.000	0.962	0.821	0.967	-0.073
Total	0.097	-0.046	-0.347	-0.097	-0.244	0.527	0.527	0.984	1.000	0.876	0.990	-0.038
WaterPollution	0.118	-0.158	-0.655	-0.188	-0.463	0.807	0.790	0.566	0.588	1.000	0.876	-0.112
no GHG	0.109	-0.032	-0.332	-0.097	-0.242	0.516	0.513	0.987	0.995	0.591	1.000	-0.054
CO2	0.264	0.076	0.157	-0.110	-0.143	0.201	0.129	0.034	0.032	-0.057	0.032	1.000

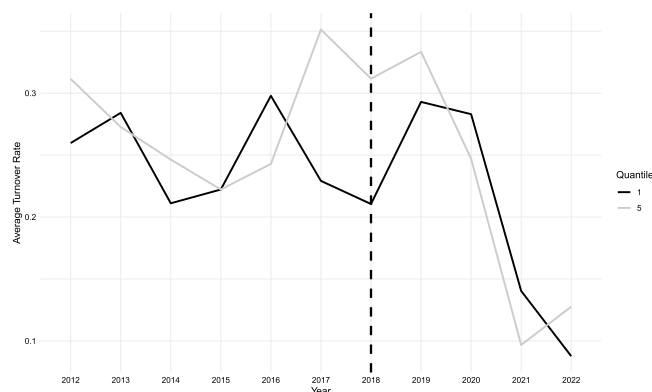


Fig. 10. Turnover rate of CBF intensities best-in-class quantiles. This figure shows the average turnover rate by quantile computed within GICS sector (Best-in-class), based on CBF intensities computed by enterprise value.

B.3.2. Estimation of the biodiversity risk premia using data from 2018 onward

As elaborated in Section 2.1, the methodology for calculating the CBF was revised in 2018, thanks to the availability of more detailed data. To analyze the impact of the methodology revision on our biodiversity factor, we calculate the turnover rate of companies by quintile, defined as the percentage of companies that move from one quantile to another each year (Fig. 10). Before and after 2018, the average turnover is of the same magnitude, approximately 25%. The stability of the turnover rate before and after 2018 alleviates concerns about the possibility that this change in methodology might have had a significant effect on the construction of the biodiversity factor.

We also repeat the estimation of the biodiversity risk premium between 2018 and 2022 (Table 9). It is worth noting that comparing the estimates with those in the main case is irrelevant given the temporal

inconsistency. However, although the price of risk of the biodiversity factor is positive over the entire universe, consistent with the negative effect of the war in Ukraine and rising rates on the asset prices of companies with a low environmental footprint, the price of biodiversity risk remains significantly negative on companies in industries with high exposure to the double materiality of biodiversity risks.

B.3.3. Estimation of the drivers of the price of biodiversity risks using the VIX instead of the risk aversion

See Table 10.

Data availability

The authors do not have permission to share data.

Table 6

Double materiality industry ranking. Industries are ranked by highest exposure to biodiversity loss. Average CBF/Sales and SBTN Scores are computed at the GICS Sub-Industry level then aggregated and matched to Fama & French 48 Industry portfolios. SBTN original ratings are transformed into quantitative scores following a linear scale.

	FF 48 code	FF 48 name	FF 48 industry long name	GICS industry	CBF/Revenue	SBTN materiality score	CBF ranking	SBTN ranking	Average ranking	Exposure
1	14	Chems	Chemicals	151 010.00	-0.39	223.42	5.00	4.00	4.50	High
2	39	Boxes	Shipping Containers	151 030.00	-0.72	159.33	4.00	5.00	4.50	High
3	38	Paper	Business Supplies	151 050.00	-1.35	90.00	1.00	14.00	7.50	High
4	22	ElcEq	Electrical Equipment	201 040.00	-0.23	105.57	8.00	10.00	9.00	High
5	1	Agric	Agriculture	302 020.00	-0.84	81.29	2.00	18.00	10.00	High
6	2	Food	Food Products	302 020.00	-0.84	81.29	3.00	19.00	11.00	High
7	17	BldMt	Construction Materials	151 020.00	-0.10	154.38	18.00	6.00	12.00	High
8	31	Util	Utilities	551 010.00	-0.06	310.00	27.00	1.00	14.00	High
9	9	Hshld	Consumer Goods	303 020.00	-0.05	254.00	30.00	2.00	16.00	High
10	28	Mines	Non-Metallic and Industrial Metal Mining	151 040.00	-0.13	78.77	13.00	20.00	16.50	High
11	36	Chips	Electronic Equipment	252 010.00	-0.08	96.23	21.00	12.00	16.50	High
12	25	Ships	Shipbuilding, Railroad Equipment	203 050.00	-0.04	247.00	31.00	3.00	17.00	High
13	10	Clths	Apparel	252 030.00	-0.10	84.22	19.00	16.00	17.50	High
14	18	Cnstr	Construction	201 030.00	-0.07	132.08	26.00	9.00	17.50	High
15	27	Gold	Precious Metals	151 040.00	-0.13	78.77	14.00	21.00	17.50	High
16	29	Coal	Coal	101 020.00	-0.08	103.86	24.00	11.00	17.50	High
17	4	Beer	Beer & Liquor	302 010.00	-0.17	74.00	11.00	25.00	18.00	Medium
18	16	Txtls	Textiles	252 030.00	-0.10	84.22	20.00	17.00	18.50	Medium
19	19	Steel	Steel Works Etc	151 040.00	-0.13	78.77	15.00	22.00	18.50	Medium
20	3	Soda	Candy & Soda	302 010.00	-0.17	74.00	12.00	26.00	19.00	Medium
21	13	Drugs	Pharmaceutical Products	352 020.00	-0.23	49.00	9.00	31.00	20.00	Medium
22	34	BusSv	Business Services	201 070.00	-0.07	89.38	25.00	15.00	20.00	Medium
23	21	Mach	Machinery	201 060.00	-0.06	92.97	28.00	13.00	20.50	Medium
24	30	Oil	Petroleum and Natural Gas	101 010.00	-0.02	136.00	34.00	7.00	20.50	Medium
25	37	LabEq	Measuring and Control Equipment	352 030.00	-0.22	49.00	10.00	32.00	21.00	Medium
26	15	Rubbr	Rubber and Plastic Products	251 010.00	-0.08	76.50	22.00	23.00	22.50	Medium
27	26	Guns	Defense	201 010.00	-0.13	68.83	17.00	28.00	22.50	Medium
28	40	Trans	Transportation	203 010.00	-0.01	135.80	38.00	8.00	23.00	Medium
29	41	Whlsl	Wholesale	251 010.00	-0.08	76.50	23.00	24.00	23.50	Medium
30	43	Meals	Restaurants, Hotels, Motels	253 010.00	-0.33	16.76	6.00	42.00	24.00	Medium
31	5	Smoke	Tobacco Products	302 030.00	-0.13	45.00	16.00	33.00	24.50	Medium
32	44	Banks	Banking	401 010.00	-0.24	6.00	7.00	43.00	25.00	Low
33	23	Autos	Automobiles and Trucks	251 020.00	-0.03	71.00	32.00	27.00	29.50	Low
34	6	Toys	Recreation	252 020.00	-0.02	62.00	33.00	29.00	31.00	Low
35	42	Rtail	Retail	255 010.00	-0.01	50.67	37.00	30.00	33.50	Low
36	35	Comps	Computers	452 020.00	-0.05	26.00	29.00	39.00	34.00	Low
37	33	PerSv	Personal Services	253 020.00	-0.02	34.00	35.00	36.00	35.50	Low
38	7	Fun	Entertainment	502 010.00	-0.00	40.38	41.00	34.00	37.50	Low
39	12	MedEq	Medical Equipment	351 030.00	-0.00	34.00	39.00	37.00	38.00	Low
40	32	Telcm	Communication	452 010.00	-0.01	26.00	36.00	40.00	38.00	Low
41	8	Books	Printing and Publishing	502 010.00	-0.00	40.38	42.00	35.00	38.50	Low
42	11	Hlth	Healthcare	351 020.00	-0.00	33.25	40.00	38.00	39.00	Low
43	45	Insur	Insurance	403 010.00	-0.00	21.75	45.00	41.00	43.00	Low
44	47	Fin	Trading	402 010.00	-0.00	6.00	43.00	44.00	43.50	Low
45	46	REst	Real Estate	402 040.00	-0.00	6.00	44.00	45.00	44.50	Low
46	20	FabPr	Fabricated Products							Low
47	24	Aero	Aircraft							Low
48	48	Other	Almost Nothing							Low

Table 7

Double materiality GICS sectors ranking. Sectors are ranked by highest exposure to biodiversity loss. Average CBF/Sales and SBTN Scores are computed at the GICS Sub-Industry level then aggregated at the Sector level. SBTN original materiality ratings are transformed into quantitative scores following a linear scale.

	GICS sector	GICS sector name	CBF/Revenue	SBTN score	CBF rank	SBTN rank	Average rank	Exposure
1	15	Materials	-0.26	136.56	2.00	2.00	2.00	High
2	30	Consumer staples	-0.33	75.51	1.00	6.00	3.50	High
3	55	Utilities	-0.07	213.80	8.00	1.00	4.50	High
4	10	Energy	-0.08	113.04	6.00	3.00	4.50	High
5	60	Real estate	-0.08	106.00	5.00	4.00	4.50	Medium
6	25	Consumer discretionary	-0.10	55.71	4.00	7.00	5.50	Medium
7	20	Industrials	-0.07	99.20	7.00	5.00	6.00	Medium
8	40	Financials	-0.13	9.94	3.00	11.00	7.00	Medium
9	35	Health care	-0.05	43.50	9.00	8.00	8.50	Low
10	45	Information technology	-0.03	38.96	10.00	9.00	9.50	Low
11	50	Communication Services	-0.00	37.56	11.00	10.00	10.50	Low

Table 8

Annual biodiversity risk premium using 30-day expected returns. This table gives the estimates of annualized biodiversity risk premia via a Fama MacBeth two-pass estimation with Newey–West standard errors. In the left panel, we use the returns of sector portfolios, while in the right panel, we use those of single stocks in the sectors most exposed to the double materiality of biodiversity risks as dependent variables. We focus on two factors: the biodiversity factor and the ex-GHG biodiversity factor. For both panels, we consider annual expected returns estimated from option prices with a 30-day horizon (Chabi-Yo et al., 2023). Risk prices are annualized. Finally, for each of the cases considered, we give risk prices based on green-minus-brown biodiversity factors constructed as value-weighted and equally weighted based on CBF intensities computed with firms’ revenues. The *t*-statistics are given in brackets and significance thresholds for *p*-values are coded as: (***) < 0.001 < (**) < 0.01 < (*) < 0.1.

Expected returns - Short Horizon 30 days								
	Entire universe				Highly exposed industries			
	EW	VW	EW	VW	EW	VW	EW	VW
Biodiv	-0.005 (0.878)	0.003 (1.621)			-0.005 (1.233)	-0.016 (1.399)		
BiodivExGHG			-0.007 (1.187)	0.003 (1.325)			-0.002 (0.744)	-0.010 (1.067)
Fama French (2015) controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carbon control	No	No	Yes	Yes	No	No	Yes	Yes

Table 9

Annual biodiversity risk premium - 2018 onward. This table gives the estimates of annualized biodiversity risk premia via a Fama MacBeth two-pass estimation with Newey–West standard errors for the sub-sample of years 2018 to 2022. In panel A, we use the returns of sector portfolios, while in panel B, we use those of single stocks in the sectors most exposed to the double materiality of biodiversity risks as dependent variables. We focus on two factors: the biodiversity factor and the ex-GHG biodiversity factor. For both panels, we consider two main cases: monthly realized returns and annual expected returns estimated from option prices (Chabi-Yo et al., 2023). Risk prices are annualized for realized returns. Finally, for each of the cases considered, we give risk prices based on green-minus-brown biodiversity factors constructed as value-weighted and equally weighted based on CBF intensities computed with firms’ revenues. The *t*-statistics are given in brackets and significance thresholds for *p*-values are coded as: (***) < 0.001 < (**) < 0.01 < (*) < 0.1.

Panel A: Entire universe								
	Realized returns				Expected returns			
	EW	VW	EW	VW	EW	VW	EW	VW
Biodiv	-0.011 (0.120)	0.007 (0.038)			0.007 (0.912)	0.049* (2.049)		
BiodivExGHG			0.164 (1.34)	0.101 (0.575)			0.014* (2.46)	0.050* (2.289)
Fama French (2015) controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carbon control	No	No	Yes	Yes	No	No	Yes	Yes
Panel B: Highly exposed industries to the double materiality biodiversity risks								
	Realized returns				Expected returns			
	EW	VW	EW	VW	EW	VW	EW	VW
Biodiv	-0.028 (0.354)	0.109 (0.637)			-0.001 (0.189)	-0.039* (1.882)		
BiodivExGHG			-0.010 (0.141)	0.139 (0.773)			0.005 (1.041)	-0.033 (1.588)
Fama French (2015) controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Carbon control	No	No	Yes	Yes	No	No	Yes	Yes

Table 10

Drivers of the biodiversity risk premia This table gives estimates of the regression of the residuals of an AR(1) on the price of risk of biodiversity and ex-GHG biodiversity on several time series as independent variables. Compared to the main estimation, this one includes the VIX in place of the risk aversion. Significance thresholds for *p*-values are coded as: + *p* < 0.1, * *p* < 0.05, ** *p* < 0.01, *** *p* < 0.001.

	Biodiversity	BiodiversityExCarbon
(Intercept)	0.000 (0.002)	0.000 (0.161)
Biodiversity attention	-0.005*** (-4.859)	-0.005*** (-4.420)
Climate attention	0.002* (2.435)	0.002* (2.589)
Consumer sentiment	0.002** (2.914)	0.002** (2.871)
Oil price	0.000 (0.149)	0.000 (-0.089)
VIX	-0.001+ (-1.903)	-0.001 (-1.371)
Num.Obs.	110	110
R2	0.408	0.379
R2 Adj.	0.374	0.343

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