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Does financing biodiversity reduce biodiversity loss? Evidence from EU funding of science and innovation

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Abstract

Recent calls for greater private capital in biodiversity finance often overlook the question of effectiveness. This article interrogates the assumption that the increased financing being called for directly reduces species-level loss. Using data on European Union-funded projects across twenty-six countries over two decades, I discover that conservation funding has been most effective in supporting forest preservation, but largely ineffective for other ecological-based measures of biodiversity. Applying a dynamic difference-in-differences framework, I show that conservation funding generally yields minimal ecological gains. In contrast, funding for biodiversity research expands biodiversity data coverage, though additional investment produces little marginal improvement. A geospatial analysis of bird sightings reveals delayed and spatially dependent impacts on avian biodiversity near funded projects. Additionally, I explore biotechnology-related biodiversity projects as a channel for private investment. These projects generate patents and genetic resources that can be commercialized, suggesting pathways for aligning biodiversity outcomes with investor incentives.

Keywords: biodiversity finance; biodiversity loss; science and innovation; conservation biotechnology.
JEL classifications: G12, G30, Q57.

1. Introduction

Assessment of the actual ecological impact of conservation and biodiversity initiatives is notoriously difficult. Of concern to policymakers is the fact that significant public capital has been expended toward Convention on Biological Diversity (CBD) pledges aimed at reducing the rate of biodiversity loss; recent estimates put the global spend on biodiversity finance at USD 78–91 billon per year[1] (OECD 2020). The question of whether or not increases in this funding over time have been effective remains an open debate in the conservation literature (Butchart, Stattersfield, and Collar 2006; Kerkvliet and Langpap 2007; Hoffmann et al. 2010; Bolam et al. 2021) and is now more germane as the finance literature has become animated with advocating for private capital to fill the biodiversity financing gap which is estimated at USD 722–967 billion per year (TNC 2020; Karolyi and Tobin-de la Puente 2023; Flammer, Giroux, and Heal 2025a). The question is nontrivial

[1] This estimate combines national expenditure across eighty-one countries of USD 67.8 billion per year, international public expenditure of USD 3.9–9.3 billion per year and private investment of USD 6.6–13.6 billion per year.

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because it is not clear whether the scale-up of private capital, through blended finance arrangements (Flammer, Giroux, and Heal 2025a), being advocated for, will catalyze the achievement of CBD targets beyond what has already been achieved by public finance. Furthermore, not much is known about the impact of biodiversity finance on biodiversity loss.[2] Can biodiversity finance actually reverse biodiversity loss? Is financing biodiversity a worthwhile trade-off for firms and investors to make or does biodiversity loss reflect forces which are beyond the capacity of capital to address?

While China accounts for a third of the USD 67.8 billion estimate of public expenditure on biodiversity among the eighty-one countries examined by the Organisation for Economic Co-operation and Development (OECD) (OECD 2020), the European Union (EU) has long been a leader in biodiversity finance, having spent approximately USD 14.5 billion per year on biodiversity between 2015 and 2017,[3] with much of this capital coming from its science and innovation programs which fund research through competitive funding calls (European Union 2018). The EU setting, therefore, provides a kind of natural laboratory for empirical investigations which can begin to offer some answers to these questions.

Biodiversity finance policy within the EU is intensely focused on biodiversity research based on the logic of conservation science which argues that deepening scientific knowledge and understanding of the root causes of biodiversity loss will translate into more effective conservation action[4] (Franklin 1993; Kareiva and Marvier 2012; Ando and Langpap 2018). This policy rationale is informed by a vast literature which demonstrates that scientific understanding of biodiversity and biodiversity loss is not only limited and contested,[5] but in many respects is also nascent and unsettled science[6] (Kim and Byrne 2006; Barnosky et al. 2011; Mendenhall, Daily and Ehrlich 2012; Leung et al. 2020; Oliver et al. 2021; Leung et al. 2022; Leung et al. 2022; Loreau et al. 2022; Murali et al. 2022; Puurtinen et al. 2022). Furthermore, it is well established that ecological outcomes are influenced by complex ecological dynamics and a range of uncontrollable and unobservable factors (e.g., infectious diseases, invasive species, natural selection). These ecological phenomena reflect the fact that nature is complex and is characterized by infinite dependencies and interactions which we cannot even begin to fathom. These features of nature, which have come to be known in the ecological literature as ecological complexity (Loehle 2004; Mazzocchi 2008; Parrott 2010; Bradbury et al. 2014), complicate both the science and practice of conservation.

Motivated by the policy rationale of the biodiversity research–conservation nexus (Srivastava and Vellend 2005; Sandbrook et al. 2013; Pettorelli, Safi, and Turner 2014; Velasco et al. 2015; Titley, Snaddon, and Turner 2017; Estoque 2024), which views biodiversity research as a critical input for effective conservation, I analyze the financing of 8,350 biodiversity projects funded by the European Commission (EC) and national science funding agencies across Europe over the last two decades.[7] I investigate the effectiveness of financing of these projects for both local-level and country-level biodiversity outcomes.

[2] The most authoritative global study on the impact of conservation, conducted by 164 scientists and conservationists and published in *Science*, explicitly noted that "we have no data on the relationship between expenditure on biodiversity and conservation success," underscoring the absence of empirical evidence linking biodiversity finance to biodiversity outcomes (Hoffmann et al. 2010).

[3] This estimate covers direct and indirect biodiversity expenditure across 12 programs: European Earth Observation Programme (Copernicus), The Framework Programme (FP) for Research and Innovation, European Regional Development Fund, Cohesion Fund, European Agricultural Guarantee Fund, European Agricultural Fund for Rural Development, European Maritime and Fisheries Fund, Programme for the Environment and Climate Action, Instrument for Pre-accession Assistance, European Neighbourhood Instrument, Development Cooperation Instrument, Partnership instrument for cooperation with third countries.

[4] A stated aim of the 2030 EU Biodiversity Strategy is to finance the production of actionable knowledge to tackle the direct and indirect drivers of biodiversity loss and ecosystem degradation.

[5] See Cardinale et al. (2018) for a review of the ongoing scientific debates.

[6] This recent series of articles published in *Nature* demonstrate how hotly contested this area of science is: Leung et al. 2020; Leung et al. 2022; Leung et al. 2022; Loreau et al. 2022; Murali et al. 2022; Puurtinen et al. 2022.

[7] The data is for projects financed between 2003 and 2023, representing twenty-one years of data on biodiversity finance across Europe.

The detailed project data, which are from the Biodiversa+ database maintained by the European Biodiversity Partnership, allow me to categorize projects as either research-oriented (RO) or conservation-oriented (CO) and empirically test the differential impact of each.

Although the data do not allow me to directly establish a moderation effect, the logic of conservation science suggests that biodiversity research likely moderates the ecological impact of conservation action[8] (Kareiva and Marvier 2012). A more testable implication of the biodiversity research–conservation nexus is that CO projects should have more of a direct link to ecological outcomes while RO projects should have more of a direct impact on efforts to collect, monitor, and analyze biodiversity data. I test these hypotheses by linking the financing of CO projects[9] firstly to geocoded data of bird sightings from the eBird Observation Dataset and then to multispecies country-level measures of species integrity, species protection, endangered species risk and deforestation for the twenty-six countries in the dataset. The measures of species integrity and species protection are two of the three Map of Life indicators developed by the Group on Earth Observations Biodiversity Observation Network (GEO BON) using geospatial data, while the measures of endangered species risk and deforestation are from United Nations data monitoring country progress toward Sustainable Development Goal (SDG) fifteen targets. SDG 15 (Life on Land) commits countries to twelve targets relating to protecting terrestrial ecosystems, combating deforestation and halting biodiversity loss. I focus on two of the twelve indicators, namely, proportion of land area covered by forest and the Red List Index (RLI) of Threatened Species. In keeping with the predictions of the biodiversity research–conservation nexus, I then separately link the financing of RO biodiversity projects to a country level measure of biodiversity data coverage. The measure, which captures the availability of species information through biodiversity research, rounds out the list of the three Map of Life indicators.

As financing is an input that enables activities that address biodiversity loss but is unlikely to be a direct driver, it is difficult to claim that an additional unit of financing reduces or increases biodiversity outcomes. Furthermore, it is theoretically unsound to assume a direct relationship between financing and biodiversity outcomes as complex ecological dynamics and measurement error complicate efforts to establish causal relationships.[10] I, therefore, interpret the direction of the relationships I examine in terms of the effectiveness or ineffectiveness of financing in supporting the projects and conservation initiatives aimed at achieving biodiversity outcomes. Focusing on the direction rather than the magnitude of the effect provides a more simplified approach as my main empirical interest is around interrogating the assumption of a positive welfare effect of biodiversity finance; an assumption which underpins much of the calls for increased financing toward biodiversity. Focusing on the direction also has the advantage of providing a clear signal about whether additional financing is generally effective or counterproductive as the direction captures meaningful information about the consistency of either a positive or negative welfare effect.[11]

While I adopt econometric tools designed for causal inference, I do not claim that the estimated relationships represent strict causal effects. Rather, these tools are employed to structure comparison groups, address treatment heterogeneity, reduce bias from time

[8] This is an empirical implication of the policy rationale which argues that biodiversity research increases the effectiveness of conservation action.

[9] Despite the focus of EU biodiversity policy on research, conservation-oriented projects in the Biodiversa+ dataset have received 68 percent of biodiversity funding over the last twenty years compared to 38 percent for research-oriented projects.

[10] The true data-generating process in ecology is nonlinear, high-dimensional, and only partially observed. Even perfect treatment-control design cannot overcome these inherent epistemic limitations.

[11] This approach aligns with the literature on policy learning under uncertainty and causal inference in complex adaptive systems (Holland 2006; Bentley and Anandhi 2020) and allows me to to evaluate whether the welfare signal of biodiversity finance is consistently positive, negative, or null across measures and margins

trends in a honest parallel trends framework (Rambachan and Roth 2023) and isolate directional signals in the data. Given the complexity of ecological systems, I adopt a pragmatic view and interpret the estimates as evidence of effectiveness, not proof of causality.[12] This inclination toward epistemic modesty is supported by sensitivity tests that challenge the robustness of the identifying assumption which informs the empirical design.[13] Despite the impediments posed by identification, three core insights were gleaned from the empirical analysis.

First, financing of CO projects appears to be most effective for forest conservation but less so for other ecological-based measures of biodiversity. Second, financing of biodiversity research expands biodiversity data coverage but is less effective at the margin. Third, a biotechnology channel offers suggestive evidence that greater private sector engagement is associated with increased biotech innovation in biodiversity projects—suggesting a viable mechanism to both incentivize and compensate private capital. In what follows, I provide a more detailed preview of these findings.

At the country-level, the results suggest that financing of CO projects at the extensive margin has been most effective for forest conservation but less so for the indicators which measure species integrity, species protection, and extinction risk of endangered species. As land use change and invasive species are significant factors in driving biodiversity loss, I develop measures for these two factors and include them, along with other controls, in these CO country-level analyses.[14] When these controls are included, the positive result for forest conservation survives and actually strengthens.[15] As it relates to RO projects and their impact on biodiversity data coverage at the extensive margin, as predicted by the biodiversity research–conservation nexus, the results show a positive and statistically significant impact indicating that, on average, funding helps improve the collection and availability of biodiversity data. I obtain similar results at the intensive margin, where projects financed above the median make up the sample.

Correspondingly, the main finding from the local-level geospatial analysis of the eBird data is that biodiversity financing of CO projects appears to have a delayed effect on avian biodiversity which is most consistently discernible for bird sightings reported within a 0–50 km radius of financed projects. These results hold across dynamic estimates which use the 55 million project–year observations in the full sample of funded projects[16] and also when the two countries with the largest number of observations are excluded, but wash out in estimation of long differences and a robustness test using the EU Common Bird Index as an alternate measure of avian biodiversity.

A key unresolved issue in mobilizing private capital for biodiversity finance is the lack of clear compensation mechanisms, given that most biodiversity projects are capital-intensive but not revenue generating. One potential incentive lies in biotechnology applications with commercial potential, particularly those in medical, pharmaceutical, and patentable domains. This approach is exemplified by the Rhino Bond, which finances the use of DNA analysis, artificial insemination, and ecological genetics to support black rhino populations in South Africa (Medina and Scales 2024). Another example is Colossal Biosciences, a US firm that raised USD 60 million in Series A funding to pursue de-extinction technologies

[12] Empirically investigating the question of effectiveness can provide useful, policy-relevant inference even in the absence of strict causality.

[13] The sensitivity tests are from the Rambachan and Roth (2023) procedure implemented in Section 5.

[14] I use the percentage of agriculture land and urban land area for each country to construct a measure of land use ratio and obtain data from the Global Register of Introduced and Invasive Species which I use to construct an invasive species ratio for each country.

[15] A possible reason we might see consistent positive results for forest cover is because land-cover–based indicators are generally more amenable to project-based intervention than species-level dynamics. Land cover can respond relatively quickly and measurably to conservation efforts, with observable changes detectable through remote sensing, whereas species dynamics evolves over longer horizons and is shaped by diffuse ecological and climatic pressures that are harder to influence through individual projects. Afforestation, wetland creation, invasive species removal, or agricultural set-asides produce immediate, observable land-cover change.

[16] That is, both conservation-oriented and research-oriented projects.

using ecological genetics (Farrow 2022; Saul 2022). Co-founded by George Church, a pioneer in CRISPR–Cas9, the company represents a commercially oriented model of conservation biotechnology. A longer-standing example is the Crop Diversity Endowment Fund (Crop Trust), established in 2004 to support the Svalbard Global Seed Vault. Now valued at approximately USD 317 million, the Crop Trust finances conservation of plant genetic resources through returns from low-risk investments and offers opportunities tailored to private investors[17] (Dempewolf, Krishnan, and Guarino 2023; Theissinger et al. 2023).

The Biodiversa+ database provides a basis to assess such biotechnology-oriented biodiversity projects. Using keyword-based text analysis of project abstracts, I identify biotech-related initiatives[18] and link their financing to two measurable outcomes: biotechnology patents and DNA sequencing. To proxy for private capital, I use the number of financial institutions per country that have signed the Finance for Biodiversity (FfB) Pledge. As the FfB pledge only became active in 2021, I make use of another proxy with a longer time series, namely, data on private Development Finance for Biodiversity (DFfB) flows reported by the OECD. These data provide a conservative measure of philanthropic commitments and private capital mobilized by development finance institutions and allows me to link to well established blended finance mechanisms (Flammer, Giroux, and Heal 2025b) for private investment directed toward biodiversity in the development finance arena. The findings suggest a commercialization pipeline which leverages initial government investment in basic science around biodiversity.

The foregoing insights documented in this article contribute to the emerging literature on biodiversity finance (Karolyi and Tobin-de la Puente 2022; Giglio et al. 2023; Garel et al. 2024; Flammer, Giroux, and Heal 2025a) by taking a step back to ask whether the increased deployment of private capital called for in these papers will actually be effective in addressing biodiversity loss and meeting biodiversity targets. This is an important question in light of what appears to be a collective failure of capital, both private and public, to significantly move the needle on climate targets (Stoddard et al. 2021).

The article also advances the conceptualization and measurement of biodiversity outcomes in financial research, which has largely relied on indirect proxies. I introduce multispecies composite indicators from Map of Life, which directly measure species integrity, protection, and data coverage and are more reflective of the metrics used in ecological science than the indirect measures used in, for example, Coqueret, Giroux, and Zerbib (2025) and Garel et al. (2024). Additionally, the Map of Life indicators, as well as the SDG 15 indicators, have significant policy relevance as they have formally been adopted in the monitoring framework of the Kunming-Montreal Global Biodiversity Framework (CBD/SBSTTA/26/2).[19]

While studies in the broader economics literature have examined the decline or extinction of keystone species such as African elephants through poaching (Brennan and Kalsi 2015), vultures in India (Frank and Sudarshan 2024), the North American bison (Taylor 2011; Feir, Gillezeau, and Jones 2024; Taylor and Weder 2024), sharks (Erhardt and Weder 2020; Taylor and Weder 2024), the northern white rhinoceros (Hildebrandt et al. 2018; 't Sas-Rolfes and Emslie 2024), and forests in India and other countries (Foster and Rosenzweig 2003), species-level geospatial indicators developed by ecologists have not, to my knowledge, been applied in empirical finance. This article, therefore, brings the broader economics literature into closer conversation with the natural sciences and is one of the first to explore the interaction between biodiversity research and conservation action.

17 In online Appendix D9, I present hand collected data from the Crop Trust financial reports. The data indicates that there is a positive correlation (30 percent) in the growth of the fund over time and a broadening of the range of species of plant genetic material deposited at the Svalbard Vault. I obtained the financial reports from: https://www.croptrust.org/who-we-are/about/annual-reports-financial-statements/ and the Svalbard data from: https://seedvault.nordgen.org/.

18 The classification procedure is detailed in online Appendix B4.

19 CBD/SBSTTA/26/2 Monitoring framework for the Kunming–Montreal Global Biodiversity Framework https://www.cbd.int/doc/c/8fad/193d/e30d0be38e537019cdbefb35/sbstta-26-02-en.pdf.

By employing scientifically validated composite indices (Jetz et al. 2012a, 2012b; Pereira et al. 2013; Navarro et al. 2017; Jetz et al. 2022), I align with the economics literature's emphasis on direct measurement while expanding the scope beyond single species. These indicators capture broader biodiversity patterns within countries while retaining species-level granularity which is absent in economic models which eschew direct measurement and treat biodiversity loss in the aggregate (Ando and Langpap 2018; Taylor and Weder 2024; Giglio et al. 2024). Furthermore, the identification of multiple measures which represent distinct aspects of biodiversity avoids oversimplification by providing a more nuanced and comprehensive picture of what is a complex scientific concept.

The article further contributes by examining genetic diversity, a less explored but crucial dimension of biodiversity, linking it to biotechnology-related investments. This approach complements recent work on genetic diversity as an innovation outcome (Moscona and Sastry 2023) and the role of government funding in facilitating innovation through basic science funding (Babina et al. 2023; Bergeaud et al. 2025). Finally, the approach I take to interpreting the direction rather than the magnitude of biodiversity finance effectiveness circumvents the econometric challenges which limit work in this area and extends recent work by Flammer, Giroux, and Heal (2025a), which stops at analyzing biodiversity deals without linking the financing actions to biodiversity outcomes.

The remainder of the article is structured as follows. Section 2 presents a theoretical framework for making sense of the results. Section 3 discusses the distribution of biodiversity finance across ecosystems within Europe and also compares funding allocation between CO and RO projects. Section 4 outlines the data and empirical strategy. The article advances in Section 5 where results are presented. Section 6 concludes.

2. Theoretical framework

Building on the ecological economics and conservation policy design literature (Ando and Langpap 2018), I conceptualize biodiversity finance effectiveness as a two-stage process. In the first stage, RO biodiversity projects enhance ecological knowledge through species discovery, monitoring, and methodological innovation. This scientific knowledge is captured in indicators such as biodiversity data coverage, species distribution models, and taxonomic completeness. In the second stage, CO projects draw upon this knowledge base to design and implement targeted interventions intended to reduce biodiversity loss and ecosystem degradation.

The biodiversity research–conservation nexus, therefore, posits a directional and indirect pathway from research to ecological outcomes. Research improves the availability and quality of biodiversity information, which in turn increases the effectiveness of conservation planning and action. However, the translation of research into conservation success is conditional on institutional capacity, ecological tractability, and the responsiveness of policy systems to scientific evidence. As such, the relationship between research and ecological outcomes is mediated and moderated by a range of factors, including time lags, measurement uncertainty, and implementation constraints.

This framework yields the following empirical predictions:

1) Research-oriented projects should exhibit a stronger and more consistent relationship with biodiversity data coverage than with direct ecological outcomes.
2) Conservation-oriented projects are expected to have a more direct, but potentially weaker or more variable, relationship with ecological outcomes such as species integrity, protection, and extinction risk. These effects are likely to depend on the degree to which conservation interventions are informed by prior research and aligned with local ecological conditions.

3) The effectiveness of biodiversity finance may vary systematically across project types and over time, reflecting ecological complexity and diminishing marginal returns to funding (Kerkvliet and Langpap 2007). In particular, species-level outcomes may be less responsive to financing than knowledge-based indicators due to nonlinear ecological dynamics and external stressors outside the control of funded projects.

This conceptualization reframes biodiversity finance not as a direct input–output relationship, but as a complex process of knowledge generation, translation, and implementation. It allows for empirical testing of whether and how financing for research and conservation differentially contributes to measurable biodiversity outcomes.

3. Biodiversity finance across Europe

While private capital for biodiversity has been growing, it is public finance which dominates the financing of biodiversity. Within Europe these public investments are largely administered by national science funding agencies which allocate the funds to various research institutions and implementing organizations through competitive funding calls to which project proponents submit proposals for funding consideration. A layer above country-level financing of biodiversity are the framework programs of the EU. Beginning in 1984, the FPs for Research and Innovation were established to support and foster research through a series of investments in the science and innovation infrastructure across the European Research Area (ERA).[20] The FPs, up until FP6, covered 5-year periods of funding availability; but from FP7 onward, programs run for seven years. The specific objectives and eligible projects for funding vary between funding periods. Starting in 2014, the funding programs were named Horizon. Horizon 2020 ran from 2014 to 2020 and has been proceeded by Horizon Europe which aims to increase EU science and innovation spending levels by 50 percent.

As a way of streamlining Horizon funding targeted toward biodiversity and creating synergies with national science funding agencies, the European Biodiversity Partnership (Biodiversa+) was established as a pan-European coordinator for the financing of biodiversity research and nature related initiatives. One of the primary objectives of Biodiversa+ is to produce actionable knowledge to tackle the direct and indirect drivers of biodiversity loss and ecosystem degradation through work packages which finance research and innovation projects across the ERA and promote the internationalization of European research and innovation.

A mapping of the funding landscape across the Biodiversa+ partnership, which includes thirty-six national science funding agencies from twenty-three countries and the EU FPs implemented across EU-27, indicates that the total amount of biodiversity financing provided for biodiversity projects implemented in Europe between 2003 and 2023 was €4.47 billion.[21] As shown in figure 1, this financing peaked in 2004 to €360 million after which there were declines until two others peaks of €290 million and €250 million in 2008 and 2015, respectively. Despite these peaks, financing actually remains below the peak of 2004 even up to 2021 when it reached €320 million and then its highest level of €480 million in 2022, representing a 50 percent increase between those 2 years. It should be noted that the peak in 2015 corresponds with the intensified roll out of Horizon 2020 which was launched the previous year. The 2021 and 2022 peaks correspond with the launch of Horizon Europe as the successor to Horizon 2020 and the release of the final draft of the Kunming Declaration, both of which took place in 2021.

[20] The FPs also operate through competitive funding calls to which project proponents submit proposals which are assessed and scored by a scientific committee in keeping with predetermined funding criteria and priorities.

[21] When projects implemented outside of Europe are taken into consideration, the total amount of funding provided by the Biodiversa+ partners and EU FPs over the two decades is €6.85 billion.

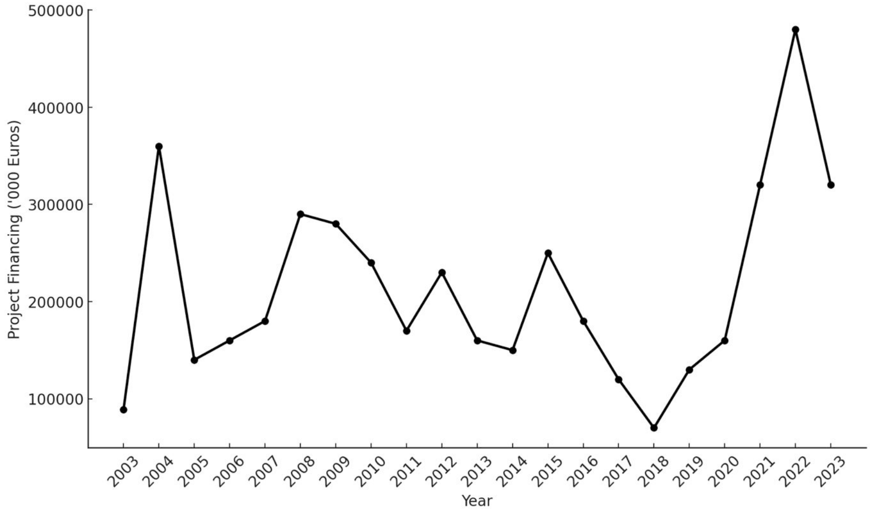

Figure 1. This figure shows the annual financing of biodiversity projects reported in the Biodiversa+ database from 2003 to 2023.

3.1 Financing across ecosystems

To build a baseline understanding of the economic geography of biodiversity finance across Europe in terms of the types of ecosystems and investment locations, I classify the Biodiversa+ projects based on whether they are directly or closely related[22] to the ecosystem biome descriptions of the four core ecosystem realms in the International Union for Conservation of Nature (IUCN) Red List of Ecosystem (RLE) Global Ecosystem Typology (GET).[23] This ecosystem-based typology of the Biodiversa+ projects reveals interesting patterns of the distribution of biodiversity finance across Europe's ecosystems. Table 1 shows a marked concentration of funding in the terrestrial realm, which accounts for 87 percent of total biodiversity finance—approximately €3.9 billion—largely reflecting the dominance of land-based projects within the European research and conservation landscape. In contrast, the marine realm received just 5 percent of total funding, while freshwater and subterranean realms each attracted only 4 percent. These figures suggest a significant terrestrial bias in biodiversity finance, with limited proportional investment in aquatic and subterranean ecosystems despite their ecological importance and vulnerability. This distribution provides a macro-level baseline for understanding the spatial priorities and ecological emphases of European biodiversity financing over the past two decades.

As shown in Table A1 (Supplementary Appendix D7), when disaggregated by biomes, biodiversity finance is further concentrated in a small number of biomes. Within the terrestrial realm, nearly all funding is directed to two biomes: the polar/alpine (cryogenic) biome (T6) and the intensive land-use biome (T7), which together account for 94 percent of terrestrial finance. Similarly, funding in the marine realm is concentrated in the marine shelf (M1) and pelagic ocean waters (M2) biomes, representing 80 percent of marine-related investments. For freshwater ecosystems, 89 percent of funding targets rivers and streams (F1), while subterranean funding is overwhelmingly directed toward anthropogenic voids (S2), which receive 98 percent of subterranean finance. This distribution highlights the

22 The classification procedure is detailed in online Appendix B1.

23 The typology defines the key biophysical features of 110 major ecosystem types throughout the oceans, freshwater and land, and describes the processes that sustain them as well as their global distributions (Keith et al., 2020). The four core realms or types of ecosystems of the typology are terrestrial (with seven biomes), marine (with four biomes), freshwater (with three biomes) and subterranean (with two biomes).

Table 1. Distribution of EU biodiversity funding across ecosystems.
This table summarizes the distribution of biodiversity finance across the four major ecosystem realms defined by the global ecosystem typology (GET) of the international union for conservation of nature (IUCN): terrestrial, marine, freshwater, and subterranean. The data are drawn from the Biodiversa+ database and reflect biodiversity projects funded by national science agencies and the European commission between 2003 and 2023. Each project was classified into one or more realms based on close alignment with the biophysical descriptions and thematic scope of the GET ecosystem categories. The results indicate that biodiversity finance within Europe is heavily concentrated in the terrestrial realm, which accounts for 87 percent of total funding (€3,897.60 million). In contrast, marine, freshwater, and subterranean realms receive significantly smaller shares, amounting to 5 percent (€231.67 million), 4 percent (€168.62 million), and 4 percent (€173.61 million) of the total, respectively. This skewed distribution suggests a terrestrial bias in the allocation of biodiversity finance, with comparatively limited investment in aquatic and subterranean ecosystems.

Ecosytem	Funding amount (millions of Euros)	Percent
Terrestrial realm (T)	3,897.60	87
Marine realm (M)	231.67	5
Freshwater realm (F)	168.62	4
Subterranean realm (S)	173.61	4
Total	**4,471.50**	**100**

dominance of a few focal biomes within each realm, reflecting both research priorities and possibly the geographic and economic characteristics of biodiversity interventions in Europe. I now turn attention to a disaggregated country level view of biodiversity finance flows across ecosystems within Europe over the last two decades. The geographic distribution of project funding across ecosystems is shown in Table 2.

Panel A highlights significant variation in both the scale and ecological scope of biodiversity funding at the national level. UK emerges as the leading national funder, contributing €695.12 million (16 percent of total funding), with a notably diversified portfolio: 15 percent of total terrestrial funding, 13 percent of marine, 9 percent of freshwater, and a dominant 30 percent of subterranean realm investments. Other major contributors include Norway (€386.30 million; 9 percent) and Portugal (EUR 223.02 million; 5 percent), both with comparatively high marine and freshwater shares. A cluster of countries—including Germany, France, Sweden, the Netherlands, and Switzerland—also demonstrate medium-scale funding volumes with varied ecological emphases. Most countries channel the majority of their biodiversity finance into terrestrial ecosystems, often exceeding 80 percent of national allocations. However, countries such as Norway, Sweden, Spain, and the UK display greater ecological breadth by allocating substantial proportions to marine, freshwater, and subterranean projects. Norway, in particular, accounts for 20 percent of total marine realm funding and 9 percent of subterranean finance. Conversely, countries such as Austria, Bulgaria, Lithuania, and Latvia show relatively narrow funding distributions, often focused on a single realm with minimal or no allocations to others.

Panel B shows that the EC plays a critical supranational role, disbursing EUR 1.88 billion, or 42 percent of all biodiversity finance. EC-managed projects are broadly distributed across realms, comprising 43 percent of terrestrial, 35 percent of marine, 54 percent of freshwater, and 20 percent of subterranean funding. The EC's dominant share in freshwater and subterranean finance suggests that centralized EU funding mechanisms may compensate for the limited realm diversification seen in many national portfolios. Taken together, these patterns underscore both the uneven geography and ecological concentration of biodiversity finance in Europe. While terrestrial systems remain the primary focus across most funding sources, a small number of countries and the EC support a more balanced realm-level investment profile, particularly in underfunded aquatic and subterranean ecosystems.

Table 2. Distribution of country funding across ecosystems.

This table presents a disaggregated view of biodiversity finance flows across European countries and the European commission (EC), classified by ecosystem realm according to the global ecosystem typology (GET). Panel A reports the absolute funding amounts and realm-specific shares for each participating country, while panel B shows aggregate funding administered directly by the EC. The data capture national and supranational investments in terrestrial (T), marine (M), freshwater (F), and subterranean (S) biodiversity projects from 2003 to 2023, based on classification of Biodiversa+ project descriptions.

	Funding amount (millions of Euros)									
Panel A	T	Percent	M	Percent	F	Percent	S	Percent	Total	Percent
Country level										
Austria	33.67	1	0	0	0	0	0	0	33.67	1
Belgium	146.36	4	5.08	2	5.42	3	5.96	3	162.82	4
Bulgaria	23.93	1	0	0	0.094	0.06	1.48	1	25.50	1
Croatia	3.59	0.09	1.81	1	0	0	0.437	0.25	5.84	0.13
Czech Republic	18.39	0.47	0.682	0.29	0.461	0.27	1.45	1	20.98	0.47
Estonia	54.12	1	6.58	3	0.693	0.41	1.44	1	62.83	1
Finland	67.44	2	1.78	1	2.88	2	6.33	4	78.43	2
France	102.62	3	8.43	4	2.55	2	10.76	6	124.36	3
Germany	68.64	2	0	0	2.74	2	0.686	0.40	72.07	2
Hungary	32.56	1	0.183	0.08	1.32	1	2.53	1	36.59	1
Ireland	17.39	0.45	0.845	0.36	3.79	2	0.288	0.17	22.31	0.50
Latvia	9.39	0.24	0.078	0.03	0.522	0.31	0.092	0.05	10.08	0.23
Lithuania	5.28	0.14	0.661	0.29	0.296	0.18	0.774	0.45	7.01	0.16
Netherlands	135.67	3	9.51	4	4.68	3	5.55	3	155.41	3
Norway	315.58	8	46.81	20	7.93	5	15.98	9	386.30	9
Poland	31.38	1	1.10	0.47	2.27	1	0.821	0.47	35.57	1
Portugal	207.40	5	9.22	4	4.14	2	2.26	1	223.02	5
Romania	47.39	1	1.21	1	1.85	1	1.05	1	51.50	1
Spain	87.82	2	14.47	6	3.95	2	20.74	12	126.98	3
Sweden	89.98	2	10.27	4	10.97	7	5.56	3	116.78	3
Switzerland	124.64	3	1.6	1	5.12	3	0.432	0.25	131.79	3
Turkey	5.49	0.14	0.200	0.09	0.387	0.23	2.00	1	8.08	0.18
United Kingdom	598.54	15	30.12	13	14.67	9	51.79	30	695.12	16
Panel B										
EU level										
EC	1670.33	43	81.03	35	91.89	54	35.20	20	1878.45	42
Total	3897.60	100	231.67	100	168.62	100	173.61	100	4471.50	100

Table A2 (Supplementary Appendix D7) provides the distribution of the number of biodiversity projects, rather than funding amounts, across countries and ecosystem realms over the 2003–2023 period. While funding allocations (Table 2) reveal where financial resources are concentrated, project counts offer insight into the breadth and intensity of participation across realms. The data illustrate that the spatial and ecological patterns of biodiversity finance in Europe are not strictly proportional to project frequency. Several divergences emerge. First, although the EC accounted for 42 percent of total funding (Table 2), it supported only 9 percent of total projects (Appendix Table A2), indicating a greater average project size and more capital-intensive funding at the EU level. Conversely, many national-level portfolios, especially from countries like Estonia, Portugal, and Poland, feature numerous small projects, often with more evenly distributed realm coverage but relatively modest funding shares. Second, countries such as UK and Norway maintain a leading position in both absolute project count and funding volume. However, UK, while accounting for 20 percent of all projects (Appendix Table A2), provided only 16 percent of total funding (Table 2), suggesting a lower average project funding per unit. The

Netherlands and Sweden similarly show strong project representation across realms with moderate funding shares, indicating a preference for distributed and possibly smaller-scale projects. Third, the ecological composition of project activity diverges from that of funding concentration in several important ways. Terrestrial realm projects dominate both in number (82 percent of total projects) and funding (87 percent of total allocations), but in other realms, the mismatch is more pronounced. The subterranean realm, for example, accounts for 7 percent of total projects but received only 4 percent of total funding, indicating a prevalence of low-cost or small-scale interventions in this domain. Similarly, freshwater projects make up 4 percent of project volume yet receive a disproportionately small share of funding. Conversely, marine projects, which account for 7 percent of total projects, receive 5 percent of total funding—suggesting a closer alignment, but still indicating slightly lower average investment per project compared to terrestrial initiatives. These patterns suggest that non-terrestrial ecosystems are addressed through a higher frequency of lower-cost projects, reflecting potentially different operational or scientific priorities. Overall, these patterns point to a mismatch between project volume and financing intensity. This divergence raises important questions about funding efficiency, research focus, and the strategic alignment of national and EU biodiversity investments.

3.2 Financing across project types

Table 3, which shows the funding distribution across biodiversity project types, reveals a pronounced emphasis on CO interventions, which accounted for approximately 62 percent (€2,770.00 million) of the total €4,471.49 million disbursed, compared to 38 percent (€1,701.49 million) allocated to RO projects. This distribution reflects a classification procedure designed to systematically map project activities to internationally recognized species-level and habitat-level indicators.[24] Projects were classified as CO if they aligned with two major conservation domains: protected area oriented (PAO) support, linked to the species protection index (SPI), and ecological outcome (EO) oriented focus, which was further divided into species habitat index (SHI), species recovery (red list index [RLI]), and forest cover (SDG 15.1.1) subcategories. These classifications were operationalized through a structured text analysis of project abstracts and titles, employing curated keyword dictionaries derived from indicator documentation and supplemented with metadata where available. This matching procedure ensured that project orientation could be traced to measurable, policy-relevant biodiversity outcomes at the country level. In contrast, RO projects were identified among those not meeting the CO criteria, using a secondary keyword-matching algorithm to detect field research, data mobilization, or policy engagement activities. The resulting funding distribution offers a baseline understanding of how biodiversity finance is being channeled between outcome-oriented conservation efforts and knowledge-generation initiatives.

Table 4, which presents the difference in means between project types, shows that, on average, CO projects are longer in duration (2.82 years versus 2.71 years), receive higher total financing (€643,000 versus €421,000), and are financed more intensely (76.97 versus 50.45) compared to RO projects.

Table A3 (Supplementary Appendix D7) provides a more granular view of the funding distribution across CO and RO biodiversity projects. Within the CO category, the overwhelming majority of funds (94 percent, or €2,594.16 million) were allocated to EO initiatives, while only 6 percent (€175.84 million) supported PAO efforts. This suggests a funding preference for interventions that directly address ecological processes and species-level outcomes rather than institutional or territorial protection per se. Panel B further disaggregates EO funding, revealing that species abundance oriented projects—which align with the SHI—received the bulk of support (64 percent), followed by species recovery

[24] The classification procedure for conservation-oriented projects is detailed in online Appendix B2 while the procedure for research-oriented projects is detailed in online Appendix B3.

Table 3. Distribution of biodiversity finance between conservation-oriented (CO) and research-oriented (RO) projects.
This table summaries funding allocations across CO and RO biodiversity projects based on a two-stage classification system. CO projects include those aligned with species protection and ecological outcome indicators (SHI, RLI, SPI, Forest cover), while RO projects were classified by abstract-level keyword matching to identify research-focused activities (FO, PO, DO). the majority of funding (62 percent) was directed toward CO projects, reflecting emphasis on ecological and habitat-level interventions.

Project type	Funding amount (millions of Euros)	Percent
RO projects	1,701.49	38
CO projects	2,770.00	62
Total	**4,471.49**	**100**

Table 4. Distribution of project characteristics.
This table reports the mean and standard deviation of key project characteristics for all biodiversity projects in the sample, and separately for RO and CO projects. The final two columns show the difference in means between CO and RO projects and the corresponding *P*-values from two-sample t-tests. On average, conservation-oriented projects are significantly longer in duration (2.82 years vs 2.71 years, $p = 0.0033$), receive significantly higher total financing (€643,000 vs €421,000, $p = 0.0034$), and exhibit significantly higher financing intensity (76.97 vs 50.45, $p = 0.0034$) compared to RO projects. All differences are statistically significant at the 1 percent level (***).

	All			RO projects			CO projects				
	N	Mean	Standard deviation (SD)	*N*	Mean	SD	*N*	Mean	SD	Diff	*P*-value
Project duration	8,350	2.77	1.71	4,039	2.71	2.05	4311	2.82	1.33	0.11	0.0033***
Project financing (€ millions)	8,350	0.536	0.345	4,039	0.421	0.129	4311	0.643	0.463	0.221	0.0034***
Financing intensity	8,350	64.14	413.13	4,039	50.45	155.34	4311	76.97	554.68	26.53	0.0034***

oriented projects linked to the RLI (28 percent), and deforestation and reforestation oriented projects associated with forest cover indicators (8 percent). This reflects a strong policy and funding alignment with biodiversity metrics that emphasize habitat modelling and spatial integrity. In contrast, Panel C shows that within the RO category, knowledge and data oriented projects—focused on informatics, digitization, and data accessibility—dominated the funding landscape (84 percent, or €1,427.91 million), with relatively modest investments in policy oriented (PO) activities (12 percent) and field research oriented (FO) efforts (4 percent). This pattern illustrates the systemic emphasis on large-scale data infrastructure over on-the-ground research or policy interface work. Taken together, the detailed breakdown underscores a dual emphasis in biodiversity finance: on one hand, ecological outcome-aligned conservation efforts; on the other, scalable knowledge systems capable of informing future interventions in keeping with the policy rationale of the biodiversity research–conservation nexus which informs EU financing of biodiversity.

Table A4 (Supplementary Appendix D7) provides a disaggregated view of biodiversity funding by country and at the EC level, offering further insight into the geographical allocation of CO and RO resources. UK emerges as the largest single-country funder, accounting for 16 percent of total funding, with a relatively balanced distribution between RO (€357.91 million) and CO (€337.22 million) projects. Portugal, Norway, and the Netherlands also feature prominently among top funders. At the EU level, the EC accounted for the largest share of total funding—42 percent (€1,878.45 million)—with a strong orientation toward CO projects (53 percent of all CO funding). This suggests that the EC plays a dominant role in financing conservation interventions with measurable ecological outcomes across member states. In contrast, smaller Eastern European countries such as Latvia, Lithuania, and Bulgaria provided modest funding, reflecting regional disparities in biodiversity investment intensity. The table also highlights countries like Switzerland and Ireland with comparatively higher shares in RO projects, suggesting differentiated national emphasis on research capacity-building versus ecological implementation. Collectively, the data suggest both a centralized conservation funding role for at the EU level and notable heterogeneity in national project orientation and investment scale.

4. Data and empirical strategy

4.1 Data Sources

4.1.1 *Biodiversity financing*

Biodiversity financing data are from the Biodiversa+ database. The project level data include the amount of funding awarded to each project, the period for which the project is funded, the project abstracts, the country and implementing organization associated with the project and whether the project is financed by an EU framework program or a national science funding agency. I utilized projects funded between 2003 and 2023. From an initial count of 12,621 projects, I implement a basic screening by removing duplicates and projects not implemented within Europe. This resulted in the final dataset of 8,350 projects.

4.1.2 *Local level biodiversity outcomes*

I proxy for local-level biodiversity outcomes using species abundance data from the eBird Observation Dataset developed and maintained by the Cornell Lab of Ornithology. eBird is one of the largest structured biodiversity datasets in the world, comprising over 100 billion bird observations contributed annually by a growing global community of birdwatchers. Initiated as a citizen science platform, eBird enables birders to record checklists detailing species observed, the date, location, and effort involved in the observation event (e.g., duration, distance traveled, and number of observers). These standardized checklists are submitted via the eBird website or mobile application, which supports offline data entry and regional checklist filters to enhance data accuracy. The data coverage is across 252 countries and dates back to the 1800s up to the present day. I extract data of observations of naturally occurring species of birds recorded by citizen scientists for the twenty-three countries in the country-funded sample of the Biodiversa+ dataset.[25] The eBird data include the scientific name of the particular species of bird, a count of the number of birds observed and the exact latitude and longitude of the location within each country where the observations were made. I utilize observations recorded between 2003 and 2023. Table 5 provides a breakdown of the count and percentage of eBird species observations per country for the total of 105 million observations reported across twenty-three of the sample countries. The majority of observations are reported in the United Kingdom (31 percent) and Spain (27 percent).[26]

4.1.3 *Country-level biodiversity outcomes*

I measure country-level biodiversity outcomes using the Map of Life Indicators and SDG 15 Performance Data.

4.1.3.1 Map of life indicators

The map of life indicators developed by the GEO BON are described in the ecological literature as Essential Biodiversity Variables (Pereira et al. 2013; Jetz et al. 2019; Jetz et al. 2022). The indicators are the SHI which measures species integrity, the SPI which measures

[25] To keep the data manageable, I excluded the three countries with projects funded solely by EU FP.
[26] I exclude these countries in robustness tests.

Table 5. Distribution of eBird observations across countries.
This table reports the number and percentage of eBird species observations of birds by country between 2003 and 2023. The data represents observations of birds reported by citizen scientists on the eBird website or in the eBird app.

	Species observations of birds	
Country	**eBird count**	**Percent**
Austria	676,262	0.64
Belgium	931,779	0.88
Bulgaria	919,989	0.87
Croatia	420,886	0.40
Czech Republic	2,792,375	2.65
Estonia	184,144	0.17
Finland	1,875,830	1.78
France	4,906,813	4.65
Germany	5,342,168	5.07
Hungary	797,244	0.76
Ireland	1,394,221	1.32
Latvia	151,554	0.14
Lithuania	323,250	0.31
Netherlands	2,260,141	2.14
Norway	1,439,438	1.37
Poland	2,134,174	2.02
Portugal	10,398,413	9.86
Romania	320,177	0.30
Spain	28,273,645	26.82
Sweden	2,881,053	2.73
Switzerland	1,504,913	1.43
Turkey	2,679,966	2.54
United Kingdom	32,810,307	31.12
Total	105,418,742	100

species protection and the Species Information Index (SII) which measures species data coverage. The data are annual country-level indicator values constructed from extensive species-level data.

The integrity of ecosystems is broadly defined by the status of their component species and the ecological processes they support and require. Integrity can be assessed by the degree of change (loss and gain) in the set of species and associated processes observed within an ecosystem and its habitats. The SHI measures this change and captures variation in the ecological intactness of ecosystems. The SHI is calculated and validated using species occurrence data combined with environmental change data informed by remote sensing. Calculations use best-possible predictions of species geographic distributions based on a variety of sources combined with species habitat information (Wilson, Lacher, and Mittermeier 2009; Jetz et al. 2012a, 2012b, 2019; Pereira et al. 2013).

The SPI measures how much of a species' range or population is currently protected relative to how much conservation area ecologists estimate is needed for its population to thrive (Jetz et al. 2022) while the SII captures how well existing data cover the species' expected range (Oliver et al. 2021) by analyzing datasets in the Global Biodiversity Information Facility (GBIF), the largest online repository of global biodiversity data. Supplementary Appendix D1 presents the country means for each measure over the sample period. Figures A1, A2, and A3 present the country means for the SHI, SPI and SII, respectively.

4.1.3.2 SDG 15 targets

SDG 15 performance data are from the SDG Indicator Database which tracks country-level progress on 12 biodiversity targets and indicators. I collect data on the forest area indicator which measures the proportion of land area covered by forest in each country and the RLI indicator which is constructed from global estimates of the extinction risk of species on the IUCN Red List of Threatened Species. The RLI is disaggregated to the national scale and weighted by the proportion of each species's distribution in each country. Figures A4 and A5 in Supplementary Appendix D2 present the country means for the RLI and forest area, respectively.

4.1.4 ***Finance for biodiversity pledge financial institutions***

To proxy for private capital geared toward biodiversity, I utilize the count of the number of financial institutions in each country that are signatories to the FfB Pledge. I obtain these data from the pledge signatory database provided on the website of the FfB Foundation which coordinates activities among the 194 financial institutions that have signed the pledge. These institutions, collectively represent €23 trillion in assets and have, by signing the pledge, committed to financing and investing in activities which safeguard biodiversity.

4.1.5 ***Biotechnology outcomes***

I link the FfB proxy to two biotechnology outcomes, namely, number of patents and number of species DNA sequenced.

4.1.5.1 Biotechnology patents

I collect country-level data on the number of patent application to the Patent Cooperation Treaty (PCT) in the biotechnology sector from the Main Science and Technology Indicators (MSTI) database provided by the OECD. I also collect data on the gross domestic expenditure and the business enterprise expenditure on R&D as a percentage of each country's GDP, the total R&D personnel per thousand total employment, and total researchers per thousand total employment in each country from the MSTI.

4.1.5.2 Species DNA

DNA data are obtained from the Barcode of Life Data Systems (BOLD) maintained by the Canadian Centre for DNA Barcoding. BOLD is a publicly available database for DNA-based species identification. Identification of unique species is achieved though DNA barcoding which assigns Barcode Index Numbers (BINs) to sequenced DNA. I obtain a yearly count of the number of BINs for each country in the dataset. The BINs represent the number of unique species DNA which have been sequenced. BOLD is the most comprehensive and curated reference barcode database for species DNA and is utilized extensively by researchers to study patterns of genetic diversity (Ratnasingham and Herbert 2007).

4.1.6 ***Control variables***

For each country in the Biodiversa+ database, I collect data on its annual GDP per capita growth and its industrial growth from the World Bank World Development Indicators Database. I use these variables to control for the impacts of both economic and industrial activity and population growth on biodiversity and ecosystem pressures discussed in the literature (Giglio et al. 2024; Taylor and Weder 2024).

In keeping with the ecological literature which has shown that land use change (Davison, Rahbek, and Morueta-Holme 2021; Semenchuk et al. 2022; Shah et al. 2022; Cabernard, Pfister, and Hellweg 2023; Rios-Touma et al. 2023) and invasive species (Simberloff et al. 2013; Blackburn et al. 2014; Katsanevakis et al. 2014; Lockwood and Robinson 2014; McGeoch et al. 2015; David et al. 2017; Henry et al. 2023; de Carvalho-Souza et al. 2024) are significant factors in driving biodiversity loss, I construct a land use ratio and an invasive species ratio for each country. To construct the land use ratio, I utilize the percentage of agriculture land area and urban land area from the World Bank World Development Indicators Database. For the invasive species ratio, I scale the annual count of invasive species reported for each country in the Global Register of Invasive Species by the total number of species observation lodged each year with the GBIF.

I control for the impact of protected areas with data on the Protected Area Coverage of Key Biodiversity Areas (KBA). The measure, which is at the country-level, is the mean percentage of each KBA that is covered by protected areas, based on data in the World Database on Protected Areas. I also control for project duration and the baseline value of biodiversity outcomes in 2003. To account for the fact that biodiversity projects in the Biodiversa+ database are financed through EU science and innovation funding, I round out the list of controls with data on the gross domestic expenditure on R&D as a percentage of GDP for each country in the dataset.[27]

4.2 Empirical strategy

Recent advances in the difference-in-differences (DiD) literature have addressed important sources of bias in settings with dynamic and staggered treatments, where the timing and intensity of treatment vary across units and over time.[28] Unlike traditional DiD models, which assume a one-time, binary treatment, dynamic treatment settings require estimators that flexibly accommodate repeated treatment switches, varying treatment intensities, and heterogeneous treatment effects over time. This is particularly relevant to biodiversity financing, where projects receive funding in intermittent cycles, reflecting the structure of EU science and innovation funding discussed earlier. To capture this complexity, I first implement a long differences model. This approach compares changes in biodiversity outcomes across two points in time—before and after financing—while controlling for a rich set of fixed effects that absorb stable differences across projects, countries, organizations, and species. The baseline long differences model is specified as follows:

$$\text{Biodiversity Outcome}_{igjs} = \beta_1 \text{Financing Treat}_{igjs} + \beta_2 \text{X}_{igjs} + \alpha_{igj} + \theta_s + \varepsilon_{igjs} \tag{1}$$

where Biodiversity Outcome_{igjs} represents the local-level and country-level biodiversity measures for species s, in project i, implemented by organization g in country j, between the baseline year (2003) and the end of the two decades covered by the sample period (2023). Financing Treat_{igjs} indicates whether the project received financing during the period, and X_{igjs} represents the control variables. This long differences approach abstracts from dynamic treatment paths but serves as a useful benchmark for identifying average effects over the full period.

To more precisely model the timing and dynamics of biodiversity responses, I complement the long differences with the dynamic DiD estimator developed by de Chaisemartin and d'Haultfoeuille (2024), hereafter referred to as the dCdH estimator. This estimator accounts for multiple treatment switches and lagged effects by constructing comparisons between "switcher" units—projects whose financing status changes at some time F_g—and "non-switcher" units, whose treatment remains constant over the same window. For each project experiencing a treatment switch, the post-switch biodiversity outcome at time $F_g - 1 + \ell$ is compared to a counterfactual where the project remained at its pre-switch treatment level. This difference is then compared to the outcome evolution of matched non-switchers that had the same treatment level as the switcher at $F_g - 1$ and remained untreated over the comparison window. The beauty of the dCdH estimator is that, by design, it algorithmically eliminates the forbidden comparisons problem which plague dynamic treatment settings (Goodman-Bacon 2021; Sun and Abraham 2021).

27 Additional details on data sources are provided in online Appendix A.
28 See de Chaisemartin and d'Haultfoeuille (2023) for a comprehensive survey of these estimators.

Formally, the dynamic treatment effect at the project-time pair (g, ℓ) is given by:

$$\delta_{g,\ell} = \mathbb{E}[Y_{g,F_g-1+\ell} - Y_{g,F_g-1+\ell}(D_{g,1}, \ldots, D_{g,1})] \quad (2)$$

In this setting, the dCdH estimator iterates over biodiversity projects switching financing status, estimating dynamic effects at each period ℓ after the switch, while controlling for potential heterogeneity in treatment timing and intensity. Unlike the long differences model, the baseline dCdH estimator does not include covariates but relies on a parallel trends and no-anticipation assumption, comparing outcome trajectories across switcher–stayer pairs to identify causal effects. In the option of the estimator which allows for controls to be imputed, I include country-level controls for GDP per capita growth, industrial growth, land use ratio, invasive species ratio, % protected area, R&D as a percentage of GDP and baseline values of the particular biodiversity outcomes being investigated in a given specification. I also impute controls for time-invariant project, country, and implementing organization characteristics.

Together, the long differences and dCdH estimators offer complementary insights: the former summarizes average changes over two decades, while the latter uncovers dynamic treatment effects that evolve gradually over time and vary by treatment duration and intensity.[29]

Before proceeding with the formal analysis, I provide further descriptive analysis of the Biodiversa+ projects beyond the financing dimensions described in Section 3.

4.3 Descriptive statistics

4.3.1 *Projects by ecosystem type*

Table 6 provides a breakdown of the 8,350 biodiversity projects in the dataset by ecosystem type, using the GET classification system. Most projects (82 percent) fall within the Terrestrial Realm, particularly in the intensive land-use (T7, 64.3 percent) and Polar/Alpine (T6, 26.1 percent) biomes. RO projects are more concentrated in intensively modified landscapes (T7: 76.6 percent), while CO projects are more prevalent in natural or sensitive biomes such as Polar/Alpine and Savannas and grasslands. Other realms are less represented: Marine (7 percent), Freshwater (4 percent), and Subterranean (7 percent). CO projects show slightly greater presence in marine deep-sea and freshwater river systems, while subterranean projects—especially those in void biomes (S2)—are more common among CO efforts, likely reflecting conservation targeting of fragile ecosystems. Overall, RO projects focus more on human-modified environments, whereas CO projects are more evenly distributed across natural systems, indicating distinct functional priorities between research and conservation initiatives.

4.3.2 *Projects by country*

Table 7 presents the distribution of Biodiversa+ projects across European countries (Panel A) and the EC as a funding body (Panel B), distinguishing between RO and CO projects. At the country level, UK stands out as the most active participant, accounting for 19.5% of all projects, followed by Spain (13.5 percent) and France (9.4 percent). This ranking remains consistent across both RO and CO subsamples, underscoring these countries' leading roles in biodiversity financing. The Netherlands, Norway, and Germany also feature prominently, each contributing between 5 and 6 percent of total projects. Notably, RO projects are more concentrated in countries like the Netherlands and Norway, while CO projects show stronger presence in Spain and the UK. For instance, the Netherlands accounts for 7.0 percent of RO projects versus just 4.0 percent of CO projects, while Spain contributes 8.7 percent of RO projects but 13.4 percent of CO projects. Panel B indicates that the European Commission directly funds 9.2 percent of all projects, with a disproportionate emphasis on CO projects (11.1 percent) relative to RO (7.1 percent). This suggests that

[29] A detailed description of the application of the dCdH estimator to the biodiversity finance setting is presented in online Appendix A6.

Table 6. Distribution of RO and CO projects across ecosystems.
This table reports the number and percentage of Biodiversa+ projects by global ecosystem typology (GET) ecosystem type. The statistics are reported for all projects in the sample (first two columns), and separately for RO projects (middle two columns) and CO projects (last two columns).

	All ($N = 8{,}350$)		RO ($N = 4{,}039$)		CO ($N = 4{,}311$)	
	N	Percent	*N*	Percent	*N*	Percent
Terrestrial realm	**6,850**	**82**	**3,439**	**85**	**3,411**	**79**
Tropical forests biome (T1)	77	1.1	5	0.1	72	2.1
Temperate-boreal forests biome (T2)	79	1.2	1	0.0	78	2.3
Shrublands biome (T3)	49	0.7	12	0.3	37	1.1
Savannas and grasslands biome (T4)	330	4.8	121	3.5	209	6.1
Deserts and semi-deserts biome (T5)	119	1.7	34	1.0	85	2.5
Polar/alpine (cryogenic) biome (T6)	1,790	26.1	631	18.3	1,159	34.0
Intensive land-use biome (T7)	4,406	64.3	2,635	76.6	1,771	51.9
Marine realm	**567**	**7**	**264**	**7**	**303**	**7**
Marine shelf biome (M1)	235	41.4	110	41.7	125	41.3
Pelagic ocean waters biome (M2)	246	43.4	109	41.3	137	45.2
Deep sea floors biome (M3)	46	8.1	23	8.7	23	7.6
Anthropogenic marine biome (M4)	40	7.1	22	8.3	18	5.9
Freshwater realm	**309**	**4**	**135**	**3**	**174**	**4**
Rivers and streams biome (F1)	231	74.8	98	72.6	133	76.4
Lakes biome (F2)	63	20.4	31	23.0	32	18.4
Artificial wetlands biome (F3)	15	4.9	6	4.4	9	5.2
Subterranean realm	**624**	**7**	**201**	**5**	**423**	**10**
Subterranean lithic biome (S1)	24	3.8	10	5.0	14	3.3
Subterranean voids biome (S2)	600	96.2	191	95.0	409	96.7
Total	**8,350**	**100**	**4,039**	**100**	**4,311**	**100**

The bold values represent the total values for the four main ecosystem types.

supranational support may be more focused on direct conservation outcomes rather than basic or applied ecological research. Taken together, these patterns reveal meaningful geographic variation in biodiversity project orientation, with northern European countries leaning more heavily toward research, and southern and western countries exhibiting a stronger conservation focus.

In Table A0 (Supplementary Appendix D7), I present the 2003 baseline year values per country for the SHI, SPI, RLI, and forest area indicators. The data show striking heterogeneity across Europe in biodiversity baselines. Northern countries such as Finland, Sweden, and Estonia exhibit very high SHI values (>100) and extensive forest coverage (up to 74 percent in Finland), signaling large, relatively intact habitats. In contrast, more densely populated or intensively managed landscapes such as Belgium, the Netherlands, and Denmark show comparatively low forest area (10–22 percent) and moderate SHI, reflecting greater historical habitat fragmentation. The SPI reveals substantial differences in protection levels: some countries such as Germany (76.6) and UK (98.8) had already placed large portions of habitats under formal protection by 2003, while others such as Romania (0.5), Turkey (0.4), and Estonia (0.6) show near absence of baseline protection. The RLI values, ranging from 0.87 (Greece) to 0.99 (Sweden, Lithuania, Estonia, Latvia), suggest that many European species populations were not yet in immediate critical decline at the start of the sample, but the EU-wide State of Nature assessments confirm that pressures from agriculture, urbanization, forestry, and climate change were already driving deterioration in habitats and species by the early 2000s (European Environment Agency 2020). The SPI data are consistent with more recent findings that Europe's conservation burden is unevenly distributed: high-biodiversity countries in the Mediterranean and Eastern Europe had low protection baselines despite harboring large numbers of species, while wealthier Western and Northern states had comparatively higher protection scores. Taken together,

Table 7. Distribution of RO and CO projects across countries.
This table reports the number and percentage of Biodiversa+ projects across European countries and the EC. Panel A reports statistics for each participating country, while Panel B shows the aggregate number of projects funded by the EC. The statistics are reported for all projects in the sample (first two columns), and separately for RO projects (middle two columns) and CO projects (last two columns).

	All ($N = 8{,}350$)		**RO ($N = 4{,}039$)**		**CO ($N = 4{,}311$)**	
Panel A	***N***	**Percent**	**N**	**Percent**	***N***	**Percent**
Country level						
Austria	110	1.3	47	1.2	63	1.5
Belgium	403	4.8	229	5.7	174	4.0
Bulgaria	64	0.8	35	0.9	29	0.7
Croatia	35	0.4	5	0.1	30	0.7
Czech Republic	98	1.2	37	0.9	61	1.4
Estonia	514	6.2	280	6.9	234	5.4
Finland	83	1.0	24	0.6	59	1.4
France	284	3.4	106	2.6	178	4.1
Germany	119	1.4	58	1.4	61	1.4
Hungary	253	3.0	161	4.0	92	2.1
Ireland	67	0.8	43	1.1	24	0.6
Latvia	17	0.2	13	0.3	4	0.1
Lithuania	39	0.5	8	0.2	31	0.7
Netherlands	456	5.5	282	7.0	174	4.0
Norway	470	5.6	209	5.2	261	6.1
Poland	269	3.2	179	4.4	90	2.1
Portugal	311	3.7	243	6.0	68	1.6
Romania	274	3.3	164	4.1	110	2.6
Spain	1130	13.5	293	7.3	837	19.4
Sweden	358	4.3	109	2.7	249	5.8
Switzerland	384	4.6	322	8.0	62	1.4
Turkey	217	2.6	135	3.3	82	1.9
United Kingdom	1629	19.5	770	19.1	859	19.9
Panel B						
EU level						
EC	766	9.2	287	7.1	479	11.1
Total	**8,350**	**100**	**4,039**	**100**	**4,311**	**100**

these baseline values underscore both the ecological richness of Europe and the uneven starting point from which biodiversity conservation and financing efforts have advanced. They contextualize subsequent biodiversity finance interventions by highlighting that, already in 2003, Europe contained countries with vast intact habitats but weak protection regimes, as well as countries with strong protection infrastructures but more heavily modified ecosystems. Importantly, I control for these baseline values in the subsequent empirical analysis which follows.

5. Results

5.1 Geospatial analysis of species occurrences of birds

I begin the formal analysis by using the eBird data to examine whether or not the number of birds observed within close proximity to areas where CO projects are implemented is related to the financing of these projects.[30]

[30] The procedure used to geocode projects and calculate distance bands using eBirds coordinates is described in online Appendix C.

Table 8 reports the results of long differences regressions which estimate the relationship between project financing of CO projects and bird sightings. All models incorporate a rich set of fixed effects to account for time-invariant sources of heterogeneity that could confound the relationship between project financing and bird observation counts. First, project-by-country-by-organization fixed effects control for any constant characteristics specific to the biodiversity projects, the national context in which the projects operate, and the implementing organization. This accounts for factors such as project design, country-level biodiversity policy, and the conservation capacity of implementing organizations, which may influence bird observations independently of financing. Second, species fixed effects absorb all time-invariant species-level factors, including differences in species' detectability, range size, and baseline abundance, which could otherwise bias comparisons across species. Finally, the models absorb the baseline level of species observations in 2003, allowing the estimated effects to reflect changes in avian biodiversity rather than preexisting differences in where species of birds are more or less commonly observed. Together, these fixed effects ensure that the estimated impact of financing reflects within-species, within-project changes over time, net of stable ecological, geographical, and organizational characteristics.

Across the sample where no distance band restrictions are imposed, CO project financing is associated with a statistically significant increase in bird observations (Models 1 and 3), suggesting that financed biodiversity projects may support improved avian biodiversity outcomes. However, this positive association does not consistently hold when interactions with species proximity to project sites are included. In Model 5, which jointly examines financing effects across three distance bands (0–50 km, 50–200 km, and 200–500 km), none of the financing–distance interaction terms are statistically significant, indicating no strong evidence that proximity moderates the biodiversity response to financing. When the sample is split into two decades (2003–2013 and 2013–2023), the financing effect estimates differ in sign—positive in the earlier decade and negative in the later decade—but neither estimate is statistically significant. This suggests considerable uncertainty about the persistence of the financing effect over time.

To complement the long differences estimates, which provide a static comparison of biodiversity outcomes before and after project financing, I employ the dCdH estimator. The dynamic estimates, presented in Table 9, suggest that the financing of CO biodiversity projects does not produce immediate improvements in bird observations.

For the estimates where no distance band restrictions are imposed, the average treatment effect is negative and statistically insignificant, and most early treatment periods exhibit small or negative coefficients. This finding aligns with the long differences results, which show that any positive association between financing and bird observations weakens when controlling for spatial proximity and temporal variation. However, ecological theory predicts that biodiversity responses to conservation interventions are inherently slow, often requiring several years for habitat restoration and population recovery to translate into observable species outcomes. Consistent with this expectation, the dynamic estimates reveal delayed positive effects emerging after fifteen or more periods, particularly at closer distances from project sites (0–50 km), where the effects are larger and statistically significant. Figure 2, presents the event study plot of the estimates which are within 0–50 km of project sites. For brevity, I have presented the remaining dCdH event study graphs for the foregoing results in Supplementary Appendix D3 and relegated all discussion of parallel trends and comparison groups to Supplementary Appendix E.

To test the sensitivity of the results to violations of parallel trends, I implement two iterations of the relative magnitude version of the `HonestDiD` package provided by

Table 8. Long differences of eBird observations (CO projects).
This table reports long differences regression estimates examining the association between financing of CO biodiversity projects and changes in bird observation counts recorded in the eBird database. Columns (1) to (5) use the full sample from 2003 to 2023, while columns (6) and (7) split the sample into two decades (2003–2013 and 2013–2023). interaction terms assess whether the financing effect varies by proximity between species observations and project locations, measured across 0–50 km, 50–200 km, and 200–500 km distance bands. All models control for the continuous distance between projects and species observations. Regressions include project–country–organization (PCO) fixed effects to account for time-invariant characteristics specific to each project, national context, and implementing organization; species fixed effects to control for species-specific differences in detectability and baseline abundance; and baseline fixed effects to absorb the initial species observation count in 2003. Standard errors are clustered by project and year.***$P<0.01$, **$P<0.05$, *$P<0.1$.

	eBird count (2003–2023)					By decade	
						2003–2013	2013–2023
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Project financing	2.053*	2.233	2.289*	1.730	1.963	0.629	−1.047
	(0.123)	(0.327)	(0.148)	(0.163)	(0.769)	(0.118)	(0.116)
Project financing × 0–50km		0.073			−0.234	−0.271	−0.762
		(0.166)			(0.906)	(0.171)	(0.194)
Project financing × 50–200km			0.080		−0.274	−0.296	−0.407
			(0.093)		(0.939)	(0.158)	(0.151)
Project financing × 2002500km				−0.115	0.123	−0.171	0.016
				(0.043)	(0.671)	(0.109)	(0.224)
0–50 km dummy					0.636	0.552	1.261
					(0.781)	(0.053)	(0.189)
50–200 km dummy					0.483	0.452	0.836
					(0.725)	(0.054)	(0.108)
200–500 km dummy					−0.142	0.152	0.113
					(0.528)	(0.029)	(0.209)
Distance	−0.131*	−0.114	−0.119	−0.112*	−0.016	0.036	0.072
	(0.008)	(0.029)	(0.016)	(0.006)	(0.033)	(0.076)	(0.033)
Constant	5.942	5.847	5.855	5.894	5.235	4.014*	5.182
	(1.405)	(1.596)	(1.326)	(1.406)	(1.125)	(0.127)	(1.144)
Adjusted R^2	0.521	0.521	0.521	0.521	0.521	0.648	0.630
PCO fixed effects (FE)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Species FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Baseline FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2,748,818	2,748,818	2,748,818	2,748,818	2,748,818	2,558,891	2,887,767

Table 9. Biodiversity finance and eBird observations (CO projects).
This table reports dCdH regression estimates examining the association between financing of CO biodiversity projects and changes in bird observation counts recorded in the eBird database. The treatment switch period indicates the number of years since a project first received financing. Standard errors are clustered by individual project units. ***$P<0.01$, **$P<0.05$, *$P<0.1$.

		Distance from project		
	eBird count (1)	0–50 km (2)	50–200 km (3)	200–500 km (4)
Average total effect (ATE)	−0.00573	1.044***	0.0753	0.311***
	(0.0599)	(0.244)	(0.065)	(0.0858)
Treatment switch period				
1	−0.0110**	0.0178	−0.00681	−0.0125**
	(0.00437)	(0.0218)	(0.0126)	(0.00588)
2	−0.00146	0.0673	−0.0382**	0.0166*
	(0.00553)	(0.0471)	(0.0158)	(0.0101)
3	−0.00304	0.0215	0.0213	0.00162
	(139.818)	(0.0660)	(0.0384)	(0.0105)
4	−0.00700	0.262**	−0.00744	0.0231**
	(0.00809)	(0.104)	(0.0431)	(0.0113)
5	−0.00868	0.0837	−0.0143	0.0242*
	(0.00923)	(0.0540)	(0.0338)	(0.0131)
6	−0.00543	0.148***	0.0148	0.0297*
	(0.0121)	(0.0441)	(0.0214)	(0.0168)
7	−0.0107	0.348***	−0.0395	0.0563**
	(0.0178)	(0.0452)	(0.0243)	(0.0264)
8	0.0351**	0.569***	0.0164	0.0922***
	(0.0149)	(0.0888)	(0.0200)	(0.0291)
9	0.00293	0.543***	−0.00857	0.119***
	(0.0224)	(0.100)	(0.0680)	(0.0302)
10	−0.0269	0.426***	−0.0368	0.0849**
	(0.0217)	(0.107)	(0.0444)	(0.0358)
11	−0.0323	0.271***	−0.0207	0.0839**
	(0.028)	(0.0877)	(0.0390)	(0.0363)
12	−0.0396	0.968***	−0.00440	0.101**
	(0.0381)	(0.205)	(0.0472)	(0.0392)
13	−0.0187	0.405***	0.00482	0.160***
	(0.0345)	(0.117)	(0.0418)	(0.0476)
14	−0.0552	0.188	−0.0160	0.138***
	(0.0399)	(0.141)	(0.0803)	(0.0458)
15	−0.0262	0.461***	0.124**	0.131***
	(0.0325)	(0.101)	(0.0548)	(0.0406)
16	0.00676	0.744***	0.142***	0.216***
	(0.0358)	(0.112)	(0.0526)	(0.0433)
17	0.148***	1.016***	0.438***	0.329***
	(0.0344)	(0.0821)	(0.0410)	(0.0591)
18	0.197***	1.932***	0.597***	0.452***
	(0.063)	(0.265)	(0.154)	(0.0878)
19	0.0970	1.362***	0.403***	0.764***
	(0.108)	(0.317)	(0.133)	(0.154)
20	0.225***	0.900	1.209***	0.167*
	(0.0423)	(1.049)	(0.216)	(0.100)
N	28,559,363	1,769,748	8,094,199	13,019,401

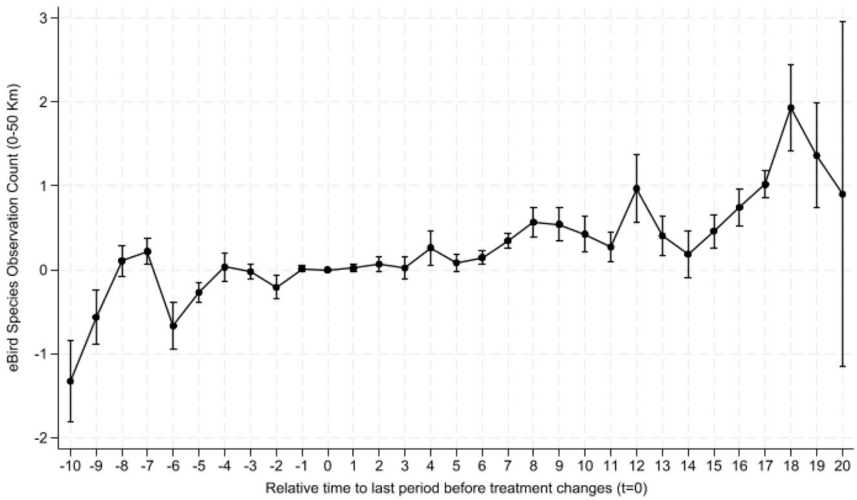

Figure 2. This figure shows the dCdH estimates of equation (2), describing the effect of biodiversity financing of conservation-oriented projects on observations of birds within a 0250 km radius of project sites. The pretreatment estimates represent placebos generated by the dCdH estimator to test the parallel trend and no anticipation assumptions.

Rambachan and Roth (2023). I now briefly discuss the estimates for observations within 0–50 km of project sites.[31]

In the first iteration, which targets the first posttreatment effect, the original 95 percent confidence interval (CI) is $[-0.025, 0.061]$, indicating no detectable immediate effect. For the relative magnitude sensitivity, the CIs widen and include zero for even mild bounds: $(-0.851, 0.898)$ at $\bar{M} = 0.5$,$(-1.715, 1.761)$ at $\bar{M} = 1$, $(-2.411, 2.446)$ at $\bar{M} = 1.5$, and $(-3.075, 3.110)$ at $\bar{M} = 2$. The breakdown value is therefore below 0.5. In the second iteration, which targets the late posttreatment average (periods 15 to 20), the original CI is (0.490, 1.648), suggesting a positive late effect. The robust CIs again include zero and are much wider:$(-13.969, 16.633)$ at $\bar{M} = 0.5$, $(-28.081, 30.220)$ at $\bar{M} = 1$,$(-39.703, 41.841)$ at $\bar{M} = 1.5$, and $(-51.324, 53.462)$ at $\bar{M} = 2$. Comparing widths at the same bound illustrates the difference in fragility: at $\bar{M} = 0.5$ the first-post interval spans 1.749 while the late–post average spans 30.602. Hence, both estimands are not robust to plausible violations of parallel trends, and the late-period average is far less informative than the first-period effect.

Taken together, these diagnostics indicate that modest and plausible deviations from parallel trends can account for the baseline patterns and strengthens support for my principled caution on causality. The suite of additional sensitivity analyses presented in Supplementary Appendix E1 show similar patterns of fragility in the identification assumptions and consistently illustrate the complexity and partial observability which characterize ecological data, thereby requiring epistemic modesty in any claims to causality.

To address the concern that biodiversity outcomes are spatially correlated, I reestimate both the long-differences and dCdH specifications using distance-band clustering of standard errors. In this approach, projects are grouped into spatial clusters defined by grid cells of 50 km, and inference is based on variation across these clusters rather than individual project units. This method accounts for the possibility that bird observation counts within a given geographic area may be jointly influenced by unobserved ecological factors or regionally correlated shocks, which would otherwise bias conventional project-level

[31] Figures for these and all other sensitivity results are presented in online Appendix E1.

clustering. The results, presented in Supplementary Tables A12 and A13 (Supplementary Appendix D10), are broadly robust to this adjustment, indicating that the observed financing effects are not driven by spatial dependence in biodiversity outcomes.[32]

As a point of comparison, I also present, in Table 10, the dCdH estimates for the full sample of projects which includes both CO and RO biodiversity projects. This larger sample of approximately 55 million project–year observations exhibits a similar pattern with an average treatment effect that is negative and statistically insignificant. As with the previous results, bird observations at closer distances from project sites (0–50 km) show more consistently positive and significant effects after fifteen or more periods.

5.2 Country-level analysis of CO projects

The biodiversity research–conservation nexus suggests that CO projects should be more effective for biodiversity outcomes which are more ecological in nature. In what follows, I test this prediction for country-level biodiversity outcomes at both the extensive and intensive margins using the two Map of Life indicators constructed from ecological data and the SDG 15 targets.

I begin at the extensive margin by examining the relationship between the financing of CO projects and country-level indicators for the SHI which measures species integrity and the SPI which measures species protection. The dCdH estimates, with and without controls, are presented in Table 11.

For the SHI without controls (column 1), the coefficients are negative and statistically significant during the first seven treatment periods. However, these effects turn positive from period 8 onward, with larger and significant gains showing up in later periods. Including controls (column 2) does not materially alter the early negative pattern, but the later positive phase exhibits a much greater delay and does not become consistently positive until periods 18, 19, and 20. While this aligns with the delayed improvements we expect to see in ecological outcomes, the average total effect (ATE) when controls are included is negative and statistically insignificant. This suggests that, over the full treatment horizon, biodiversity financing of conservation projects does not yield a statistically discernible improvement in the SHI at the extensive margin. The results therefore point to an overall null effect on average, despite evidence of eventual gains in later periods.

By contrast, SPI outcomes (columns 3 and 4) are markedly weaker or negative. Without controls, early coefficients fluctuate around zero and become positive in mid-periods, though only sporadically significant. With controls, the pattern is dominated by persistent and statistically significant negative effects from period 2 onward. Consistent with this trajectory, the ATE with controls is large, negative, and statistically significant, indicating that, on average, biodiversity financing of conservation projects is largely ineffective at the extensive margin.

In terms of sensitivity to violations of the parallel trends assumption, the iteration of the Rambachan and Roth (2023) procedure that targets the first posttreatment effect shows that for the SHI at the extensive margin the conventional 95 percent CI is $(-0.082, -0.039)$, indicating a small negative effect (fig. A38, Supplementary Appendix E1). Under the relative magnitude restriction, the robust CIs immediately widen and cover zero for modest bounds: $(-1.010, 0.885)$ at $\bar{M} = 0.5$ and $(-1.956, 1.831)$ at $\bar{M} = 1$ (widening further at 1.5 and 2). The breakdown value is therefore < 0.5, so relatively small deviations from parallel trends can explain the baseline estimate. For the late post–treatment average iteration (fig. A39, Supplementary Appendix E1), the conventional CI for the SHI is (0.841, 1.120), but with the relative magnitude restrictions robust CIs are extremely

[32] The dCdH results indicate persistent local (0–50 km) dynamics, weaker intermediate diffusion, and no robust far-field effects after accounting for spatial dependence. This is the exact pattern that was produced with project unit clustering.

Table 10. Biodiversity finance and eBird observations (CO and RO projects).
This table reports dCdH regression estimates examining the association between financing of both CO and RO biodiversity projects and changes in bird observation counts recorded in the eBird database. The treatment switch period indicates the number of years since a project first received financing. Standard errors are clustered by individual project units. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

		Distance from project		
	eBird count (1)	0–50 km (2)	50–200 km (3)	200–500 km (4)
Average total effect (ATE)	−0.168	1.114**	−0.204	0.127
	(0.104)	(0.115)	(0.127)	(0.065)
Treatment switch period				
1	−0.017**	0.054**	−0.0163**	−0.014 **
	(0.003)	(0.013)	(0.00725)	(0.004)
2	−0.017*	0.112**	−0.0477***	−0.005
	(0.008)	(0.023)	(0.00848)	(0.008)
3	−0.024**	0.100**	−0.0301**	−0.033**
	(0.007)	(0.028)	(0.0144)	(0.008)
4	−0.011	0.412**	−0.00642	−0.002
	(0.007)	(0.069)	(0.0169)	(0.008)
5	−0.015	0.191**	−0.0541**	0.000
	(0.008)	(0.055)	(0.0252)	(0.009)
6	−0.015	0.189**	−0.0457	0.004
	(0.011)	(0.029)	(0.0321)	(0.012)
7	−0.026	0.403**	−0.0862***	0.022
	(0.019)	(0.046)	(0.0316)	(0.019)
8	−0.009	0.632**	−0.0448	0.022
	(0.033)	(0.053)	(0.0353)	(0.021)
9	−0.014	0.739**	−0.0171	0.052 *
	(0.015)	(0.061)	(0.0283)	(0.021)
10	−0.066	0.503**	−0.113**	0.041
	(0.038)	(0.056)	(0.0497)	(0.026)
11	−0.057*	0.324**	−0.0456	0.014
	(0.022)	(0.043)	(0.0334)	(0.026)
12	−0.081*	1.070**	−0.101	0.033
	(0.034)	(0.114)	(0.0633)	(0.029)
13	−0.122	0.404**	−0.183*	0.068 *
	(0.077)	(0.071)	(0.0986)	(0.034)
14	−0.148**	0.257**	−0.147**	0.029
	(0.049)	(0.065)	(0.0688)	(0.035)
15	−0.162*	0.444**	−0.145	0.013
	(0.082)	(0.057)	(0.112)	(0.032)
16	−0.124	0.824**	−0.114	0.125**
	(0.081)	(0.079)	(0.118)	(0.032)
17	−0.016	0.924**	0.0535	0.225**
	(0.093)	(0.061)	(0.144)	(0.048)
18	−0.059	1.706**	0.0592	0.356**
	(0.103)	(0.185)	(0.159)	(0.074)
19	−0.2890	0.782**	−0.553	0.703**
	(0.287)	(0.164)	(0.427)	(0.134)
20	−0.523	0.582	−0.897	−0.061
	(0.657)	(0.439)	(0.888)	(0.099)
N	54,924,880	3,992,379	18,396,317	23,347,153

Table 11. Biodiversity finance and map of life (MOL) indicators (extensive margin).
This table reports extensive margin dCdH estimates of the dynamic treatment effects of biodiversity financing on country-level MOL indicators for the species habitat index (SHI), and species protection index (SPI). columns (1) and (2) present SHI results without and with controls, respectively; columns (3) and (4) present SPI results without and with controls. The treatment switch period indicates the number of years since a project first received financing. The controls which are country-level variables include GDP per capita growth, industrial growth, land use ratio, invasive species ratio, percent protected area, R&D as a percentage of GDP and baseline values of the SHI and SPI. Standard errors are clustered by individual project units. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

	MOL indicators (extensive margin)			
	SHI (1)	SHI (2)	SPI (3)	SPI (4)
Average total effect (ATE)	0.121*	−0.612	1.238	−8.258**
	(0.062)	(0.682)	(2.151)	(1.058)
Treatment switch period				
1	−0.061**	−0.082**	0.004	−0.065
	(0.011)	(0.012)	(0.111)	(0.065)
2	−0.086**	−0.140**	0.004	−0.538**
	(0.013)	(0.018)	(0.214)	(0.098)
3	−0.077**	−0.139**	−0.049	−0.992**
	(0.013)	(0.025)	(0.417)	(0.165)
4	−0.038*	−0.134	−0.232	−1.443**
	(0.015)	(0.097)	(0.607)	(0.251)
5	−0.038*	−0.183	−0.371	−1.595**
	(0.018)	(0.373)	(0.603)	(0.321)
6	−0.084**	−0.293	−0.726	−2.121**
	(0.019)	(0.867)	(0.563)	(0.398)
7	−0.091**	−0.337	−0.841	−2.771**
	(0.021)	(0.877)	(0.682)	(0.425)
8	0.086**	−0.167	−1.097	−2.536**
	(0.024)	(0.455)	(0.751)	(0.392)
9	0.067**	−0.246	−0.391	−2.744**
	(0.024)	(0.257)	(0.867)	(0.435)
10	0.039	−0.337**	0.515	−2.902**
	(0.026)	(0.064)	(0.974)	(0.482)
11	0.129**	−0.310**	1.336	−3.106**
	(0.026)	(0.048)	(1.077)	(0.535)
12	0.065*	−0.383**	2.927*	−3.004**
	(0.029)	(0.053)	(1.154)	(0.587)
13	−0.069	−0.587**	2.733*	−3.736**
	(0.035)	(0.059)	(1.316)	(0.613)
14	0.206**	−0.282**	4.028**	−3.225**
	(0.039)	(0.068)	(1.389)	(0.656)
15	0.343**	−0.136	−0.476	−6.101**
	(0.044)	(0.077)	(1.462)	(0.686)
16	0.241**	−0.247**	3.097	−7.620**
	(0.051)	(0.089)	(1.717)	(0.744)
17	0.172*	−0.095	3.571	−9.330**
	(0.071)	(0.108)	(1.842)	(0.882)
18	0.257*	0.296*	4.813*	−10.330**
	(0.111)	(0.136)	(2.059)	(1.102)
19	1.291**	1.546**	2.911	−9.876**
	(0.133)	(0.193)	(2.33)	(1.503)
20	3.578**	4.438**	−19.107**	−2.353
	(0.122)	(0.104)	(2.344)	(1.361)
Controls	No	Yes	No	Yes
N	90,531	90,531	90,531	90,531

wide and include zero even for mild bounds: $(-15.448, 17.408)$ at $\bar{M}=0.5$ and $(-30.448, 32.409)$ at $\bar{M}=1$ (expanding further at 1.5 and 2).

For the SPI at the extensive margin, the iteration of the Rambachan and Roth (2023) procedure which targets the first posttreatment effect shows that the conventional 95 percent CI already spans zero, $(-0.211, 0.219)$, indicating no immediate effect (fig. A40, Supplementary Appendix E1). Under the relative magnitude restriction, the robust CIs are very wide and include zero even for mild bounds: $(-14.519, 14.528)$ at $\bar{M}=0.5$ (width $=29.047$),$(-28.903, 28.911)$ at $\bar{M}=1$ (width $=57.814$), widening further at $\bar{M}=1.5$ and $\bar{M}=2$. The breakdown value is therefore <0.5; modest deviations from parallel trends can readily account for the baseline estimate. For the late posttreatment average (fig. A41, Supplementary Appendix E1), the conventional CI is again non–significant, $(-4.096, 2.365)$. The robust CIs explode: $(-255.276, 253.545)$ at $\bar{M}=0.5$ (width $=508.821$), $(-501.279, 499.548)$ at $\bar{M}=1$ (width $=1000.827$), and they grow further at $\bar{M}=1.5$ and $\bar{M}=2$.

At the intensive margin, where projects are financed above the median, the results, shown in Table 12, are qualitatively similar. For the SHI, the dynamic estimates without controls (column 1) again show early negative effects with delayed positive effects in periods 18, 19, and 20 when controls are included (column 2). The ATE with controls remains negative and statistically insignificant, indicating no average improvement over the treatment horizon. The SPI results are even more closely aligned with the extensive margin pattern of weakness. Without controls (column 3), coefficients are mostly negative or near zero throughout most periods, and with controls (column 4) they are overwhelmingly negative and significant. The ATE with controls is large, negative, and statistically significant.

In terms of sensitivity to violations of the parallel trend assumption, the iteration of the Rambachan and Roth (2023) procedure which targets the first posttreatment effect shows that for the SHI at the intensive margin the conventional 95 percent CI is $(-0.082, -0.011)$, indicating a small negative baseline effect (fig. A42, Supplementary Appendix E1). Under the relative magnitude restriction, the robust CIs widen and cover zero even for mild bounds: $(-1.301, 1.209)$ at $\bar{M}=0.5$ (width $=2.510$),$(-2.197, 2.104)$ at $\bar{M}=1$ (width $=4.301$),$(-3.092, 3.000)$ at $\bar{M}=1.5$ (width $=6.192$), and $(-3.988, 3.895)$ at $\bar{M}=2$ (width $=7.883$). For the late post-treatment average iteration (fig. A43, Supplementary Appendix E1), the conventional CI already spans zero, $(-2.679, 5.542)$. The robust CIs generated by the Rambachan and Roth (2023) procedure are much wider: $(-25.617, 34.940)$ at $\bar{M}=0.5$ (width $=60.557$),$(-55.129, 64.595)$ at $\bar{M}=1$ (width $=119.724$),$(-86.103, 90.391)$ at $\bar{M}=1.5$ (width $=176.494$), and $(-103.200, 106.063)$ at $\bar{M}=2$ (width $=209.263$). As with the extensive margin results, the breakdown value for both iterations of the estimator is <0.5, indicating non-robustness of the identification assumption at the intensive margin. A similar pattern of non-robustness to violations of the parallel trend assumption is exhibited for the intensive margin SPI using both the first posttreatment effect (fig. A44, Supplementary Appendix E1) and late posttreatment average (fig. A45, Supplementary Appendix E1) iterations of the Rambachan and Roth (2023) procedure.

Taken together, both the extensive and intensive margin results suggest that increased financing for conservation projects across Europe over the last two decades has, on average, been ineffective for country-level measures of species integrity and species protection as measured by the SHI and SPI.

To examine whether biodiversity finance has been effective in helping the sample countries meet their SDG 15 targets, I examine the relationship between the financing of CO projects and country-level indicators for the RLI and forest area. The extensive margin results are presented in Table 13 and the intensive margin results are presented in Table 14.

The extensive and intensive margin estimates together reveal a consistent pattern; biodiversity finance for CO projects is associated with statistically significant increases in forest

Table 12. Biodiversity finance and map of life (MOL) indicators (intensive margin)
This table reports intensive margin dCdH estimates of the dynamic treatment effects of biodiversity financing on country-level indicators for the species habitat index (SHI) and species protection index (SPI). columns (1) and (2) present SHI results without and with controls, respectively; columns (3) and (4) present SPI results without and with controls. The treatment switch period indicates the number of years since a project first received financing. The controls which are country-level variables include GDP per capita growth, industrial growth, land use ratio, invasive species ratio, % protected area, R&D as a percentage of GDP and baseline values of the SHI and SPI. Standard errors are clustered by individual project units. ***$P<0.01$, **$P<0.05$, *$P<0.1$.

	MOL indicators (intensive margin)			
	SHI (1)	SHI (2)	SPI (3)	SPI (4)
Average total effect (ATE)	0.259	−0.612	−4.884	−6.736 **
	(0.731)	(0.682)	(7.959)	(1.357)
Treatment switch period				
1	−0.046**	−0.082**	−0.113	−0.106
	(0.018)	(0.012)	(0.155)	(0.103)
2	−0.059**	−0.140**	−0.171	−0.588**
	(0.021)	(0.018)	(0.304)	(0.175)
3	−0.039	−0.139**	−0.098	−1.023**
	(0.021)	(0.025)	(0.592)	(0.253)
4	−0.001	−0.134	−0.468	−1.707**
	(0.041)	(0.097)	(0.831)	(0.326)
5	0.029	−0.183	−0.863	−1.982**
	(0.062)	(0.373)	(0.796)	(0.447)
6	−0.034	−0.293	−1.703*	−2.681**
	(0.089)	(0.867)	(0.805)	(0.589)
7	−0.061	−0.337	−2.268*	−3.650**
	(0.102)	(0.877)	(1.038)	(0.645)
8	0.151	−0.167	−2.764	−3.369**
	(0.291)	(0.455)	(1.811)	(0.991)
9	0.187	−0.246	−2.878	−3.092*
	(0.329)	(0.257)	(2.149)	(1.211)
10	0.064	−0.337**	−2.424	−3.643**
	(0.279)	(0.064)	(2.045)	(1.117)
11	0.225	−0.310**	−2.413	−3.615*
	(0.432)	(0.048)	(2.555)	(1.405)
12	0.183	−0.383**	−1.393	−2.733
	(0.485)	(0.053)	(3.287)	(1.812)
13	0.009	−0.587**	−1.791	−3.697**
	(0.392)	(0.059)	(4.364)	(1.386)
14	0.259	−0.282**	−0.394	−3.405*
	(0.624)	(0.068)	(5.944)	(1.665)
15	0.461	−0.136	−5.458	−6.153**
	(0.862)	(0.077)	(14.275)	(1.573)
16	0.501	−0.247**	−4.623	−6.486**
	(1.043)	(0.089)	(17.636)	(1.893)
17	0.553	−0.095	−9.251	−5.399*
	(1.554)	(0.108)	(26.475)	(2.751)
18	0.516	0.296*	−6.071	−5.953*
	(1.691)	(0.136)	(27.849)	(2.751)
19	2.080	1.546**	−13.365	−0.671
	(3.038)	(0.193)	(41.764)	(3.907)
20	4.481	4.438**	−41.534	9.207
	(4.407)	(0.104)	(68.243)	(4.824)
Controls	No	Yes	No	Yes
N	46,557	46,557	46,557	46,557

Table 13. Biodiversity finance and SDG 15 targets (extensive margin).
This table reports extensive margin dCdH estimates of the dynamic treatment effects of biodiversity financing on country-level SDG 15 targets for the red list index (RLI) and Forest area. Columns (1) and (2) present RLI results without and with controls, respectively; columns (3) and (4) present Forest area results without and with controls. The treatment switch period indicates the number of years since a project first received financing. The controls which are country-level variables include GDP per capita growth, industrial growth, land use ratio, invasive species ratio, percent protected area, R&D as a percentage of GDP and baseline values of the RLI and Forest area. Standard errors are clustered by individual project units.
$^{***}P<0.01$, $^{**}P<0.05$, $^{*}P<0.1$.

	SDG 15 indicators (extensive margin)			
	RLI (1)	RLI (2)	Forest area (3)	Forest area (4)
Average total effect (ATE)	−0.007**	−0.001	0.952**	1.223**
	(0.001)	(0.003)	(0.079)	(0.087)
Treatment switch period				
1	−0.001	−0.001	0.023**	0.025**
	(0.001)	(0.001)	(0.005)	(0.005)
2	−0.000**	−0.001	0.034**	0.044**
	(0.001)	(0.001)	(0.008)	(0.008)
3	−0.000**	−0.000**	0.014	0.023*
	(0.001)	(0.001)	(0.011)	(0.011)
4	−0.000**	−0.001	0.015	0.019
	(0.001)	(0.001)	(0.016)	(0.016)
5	−0.000**	−0.001	0.055**	0.057**
	(0.001)	(0.001)	(0.021)	(0.019)
6	−0.000**	−0.001	0.096**	0.098**
	(0.001)	(0.004)	(0.024)	(0.022)
7	−0.000**	−0.001	0.174**	0.188 **
	(0.001)	(0.004)	(0.026)	(0.024)
8	−0.002**	−0.001	0.245**	0.288**
	(0.001)	(0.002)	(0.027)	(0.027)
9	−0.002**	−0.001	0.351**	0.405**
	(0.001)	(0.001)	(0.031)	(0.031)
10	−0.003**	−0.001**	0.413**	0.474**
	(0.001)	(0.001)	(0.034)	(0.034)
11	−0.003**	−0.001**	0.464**	0.552**
	(0.001)	(0.001)	(0.039)	(0.039)
12	−0.004**	−0.001*	0.545**	0.658**
	(0.001)	(0.001)	(0.043)	(0.045)
13	−0.004**	−0.001	0.590**	0.728**
	(0.001)	(0.001)	(0.052)	(0.053)
14	−0.005**	−0.001	0.813**	1.018**
	(0.001)	(0.001)	(0.055)	(0.062)
15	−0.006**	−0.001	0.831**	1.129**
	(0.001)	(0.001)	(0.057)	(0.072)
16	−0.007**	−0.001	0.780**	1.170**
	(0.001)	(0.001)	(0.064)	(0.079)
17	−0.009**	0.003**	0.995**	1.477**
	(0.001)	(0.001)	(0.066)	(0.108)
18	−0.010**	0.007**	1.194**	1.790**
	(0.001)	(0.001)	(0.073)	(0.144)
19	−0.011**	0.012**	1.407**	2.290**
	(0.001)	(0.002)	(0.086)	(0.205)
20	−0.012**	0.023**	2.388**	3.590**
	(0.001)	(0.001)	(0.089)	(0.332)
Controls	No	Yes	No	Yes
N	90,531	90,531	90,531	90,531

Table 14. Biodiversity finance and SDG 15 targets (intensive margin).

This table reports intensive margin dCdH estimates of the dynamic treatment effects of biodiversity financing on country-level SDG 15 targets for the red list index (RLI) and Forest area. Columns (1) and (2) present RLI results without and with controls, respectively; columns (3) and (4) present Forest area results without and with controls. The treatment switch period indicates the number of years since a project first received financing. The controls which are country-level variables include GDP per capita growth, industrial growth, land use ratio, invasive species ratio, percent protected area, R&D as a percentage of GDP and baseline values of the RLI and Forest area. Standard errors are clustered by individual project units. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

	SDG 15 Indicators (Intensive margin)			
	RLI (1)	RLI (2)	Forest Area (3)	Forest Area (4)
Average total effect (ATE)	−0.007**	−0.001	0.588**	0.693**
	(0.001)	(0.046)	(0.088)	(0.171)
Treatment switch period				
1	−0.000**	−0.001	0.011	0.016**
	(0.001)	(0.001)	(0.006)	(0.006)
2	−0.000**	−0.001	0.033**	0.043**
	(0.001)	(0.002)	(0.011)	(0.012)
3	−0.000**	−0.001	0.034*	0.044 *
	(0.001)	(0.003)	(0.014)	(0.018)
4	−0.000**	−0.001	0.042*	0.057**
	(0.001)	(0.002)	(0.021)	(0.021)
5	−0.000**	−0.001	0.070**	0.084**
	(0.001)	(0.004)	(0.023)	(0.027)
6	−0.002**	−0.002	0.095**	0.118**
	(0.001)	(0.006)	(0.026)	(0.028)
7	−0.002**	−0.002	0.130**	0.172**
	(0.001)	(0.006)	(0.026)	(0.031)
8	−0.003**	−0.001	0.194**	0.238**
	(0.001)	(0.013)	(0.026)	(0.061)
9	−0.004**	−0.001	0.311**	0.352**
	(0.001)	(0.017)	(0.041)	(0.061)
10	−0.004**	−0.002	0.362**	0.421**
	(0.001)	(0.015)	(0.041)	(0.063)
11	−0.005**	−0.001	0.407**	0.472**
	(0.001)	(0.021)	(0.047)	(0.084)
12	−0.005**	−0.001	0.456**	0.517**
	(0.001)	(0.029)	(0.055)	(0.114)
13	−0.005**	−0.001	0.456**	0.561**
	(0.001)	(0.028)	(0.059)	(0.104)
14	−0.006**	−0.001	0.608**	0.700**
	(0.001)	(0.041)	(0.096)	(0.144)
15	−0.007**	0.003	0.640**	0.757**
	(0.001)	(0.057)	(0.118)	(0.188)
16	−0.007**	0.006	0.592**	0.753**
	(0.001)	(0.073)	(0.137)	(0.231)
17	−0.008**	0.009	0.735**	0.829 *
	(0.001)	(0.116)	(0.191)	(0.385)
18	−0.008**	0.012	0.651**	0.747
	(0.001)	(0.127)	(0.203)	(0.442)
19	−0.007**	0.021	0.804**	0.826
	(0.002)	(0.201)	(0.291)	(0.705)
20	−0.007**	0.036	1.334**	0.926
	(0.002)	(0.349)	(0.454)	(1.203)
Controls	No	Yes	No	Yes
N	46,557	46,557	46,557	46,557

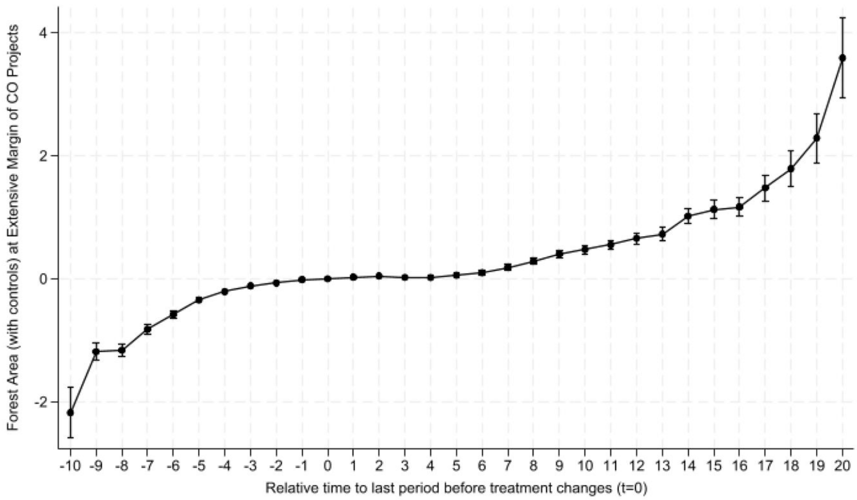

Figure 3. This figure shows the dCdH estimates (with controls) of equation (2), describing the effect of biodiversity financing (at the extensive margin) of conservation-oriented projects on Forest Area Cover. The pretreatment estimates represent placebos generated by the dCdH estimator to test the parallel trend and no anticipation assumptions.

area but limited or delayed improvements in species extinction risk as measured by the RLI.

At the extensive margin, the ATE indicate forest area gains following treatment, while RLI effects are small and negative on average, with only the later treatment periods in the specification with controls, showing small positive coefficients. Dynamic treatment effects show that the forest area response, illustrated in figure 3 for the specification with controls, emerges immediately, with statistically significant gains from the first year after treatment and a steady increase over time. In contrast, RLI coefficients remain negative and statistically significant through most of the treatment window.

As before, I conduct sensitivity to violations of the parallel trend assumption. The iteration of the Rambachan and Roth (2023) procedure which targets the first posttreatment effect shows that for the RLI at the extensive margin (fig. A46, Supplementary Appendix E1) the conventional 95 percent CI is essentially null, $(-0.000, -0.000)$. Under the relative magnitude restriction imposed by the estimator, the robust CIs remain tightly centered around zero and include it for all bounds considered: $(-0.004, 0.004)$ at $\bar{M}=0.5$, $(-0.008, 0.008)$ at $\bar{M}=1$, $(-0.011, 0.011)$ at $\bar{M}=1.5$, and $(-0.015, 0.015)$ at $\bar{M}=2$. Thus, there is no evidence of an immediate effect, and even allowing for plausible violations of parallel trends yields very narrow intervals around zero (e.g., width $=0.008$ at $\bar{M}=0.5$). For the late posttreatment average (fig. A47, online Appendix E1), the conventional CI is negative and statistically different from zero, $(-0.008, -0.006)$, but robustness quickly eliminates significance: the robust CI is $(-0.082, 0.068)$ at $\bar{M}=0.5$, $(-0.146, 0.132)$ at $\bar{M}=1$, $(-0.211, 0.197)$ at $\bar{M}=1.5$, and $(-0.275, 0.261)$ at $\bar{M}=2$. Hence the breakdown value is <0.5 for the late-period estimand. Overall, the extensive margin results for the RLI shows no robust first-period effect and a late-period effect that is not robust once modest violations are allowed. A similar pattern of non-robustness to violations of the parallel trend assumption is exhibited for Forest Area using both the first posttreatment effect (fig. A48, Supplementary Appendix E1) and late posttreatment average (fig. A49, Supplementary Appendix E1) iterations of the Rambachan and Roth (2023) procedure.

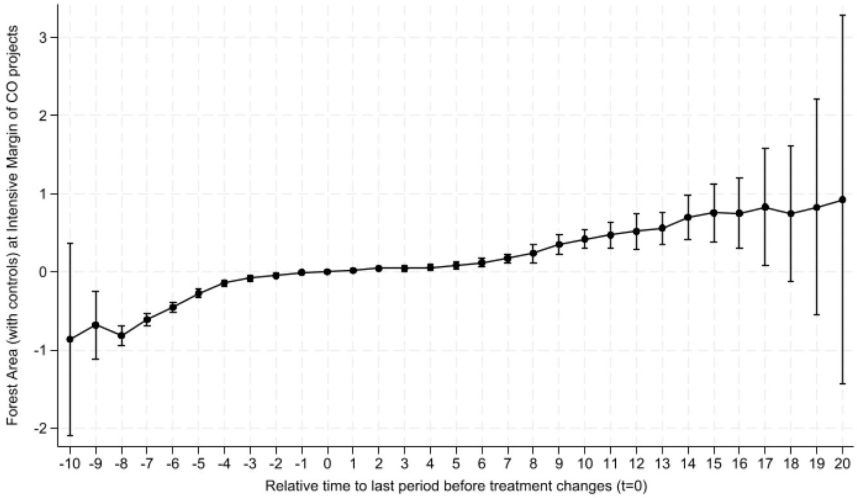

Figure 4. This figure shows the dCdH estimates (with controls) of equation (2), describing the effect of biodiversity financing (at the intensive margin) of conservation-oriented projects on Forest Area Cover. The pretreatment estimates represent placebos generated by the dCdH estimator to test the parallel trend and no anticipation assumptions.

The intensive margin results display a similar pattern. Here too, gains in forest area, illustrated in figure 4 for the specification with controls, appear early (period 2) and persist over the twenty treatment periods. The RLI coefficients again remain predominantly negative and significant, with only a few late treatment periods turning positive and statistically insignificant. As it relates to identification robustness for the RLI at the intensive margin, the first posttreatment effect (fig. A50, Supplementary Appendix E1) and late posttreatment average (fig. A51, Supplementary Appendix E1) Rambachan and Roth (2024) estimates for robust CIs are not robust to modest violations of parallel trends. For forest area at the intensive margin, the first posttreatment effect (fig. A52, Supplementary Appendix E1) and late posttreatment average (fig. A53, Supplementary Appendix E1) Rambachan and Roth (2023) estimates also show fragility in identification robustness, albeit to a less degree.

Taken together, the results imply that while biodiversity finance appears effective at expanding forest cover in both extensive and intensive margins, its impact on species extinction risk is muted in the short and medium term, potentially reflecting the long ecological time frames required for improvements in species conservation status.[33] As with the eBird results, I also address concerns of spatial dependence and reestimate the extensive and intensive margin dCdH specifications (without controls) using distance-band clustering of standard errors. The results, presented in Appendix Tables A14 and A15 (Supplementary Appendix D10), also demonstrate robustness to this adjustment, indicating that the observed financing effects are not driven by spatial dependence.

For the foregoing family of ecological outcomes (SHI, SPI, RLI, and Forest Area), I implement a simple multiple-testing adjustment using the Westfall–Young (Westfall and Young 1993) free step-down procedure with cluster bootstrap at the distance-cluster level.[34] The estimand per outcome is the late posttreatment average of event times +6 to

[33] For brevity I have presented the related dCdH event study graphs for the foregoing results in online Appendix D4–D5 and relegated all discussion of parallel trends and comparison groups to online Appendix E.

[34] To do this I use wyoung, a Stata command that controls the family-wise error rate using the free step-down resampling methodology of Westfall and Young (1993). The command also implements the Bonferroni correction and Sidák correction methods.

+15. The results, reported in Table A16 (Supplementary Appendix D11), show that Forest Area remains statistically significant after Westfall–Young family-wise error control ($p_{\mathrm{WY}} < 0.05$), whereas SHI, SPI, and RLI do not. Alternative multiple-testing adjustment methods which use the Bonferroni correction and Sidák correction approaches also indicate that the SHI, SPI, RLI are not significant regardless of adjustment method, and only Forest Area shows some evidence of significance after accounting for multiple testing. Results are based on $N_{\mathrm{boot}} = 5,000$ cluster resamples with a fixed seed.

5.3 Country-level analysis of research-oriented projects

For RO projects, the research–conservation nexus predicts effectiveness for biodiversity data collection. I test this prediction using the SII, the Map of Life indicator which measures species data coverage.

For RO projects, the extensive margin results in Table 15 show partial support for the research–conservation nexus prediction that biodiversity financing improves species data coverage, as measured by the SII.

In the specification without controls (column 1), the ATE is positive but statistically insignificant. When controls are included (column 2), the ATE remains positive and becomes significant.

For the dynamic treatment effects across the twenty treatment-switch periods, the pattern is more nuanced. Early periods (e.g., periods 1–3) show no improvement or even small negative effects, with period 2 exhibiting a statistically significant decline in SII in both specifications. From around period 6 onward, however, the controlled specification (column 2) records a consistent run of positive and significant estimates through to period 11, peaking at 2.462 in period 11. Period 15 also stands out with significant gains in both columns (1.267 in column 1 and 4.176 in column 2). Beyond this, coefficients are generally positive but imprecisely estimated, reflecting wide standard errors, particularly in the later periods.

The fragility of these results is borne out in the sensitivity assessments for violations of the identifying assumption. In the iteration of the Rambachan and Roth (2023) procedure which targets the first posttreatment effect, the SII at the extensive margin (fig. A54, Supplementary Appendix E1) shows a conventional 95 percent CI of $(-0.185, 0.139)$, that is, no immediate effect. Under the relative magnitude restriction imposed by the Rambachan and Roth (2023) procedure, the robust CIs are wide and include zero even for mild bounds: $(-9.225, 9.179)$ at $\bar{M} = 0.5$ (width $= 18.404$), $(-16.772, 16.726)$ at $\bar{M} = 1$ (width $= 33.498$), widening further at $\bar{M} = 1.5$ and $\bar{M} = 2$. The breakdown value is therefore < 0.5, so modest deviations from parallel trends can already explain the baseline estimate. For the late posttreatment average iteration (fig. A55, Supplementary Appendix E1) of the estimator, the conventional CI is again nonsignificant, $(-18.264, 18.532)$. The robust CIs explode: $(-319.679, 319.946)$ at $\bar{M} = 0.5$ (width $= 639.625$), $(-451.752, 452.020)$ at $\bar{M} = 1$ (width $= 903.772$), with even larger intervals at $\bar{M} = 1.5$ and $\bar{M} = 2$. Here, as well, the breakdown value is < 0.5.

For the intensive margin, presented in Table 16, the ATEs are negative in both specifications, with the magnitude and statistical significance increasing once controls are included. Without controls (column 1), the ATE is −0.657 and statistically insignificant. In the controlled specification (column 2), the ATE falls to −1.860 and is significant at the 5 percent level, suggesting that, on average, financing does not increase species data coverage at the margin.

The dynamic estimates reveal a marked shift from neutral or small positive values in the initial treatment-switch periods (periods 1–4) to consistently negative effects from period 6 onwards. In the controlled specification, several of these later-period declines are statistically significant. For example, periods 6–9 show modest but significant reductions in SII (ranging from −0.607 to −1.016), while periods 12–17 record larger and more persistent

Table 15. Biodiversity finance and species information index (SII) (extensive margin).
This table reports extensive margin dCdH estimates of the dynamic treatment effects of biodiversity financing of research-oriented projects for the SII. Columns (1) and (2) present the SII results without and with controls, respectively. The treatment switch period indicates the number of years since a project first received financing. The controls which are country-level variables include GDP per capita growth, industrial growth, land use ratio, invasive species ratio, percent protected area, R&D as a percentage of GDP and baseline values of the SII. Standard errors are clustered by individual project units.***$P<0.01$,** $P<0.05$, *$P<0.1$.

	MOL indicator (Extensive margin)	
	SII (1)	SII (2)
Average total effect (ATE)	0.895	5.273*
	(1.549)	(2.638)
Treatment switch period		
1	−0.023	0.032
	(0.083)	(0.081)
2	−0.524*	−0.438*
	(0.252)	(0.206)
3	−0.496	−0.366
	(0.485)	(0.511)
4	0.750	0.960
	(0.894)	(0.875)
5	0.752	1.051
	(0.765)	(0.681)
6	0.715	1.123*
	(0.657)	(0.541)
7	1.012	1.497**
	(0.831)	(0.574)
8	0.836	1.674**
	(0.521)	(0.334)
9	0.676	1.894**
	(0.678)	(0.403)
10	−0.166	1.538*
	(0.415)	(0.627)
11	0.155	2.462**
	(0.275)	(0.321)
12	−1.273	1.329
	(1.773)	(1.738)
13	−1.107	1.262
	(1.088)	(1.561)
14	−0.705	1.716
	(1.083)	(1.994)
15	1.267*	4.176*
	(0.634)	(1.888)
16	2.366	6.031
	(2.119)	(3.454)
17	1.961	7.457
	(5.148)	(6.926)
18	3.307	9.915
	(3.813)	(6.122)
19	2.300	13.578
	(9.428)	(12.434)
20	−10.397	7.537
	(35.489)	(42.166)
Controls	No	Yes
N	84,819	84,819

Table 16. Biodiversity finance and SII (intensive margin).
This table reports intensive margin dCdH estimates of the dynamic treatment effects of biodiversity financing of research-oriented projects for the species information index (SII). columns (1) and (2) present the SII results without and with controls, respectively. The treatment switch period indicates the number of years since a project first received financing. The controls which are country-level variables include GDP per capita growth, industrial growth, land use ratio, invasive species ratio, % protected area, R&D as a percentage of GDP and baseline values of the SII. Standard errors are clustered by individual project units.***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

	MOL indicator (Intensive margin)	
	SII **(1)**	**SII** **(2)**
Average total effect (ATE)	−0.657	−1.860**
	(0.635)	(0.719)
Treatment switch period		
1	0.116	0.061
	(0.085)	(0.084)
2	0.163	−0.021
	(0.137)	(0.134)
3	0.295	0.088
	(0.189)	(0.191)
4	0.209	0.020
	(0.223)	(0.232)
5	−0.101	−0.307
	(0.251)	(0.267)
6	−0.429	−0.607*
	(0.272)	(0.294)
7	−0.678*	−1.016**
	(0.293)	(0.323)
8	−0.517	−0.923**
	(0.315)	(0.353)
9	−0.456	−0.816*
	(0.305)	(0.338)
10	−0.305	−0.625
	(0.342)	(0.391)
11	−0.403	−0.772
	(0.363)	(0.424)
12	−0.567	−1.061 *
	(0.413)	(0.482)
13	−1.121*	−1.931**
	(0.493)	(0.561)
14	−1.420*	−2.730**
	(0.587)	(0.658)
15	−0.398	−2.793**
	(0.713)	(0.758)
16	−0.596	−2.939**
	(0.868)	(0.907)
17	−1.363	−3.055**
	(0.849)	(0.937)
18	0.557	−1.933
	(0.881)	(1.021)
19	2.285	−1.266
	(1.236)	(1.277)
Controls	No	Yes
N	41,097	41,097

declines (−1.061 to −3.055), all significant at the 5 percent level. The pattern indicates that the negative effects deepen over time, peaking in the mid-to-late treatment periods before becoming more variable in the final two periods. As with the extensive margin, a similar pattern of non-robustness to violations of the parallel trend assumption is exhibited for these results using both the first post–treatment effect (fig. A56, Supplementary Appendix E1) and late posttreatment average (fig. A57, Supplementary Appendix E1) iterations of the Rambachan and Roth (2023) procedure.

Overall, the intensive margin results suggest that while financing RO biodiversity projects may expand data coverage at the extensive margin, scaling up funding does not produce proportionate gains in the amount of biodiversity data produced by biodiversity research. These results likely reflect diminishing marginal returns, shifts in project priorities toward activities not captured by the SII (such as capacity building, genetic analysis, or non-observational research), or the increasing difficulty of achieving further gains once easily accessible species and locations have been researched and published.[35]

5.4 Biodiversity financing and biotechnology outcomes

A little known fact about biodiversity and conservation projects is the application of DNA technology, genetic biotechnology, and patenting associated with these projects (Krehenwinkel et al. 2019; Keck et al. 2022). Utilizing a basic key word matching textual analysis procedure to read the Biodiversa+ project abstracts, I identify projects of this nature,[36] the financing of which I link to two biotechnology outcomes: biotechnology patents and the number of species DNA sequenced as represented by BINs.

The results, which are presented in Table 17, suggest that biodiversity financing was, on average, ineffective for species genetic diversity and biotechnology patenting. Column 1 (without controls) and column 2 (with controls) both show negative and, for many treatment periods, statistically significant effects of biodiversity financing on species DNA sequencing (BINs). The ATE is negative in both specifications, although only the controlled specification (column 2) is significant, indicating that, on average, financed projects are associated with a reduction of approximately 1,046 BINs. The period-by-period estimates reveal that this negative relationship emerges early—becoming significant from period 3 onwards—and persists for much of the observation window, with the largest declines observed in periods 6–10 and particularly in period 7, where sequencing is reduced by over 1,190 BINs in the controlled model. Interestingly, from period 14 onwards, the sign reverses, and several late treatment periods (14, 15, 17, 19, and especially 20) show large, statistically significant positive coefficients, suggesting a delayed rebound or longer-term effect on genetic sequencing output.

Columns 3 and 4 report effects on biotechnology patenting. The ATEs are positive in both specifications, though neither is statistically significant, suggesting no robust average impact. Period-specific estimates indicate a more nuanced dynamic: significant increases in patent counts are concentrated in a few treatment periods, notably periods 1, 6, and 7, where the controlled model shows increases of around 5–19 patents. While several other positive coefficients appear in later periods (e.g., periods 11–13, 16–19), they are generally imprecisely estimated. Strikingly, period 20 shows a large and significant negative effect (around −143 to −145 patents), suggesting a sharp contraction in patenting activity at the very end of the treatment window.[37]

[35] For brevity I have presented the related dCdH event study graphs for the foregoing results in online Appendix D4–D5 and relegated all discussion of parallel trends and comparison groups to online Appendix E.
[36] In online Appendix F, I present a case study of biotech company Dalan Animal Health (https://www.dalan.com/) which produces vaccines to combat disease and species collapse in bees and shrimp populations. Dalan grew out of a biotechnology-oriented biodiversity project that I was able to identify in the Biodiversa+ database.
[37] For brevity I have presented the related dCdH event study graphs for the foregoing results in online Appendix D6 and relegated all discussion of parallel trends and comparison groups to online Appendix E.

Table 17. Biodiversity finance and biotechnology outcomes.
This table reports dCdH estimates of the impact of financing of biotech related biodiversity projects on two biotechnology outcomes: the number of species DNA sequences and biotechnology patents. Columns (1) and (2) present results for species DNA, without and with controls respectively; columns (3) and (4) present results for biotechnology patents, without and with controls, respectively. The treatment switch period indicates the number of years since a project first received financing. The controls which are country-level variables include R&D as a percentage of GDP, business enterprise expenditure on R&D as a percentage of GDP, the total R&D personnel per thousand total employment and the total researchers per thousand total employment in each country. Standard errors are clustered by individual project units. $^{***}P<0.01$, $^{**}P<0.05$, $^{*}P<0.1$.

	Biotechnology outcomes			
	Species DNA (1)	Species DNA (2)	Biotech patents (3)	Biotech patents (4)
Average total effect (ATE)	−497.049	−1045.724**	23.104	35.575
	(354.782)	(338.252)	(32.804)	(42.254)
Treatment switch period				
1	45.563	35.007	5.470**	5.463**
	(32.804)	(32.608)	(1.032)	(1.028)
2	110.865	76.515	5.989	6.495
	(283.326)	(287.739)	(4.268)	(4.411)
3	−421.039**	−501.565**	7.683	8.777
	(44.486)	(48.212)	(4.418)	(4.645)
4	−421.463**	−509.865**	7.003	8.356
	(52.988)	(57.303)	(4.121)	(4.518)
5	−443.731**	−560.539**	5.415	7.051
	(60.147)	(66.752)	(3.716)	(4.356)
6	−609.524**	−746.338**	8.850**	10.776**
	(85.064)	(94.478)	(3.302)	(3.765)
7	−1015.492**	−1190.932**	16.310**	18.939**
	(108.706)	(121.512)	(4.929)	(5.755)
8	−660.527**	−828.398**	5.859	10.081
	(131.722)	(141.529)	(8.909)	(11.152)
9	−617.496**	−794.344**	2.092	7.816
	(142.118)	(152.846)	(8.968)	(11.586)
10	−438.712**	−617.595**	0.357	5.935
	(144.644)	(161.496)	(9.451)	(11.981)
11	−377.625*	−665.521**	5.937	14.114
	(171.611)	(191.306)	(11.393)	(16.639)
12	−184.782	−513.939*	7.672	17.152
	(181.761)	(207.079)	(15.807)	(22.481)
13	−108.778	−458.308*	11.247	20.504
	(218.442)	(225.444)	(15.779)	(22.025)
14	1014.807**	652.760*	6.122	15.558
	(244.853)	(264.362)	(21.134)	(28.722)
15	785.177**	442.621	5.861	13.251
	(268.935)	(301.687)	(20.546)	(27.426)
16	640.322	203.365	14.571	24.696
	(328.58)	(414.423)	(29.015)	(39.277)
17	786.101*	491.025	17.094	21.682
	(393.427)	(422.947)	(38.229)	(46.063)
18	753.914	438.078	29.181	33.456
	(534.364)	(514.675)	(48.183)	(59.901)
19	2475.287**	2152.523**	37.716	42.832
	(662.124)	(732.676)	(70.296)	(92.118)
20	12925.377**	13290.108**	−143.057	−145.252
	(1072.693)	(1327.47)	(133.952)	(170.125)
Controls	No	Yes	No	Yes
N	113,337	113,337	113,337	113,337

5.5 Use case for private investment in biodiversity projects

An unanswered question in the calls for greater private capital in the financing of biodiversity is the mechanism by which this capital would be compensated given that most biodiversity projects and conservation initiatives are capital intensive but not revenue generating. One possible answer to this question is that private capital directed toward biodiversity projects would, perhaps, benefit most from investment in biodiversity projects which involve biotechnology. This is because biotech-related projects, such as those involving DNA technology, have the potential to generate cash flows (e.g., through intellectual property, commercialization of genetic resources, or biodiversity monitoring technologies), which could make them more attractive to private investors. I explore the use of biotechnology applications in biodiversity projects as a use case for private investment by presenting correlational evidence of the relationship between the number of financial institutions in a country which are signatories to the FfB pledge and the biotechnology outcomes produced by biodiversity projects which involve biotechnology. Signatories to the FfB pledge have committed to increase investment and capital allocation toward biodiversity.

As the FfB pledge only became active in 2021, I make use of another proxy with a longer time series, namely, data on private DFfB flows reported by the OECD.[38] These estimates provide a conservative measure of philanthropic commitments and private capital mobilized by development finance institutions (OECD 2023) and allows me to link to well established blended finance mechanisms (Flammer, Giroux, and Heal 2025b) for private investment directed toward biodiversity in the development finance arena.[39]

I treat the number of FfB signatories and the private DFfB flows as a proxies for private capital directed toward biodiversity and run a panel regression where the outcome variables are the number of species sequenced through DNA barcoding (species DNA) and the number of patent application to the PCT in the biotechnology sector (biotech patents). The main variable of interest is the interaction term between the proxies and a dummy variable which identifies whether or not a project in the country-level sample is biotech-related. This interaction term captures the additional effect of private capital on biotech-related projects. I include as controls the gross domestic expenditure on R&D as a percentage of each country's GDP (GERD XGDP), business enterprise expenditure on R&D as a percentage of each country's GDP (BERD XGDP), the total R&D personnel per thousand total employment (TT TTXEM) and the total researchers per thousand total employment in each country (TT RSXEM). These controls account for the influence of various elements of a country's science and innovation ecosystem on biotechnology outcomes.

The FfB signatory results for species DNA, reported in Panel A of Table 18, show that for each additional FfB signatory, the number of species sequenced across countries in the sample increases by 39.273. The results for the interaction term, shown in column 2, suggest that for each additional FfB signatory, the number of species sequenced increases by an additional 29.778 in biotech projects, compared to non-biotech projects. The results for biotech patents, reported in column 3 and column 4, shows that for each additional FfB signatory, the number of biotech patents increases by 8.877. The results for the interaction term, shown in column 4, suggest that for each additional FfB signatory, the number of biotech patents increases by an additional 6.757 in biotech projects, compared to non-biotech projects.

The private DFfB flows results, reported in Panel B, also show a positive correlation for both DNA sequencing and biotech patents.

[38] I obtain this data from OECD (2023), a decade of development finance for biodiversity, https://doi.org/10.1787/e6c182aa-en.

[39] In its DFfB publications, the OECD defines "private flows" as finance originating outside the public sector, including philanthropic foundations and private investment mobilized by public development finance. Adjusted, or biodiversity-specific, flows retain 100 percent of projects with biodiversity as a principal objective and apply a 40 percent coefficient to projects where biodiversity is only a significant objective, thereby avoiding overstatement of contributions.

Table 18. Private capital and biotechnology outcomes.
This table shows results for regressions of private capital (proxied for by the number of finance for biodiversity (FfB) signatories and private DFfB flows) on biotechnology outcomes. Results for FfB signatories are shown in panel a and results for private developmental finance for biodiversity (DFfB) flows are shown in panel B. The dependent variables are biotechnology outputs: species DNA (columns 1 and 2) and biotech patents (columns 3 and 4). the key independent variables are the interaction terms of FfB signatories and biotech-related projects and private DFfB flows and biotech-related projects. Standard errors are clustered by project. ***$P<0.01$, **$P<0.05$, *$P<0.1$.

	Biotechnology outcomes			
Panel A	**Species DNA (1)**	**Species DNA (2)**	**Biotech patents (3)**	**Biotech patents (4)**
Number of FfB signatories	39.273**		8.877**	
	(1.275)		(0.104)	
FfB Signatories × biotech projects		29.778**		6.757**
		(1.303)		(0.098)
GERD XGDP	7367.275**	7295.396**	−187.574**	−203.746**
	(186.972)	(182.776)	(8.133)	(9.991)
BERD XGDP	−3989.258**	−3794.071**	323.707**	367.657**
	(173.11)	(166.485)	(7.898)	(10.873)
TP TTXEM	−823.239**	−798.903**	−6.767**	−1.284
	(19.604)	(20.412)	(0.689)	(0.916)
TP RSXEM	369.732**	347.973**	−3.689**	−8.595**
	(21.373)	(22.432)	(0.924)	(1.191)
Constant	−693.096**	−662.347**	176.869**	183.797**
	(12.557)	(55.969)	(4.443)	(5.597)
Adjusted R^2	0.157	0.150	0.517	0.337
PCO fixed effects (FE)	No	No	No	No
Panel B				
Private DFfB flows	46.722**		1.928**	
	(6.997)		(0.221)	
Private DFfB flows × biotech projects		−5.214		1.872**
		(8.104)		(0.265)
GERD XGDP	14674.071**	14625.958**	−197.431**	−198.314**
	(234.483)	(233.864)	(5.521)	(5.457)
BERD XGDP	−7945.224**	−7905.412**	232.498**	233.278**
	(218.255)	(218.396)	(6.416)	(6.359)
TP TTXEM	−518.353**	−511.395**	−6.578**	−6.473**
	(24.342)	(24.295)	(0.372)	(0.367)
TP RSXEM	−293.564**	−300.374**	1.329**	1.232**
	(27.736)	(27.768)	(0.354)	(0.352)
Constant	−7342.128**	−7308.747**	366.633**	367.129**
	(137.222)	(136.973)	(3.484)	(3.474)
Adjusted R^2	0.342	0.342	0.777	0.777
PCO FE	Yes	Yes	Yes	Yes
N	175,350	175,350	175,350	175,350

The positive relationship between private capital directed toward biodiversity and biotechnology outcomes provides some support for the use case of private investment in biotech-related biodiversity. The results are, however, suggestive and should not be taken as definitive proof that biodiversity finance drives biotechnology outcomes.

5.6 Robustness

An immediate concern for the geospatial analysis conducted with the eBird Observation Dataset is that the results may be driven by UK and Spain—countries with the most observations in the dataset.[40] To mitigate this concern, I remove these countries and rerun the dCdH regressions with the reduced sample. The reduced sample results, reported in Table A17 (Supplementary Appendix D12), confirm that the patterns observed in the full sample are not driven by UK or Spain. The average treatment effect remains statistically

[40] Both countries account for 58 percent of the observations.

insignificant for overall eBird counts, but becomes positive and significant within 0–50 km and 200–500 km of project sites, consistent with the full-sample findings. The dynamic estimates also follow a similar trajectory.

Another challenge with the e-Birds data is just how noisy it is. Observations are unevenly distributed across space and time, often concentrated in more accessible areas or countries with larger birdwatching communities, and counts depend on volunteer effort and skill. This makes it difficult to separate real changes in bird populations from variation in observer effort, methods, or geographic coverage. While it does not contain the granularity and spatial variation offered by e-Birds, the EU Common Bird Index combines long-term, systematically collected data with statistical corrections and weighting of bird populations across Europe, yielding a more robust and representative indicator of change in species observations of birds over time. The EU Common Bird Index tracks changes in population abundance of 168 common bird species across the EU, with subsets for farmland birds (thirty-nine species) and forest birds (thirty-four species). Aggregated at the EU level using 1990 as the baseline, the index for each group is presented as a smoothed time series with 95 percent confidence limits, serving as a critical indicator of ecosystem health and biodiversity trends. Data originate from the Pan-European Common Bird Monitoring Scheme (PECBMS), coordinated by the Czech Society for Ornithology (CSO).[41] dCdH estimates for the index are presented in Table A18 (Supplementary Appendix D12).

The estimates based on the EU Common Bird Index reveal no statistically detectable treatment effects. Both the average treatment effect and the dynamic coefficients across treatment periods are indistinguishable from zero, regardless of the inclusion of controls. This stands in contrast to the e-Bird analysis, where delayed but significant positive responses to project financing emerged at closer distances to project sites. The discrepancy reflects the very different properties of the two datasets. The e-Bird data capture fine-grained, highly localized changes in species observations in the immediate vicinity of project activity, but they are noisy and subject to biases in sampling effort and spatial coverage. By contrast, the EU Common Bird Index is constructed to represent continent-wide trends in bird populations. It pools long-term, systematically collected data from national schemes, applies statistical corrections and weighting, and smooths the resulting series to reflect gradual shifts in population abundance. As such, the index is well-suited for tracking ecosystem health at the regional scale, but less sensitive to detecting the localized ecological recoveries that biodiversity financing may trigger. The absence of discernible treatment effects in the EU Common Bird Index therefore suggests that while projects may foster local improvements detectable in citizen-science data, such impacts are unlikely to be large or widespread enough to alter aggregate population trajectories at the EU level. In this sense, the two results should be interpreted as complementary, in that, one shows potential local ecological gains while the other underscores the difficulty of translating these gains into continental-scale biodiversity indicators.

An empirical concern for the intensive margin country-level results is the fact that projects financed above the median may be inherently different in ways that correlate with the biodiversity outcome measures. To address this concern, I investigate the differential effect of the 2017 adoption of the EU Nature Directive Action Plan which would have resulted in increased financing for European Commission funded biodiversity projects. Treating the adoption of the action plan as an exogenous shock to the financing of biodiversity, I utilize a single treatment DiD design where projects financed at the EU-level by the European Commission are assigned to the treatment group and projects financed at the country-level by national science funding agencies are assigned to the control group. Additionally, the years post 2017 are assigned a 1 and all other years 0.

[41] I obtain the yearly data for the index from the website of the European Environment Agency https://www.eea.europa.eu/en/analysis/indicators/common-bird-index-in-europe and use it as an alternative measure.

The robustness results from the single-treatment DiD design, reported in Tables A19 and A20 (Supplementary Appendix D12), are broadly consistent with the intensive margin dynamic estimates and suggest that the results are not driven by differences in projects financed above the median. For the Map of Life indicators, the SHI remains statistically insignificant on average, while the SPI shows large and significant negative coefficients in the controlled specification, mirroring the intensive margin finding of persistent weakness in species protection. Similarly, the SII is negative and statistically significant when controls are included, consistent with the earlier result that financing is associated with reductions in species data coverage.

Turning to the SDG 15 indicators, the single-treatment DiD results again align closely with the intensive margin dynamics. The RLI remains negative and statistically significant across both specifications, while forest area shows positive and significant effects, particularly in the uncontrolled specification, though the magnitude weakens once controls are introduced. These findings replicate the pattern observed in the intensive margin dynamic results, where forest area gains appear early and persist, but RLI responses remain negative on average.

For further robustness and to sense check group specific pre-trends and composition, I reestimate the single-treatment DiD using the xtdidregess command. While the command restricts me to a less stringent specification which excludes the rich set of fixed effects which I used to discipline the previous model, it allows me to easily extract trend plots and observe the composition of the treatment and control groups. The descriptive plots (fig. A58–A62, Supplementary Appendix E2) confirm that treated projects (EU-funded) and control projects (country-funded) differ in levels across most biodiversity outcomes, but the pre-2017 trajectories are broadly parallel. This pattern reduces concerns that compositional imbalance drives the results: although the treatment group is smaller in size (766 versus 7,584 control projects) and consistently positioned at higher or lower levels depending on the outcome, there is no evidence of systematic divergence in slopes during the pre-period. Instead, the groups move in roughly parallel fashion before the Action Plan shock, consistent with the common trends assumption. Taken together, these diagnostics suggest that the DiD estimates are not mechanically generated by differences in project composition or pre-trend violations, but reflect genuine shifts in post-2017 dynamics.

Importantly as well, the direction and patterns of significance of the point estimates for the less stringent specification provide meaningful corroboration for the intensive-margin results. Across outcomes, the xtdidregress estimates reproduce the core patterns from the richer specification and thus bolster the single-treatment DiD as a clean yardstick for contrasting extensive and intensive margins. Specifically, treated units experience a statistically significant relative decline in the ecological measures (RLI and SPI) and no robust improvement in the SII, mirroring the negative or non-positive intensive margin results. Forest Area shows a modest but significant relative increase, consistent with an extensive-margin gain that attenuates once richer fixed effects are imposed. The only material divergence is the SHI, where xtdidregress yields a small positive effect that is absorbed by the fuller fixed-effects structure, marking SHI as specification-sensitive. Taken together with the parallel pre-trend and stable-composition diagnostics, this concordance indicates that the post-2017 contrasts are not an artefact of modelling choices and the single-treatment DiD provides a transparent, policy-anchored comparison that corroborates the baseline interpretation.

5.7 Policy and investment implications

How should investors and policymakers make use of these findings? From the point of view of effectiveness per euro for CO projects, the estimates at the intensive margin suggest that investment in forest conservation will be most effective. Raising funding from at-or-below the median to above the median corresponds to an average increase of about €0.53

million in conservation financing per country-year. Scaling the dCdH intensive margin coefficients by this observed funding gap implies that every €1 million invested is associated with an increase of roughly 1.1 to 1.3 units in Forest Area, depending on the inclusion of controls. Evidence from Flammer, Giroux, and Heal (2025a) shows that the average blended finance deal amounts to about USD $29.2 million, a scale that dwarfs the country-year funding increments examined in the intensive-margin analysis. Since moving from below to above the median in conservation funding corresponds to roughly €0.53 million in additional financing and yields an estimated 1.1–1.3 units of Forest Area per €1 million, a single blended finance deal, at nearly €27–28 million, maps into expected gains on the order of 30–36 units of Forest Area if impacts scale proportionally. This comparison highlights how blended finance structures, by mobilizing larger capital commitments, can dramatically amplify the kinds of biodiversity improvements captured at the intensive margin. Given the previous caveats on causality and the fact that we know that ecological impacts do not actually scale proportionally, these financing implications are presented with an abundance of caution. In keeping with this spirit of caution, I also present a back-of-the-envelope commercialization pipeline for the biotechnology channel and hasten to note that it is only suggestive as it is based on correlational patterns rather than causal estimates.

Using the biotech estimates as a back-of-the-envelope guide, and treating Private Official Development Assistance (ODA) Biodiversity Flows as denominated in millions of euros, I trace a simple commercialization pipeline per euro of private investment. The results suggest that €1 million of private biodiversity finance is associated with approximately forty-seven additional species sequenced, while the corresponding effect on biotech patents is about 3.8 additional applications in projects with a biotechnology focus. This sequencing-to-patent progression illustrates how biodiversity finance could possibly generate tangible outputs from the R&D spillover of public funding for basic science and research documented by Bergeaud et al. (2025). Scaling these effects to practical benchmarks, roughly €13 million would be required to generate fifty additional biotech patent applications, while sequencing 5,000 new species would require about €107 million. Doubling these targets to 100 patents and 10,000 sequences would require on the order of €26 million and €214 million, respectively. These figures, while only indicative, demonstrate how private capital could plausibly flow through a biodiversity–biotechnology pipeline, yielding outputs that are both scientifically valuable and commercially relevant. It is important to note, however, that these estimates are correlational, assume local linearity, and depend on the scale of the private flows variable, but they provide a transparent and intuitive measure of what private investment might achieve in this domain.

6. Concluding discussion

The findings reported in this study provide new insights into the effectiveness of biodiversity finance and contribute to the broader debate on whether scaling up public and private capital can meaningfully reduce biodiversity loss. By examining 8,350 biodiversity projects financed across Europe over two decades and linking them to local- and country-level ecological outcomes, I draw attention to both the potential and the limits of biodiversity finance. The results caution against assuming that greater volumes of financing alone can resolve biodiversity loss.

At the local level, the analysis of geo-coded avian data reveals that CO financing exhibits delayed but discernible positive effects on bird sightings within 0–50 km of financed projects. These effects, however, weaken when tested using alternative long-difference specifications and the EU Common Bird Index. At the country level, biodiversity financing has been most consistently effective in supporting forest conservation, with the positive results strengthening when controls for land use change and invasive species are included. By contrast, financing does not translate into measurable improvements in species integrity, species protection, or reductions in extinction risk. These results are consistent with the literature on ecological complexity, which emphasizes that drivers of biodiversity loss such as invasive species and land use change often overwhelm project-level interventions.

As predicted by the biodiversity research–conservation nexus, RO projects funded under the EU's science and innovation programs are effective in expanding biodiversity data coverage. This underscores the value of research funding in generating actionable knowledge and building infrastructure for long-term monitoring. However, the effectiveness of financing at the intensive margin is weaker: projects financed above the median do not exhibit consistently positive effects on either ecological indicators or biodiversity data coverage.

The study also demonstrates the potential of biotechnology as a pathway for incentivizing private capital. EU financing of biodiversity is associated with increases in DNA sequencing but has a limited effect on biotechnology patenting. However, correlational evidence suggests that private sector engagement is positively related to biotech innovation in biodiversity projects. This highlights a promising avenue for aligning private investment with biodiversity goals, particularly where research outputs have commercial applications in medicine, pharmaceuticals, and ecological genetics.

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Supplementary material

Supplementary material is available at *Review of Finance* online.

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Data availability

The data underlying this article are available in ResearchBox Box #5014, at https://researchbox.org/5014.

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