Financing Nature: Investment Funds and Biodiversity Risks*

Daniel Marcel te Kaat† Alexander Raabe‡

February 23, 2026

Abstract

How do international investors adjust portfolios in response to biodiversity risk? Using monthly data on investment fund portfolios, we show that the 2021 Kunming Declaration led fund managers to reallocate portfolios from high-biodiversity risk countries to less risky ones, while ultimate fund investors remained unresponsive. Fund managers reduced exposures to extremely high biodiversity risk without seizing low biodiversity risk as an opportunity for profit, characterizing biodiversity as downside risk factor. Investment funds drive cross-country spillovers as the reallocation triggers significant capital flows benefiting countries in the same geographic region, but outside of a fund's hitherto established portfolio. Using a novel measure of legal action to protect nature, we demonstrate that countries taking more legal acts are partially shielded from funds reducing their exposure to high-biodiversity risk countries.

Keywords: Biodiversity, Risk, Portfolio Reallocation, Cross-border Capital Flows, Spillovers, Contagion, Investment Fund, Kunming Declaration, Nature-positive, Sustainable Finance
JEL Classifications: F3, G1, G2, Q5

*We thank Tobias Berg, Cédric Tille, Steven Ongena, Peter Rosenkranz (discussant) and Alexander F. Wagner, as well as conference and seminar participants at the ADB, ADB-ADBI-APAEA-Bank Indonesia Workshop, Bank for International Settlements, Graduate Institute Geneva (Hoffmann Center for Global Sustainability), the Conference on Biodiversity in Finance and Accounting, the European Investment Bank, the European Commission Joint Research Centre's 7th Summer School on Sustainable Finance and the 19th East Asian Economic Association International Conference. We are grateful to Rainiel Aquino, Pilar Capulong Dayag, and Yuanjie Tian for excellent research assistance. We also thank Simon Ferrier (CSIRO) for kindly sharing data on the Biodiversity Habitat Index, and Andres Vatter Rubio (FAO) for advice on the FAOLEX database. The views expressed are those of the authors and do not reflect the views and policies of ADB or its Board of Governors or the governments they represent.

†Corresponding author, University of Groningen (d.m.te.kaat@rug.nl)

‡Asian Development Bank and Centre for Applied Macroeconomic Analysis at the Australian National University (araabe@adb.org)

1 Introduction

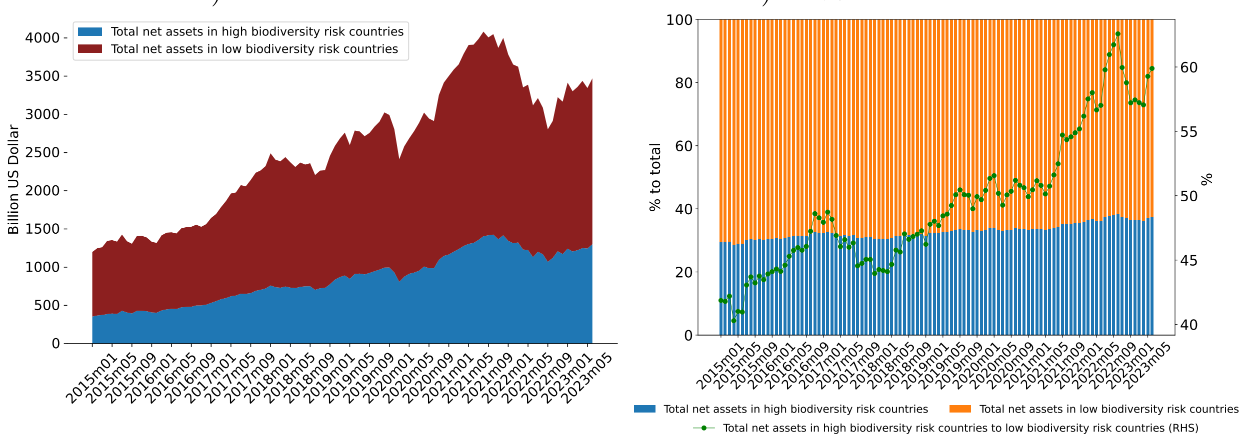
Biodiversity is fundamental to any economic activity. Yet, biodiversity declined by 73% globally over the period 1970 to 2020, faster than at any time in human history. The rate of species extinction exceeds its natural rate by a factor of a thousand, leaving 1 million animal and plant species threatened by extinction (Brondízio et al., 2021; Deutz et al., 2020). Evidence for a 6th mass extinction abounds, and—absent policy action—up to half of all species are expected to be lost by 2050 (Ceballos et al., 2020; Deutz et al., 2020). Thriving biodiversity enables essential ecosystem services, such as the provision of food and raw materials, filtering of air and water, and pollination (Principles for Responsible Investment (PRI), 2024). With half of global value added directly depending on nature, acute biodiversity losses are expected to stifle growth and undermine financial stability (Johnson et al., 2021; Gardes-Landolfini et al., 2024). Failure to correctly price the exposure to such biodiversity losses can give rise to significant transition risk and—upon sudden materialization—large adjustment costs. We ask how investors reallocate portfolios in response to such mispriced biodiversity risk. We further investigate ensuing international spillovers, and assess policies effective at dampening outflows from countries with high biodiversity risks.

To study these questions, we focus on investment funds' portfolio reallocations around the October 2021 Kunming Declaration (KD), signed by over 100 countries as commitment to a new ambitious global framework to address biodiversity losses by 2030. The latter was eventually adopted as Global Biodiversity Framework (GBF) in Montreal in December 2022 at the 15th Conference of the Parties (COP15) of the United Nations Convention on Biological Diversity. Still, the KD was the first globally noticeable signal of a major negotiation breakthrough and foreshadowed a significant policy change for financial markets. Governments of 190 countries signed the GBF, setting clear objectives along a global road map for conserving, protecting, restoring, and sustainably managing biodiversity, and urging signatories to align financial flows with biodiversity protection. Its global scope combined with explicit quantitative targets makes the GBF the most important international agreement on biodiversity, comparable to the Paris Agreement for climate change.

Prior to the KD, markets did not price the exposure to biodiversity risks, with several studies reporting the lack of a biodiversity risk premium (Garel et al., 2024; Coqueret et al., 2024; Zhou et al., 2023; Huang et al., 2024). The same holds true for global investment funds. Since 2015 up until the KD, the ratio of fund investments in high-biodiversity risk countries to investments in low-biodiversity risk countries increased from 42% to 55%. Over the same period, funds tripled their holdings in high-biodiversity risk countries while holdings in less risky countries doubled (Figure 1).

Figure 1 Fund AUM in High- vs. Low-Biodiversity Risk Countries

a) in billion USD　　　　b) in % of total and as ratio



Note: High-biodiversity risk countries are those in the upper 25th percentile of the in-sample cross-country distribution of the Endangered Species Score as provided by Giglio et al. (2023). Low-biodiversity risk countries are in the lower 75th percentile.

Source: EPFR, Authors' Calculations.

The KD changed funds' portfolio allocations instantly. We document that the KD tilted the balance of risks to the downside, forcing portfolio adjustments in response to revealed biodiversity risk. Specifically, we use difference-in-difference estimations to show that the KD announcement induced funds to reallocate portfolios to countries with a lower biodiversity risk. Akin to a 'flight to biodiversity safety', funds lowered portfolio shares of risky countries by 0.1 pp cumulatively over 2 months after the announcement. This adjustment is economically significant: Absent changes to funds' assets under management (AUM) in the same period— as confirmed in the data—, and given time-invariant cash shares of about 2% on average, an analysis of country-specific investment fund flows confirms that the de-risking implies cumulative capital outflows of 0.45% of the median country-level GDP. On the flip side, investment funds increased positions and thus flows to less risky countries outside of the hitherto established portfolio, notably within the same geographic region. This fund behavior points at a portfolio expansion at the extensive margin at the expense of existing positions, and highlights how funds contributed not only to cross-country spillovers, but also to portfolio-wide contagion.

As funds hold about 90% of global AUM, these portfolio shifts are indicative of the global asset management industry's response to biodiversity risks. In contrast, ultimate fund investors remained unresponsive to the KD announcement, possibly reflecting investors' weaker personal experience of biodiversity loss compared to climate change related phenomena like heat stress, as confirmed by Garel et al. (2024), Choi et al. (2020), and Di Giuli et al. (2024). The reallocation in response to biodiversity risk is most pronounced for extreme biodiversity risk in the upper 25th percentile of the cross-country risk distribution, suggestive of a differential treatment similar to heightened portfolio sensitivity to high sovereign risk as described in Converse and Mallucci (2023). The non-linearity in response to biodiversity risk suggests that fund managers price biodiversity losses to guard against downside risk rather than investing in low-biodiversity risk countries as an upside opportunity. This holds even for funds with a dedicated investment mandate focused on sustainability or biodiversity.

What can authorities in high-biodiversity risk countries do to attenuate capital outflows when biodiversity risk materializes due to shifts in risk perception? We conjecture that nature conservation, as increasingly enshrined in law, signals a more productive use of capital for investments sensitive to ecosystem health, dampening KD-induced outflows even for countries with elevated biodiversity risk. Funds' sensitivity to biodiversity risk may also decline because legislation to protect nature reduces policy uncertainty that would otherwise imply higher transition risk in expectation of more stringent nature-related policies (Garel et al., 2024). Thus, legally anchored nature conservation might be as effective as climate laws in attracting portfolio fund investments (Ciminelli et al., 2025).[1] We construct a novel measure of legal action to protect nature, and demonstrate that countries with more legal acts aimed at nature conservation experienced fewer fund withdrawals upon KD announcement. We measure a country's track record in nature positive legal action by the count of legislations, regulations and policies enacted as well as international agreements signed in the three years prior to the KD, differentiating between legal acts related to protecting (i) wild species and ecosystems, (ii) forestry, and (iii) fisheries.

In contrast, policies only indirectly related to nature conservation, such as mitigating climate change and prudent macroeconomic management, do not provide protection against funds withdrawing in response to revealed biodiversity risks. The role of biodiversity-related legal actions for funds' portfolio allocations neither varies by stringency of legal commitment as implied by the types of legal acts—with the commitment arguably higher for laws than for policies—, nor across domains (wild species vs. fishery vs. forestry).

Why does the KD induce a shift in fund portfolios away from high-biodiversity risk countries? Biodiversity risk suppresses productivity while driving up costs of investee firms, and thus lowers fund returns, in turn requiring fund managers to factor associated risks into investment decisions. As most economic output depends on nature, deteriorating biodiversity may entail productivity declines or production at higher costs for ecosystem services. For instance, three quarters of crop types require pollination by insects (Ritchie, 2021). Thus, the rapid decline in pollinators increases production costs for agribusinesses (Sánchez-Bayo and Wyckhuys, 2019). Cash flows exposed to biodiversity risk may also fall in expectation of more stringent nature-related financial regulation as compliance costs and litigation aimed at preserving biodiversity are on the rise (Hoepner et al., 2023; Garel et al., 2024). Shifts in consumer preferences to products with lower biodiversity footprint entail similar transition

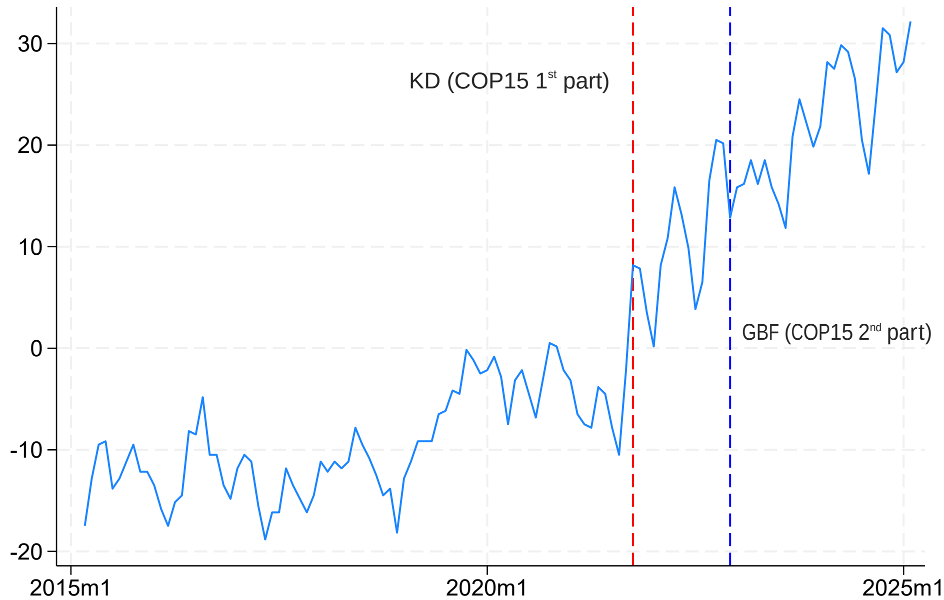
[1] Ciminelli et al. (2025) argue that climate laws act as commitment device to pursue policies tackling climate change, and to clarify responsibilities among government entities, both lowering uncertainty for investors.

risk. In addition, the cost of financing may increase as the double materiality of biodiversity risks—if suddenly revealed—may lower borrowers' creditworthiness, leading to shifts in the economy-wide credit allocation (Becker et al., 2025). This is amplified by bank corporate loan portfolios' significant dependence on nature (Boldrini et al., 2023; Calice et al., 2023; Gardes-Landolfini et al., 2024; Ramos-Francia et al., 2023; Svartzman et al., 2021), albeit more moderate in Europe (Arlt et al., 2024). The KD made fund managers keenly aware of these risks, similar to major policy announcements on climate change raising investor attention to related transition risks (Alessi et al., 2023; Alessi et al., 2024; Monasterolo and De Angelis, 2020; te Kaat et al., 2024). A sharp increase in attention to biodiversity losses upon the KD news release marked a permanent sea-change in the perception of biodiversity risks as measured by a permanently higher and rising Google trend for the term "biodiversity" in the category "finance", with attention peaking again upon the second part of COP15 in 2022, and COP16 in 2024 (Figure 2).

The ensuing rise in transition risk triggered a shift in expectations of future cash flows from highly ecosystem-dependent investments to less nature-exposed investments. The commensurate increase in preferences for assets with low biodiversity risk raised the realized returns of funds predominantly exposed to low-biodiversity risk countries relative to funds mostly investing in high-biodiversity risk countries. We document this shift in realized returns in Appendix C. The shift in relative returns is consistent with prior work suggesting a KD-induced drop in realized returns of firms with high biodiversity footprint (Coqueret et al., 2024; Garel et al., 2024; Giglio et al., 2023), akin to similar return shifts in response to climate risks (Ardia et al., 2023; Bolton and Kacperczyk, 2023; Choi et al., 2020; Engle et al., 2020; Pástor et al., 2022).

We measure biodiversity risk exposure by the Endangered Species Score as provided by Giglio et al. (2023). The score is derived as ratio of threatened species to all species in a country, and comprises vulnerable, endangered, and critically endangered species of all taxa on the IUCN Red List. In most specifications, the country-level score enters the analysis as

Figure 2 Google Trend for "Biodiversity" in Finance



Note: Monthly Google Search Volume Index for the term "biodiversity" in the category "finance", demeaned over the period January 2015 to February 2025, 3 week rolling averages.
Source: Google, Authors' calculations.

a dummy equal to one if exceeding the 75th percentile of its in-sample distribution, accounting for the non-linear biodiversity risk perception reported above. Results are qualitatively robust to alternative percentile thresholds above the median. They are also robust to alternative measures of country-specific biodiversity risk such as the aggregate extinction risk of species, as measured by the ICUN Red List, and the Biodiversity Habitat Index measuring the impact of habitat loss. Similarly, results hold for excess biodiversity risk defined as the difference between the country-specific risk and the portfolio share weighted average biodiversity risk of all other countries in a fund's portfolio.

We merge the data on biodiversity risk with a granular database on funds' cross-country portfolios obtained from EPFR, covering some 30,000 bond and equity funds representing the near universe of the fund industry's AUM. The final dataset contains 2,323 funds domiciled in 26 countries, and in turn investing in 118 countries. The portfolio allocation data varies across time, funds and recipient countries, allowing us to control for fund characteristics, macroeconomic fundamentals and countries' policy choices. To isolate the KD effect on the supply of fund investments, it is crucial to control for recipient country demand for funds' investments. To this end, we expand the analysis studying how results vary across fund types, allowing us to include country-time fixed effects absorbing all time-varying country-specific characteristics possibly attracting fund investments. The monthly frequency of the portfolio allocation data is crucial to detect funds' adjustments to biodiversity risk shocks. Lower-frequency allocation data, as available from other providers than EPFR, would not allow to disentangle funds' KD-related shifts from other simultaneous events.

Using the merged data set, we estimate difference-in-difference (DiD) specifications symmetrically centered on 4 months around the KD announced in October 2021, relating fund-level country portfolio shares to country-level biodiversity risk, as well as other country and fund characteristics. Parallel pre-trends between the treatment (high-biodiversity risk countries) and control group (low-biodiversity risk countries) are an important identifying assumption. Analyses tracing out the effect over time before and after the KD, together with DiD estimations around placebo periods, provide reassurance that parallel pre-trends hold. Interacting the treatment indicator with fund characteristics yields important heterogeneous effects for different fund types. Actively managed funds' portfolio allocations are more sensitive to biodiversity risk shocks, as allowed by a higher tracking error relative to benchmark-bound ETFs. Moreover, funds are more likely to tilt portfolios in favor of less risky countries if the pre-KD country-specific position was underweight relative to a fund's historic allocation. Funds with a larger fraction of share classes marketed to retail instead of institutional investors also reallocate portfolios more significantly. This is consistent with the notion that institutional investors pursue long-term investments, resulting in lower sensitivities to biodiversity risk materialization. This contrasts with funds catering to retail investors, which are likely to experience larger redemptions as risks materialize. To lessen redemptions, these funds may reallocate portfolios more towards countries with lower biodiversity risks. We further find that funds with a greater pre-KD portfolio share invested in industries that are more affected by biodiversity risks, such as energy or food production, react more significantly.

Funds reallocate portfolios uniquely in response to KD-revealed biodiversity risks, beyond other country-specific risks. The empirical framework notably controls for climate change-related transition risks and geopolitical risk. That is, we identify KD-induced portfolio reallocations exclusively driven by biodiversity risk. Moreover, repeating the analysis for other biodiversity and environmental risk-related events underlines the KD' specificity in raising attention to biodiversity risks. Notably, we do not detect any reallocations around the signing of the GBF on December 7, 2022, suggesting that the final agreement does not contain informational value beyond the previously announced KD. Further, we show that funds do not undertake biodiversity-related portfolio adjustments around the launch of the Task Force on Nature-Related Financial Disclosures, GBF-related negotiations in April 2022, the announcement of the European Union (EU) Biodiversity Strategy in May 2020, the Paris Agreement, or the EU Green Deal, among others.

We rule out that ultimate fund investors drive our results. To this end, we study the KD impact on ultimate investor flows instead of portfolio shares, and compare and contrast the effect of such fund-level flows with a funds' investment flows to recipient countries (and hence with fund-country-level flows). We obtain the latter by combining the portfolio allocations across countries with information about ultimate investors' flows into investment funds. Findings at the fund-country level suggest outflows from high-biodiversity risk countries upon KD announcements. At the same time, a fund's average biodiversity risk exposure across countries in its portfolio does not affect ultimate investor flows into a fund when the KD is announced. As fund-level flows abstract from fund managers' allocation decisions and thus can only be driven by investors' decisions, we ascertain that fund managers' active portfolio allocations drive changes in fund-country-level portfolio capital flows, not ultimate investors' decisions.[2] The results stand confirmed when we employ flows into funds at the daily frequency, i.e., higher than the monthly frequency data available for portfolio shares. Given no response of ultimate investors at the daily frequency, the evidence for fund-country flows confirms that the KD triggered significant cross-border capital flows only via shifts in fund managers' country allocations.

The results are robust to a range of additional tests. Specifically, (i) we vary the time window around the KD from 1 to 4 months, (ii) sequentially drop the largest fund domiciles US, Luxembourg and Ireland, (iii) drop funds managed by the largest asset managers, (iv) replace the dependent variable—in the baseline analysis computed as the change in the IHS-transformed portfolio shares—by the level, absolute changes and log-differences of the portfolio shares, (v) explore variations of standard error clustering, and (vi) account for an extensive set of controls, including a fund's benchmark change in country allocations, as well as country-level bond and equity returns to eliminate valuation effects driving our results.

Our analysis reflects several strands of the literature. First, we go beyond the nascent literature on biodiversity asset pricing, showing how global investors respond to biodiversity risks, post-KD recognized as financially relevant (Gjerde et al., 2025). Pioneering work by Garel et al. (2024) put forward a firm-level measure of biodiversity footprint to examine the impact on stock returns, and identifies a biodiversity premium in the post-KD period. That is, stocks of firms with large footprints decline in value after the KD. Xin et al. (2023) provide further evidence showing the lack of risk premium in the period 2013-2020. Coqueret et al. (2024) confirm the salience of biodiversity risks after the KD, documenting an increase in realized returns for firms with a low exposure to biodiversity transition and physical risks. Similarly, Bohnet et al. (2025) demonstrate this effect for firms with low deforestation exposure. Han et al. (2024) find higher refinancing costs and lower bond issuances at higher spreads for firms endowed with high biodiversity, pointing at the pricing of transition risks.

[2] We have no information about the residence of ultimate investors in the funds, and only know funds' domiciles and recipient countries of fund investments.

Closely related, Giglio et al. (2023) develop measures of US firms' biodiversity risks and find that portfolio returns positively correlate with biodiversity news. Focusing on infrastructure firms, Hoepner et al. (2023) find improved financing conditions for firms with better biodiversity risk management. Becker et al. (2025) and Deng and Lin (2025) demonstrate that the biodiversity risk premium applies in the syndicated loan market, with loan pricing correlating positively with borrowers' biodiversity risk. A vast body of literature on sustainable asset pricing documented a similar risk premium for exposure to climate risk (see, e.g., Aswani et al., 2024, Ardia et al., 2023, Bolton and Kacperczyk, 2021, Cheng et al., 2024, Choi et al., 2020, Engle et al., 2020, De Angelis et al., 2023, Faccini et al., 2023, Ma et al., 2024, Hsu et al., 2023, Krueger et al., 2020, Sautner et al., 2023, Luo, 2022, Seltzer et al., 2022, and Pástor et al., 2021). The above papers show that the KD induced investors to demand additional compensation for biodiversity risk exposure. Our work suggests that the risk premium does not fully compensate investors for biodiversity risks, leading investment funds to reposition portfolios.

Second, our work highlights the sensitivity of financial intermediaries' portfolios to biodiversity risks. Ramos-Francia et al. (2023) study banks in Mexico, and show how natural capital losses induce a reallocation of deposit supplies. In contrast, we focus on global investment funds, and their portfolios' response to biodiversity transition risks. Our work also relates to the broader literature on the determinants of fund portfolios, which previously studied the effect of capital controls (Forbes et al., 2016), government and corporate transparency (Gelos and Wei, 2005), and currency denomination (Maggiori et al., 2020). Further, we show that biodiversity risk drives fund performance, which has been shown to affect portfolio allocations (Broner et al., 2006; Camanho et al., 2022).

Third, our focus on the Kunming Declaration ties in with a large body of literature discussing financial intermediaries' response to environmental policies. Banks play a central role for international spillover of domestic climate policies (Benincasa et al., 2023; Laeven and Popov, 2023; Demirgüç-Kunt et al., 2023). Major international policy agreements like the Paris Agreement and EU Green Deal provoke investors' portfolio reallocations (Alessi et al., 2023; Alessi et al., 2024; Monasterolo and De Angelis, 2020). te Kaat et al. (2024) highlight the role for investment funds for the international spillover of climate policies, and demonstrate how the US Inflation Reduction Act raises investors' flows into sustainable investment funds. In turn, sustainable funds increased cross-border investments worldwide, notably into countries with more effective climate policies, highlighting how funds facilitate the international spillover of climate risks. This paper extends the idea to biodiversity risks revealed by the Kunming Declaration. As funds pivot away from high-biodiversity risk countries, less risky countries experience sizable inflows. Beyond climate risks, investments funds have thus turned into an important conduit for the international spillover of environmental risks, adding to previous insights on funds as international transmission vectors for monetary policy (Dahlhaus and Vasishtha, 2014; Ciminelli et al., 2022) and the Global Financial Cycle (Davis and Zlate, 2023; Converse et al., 2023).

Fourth, we contribute to a long-standing inquiry into investment funds' contribution to cross-country contagion in the tradition of seminal work by Frankel and Schmukler (1996), Calvo and Mendoza (2000), and Kaminsky et al. (2004).[3] Recently, Converse et al. (2023) studied funds' portfolio reallocations in response to sovereign risk, and do not find evidence for regional contagion. That is, funds do not sell assets in other countries in the same region when sovereign risk rises in one country. In contrast, we find that funds' reaction to biodiversity risks revealed by the KD contribute to portfolio-wide contagion. As funds reallocate away from high-biodiversity risk countries, new positions open in less risky countries outside of a fund's established portfolio, but within the same region.

Fifth, we document that legal acts to protect nature dampen funds' reallocations away from high-biodiversity risk countries. The finding mirrors Garel et al. (2024), who show that the biodiversity footprint premium of stock returns declines as countries take more policy actions to protect biodiversity. The rationale is that already high biodiversity protection makes

[3]See Gelos (2011) for a detailed overview

additional tightening of policy stringency less likely, and thus lowers transition risks arising from any "catch-up" regulations. Similarly, climate laws have been shown to reduce policy uncertainty, thus acting as pull factor for sustainability-oriented portfolio flows (Ciminelli et al., 2025). The enquiry into legal acts attracting foreign biodiversity finance speaks to the nascent literature on how to finance nature conservation (Flammer et al., 2025), and is grounded in earlier enquiries into the role of environmental policies shaping capital flows (Co et al., 2002).

Our paper is structured as follows. Section 2 reviews the KD, introduces the data set, and presents summary statistics. Section 3 explains the regression framework and presents main results. The section also discusses robustness checks, compares reallocations around the KD with those around other major environment-related global events, dissects results by fund characteristics, and explores the effectiveness of policies in reducing portfolio reallocations to dampen associated capital outflows from high-biodiversity risk countries. Section 4 explores spillover patterns and funds' contributions to regional contagion. Section 5 studies effects on cross-border flows. Section 6 concludes. Appendices discuss additional results and robustness checks in detail.

2 Data and the KD

In this paper, we investigate how fund managers respond to the KD by reflecting biodiversity risks in the portfolio allocation across countries. This section reviews the KD, describes the data and provides summary statistics.

2.1 Kunming Declaration as a Biodiversity Minsky Moment

Adopted in Kunming on October 13, 2021, the KD concluded the first part of COP15, and helped maintain political momentum for the negotiations of the GBF, eventually adopted during the second part held in Montreal. Originally scheduled to be held in the People's

Republic of China, this second part moved to Canada due to Covid-19 related pandemic restrictions. The COP15 and the GBF as its outcome stand out from previous UN events on biodiversity. Only a handful of agreements have been reached under the auspices of the CBD since entering into force in 1993. Several COPs agreed on targets to restore biodiversity, such as the Aichi targets, but most were not achieved (Convention on Biological Diversity Secretariat, 2020). Following a multi-year effort of consultations and negotiations among the parties to the CBD, the GBF constitutes major progress on the nature protection agenda. Governments of 190 countries agreed on a global road map for conserving, protecting, restoring, and sustainably managing biodiversity, and to sign an international treaty as commitment enshrined in 4 goals and 23 explicit quantitative targets to reverse biodiversity losses.[4] Examples are to protect 30% of ecosystems by 2030, increase annual biodiversity finance to USD 200 billion by 2030, and phase out harmful subsidies. Coupled with a call to aligning financial flows with nature-positive investments, this is what makes COP15 the the most important UN event on biodiversity (CBD Secretariat, 2021), with the GBF often hailed as "Paris Agreement for Nature".

The KD as the first part of COP15 was key in signaling this breakthrough agreement to markets. Governments of over 100 countries committed to developing an ambitious global framework to reverse biodiversity losses by 2030.[5] Thus, the KD arguably raised investor attention to biodiversity risks akin to a Minsky moment for biodiversity losses. As transition risks were suddenly revealed, highly ecosystem-dependent assets or those with deep biodiversity footprint became instantly less attractive. A measure of biodiversity attention specifically relevant to investors confirms the sharp increase and step change around the KD (Figure 2). As we demonstrate in Section 3.5, it is indeed the KD's signal that triggered funds' reallocations, not the signing of the GBF in Montreal. In line with the efficient mar-

[4] The goals comprise: 1) Ecosystem integrity to reduce the rate of extinction of all species; 2.) Sustainable use and management of biodiversity; 3) Fair sharing of the benefits from the use of genetic resources; 4) Mobilizing implementation financing for developing countries.

[5] The KD commits all signatories to incorporate biodiversity into all decision-making processes, phase out harmful subsidies, strengthen the rule of law, and increasing financial, technological, and capacity-building support to developing countries (Nations, 2021).

ket hypothesis, the Montreal summit was largely anticipated by the KD. Comparisons with the effect of other environmental risk related events discussed in Section 3.5 confirms the KD's unique role in shaping investor beliefs to account for biodiversity risks, and informs our benchmark analytical approach in centering difference-in-difference estimations around the KD.

2.2 Fund-Country-Level Data

Our principal data set for analyzing the effects of the KD on funds' country allocations is EPFR Global's "Country Allocations" data set. This dataset provides monthly fund-level records of the percentages of a fund's AUM allocated to each country, and is ideally suited to study portfolio reallocations as EPFR Global is an exclusive source of fund-country-level asset allocation data at monthly frequency. This high frequency is essential, as fund managers are expected to reposition promptly in response to biodiversity-related transition risks revealed by the KD. In a KD-centered event study, lower frequency data would not allow to tightly associate portfolio shifts to specific events. EPFR data cover 94% and 86% of the investment fund industry's total global AUM of equity and bond funds, respectively (Emerging Portfolio Fund Research (EPFR), 2024). The analysis in this paper thus captures the relevant developments in global investment fund assets.[6] Survivorship bias is not a concern as EPFR data cover both newly created and closed funds. Given that our enquiry focuses on funds' portfolio reallocations, we conduct all analyses for multi-country funds only, i.e., funds with investments in more than one country.

We follow Forbes et al. (2016) in defining our main dependent variable as the month-on-month growth in a fund's country specific portfolio shares. Specifically, we use the change in the inverse-hyperbolic sine (IHS) transformed portfolio share. This transformation approximates the natural logarithm while permitting us to keep zero-valued country allocation shares (Bellemare and Wichman, 2020; Burbidge et al., 1988). Our analysis hence considers

[6] Kaufmann (2023) confirms the high coverage of investment fund's global AUM by comparing EPFR's data with investment fund AUM reported by the Financial Stability Board.

both the extensive and intensive margin of portfolio reallocations. Robustness checks using the log-difference, the absolute change or the (IHS-transformed) level of the portfolio share yield qualitatively similar results.

In addition to analyzing portfolio allocations across countries, we ask whether these KD-induced reallocations translate into portfolio investment flows across countries. To this end, we obtain fund-country-level flows by crossing the portfolio shares obtained from the fund-country-level country allocation data set with data on flows into funds by ultimate investors taken from EPFR's "Fund Flows" database, and scale these by a fund's AUM. This procedure is supported by low and time-invariant cash shares, implying that fund managers fully distribute additional inflows from investors across portfolio assets in recipient countries. That is, we can track how ultimate investors' flows into funds map into various countries as channeled through investment funds. The "Fund Flows" data have been used in several studies (e.g., Bettendorf and Karadimitropoulou, 2023, Converse and Mallucci, 2019, Converse et al., 2023, Forbes et al., 2016, Koepke and Paetzold, 2024, te Kaat et al., 2024). All flow data are valuation-adjusted.

To corroborate our finding of cross-country portfolio reallocations, we disentangle the investment decisions of fund managers and ultimate investors, as both could drive changes in fund-country-level flows as computed above. To this end, we present specifications at the fund level—thus abstracting from fund managers' decisions and focusing on investors' flows into funds—and examine whether the KD incentivized ultimate investors to adjust their flows from more biodiversity risk-exposed funds to less exposed ones. We run this analysis with data at monthly but also daily frequency, at which only fund-level but not fund-country-specific flows are available. We again obtain the fund-level flows from EPFR's "Fund Flows" database, and scale them by AUM.

In addition, we compute control variables as follows: First, we measure a fund's size by its AUM, use month-on-month returns as performance indicator, and compute the fraction of share classes within the same fund that is marketed to retail, as opposed to institutional, investors. Second, we define various dummy indicators to denote a fund's asset class (bonds vs. equities), actively managed vs. ETF, and its sustainability credentials as assessed by EPFR. We also control for funds' domiciles by means of fixed effects. Third, we determine a fund's country-specific position as over- or underweight as a fund's current country allocation share net of a fund's average share vis-a-vis this country in the pre-KD period between 2015:M1-2021:M9. Fourth, some specifications seek to rule out that a fund's portfolio allocation is driven by its benchmark. For this, we control for the average IHS-transformed change in the country allocation of all funds with the same benchmark. Finally, we gauge a fund's biodiversity risk exposure through the biodiversity commitment of its investee companies. For this, a fund-level variable we source from Bloomberg indicates the market value weighted percentage of a fund's AUM invested in companies with an active biodiversity policy, i.e., firms taking dedicated initiatives to protect biodiversity.

We clean the raw data in four steps. First, in line with Converse and Mallucci (2019), we drop fund-country pairs for which portfolio shares are always zero during 2015:M1-2023:M6. This serves to distinguish between zero allocations resulting from an investment decision, and zero allocations due to a country being outside of the geographic scope of a fund's investment mandate. For instance, a fund with an investment mandate limited to Asia is not mandated to invest in Brazil. Second, we drop fund-country pairs with a country allocation share of more than 100% and less than 0%. Third, the EPFR country allocation data include not only individual countries but also geographical regions, such as the euro area. As we cannot match these regions with the country characteristics further described below, we exclude the corresponding fund-country pairs. In steps 2 and 3 combined, we only lose about 10% of the initial observations. Finally, we winsorize the outcome variables at the 1% and 99% levels to mitigate the impact of outliers. After these steps, our benchmark sample includes 2,323 funds domiciled in 26 different countries and allocating their AUM to 118 different destination countries.

2.3 Country-Level Data

We match the data on funds' portfolio allocations and fund-country-specific flows with a comprehensive set of recipient country characteristics. To study the treatment effect on portfolio reallocations around the KD, country-level measures of biodiversity risk take center stage: Our main gauge is the Endangered Species Score provided by Giglio et al. (2023), defined as the ratio of threatened species to all species in a country, and comprises vulnerable, endangered, and critically endangered species of all taxa on the IUCN Red List. Higher values indicate larger biodiversity risk. We use the country-level score continuously, and as a dummy equal to one if exceeding the 75th percentile of its in-sample distribution, zero else, with other percentile cutoffs reported in Section 3.4. The dummy specification serves to focus the analysis on investors' sensitivity to extreme biodiversity risk. As per Figure A1, biodiversity risk is most pronounced in Sri Lanka (25.3%), Spain (25.0%) and Turkey (21.9%), and least in Botswana (2.5%), Zimbabwe (3.2%) and Belarus (3.3%), with the share of threatened species indicated in brackets.

For robustness, we employ other measures of biodiversity risk in a similar fashion. These are the aggregate extinction risk of species as measured by the ICUN Red List Index (RLI), and the Biodiversity Habitat Index (BHI) measuring the impact of habitat loss, provided by IUCN (2025) and Harwood et al. (2022), respectively. The former measures the overall trend in species' extinction risk in a country. [7] The latter indicates the "effects of habitat loss, degradation, and fragmentation on the expected retention of terrestrial biodiversity" using remote sensing data.[8]

Conjecturing that investors are most sensitive to deviations from average risk, we also employ measures of excess biodiversity risk in the spirit of Converse and Mallucci (2019). To this end, we compute the excess risk for all biodiversity risk measures as the difference between the country-specific risk and the portfolio share weighted average biodiversity risk

[7] Please see Butchart et al. (2007) for details on the methodology.

[8] Methodological details are documented at https://gbf-indicators.org/metadata/other/A-4-C

of all other countries in a fund's portfolio.

As investors price the cross-country differences in biodiversity risk upon KD announcement, we also investigate cross-border spillovers. To this end, we compute (i) the simple average regional biodiversity risk of all other countries in the *same* region, with regions being Asia, Europe, Africa, Middle East, North America and South America, and (ii) the simple average biodiversity risk in all *other* regions. Second, in order to study within-portfolio spillovers, we compute the average biodiversity risk of all other countries in a fund's portfolio, where each country's biodiversity risk is weighted by its current portfolio share.

Investment fund allocations may react to various other country-specific risks and mitigating policy actions that we seek to differentiate biodiversity risk from. For instance, climate change is a key driver of biodiversity losses, and related measures, such as carbon emissions, could explain the link between biodiversity risk and portfolio reallocations around the KD. Thus, we control for climate risks proxied by (i) carbon emission intensities, (ii) the NDgain index as measure of vulnerability to climate change and a country's coping capacity (Initiative et al., 2023), (iii) the INFORM climate change risk index assessing the potential future impacts of climate change on the risk of humanitarian crises and disasters, and (iv) the Bloomberg's climate policy score summarizing a country's progress in emission reduction, power sector decarbonization, and the policy commitment to address climate change. Biodiversity risk may also be reflected in other sovereign risk types, such as geopolitical risk a la Caldara and Iacoviello (2022) and Caldara et al. (2023). We duly control for the latter.

Biodiversity risk may also correlate with macroeconomic and financial country characteristics, as Appendix Table A12 shows. For instance, past industrialization may have come at the expense of nature. Conversely, richer nations may have the means to cure past damages to nature. Both favor a close correlation of biodiversity risk and income levels, leading to biased estimates. We alleviate concerns about omission biases by controlling for quarterly GDP per capita. We further control for a host of other macroeconomic variables that are also often seen as capital flow drivers, such as monetary policy rate differentials with the

US, stock market capitalization, Moody's sovereign credit ratings, capital account openness based on the Chinn-Ito-index (Chinn and Ito, 2008),[9] and the rule of law.

2.4 Selected Summary Statistics

In this sub-section, we present selected summary statistics for the sample underpinning our benchmark regression in column (6), Table 2. Table 1 illustrates that the changes in the IHS-transformed country allocation share average to close to zero given a mean of -0.08%, but vary widely as can be gleaned from the standard deviation of 9.3%

Over the period 2021:M8-2021:M11, funds on average received net inflows of 0.2% of their AUM, with lagged AUM ranging from $ billion 0 to 368 and a mean of 2.9. The sample consists of about two thirds equity funds, and one third ETFs, the average biodiversity commitment of all funds stands at 62%, and some 12% of fund are labeled as sustainable. On average, funds experience negative returns of -2.6%, and the average deviation from a fund's target allocation is a mere 0.07 percentage points, suggesting a small tracking error.

At the country level, Table 1 suggests that the average biodiversity risk reaches 13%, with a standard deviation of 4.8%. Quarterly GDP per capita takes an average value of slightly more than 9,200 USD per capita, the majority of countries in the sample have a fully-liberalized capital account, the interest rate differential to the US equals 4.2 percentage points, the average stock market capitalization over GDP is 57.4%, bond yields (monthly stock returns) amount to 1.6% (0.51%) on average, and the average Bloomberg climate policy score is 4.8, with a range of 1.8-6.9 out of its theoretical range of 0-10.

[9] The Chinn-Ito index measures countries' *net* capital account openness. We control for inflow and outflow openness separately using the Fernández et al. (2016) index, and results remain qualitatively unchanged (not reported).

Table 1 Selected Summary Statistics

Variable	Obs	Mean	Std. dev.	Min	Median	Max	Unit
$Share_{i,j,c,t}$	210,914	3.936	8.544	0.000	0.871	94.703	%
$\Delta IHS(Share)_{i,j,c,t}$	210,914	-0.080	9.267	-48.555	0.000	48.200	%
$\Delta Share_{i,j,c,t}$	210,914	-0.001	0.580	-27.383	0.000	23.560	%
$\Delta Ln(Share)_{i,j,c,t}$	156,602	-0.295	13.089	-62.253	-0.048	59.399	%
$IHSShare_{i,j,c,t}$	210,914	1.174	1.241	0.000	0.787	5.244	%
$\Delta Benchmark_{i,j,c,t}$	203,421	-0.062	7.436	-38.591	0.000	39.304	%
$\text{Flows}_{i,j,t}$	210,914	0.199	5.651	-44.247	0.000	34.627	%
$\text{Flows}_{i,j,c,t}$	210,914	0.005	0.316	-2.565	0.000	2.382	%
$\text{AUM}_{i,j,t-1}$	210,914	2.944	15.449	0.001	0.548	367.697	$ billion
Retail $\text{Share}_{i,j}$	210,914	31.887	34.323	0.000	25.000	100.000	%
$\text{ETF}_{i,j}$	210,914	0.358	0.479	0.000	0.000	1.000	0/1
$\text{Sustainable}_{i,j}$	210,914	0.116	0.320	0.000	0.000	1.000	0/1
Biodiversity $\text{Share}_{i,j}$	142,064	62.053	19.496	0.000	67.781	100.000	-
$\text{Return}_{i,j}$	210,914	-2.608	1.751	-10.749	-2.685	6.635	%
$\text{Deviation}_{i,j,c}$	210,914	0.065	2.113	-53.757	0.000	41.360	pp
Biodiversity Risk_c	210,914	13.006	4.826	2.545	12.883	25.349	%
High Risk_c	210,914	0.231	0.421	0.000	0.000	1.000	%
High Excess $\text{Risk}_{i,j,c}$	210,898	0.248	0.432	0.000	0.000	1.000	%
Excess Biodiversity $\text{Risk}_{i,j,c}$	210,898	-1.405	5.224	-14.628	-1.626	16.413	%
Equity $\text{Return}_{c,t}$	203,231	0.514	4.320	-20.790	0.967	29.013	$
Bond $\text{Yield}_{c,t}$	133,897	1.639	3.347	-0.790	0.430	18.580	$
GDP p.c_c	181,562	9238.326	6925.844	263.689	8926.281	26916.205	$
Rating_c	210,506	6.616	4.955	1	5	21	1-21
Capital Account Openness_c	210,512	0.763	0.335	0.000	1.000	1.000	[0,1]
Rule of Law_c	210,914	0.734	0.907	-1.732	0.914	2.058	-
Interest Rate Differential_c	113,422	4.151	6.784	-0.190	1.910	37.910	%
Capitalization_c	146,456	57.415	72.745	0.003	27.192	307.958	%
Climate Policy Score_c	184,854	4.838	1.260	1.801	4.919	6.922	-
Carbon Intensity_c	210,914	0.174	0.106	0.043	0.137	0.694	-
ND Gain Index_c	210,914	60.377	9.311	34.087	61.851	73.887	-
INFORM index_c	210,914	2.793	1.304	0.6	2.4	7.2	-
Geopolitical Risk_c	156,617	0.243	0.432	0.000	0.078	2.329	-

This table reports summary statistics for the sample used for the benchmark regression in column (6), Table 2. We provide detailed data definitions and sources in Table A1.

3 Does the KD Lead Investment Funds to Reallocate Away from High-Biodiversity Risk Countries?

3.1 Econometric Approach

We estimate difference-in-difference regressions at the fund-country level, with a four-months window centered around the KD announcement in October 2021, as follows:

$$\Delta Share_{i,j,c,t} = \alpha_{i,j,t} + \alpha_{i,j,c} + \beta \cdot (\text{Post}_t \times \text{Biodiversity Risk}_{c,pre}) + \epsilon_{i,j,c,t} \tag{1}$$

where the dependent variable is the change in the IHS-transformed share of fund i's AUM allocated to country c in month t, with the fund domiciled in country j. Our main variable of interest is the interaction term between a dummy that takes the value of one after the KD (i.e., in 2021:M10 and 2021:M11), zero else, and the country-level biodiversity risk variables described above, fixed at their pre-KD levels in 2021:M9. The regressions include fund-month fixed effects α_{ijt} to control for fund-time-specific heterogeneity that might affect funds' asset allocations, thus absorbing time-varying fund-level performance, size, and ultimate investors' flows into funds. We include fund-country fixed effects α_{ijc} to control for time-invariant fund-country-specific effects, including a fund's geographic preferences as given by its investment mandate. Standard errors are clustered at the country level to account for correlation of residuals across funds within countries. As we show below, clustering at the fund level or double-clustering at the fund and country levels yields similar results. In most regressions, we also weigh the observations by fund-level AUM as larger funds are likely to account for a larger share of cross-country flows resulting from the portfolio reallocations.

To capture funds' heterogeneous reallocation responses depending on their respective investment profile, we expand Equation 1 by introducing a triple interaction between the

Post-dummy, country-level biodiversity risk, and fund characteristics:

$$\Delta Share_{i,j,c,t} = \alpha_{i,j,t} + \alpha_{i,j,c} + \gamma \cdot (\text{Post}_t \times \text{Biodiversity Risk}_{c,pre}) + \epsilon \cdot (\text{Post}_t \times \text{Biodiversity Risk}_{c,pre} \times \text{X}_{i,j,pre}) + \epsilon_{i,j,c,t} \tag{2}$$

where the fund characteristics X are fixed at their 2021:M9 values in the pre-treatment period, and take the form of dummy variables for equity vs. bond funds, ETF vs. actively managed funds, sustainable labeled vs. conventional funds, or continuous variables measuring a fund's share classes marketed to retail investors (relative to all share classes of a fund), the share of AUM invested in firms with a biodiversity policy, performance, and country-specific position over- or underweight.[10] The dependent variable and all other regressors are defined as in Equation 1, and standard errors are clustered at country level. Importantly, the triple interaction in Equation 2 allows us to add country-time fixed effects to absorb country-specific demand for funds' investments, thus identifying the KD's supply effect.

Biodiversity risks may correlate with other types of risks, and recipient countries' macroeconomic characteristics indicating a non-random distribution. To address these concerns, we horserace our post-biodiversity risk interaction of interest with the corresponding interactions of various country characteristics, and—separately—other risk categories. The former include GDP per capita, interest rate differentials vis-a-vis the US, capital account openness, stock market capitalization, credit ratings, and the rule of law. The latter comprise various measures of climate risks and geopolitical risks, as explained in Section 2. Results in Section 3.4 suggest that including the above hardly changes our coefficient of interest in magnitude or statistical significance.

[10] In the latter case, the matrix $X_{i,j,pre}$ in Equation 2 becomes $X_{i,j,c,pre}$, as the variables are country-fund-specific.

3.2 Benchmark Results

This section presents our benchmark results corresponding to Equation 1. Overall, results confirm that the KD induces investment funds to reallocate portfolios towards low-biodiversity risk countries, as evidenced by negative post-biodiversity interaction coefficients.

Table 2 Benchmark Results

Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post_t$	0.533	0.540					
	(0.552)	(0.557)					
$Biodiversity\ Risk_c$	0.031		0.027				
	(0.026)		(0.024)				
$Post_t \times Biodiversity\ Risk_c$	-0.065	-0.066	-0.068*	-0.068*			
	(0.040)	(0.040)	(0.040)	(0.040)			
$Post_t \times High\ Risk_c$					-1.253**	-1.340***	-6.420*
					(0.544)	(0.496)	(3.776)
$Post_t \times High\ Risk_c \times Intensive_{ict}$							5.144
							(3.874)
Fund-Country FE	No	Yes	No	Yes	Yes	Yes	Yes
Fund-Time FE	No	No	Yes	Yes	Yes	Yes	Yes
Observations	211,101	210,940	211,075	210,914	210,914	210,914	210,914
R-squared	0.001	0.253	0.046	0.288	0.289	0.303	0.303

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the double interaction between a post-KD dummy equal to one after 2021:M9, and a continuous country-level biodiversity risk measure (columns 1-4) or a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of the entire in-sample distribution, denoted as *High Risk*. Column (7) includes a triple interaction between the post-KD dummy, the country-level biodiversity risk dummy, and a dummy that is one when growth does *not* happen along the extensive margin, i.e., when a fund's country-specific position does not change from zero to a positive value or vice versa, noted by *Intensive*. In this specification, all lower-order interactions of the triple interaction are included, unless they are absorbed by the fixed effects, but omitted for brevity. The regressions include fund-time and fund-country fixed effects as indicated in each column. The regressions in columns (6)-(7) are estimated by weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

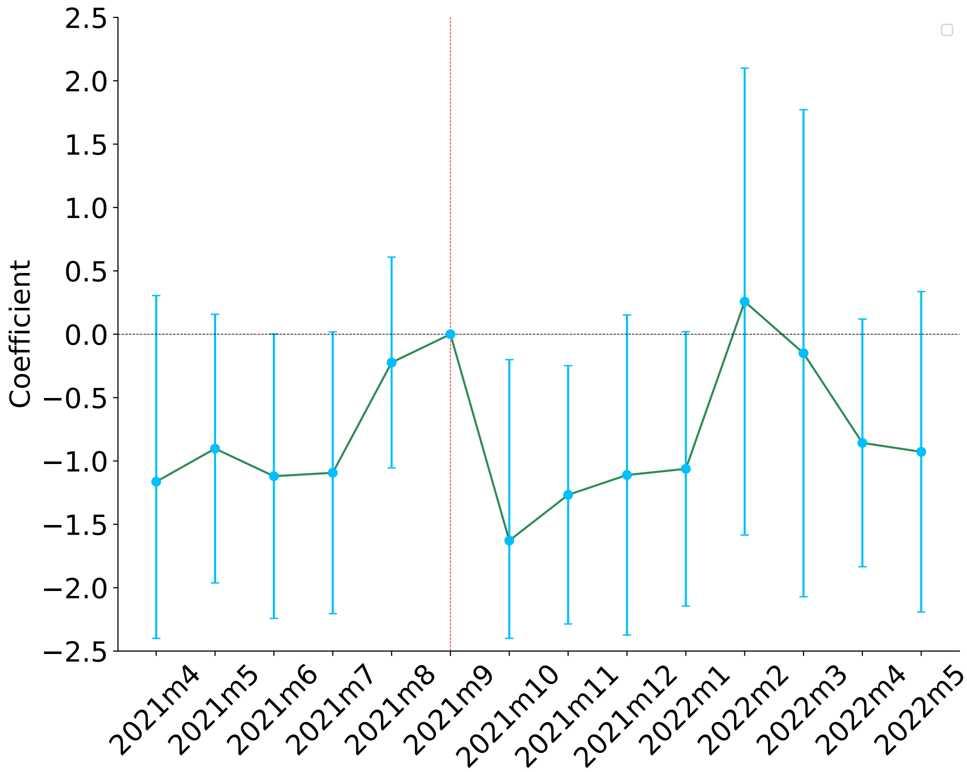
Specifically, in columns (1)-(4) of Table 2, we employ our principal measure of country-level biodiversity risk in its continuous form. Specifications only differ in their use of fixed effects. In all of the regressions, we find the double interaction coefficient to be negative, but it is estimated imprecisely, reaching only a 10% significance level. In column (5), the precision increases markedly when we replace the continuous country-level biodiversity risk variable with a dummy that takes the value of one for countries with biodiversity risk in the upper 25% of the in-sample distribution, denoted as *High Risk*. Both statistical significance and coefficient size increase further when we weigh the regressions by fund-level AUM (column 6), with the p-value falling to 0.008. Going forward, column (6) constitutes our baseline result and preferred specification.

These results strongly suggest that investment funds reduce their exposure to countries with extremely high biodiversity risk after the KD. The estimate of column (6) implies that funds lower their exposure to high-biodiversity risk countries by 1.34% each month relative to all other countries. This is economically meaningful: Given an average country allocation share in the sample of 4%, the estimate translates into a 0.054 pp (=4*1.34/100) decrease in the country allocation share for the average country in each post-KD month. As we show below, the KD significantly affects portfolio allocation shares for two months, leading to a cumulative effect of 0.11 pp in reduced allocation to risky countries. What does the reallocation entail for cross-country portfolio flows? Based on EPFR's coverage of 50 trillion USD AUM globally, and 118 countries in our benchmark sample, country-level AUM equal 0.42 trillion USD (=50/118) on average. A 0.11 pp decrease in the portfolio share for the average country then implies outflows of 0.46 billion USD, or 0.45% of the median country-level annual GDP.

The more pronounced result for the dummy variable version of our biodiversity risk measure aligns well with the left-skewed distribution of biodiversity risk across countries. While few countries score in the extreme range of 20-25% of threatened species, most other countries' scores lie in the lower range of 3-15% (Figure A1). In fact, as we show in Table A11 of the Appendix, we do not obtain similarly statistically significant results for alternative thresholds of defining the *High Risk* dummy at the upper 25th, 33rd or 50th (median) percentile of the biodiversity risk distribution. In contrast, using the 67th percentile leaves our results largely unchanged. The nonlinear fund response to biodiversity risks suggests a differential treatment of recipient countries, similar to sovereign risk as described in Converse and Mallucci (2023). Thus, fund managers price biodiversity losses to guard against downside risk, rather than investing in low-biodiversity risk countries as an upside opportunity.

A key identification assumption is that fund managers would have kept the allocations across high-and low-biodiversity risk unchanged if not for the KD. Tests on parallel trends reported in Section A5 lend credence for the assumption to hold. For this, we run placebo regressions estimating Equation 1 around 6 placebo event months that precede our benchmark analysis. In all of these 6 months, no biodiversity-related events of global policy relevance were recorded and investors' biodiversity attention hence hardly changed (see Figure 2). In support of the parallel trends assumption, we find that the double interaction coefficient β is always statistically insignificant. We further buttress parallel trends by interacting month dummies with country-level biodiversity risks, using the month before the KD (2021:M9) as reference month. The double interaction coefficients of interest for the pre-KD months all remain statistically insignificant, as per Figure 3.

Figure 3 Dynamic Effects of the KD



The figure plots the coefficients from a WLS regression of the IHS-transformed fund-country-level portfolio share changes on the interaction between month dummies and the biodiversity risk dummy *High Risk*, controlling for fund-country and fund-time fixed effects, applied to the monthly fund-level sample from 2021:M2-2022:M7.

3.3 Portfolio Reallocations at Extensive and Intensive Margins

This section seeks to disentangle reallocations at the extensive and intensive margins to shed light on cross-country spillover patterns induced by the KD, as further discussed in Section 4. Specifically, fund managers could *reduce* the share of AUM invested into a high-biodiversity risk country (intensive margin) or *stop* allocating any funds to this country altogether (extensive margin). At the same time, they could *increase* their allocations to less risky countries (intensive margin) or *start* allocating funds to such countries (extensive margin).

To disentangle these cases, we interact our post-KD-biodiversity risk double interaction of interest with another dummy that takes the value of one when, on a month-to-month basis, the fund-specific portfolio share allocated to a country did *not* grow along the extensive margin (i.e., lagged and current portfolio shares did not growth from zero to positive or vice versa), with the dummy denoted as *Intensive*. As column (7) in Table 3 shows, the double interaction between the post-KD dummy and country-level biodiversity risk remains negative, statistically significant, and increases substantially in magnitude relative to our previous results. In the presence of the triple interaction term, this large double interaction coefficient represents the effect on the portfolio adjustments along the extensive margin, which hence appear very relevant. In contrast, the reallocations along the intensive margin are more limited, as the positive triple interaction coefficient indicates, although its statistical significance lies slightly below conventional levels.[11] As we show in Table A3 in the Appendix, our benchmark result of column (6) in Table 3 is robust, but estimated more imprecisely, when we use the level or absolute change in country allocation shares as outcome. Given the importance of the extensive margin highlighted here, this imprecision is not too surprising, as growth rates, in contrast to levels and absolute changes, implicitly give a larger weight

[11] The adjustments along the intensive margin identified here also include cases where portfolio shares remain equal to zero. In unreported specifications, we separate these cases from true adjustments along the intensive margin (i.e., where lagged and current portfolio shares are strictly larger than zero), and we still find the intensive margin to play a smaller role than the extensive one.

to observations that change along the extensive margin, i.e., from a small number to zero or vice versa.

3.4 Robustness Checks

This sub-section addresses endogeneity concerns about biodiversity risks, and reports on an extensive set of robustness checks. As highlighted in Section 2, biodiversity risk may be closely correlated with macroeconomic characteristics and other country-specific risks. Such correlations may introduce bias in our estimations. This is why we explicitly control for a wide range of recipient country characteristics (fixed in 2021:M9) in their interactions with the post-KD dummy. Column (1) of Table 3 controls for the interactions of macroeconomic characteristics, including GDP per capita, interest rate differentials vis-a-vis the US, capital account openness, stock market capitalization, credit ratings and the rule of law. Column (2) saturates the benchmark regression with the interactions of country risk indicators, in particular geopolitical risk and various measures of climate risks, as laid out in in Section 2.

Table 3 illustrates that these additional controls hardly affect our coefficient of interest. In both columns (1) and (2), the double interaction coefficient lies in the range of -1.8 and -2.0, compared with the benchmark effect of -1.4, suggesting that the additional controls' omission introduces attenuation bias, if anything. Most additional controls enter statistically insignificantly. Importantly, results in column (2) assure us that the sensitivity of fund portfolios around the KD—clearly a biodiversity-centered event—is specific to biodiversity risk rather than other forms of country-level risk.

In unreported regressions, we add each macroeconomic control or other risk type individually instead of the horseracing discussed here. This raises the statistical significance of our coefficient of interest due to larger sample sizes. Horseracing all of the interactions of columns (1)-(2) in one specification also preserves the statistical significance of the post-biodiversity risk interaction, albeit reducing observations by three fourth due to missing data.

Appendix B discusses a battery of additional robustness checks all of which leave our

Table 3 Controlling for Country Characteristics and Other Risk Types

Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$	
	(1)	(2)
$Post_t \times$ *High Risk*$_c$	-1.988**	-1.862**
	(0.914)	(0.728)
$Post_t \times GDPp.c_c$	0.000	
	(0.000)	
$Post_t \times CreditRating_c$	0.077	
	(0.122)	
$Post_t \times CapitalAccountOpeneness_c$	0.021	
	(1.563)	
$Post_t \times Ruleoflaw_c$	-0.493	
	(0.833)	
$Post_t \times InterestRateDifferential_c$	-0.098*	
	(0.054)	
$Post_t \times Capitalization_c$	0.001	
	(0.004)	
$Post_t \times ClimatePolicy_c$		0.572
		(0.486)
$Post_t \times CarbonIntensity_c$		4.757
		(6.752)
$Post_t \times NDGainIndex_c$		0.075
		(0.068)
$Post_t \times INFORMIndex_c$		0.410
		(0.323)
$Post_t \times Geopoliticalrisk_c$		-0.012
		(0.512)
Fund-Country FE	Yes	Yes
Fund-Time FE	Yes	Yes
Observations	88,010	140,541
R-squared	0.353	0.312

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the double interaction between a post-KD dummy equal to one after 2021:M9, and a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution. Column (1) controls for the interactions between the post-KD dummy and several macroeconomic characteristics, fixed in the pre-KD period. Column (2) controls for interactions with country-level geopolitical and climate risk indicators. The regressions include fund-time and fund-country fixed effects. The regressions are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

main results unscathed. We summarize the tests as follows: Benchmark results are robust to (i) varying the window size around the KD, and to dropping the month of the KD announcement itself (2021:M10); (ii) controlling for the lagged country allocation shares, (iii) using the level, log-difference or absolute change in country allocation shares as dependent variable; (iv) clustering standard errors at the fund or fund-country level; (v) dropping funds belonging to the two largest fund families Vanguard and Blackrock; (vi) dropping or exclusively focusing on the dominant domicile countries, i.e., countries where most funds are domiciled (Ireland, Luxembourg, US); (vii) controlling for changes in the country allocations of a fund's benchmark; (viii) controlling for country-level bond and equity returns to account for valuation changes and capital pull factors; and (ix) focusing on cross-border funds to avoid home bias by dropping all funds investing—even if only partially—in the jurisdiction of their respective domiciles. Further, results are robust to measuring biodiversity risk as the difference between the country-specific risk and the portfolio share weighted average biodiversity risk of all other countries in a fund's portfolio, similar to the concept of excess risk in Converse and Mallucci (2019). Results also hold when we use alternative biodiversity risk measures, such as the BHI and RLI indices explained in Section 2.

3.5 Studying Portfolio Reallocations Around Other Events

While the KD arguably raised financial markets' attention to biodiversity losses, other closely related events could have provided similar informational value about future cash flows impacted by deteriorating ecosystems. Thus, we examine funds' cross-country portfolio reallocations around other events related to biodiversity and the GBF, and other major environment-related agreements and policies of global reach.

First, we estimate versions of Equation 1 around (i) the launch of the Taskforce on Nature-related Financial Disclosures (TNFD) in June 2021; (ii) the March 2022 negotiations in Geneva leading to the final GBF signing; and (iii) the conclusion of the GBF in Montreal in December 2022, with Section 2.1 providing details on these events. In addition, we also study whether significant reallocations occurred around (iv) the announcement of the EU biodiversity strategy in May 2020; (v) the amendment to France's Article 173 of the law on Energy Transition for Green Growth in July 2019; (vi) the announcement of the EU taxonomy for sustainable activities of June 2020; as well as (vii) the implementation of article 29 of France's Energy and Climate law in May 2021. The three latter events all put special emphasis on biodiversity preservation and restoration.

Table 4 shows that in most of the seven cases, the double interaction of interest remains negative, but none of them enters statistically significantly. Thus, the signaling effect of the KD as major step towards the GBF prevails in triggering funds' portfolio reallocations relative to other biodiversity-related events. Most importantly, neither the subsequent meetings in Geneva nor the final summit in Montreal led fund managers to update their beliefs about the salience of biodiversity losses for investment decisions.

Second, we study portfolio reallocations around major events closely related to the global environmental and climate policy agenda. For this, we apply Equation 1 to (i) the Paris Agreement of December 2015; (ii) the European Green Deal of December 2019; and (iii) the announcement of the US Inflation Reduction Act (IRA) in September 2021. For each of these events, columns (8)-(10) in Table 4 show statistically insignificant double interaction coefficients of interest. Given the lack of cross-country allocation sensitivity to biodiversity risks around these events, we deduce that it is the KD that raised fund managers' attention to biodiversity risks, not other events on the global sustainability agenda. Combined with insights gained in te Kaat et al. (2024), we acknowledge the specificity of funds' reallocation response, implying a direct mapping between specific risk categories and associated events.[12]

[12] te Kaat et al. (2024) show that around the announcement of the IRA—itself perceived as a major realization of climate transition risk—i) ultimate investors reallocated investments to sustainable-labeled funds, and ii) all type of funds reallocated portfolios towards countries with more effective climate policies. In contrast, this paper shows that biodiversity risks are irrelevant to the explanation of portfolio reallocations around the IRA.

Table 4 Other Events

	2021m6	2022m4	2022m12	2020m5	2019m7	2020m6	2021m5	2015m12	2019m12	2021m9
	Launch of TNFD	Negotiations in Geneva	Signing in Montreal	EU Biodiv. Strategy	France Article 173	EU Taxonomy	France Article 29	Paris Agreement	Green Deal	IRA
Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$Post_t \times High\ Risk_c$	-0.061	-0.979	-0.143	0.181	0.542	-0.228	-0.061	0.517	0.509	-0.150
	(0.502)	(0.852)	(0.385)	(0.680)	(0.404)	(0.471)	(0.502)	(0.454)	(0.456)	(0.433)
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	205,628	205,431	207,089	201,429	202,927	201,015	205,628	121,113	201,383	210,301
R-squared	0.310	0.331	0.292	0.278	0.305	0.296	0.309	0.353	0.280	0.320

The table is based on monthly fund-country-level data for the four months around the respective events. These events are: the launch of the TNFD in June 2021; the Geneva negotiations of March 2022; the signing of the KD in December 2022 in Montreal; the EU's announcement of its biodiversity strategy in May 2020; the amendment to France's Article 173 of the law on Energy Transition for Green Growth in July 2019; the announcement of the EU's taxonomy for sustainable activities of June 2020; the implementation of article 29 of France's Energy and Climate law in May 2021; the Paris Agreement of December 2015; the European Green Deal of December 2019; and the announcement of the US Inflation Reduction Act of September 2021. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the double interaction between a post-event dummy and a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution. The regressions include fund-time and fund-country fixed effects and are estimated via weighted least squares, using a fund's pre-event AUM as weight. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

3.6 Dissecting Results by Fund Characteristics

Using specifications as per Equation 2, we estimate heterogeneous reallocation responses to the KD depending on fund types and relevant characteristics. Starting with heterogeneity by fund type, column (1) of Table 5 shows that the reallocation away from countries with high biodiversity risk is more pronounced for actively-managed funds, albeit the differential response of ETFs and active funds, indicated by the triple interaction coefficient, is only statistically significant at the 10% level. This muted ETF reaction may be due to ETF's smaller tracking error permitted vis-a-vis their respective benchmark. Nevertheless, even ETFs reallocate their portfolios away from high-biodiversity risk countries, i.e., the marginal effect for ETFs is statistically significant at the 5% level.[13] Column (2) distinguishes between bond and equity funds. The statistically insignificant triple interaction coefficient shows that our benchmark results do not differ between bond and equity funds. If anything, the negative

[13]Unreported estimations via unweighted least squares and additionally controlling for an ETF's benchmark show that the reallocation by ETFs is linked to the benchmark's reallocation response to the KD.

coefficient implies an economically larger effect for equity funds.

In column (3), we study whether the reallocations are stronger for funds that market a larger fraction of their share classes to retail instead of institutional investors. Institutional investors, such as pension and insurance-managed funds, adopt a longer-term investment strategy. That is, funds catering mostly to institutional investors can be expected to keep allocations more stable over time resulting in a lower sensitivity to the KD. In contrast, funds attracting inflows mostly from retail investors are likely to adjust portfolio shares more: their managers are likely to anticipate higher redemptions as biodiversity risks materialize and, to protect this downside, they reallocate towards countries with a lower biodiversity risks after the KD. We find this hypothesis confirmed, with a triple interaction coefficient entering negatively and statistically significantly at the 5% level.

Next, we investigate how the reallocation patterns may vary across funds' environmental commitments. In column (4), we study the differential response of sustainable vs. conventional funds. The negatively significant triple interaction suggests that sustainable funds reallocate away from high-biodiversity risk countries even more actively, but this effect is again not statistically significant. The same is true for funds with a high ex-ante share of AUM invested in firms with an active biodiversity policy (column 5).[14]

Further, we study how various fund characteristics alter reallocations after the KD. Column (6) demonstrates that highly performing funds before the declaration are *less* likely to rebalance portfolios, although again the triple coefficient is below conventional significance levels.[15] Finally, in column (7), we study whether a fund's over- or underweight vis-a-vis a specific country affects its response to the KD. These are defined as the deviations from a fund's long-run, pre-KD (2015:M1-2023:M9) average portfolio share in a country, which is akin to a target portfolio allocation.[16] The positive (negative) double interaction between the post-dummy and a fund's position underweight (overweight) implies that fund managers

[14]For standardization, we demean the share of AUM invested in firms with an active biodiversity policy.
[15]We note that performance is also demeaned.
[16]Portfolio shares are highly autocorrelated over time, supporting the notion of a target allocation.

increase (reduce) their exposure to underweighted (overweighted) countries. However, the negative triple interaction coefficient between the post-dummy, a fund's *underweight* and recipient countries' biodiversity risk dummy implies that the convergence for underweighted countries is substantially smaller (both economically and statistically) when these countries have a high biodiversity risk. Put differently, fund managers (i) increase their exposure to underweighted countries with lower biodiversity risk, and (ii) at the same time reduce their exposure to *all* overweighted countries regardless of a country's biodiversity risk.

These results stand confirmed in unweighted regressions, albeit at somewhat lower statistical significance (Table A9 of Appendix D). The same is true when saturating the regressions with country-time fixed effects to control for time-country-specific heterogeneity, including demand for funds' investments (Table A10).

3.7 Industry Heterogeneity

Giglio et al. (2023) document substantial heterogeneity in the extent to which different industries are affected by biodiversity risks. In this sub-section, we examine whether our benchmark results depend on a fund's pre-KD portfolio share invested in more vs. less affected industries. We hypothesize that funds with a greater exposure to more affected industries reallocate their portfolios even more significantly towards low-risk countries, as biodiversity risks hit them even more.

Leveraging EPFR data on equity funds' industry allocations, the following regressions split the sample into funds that have a pre-KD exposure to more affected industries below and above, respectively, the in-sample median. In columns (1)-(2), we use a broad definition of industries that are most sensitive to biodiversity risks, which includes the energy industry, food/beverage/tobacco, pharmaceuticals, materials, and real estate.[17] In columns (3)-(4), we then employ a tighter definition that only includes the two most affected industries according to Giglio et al. (2023)—food/beverage/tobacco and energy.

[17] These are the five industries with the highest survey-based biodiveristy risk scores in Giglio et al. (2023).

Table 5 Dissecting Results by Fund Characteristics

Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post_t \times High\ Risk_c$	-1.500***	-0.956***	-1.388***	-1.316***	-1.181**	-1.277***	-1.106***
	(0.529)	(0.488)	(0.502)	(0.478)	(0.478)	(0.441)	(0.395)
$Post_t \times High\ Risk_c \times ETF_{i,j}$	0.419*						
	(0.229)						
$Post_t \times High\ Risk_c \times Equity_{i,j}$		-0.495					
		(0.692)					
$Post_t \times High\ Risk_c \times RetailShare_{i,j}$			-0.007**				
			(0.004)				
$Post_t \times High\ Risk_c \times Sustainable_{i,j}$				-0.612			
				(0.502)			
$Post_t \times High\ Risk_c \times BiodiversityShare_{i,j}$					-0.008		
					(0.014)		
$Post_t \times High\ Risk_c \times Return_{i,j}$						0.167	
						(0.191)	
$Post_t \times Overweight_{i,j,c}$							-0.721***
							(0.221)
$Post_t \times High\ Risk_c \times Overweight_{i,j,c}$							0.142
							(0.562)
$Post_t \times Underweight_{i,j,c}$							0.875***
							(0.291)
$Post_t \times High\ Risk_c \times Underweight_{i,j,c}$							-0.914**
							(0.420)
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210,914	210,914	210,914	210,914	142,064	210,914	210,914
R-squared	0.303	0.303	0.303	0.303	0.298	0.303	0.310

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the triple interaction between a post-KD dummy equal to one after 2021:M9, a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution, and the following fund characteristics fixed in the pre-KD period: an ETF dummy, an equity fund dummy, a fund's fraction of share classes marketed to retail investors, a dummy indicating sustainable funds, a fund's share of holdings in investee firms with active biodiversity policies, a fund's performance, and a fund's position over- and underweight relative to its historical allocation to a particular country. The regressions include fund-time and fund-country fixed effects. Regressions are weighted by a fund's pre-KD AUM. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

As Table 6 shows and consistent with our hypothesis, only funds with a large exposure to more affected industries reallocate their portfolios towards low-risk countries after the KD. Specifically, whereas the reallocation effects are not statistically significant in the subsamples of funds that have a lower exposure to more affected industries (columns 1 and 3), funds with a greater exposure tilt portfolios in a statistically significant manner (columns 2 and 4). For these funds, the point estimate is even larger than our benchmark coefficient shown in column (6) of Table 2.

Table 6 Industry Heterogeneity

	Broad Biodiv. Exposure		Narrow Biodiv. Exposure	
	below median	above median	below median	above median
Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$			
	(1)	(2)	(3)	(4)
$Post_t \times High\ Risk_c$	-1.035	-1.375**	-0.894	-1.402**
	(0.708)	(0.566)	(0.725)	(0.574)
Fund-Country FE	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes
Observations	47,662	48,675	48,288	48,049
R-squared	0.344	0.308	0.337	0.316

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the double interaction between a post-KD dummy equal to one after 2021:M9, and a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of the entire in-sample distribution, denoted as *High Risk*. In each column, we split the sample into funds with an exposure to biodiversity-affected industries below vs. above the median, using a broad and narrow definition as detailed in the main text. The regressions include fund-time and fund-country fixed effects as indicated in each column. The regressions are estimated by weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

3.8 Which Policies are Effective in Moderating Portfolio Reallocations?

We explore how countries' policy choices may attenuate the above identified portfolio reallocations following the KD. As later discussed in Section 4, the reallocations trigger significant cross-country capital flow shifts from high- to low-biodiversity risk countries. The associated outflows from risky countries can tighten financing conditions in exposed sectors, uncovering balance sheet vulnerabilities. Policy makers may seek to reduce this volatility to safeguard macro-financial stability. Given ample literature, we refrain from studying the impact of standard capital controls and macroprudential tools deployable in the short-term to ensure financial stability. Instead, we focus on structural environmental and macroeconomic policies possibly supporting high-biodiversity risk countries to preserve fund investments.

First, we seek to understand the role of directly biodiversity-related policies for funds to minimize the reallocation away from risky countries. We hypothesize that nature conservation by law signals a more productive use of capital for investments sensitive to ecosystem health, since investee firms' processes, products and services are likely to align with nature conservation, holistically supported by governance frameworks and public policies. Associated legal acts to protect nature are also conjectured to attract investments, as they reduce policy uncertainty and provide the opportunity for legal recourse, as reported in Ciminelli et al. (2025)[18] and Averchenkova et al. (2020), respectively. Better nature protection lowers the policy uncertainty about more stringent nature-related regulations, thus lowering transition risks Garel et al. (2024). To distill insights on the effects of biodiversity-related legal acts, we derive a novel measure of a country's track record in nature-positive legal action. Using the FAOLEX database—a comprehensive repository of environment-related legal acts—, we proxy the track record by the count of international agreements signed as well as legislations, regulations and policies enacted by a country in the 36 months prior to the KD.[19] Fund managers' recency bias implies that legal acts in the 36 pre-KD months are paid most attention to. A count computed over a period longer than 36 months reduces

[18] Ciminelli et al. (2025) argue that climate laws act as commitment device to pursue policies tackling climate change, and to clarify responsibilities among government entities, both lowering uncertainty for investors.

[19] For details, see: https://www.fao.org/faolex/en/. For agreements or legislations enacted by multiple countries, we consider the legal act as individually allocated to each country. For instance, Angola, the European Union, Iceland, Republic of Korea, Namibia, Norway, South Africa, United Kingdom of Great Britain and Northern Ireland, and the United States of America signed the "Convention on the conservation and management of fishery resources in the South-East Atlantic Ocean" on 20 April 2001. We associate the legal act with each of these countries, meaning the count increases by one for each. However, there are no such multi-country assignments in the 36 months period before the KD.

the statistical significance of the subsequently reported results. We exclusively focus on legal acts classified by FAOLEX in the primary subjects i) wild species and ecosystems, ii) forestry, and iii) fisheries, and test the relevance of the overall count of associated legal acts as well as of the count specific to each of these categories.[20] We then include the count of biodiversity-related legal acts in the previously employed triple interaction specification. A positive and statistically significant coefficient would suggest that such legal acts attenuate funds' reallocation away from high-biodiversity risk countries upon materialization of biodiversity risk around the KD.

Column (3) of Table 7 confirms our conjecture. The triple interaction estimate for the aggregate count of biodiversity-related acts enters positively and statistically significantly at the 10% level. In columns (4)-(6), we focus on the counts in the sub-categories 'wild species and ecosystems', 'forestry', and 'fisheries', respectively. The triple coefficient is positive and strongly statistically significant for legal acts related to 'forestry', followed by 'wild species and ecosystems'. For 'fisheries', the coefficient estimate is slightly below conventional statistical significance. Further, we explore how the role of legal acts may vary depending on the stringency of legal commitment implied by the types of legal acts. For instance, laws are considered more binding than mere policies. Unreported results show that the stringency of legal acts does not affect portfolio reallocations. Overall, these results corroborate that taking nature-positive legal action lowers the reallocation away from high-biodiversity risk countries.

Second, we investigate the role of policies only indirectly related to biodiversity outcomes and ask how the quality of macroeconomic policies, as measured by Moody's credit ratings, or climate policies modulate the KD's impact on funds' portfolio reallocations.[21] High credit ratings are conjectured to soften funds' response to biodiversity risks revealed by the KD, suggesting that high-quality macroeconomic fundamentals partially offset biodiversity risks.

[20]Other categories in FAOLEX are agriculture and rural development, climate change cultivated plants, disaster risk, food and nutrition, indigenous people, land and soil, livestock, miscellaneous, social protection, mineral resources, and energy and water.

[21]Both variables are standardized by subtracting the in-sample mean.

Table 7 Role of Environmental and Macroeconomic Policies

Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times High\ Risk_c$	-1.379***	-1.408***	-1.979***	-1.970***	-1.631***	-1.451**
	(0.510)	(0.496)	(0.729)	(0.736)	(0.553)	(0.595)
$Post_t \times CreditRating_c$	-0.0942**					
	(0.041)					
$Post_t \times High\ Risk_c \times CreditRating_c$	0.106					
	(0.079)					
$Post_t \times ClimatePolicy_c$		0.284				
		(0.207)				
$Post_t \times High\ Risk_c \times ClimatePolicy_c$		0.304				
		(0.590)				
$Post_t \times BiodiversityActs_c$			-0.010**			
			(0.005)			
$Post_t \times High\ Risk_c \times BiodiversityActs_c$			0.065*			
			(0.035)			
$Post_t \times WildSpeciesActs_c$				-0.013***		
				(0.004)		
$Post_t \times High\ Risk_c \times WildSpeciesActs_c$				0.0748*		
				(0.044)		
$Post_t \times ForestryActs_c$					-0.103***	
					(0.034)	
$Post_t \times High\ Risk_c \times ForestryActs_c$					0.285***	
					(0.108)	
$Post_t \times FisheryActs_c$						0.132***
						(0.034)
$Post_t \times High\ Risk_c \times FisheryActs_c$						0.502
						(0.335)
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.304	0.301	0.303	0.303	0.303	0.303
Observations	210,506	184,822	203,280	203,280	203,280	203,280

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the triple interaction between—on one hand—the post-KD dummy equal to one after 2021:M9 and the biodiversity risk dummy *High Risk* and—on the other—i) country-level ratings (column 1), ii) the Bloomberg climate policy scores (column 2), and iii) aggregate biodiversity-related legal acts in the 36 pre-KD months (column 3), respectively. Columns (4)-(6) break down the latter into legal acts related to 'wild species and ecosystems', 'forestry', and 'fisheries', respectively. The regressions include fund-time and fund-country fixed effects. The regressions are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

In contrast, low credit ratings may amplify the flight to biodiversity safety. Similar to nature-positive legal acts, effective climate policies may signal a more productive use of scarce additional fund investments for climate action, including through an economy's enhanced capacity to channel fund flows into climate change-related investments, helped by lower policy uncertainty and legal recourse. Fund investments are known to respond well to climate policies, as shown in te Kaat et al. (2024). With climate change being one of the key drivers of biodiversity losses, policies effective in tackling climate change are expected to raise the return on ecosystem-sensitive investments. Thus, more effective climate policies, as measured by the Bloomberg Government Climate Risk Score, will likely dampen KD-induced reallocations. To identify the role of credit ratings and climate policies, we include in our regressions the triple interaction between the post-KD dummy, the country-level biodiversity risk dummy, and these two characteristics. Columns (1)-(2) of Table 7 show that both variables do not play any role in funds' reallocation away from high-biodiversity risk countries, as evidenced by statistically insignificant triple interaction coefficients. In other words, improving policies not immediately nature-relevant, such as raising a country's credit rating or climate score, does not shield high-biodiversity risk economies from funds reallocating away when biodiversity risks are exposed.

4 Cross-Country Spillovers

Previous sections show that funds reduce exposure to high-biodiversity risk countries after the KD. As funds dial down the exposure to risky countries, portfolio reallocation entails that less risky countries gain in portfolio shares. In this section, we study explicitly which countries benefit from the KD-induced reallocations. The analysis speaks to the long-standing enquiry into investment funds' contribution to (regional) contagion (Broner et al., 2006; Kaminsky et al., 2004). As discussed in Section 3.3, funds may reallocate along the intensive or extensive margins. The latter refers to new positions outside of a fund's hitherto established portfolio, which may further be differentiated into new positions within and outside of the same geographical region. A flight to biodiversity safety in favor of new positions outside a fund's existing portfolio, but within the same region, would provide evidence for portfolio-wide contagion, i.e., a retrenchment only from a fund's existing portfolio. Reallocations away from high-biodiversity risk countries in favor of new positions in other regions would lend support for funds even driving regional contagion.

We follow Converse et al. (2023) and augment Equation 1 by the interaction between the post-KD dummy and the weighted average biodiversity risk of all other countries in a fund's portfolio. To address funds' role for portfolio-wide and regional contagion, further specifications add the average biodiversity risk of all other countries in the same region, and the average biodiversity risk in all other regions,[22] whereby regions denote Europe, Africa, Middle East, Asia and the Pacific, North America, and South America. We further adjust the benchmark model twofold: First, we define the outcome variable as the level of portfolio shares (instead of growth rates) to allow for changes in the dependent variable to sum to zero. Second, again following Converse et al. (2023), we cluster the standard errors at the fund level, as they are in such spillover regressions more likely correlated within funds and not within countries.

[22]Both variables are standardized by subtracting the in-sample mean and dividing by the standard deviation, so as to make them comparable to each other.

Table 8 portrays the results. In column (1), the negative and statistically significant coefficient on the double interaction term with the fund-level, weighted biodiversity risk implies that a portfolio-wide elevated biodiversity risk leads funds to reduce exposures to all countries in the existing portfolio. The positive and significant coefficient on the average biodiversity risk of all other countries in the *same* region in columns (2) to (4) signals that funds establish new positions along the extensive margin, i.e., in countries not part of the pre-KD portfolio. Further adding the average biodiversity risk in all *other* regions in column (3) shows that the new positions remain limited to the same geographical region. Countries in other regions do not see new positions opened. In column (4), we repeat the exercise of column (3) exclusively for multi-region funds as single-region funds by definition do not reallocate into other regions. While the coefficient on the average biodiversity risk in all *other* regions now becomes weakly significant, the coefficient on the the average biodiversity risk of all other countries in the *same* region is estimated more precisely and larger in economic terms, implying that spillovers are most pronounced within the same region.

We conclude that the KD fostered cross-country spillovers and portfolio-wide contagion. After the KD, funds lower portfolio shares of *all* countries included in the pre-KD portfolio when this portfolio exhibits high biodiversity risk. Funds reallocate investments to other countries not yet invested in, and predominantly within the same region.

5 Does the KD Induce Cross-Border Portfolio Flows?

Section 3 shows that fund managers reallocate their portfolios towards countries with a lower biodiversity risk after the KD. Next, we examine whether these reallocations imply cross-border portfolio investment flows.

This exercise not only helps elucidate real effects of portfolio reallocations, but also serves to clean our benchmark result from any interference by ultimate investors' flows into funds. Ultimate investors may respond to the KD by altering their allocations to individual funds,

Table 8 Cross-Country Spillovers

Dependent Variable:	$Share_{i,j,c,t}$			
	(1)	(2)	(3)	(4)
$Post_t \times$ *Biodiversity Risk*$_c$	-0.005***	-0.005***	-0.004***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
$Post_t \times$ *Fund Average Risk*$_{i,c}$	-0.124***	-0.125***	-0.130***	-0.134***
	(0.026)	(0.026)	(0.026)	(0.027)
$Post_t \times$ *Same Region Average Risk*$_c$		0.007***	0.014**	0.016**
		(0.003)	(0.007)	(0.006)
$Post_t \times$ *Other Region Average Risk*$_c$			0.009	0.011*
			(0.006)	(0.006)
Fund-Country FE	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes
Observations	212,730	212,730	212,730	192,230
R-squared	0.999	0.999	0.999	0.999

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressors are the double interactions between a post-KD dummy equal to one after 2021:M9, and (i) a country's continuous biodiversity risk, (ii) the weighted average biodiversity risk across all other countries in a fund's portfolio, (iii) the average biodiversity risk of all other countries in the *same* geographical region, and (iv) the average biodiversity risk of all countries in *other* regions. Column (4) excludes all single-region funds. The regressions include fund-time and fund-country fixed effects. The regressions are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the fund level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

shifting away from those with high average biodiversity risk exposure. This may affect cross-border flows, as the latter are obtained as product of portfolio shares and flows into a fund, and thus sensitive to changes in ultimate investor preferences. In addition, fund managers' reallocation decisions may also be a function of a fund's AUM, which vary with investors' shifts. To disentangle the decision margins by fund managers and ultimate investors, we compare and contrast the KD effect on flows at the fund level, i.e., aggregate flows into a fund, with flows at the fund-country level, i.e., funds' investment flows to specific recipient countries.[23] While the latter reflects the combination of both fund managers' and investors' decisions, fund-level flows abstract from managers' decisions.

5.1 Econometric Approach

First, we examine how the KD changed ultimate investors' flows into funds depending on a fund's average biodiversity risk exposure. The regression is estimated at the fund level and specified as follows:

$$Flows_{i,j,t} = \alpha_{i,j} + \alpha_{j,t} + \nu \cdot (\text{Post}_t \times \text{Biodiversity Risk}_{i,j,pre}) + \epsilon_{i,j,t} \tag{3}$$

where $Flows_{i,j,t}$ are the valuation-adjusted investor flows into fund i, domiciled in country j in month t, scaled by AUM, and $BiodiversityRisk_{i,j,pre}$ is the weighted biodiversity risk of all countries in a fund's portfolio, with current portfolio shares used as weights.[24] The interaction of interest is between the post-KD dummy and $BiodiversityRisk_{i,j,pre}$. The specification adds fund and domicile-time fixed effects. Standard errors are clustered at the fund level.

Second, we study how fund managers' reallocations and investors' shifts taken together

[23] Note that 'flows into funds' and 'funds' flows into *all* countries can be used interchangeably given low and time-invariant cash shares in fund portfolios of about 2% on average.

[24] All flow variables used as outcomes in this section are winsorized at the 0.5 and 99.5% levels to mitigate the effect of outliers.

affect cross-border investment flows. We estimate a regression at the fund-country level with the following set up:

$$Flows_{i,j,c,t} = \alpha_{i,j,t} + \alpha_{i,j,c} + \beta \cdot (\text{Post}_t \times \text{Biodiversity Risk}_{c,pre}) + \epsilon_{i,j,c,t} \tag{4}$$

where the dependent variable is the product of aggregate flows into fund i domiciled in country j and the allocation shares of the same fund to recipient countries c in month t, scaled by AUM. The key regressor is the post-KD dummy interacted with the country-level biodiversity risk, as in Section 3. We incorporate fund-country and fund-time fixed effects.

5.2 Results

Columns (1) and (2) of Table 9 show results at the fund level corresponding to Equation 3. Results in column (1) are based on a continuous version of a fund's biodiversity risk exposure. Column (2) uses this variable as dummy equal to one if it exceeds the 75th percentile of the in-sample distribution. The interaction term enters statistically insignificantly in both specifications.[25] With the specification at the fund level abstracting from fund managers' reallocation decisions, the result suggests that flows into funds—and by implication into *all* recipient countries—are not driven by investors' response to the KD differentiated by funds' biodiversity risk exposure. We bolster this finding by estimating Equation 3 on fund-level flow data at daily frequency, using a narrow window of 10 (i.e., 5 days pre- and post-KD) and 40 trading days around the KD.[26] The interaction coefficient remains statistically insignificant (not reported).

In contrast, the negative and statistically significant interaction coefficient in column (3) from an estimation of Equation 4 indicates that the KD depresses fund-country-level flows

[25]The result is robust to other choices of the percentile threshold defining the fund-level biodiversity risk dummy (e.g., the median or 67th percentile).

[26]Data on flows into funds are available at daily frequency. However, the country allocation data used in most of this paper are only available at monthly frequency.

Table 9 Evidence for Cross-Border Portfolio Investment Flows

	(1) $\text{Flows}_{i,j,t}$	(2) $\text{Flows}_{i,j,t}$	(3) $\text{Flows}_{i,j,c,t}$
$Post_t \times Weighted\ Biodiversity\ Risk_{i,j}$	-0.029		
	(0.043)		
$Post_t \times High\ Risk_{i,j}$		-0.048	
		(0.187)	
$Post_t \times High\ Risk_c$			-0.004**
			(0.002)
Fund FE	Yes	Yes	No
Domicile-Time FE	Yes	Yes	No
Fund-Country FE	No	No	Yes
Fund-Time FE	No	No	Yes
Observations	9,195	9,195	212,754
R-squared	0.486	0.486	0.686

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable in columns (1)-(2) is the fund-level inflow, scaled by a fund's AUM. In column (3), it is fund-country-level flows over AUM. The key regressor is the double interaction between a post-KD dummy equal to one after 2021:M9, and a fund's weighted biodiversity risk taking into account all countries in the portfolio. Column (2) replaces this continuous measure with a dummy equal to one if the variable is in the top 25% of the in-sample distribution. Column (3) employs the country-level high biodiversity risk dummy from the benchmark specification presented in Table 2, column (6). The regressions include fund and domicile-time fixed effects (columns 1 and 2) and fund-time and fund-country fixed effects (column 3). The regression are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the fund level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

into high-risk countries, and raises flows into less risky countries. This is consistent with our benchmark finding of funds reallocating away from high-biodiversity risk countries upon KD announcement. Coupled with the above insight on ultimate investors' insensitivity to the KD, the result confirms fund managers as key decision-making unit for funds' reallocations across countries.

We finally note that cross-country flows triggered by the KD are likely more pronounced for funds with exclusively cross-border positions compared to funds also investing some positive fraction of AUM in the domicile country. Limiting the sample to cross-border funds leaves the results unchanged. These results are available upon request.

6 Conclusion

This paper studies investment funds' response to biodiversity risks revealed by the KD in October 2021, using monthly data on funds' portfolio allocations to individual countries from EPFR Global. The KD is hailed as a key milestone towards a new, ambitious global policy framework to address biodiversity losses. With the framework adopted only in December 2022, the KD was the earliest and most noticeable public signal of commitment of governments worldwide to bring about significant regulatory changes to align financial flows with nature-positive investment needs, and to streamline biodiversity into financial regulations.

We document in a difference-in-difference setting that the KD induced investment funds to reallocate portfolios from high-biodiversity risk countries to less risky ones. After the KD, fund portfolios are most sensitive to extremely high biodiversity risks. In contrast, extremely low risk does not attract significantly higher portfolio allocations, characterizing biodiversity risk as downside risk factor only. The reallocation is driven by fund managers, not ultimate investors in funds. Our work thus highlights the salience of biodiversity losses for decisions by investment professionals. A concomitant step increase in global attention to biodiversity highlights the KD's signaling of biodiversity-related transition risks to financial markets. The KD's role is shown to be unique relative to a range of other biodiversity- and broader environment-related policy events of global significance.

Having established the concept of 'flight to biodiversity safety', we investigate whether funds contribute to (regional) contagion. We find that funds retrench from the entire pre-KD portfolio when this portfolio exhibits high biodiversity risk. Instead, funds open new positions in other countries in the same geographical region, but hitherto outside of a fund's portfolio. Thus, funds fuel cross-country spillovers and portfolio-wide contagion within the same region, but not regional contagion. The reallocations are mirrored by significant cross-border portfolio capital flows. Given potential financial stability repercussions for high-biodiversity risk countries, we shed light on the policies effective at dampening outflows from such countries. Based on a new measure of nature-protecting legal action, our work highlights that nature-positive legal acts should be the key policy lever to preserve fund investments. Policies only indirectly related to nature conservation, such as mitigating climate change and strengthening macroeconomic fundamentals, are not effective in modulating portfolio reallocations.

Overall, this work characterizes how biodiversity risks shape funds' investment decisions, and establishes funds as an important conduit for the international spillover of biodiversity risks. Clarifying how balance sheets of other financial intermediaries respond to biodiversity risks would constitute a worthwhile avenue for future research.

References

Alessi, L., S. Battiston, and V. Kvedaras (2024): "Over with carbon? Investors' reaction to the Paris Agreement and the US withdrawal," *Journal of Financial Stability*, 71, 101232.

Alessi, L., E. Ossola, and R. Panzica (2023): "When do investors go green? Evidence from a time-varying asset-pricing model," *International Review of Financial Analysis*, 90, 102898.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht (2023): "Climate change concerns and the performance of green vs. brown stocks," *Management Science*, 69, 7607–7632.

Arlt, S., T. Berg, X. Hut, and D. Streitz (2024): "A Biodiversity Stress Test of the Financial System," *SSRN*.

Aswani, J., A. Raghunandan, and S. Rajgopal (2024): "Are Carbon Emissions Associated with Stock Returns?" *Review of Finance*, 28, 75–106.

Averchenkova, A., S. Fankhauser, and J. Finnegan (2020): "The impact of Strategic Climate Legislation: Evidence from Expert Interviews on the UK Climate Change Act," 21.

Becker, A., F. E. Di Girolamo, and C. Rho (2025): "Loan Pricing and Biodiversity Exposure: Nature-related Spillovers to the Financial Sector," *Research in International Business and Finance*, 75, 102724.

Bellemare, M. F. and C. J. Wichman (2020): "Elasticities and the inverse hyperbolic sine transformation," *Oxford Bulletin of Economics and Statistics*, 82, 50–61.

Benincasa, E., G. Kabas, and S. Ongena (2023): "Uncoordinated Climate Policies: Implications for Cross-Border Lending," in *econpol Forum*, CESifo, vol. 24, 28–30.

Bettendorf, T. and A. Karadimitropoulou (2023): "Time-variation in the effects of push and pull factors on portfolio flows: Evidence from a Bayesian dynamic factor model," *Journal of Economic Dynamics and Control*, 156, 104756.

Block, S., J. Emerson, D. Esty, A. de Sherbinin, and e. a. Wendling, Z.A. (2024): "2024 Environmental Performance Index," *New Haven, CT: Yale Center for Environmental Law Policy. epi.yale.edu.*

Bohnet, M.-P., P. Fliegel, and T. Tax (2025): "Not Just Knocking on Wood: The Short-and Long-Term Pricing of Deforestation Risk on Global Financial Markets," *SSRN Electronic Journal*.

Boldrini, S., A. Ceglar, C. Lelli, L. Parisi, and I. Heemskerk (2023): "Living in a World of Disappearing Nature: Physical Risk and the Implications for Financial Stability," *ECB Occasional Paper*, available at SSRN: https://ssrn.com/abstract=4630721 or http://dx.doi.org/10.2139/ssrn.4630721.

Bolton, P. and M. Kacperczyk (2021): "Do investors care about carbon risk?" *Journal of financial economics*, 142, 517–549.

——— (2023): "Global pricing of carbon-transition risk," *The Journal of Finance*, 78, 3677–3754.

Brondízio, E., J. Settele, S. Diaz, H. T. Ngo, G. Experts, and A. Mohamed (2021): *Global assessment report on biodiversity and ecosystem services of the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services.*

Broner, F. A., R. Gaston Gelos, and C. M. Reinhart (2006): "When in Peril, Retrench: Testing the Portfolio Channel of Contagion," *Journal of International Economics*, 69, 203–230, emerging Markets.

Burbidge, J. B., L. Magee, and A. L. Robb (1988): "Alternative transformations to handle extreme values of the dependent variable," *Journal of the American statistical Association*, 83, 123–127.

Butchart, S. H., H. R. Akçakaya, J. Chanson, J. E. Baillie, B. Collen, S. Quader, W. Turner, R. Amin, S. Stuart, and C. Hilton-Taylor (2007): "Improvements to the Red List Index," *PLoS ONE*, 2.

Caldara, D., S. Conlisk, M. Iacoviello, and M. Penn (2023): "Do geopolitical risks raise or lower inflation," *Tech. rep., Federal Reserve Board*, 1–32.

Caldara, D. and M. Iacoviello (2022): "Measuring geopolitical risk," *American Economic Review*, 112, 1194–1225.

Calice, P., F. D. Kalan, N. Dunz, and F. Miguel (2023): "Biodiversity and Finance," *A Preliminary Assessment of Physical Risks for the Banking Sector in Emerging Markets. World Bank Policy Research Working Paper*, 10432.

Calvo, G. A. and E. G. Mendoza (2000): "Rational Contagion and the Globalization of Securities Markets," *Journal of International Economics*, 51, 79–113.

Camanho, N., H. Hau, and H. Rey (2022): "Global Portfolio Rebalancing and Exchange Rates," *The Review of Financial Studies*, 35, 5228–5274.

CBD Secretariat (2021): *Financial Sector Guide for the Convention on Biological Diversity*, accessed: 2024-07-25.

Ceballos, G., P. R. Ehrlich, and P. H. Raven (2020): "Vertebrates on the Brink as Indicators of Biological Annihilation and the Sixth Mass Extinction," *Proceedings of the National Academy of Sciences*, 117, 13596–13602.

Cheng, G., E. Jondeau, B. Mojon, and D. Vayanos (2024): "The Impact of Green

Investors on Stock Prices," NBER Working Paper 32317, National Bureau of Economic Research.

Chinn, M. D. and H. Ito (2006): "What matters for financial development? Capital controls, institutions, and interactions," *Journal of development economics*, 81, 163–192.

——— (2008): "A new measure of financial openness," *Journal of comparative policy analysis*, 10, 309–322.

Choi, D., Z. Gao, and W. Jiang (2020): "Attention to global warming," *The Review of Financial Studies*, 33, 1112–1145.

Ciminelli, G., F. M. D'Arcangelo, M. Pisu, and S. Tian (2025): "The Value of Commitment: How Climate Laws Influence Sustainable Investment," *Asian Development Bank Working Paper (forthcoming).*

Ciminelli, G., J. Rogers, and W. Wu (2022): "The effects of US monetary policy on international mutual fund investment," *Journal of International Money and Finance*, 127, 102676.

Co, C. Y., H. Folmer, T. Jeppesen, J. A. List, and W. Warren Mchone (2002): *The Impact of Environmental Regulations on Capital Flows: Some Methodological Considerations*, Dordrecht: Springer Netherlands, 177–184.

Convention on Biological Diversity Secretariat (2020): *Global Biodiversity Outlook 5.*

Converse, N., E. Levy-Yeyati, and T. Williams (2023): "How ETFs amplify the global financial cycle in emerging markets," *The Review of Financial Studies*, 36, 3423–3462.

Converse, N. and E. Mallucci (2019): "Differential Treatment in the Bond Market: Sovereign Risk and Mutual Fund Portfolios," *International Finance Discussion Paper.*

——— (2023): "Differential Treatment in the Bond Market: Sovereign Risk and Mutual Fund Portfolios," *Journal of International Economics*, 145, 103823.

Coqueret, G., T. Giroux, and O. D. Zerbib (2024): "The biodiversity premium," *Available at SSRN 4489550*.

Dahlhaus, T. and G. Vasishtha (2014): "The impact of US monetary policy normalization on capital flows to emerging-market economies," Working Paper 2014-53, Bank of Canada.

Davis, J. S. and A. Zlate (2023): "The global financial cycle and capital flows during the COVID-19 pandemic," *European Economic Review*, 156, 104477.

De Angelis, T., P. Tankov, and O. D. Zerbib (2023): "Climate Impact Investing," *Management Science*, 69, 7669–7692.

Demirgüç-Kunt, A., A. Pedraza, F. Pulga, and C. Ruiz-Ortega (2023): "Global bank lending under climate policy," *IMF Economic Review*, 1–44.

Deng, M. and T.-C. Lin (2025): "Guardians of the Biodiversity: Do Banks Care about Firm's Biodiversity Risk?" .

Deutz, A., G. Heal, R. Niu, E. Swanson, T. Townshend, Z. Li, A. Delmar, A. Meghji, S. Sethi, and J. Puente (2020): "Financing Nature: Closing the Global Biodiversity Financing Gap," .

Di Giuli, A., A. Garel, R. Michaely, and A. Romec (2024): "Climate Change and Mutual Fund Voting on Climate Proposals," *European Corporate Governance Institute – Finance Working Paper No. 815/2022, HKU Jockey Club Enterprise Sustainability Global Research Institute - Archive*, available at SSRN: https://ssrn.com/abstract=3997730.

Emerging Portfolio Fund Research (EPFR) (2024): "Global Fund Data Collection," .

Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebel (2020): "Hedging climate change news," *The Review of Financial Studies*, 33, 1184–1216.

Faccini, R., R. Matin, and G. Skiadopoulos (2023): "Dissecting Climate Risks: Are They Reflected in Stock Prices?" *Journal of Banking & Finance*, 155, 106948.

Fernández, A., M. W. Klein, A. Rebucci, M. Schindler, and M. Uribe (2016): "Capital Control Measures: A New Dataset." *IMF Economic Review*, 64.

Flammer, C., T. Giroux, and G. Heal (2025): "Biodiversity Finance," Tech. rep., Journal of Financial Economics.

Forbes, K., M. Fratzscher, T. Kostka, and R. Straub (2016): "Bubble thy neighbour: Portfolio effects and externalities from capital controls," *Journal of International Economics*, 99, 85–104.

Frankel, J. A. and S. L. Schmukler (1996): "Crisis, Contagion, and Country Funds: Effects on East Asia and Latin America," Pacific Basin Working Paper Series 96-04, Federal Reserve Bank of San Francisco.

Gardes-Landolfini, C., W. Oman, J. Fraser, M. M. de Oca Leon, and Y. Bella (2024): "Embedded in Nature: Nature-Related Economic and Financial Risks and Policy Considerations," *Staff Climate Notes*, 2024, 1.

Garel, A., A. Romec, Z. Sautner, and A. F. Wagner (2024): "Do investors care about biodiversity?" *Review of Finance*, 28, 1151–1186.

Gelos, G. (2011): "International Mutual Funds, Capital Flow Volatility, and Contagion – A Survey," Working paper, International Monetary Fund, Western Hemisphere Department.

Gelos, R. G. and S.-J. Wei (2005): "Transparency and International Portfolio Holdings," *The Journal of Finance*, 60, 2987–3020.

Giglio, S., T. Kuchler, J. Stroebel, and X. Zeng (2023): "Biodiversity risk," Tech. rep., National bureau of economic research.

Gjerde, S., Z. Sautner, A. F. Wagner, and A. Wegerich (2025): "Corporate Nature Risk Perceptions," *Available at SSRN.*

Han, X., Y. P. Li, and P. L. Mu (2024): "Indebted to Nature: Corporate Biodiversity Endowment and Bond Market Reactions," *Available at SSRN 5280213.*

Harwood, T., C. Ware, A. Hoskins, S. Ferrier, A. Bush, M. Golebiewski, S. Hill, N. Ota, J. Perry, A. Purvis, and K. Williams (2022): "BHI v2: Biodiversity Habitat Index: 30s Global Time Series," Data Collection.

Hoepner, A. G., J. Klausmann, M. Leippold, and J. Rillaerts (2023): "Beyond climate: The impact of biodiversity, water, and pollution on the CDS term structure," .

Hsu, P.-H., K. Li, and C.-Y. Tsou (2023): "The pollution premium," *The Journal of Finance*, 78, 1343–1392.

Huang, Y., A. Créti, B. Jiang, and M. E. Sanin (2024): "Biodiversity Risk, Firm Performance, and Market Mispricing," *Firm Performance, and Market Mispricing (February 1, 2024).*

Initiative, N. D. G. A. et al. (2023): "Notre Dame Global Adaptation Initiative—Country Index," .

IUCN (2025): "The IUCN Red List of Threatened Species. Version 2024-2." *https://www.iucnredlist.org. Accessed on 10 January 2025.*

Johnson, J. A., G. Ruta, U. Baldos, R. Cervigni, S. Chonabayashi, E. Corong, O. Gavryliuk, J. Gerber, T. Hertel, C. Nootenboom, S. Polasky, J. Gerber,

G. Ruta, and S. Polasky (2021): *The Economic Case for Nature: A Global Earth-Economy Model to Assess Development Policy Pathways*, Washington, DC: World Bank, license: CC BY 3.0 IGO.

Kaminsky, G., R. K. Lyons, and S. L. Schmukler (2004): "Managers, Investors, and Crises: Mutual Fund Strategies in Emerging Markets," *Journal of International Economics*, 64, 113–134.

Kaufmann, C. (2023): "Investment Funds, Monetary Policy, and the Global Financial Cycle," *Journal of the European Economic Association*, 21, 593–636.

Koepke, R. and S. Paetzold (2024): "Capital flow data—A guide for empirical analysis and real-time tracking," *International Journal of Finance & Economics*, 29, 311–331.

Krueger, P., Z. Sautner, and L. T. Starks (2020): "The Importance of Climate Risks for Institutional Investors," *The Review of Financial Studies*, 33, 1067–1111.

Laeven, L. and A. Popov (2023): "Carbon taxes and the geography of fossil lending," *Journal of International Economics*, 144, 103797.

Luo, D. (2022): "ESG, Liquidity, and Stock Returns," *Journal of International Financial Markets, Institutions and Money*, 78, 101526.

Ma, F., H. Wu, and Q. Zeng (2024): "Biodiversity and Stock Returns," *International Review of Financial Analysis*, 95, 103386.

Maggiori, M., B. Neiman, and J. Schreger (2020): "International Currencies and Capital Allocation," *Journal of Political Economy*, 128, 2019–2066.

Monasterolo, I. and L. De Angelis (2020): "Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement," *Ecological Economics*, 170, 106571.

Nations, U. (2021): "Kunming Declaration: Ecological Civilization: Building a Shared Future for All Life on Earth," .

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2021): "Sustainable investing in equilibrium," *Journal of financial economics*, 142, 550–571.

——— (2022): "Dissecting green returns," *Journal of financial economics*, 146, 403–424.

Principles for Responsible Investment (PRI) (2024): "An Introduction to Responsible Investment: Biodiversity for Asset Owners," .

Ramos-Francia, P. Karlström, R. Montañez-Enríquez, and M. O. Busch (2023): "Stranded in the Wastelands? Natural Capital Depletion and Bank Deposit Reallocation," *SSRN Electronic Journal*.

Ritchie, H. (2021): "How Much of the World's Food Production is Dependent on Pollinators?" *Our World in Data*, https://ourworldindata.org/pollinator-dependence.

Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang (2023): "Firm-Level Climate Change Exposure," *The Journal of Finance*, 78, 1449–1498.

Seltzer, L. H., L. Starks, and Q. Zhu (2022): "Climate Regulatory Risk and Corporate Bonds," Working Paper 29994, National Bureau of Economic Research.

Svartzman, R., E. Espagne, G. Julien, H.-L. Paul, S. Mathilde, T. Allen, J. Berger, J. Calas, A. Godin, and A. Vallier (2021): "A'Silent Spring'for the Financial System? Exploring Biodiversity-Related Financial Risks in France," *Banque de France Working Paper*.

Sánchez-Bayo, F. and K. A. Wyckhuys (2019): "Worldwide Decline of the Entomofauna: A Review of its Drivers," *Biological Conservation*, 232, 8–27.

te Kaat, D., A. Raabe, and Y. Tian (2024): "Greening thy Neighbor: How the US Inflation Reduction Act Drives Climate Finance Globally," *Available at SSRN 4950931.*

Xin, W., L. Grant, B. Groom, and C. Zhang (2023): "Biodiversity Confusion: The Impact of ESG Biodiversity Ratings on Asset Prices," .

Zhou, Y., S. Wu, and S. Peng (2023): "Effect of Biodiversity Attentions on Stock Returns Across Different Sectors: Evidence from a Quantile-On-Quantile Method," Available at SSRN: https://ssrn.com/abstract=4849365 or http://dx.doi.org/10.2139/ssrn.4849365.

Appendix

A Data Appendix

Table A1 Variable Definitions and Data Sources

Variable	Definition	Unit	Source
$\Delta IHS(Share)_{i,j,c,t}$	Monthly change in IHS-transformed portfolio share of fund i allocated to recipient country c	%	EPFR, author calculated
$\Delta Share_{i,j,c,t}$	Monthly change in portfolio share of fund i allocated to recipient country c	%	EPFR, author calculated
$\Delta Ln(Share)_{i,j,c,t}$	Monthly change in logarithm of portfolio share of fund i allocated to recipient country c	%	EPFR, author calculated
$IHSShare_{i,j,c,t}$	IHS-transformed portfolio share of fund i allocated to recipient country c	%	EPFR, author calculated
$\Delta Benchmark_{i,j,c,t}$	Monthly average change in IHS-transformed portfolio shares of the benchmark that a specific fund i tracks	%	EPFR, author calculated
$\text{Flows}_{i,j,t}$	Monthly flows into fund i domiciled in country j, scaled by fund-level AUM	%	EPFR
$\text{Flows}_{i,j,c,t}$	Monthly flows into fund i-recipient country c pair, scaled by fund-level AUM	%	EPFR
$\text{AUM}_{i,j,t-1}$	Monthly lagged AUM of fund i domiciled in country j	$ billion	EPFR
$\text{Sustainable}_{i,j}$	=1 when a fund is classified as sustainable as per EPFR	0/1	EPFR
$\text{Return}_{i,j}$	Monthly performance of fund i	%	EPFR
$\text{Retail Share}_{i,j}$	The fraction of share classes within a fund marketed to retail investors	%	EPFR
$\text{ETF}_{i,j}$	=1 if a fund is an ETF	0/1	EPFR
$\text{Equity}_{i,j}$	=1 if a fund is an equity fund	0/1	EPFR
$\text{Biodiversity Share}_{i,j}$	Market value weighted percentage of a fund's AUM invested in companies with an active biodiversity policy	%	Bloomberg
$\text{Deviation}_{i,j,c}$	A fund's deviation in country allocation share from pre-KD, long-run (2015:M1-2021:M9) median	percentage points	EPFR
$\text{Overweight}_{i,j,c}$	= Deviation if $Deviation > 0$, 0 else	percentage points	EPFR
$\text{Underweight}_{i,j,c}$	= (-1) Deviation if $Deviation < 0$, 0 else	percentage points	EPFR
Post_{t}	=1 after 2021:M9	0/1	author calculated
$\text{Biodiversity Risk}_{c}$	Country-level share of endangered species	%	Giglio et al. (2023)
$\text{Weighted Biodiversity Risk}_{i,j}$	The weighted fund-level biodiversity risk	%	author calculation
High Risk_{c}	=1 if a country is in the upper 25% of biodiversity risk variable	0/1	author calculated
$\text{High Risk}_{i,j}$	=1 if a fund weighted biodiversity risk is in the upper 25% of the distribution	0/1	author calculated
$\text{Excess Biodiversity Risk}_{i,c}$	Country-level share of endangered species less the weighted average risk of all other countries in fund i's portfolio	%	author calculated
$\text{High Excess Risk}_{i,c}$	=1 if a country's excess biodiversity risk is in the upper 25% of the distribution	0/1	author calculated
High RLI Risk_{c}	=1 if a country's Red List Index is in the lowest 25% of the distribution	0/1	IUCN (2025), author calculated
High BHI Risk_{c}	=1 if a country's Biodiversity Habitat Loss Index is in the upper 25% of the distribution	0/1	Block et al. (2024), author calculated
$\text{Climate Policy Score}_{c}$	Bloomberg Government Climate Score	-	Bloomberg
$\text{Capital Account Openness}_{c}$	Chinn-Ito index	[0,1]	Chinn and Ito (2006)
GDP p.c_{c}	Quarterly PPP-adjusted GDP per capita in nominal USD	$	IMF
Rule of Law_{c}	Rule of law index	-	World Bank
$\text{Interest Rate Differential}_{c}$	Short-term interest rate differential vis-a-vis US	%	Haver, author calculation
$\text{Capitalization}_{c}$	Stock market capitalization over GDP	%	World Bank
$\text{Carbon Intensity}_{c}$	Carbon intensity over GDP	%	World Bank
$\text{Geopolitical Risk}_{c}$	Geopolitical risk index	-	Caldara and Iacoviello (2022); Caldara et al. (2023)
ND Gain Index_{c}	Country-specific net vulnerability to climate change, accounting for resilience	-	Initiative et al. (2023)
INFORM index_{c}	Impact of climate change on a country's capacity to cope with disasters and humanitarian crises	-	European Commission, Joint Research Centre
Credit Rating_{c}	Numerical credit rating	1-21	Moody's
$\text{Equity Return}_{c,t}$	Current stock market return	%	CEIC
$\text{Bond Yield}_{c,t}$	Current bond yield	%	CEIC
$FundAverageRisk_{i,c}$	Weighted fund-level average biodiversity risk, using current portfolio shares as weight and excluding the country itself	%	author calculated
$SameRegionAverageRisk_{c}$	Average regional biodiversity risk, excluding the country itself	%	author calculated
$OtherRegionAverageRisk_{c}$	Average biodiversity risk of all regions other than a country's region itself	%	author calculated
$BiodiversityActs_{c}$	Country-specific number of biodiversity-related actions in the 3 pre-KD years	-	FAOLEX, author calculated
$WildSpeciesActs_{c}$	Country-specific number of wild species-related actions in the 3 pre-KD years	-	FAOLEX, author calculated
$ForestryActs_{c}$	Country-specific number of forestry-related actions in the 3 pre-KD years	-	FAOLEX, author calculated
$FisheryActs_{c}$	Country-specific number of fishery-related actions in the 3 pre-KD years	-	FAOLEX, author calculated

B Robustness Checks in Detail

B.1 Additional Controls and Alternative Estimation Windows

Results documented throughout the paper are robust along multiple dimensions. In column (1) of Table A2, we control for a country's current stock returns and bond yields. This is important because changes in country allocation shares might be driven by valuation effects. The value of underlying securities in a fund's portfolio may raise portfolio shares in those securities unless fund managers actively divest from such holdings. Controlling for country-level returns also addresses endogeneity concerns that demand rather than supply factors explain our results. Country-time fixed effects added in Table A10 control yet more tightly for such demand factors, as reported below.

In column (2), we control for the average change in the portfolio allocations to a country, with the average computed across all funds having the same benchmark as a specific fund i. This helps rule out that results are driven by funds mirroring the benchmark they track. Again, our previous estimates remain significant.

In column (3), we drop funds belonging to the two largest fund families in our sample, Blackrock and Vanguard. The interaction coefficient of interest increases in magnitude relative to the benchmark estimate. This is evidence that the paper's findings are not driven by funds from dominant fund families.

In column (4), we drop funds investing a positive fraction of their AUM into the domicile country. Such funds may be fundamentally different from purely internationally investing funds, e.g., because they have a domestic investment mandate, and may only invest abroad for diversification purposes. Such domestically oriented funds may thus introduce home bias into our benchmark results. Column (4) shows that this concern is unwarranted, with a coefficient estimate being only marginally smaller than that in the benchmark specification.

In column (5), we drop the announcement month of the KD, which we treated as post-KD month in the benchmark specification. This also leaves our main result largely unaffected.

Next, we change the window size around the KD. While column (6) studies a one-pre- and one-post-month window, column (7) focuses on three and column (8) on four pre- and post-KD months. In all three cases, our benchmark results stand confirmed, with a statistical significance at least at the 10% level.

Table A2 Additional Controls and Alternative Estimation Windows

Dependent Variable:	Additional controls	Add benchmark	Drop 2 largest fund fammilies	Cross-border funds only	Drop 2021:M10	Windows 1/1	Windows 3/3	Windows 4/4
	$\Delta IHS(Share)_{i,j,c,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Post_t \times High\ Risk_c$	-1.575***	-0.665***	-1.546***	-1.260**	-1.152**	-1.622**	-0.900**	-0.665*
	(0.444)	(0.243)	(0.581)	(0.496)	(0.496)	(0.860)	(0.456)	(0.368)
$EquityReturn_c$	0.224***							
	(0.058)							
$BondYield_c$	0.004							
	(0.108)							
$\Delta Benchmark_{i,j,c,t}$		0.507***						
		(0.028)						
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,956	203,379	174,248	106,917	157,921	104,362	314,156	416,302
R-squared	0.334	0.451	0.304	0.293	0.375	0.542	0.217	0.167

The table is based on monthly fund-country-level data. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the double interaction between a post-KD dummy equal to one after 2021:M9, and a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution. The regressions include fund-time and fund-country fixed effects. The regression are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Column (1) controls for country-level stock returns and bond yields; column (2) for average IHS-transformed country allocation shares of a fund's benchmark; column (3) drops the two largest fund families, Blackrock and Vanguard; column (4) drops funds that invest some positive share of the AUM in their home country; column (5) drops the KD announcement month 2021:M10; columns (6)-(8) consider one, three, and four pre- and post-KD months for the estimation, respectively. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

B.2 Varying the Dependent Variable and Clustering Options

In Table A3, column (1), we control for the lagged IHS-transformed country allocation share to capture convergence effects in funds' portfolio allocations. The estimate of -1.02 implies that this only marginally reduces the economic significance of the benchmark results.

In columns (2) to (4) we modify the dependent variable. Column (2) employs the level of the IHS-transformed country allocation share, as opposed to the change used in the benchmark specification; column (3) computes the outcome as the *absolute* change in portfolio allocation shares; and column (4) uses the change in the logarithm of portfolio shares. The latter reduces observations significantly, as zero allocations drop out and we can hence only consider the intensive margin of portfolio adjustments. In all specifications, our results survive qualitatively, but they are estimated more imprecisely in columns (3) and (4).

In columns (5)-(7), we use alternative clustering strategies. Column (5) clusters standard errors at the fund level, following Converse and Mallucci (2019). In column (6), we double cluster at the fund and country level, as in Forbes et al. (2016). Column (7) clusters at the fund-country level. In all cases, the statistical significance of the double interaction of interest exceeds the benchmark results, which hence characterizes the latter as quite conservative.

Table A3 Varying the Dependent Variable and Clustering Options

					SE (fund level)	SE (fund and country level)	SE (fund-country level)
Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$	$IHSShare_{i,j,c,t}$	$\Delta Share_{i,j,c,t}$	$\Delta Ln(Share)_{i,j,c,t}$		$\Delta IHS(Share)_{i,j,c,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post_t \times High\ Risk_c$	-1.018**	-0.010**	-0.088	-1.804*	-1.340***	-1.340***	-1.340***
	(0.417)	(0.004)	(0.054)	(1.008)	(0.094)	(0.474)	(0.144)
$LaggedShare_{i,c,j,t}$	-34.816***	0.382***					
	(1.494)	(0.038)					
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210,914	210,914	210,914	155,808	210,914	210,914	210,914
R-squared	0.467	0.998	0.258	0.344	0.303	0.303	0.303

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share (columns 1 and 5-7), the level of the IHS-transformed country share (column 2), the absolute change in the country share (column 3), and its log-difference (column 4). The key regressor is the double interaction between a post-KD dummy equal to one after 2021:M9, and a dummy equal to one if the country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution. Columns (1)-(2) control for the lagged level of the IHS-transformed country allocation share. The regressions include fund-time and fund-country fixed effects. The regressions are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Standard errors are clustered at the country level (columns 1-4), at the fund level (column 5), at the fund and country level (column 6), and at the fund-country level (column 7). Standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

B.3 Differentiating by Fund Domicile

Most funds are domiciled in Ireland, Luxembourg and the US, with the share of observations in our matched sample in these jurisdictions corresponding to 14.0%, 32.3%, and 30.8%, respectively.

In Table A4, we first drop these three domiciles sequentially from the sample (columns 1-3). Afterwards, we restrict the analysis to each at a time (columns 4-6). Across all these specifications, our coefficient of interest is statistically significant and lies in the range of -0.9

and -1.4, compared with the benchmark estimate of -1.34 in column (6) of Table 2. Thus, the benchmark results are not driven by specific domicile countries, and hold for funds domiciled anywhere.

Table A4 Differentiating by Fund Domicile

Domicile:	Drop LU	Drop US	Drop IE	Only LU	Only US	Only IE
Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times High\ Risk_c$	-1.336**	-1.228**	-1.386***	-1.360***	-1.396***	-0.921*
	(0.519)	(0.511)	(0.501)	(0.503)	(0.518)	(0.511)
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	142,725	125,790	181,288	68,189	55,772	29,626
R-squared	0.312	0.301	0.304	0.289	0.317	0.293

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the double interaction between a post-KD dummy equal to one after 2021:M9, and a dummy equal to one if the country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution. The regressions include fund-time and fund-country fixed effects. The regressions are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Columns (1)-(3) drop funds domiciled in Luxembourg, the US and Ireland, respectively; columns (4)-(6) focus only on these domiciles. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

B.4 Placebo Periods

In Table A5, we estimate 6 different placebo specifications, each of which estimates Equation 1 on samples of the same length as our baseline analysis around the 6 months that precede our benchmark sample period, i.e., we treat each of the months January to June 2021 as placebo event month.[A1] None of these periods witnessed biodiversity-related policy initiatives of global scope, as also corroborated by the lack of significant upward movements in attention to financially-relevant biodiversity issues shown in Figure 2. Thus, the double interaction between country-level biodiversity risk and a dummy that takes the value of one for the placebo event month and the month afterwards should be statistically insignificant. Results in columns (1) to (6) confirm this, further buttressing the parallel trend assumption underlying our difference-in-differences analysis.

[A1] We do not estimate placebo specifications around July 2021 as August 2021—a pre-event month in our benchmark analysis—would be included in the placebo regression.

Table A5 Placebo Periods

	2021:M6	2021:M5	2021:M4	2021:M3	2021:M2	2021:M1
Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$Post_t \times High\ Risk_c$	-0.072	0.259	0.036	-0.171	0.083	-0.309
	(0.510)	(0.372)	(0.360)	(0.414)	(0.487)	(0.517)
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	201,652	200,349	197,108	193,985	189,719	188,307
R-squared	0.305	0.289	0.290	0.288	0.293	0.298

The table is based on monthly fund-country-level data for the period January to June 2021, which serve as placebo events. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the double interaction between a dummy equal to one for the respective placebo event month and the subsequent month and a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution. The regressions include fund-time and fund-country fixed effects. The regressions are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

B.5 Alternative Measures of Biodiversity Risk

We employ two alternative biodiversity risk variables, the RLI and BHI, portrayed in Section 2.3. Mirroring the use of our main gauge of country-level biodiversity risk, we focus on extremely high risk. For this, we transform both indices into dummies. For the RLI, the dummy equals one for countries in the upper 25% of the in-sample distribution. For the BHI, the dummy equals one for countries in the lower 25% of the in-sample distribution, indicating larger biodiversity losses.

Columns (1) and (2) for the RLI and (3) and (4) for the BHI report estimation results in a one-month and two-month window around the KD, respectively. The interaction coefficient enters negatively regardless of the specification. Interestingly, the RLI and BHI enter statistically significantly in different window sizes. The interaction using the RLI is statistically significant in the one-month window only, and the interaction using the BHI in the two-months window, suggesting some sensitivity of results to the measure of biodiversity risk. Overall, however, these tests confirm our benchmark result using the alternative measures of biodiversity risk discussed here.

Table A6 Alternative Biodiversity Measures

Dependent Variable:	1/1	2/2	1/1	2/2
	$\Delta IHS(Share)_{i,j,c,t}$			
	(1)	(2)	(3)	(4)
$Post_t \times High\ RLI\ Risk_c$	-1.576*	-0.583		
	(0.830)	(0.555)		
$Post_t \times High\ BHI\ Risk_c$			-0.435	-0.857**
			(0.602)	(0.419)
Fund-Country FE	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes
Observations	110,738	223,811	99,832	201,474
R-squared	0.512	0.290	0.538	0.299

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the interaction between a post-KD dummy equal to one after 2021:M9, and a dummy equal to one if the country-level biodiversity risk, as measured by the BHI or RLI, is in the upper or lower 25% of the in-sample distribution, respectively. The regressions include fund-time and fund-country fixed effects. The regressions are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

B.6 Excess Biodiversity Risk

We apply a concept of excess risk a la Converse and Mallucci (2019) to explore whether funds are sensitive to deviations from average risk in the portfolio. Excess risk is defined as difference between the country-specific risk and the portfolio share weighted average biodiversity risk of all other countries in a fund's portfolio.

Table A7 shows the results of using the excess biodiversity risk interacted with the post-KD dummy as main regressor. The double interaction coefficient is statistically significant when we employ the continuous version of the excess risk variable (column 1). In column (2), we transform the excess risk variable into a dummy equal to one for values above the 75th percentile of the in-sample distribution, denoting extremely high excess risk. We notice a 10-fold increase in the coefficient size at unchanged statistical significance. This lends credence to biodiversity risk being priced as downside risk factor, not upside opportunity. In column (3), we horserace the excess biodiversity risk dummy with the biodiversity risk dummy as used in the benchmark regressions, with the latter ignoring the average risk in other countries. The dummy as defined in the benchmark regressions wins the horse race, meaning that fund managers mostly care about a country's own biodiversity risk, and pay less attention to how this country-specific risk relates to the average portfolio risk. This result is consistent with our previous evidence on within-portfolio contagion discussed in Section 4. There, we show that—in response to the KD—a high average biodiversity risk in the portfolio does not induce fund managers to increase their portfolio shares in less risky countries that the fund is already invested in. Instead, fund managers open entirely new positions in the same region when the KD was announced.

Table A7 Excess Biodiversity Risk

Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$		
	(1)	(2)	(3)
$Post_t \times Excess\ Biodiversity\ Risk_{i,c}$	-0.084**		
	(0.038)		
$Post_t \times High\ Excess\ Risk_{i,c}$		-0.807**	0.464
		(0.373)	(0.442)
$Post_t \times High\ Risk_c$			-1.715**
			(0.660)
Fund-Country FE	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes
Observations	210,890	210,890	210,890
R-squared	0.302	0.302	0.303

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the double interaction between a post-KD dummy equal to one after 2021:M9, and the continuous country-level excess biodiversity risk (column 1) or a dummy equal to one if country-level excess biodiversity risk exceeds the 75th percentile of its in-sample distribution (column 2). Column (3) horseraces the latter with the post-KD-biodiversity risk dummy from our benchmark analysis. The regressions include fund-time and fund-country fixed effects. The regressions are estimated via weighted least squares, using a fund's pre-KD AUM as weight. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

C Shifts in Relative Fund Returns

We argue that the rise in transition risk associated with the KD triggered a shift in expectations of future cash flows away from highly ecosystem-dependent investments towards less nature-exposed investments. In this section, we provide evidence that this relative change in expected future cash flows instantly manifests itself in a shift in realized returns. Markets immediately priced the KD, as realized returns of funds predominantly exposed to low-biodiversity risk countries increased relative to funds mostly investing in high-biodiversity countries.

We reach these conclusions by regressing monthly fund returns on the interaction between the post-KD dummy and the fund-level share of holdings with biodiversity commitment. As per Section 3.6, a higher fund-level commitment entails higher exposure to low-biodiversity risk countries. Column (1) of Table A8 shows an increase in relative returns of funds with a higher biodiversity commitment after the KD. The relevant coefficient is positive and statistically significant at the 1% level.

In a next step, we address endogeneity concerns. The above-identified return increase could be driven by simultaneous portfolio reallocations by fund managers and/or by ultimate investors shifting flows from funds with low to high-biodiversity commitment. To isolate the immediate change in the pricing of expected cash flows, we conduct two sample splits. First, we split the sample into funds with few portfolio reallocations in the four months around the KD vs. those with more active reallocations. Specifically, we take the standard deviation of the fund-country-specific portfolio shares in the two pre-KD and two post-KD months as measure of fund managers' reallocation activeness, and split the fund sample at the median.[A2] As per columns (2) and (3), the finding survives in both sub-samples: Returns for funds with greater biodiversity commitment increase, implying that the return differentials identified in column (1) cannot be an endogenous result of fund managers' reallocations.

[A2] We scale the fund-country-specific portfolio share standard deviations by the corresponding means to control for fund size. The results are similar without scaling.

Second, we split the sample into funds receiving fewer vs. more inflows from ultimate investors in the four months around KD, scaled by fund-specific AUM, with the split applied at the sample median. Results in columns (4) and (5) confirm that the return response is also unrelated to ultimate investors' allocation decisions.

Table A8 Evidence for Fund Returns

	full sample	fewer portfolio reallocations	more active portfolio reallocations	lower inflows	higher inflows
Dependent Variable:	$\text{Return}_{i,j,t}$				
	(1)	(2)	(3)	(4)	(5)
$Post_t \times BiodiversityShare_{i,j}$	0.011***	0.007*	0.018***	0.011**	0.010**
	(0.003)	(0.004)	(0.006)	(0.004)	(0.005)
Domicile-Time FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
Observations	6,199	3,067	3,119	3,092	3,099
R-squared	0.744	0.814	0.639	0.680	0.784

The table is based on monthly fund-level data from 2021:M8-2021:M11. The dependent variable is the monthly fund-level return. The key regressor is the interaction between the post-KD dummy and the fund-specific share of holdings with biodiversity commitment. Column (1) estimates the regression on the full fund sample. In columns (2) and (3), we split the sample at the median into funds with more and less active reallocations in country-specific portfolio shares, with activeness defined by the standard deviation of fund-country-specific portfolio shares in the two pre-KD and two post-KD months. In columns (4) and (5), we split the sample into funds with total inflows during the benchmark sample period into the lower 50% of the distribution and those in the upper 50%. The regressions include domicile-time and fund fixed effects, and are estimated via weighted least squares, using a fund's pre-event AUM as weight. Standard errors clustered at the fund level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

D Additional Tables

Table A9 Fund Heterogeneity: Unweighted Results

Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post_t \times High\ Risk_c$	-1.451**	-0.605	-1.268**	-1.174**	-1.213**	-1.281**	-1.044**
	(0.581)	(0.421)	(0.545)	(0.524)	(0.536)	(0.560)	(0.429)
$Post_t \times High\ Risk_c \times ETF_{i,j}$	0.546						
	(0.354)						
$Post_t \times High\ Risk_c \times Equity_{i,j}$		-1.015					
		(0.790)					
$Post_t \times High\ Risk_c \times RetailShare_{i,j}$			-0.008*				
			(0.004)				
$Post_t \times High\ Risk_c \times Sustainable_{i,j}$				-0.691			
				(0.444)			
$Post_t \times High\ Risk_c \times BiodiversityShare_{i,j}$					-0.002		
					(0.014)		
$Post_t \times High\ Risk_c \times Return_{i,j}$						0.179	
						(0.157)	
$Post_t \times Overweight_{i,j,c}$							-0.897***
							(0.182)
$Post_t \times High\ Risk_c \times Overweight_{i,j,c}$							0.249
							(0.455)
$Post_t \times Underweight_{i,j,c}$							0.884***
							(0.127)
$Post_t \times High\ Risk_c \times Underweight_{i,j,c}$							-0.554***
							(0.153)
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210,914	210,914	210,914	210,914	142,064	210,914	210,914
R-squared	0.289	0.289	0.289	0.289	0.280	0.289	0.296

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the triple interaction between a post-KD dummy equal to one after 2021:M9, a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution, and the following fund characteristics fixed in the pre-KD period: an ETF dummy, an equity fund dummy, a fund's fraction of share classes marketed to retail investors, a dummy indicating sustainable funds, a fund's share of holdings with biodiversity commitment, a fund's performance, and a fund's over- and underweight position vis-a-vis a specific country. The regressions include fund-time and fund-country fixed effects. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A10 Fund Heterogeneity: Country-Time Fixed Effects

Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$Post_t \times High\ Risk_c \times ETF_{i,j}$	0.527						
	(0.321)						
$Post_t \times High\ Risk_c \times Equity_{i,j}$		-0.610					
		(0.734)					
$Post_t \times High\ Risk_c \times RetailShare_{i,j}$			-0.007*				
			(0.004)				
$Post_t \times High\ Risk_c \times Sustainable_{i,j}$				-0.494			
				(0.381)			
$Post_t \times High\ Risk_c \times BiodiversityShare_{i,j}$					-0.010		
					(0.013)		
$Post_t \times High\ Risk_c \times Return_{i,j}$						0.140	
						(0.147)	
$Post_t \times Overweight_{i,j,c}$							-0.938***
							(0.181)
$Post_t \times High\ Risk_c \times Overweight_{i,j,c}$							0.275
							(0.382)
$Post_t \times Underweight_{i,j,c}$							0.803***
							(0.112)
$Post_t \times High\ Risk_c \times Underweight_{i,j,c}$							-0.403**
							(0.160)
Fund-Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	210,908	210,908	210,908	210,908	142,060	210,908	210,908
R-squared	0.306	0.306	0.306	0.306	0.298	0.307	0.314

The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressor is the triple interaction between a post-KD dummy equal to one after 2021:M9, a dummy equal to one if country-level biodiversity risk exceeds the 75th percentile of its in-sample distribution, and the following fund characteristics fixed in the pre-KD period: an ETF dummy, an equity fund dummy, a fund's fraction of share classes marketed to retail investors, a dummy indicating sustainable funds, a fund's share of holdings with biodiversity commitment, a fund's performance, and a fund's over- and underweight position vis-a-vis a specific country. The regressions include fund-time, country-time and fund-country fixed effects. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A11 Varying the Threshold to Define High-biodiversity Risk Countries

	25th percentile	33rd percentile	median	67th percentile
Dependent Variable:	$\Delta IHS(Share)_{i,j,c,t}$			
	(1)	(2)	(3)	(4)
$Post_t \times High\ Risk_c$	-0.648	-0.490	-0.430	-1.021**
	(0.501)	(0.444)	(0.429)	(0.449)
Fund-Country FE	Yes	Yes	Yes	Yes
Fund-Time FE	Yes	Yes	Yes	Yes
Observations	210,914	210,914	210,914	210,914
R-squared	0.301	0.301	0.301	0.302

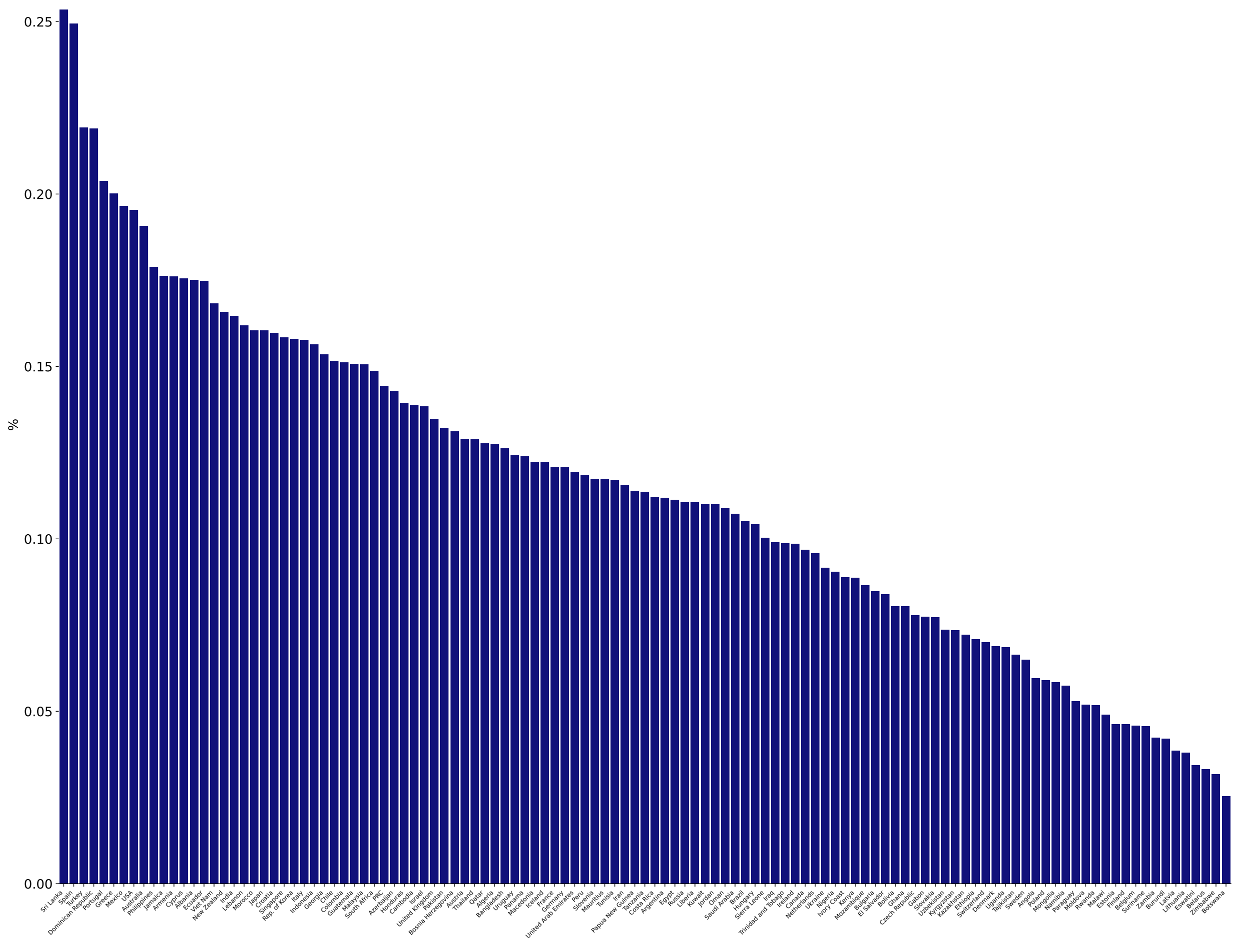
The table is based on monthly fund-country-level data from 2021:M8-2021:M11. The dependent variable is the change in the IHS-transformed fund-country-specific allocation share. The key regressors are the double interaction between a post-KD dummy equal to one after 2021:M9, and dummies equal to one if country-level biodiversity risk exceeds the 25th, 33rd, 50th, or 67th percentile of the in-sample distribution, respectively. The regressions include fund-time and fund-country fixed effects. Regressions are weighted by a fund's pre-KD AUM. Standard errors clustered at the country level are shown in parentheses. *, ** and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A12 Correlation Between Macroeconomic Variables

Variables	Biodiversity $Risk_c$
GDP $p.c_c$	-0.223
$Rating_c$	0.191
Capital Account $Openness_c$	-0.065
Rule of Law_c	-0.190
Interest Rate $Differential_c$	-0.103
$Capitalization_c$	0.123
ND Gain $Index_c$	-0.182
Climate Policy $Score_c$	-0.244
Carbon $Intensity_c$	0.094
INFORM $Risk_c$	0.284
Geopolitical $Risk_c$	0.275

E Additional Figures

Figure A1 Distribution of Biodiversity Risk Across Countries



Note: This figure shows the cross-country distribution of the Endangered Species Score as used in the benchmark regression in column (6) of Table 2. Source: Giglio et al. (2023)