Biodiversity and Climate: Friends or Foes?[†]

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Abstract

We propose a portfolio optimization framework that jointly incorporates biodiversity and climate considerations. Our empirical application to sovereign bonds demonstrates that investors can construct portfolios that enhance both biodiversity and climate outcomes without sacrificing absolute risk-adjusted returns. While adding a biodiversity objective to a portfolio with an existing climate objective may slightly reduce relative performance, this reduction diminishes for more ambitious sustainable portfolios and dissipates when long-only constraints are removed. Our findings are robust across various choices of sustainability measures and modeling approaches.

Keywords: Biodiversity Risk, Climate Risk, Portfolio Optimization, Sustainability Trade-Offs, Sovereign Bonds, Tracking-Error.

[†]These are the views of the authors, and should not be attributed to the World Bank, its Board of Directors, or any of the countries they represent. We remain solely responsible for any mistake or error. We thank Ha Dao for helpful data assistance.

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Climate change is a primary driver of biodiversity loss. And climate change depends on biodiversity as part of the solution. So clearly the two are linked, and cannot be separated.

Elizabeth Mrema, Executive Secretary, United Nations Convention on Biological Diversity

1 Introduction

Like policymakers and businesses, environmental damage and its economic consequences have become a priority concern for investors. While the focus was initially put on the implications of climate change, investors' interest has more recently evolved towards an additional type of sustainability risk. Biodiversity[1] matters to humans and the planet for their well-being and the many services provided, including crop pollination, water purification, nutrient cycling, soil formation, flood protection, and carbon sequestration. The critical importance of nature for economies is increasingly recognized and quantified (Dasgupta, 2021; World Bank, 2021). Accordingly, any damage to nature implying biodiversity loss has a substantial economic impact and is of increasing concern to investors. For instance, biodiversity loss was ranked in 2024 as the third risk by the World Economic Forum, while it was not mentioned five years before, contrary to climate change, already listed as a critical risk by then.

Despite this need, academic studies of biodiversity finance have remained scarce, as emphasized by the call for more research in Starks (2023). Most studies focus on corporate issuers, either through biodiversity finance deals (Flammer et al., 2023), credit instruments (Cherief et al., 2022; Hoepner et al., 2023), or public equities (Giglio et al., 2023; Garel et al., 2024; Coqueret et al., 2023). These empirical analyses are based on companies' biodiversity footprint measures or tex-

[1]The Convention on Biological Diversity signed by 150 government leaders at the Rio Earth Summit in 1992 defines biodiversity as "the variability among living organisms from all sources including, among other things, terrestrial, marine, and other aquatic ecosystems and the ecological complexes of which they are part; this includes diversity within species, between species, and of ecosystems".

tual analysis of newspapers and firms' official documents[2]. In particular, the authors show that biodiversity risks are significantly priced.

Our paper contributes to the literature in two ways. Our first contribution is methodological. We present an analytical framework that allows for incorporating more than one sustainability dimension into optimal portfolios, deriving closed-form solutions for portfolio composition, risk level, and risk contributions for an investor seeking to minimize tracking error risk under two sustainable objectives. This constitutes a relevant approach for investors who want to consider biodiversity *in addition* to climate and allows them to study the associated trade-offs with this joint objective when building investment portfolios. As the introductory quote reflects, biodiversity and climate cannot be considered entirely independently. While biodiversity plays a role in climate change through carbon sequestration[3], climate change affects biodiversity by altering marine, terrestrial, and freshwater ecosystems. We offer a tractable solution to this problem, expanding the previous literature on tri-criterion portfolio selection including Environmental, Social, and Governance (ESG) criteria in addition to return and risk (Jessen, 2012; Utz et al., 2014; Pedersen et al., 2021), or the one on tracking error portfolio optimization in the presence of a sustainable investment objective (Blitz et al., 2024; Soupe and Kovarcik, 2024).

Secondly, we are among the first two, along with Giglio et al. (2024), to study the importance of biodiversity risks for sovereign bond portfolios. With more than USD 60 trillion, sovereign bonds are one of the most important asset classes for investors. However, there is a relatively limited number of studies investigating the integration of sustainability objectives into sovereign bond portfolios, as most of the literature has focused on equity and corporate bond investments (Andersson et al., 2016; Bolton et al., 2022; Roncalli et al., 2021; Bajo and Rodríguez, 2023). The only exceptions are the recent studies on low-carbon and net-zero investing strategies for sovereign bond portfolios (Barahhou et al., 2023; Cheng et al., 2022; Schwaiger et al., 2023), or the recent study of Giglio et al. (2024) on the impact of biodiversity on the spreads of countries' credit default swaps. This text expands the literature by considering jointly the integration of biodiversity and

[2]Newspapers textual analyses have previously been shown to be useful for climate risks modeling (Engle et al., 2020; De Nard et al., 2024).

[3]The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) estimates that investment in nature-based solutions could contribute to nearly 37% of the climate change mitigation needed by 2030.

climate risks[4].

Our empirical application, summarized in Figure 1, draws valuable conclusions. Investors can jointly improve their portfolios' biodiversity and climate exposures without compromising on absolute risk-adjusted returns (Sharpe ratio), showing that biodiversity and climate behave like *friends* in optimal allocations. Conversely, when one looks at returns relative to a market capitalization benchmark, results point to a *foes* interpretation: adding a biodiversity objective in addition to climate slightly deteriorates its relative risk-adjusted returns (Information ratio). Nonetheless, this deterioration tends to decrease for portfolios with more ambitious biodiversity and climate improvements. We further show that those results, obtained for 21 countries over 21 years, using both forest area and CO2 emissions per capita as the sustainability targets, are robust to alternative biodiversity and climate measures or portfolio construction set-ups. In particular, when we remove long-only constraints from the optimal construction framework, the *trade-off* between biodiversity and climate goals dissipates, and both sustainable goals can be considered as *friends*.

2 Analytical Framework

We start by presenting an analytical framework to characterize the trade-offs faced by investors when building a portfolio with two sustainable objectives. Because practical implementations of sustainability strategies within a given asset class are generally performed in a relative framework, i.e., by overweighting or underweighting portfolio components versus a benchmark (Andersson et al., 2016; Bolton et al., 2022; Bajo and Rodríguez, 2023; Barahhou et al., 2023; Blitz et al., 2024; Cheng et al., 2022), we focus on the tracking error as the risk measure used for portfolio construction.

[4]This way, we attempt to provide an answer to the development suggested by Giglio et al. (2024) who wrote: "We intentionally focus this paper on the economic effects of biodiversity loss, which we view as a conceptually distinct challenge to climate change. However, the two clearly interact in important ways that could be explored more explicitly in future work." (p. 6).

2.1 Relative risk minimization with two sustainable investment objectives

The optimal portfolio construction problem that minimizes the tracking error variance has been analyzed in the relative return-risk space by Roll (1992) and Jorion (2003), and in the augmented relative return-risk-sustainability space by Blitz et al. (2024) or Soupe and Kovarcik (2024). We expand on this literature by considering a program that aims at minimizing the tracking error variance under *two* sustainable investment objectives:

$$\Delta \boldsymbol{w}^* = \arg\min_{\Delta \boldsymbol{w}} \frac{1}{2} \Delta \boldsymbol{w}^T \boldsymbol{\Omega} \Delta \boldsymbol{w} \quad \text{s.t.} \quad \boldsymbol{s}_1^T \Delta \boldsymbol{w} = \Delta s_1^*, \quad \boldsymbol{s}_2^T \Delta \boldsymbol{w} = \Delta s_2^*, \quad \boldsymbol{1}^T \Delta \boldsymbol{w} = 0. \tag{1}$$

$\boldsymbol{w}$ is the $N \times 1$ vector of portfolio weights and $\Delta \boldsymbol{w}$ is the $N \times 1$ vector of active weights relative to a given benchmark portfolio, with $\Delta \boldsymbol{w} = \boldsymbol{w} - \boldsymbol{w}_b$ for $\boldsymbol{w}_b$ the vector of benchmark weights. $\boldsymbol{\Omega}$ is the $N \times N$ variance-covariance matrix of asset returns, where N is the number of assets. $\boldsymbol{s}_k$ is the vector of values for the k-th sustainable investment characteristic, with Δs_k^* the associated target change relative to the benchmark. This target change can be positive or negative depending on whether the investor seeks to increase the sustainability characteristic of the portfolio (e.g., in the case of forest area in our empirical application) or decrease it (e.g., in the case of carbon footprint in our empirical application). The last constraint expresses the fact that the active weights are summing to zero, i.e., the portfolio is fully invested and not leveraged.

We show in Appendix A that the optimal portfolio solving Program (1) is given by:

$$\Delta \boldsymbol{w}^* = \theta_1 \, \boldsymbol{w}_{\text{SCM}_1} + \theta_2 \, \boldsymbol{w}_{\text{SCM}_2} - (\theta_1 + \theta_2) \, \boldsymbol{w}_{\text{GMV}}. \tag{2}$$

Hence, the optimal portfolio can be described as a three-fund portfolio. Each of them corresponds to a specific element in the optimization program (1). The first two sub-portfolios, obtained as $\boldsymbol{w}_{\text{SCM}_k} = \frac{\boldsymbol{\Omega}^{-1} \boldsymbol{s}_k}{\boldsymbol{1}^T \boldsymbol{\Omega}^{-1} \boldsymbol{s}_k}$, have expressions similar to the ones of factor-mimicking portfolios, i.e., portfolios that maximizes the correlation to a specific risk factor (Fama, 1996). In this case, the SCM portfolios maximize their respective sustainability characteristic-to-risk ratio, reflecting the sustainability constraints in (1). The last portfolio is the traditional global minimum variance (GMV) portfolio, $\boldsymbol{w}_{\text{GMV}} = \frac{\boldsymbol{\Omega}^{-1} \boldsymbol{1}}{\boldsymbol{1}^T \boldsymbol{\Omega}^{-1} \boldsymbol{1}}$, which is defined as the portfolio with the lowest achievable risk (variance). Altogether, any point on the efficient frontier can be reached by a specific combination of these three sub-portfolios, reflecting the investor's relative preferences for both types of sustainability characteristics and risk. The (scaled) implied preferences for sustainability goals are expressed by the scalars $\theta_k = (\mathbf{1}^T\, \boldsymbol{\Omega}^{-1}\, \boldsymbol{s}_k)\, \lambda_k$, with $k = (1, 2)$, for λ_k the Lagrangian multipliers associated to the constraints in (1). We provide their expression in the next subsection.

2.2 Decomposition of the active risk for the optimal portfolio with two sustainability objectives

To analyze the impact of the sustainable targets on the portfolio's active risk level and its decomposition, we first establish the closed-form formulas for the sustainability objectives preferences, θ_k for $k = 1, 2$, as (see Appendix A):

$$\theta_1 = (\mathbf{1}^T\, \boldsymbol{\Omega}^{-1}\, \boldsymbol{s}_1)\, \left[\pi_{11}\, \Delta s_1^* + \pi_{12}\, \Delta s_2^*\right], \qquad \theta_2 = (\mathbf{1}^T\, \boldsymbol{\Omega}^{-1}\, \boldsymbol{s}_2)\, \left[\pi_{12}\, \Delta s_1^* + \pi_{22}\, \Delta s_2^*\right]. \tag{3}$$

Hence, the sustainability preferences are linear functions of the target changes in the sustainable characteristics Δs_k^*. π_{11} and π_{22} are positive scalars[5] expressing the individual preferences for both sustainability objectives and depend only on these individual characteristics. By contrast, π_{12} depends on both sustainable characteristics and can be positive or negative, reflecting the trade-off between both sustainability objectives as we discuss below.

The trade-off naturally appears through the active risk of the optimal portfolio. More specifically, we show in Appendix A that the optimal tracking error volatility is given by:

$$\mathrm{TEV}^* = \left[\pi_{11}\, (\Delta s_1^*)^2 + \pi_{22}\, (\Delta s_2^*)^2 + 2\, \pi_{12}\, \Delta s_1^* \Delta s_2^*\right]^{1/2}. \tag{4}$$

Expression (4) gives the minimum tracking error volatility achievable for target changes in sustainability metrics. We infer from (4) that the sensitivities of the tracking error to the sustainability target changes are given by:

$$\frac{\partial \mathrm{TEV}^*}{\partial \Delta s_1^*} = \frac{\pi_{11} \Delta s_1^* + \pi_{12} \Delta s_2^*}{\mathrm{TEV}^*}, \qquad \frac{\partial \mathrm{TEV}^*}{\partial \Delta s_2^*} = \frac{\pi_{22} \Delta s_2^* + \pi_{12} \Delta s_1^*}{\mathrm{TEV}^*}. \tag{5}$$

We retrieve the known result on the linearity of the sensitivity of the risk measure to changes in sustainability targets (see Jessen (2012) for variance, and Soupe and Kovarcik (2024) for tracking error variance), but here expand it to the two dimensions case. A core difference with the single sustainability case is that any non-zero target change in the k^{th} sustainable investment portfolio

[5] Analytic values of these parameters are provided in Appendix A.

characteristic, Δs_k^*, will generate tracking error directly through π_{kk} and indirectly through the cross-term π_{12}. Suppose we imagine a similar targeted change in both sustainability characteristics of the portfolio, $\Delta s_1^* = \Delta s_2^*$. We immediately see that the reaction of the tracking error will depend on $\pi_{11} + 2\pi_{12} + \pi_{22}$. As π_{11} and π_{22} are both positive (see Appendix A), we see that π_{12}, whose sign is undetermined (also see Appendix A), ultimately reflects the trade-off between both sustainable objectives. Indeed, the tracking-error reaction will be higher (respectively, smaller) if π_{12} is positive (respectively, negative). As shown in Appendix A, π_{12} primarily depends on the covariance of sustainability metrics across all assets through the cross-product term $\phi_{\boldsymbol{s}_1\boldsymbol{s}_2} \equiv \boldsymbol{s}_1^T \boldsymbol{\Omega}^{-1} \boldsymbol{s}_2$. In particular, π_{12} will be positive if both metrics are consistent and negative otherwise.

Considered jointly, Equations (4) and (5) finally reveal another interesting aspect. It is straightforward to see that they lead to:

$$\text{TEV}^* = \Delta s_1^* \frac{\partial \text{TEV}^*}{\partial \Delta s_1^*} + \Delta s_2^* \frac{\partial \text{TEV}^*}{\partial \Delta s_2^*}. \tag{6}$$

Readers familiar with risk budgeting principles will recognize Equation (6) as a tracking error decomposition. Indeed, the first term (resp., second term) of the right-hand side of the equation can be interpreted as the contribution to the tracking error coming from the first (resp., second) sustainability objective.

We can expand this idea further by looking at the asset dimension as well. Using standard risk decomposition principles and the optimal portfolio weights from (2), we infer that the tracking error volatility can be decomposed as (see Appendix A)[6]:

$$\text{TEV}^* = \left(\underbrace{\lambda_1 \sum_{i=1}^{N} \Delta w_i^* s_{1i}}_{\text{Contribution of SCM}_1} + \underbrace{\lambda_2 \sum_{i=1}^{N} \Delta w_i^* s_{2i}}_{\text{Contribution of SCM}_2} \right) / \text{TEV}^*. \tag{7}$$

Thanks to the decomposition of the optimal portfolio in a three-fund portfolio, we accordingly can decompose the portfolio active risk across two dimensions: (i) individual assets and (ii) sustainability characteristics $\boldsymbol{s}_k$. In the case study subsection 4.2, we illustrate this decomposition for a specific date. We first introduce the data that we use for this.

[6]In practice, we can note that the last term ("Contribution of GMV") vanishes due to the target associated to the third objective in the optimization program (3), i.e., $\sum_{i=1}^N \Delta w_i^* = 0$.

3 Data

We use two different types of data for our analysis: (i) sovereign bond indices and (ii) sustainability biodiversity and climate country characteristics.

3.1 Sovereign bond indices

The sovereign bond data are obtained from the ICE BofAML Indices, which are widely used by investors. Based on data availability for the bond indices and the sustainability country metrics (as described below), we select a universe of 21 developed market countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States of America. For each country, we retrieve every month between January 2003 and December 2023, the market capitalization in USD and the total returns hedged to USD. We compute the sovereign benchmark weights from the market capitalization observed at each end of the month[7].

Table 1 presents the main descriptive statistics of the bond indices for the sample countries. The index composition is highly concentrated, as the six countries with an average market value exceeding 1 trillion USD over the entire sample period (namely the US, Japan, UK, France, Italy, and Germany) account for 86% of the total market value. When hedged back to USD, the annualized return averages 3.78% across all countries, ranging from 2.31% for Australia and New Zealand to 8.70% for Greece. These return levels are indicative of the prevailing conditions in developed sovereign debt markets during the period of analysis.

3.2 Sustainability country characteristics

We consider two main sustainability characteristics for each country: biodiversity and climate. We use different data sources. In the baseline case, we rely on data available from the World Bank Sovereign ESG Data portal [8]. This portal is widely used by policy-makers and investors, serving

[7]The correlation of the monthly returns of this reconstructed benchmark with the ones of the original benchmark from which the countries are selected (ICE BofA Developed Markets Sovereign Bond Index, whose Bloomberg code is WSAV Index) is larger than 99.9%.

[8]See https://esgdata.worldbank.org/.

as a central, free reference database for assessing sovereign sustainable risks and characteristics. While the database covers various dimensions, including governance and social issues, we restrict here to indicators related to environmental issues, specifically biodiversity and climate. As we discuss below, both dimensions can be measured in many different ways. However, for our baseline case, we select indicators that are straightforward to understand, commonly used by policy-makers or investors, and, crucially for our empirical analysis, can be measured consistently across countries over a long historical period. Accordingly, for biodiversity, we use the forest area expressed as a percentage of the total country area. For climate, we use CO2 emissions per capita, measured in metric tons per capita. Both indicators are available on an annual basis, and we use them from 2000 to 2020 for the empirical study. The rationale for this lag between bond indices and sustainability data is to account for the typical delay in the publication of biodiversity and climate data, which averages between 2 and 3 years.

Table 1 presents the average values for the biodiversity (forest area) and climate (CO2) indicators across the different countries in the full sample. For the biodiversity indicator, we observe that, on average, approximately one-third of the total land area is covered by forests. For the climate indicator, the average carbon emissions amount to 8.9 tons per capita. To illustrate the evolution over time of these indicators, Figure 2 presents their weighted-average values across all countries, calculated using either market capitalization weights or equal weights. For the biodiversity indicator, we find that it has remained stable for the largest countries in the index (solid line), whereas it has shown a steady increase for the typical country (dashed line). By contrast, the climate indicator has improved over time (i.e., CO2 emissions have decreased, for both the countries with the highest market values (solid line) and the typical country (dashed line). Beyond these trends, we observe a consistent difference between the two sustainability indicators: weighting more heavily toward the largest issuers (based on market capitalization; solid line) results in a better sustainability outcome for biodiversity (larger forest area) but a worse one for climate (higher emissions per capita). This suggests a potential trade-off between the two sustainability indicators, implying that investors might face a choice between prioritizing one over the other. However, Figure 3 shows that, on average, over the full sample across all developed countries, there is a modest but negative correlation (-0.13), indicating that better biodiversity outcomes (higher forest area) can be associated with better climate outcomes (lower CO2 emissions). This suggests that it may be possible for investors to enhance both dimensions simultaneously. We investigate this question of potential sustainable investment trade-offs in more detail in the empirical section, and particularly in subsection 4.2.

Before this, we discuss our choice of biodiversity and climate indicators. As stated before, for our baseline results, we have voluntarily selected indicators that have the advantage of measuring the sustainability outcomes in easy-to-understand units, and consistently across time and geographies. However, they might be perceived as too simplistic to fully capture the diversity and complexity of sustainability issues. For climate indicators, properly scaled carbon emissions have become the standard approach, for policy-makers, investors, and academics alike. Recently, some criticisms have arisen in the context of net-zero transition, suggesting replacing these indicators with more forward-looking ones, such as the NDC (Nationally Determined Contributions) net-zero commitments under the Paris Agreement, or more specialized ones such as green energy spending or green bond issuance. Some authors suggest combining these different indicators, a recent example being Barahhou et al. (2023) analysis of potential net-zero trajectories for sovereign issuers. A key limitation of such measures is that they are only available for short samples and/or without significant variation over time. This makes them less relevant for historical analysis on the incorporation of sustainable investment characteristics in actively managed investment portfolios, such as the ones we perform below.

The problem is more acute for biodiversity indicators. There is no single measure perceived as core in the same consensual way as carbon emissions are for climate. The IPBES[9] framework refers to a combination of different drivers for biodiversity loss: land and sea use, natural resource exploitation, pollution, invasive species, and climate change. Studies that rely on measures based on textual sentiment analysis (Giglio et al., 2023; Cherief et al., 2022) use a large set of keywords such as “biodiversity, ecosystem(s), ecology (ecological), habitat(s), species, (rain)forest(s), deforestation, fauna, flora, marine, tropical, freshwater, wetland, wildlife, coral, aquatic, desertification, carbon sink(s), ecosphere, or biosphere.”. Hoepner et al. (2023) uses a data provider

[9]The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) is an intergovernmental organization that aims to provide a scientific basis for governments and decision-makers to develop effective policy instruments to protect biodiversity. It is the biodiversity equivalent of the Intergovernmental Panel on Climate Change (IPCC).

EU-regulation-compliant KPI measures related to "biodiversity, water preservation, and pollution prevention". Recent research quantifies the biodiversity loss by using estimates of "Mean Species Abundance" (Garel et al., 2024; Coqueret et al., 2023). This concept reflects the relative abundance of native species in ecosystems, compared to their abundance in undisturbed ecosystems. These measures can be retrieved through data providers, who also propose more specific indicators such as prime areas for conservation, or deforestation risk metrics.

In this paper, as an alternative to the simple and direct sustainability indicators used in our baseline, we rely on the Environmental Performance Index (EPI) co-developed by Yale University and Columbia University[10], also used by Giglio et al. (2024). The freely available EPI is an interesting alternative to our basic sustainability measures as it offers biodiversity and climate scores for a large number of countries (180 in 2022) and over a longer history than alternative databases. More specifically, in the alternative analysis below, we replace the forest area with EPI's "ecosystem vitality" score and the CO2 emissions per capita with EPI's "climate change". As of 2022, the selected EPI's biodiversity ("ecosystem vitality") indicator combines terrestrial biome protection, marine protected areas, species habitat and protection indices, tree cover loss, grassland loss, wetland loss, fish stock status, marine trophic index, fish caught by trawling, acid rain, SO_2 (sulfur dioxide) and NO_x (nitrogen oxides) growth rates, sustainable nitrogen and pesticides use, and wastewater treatment. At the same date, the EPI's climate change indicator combines projected GHG emissions in 2050, GHG emissions per capita, growth rates in CO2, CH_4 (methane), fluorinated gases, black carbon, and N_2O (nitrous oxide), CO2 from land cover, and GHG intensity trend.

In Figure 4, we display scatter-plot charts comparing the baseline indicators (forest area and CO2) coming from the World Bank ESG portal (WB) with the Yale Environmental Performance Index (EPI). This confirms the expected lower consistency for biodiversity data than for climate data. In the next section, we investigate whether these differences in indicators translate into different investment portfolio results.

[10] See https://epi.yale.edu/ and Wolf et al. (2022).

4 Empirical Results

We next turn to the results of an empirical study investigating the inclusion of both biodiversity and climate objectives in sovereign bond portfolio optimization.

4.1 Methodology

Following the sustainability investing analytical framework described in Section 2, the portfolio construction methodology consists of minimizing the tracking error variance relative to the market capitalization benchmark for different levels of biodiversity and climate characteristic improvements.

More specifically, every month, we run a portfolio optimization program similar to optimization program (1). Δs_1^* and Δs_2^* represent variations in biodiversity and climate targets, expressed as percentage changes versus the corresponding sustainability level of the benchmark. Since the original data is annual, the sustainability characteristics are unchanged during the year. For biodiversity, the improvements are evaluated by examining *positive* changes in the portfolio's forest area by steps of 10% compared to the benchmark level: 0% (equal to the benchmark level), +10%, +20%, +30%. For climate, the improvements are assessed by examining *negative* changes in the portfolio's CO2 emissions also in increments of 10% compared to the benchmark level: 0% (equal to the benchmark level), -10%, -20%, -30%. These levels are calibrated based on achievable changes in the sustainability targets, considering the cross-country dispersion and the market capitalization weights of the benchmark. Overall, these different sustainability target changes result in 16 different portfolio strategy backtests, including one for the benchmark (retrieved as a special case with zero-change in climate and biodiversity targets).

At each optimization date, we estimate the covariance matrix $\widehat{\boldsymbol{\Omega}}$ using monthly total returns over the previous five years (60 observations). In addition to the three constraints of Program (1), we add a long-only constraint on the optimal portfolio weights, namely $\boldsymbol{w}^* = \Delta\boldsymbol{w}^* + \boldsymbol{w}_b \geq \mathbf{0}$. This implies that the ex-ante optimized tracking error variances, i.e., $\Delta\boldsymbol{w}^{*T}\widehat{\boldsymbol{\Omega}}\Delta\boldsymbol{w}^*$, will be larger than those obtained without the long-only constraint. This approach allows to comply with more realistic investor implementations. In Section 4.3.2, we will discuss the implications of allowing negative portfolio weights.

The optimized portfolio weights and the benchmark weights are held over the following month. We store the realized bond allocations and the associated total currency-hedged returns. For both the optimized and benchmark portfolios, we compute a set of absolute portfolio statistics: compound annualized geometric returns (CAGR), annualized volatility, Sharpe ratio with risk-free rate based on one-month USD interest rate over the sample, maximum drawdown, Calmar ratio (ratio between return over risk-free rate and maximum drawdown) and turnover, measured as the annualized average changes (in absolute terms) between new optimal country portfolio weights and drifted weights from the previous rebalancing date. We also compute a set of relative statistics based on the annualized excess returns of the optimized portfolio over the benchmark: alpha measured as the average excess return, tracking error measured as the standard deviation of excess returns, and information ratio measured as the ratio of alpha to tracking error.

4.2 An illustration of biodiversity and climate trade-offs

Before moving to the full sample empirical backtests in Section 4.3, we first investigate empirically the optimal trade-off between biodiversity and climate in the sovereign bond allocation. For this, we focus on the latest date of the backtesting exercise, i.e., the sovereign bond portfolios determined at the end of November 2023 for holding during December 2023. We first represent several two-dimensional projections of the efficient frontier obtained from our sovereign bond portfolio optimization under biodiversity and climate objectives. Then, we analyze the trade-off between biodiversity and climate, both with and without long-only constraints.

To investigate the decomposition of the ex-ante tracking error volatility between its biodiversity and climate components, Figure 5 provides the results for 9 cases, using the combination of +10%, +20%, +30% increase in forest area and -10%, -20%, -30% decrease in carbon emissions (versus the benchmark level). As expected, the higher the objectives' absolute value, the higher the tracking error volatility necessary to reach them. Moreover, the climate objective contributes more significantly to the tracking error volatility than the biodiversity one. The combination (+10% biodiversity, -10% climate) exhibits an eight times higher contribution from the climate objective: the total tracking error is 0.106% allocated with 0.012% for biodiversity and 0.094% for climate. The only case where the two sustainability objectives have similar contributions is the combination (+30% biodiversity, -10% climate) in which the biodiversity contribution represents

0.065%, while the climate one is equal to 0.077%, for a total tracking error volatility of 0.142%.

In Figures 6 and Figure 7, we show two-dimensional representations of the risk-biodiversity-climate efficient frontier. The top panel of Figure 6 represents the forest area (% of land) and the tracking error volatility for different levels of CO2 emissions (metric tons per capita), from 0% to -30% relative to the benchmark. Each point corresponds to the long-short bond portfolio that minimizes the ex-ante tracking error volatility for given levels of forest area and CO2 emissions. The black dot corresponds to the benchmark. The curves exhibit a positive relationship between the forest area and the tracking error volatility. We also observe that the higher the reduction in CO2 emissions (curve moving to the right), the higher the tracking error levels. Also, the linearity of the left curve is due to the absence of change in the CO2 emissions with respect to the benchmark. The bottom panel of Figure 6 exhibits the CO2 emissions (metric tons per capita, inverted scale) and the tracking error volatility for different levels of forest area (as % of land), from 0% to +30% relative to the benchmark. Each point corresponds to the long-short sovereign bond portfolio that minimizes the ex-ante tracking error volatility for given levels of CO2 emissions and forest area. The black dot corresponds to the benchmark. The curves exhibit a positive relationship between the CO2 emissions and the tracking error volatility. One can notice that the curve slopes are flatter than those obtained in the upper panel (i.e., forest area versus TE volatility), which means that improving the biodiversity measure is less costly than improving the climate one, in terms of tracking error. This is consistent with the previous results on tracking error volatility decomposition. We also observe that the higher the increase in forest area (curve moving to the right), the higher the tracking error volatility levels, however, the impact of imposing higher levels of forest area on the tracking error volatility is lower for higher levels of CO2 emissions. Also, similarly to the top figure, the linearity of the left curve is due to the absence of change in the forest area with respect to the benchmark.

To better understand the relation between biodiversity and climate in the active portfolio, we search for the set of portfolios that minimize the level of CO2 emissions for a given level of tracking error volatility and a given level of forest area. To do so, we study an optimization program equivalent to Program (1), but instead of minimizing the ex-ante tracking error volatility for a target level of CO2 emissions per emission, we minimize the CO2 emissions for a target level of ex-ante tracking error, all other constraints remaining the same. The top panel of Figure 7 represents the results of this optimization for different levels of tracking error volatility. We run the optimization program, with different levels of forest area (from 85% to 130% of the percentage of land of the benchmark) and four levels of tracking error volatility (0.3%, 0.5%, 0.7%, 0.9%). The black dot represents the (market capitalization) benchmark. Two main results are observed. First, all the efficient portfolios appear to have lower CO2 emissions per capita compared to the benchmark. In other words, the allowance for tracking error tolerance through active weights achieves a reduction in the level of CO2 emissions compared to the benchmark. The higher the tracking error tolerance, the higher the reduction in CO2 emissions. Second, moving up along the frontier to improve biodiversity can be made at a very low cost in terms of CO2 emissions, and this stays valid for different levels of tracking error volatility. This result is consistent with the estimated parameter in Equation (4). Its value, $\widehat{\pi_{12}} = -9.672 \times 10^{-6}$, reflects a limited trade-off between both sustainability objectives. Therefore, in this example, biodiversity and climate are not significant foes as biodiversity can be improved at almost no cost in terms of climate risk.

To further explore the trade-off, we introduce long-only constraints in the bottom panel of Figure 7. First, we notice that the reduction in CO2 emissions is less significant than for the long-short case for the same levels of tracking error volatility. The introduction of long-only constraints leads to higher minimum CO2 emission levels. For example, at 0.5% tracking error volatility level, the CO2 emissions per capita stand around 8 metric tons for long-only portfolios while reaching levels below 5 metric tons for long-short portfolios. Similarly, at 0.9% tracking error volatility level, the CO2 emissions per capita stand around 6.5-7 metric tons for long-only portfolios, while being lower than one metric ton for long-short portfolios. These lower levels were obtained through short positions. Second, all iso-tracking error volatility frontiers exhibit a convex profile. A consequence is that all portfolios that lie on the lower part of each curve, i.e., in areas ① or ②, are inefficient. It means that for a given level of tracking error volatility and a given level of CO2 emissions, one can always find a portfolio on the upper part of the curve, i.e., in area ③, that is associated with a higher forest area. One can also notice that the minimum levels of CO2 emissions for each level of tracking error volatility are slightly above 40% of forest area for a level of tracking error volatility of 0.3% (blue line), up to about 45% for a level of tracking error volatility of 0.9% (red line). Consequently, for forest area values between the benchmark level and the minimum point level, i.e., in area ②, one can simultaneously increase the forest area and decrease the CO2 emissions compared to those of the benchmark. However, for forest area values above minimum point levels, in area ①, the investor faces a *trade-off* between climate and biodiversity impacts, i.e., an additional increase in the forest area leads to increased CO2 emissions: biodiversity and climate appear to be foes. Moreover, the lower the tracking error volatility, the higher the trade-off (or, equivalently, the higher the curvature). These results show that the trade-off observed in long-only sovereign bond portfolios is mainly due to long-only constraints that limit the amplitude of the possible active bond weights.

4.3 Backtesting for sovereign bond portfolios

4.3.1 Baseline sample results

The baseline sample uses simple sustainability indicators (CO2 emissions per capita and forest area) and assumes long-only constraints. We later investigate other data sources and set-ups. Due to data constraints, the sample is available over the period from January 2003 to December 2023, which represents 21 years of backtesting. We analyze 16 different implementations of the active fixed-income strategies, as we investigate four types of percentage changes (0%; ±10%; ±20%; ±30%) versus the benchmark for each of the sustainable metrics. For the easiness of reading, the results are presented by subgroups where we fix the change in CO2 emissions (climate) and let the change in forest area (biodiversity) vary. The benchmark can be retrieved as a special case for no change in CO2 emissions and forest area and is specifically identified as such in the tables and figures[11].

For every month of the sample, Figure 8 displays the minimal ex-ante tracking error volatility relative to the benchmark that is necessary to at least reach specific sustainability improvements. We observe that for each objective of CO2 emissions reduction (corresponding to each quadrant), the tracking error volatility increases with forest area (i.e., better biodiversity content). Naturally, the higher the targeted reduction in CO2 emissions, the higher the increase in tracking error volatility necessary to reach a specific forest area increase. This is expected as higher sustainable improvement targets naturally require larger active weights and, hence, larger tracking error volatility. Required ex-ante tracking error budgets vary over time and are notably larger when

[11] By analogy to other cases, "Benchmark" corresponds to "Forest +0% & CO2 -0%".

underlying volatility in sovereign bond markets increases, as observed in the aftermaths of shocks such as the Great Financial Crisis or the post-COVID inflation jump.

How do these ex-ante active risks translate ex-post? Figure 9 displays the realized (or ex-post) tracking error volatility for different levels of sustainable targets relative to the benchmark. In the top panel, we represent the tracking error volatility versus the forest area for different improvements in the climate objective by steps of 10% (CO2 decreases), while in the bottom panel, we represent the tracking error volatility versus the CO2 emissions for different improvements in the biodiversity objective (forest area increases). The increase in ex-post tracking error volatility as the investor seeks to improve the sustainability characteristics of his sovereign bond portfolio follows a well-ordered hierarchy, consistently with the ex-ante results shown in Figure 8 for a specific date. Increasing sustainability content always implies higher realized active risk. However, we observe that, for a given sustainable characteristic, the tracking error volatility increase is more pronounced for low improvements of the other sustainable characteristic. In the top panel, reducing the C02 emissions by 30% vs the benchmark requires an additional 0.8% tracking error volatility when one targets no improvement in biodiversity, but only an additional 0.5% tracking error volatility when one targets a 30% improvement in biodiversity. This difference is even greater when one focuses on improvements in the biodiversity (bottom panel): improving the sovereign bond portfolio biodiversity content by 30% only creates around +0.1% of additional active risk when one targets to jointly improve climate by +30% while it requires close to +0.4% of additional active risk when we target a similar climate content than the benchmark. We notice the striking similarity between the frontiers drawn in Figures 6 and 9, although the former ones are established ex-ante for a specific date while the latter are established ex-post over the full sample and with long-only constraints. All in all, we observe that improvement in biodiversity measures is easy to implement for investors with already a significant active position in climate metrics, as can be seen for the near-vertical curve obtained in the top panel for a 30% in CO2 emissions, which states that the improvement in forest area is seamless from an active risk perspective. This confirms ex-ante results according to which biodiversity and climate tend to be more friends for more ambitious sustainable (active) portfolios.

To analyze more broadly the implications of sustainability improvement on sovereign bond portfolios, Table 2 presents the associated absolute portfolio statistics for each of the 16 alternative fixed-income portfolios, including the benchmark (obtained as the special case of no change in both sustainability characteristics). In terms of performance, we initially remark that improvements in climate (CO2 decrease) lead to higher returns. For instance, assuming no change in terms of biodiversity versus the benchmark, the average annualized return increases from 3.08% to 3.29% when one moves from the benchmark to a 30% reduction in CO2 emissions. This increase in average return for better climate outcomes remains true, regardless of the fixed increase in biodiversity we select. We observe similar patterns when one corrects for the risk level, as shown by increasing Sharpe or Calmar ratios for lower CO2 emissions. This outperformance of climate-tilted portfolios confirms previous results in the literature (Cheng et al., 2022; Schwaiger et al., 2023), over a longer time horizon. Compared to these studies, our portfolio construction framework enables us to analyze what happens when one adds another sustainable dimension, namely, biodiversity. For any given level of targeted improvement in climate (CO2 emissions reduction), improvements in biodiversity (increase in forest area) lead to slightly lower returns. However, we observe that the risk tends to decrease as well, as it is always the case for volatility and, in most instances, for the maximum drawdown. Altogether, Sharpe ratios or Calmar ratios remain stable, meaning that one can significantly improve the biodiversity content of the sovereign bond portfolio without deteriorating the risk-adjusted returns, for any climate improvement. It is interesting to notice that the highest Sharpe and Calmar ratios are achieved by the most demanding portfolio regarding forest area increase and CO2 emission reduction (i.e., forest+30%, & CO2-30%). Finally, higher biodiversity improvement targets naturally lead to a higher turnover, but which become negligible for portfolios that jointly seek to significantly improve the climate dimension.

In Table 3, we look at the performance of the 16 fixed-income portfolio strategies relative to the benchmark. Tracking error volatility metrics vary between 0 and 1%, which shows that significant improvement in both the biodiversity and climate dimensions can be achieved without deviating too much from the benchmark. Although we do not necessarily expect the sustainable active risk to generate alpha, we observe that only two fixed-income strategies lead to negative excess returns. Overall, the strategies tend to outperform the benchmark, and we notice that the excess return increases primarily come from improvements in climate, while adding biodiversity leads to reducing them. Altogether, higher information ratios are obtained for lower biodiversity objectives, but we notice that targeting biodiversity improvement is less costly (in terms of absolute or risk-adjusted excess returns) for sovereign bond portfolios that jointly target stronger climate improvement. This suggests that biodiversity and climate objectives behave like foes when analyzing risk and return performance statistics relative to the benchmark, but this trade-off tends to decrease for more ambitious (sustainable active) portfolios.

Summing up these initial results, investors can improve the biodiversity and climate characteristics of their sovereign bond portfolios without deteriorating their absolute risk-adjusted return (both Sharpe and Calmar ratios), making the two sustainability objectives act more as friends than foes. However, when the investor focuses on the relative risk with respect to the market capitalization benchmark, adding biodiversity to a sovereign bond portfolio with existing CO2 emissions targets will always increase the relative risk and deteriorate the alpha. Nonetheless, it appears easier to do it for fixed-income portfolios with ambitious climate targets (e.g., reducing the CO2 emissions by 30%), as the additional active risk and cost (directly through the realized historical excess returns or indirectly through the trading costs associated with the additional turnover) are limited, making both sustainable objective more friends for ambitious sustainable active portfolios. We now turn to test whether these results are robust to variations in the data sources or the model set-ups[12].

4.3.2 Robustness results

As discussed in Section 3, we first look at alternative sustainability indicators, by replacing the simple biodiversity and climate indicators with their EPI equivalents. Results over the full sample (January 2003 to December 2023) are displayed in Tables 4 and 5, respectively. As the cross-sectional dispersion of country-level EPI scores is smaller than for the original sustainability indicators, which is expected due to their higher diversification, we reduce the range of variation of the sustainable sovereign portfolio characteristic improvements. Even though the sustainability country indicators are different from the baseline case, as discussed in Section 3.2, the results point to similar conclusions favorable to the inclusion of sustainable objectives, albeit slightly different. With these more diversified sustainability metrics, average returns tend to increase with higher content for both climate and biodiversity. This time, however, the risk increases as well, for both

[12]We have also performed additional robustness checks using a sovereign bond universe of emerging countries and observed similar patterns for the absolute and relative portfolio statistics. Results are available upon request.

volatility and maximum drawdown. All in all, we retrieve the result of stable risk-adjusted returns when one seeks to improve the sustainability content of the fixed-income portfolio. Furthermore, this is achieved with a modest increase in turnover. Looking at relative returns with respect to the benchmark, we observe that they are all positive over the period and that higher information ratios are obtained for more sustainability-constrained portfolios. These results indicate that improving the sustainability of sovereign bond portfolios without deteriorating performance is robust across alternative measures of biodiversity and climate[13].

As an additional robustness test, we investigate the impact of portfolio constraints, by removing the long-only constraint. While shorting bonds will not be achievable by all investors, this constitutes a relevant exercise to measure this impact. The results are presented in Tables 6 and 7. While displaying similar patterns, we notice some subtle differences versus the baseline results. Notably, the portfolio profiles become much more stable across specifications. Here again, investors can significantly improve the sustainability content, but the change in the risk-return profile versus the benchmark is more limited. This is observed for both absolute returns and excess returns versus the benchmark. As noticeable evidence, realized tracking error volatility figures are significantly smaller. The cost, though, is that the long-short implementation involves a significantly higher turnover.

5 Conclusion

Sustainability goals have become a crucial component of fixed-income investment strategies. In addition to global ESG considerations, investors are increasingly prioritizing biodiversity and climate risks. Our paper contributes to the emerging literature on biodiversity finance by introducing a construction framework that enables investors to simultaneously integrate biodiversity and climate risks. This approach allows investors to optimally address both biodiversity and climate objectives while also considering other portfolio dimensions, such as relative risk and portfolio constraints.

Our empirical analysis of 21 developed countries over more than 20 years demonstrates that it

[13] To further elaborate on those ideas, we have tested the sensitivity of the results to climate measures by replacing CO2 emissions per capita with CO2 emissions per GDP as the climate indicator, which is a popular indicator; see e.g. Cheng et al. (2022). The results, not reproduced to save space but available upon request, further confirm the robustness of alternative ways to normalize countries' carbon emissions.

is possible to design enhanced biodiversity and climate sovereign portfolios without compromising absolute risk-adjusted returns. Introducing a biodiversity objective to a sovereign portfolio that already has a climate objective slightly worsens its relative performance; however, this deterioration diminishes for more ambitious sustainable portfolios. We find that this trade-off is primarily due to the presence of long-only constraints in portfolio construction. Specifically, an increase in forest area often leads to an increase in CO2 emissions. Furthermore, the trade-off becomes more pronounced as the tracking error variance decreases. Our findings remain robust across different choices of sustainability country measures and modeling approaches.

Reflecting on the introductory quote, our research demonstrates that investors should seize the opportunity to enhance both biodiversity and climate dimensions simultaneously. Such joint objectives will become increasingly important for investors, policymakers, and academics alike. Currently, the literature on the trade-offs generated by sustainability considerations is limited. Amenc et al. (2023) investigates the trade-offs between ESG and climate within global equity universes, showing some "green dilution" when investors use ESG ratings. Van Zanten and Huij (2022) show that companies' ESG and Sustainable Development Goals (SDG) ratings cannot be used interchangeably. In the biodiversity literature, Garel et al. (2024) and Giglio et al. (2023) show that biodiversity and climate risks have different pricing implications. Thanks to its flexibility, our sustainable portfolio construction framework can be used to investigate such sustainability trade-offs across different investment universes or with additional practical portfolio constraints.

References

Amenc, N., Goltz, F., and Naly, A. (2023). Green Dilution: How ESG Scores Conflict with Climate Investing. *Scientific Beta Working paper*.

Andersson, M., Bolton, P., and Samama, F. (2016). Hedging Climate Risk. *Financial Analysts Journal*, 72(3):13–32.

Bajo, M. and Rodríguez, E. (2023). Green Parity and the Decarbonization of Corporate Bond Portfolios. *Financial Analysts Journal*, 79(4):118–137.

Barahhou, I., Ferreira, P., and Maalej, Y. (2023). A Framework to Align Sovereign Bond Portfolios with Net Zero Trajectories. *SSRN Working Paper*.

Best, M. J. and Grauer, R. R. (1990). The Efficient Set Mathematics When Mean-Variance Problems Are Subject to General Linear Constraints. *Journal of Economics and Business*, 42(2):105–120.

Blitz, D., Chen, M., Howard, C., and Lohre, H. (2024). 3D Investing: Jointly Optimizing Return, Risk, and Sustainability. *Financial Analysts Journal*, 80(3):59–75.

Bolton, P., Kacperczyk, M., and Samama, F. (2022). Net-Zero Carbon Portfolio Alignment. *Financial Analysts Journal*, 78(2):19–33.

Cheng, G., Jondeau, E., and Mojon, B. (2022). Building Portfolios of Sovereign Securities with Decreasing Carbon Footprints. *Swiss Finance Institute Research Paper*, (22-66).

Cherief, A., Sekine, T., and Stagnol, L. (2022). The Market Effect of Acute Biodiversity Risk: The Case of Corporate Bonds. *SSRN Working Paper*.

Coqueret, G., Giroux, T., and Zerbib, O. D. (2023). The Biodiversity Premium. *SSRN Working Paper*.

Dasgupta, P. (2021). *The Economics of Biodiversity: The Dasgupta Review*. HM Treasury.

De Nard, G., Engle, R. F., and Kelly, B. (2024). Factor-Mimicking Portfolios for Climate Risk. *Financial Analysts Journal*, 80(3):37–5822.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging Climate Change News. *The Review of Financial Studies*, 33(3):1184–1216.

Fama, E. F. (1996). Multifactor Portfolio Efficiency and Multifactor Asset Pricing. *Journal of Financial and Quantitative Analysis*, 31(4):441–465.

Flammer, C., Giroux, T., and Heal, G. (2023). Biodiversity Finance. *NBER Working Paper*.

Garel, A., Romec, A., Sautner, Z., and Wagner, A. F. (2024). Do Investors Care About Biodiversity? *Review of Finance*, 28(4):1151–1186.

Giglio, S., Kuchler, T., Stroebel, J., and Wang, O. (2024). The Economics of Biodiversity Loss. *NBER Working Paper*.

Giglio, S., Kuchler, T., Stroebel, J., and Zeng, X. (2023). Biodiversity Risk. *NBER Working Paper*.

Hoepner, A. G., Klausmann, J., Leippold, M., and Rillaerts, J. (2023). Beyond Climate: The Impact of Biodiversity, Water, and Pollution on the CDS Term Structure. *Swiss Finance Institute Working Paper*.

Jessen, P. (2012). Optimal Responsible Investment. *Applied Financial Economics*, 22(21):1827–1840.

Jorion, P. (2003). Portfolio Optimization With Tracking-Error Constraints. *Financial Analysts Journal*, 59(5):70–82.

Markowitz, H. M. (1952). Portfolio Selection. *The Journal of Finance*, 7(1):77–91.

Pedersen, L. H., Fitzgibbons, S., and Pomorski, L. (2021). Responsible Investing: The ESG-Efficient Frontier. *Journal of Financial Economics*, 142(2):572–597.

Roll, R. (1992). A Mean/Variance Analysis of Tracking Error. *The Journal of Portfolio Management*, 18(4):13–22.

Roncalli, T. (2013). *Introduction to Risk Parity and Budgeting*. CRC Press.

Roncalli, T., Le Guenedal, T., Lepetit, F., Roncalli, T., and Sekine, T. (2021). The Market Measure of Carbon Risk and Its Impact on the Minimum Variance Portfolio. *The Journal of Portfolio Management*, 47(9):54–68.

Schwaiger, K., Ali, R., and Ang, A. (2023). Net-Zero Sovereign Bond Portfolios. *Evolving Practices in Public Investment Management*, pages 167–184.

Soupe, F. and Kovarcik, G. (2024). Impact of ESG Objectives on a Portfolio. *The Journal of Portfolio Management*, 50(6).

Starks, L. (2023). Sustainable Finance and E, S, & G issues: Values versus Value. *Journal of Finance*, 78(4):1837–1872.

Utz, S., Wimmer, M., Hirschberger, M., and Steuer, R. E. (2014). Tri-criterion Inverse Portfolio Optimization with Application to Socially Responsible Mutual Funds. *European Journal of Operational Research*, 234(2):491–498.

Van Zanten, J. A. and Huij, J. (2022). ESG to SDG: Do Sustainable Investing Ratings Align with the Sustainability Preferences of Investors, Regulators, and Scientists? *Regulators, and Scientists*.

Wolf, M., Emerson, J., Esty, D., de Sherbinin, A., and Wendling, Z. (2022). 2022 Environmental Performance Index. *Yale Center for Environmental Law Policy Working paper*.

World Bank (2021). *The Changing Wealth of Nations 2021: Managing Assets For The Future*. The World Bank.

A Detailed Analytical Results

This Appendix details the analytical results of Section 2. To derive the solution to the optimization program (1), we start from general results on portfolio optimization (Best and Grauer, 1990). We consider the case of an investor seeking to solve the following optimization program:

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} \frac{1}{2}\boldsymbol{w}^T \boldsymbol{\Omega}\, \boldsymbol{w} \quad \text{s.t. } \boldsymbol{C}^T \boldsymbol{w} = \boldsymbol{c}^{\boldsymbol{*}}. \tag{A1}$$

$\boldsymbol{w}$ is the $N \times 1$ vector of portfolio weights, where N is the number of assets, and $\boldsymbol{\Omega}$ is the $N \times N$ variance-covariance matrix of asset returns. $\boldsymbol{C}$ is an $N \times K$ matrix collecting the individual characteristics associated with the objectives, where K is the number of objectives. It can be written as $\boldsymbol{C} = (\boldsymbol{c}_1, \ldots, \boldsymbol{c}_k, \ldots, \boldsymbol{c}_K)$ where each $\boldsymbol{c}_k$ is an $N \times 1$ vector containing the characteristics associated to the k^{th} objective. Finally, $\boldsymbol{c}^{\boldsymbol{*}}$ is a $K \times 1$ vector containing the targets associated with the objectives. Solving for Program (A1) yields:

$$\boldsymbol{w}^* = \boldsymbol{\Omega}^{-1} \boldsymbol{C}\boldsymbol{\lambda}, \tag{A2}$$

where the Lagrangian multipliers are identified as:

$$\boldsymbol{\lambda} = \left(\boldsymbol{C}^T \boldsymbol{\Omega}^{-1} \boldsymbol{C}\right)^{-1} \boldsymbol{c}^* \equiv \boldsymbol{\Phi}^{-1} \boldsymbol{c}^*. \tag{A3}$$

$\boldsymbol{\Phi}$ is the $K \times K$ matrix collecting the portfolio characteristics associated to the K objectives, for portfolio weights $\boldsymbol{w}^*$. It is, in general, invertible because $\boldsymbol{\Omega}$ is a properly defined covariance matrix and the K constraints are linearly independent. $\boldsymbol{\Phi}$ can be rewritten as:

$$\boldsymbol{\Phi} = \begin{pmatrix} \boldsymbol{c}_1^T \boldsymbol{\Omega}^{-1} \boldsymbol{c}_1 & \cdots & \boldsymbol{c}_1^T \boldsymbol{\Omega}^{-1} \boldsymbol{c}_K \\ \vdots & \ddots & \vdots \\ \boldsymbol{c}_K^T \boldsymbol{\Omega}^{-1} \boldsymbol{c}_1 & \cdots & \boldsymbol{c}_K^T \boldsymbol{\Omega}^{-1} \boldsymbol{c}_K \end{pmatrix} = \begin{pmatrix} \phi_{\boldsymbol{c}_1\boldsymbol{c}_1} & \cdots & \phi_{\boldsymbol{c}_1\boldsymbol{c}_K} \\ \vdots & \ddots & \vdots \\ \phi_{\boldsymbol{c}_1\boldsymbol{c}_K} & \cdots & \phi_{\boldsymbol{c}_K\boldsymbol{c}_K} \end{pmatrix}, \tag{A4}$$

where we use the notation $\phi_{\boldsymbol{c}_k\boldsymbol{c}_l}$ to denote the scalars $\boldsymbol{c}_k^T \boldsymbol{\Omega}^{-1} \boldsymbol{c}_l \in R$ for any vectors $\boldsymbol{c}_k, \boldsymbol{c}_l \in R^N$, and where we use the symmetry $\phi_{\boldsymbol{c}_k\boldsymbol{c}_l} = \phi_{\boldsymbol{c}_l\boldsymbol{c}_k}$ due to the symmetry of $\boldsymbol{\Omega}$ which is a covariance matrix. Plugging (A3) into (A2) yields the optimal portfolio solution as:

$$\boldsymbol{w}^* = \boldsymbol{\Omega}^{-1} \boldsymbol{C}\, \boldsymbol{\Phi}^{-1} \boldsymbol{c}^*, \tag{A5}$$

and the risk associated with the optimal portfolio as:

$$\boldsymbol{w}^{*T} \boldsymbol{\Omega}\, \boldsymbol{w}^* = \boldsymbol{c}^{*T} \boldsymbol{\Phi}^{-1} \boldsymbol{c}^*. \tag{A6}$$

From the vectorial expressions of $\boldsymbol{C}$ and $\boldsymbol{\lambda}$, Equation (A2) can also be expressed as:

$$\boldsymbol{w}^* = \sum_{k=1}^{K} \lambda_k \, \boldsymbol{\Omega}^{-1} \, \boldsymbol{c}_k. \tag{A7}$$

Introducing the following specific portfolios $\boldsymbol{w}_{\boldsymbol{c}_k} = \frac{\boldsymbol{\Omega}^{-1} \boldsymbol{c}_k}{\mathbf{1}^T \boldsymbol{\Omega}^{-1} \boldsymbol{c}_k}$ for $k = 1, ..., K$, the solution (A7) can be rewritten as:

$$\boldsymbol{w}^* = \sum_{k=1}^{K} \alpha_i \, \boldsymbol{w}_{\boldsymbol{c}_k}, \tag{A8}$$

where $\alpha_k = \lambda_k \, (\mathbf{1}^T \, \boldsymbol{\Omega}^{-1} \, \boldsymbol{c}_k)$ is the scaled preference for objective k. Hence, the solution is a linear combination of K specific portfolios corresponding to each objective k. In particular, the k^{th} specific portfolio is derived by finding the solution to the following optimization problem:

$$\boldsymbol{w}_{\boldsymbol{c}_k} = \arg\max_{\boldsymbol{w}} \frac{\boldsymbol{w}^T \, \boldsymbol{c}_k}{\sqrt{\boldsymbol{w}^T \, \boldsymbol{\Omega} \, \boldsymbol{w}}} \quad \text{s.t. } \mathbf{1}^T \, \boldsymbol{w} = 1, \tag{A9}$$

which shows that $\boldsymbol{w}_{\boldsymbol{c}_k}$ is designed to achieve the highest k^{th} characteristic level per unit of portfolio volatility. When the characteristic vector $\boldsymbol{c}_k$ contains exposures to a well-defined risk factor, typically under the form of betas, then the maximum characteristic-to-risk portfolios, $\boldsymbol{w}_{\boldsymbol{c}_k}$, can be interpreted as a factor-mimicking portfolio to the k^{th} risk factor (Fama, 1996). In this case, one can show that this portfolio maximizes the correlation to this specific risk factor.

This analytical framework encompasses major canonical portfolio construction methodologies such as the standard mean-variance-optimization (MVO) problem with no risk-free asset from Markowitz (1952) or the multifactor optimization problem from Fama (1996) underlying the Intertemporal Capital Asset Pricing Model. Solution (A8) shows that the optimal portfolio extends the two-fund combination associated with Markowitz's original program to a K-fund combination (Fama, 1996).

We next use these results in order to determine the optimal portfolio construction when the investor aims at minimizing the portfolio tracking error while considering two sustainable investment objectives, such as biodiversity and climate, i.e., the optimization program (1). We use the general solution (A8) with $K = 3$, $\boldsymbol{c}_1 = \boldsymbol{s}_1$, $c_1^* = \Delta s_1^*$, $\boldsymbol{c}_2 = \boldsymbol{s}_2$, $c_2^* = \Delta s_2^*$, $\boldsymbol{c}_3 = \mathbf{1}$, and $c_3^* = 0$. Introducing the three specific portfolios $\boldsymbol{w}_{\text{SCM}_1} = \frac{\boldsymbol{\Omega}^{-1} \boldsymbol{s}_1}{\mathbf{1}^T \boldsymbol{\Omega}^{-1} \boldsymbol{s}_1}$, $\boldsymbol{w}_{\text{SCM}_2} = \frac{\boldsymbol{\Omega}^{-1} \boldsymbol{s}_2}{\mathbf{1}^T \boldsymbol{\Omega}^{-1} \boldsymbol{s}_2}$, and $\boldsymbol{w}_{\text{GMV}} = \frac{\boldsymbol{\Omega}^{-1} \mathbf{1}}{\mathbf{1}^T \boldsymbol{\Omega}^{-1} \mathbf{1}}$, the solution of the optimization program (1) becomes:

$$\Delta \boldsymbol{w}^* = \theta_1 \, \boldsymbol{w}_{\text{SCM}_1} + \theta_2 \, \boldsymbol{w}_{\text{SCM}_2} - (\theta_1 + \theta_2) \, \boldsymbol{w}_{\text{GMV}}, \tag{A10}$$

where $\theta_k = (\mathbf{1}^T \mathbf{\Omega}^{-1} \boldsymbol{s}_k)\, \lambda_k$ is the scaled preference for sustainability characteristic k.

We next denote by $\mathbf{\Pi}$ the 3×3 inverse of matrix $\mathbf{\Phi}^{-1}$, with typical element π_{ij} for $i, j = 1, 2, 3$. Using the fact that the target objective vector $\boldsymbol{c}^*$ is equal to $(\Delta s_1^* \;\; \Delta s_2^* \;\; 0)^T$, we can compute the Lagrangian multipliers in (A3) as:

$$\boldsymbol{\lambda} = \mathbf{\Phi}^{-1}\, \boldsymbol{c}^* = \mathbf{\Pi}\, (\Delta s_1^* \;\; \Delta s_2^* \;\; 0)^T = \begin{pmatrix} \pi_{11}\, \Delta s_1^* + \pi_{12}\, \Delta s_2^* \\ \pi_{12}\, \Delta s_1^* + \pi_{22}\, \Delta s_2^* \\ \pi_{13}\, \Delta s_1^* + \pi_{23}\, \Delta s_2^* \end{pmatrix} \tag{A10}$$

This expression, combined with $\theta_k = (\mathbf{1}^T \mathbf{\Omega}^{-1} \boldsymbol{s}_k)\, \lambda_k$, easily leads to the result given in Equation (3). To get a better understanding of the parameters of the inverse matrix $\mathbf{\Pi}$ that are used in the solution (A10), i.e., π_{11}, π_{22} and π_{12}, we use Cramer's rule for the inverse of a matrix and obtain:

$$\pi_{11} = \frac{\left(\phi_{\mathbf{11}}\, \phi_{\boldsymbol{s}_2 \boldsymbol{s}_2} - \phi_{\boldsymbol{s}_2 \mathbf{1}}^2\right)}{|\mathbf{\Phi}|}, \pi_{22} = \frac{\left(\phi_{\mathbf{11}}\, \phi_{\boldsymbol{s}_1 \boldsymbol{s}_1} - \phi_{\boldsymbol{s}_1 \mathbf{1}}^2\right)}{|\mathbf{\Phi}|}, \pi_{12} = \frac{\left(\phi_{\boldsymbol{s}_1 \mathbf{1}}\, \phi_{\boldsymbol{s}_2 \mathbf{1}} - \phi_{\mathbf{11}} \phi_{\boldsymbol{s}_1 \boldsymbol{s}_2}\right)}{|\mathbf{\Phi}|}, \tag{A11}$$

where the determinant is given by $|\mathbf{\Phi}| = \phi_{\boldsymbol{s}_1 \boldsymbol{s}_1} \phi_{\boldsymbol{s}_2 \boldsymbol{s}_2} \phi_{\mathbf{11}} + 2 \phi_{\boldsymbol{s}_1 \mathbf{1}} \phi_{\boldsymbol{s}_2 \mathbf{1}} \phi_{\boldsymbol{s}_1 \boldsymbol{s}_2} - \phi_{\boldsymbol{s}_1 \mathbf{1}}^2 \phi_{\boldsymbol{s}_2 \boldsymbol{s}_2} - \phi_{\mathbf{11}} \phi_{\boldsymbol{s}_1 \boldsymbol{s}_2}^2 - \phi_{\boldsymbol{s}_1 \boldsymbol{s}_1} \phi_{\boldsymbol{s}_2 \mathbf{1}}^2 > 0$ by positive definiteness of $\mathbf{\Phi}$.

To obtain the minimal tracking error volatility of the active portfolio, TEV*, we can use the expression given on the right-hand side of Equation (A6). By left-multiplying the expression (A10) with $\boldsymbol{c}^{*T} = (\Delta s_1^* \;\; \Delta s_2^* \;\; 0)$, we obtain:

$$\text{TEV}^* = \sqrt{\boldsymbol{c}^{*T}\, \mathbf{\Phi}^{-1}\, \boldsymbol{c}^*} = \left[\pi_{11}\, (\Delta s_1^*)^2 + \pi_{22}\, (\Delta s_2^*)^2 + 2\, \pi_{12}\, \Delta s_1^* \Delta s_2^*\right]^{1/2}. \tag{A12}$$

In particular, the sensitivity of the tracking error to the sustainability target changes Δs_i^*, $i = 1, 2$ is a linear function of the target change itself:

$$\frac{\partial \text{TEV}^*}{\partial \Delta s_1^*} = \frac{\pi_{11} \Delta s_1^* + \pi_{12} \Delta s_2^*}{\text{TEV}^*}, \qquad \frac{\partial \text{TEV}^*}{\partial \Delta s_2^*} = \frac{\pi_{22} \Delta s_2^* + \pi_{12} \Delta s_1^*}{\text{TEV}^*}. \tag{A13}$$

As shown by (A13), the tracking error volatility reaction to target changes in sustainability metrics depends on π_{11}, π_{22} and π_{12}. Their expressions are given in Equation (A11), and it is useful to determine their sign to better understand the tracking-error sensitivity. We first observe that because the covariance matrix $\mathbf{\Omega}$ is symmetric positive semidefinite, its inverse $\mathbf{\Omega}^{-\mathbf{1}}$ (the precision matrix) is also symmetric positive semidefinite. Hence, we note that $\mathbf{\Phi} = \boldsymbol{C}^T \mathbf{\Omega}^{-1} \boldsymbol{C}$ is also symmetric positive semidefinite, which implies that $\mathbf{\Pi} = \mathbf{\Phi}^{-1}$ is symmetric positive semidefinite too, and it follows that all the diagonal elements of $\mathbf{\Pi}$ are positive.

Therefore, the first two components of TEV*, namely $\pi_{11}\,(\Delta s_1^*)^2$ and $\pi_{22}\,(\Delta s_2^*)^2$ are positive. Now, if we denote by $\mathrm{cov}_{\mathrm{SCM}_1,\mathrm{SCM}_2}$ and $\mathrm{var}_{\mathrm{GMV}}$ the covariance between the two sustainability characteristic-mimicking portfolios and the variance of the GMV portfolio, respectively, we have:

$$\mathrm{cov}_{\mathrm{SCM}_1,\mathrm{SCM}_2} = \boldsymbol{w}_{\mathrm{SCM}_1}^T \Omega \boldsymbol{w}_{\mathrm{SCM}_2} = \frac{\phi_{\boldsymbol{s}_1\boldsymbol{s}_2}}{\phi_{\boldsymbol{s}_1\mathbf{1}}\,\phi_{\boldsymbol{s}_2\mathbf{1}}}, \quad \mathrm{var}_{\mathrm{GMV}} = \boldsymbol{w}_{\mathrm{GMV}}^T \Omega \boldsymbol{w}_{\mathrm{GMV}} = \frac{1}{\phi_{\mathbf{11}}}.$$

Hence, the numerator of π_{12} can be rewritten as:

$$\phi_{\boldsymbol{s}_1\mathbf{1}}\,\phi_{\boldsymbol{s}_2\mathbf{1}} - \phi_{\mathbf{11}}\phi_{\boldsymbol{s}_1\boldsymbol{s}_2} = \phi_{\mathbf{11}}\,\phi_{\boldsymbol{s}_1\mathbf{1}}\,\phi_{\boldsymbol{s}_2\mathbf{1}}\left(\frac{1}{\phi_{\mathbf{11}}} - \frac{\phi_{\boldsymbol{s}_1\boldsymbol{s}_2}}{\phi_{\boldsymbol{s}_1\mathbf{1}}\,\phi_{\boldsymbol{s}_2\mathbf{1}}}\right) = \phi_{\boldsymbol{s}_1\mathbf{1}}\,\phi_{\boldsymbol{s}_2\mathbf{1}}\frac{\mathrm{var}_{\mathrm{GMV}} - \mathrm{cov}_{\mathrm{SCM}_1,\mathrm{SCM}_2}}{\mathrm{var}_{\mathrm{GMV}}},$$

so, contrary to π_{11} and π_{22}, we cannot conclude on the sign of π_{12}.

Finally, it is useful to decompose the portfolio risk into its main components. Using standard risk decomposition principles (Roncalli, 2013), the tracking error volatility can be decomposed as:

$$\mathrm{TEV}^* = \left(\sum_{i=1}^{N} \Delta w_i^* \left[\boldsymbol{\Omega}\,\Delta\boldsymbol{w}^*\right]_i\right) / \mathrm{TEV}^*. \tag{A14}$$

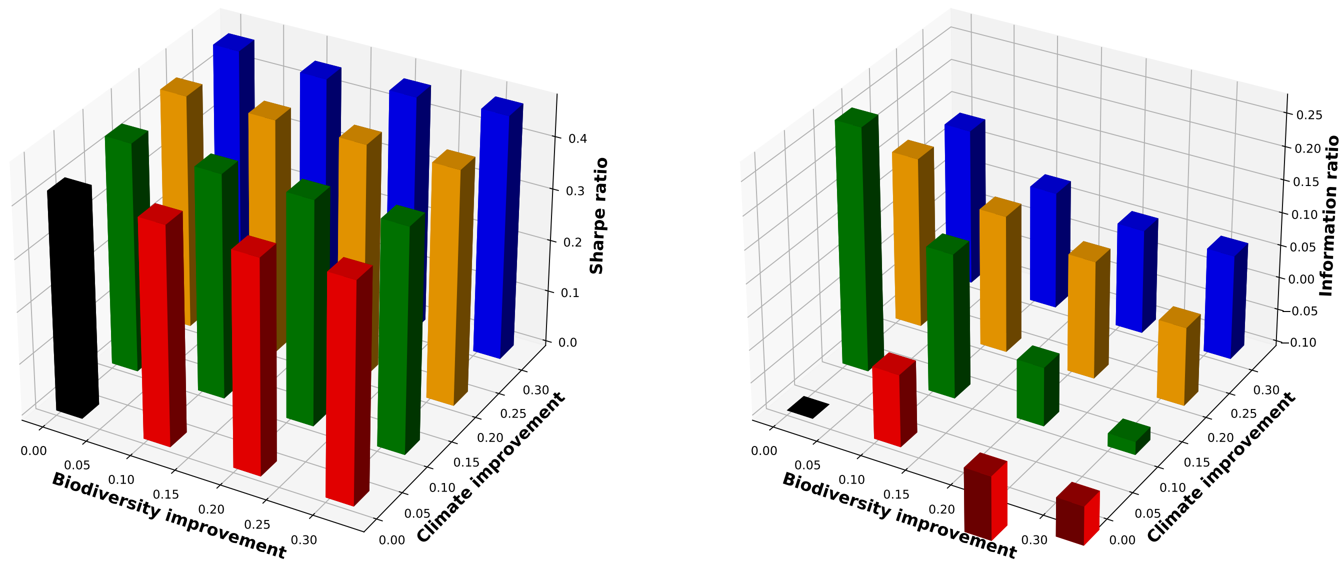
Using the optimal portfolio weights in (A10), we deduce that:

$$\begin{aligned}
\mathrm{TEV}^* &= \frac{1}{\mathrm{TEV}^*}\left(\sum_{i=1}^{N} \Delta w_i^* \left[\boldsymbol{\Omega}\left(\theta_1\,\boldsymbol{w}_{\mathrm{SCM}_1} + \theta_2\,\boldsymbol{w}_{\mathrm{SCM}_2} - (\theta_1+\theta_2)\,\boldsymbol{w}_{\mathrm{GMV}}\right)\right]_i\right), \\
&= \frac{1}{\mathrm{TEV}^*}\left(\sum_{i=1}^{N} \Delta w_i^* \left[\boldsymbol{\Omega}\left(\theta_1\,\frac{\boldsymbol{\Omega}^{-1}\,\boldsymbol{s}_1}{\mathbf{1}^T\,\boldsymbol{\Omega}^{-1}\,\boldsymbol{s}_1} + \theta_2\,\frac{\boldsymbol{\Omega}^{-1}\,\boldsymbol{s}_2}{\mathbf{1}^T\,\boldsymbol{\Omega}^{-1}\,\boldsymbol{s}_2} - (\theta_1+\theta_2)\,\frac{\boldsymbol{\Omega}^{-1}\,\mathbf{1}}{\mathbf{1}^T\,\boldsymbol{\Omega}^{-1}\,\mathbf{1}}\right)\right]_i\right), \\
&= \frac{1}{\mathrm{TEV}^*}\left(\underbrace{\lambda_1\sum_{i=1}^{N}\Delta w_i^* s_{1i}}_{\text{Contribution of SCM}_1} + \underbrace{\lambda_2\sum_{i=1}^{N}\Delta w_i^* s_{2i}}_{\text{Contribution of SCM}_2}\right).
\end{aligned} \tag{A15}$$

Equation (A15) provides a decomposition of the tracking error volatility across assets, as indexed through i, and the individual sustainability characteristics for each asset, s_{1i} and s_{2i}. One can notice that, when aggregated across all assets, the last term in (A15) vanishes as the sum of active weights is constrained to zero, $\sum_{i=1}^{N}\Delta w_i^* = 0$, through the design of the optimization program (1).

B Tables and Figures

Figure 1: Impact of Biodiversity and Climate Improvement on Sharpe ratio (left) and Information ratio (right)



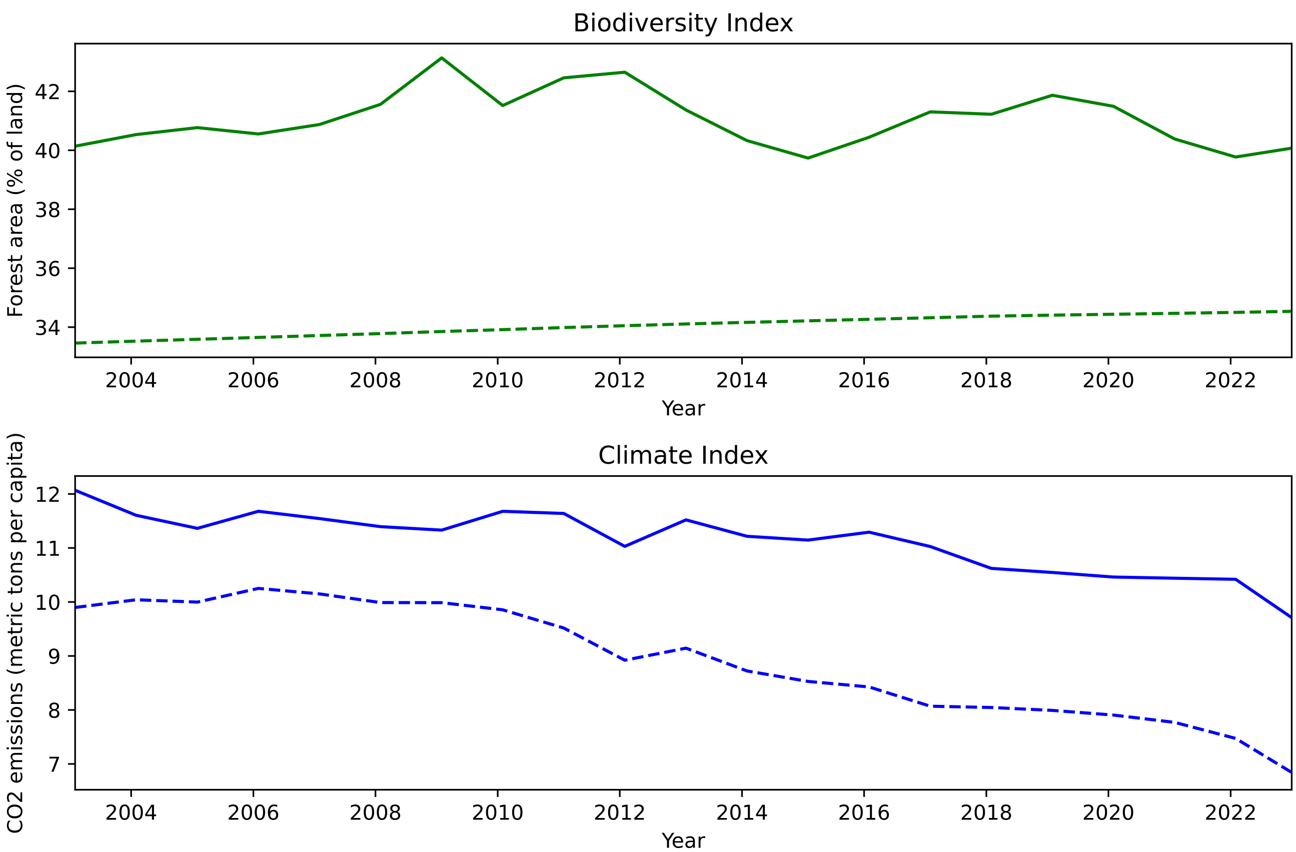
Notes. The Figure summarizes the impact of targeted improvement vs the market-capitalization sovereign bonds benchmark in biodiversity (measured by forest area as % of total land) and climate (measured by CO2 emissions per capita) metrics for the Sharpe ratio (left panel) and the Information ratio (right panel). Each bar represents a specific active fixed-income strategy based on different targeted improvements in biodiversity and climate metrics (horizontal scales), with the impact on risk-adjusted returns represented on the vertical scale. Black bars denote the market-capitalization benchmark, while the other colors indicate different levels of climate improvement (+10% for red bars, +20% for yellow bars, +30% for blue bars). The analysis is based on a universe of 21 developed countries' bond markets, covering the period from January 2003 to December 2023. Detailed results are provided in Tables 2 and 3.

Table 1: Descriptive Statistics of Bond Indices and Sustainability Data

	Avg. Ret	Vol.	TE	Market Value	Forest Area	CO2 Em.
Australia	2.31	4.54	2.85	235,063	17.14	17.26
Austria	3.66	5.41	2.82	225,603	46.85	8.04
Belgium	3.88	5.70	3.23	370,437	22.58	9.42
Canada	3.20	4.22	2.15	341,480	38.74	16.05
Denmark	3.61	5.61	3.10	98,984	14.94	8.03
Finland	3.27	4.40	2.06	86,531	73.52	10.12
France	3.67	5.02	2.46	1,387,474	29.84	5.30
Germany	3.35	4.63	2.10	1,194,668	32.67	9.33
Greece	8.70	23.09	23.15	111,271	29.66	7.67
Ireland	4.69	7.84	6.47	101,632	10.37	9.23
Italy	4.69	6.10	4.90	1,370,549	30.42	6.70
Japan	2.97	2.30	2.74	5,881,858	68.40	9.22
Netherlands	3.40	5.03	2.40	323,842	10.89	9.62
New Zealand	2.31	4.08	2.89	38,369	37.42	7.40
Norway	2.79	3.33	2.69	38,109	33.21	7.70
Portugal	5.47	9.65	9.09	124,434	35.85	5.18
Spain	4.45	5.74	4.24	717,783	36.38	6.37
Sweden	3.31	4.38	2.46	75,021	68.89	4.76
Switzerland	3.87	5.26	3.30	86,098	31.22	5.40
United Kingdom	3.08	7.13	4.57	1,394,593	12.70	7.43
United States	2.84	4.80	2.11	7,505,338	33.63	17.25

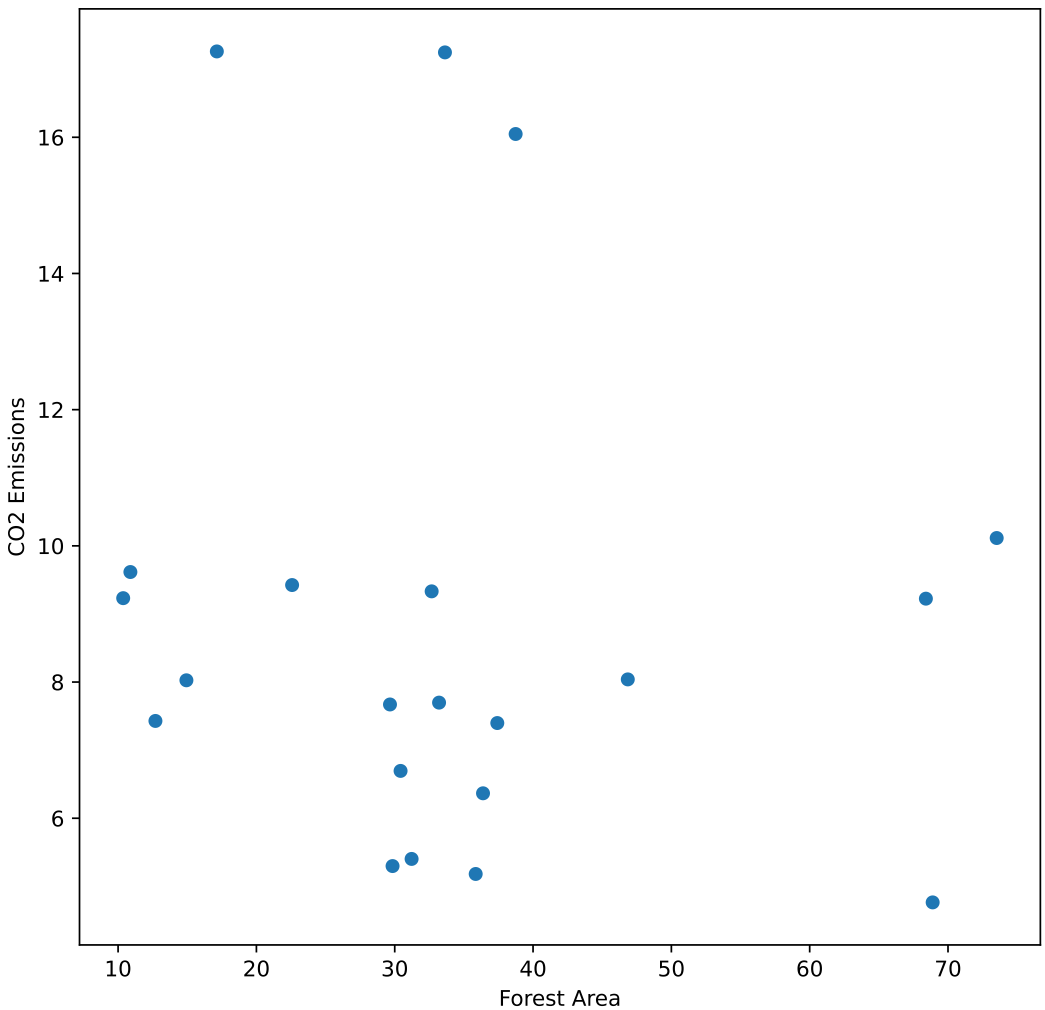
Notes. The Table contains the main descriptive statistics of the data used in the empirical section, i.e., the annualized sample average return "Avg. Ret" and volatility "Vol." of bond indices returns (in percentage), the tracking error volatility "TE" of the country bond index vs the market capitalization benchmark, the average country market capitalization values (in million USD), the average country forest area (as % of total country land area) and the domestic CO2 emissions (in tons per capita). All returns are hedged to USD and observed over the period between January 2003 and December 2023.

Figure 2: Biodiversity and Climate Characteristics Across Time



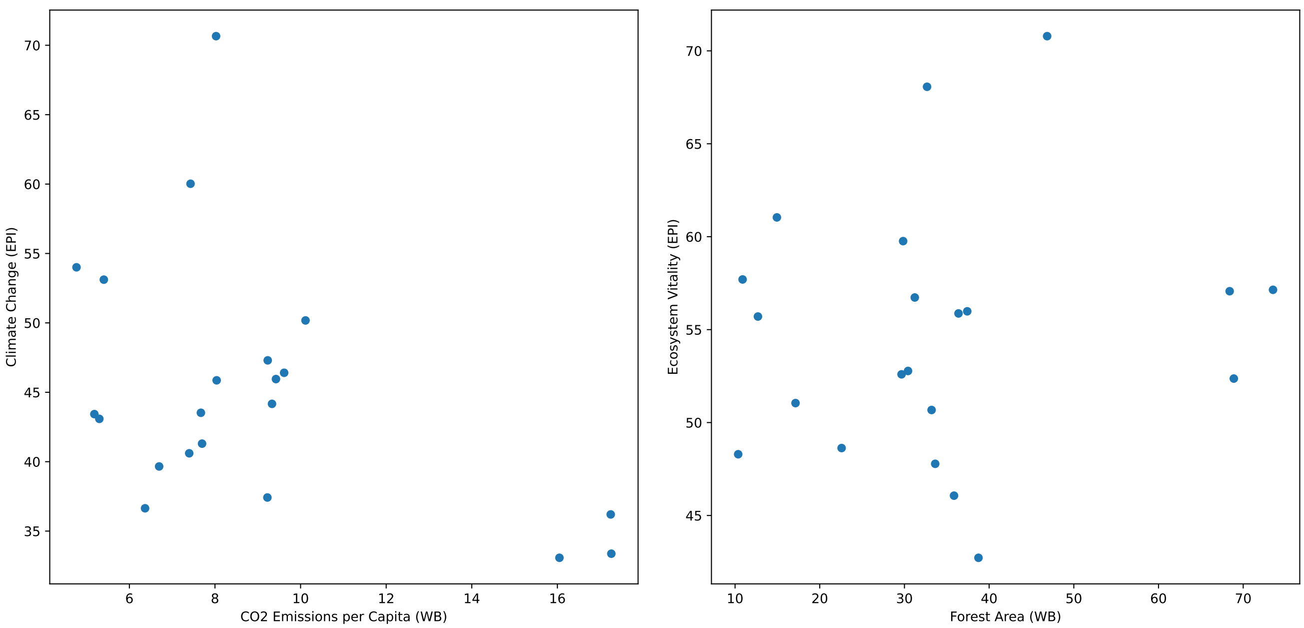
Notes. For each calendar year, the figure shows the weighted average forest area (as % of total land area; top panel) and CO2 emissions (in metric tons per capita; bottom panel) across all countries. The cross-country weights are calculated based on either market capitalization (solid lines) or equal weights (dashed lines).

Figure 3: Biodiversity and Climate Characteristics Across Countries



Notes. The figure displays each country's average biodiversity (measured as forest area % of total land area) and climate characteristics (measured as CO2 emissions in tons per capita). The average values are calculated over the period from 2000 to 2020.

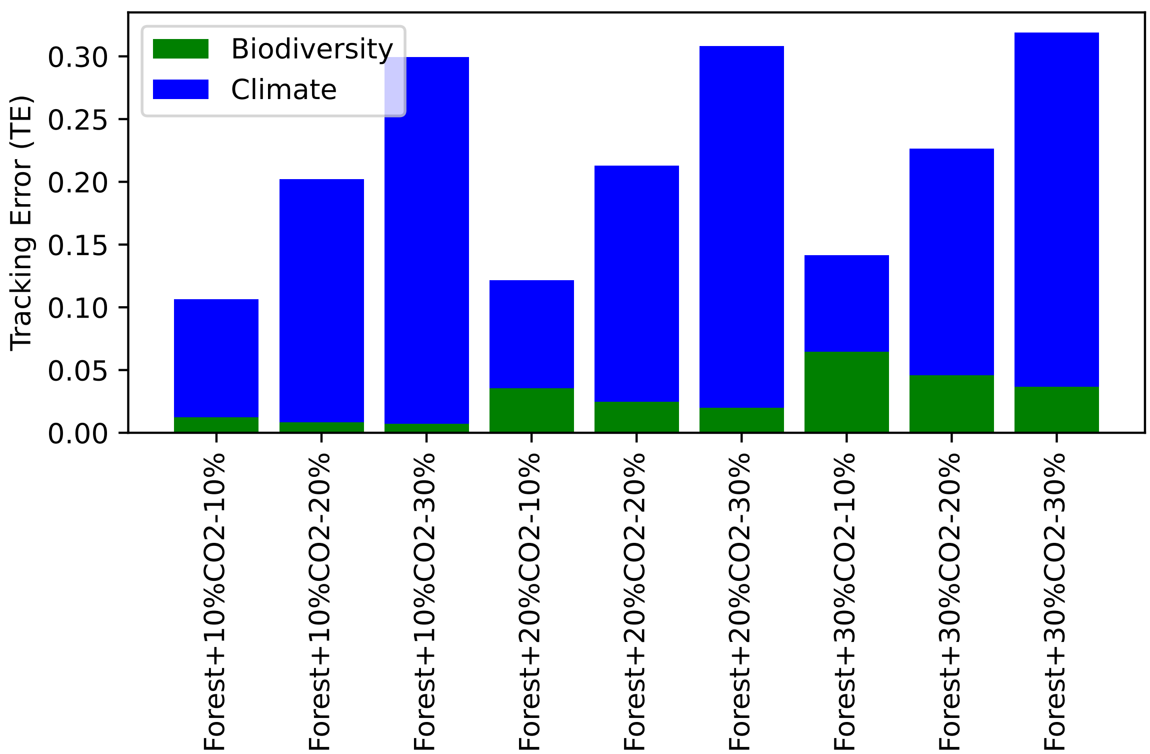
Figure 4: Consistency Between Sustainability Metrics Across Data Sources



Notes. This figure compares country-level sustainability metrics from the World Bank ESG portal (WB) and the Yale Environmental Performance Index (EPI).

Figure 5: Ex-Ante Tracking Error Decomposition

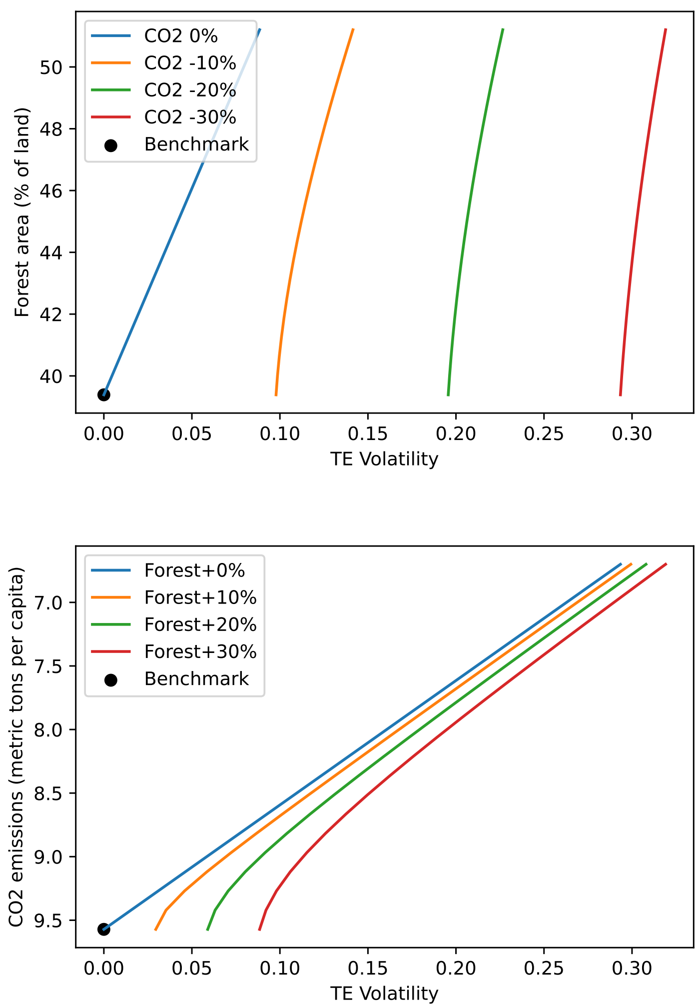
December 2023



Notes. The Figure represents contributions to the ex-ante tracking error volatility (in % p.a.) from the changes in CO2 emissions (in metric tons per capita) and Forest area (as % of total land) relative to the market capitalization benchmark for December 2023. Each bar represents a combination of a decrease in CO2 emissions (from -10% to -30% relative to the benchmark) and an increase in the level of Forest area (from +10% to +30% relative to the benchmark).

Figure 6: Ex-Ante Efficient Frontier: Tracking Error Volatility vs Sustainability Objectives

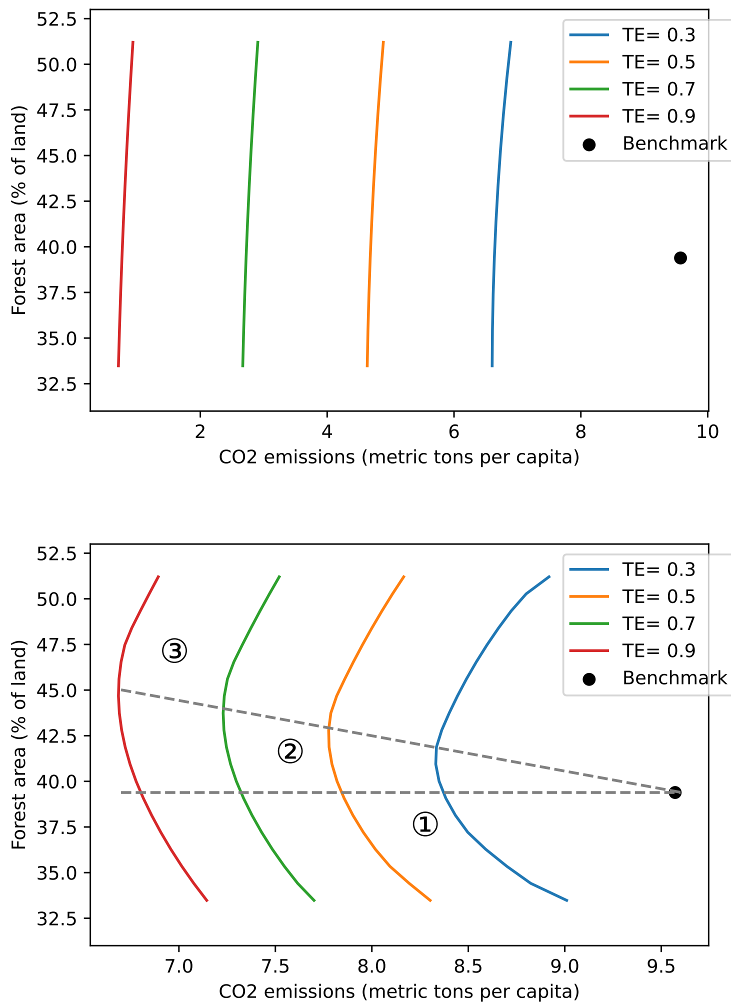
December 2023



Notes. The top panel of the figure illustrates the forest area (as % of total land) and the associated tracking error volatility (in % p.a.), for varying levels of CO2 emissions (in metric tons per capita), ranging from 0% down to -30% relative to the benchmark. The bottom panel shows the CO2 emissions (in metric tons per capita, inverted scale) and the associated tracking error volatility (in % p.a.), for different levels of forest area (as % of land), ranging from 0% to +30% relative to the benchmark. Each point represents a long-short bond portfolio designed to minimize the ex-ante tracking error volatility for given levels of forest area and CO2 emissions in December 2023. The black dot identifies the benchmark.

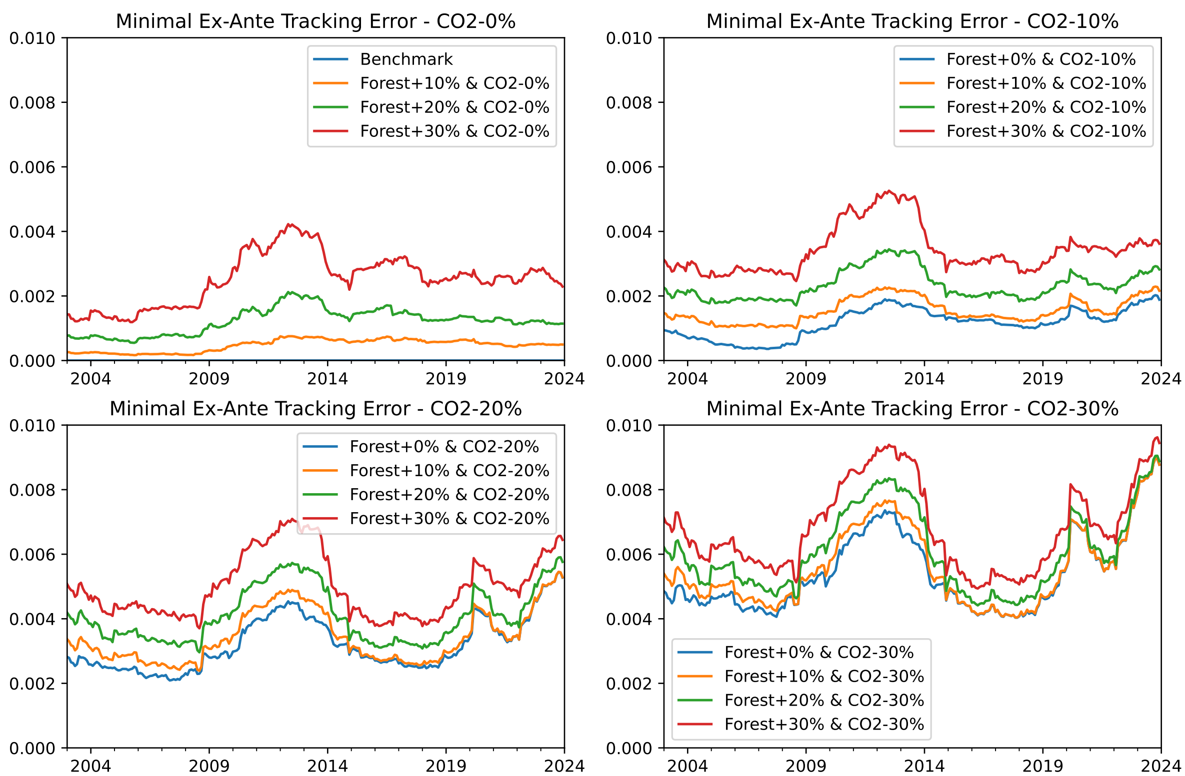
Figure 7: Ex-Ante Efficient Frontier with and without Short-Selling Constraints: CO2 Emissions vs Forest Area

December 2023



Notes. The Figures show the CO2 emissions (in metric tons per capita) and Forest area (as % of total land) for different levels of tracking error volatility (0.3%, 0.5%, 0.7%, 0.9%) relative to the market capitalization benchmark as of December 2023. Each point in the top panel (resp. bottom panel) represents the long-short (resp. long-only) bond portfolio that minimizes the level of CO2 emissions for a given level of tracking error and a given level of Forest area (ranging from 85% to 130% of the percentage of land of the benchmark). The black dot indicates the benchmark.

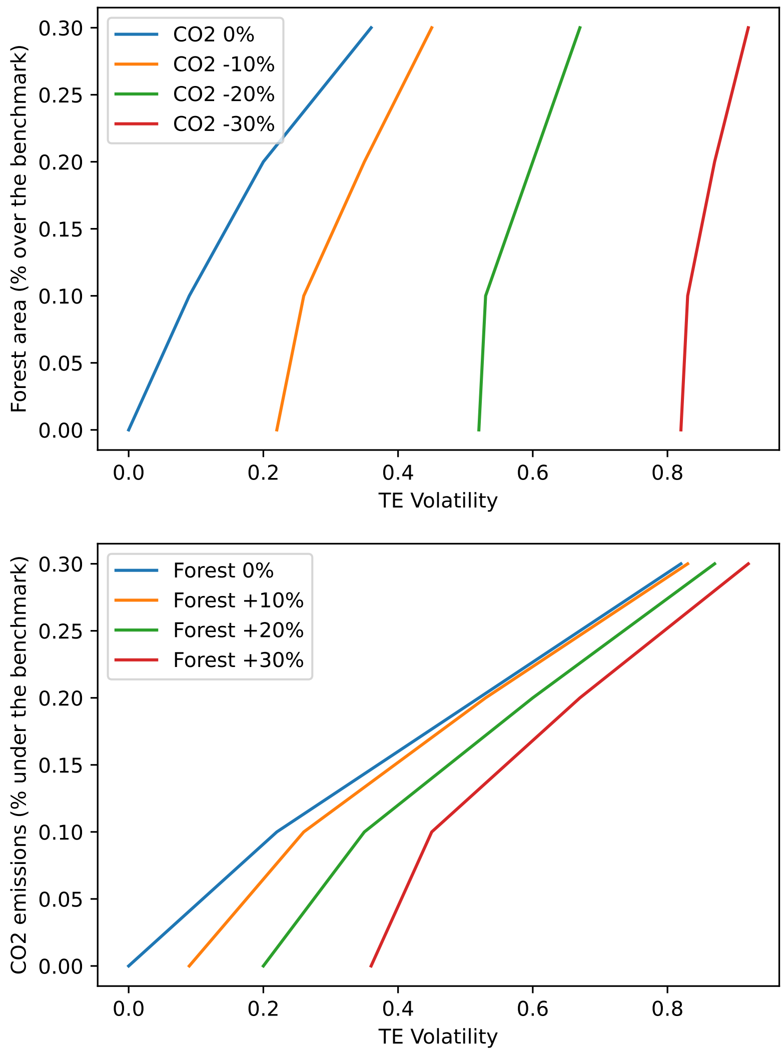
Figure 8: Ex-Ante Tracking Error Relative to the Benchmark



Notes. The Figure shows the minimal ex-ante tracking error volatility (% p.a.) relative to the benchmark portfolio for the 16 portfolio strategies between January 2003 and December 2023. Forest+x% & CO2-y% correspond to the strategy that minimizes the level of tracking error with the following constraints: (i) the biodiversity indicator equals $(1 + x)\%$ of the biodiversity indicator of the benchmark, and (ii) the climate indicator equals $(1 - y)\%$ of the climate indicator of the benchmark.

Figure 9: Ex-Post Efficient Frontier: Tracking Error vs Sustainability Objectives

Full sample



Notes. The top panel of the figure shows the improvement in forest area, ranging from 0% down to +30% relative to the benchmark, and the associated tracking error volatility for various levels of CO2 emissions improvement, ranging from 0% to -30%) relative to the benchmark. The bottom panel displays the improvement in CO2 emissions, ranging from 0% to -30% relative to the benchmark portfolio, and the associated tracking error volatility for various levels of forest area improvement, ranging from 0% down to +30% relative to the benchmark portfolio. These ex-post metrics have been computed over a backtesting period from January 2003 to December 2023.

Table 2: **Climate-Biodiversity Strategy: Absolute Portfolio Statistics**

	CAGR	Ann. Vol.	Sharpe Ratio	Max. DD	Calmar Ratio	Turnover
Forest+0% & CO2-0% (Bench.)	3.08%	3.56%	0.42	14.61%	0.10	10.07%
Forest+10% & CO2-0%	3.09%	3.56%	0.42	14.78%	0.10	19.64%
Forest+20% & CO2-0%	3.06%	3.54%	0.41	14.80%	0.10	23.45%
Forest+30% & CO2-0%	3.06%	3.50%	0.42	14.79%	0.10	22.87%
Forest+0% & CO2-10%	3.17%	3.58%	0.44	14.59%	0.11	21.98%
Forest+10% & CO2-10%	3.14%	3.55%	0.43	14.56%	0.11	26.74%
Forest+20% & CO2-10%	3.12%	3.53%	0.43	14.54%	0.10	28.37%
Forest+30% & CO2-10%	3.10%	3.49%	0.43	14.37%	0.10	30.82%
Forest+0% & CO2-20%	3.22%	3.60%	0.45	14.64%	0.11	33.45%
Forest+10% & CO2-20%	3.20%	3.56%	0.45	14.49%	0.11	30.18%
Forest+20% & CO2-20%	3.19%	3.52%	0.45	14.17%	0.11	36.65%
Forest+30% & CO2-20%	3.17%	3.48%	0.45	14.04%	0.11	39.99%
Forest+0% & CO2-30%	3.29%	3.64%	0.46	14.64%	0.12	41.63%
Forest+10% & CO2-30%	3.24%	3.60%	0.45	14.58%	0.11	40.03%
Forest+20% & CO2-30%	3.23%	3.55%	0.46	14.28%	0.11	44.80%
Forest+30% & CO2-30%	3.24%	3.50%	0.47	13.75%	0.12	45.41%

Notes. The Table presents the analytics for the 16 fixed-income portfolio strategies over the period from January 2003 to December 2023. Forest+x% & CO2-y% refers to the bond investing strategy that minimizes the level of tracking error subject to the following constraints: (i) the biodiversity indicator is equal to $(1 + x)\%$ of the biodiversity indicator of the market capitalization benchmark, and (ii) the climate indicator is equal to $(1 - y)\%$ of the climate indicator of the benchmark. "CAGR" stands for Compound Annual Growth Rate, "Ann. Vol." for Annualized Volatility, "S.R." for Sharpe Ratio, "Max. DD" for Maximum Drawdown, "Turnover" for One-Way Turnover.

Table 3: Climate-Biodiversity Strategy: Portfolio Statistics Relative to the Benchmark

	Alpha	Tracking Error	Information Ratio
Forest+10% & CO2-0%	0.01%	0.09%	0.11
Forest+20% & CO2-0%	-0.02%	0.20%	-0.10
Forest+30% & CO2-0%	-0.02%	0.36%	-0.06
Forest+0% & CO2-10%	0.08%	0.22%	0.37
Forest+10% & CO2-10%	0.06%	0.26%	0.22
Forest+20% & CO2-10%	0.03%	0.35%	0.09
Forest+30% & CO2-10%	0.01%	0.45%	0.02
Forest+0% & CO2-20%	0.14%	0.52%	0.26
Forest+10% & CO2-20%	0.11%	0.53%	0.21
Forest+20% & CO2-20%	0.10%	0.60%	0.18
Forest+30% & CO2-20%	0.08%	0.67%	0.12
Forest+0% & CO2-30%	0.20%	0.82%	0.24
Forest+10% & CO2-30%	0.15%	0.83%	0.18
Forest+20% & CO2-30%	0.14%	0.87%	0.16
Forest+30% & CO2-30%	0.15%	0.92%	0.16

Notes. The Table presents the analytics relative to the market capitalization benchmark computed for the 16 fixed-income portfolio strategies over the period from January 2003 to December 2023. Forest+x% & CO2-y% refers to the sovereign bond investing strategy that minimizes the level of tracking error under the following constraints: (i) the biodiversity indicator is equal to $(1 + x)\%$ of the biodiversity indicator of the benchmark, and (ii) the climate indicator is equal to $(1 - y)\%$ of the climate indicator of the benchmark.

Table 4: Climate-Biodiversity Strategy: Absolute Portfolio Statistics

Yale EPI Sustainable Indicators

	CAGR	Ann. Vol.	Sharpe Ratio	Max. DD	Calmar Ratio	Turnover
ECO+0% & CCH+0% (Bench.)	3.08%	3.56%	0.42	14.61%	0.10	10.07%
ECO+3% & CCH+0%	3.10%	3.58%	0.42	14.75%	0.10	19.35%
ECO+6% & CCH+0%	3.12%	3.66%	0.42	15.41%	0.10	24.54%
ECO+9% & CCH+0%	3.16%	3.75%	0.42	16.02%	0.10	29.94%
ECO+0% & CCH+5%	3.13%	3.59%	0.43	14.63%	0.10	23.55%
ECO+3% & CCH+5%	3.15%	3.62%	0.43	14.97%	0.10	26.56%
ECO+6% & CCH+5%	3.16%	3.69%	0.42	15.65%	0.10	28.05%
ECO+9% & CCH+5%	3.17%	3.77%	0.42	16.26%	0.10	31.38%
ECO+0% & CCH+10%	3.22%	3.63%	0.45	14.75%	0.11	31.87%
ECO+3% & CCH+10%	3.22%	3.67%	0.44	15.27%	0.11	33.41%
ECO+6% & CCH+10%	3.23%	3.75%	0.44	15.91%	0.10	37.69%
ECO+9% & CCH+10%	3.26%	3.84%	0.44	16.46%	0.10	38.29%
ECO+0% & CCH+15%	3.31%	3.69%	0.46	14.86%	0.12	41.31%
ECO+3% & CCH+15%	3.31%	3.74%	0.46	15.55%	0.11	43.36%
ECO+6% & CCH+15%	3.32%	3.81%	0.45	16.16%	0.11	47.30%
ECO+9% & CCH+15%	3.34%	3.89%	0.45	16.61%	0.11	45.56%

Notes. The Table presents the analytics computed for the 16 sovereign bond portfolio strategies using Yale EPI sustainable indicators over the period from January 2003 to December 2023. See Table 2 for details on calculated metrics.

Table 5: Climate-Biodiversity Strategy: Portfolio Statistics Relative to the Benchmark

Yale EPI Sustainable Indicators

	Alpha	Tracking Error	Information Ratio
ECO+3% & CCH+0%	0.02%	0.15%	0.14
ECO+6% & CCH+0%	0.04%	0.40%	0.10
ECO+9% & CCH+0%	0.08%	0.66%	0.12
ECO+0% & CCH+5%	0.05%	0.15%	0.32
ECO+3% & CCH+5%	0.06%	0.26%	0.25
ECO+6% & CCH+5%	0.08%	0.46%	0.17
ECO+9% & CCH+5%	0.10%	0.70%	0.14
ECO+0% & CCH+10%	0.13%	0.33%	0.39
ECO+3% & CCH+10%	0.14%	0.42%	0.32
ECO+6% & CCH+10%	0.15%	0.59%	0.25
ECO+9% & CCH+10%	0.18%	0.80%	0.23
ECO+0% & CCH+15%	0.23%	0.55%	0.42
ECO+3% & CCH+15%	0.23%	0.62%	0.37
ECO+6% & CCH+15%	0.24%	0.76%	0.32
ECO+9% & CCH+15%	0.26%	0.93%	0.28

Notes. The Table presents the analytics relative to the market capitalization benchmark for the 16 sovereign bond portfolio strategies using Yale EPI sustainable indicators over the period from January 2003 to December 2023. See Table 3 for details on calculated metrics.

Table 6: Climate-Biodiversity Strategy: Absolute Portfolio Analytics

Long-Short Portfolios

	CAGR	Ann. Vol.	Sharpe Ratio	Max. DD	Calmar Ratio	Turnover
Forest+0% & CO2-0% (Bench.)	3.08%	3.56%	0.42	14.61%	0.10	10.07%
Forest+10% & CO2-0%	3.09%	3.55%	0.42	14.52%	0.10	26.24%
Forest+20% & CO2-0%	3.09%	3.54%	0.42	14.43%	0.10	41.05%
Forest+30% & CO2-0%	3.10%	3.53%	0.43	14.35%	0.10	53.61%
Forest+0% & CO2-10%	3.12%	3.56%	0.43	14.38%	0.11	53.23%
Forest+10% & CO2-10%	3.12%	3.56%	0.43	14.33%	0.11	50.05%
Forest+20% & CO2-10%	3.12%	3.55%	0.43	14.25%	0.11	57.46%
Forest+30% & CO2-10%	3.12%	3.54%	0.43	14.20%	0.11	67.66%
Forest+0% & CO2-20%	3.15%	3.58%	0.43	14.23%	0.11	103.04%
Forest+10% & CO2-20%	3.15%	3.57%	0.43	14.21%	0.11	97.81%
Forest+20% & CO2-20%	3.15%	3.57%	0.44	14.21%	0.11	96.17%
Forest+30% & CO2-20%	3.15%	3.55%	0.44	14.16%	0.11	104.93%
Forest+0% & CO2-30%	3.17%	3.60%	0.44	14.15%	0.11	149.64%
Forest+10% & CO2-30%	3.18%	3.60%	0.44	14.10%	0.11	146.61%
Forest+20% & CO2-30%	3.18%	3.60%	0.44	14.14%	0.11	141.64%
Forest+30% & CO2-30%	3.17%	3.59%	0.44	14.09%	0.11	146.52%

Notes. The Table presents the analytics for the 16 sovereign bond portfolio strategies over the period from January 2003 to December 2023, with short bond positions authorized. See Table 2 for details on calculated metrics.

Table 7: Climate-Biodiversity Strategy: Portfolio Analytics Relative to the Benchmark

Long-Short Portfolios

	Alpha	Tracking Error	Information Ratio
Forest+10% & CO2-0%	0.01%	0.07%	0.11
Forest+20% & CO2-0%	0.01%	0.14%	0.05
Forest+30% & CO2-0%	0.01%	0.21%	0.07
Forest+0% & CO2-10%	0.04%	0.20%	0.18
Forest+10% & CO2-10%	0.04%	0.20%	0.19
Forest+20% & CO2-10%	0.04%	0.22%	0.16
Forest+30% & CO2-10%	0.04%	0.26%	0.14
Forest+0% & CO2-20%	0.06%	0.41%	0.15
Forest+10% & CO2-20%	0.06%	0.40%	0.15
Forest+20% & CO2-20%	0.07%	0.41%	0.16
Forest+30% & CO2-20%	0.07%	0.43%	0.16
Forest+0% & CO2-30%	0.09%	0.61%	0.15
Forest+10% & CO2-30%	0.10%	0.61%	0.16
Forest+20% & CO2-30%	0.10%	0.61%	0.16
Forest+30% & CO2-30%	0.09%	0.62%	0.14

Notes. The Table presents the analytics relative to the market capitalization benchmark for the 16 sovereign bond portfolio strategies over the period from January 2003 to December 2023, with short bond positions authorized. See Table 2 for details on calculated metrics.