Biodiversity Offsets*

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Abstract

We provide the first empirical analysis of the effectiveness of "biodiversity offsets" – a financial instrument through which investors offset biodiversity losses by funding the conservation of ecologically equivalent habitat nearby. Focusing on the oldest biodiversity offsetting program in the world, we find cross-sectional evidence–corroborated by four decades of satellite imagery of land-use change–that the offset projects reduce anthropogenic pressure on ecosystems. The same projects have substantial local spillovers on bird populations, with species diversity significantly increasing in neighboring areas. To better guide the development of biodiversity offset markets more broadly, we provide an overview of the existing suite of biodiversity data as well as a detailed discussion of the institutional framework of the offset program–which could explain the program's effectiveness.

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1 Introduction

Rapid biodiversity loss is one of the defining features of the 21st century. During this period, vertebrates have gone extinct at up to 100 times their historic rate, and a 2019 IPBES (Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services) Global Assessment found that at least one million animal and plant species–roughly a ninth of all known species–now face the same fate (IPBES, 2019; Ceballos et al., 2015). Concerns about the impact of ecosystem degradation on investment are growing, with 48% of companies in a 2025 survey of a large asset owner indicating that they believe these losses are financially material (Gjerde et al., 2025). Such trends underscores an urgent need for effective interventions to halt and reverse the unprecedented nature loss (Karolyi and Tobin-de la Puente, 2023).

While traditional policy tools, such as Pigouvian taxes, can internalize the costs of biodiversity loss, "biodiversity finance" complements these measures by enabling private investors to directly fund conservation efforts in exchange for the benefits of ecosystem preservation (Flammer et al., 2025). One prominent yet severely understudied form of such biodiversity finance are "biodiversity offsets," where private investors compensate landowners for setting aside ecologically valuable land for habitat restoration. A leading example of such biodiversity offsets can be found in the United States, where the U.S. Fish and Wildlife Service (USFWS) has been overseeing one of the oldest programs of its kind in the world – conservation banking (CB). As of 2022, the CB program conserved 260,000 acres of critical habitat for 57 endangered and threatened species (USFWS, 2022). However, the ultimate success of these market-based environmental interventions hinges on their capacity to deliver real, measurable ecological impact (Aspelund and Russo, 2025).

This paper provides the first empirical analysis of the effectiveness of these biodiversity offset projects. Combining administrative data, gridded ecological measures of biodiversity, bird population survey data, and satellite-based measures of land-use change, we evaluate whether the USFWS-overseen conservation banks causally improve biodiversity conditions in the intervention areas. We also explore the strengths and weaknesses of the high-resolution biodiversity data underlying our analysis, along with an in-depth discussion on the institutional framework surrounding the USFWS CB.

We begin by using gridded biodiversity metrics to examine cross-sectional differences between areas inside CBs and their immediate surroundings. Synthesizing three different biodiversity metrics, we find evidence suggesting that while the number of species found are similar inside the CBs versus the outside, the CBs tend to encompass larger areas of critical habitat and have greater ecological intactness. We carry out subsample analyses which indirectly suggest that such effects are driven not by selection into ecologically valuable lands, but rather

by treatment effects from CBs. Finally, we find that "sold-out" banks exhibit relatively higher biodiversity metric values compared to their surroundings, providing suggestive evidence of market sorting toward higher-quality ecological assets.

We then evaluate the mechanisms surrounding such cross-sectional differences, using a panel data of land-use change spanning four decades. We find that areas within the CBs experience substantially less disturbances from human-driven causes (e.g., logging). Such effects are sustained over more than 20 years and are economically and statistically significant; the results are driven primarily by suppressing agricultural expansion. This is consistent with CBs preserving the habitats of the targeted species and thus reducing the pressure on the wildlife.

Lastly, we assess whether such sustained suppression of habitat loss translates to improvements in actual, observed biodiversity. Combining the footprint of CBs with four decades of systematic bird biodiversity survey, we find that increases in CBs are linked with long-run increases in the number of species discovered, and lead to a population structure more evenly distributed across species–whereby previously dominant species diminish in population size, and rare species increase in population. The impacts of CBs are localized, being focused on locations up to 5km distance away. Importantly, the changes in population composition are driven not by the several specific bird species that are targeted by the CBs themselves–but are instead explained by the overall bird population changing in their composition.

Taken together, the empirical results strongly suggest significant positive impacts from the USFWS-overseen conservation banking program, where adoption of the biodiversity offset project leads to sustained improvements in biodiversity–driven by the suppression of anthropogenic land-use change.

Such positive effects of biodiversity offsets overseen by the USFWS stand in stark contrast to the recent empirical literature on *carbon* offsets (Badgley et al., 2022; Haya et al., 2023; Calel et al., 2025), where studies have found excessive quantities of credits being issued compared to the causal estimates of the tons of carbon sequestered (or carbon emissions avoided). One defining characteristic that distinguishes the CBs from carbon offset market is the very strong engagement from the regulatory entity (USFWS). Contrary to carbon offsets, where the regulatory entities are either non-existent or do not actively verify the sequestration activities, in the CB program the USFWS plays a very active role–even reserving the discretion to not authorize offset credits to be generated when they find the restoration activities to be unsatisfactory (USFWS, 2013, see Section 2). The results highlight the potential role of the USFWS-regulated CB market as a blueprint for the burgeoning biodiversity offset market (Wunder et al., 2025).

In a more broader context, our study also speaks to the rapidly expanding literature on

biodiversity finance (Garel et al., 2024; Gjerde et al., 2025; Akbari et al., 2025; Giglio et al., 2025). Contrary to previous studies, which have been primarily focused on assessing the capitalization of biodiversity *risk*, we focus on the biodiversity projects that private investors are aiming to fund. We showcase how different ecological data and well-known principles of biodiversity measurement (Shannon, 1948; Pielou, 1966) can be harnessed to evaluate the effectiveness of the conservation projects.

We also contribute to the rich ecological literature on the efficacy of place-based conservation. Our cross-sectional and event-study results corroborate the results found in seminal papers in ecological sciences on the effectiveness of protected areas such as Bruner et al. (2001) and Andam et al. (2008), which find that protected areas are broadly successful in limiting habitat conversion and human encroachment. Finally, our results speak to the broader ecological literature pointing toward management practices and regulatory oversight as a key determinant of protected area effectiveness (Leverington et al., 2010; Laurance et al., 2012; Geldmann et al., 2013; Coad et al., 2019). The positive outcomes we document may reflect the relatively robust institutional framework that USFWS oversight provides, distinguishing CBs from the underfunded or poorly governed reserves that characterize the lower end of global protected area performance.

The remainder of the paper is structured as follows. Section 2 provides the institutional background on CBs and discusses in detail the challenges of measuring biodiversity. Section 3 explores our data, and Section 4 presents our empirical strategy and the results. Section 5 concludes.

2 Background

2.1 Institutional Background

2.1.1 Compensatory Mitigation under the Endangered Species Act

Our land-use policy of interest, conservation banks (CBs), is adopted and enforced under the framework of the U.S. federal Endangered Species Act (ESA) of 1973. The federal ESA prohibits the "take" of approximately 1,500 species, the judicial definition of which has evolved to cover not only active killing or injury of the protected species, but also any significant degradation of the species' habitat. Under Section 10 of the ESA, private developers who intend to engage in projects that will result in the "take" of protected species must obtain an "incidental take permit" *before* initiating their projects. This can be highly costly to firms, with empirical studies showing that it places substantial constraints on economic activity of the regulated industries, leading to business closures and workforce layoffs (Ferris and Frank, 2021).

Through the permit approval procedure, the United States Fish and Wildlife Services (US-

FWS), which oversees the implementation of ESA for land and freshwater species,[1] can mandate the project developers to carry out "compensatory mitigation" in order to offset their adverse impacts. Such compensatory mitigation can be achieved through three mechanisms (USFWS, 2013): proponent-responsible mitigation (PRM), in-lieu fee (ILF) programs, and purchasing credits from conservation banks. Under PRM, developers assume responsibility, and the ultimate liability, for implementing and managing mitigation on their own sites. ILF programs, by contrast, require developers to pay into a publicly administered fund that finances mitigation projects. Lastly, CB allows developers to purchase credits from pre-approved sites that are "permanently protected land that is managed for endangered, threatened, or other at-risk species" (p. 7, USFWS, 2013). We discuss the processes for CB credit generation in further detail below.

Crucially, from the private developers' perspective, CBs hold the appeal of completely transferring their liability to the "bank sponsor" who operate and oversee the CB sites (Fox and Nino-Murcia, 2005). Such transfer of liabilities stands in contrast to PRMs, which hold developers ultimately accountable for a complete mitigation of their damages. The project developers' preference for CBs over PRMs, coupled with the USFWS' preference of CBs and PRMs over ILFs[2], have meant that CBs have been the preferred mode of compensatory mitigation for many incidental take permits.

2.1.2 Conservation Banking: Development and Credit Generation

Although CB as a compensatory mechanism was introduced federally by the USFWS in 2003 (USFWS, 2003), its establishment is predated by California's 1995 conservation bank system, which in itself was inspired by the wetland banking system of the Clean Water Act (U.S. CFR §332.3(b)(2) and §332.3(b)(3)). While cross-registrations across the two CB systems are not allowed, the pioneering nature of the California's CB policies explain the prominence of California-based banks even in the federal CB system.

Importantly, the federal CB policy differs from traditional environmental offset programs (e.g., compliance offset programs for carbon pollution, California Air Resources Board, 2015) in the amount of monitoring and cooperation involved from the regulatory agency (USFWS). According to USFWS (2013), any potential supplier of CB credits ("bank sponsors") must contact the USFWS office to receive the office's decision on whether their site can meaningfully contribute to the conservation of endangered species. If the USFWS provides this initial confirmation, the bank sponsor then must work with USFWS in developing the terms of operation

[1] In contrast to freshwater and land species, marine species and anadromous fish are overseen by the National Marine Fisheries Service (NMFS). We leave the impact of conservation finance mechanisms in the protection of aquatic species to future work.

[2] "The in-lieu fee sponsor provides the mitigation when sufficient funds have been collected to implement a mitigation project and takes on the liability of the success of the mitigation. This option is used only if appropriate for the species and no existing mitigation opportunities are available (p.2, USFWS, 2013)."

of the CB ("banking agreement"). Furthermore, even after the banking agreement is executed by the bank sponsor (i.e., the habitats have been restored and preserved), the USFWS must authorize the credits for them to be eligible for purchase by developers.

In addition to the USFWS's active participation in CB project development, various other elements of the CB policy imply a strong potential for achieving significant conservation outcomes. For example, all bank sponsors under the CB are obliged to set aside an endowment that will fund all their conservation activities in perpetuity. The bank sponsors also must contain a detailed plan of monitoring and site management practices in their banking agreement, which will be evaluated by USFWS for their scientific basis (USFWS, 2003).

How exactly does the USFWS translate an acre of land into a CB credit, purchasable by polluters? We delineate two different (and potentially overlapping) types of credits that a conservation bank can generate within its borders. First are habitat-specific which are derived from general habitat/ecosystem types (e.g., Coastal Sage Scrub, Vernal Pools), called "habitat conservation banking" credits. The second are species-specific which are derived from the extant habitat of particular protected species (e.g., Burrowing Owls, California Tiger Salamander), called "species conservation banking" credits. Given these designations, the USFWS may mandate a project impacting burrowing owls (species) and coastal sage scrub (habitat) to purchase credits from each of these CB acres. Importantly, although a given acre may generate multiple habitat or species credits, these credits cannot be subdivided to satisfy separate mitigation requirements across projects; the full bundle must be purchased as a whole. Once purchased, the corresponding acreage is permanently retired and cannot be resold to satisfy different regulatory requirements.

To the extent individual sites will differ in the distribution of species and habitats enclosed, a single conservation bank can generate a diverse offset inventory based on its habitat heterogeneity. We illustrate this possibility with an hypothetical example of a 25-acre CB site (Figure 1). The site has three forms credits that can be generated: habitat credits for Coastal Sage Scrub (CSS, green), species credits for Burrowing Owl (BUOW, orange), and species credits for California Gnatcatcher (CAGN, purple). Due to the overlapping ranges of species and habitats, the 25-acre site has 11 acres eligible for CSS, 9 acres BUOW, 3 acres for CAGN and CSS, 1 acre for BUOW and CSS, and 1 acre for CAGN, BUOW, and CSS. A prospective bank sponsor must work with the USFWS field office to identify such habitats and show the existence of listed species to obtain an approval of the CB site.

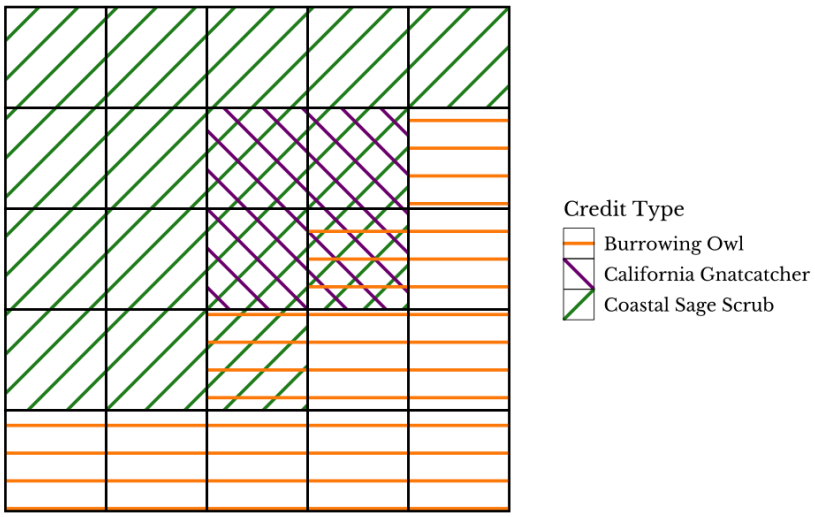


Figure 1. Example Conservation Bank

Notes: Figure illustrates an example conservation bank, with each square representing an acre of land. Green lines show Coastal Sage Scrub "habitat" credits, purple line shows California gnatcatcher "species" credits, and orange lines the burrowing owl "species" credits.

2.2 Biodiversity: Measurement and high-resolution metrics

2.2.1 Defining and Measuring Biodiversity

According to the Dasgupta Review (Dasgupta, 2021), "biodiversity" encompasses the variety of life in all its forms and at all levels including: genes (the genetic material within individuals), species (populations capable of producing fertile offspring), and ecosystems (communities of organisms and their abiotic environment). While this definition is broad, our analysis focuses specifically on the diversity between species (interspecific diversity) and the diversity among individuals of the same species (intraspecific diversity).

Interspecific diversity consists of two fundamental dimensions: species richness (the number of unique species in an area) and species evenness (the relative abundances of those species). These dimensions can characterize biodiversity in fundamentally different ways: species richness captures changes in community membership through colonizations and extinctions and is therefore a central focus of conservation biology. However, richness alone provides limited information about the biomass, primary production, or competitive interactions within an ecosystem. For example, an ecosystem may exhibit high species richness even when it is dominated by a single species. In such cases, high richness can mask underlying ecological degradation when the ecological community's functions becomes disproportionately reliant on a small subset of species.

By contrast, species evenness reflects the extent to which individual abundances are dominated by a few species. Changes in evenness within groups of organisms that perform similar ecological roles (i.e. functional groups) reflect shifts in dominance and competitive balance among species and can occur even in the absence of local species loss. This makes evenness particularly informative about compositional change and ecological stress. However, evenness alone is insufficient as a singular metric of biodiversity because it is conditional on species richness: a community composed of a single species is perfectly even by definition, yet lacks functional redundancy and trophic complexity. Evenness therefore conveys information about balance among existing species, but not about the breadth of ecological roles present.

As such, the ecological literature has long recognized the importance of considering both richness and evenness in characterizing biodiversity. Several indexes synthesize these two dimensions into a single measure, but we focus on the two most widely used metrics: the Shannon–Wiener Diversity Index H and Simpson's Diversity Index D (Shannon, 1948; Simpson, 1949). These are calculated as follows:

$$\text{Shannon-Wiener Diversity Index: } H = -\sum_{i=1}^{S} p_i \log(p_i) \tag{1}$$

$$\text{Simpson's Diversity Index: } D = 1 - \frac{\sum_{i=1}^{S} n_i(n_i - 1)}{N(N-1)} \tag{2}$$

where S denotes species richness (the total number of unique species), n_i represents the number of individuals belonging to species i, and $N = \sum n_i$ is the total number of individuals across all species. The term $p_i = \frac{n_i}{N}$ represents the relative size of abundance (i.e., population) of species i within the community. for what Although both indexes combine information on richness and evenness, they differ fundamentally in how they weight species abundances (species population). The Shannon–Wiener index places relatively greater weight on rare species, making it sensitive to the gain or loss of rare species. By contrast, Simpson's index places greater weight on common species and is therefore more responsive to shifts in dominance among the most abundant species.[3]

Lastly, the Shannon-Wiener index can be normalized to yield Pielou's Evenness Index (Pielou, 1966):

$$\text{Pielou's Evenness Index } J = \frac{H}{\log(S)} \tag{3}$$

[3]Although the two indices are frequently highly correlated in empirical applications, divergence between them can nonetheless provide diagnostic insight into patterns of community restructuring. An increase in Shannon–Wiener diversity without a corresponding increase in Simpson's diversity indicates that gains in biodiversity are primarily driven by the colonization or proliferation of rare species. Conversely, a decline in Simpson's diversity accompanied by relatively smaller changes in the Shannon–Wiener index indicates increasing dominance by one or a few common species, consistent with growing competitive imbalance.

Pielou's index isolates the evenness component of diversity by removing the influence of species richness, allowing changes in relative abundances to be examined directly. Unlike Shannon–Wiener and Simpson's indices, which jointly reflect richness and evenness, Pielou's index provides a complementary measure of compositional balance that is particularly informative when species richness remains stable.

By employing this suite of complementary metrics (species richness, Shannon–Wiener diversity, Simpson's diversity, and Pielou's evenness) we ensure that our analysis captures multiple relevant dimensions of biodiversity. Evaluating these outcomes in tandem allows us to better characterize the mechanisms underpinning the structural evolution of the community, revealing whether ecological shifts are occurring through changes in species occupancy or through shifts in competitive dominance that alter the community's internal balance.

2.2.2 Biodiversity data: A brief survey and application to biodiversity finance

As alluded to earlier, remarkable progress has been made in the availability of ecological data capturing biodiversity at fine spatial scales (Burgess et al., 2024). The biodiversity data sets differ in their generation process, temporal coverage, and the specific aspects of biodiversity covered. The four panels of Table 1 correspond to the broad categories into which such biodiversity data fall.

The first type, exemplified by the Biodiversity Intactness Index (BII, Newbold et al., 2016), provide model-based predictions of local biodiversity at fine spatial resolution. Such models are fitted on ecological data (e.g., abundance of specific taxa) from numerous peer-reviewed studies, with anthropogenic sources of biodiversity pressure (e.g., land-use change) as predictor variables. The models are then extrapolated to the entire globe.

Because these data sets are cross-sectional, they are particularly useful for capturing spatial variation in biodiversity. Consequently, absent plausibly exogenous cross-sectional variations in the policy, this limits their use for reduced-form estimations of conservation policies' impact. More importantly, considerable attention to the assumptions implicit in the data is in order. For example, though both BII and Mean Species Abundance (MSA) incorporate richness into their calculations, they are much more sensitive to changes in abundances. Furthermore, the two models also do not distinguish species based on their conservation status, weighing critically endangered and non-threatened species equally. Using such data to capture biodiversity may not be appropriate when the firm activity is expected to disproportionately affect vulnerable species, or primarily affect species richness and evenness, while not altering the population size.

The second type of data (panel B, Table 1) obtain gridded estimates of biodiversity by directly relying on ecological surveys. For example, eBird Status and Trends data sets rely on citizen

Table 1. Examples of high-resolution biodiversity data

Name	Spatial Coverage and resolution	Original data source for biodiversity	Temporal coverage and Resolution	Measures abundance/richness?	Weigh species according to conservation status?	Reference
A. Model-based/predicted global biodiversity products						
Biodiversity Intactness Index (BII)	Global, 1km	Global site-level surveys	2015, cross-sectional	Yes/No	No	Scholes and Biggs (2005); Newbold et al. (2016)
#Mean Species Abundance (MSA)	Global, 300m	Global site-level surveys	2015, cross-sectional	Yes/No	No	Schipper et al. (2020)
#Species threat abatement and restoration (STAR)	Global, 5km	IUCN Red List range	2015, cross-sectional	Yes/Yes, indirectly†	Yes	Mair et al. (2021)
B. Ecological survey-based gridded biodiversity products						
eBird Trends	Global, 27km	Citizen science (eBird research quality observations)	2012-2021 trend, 2013-2022 trend	Yes/Yes*	Yes**	Fink et al. (2023)
eBird Status	Global, 3km	Citizen science (eBird research quality observations)	2021-, annual	Yes/Yes*	Yes**	Fink et al. (2020)
TreeMap	Continental U.S., 30m	U.S. Forest Service's Forest Inventory and Analysis surveys	2016, 2020, 2022, annual	Yes/Yes	Yes**	Riley et al. (2022)
C. Ecological surveys at fixed sites						

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Table 1 – continued from previous page

Name	Spatial Coverage and resolution	Original data source for biodiversity	Temporal coverage and Resolution	Measures abundance/richness?	Weigh species according to conservation status?	Reference
#North American Breeding Bird Survey	North America, ~ 4,000 routes	Bird identification by trained volunteers along vehicle routes	1966-, annual	Yes/Yes*	Yes**	Sauer et al. (2017)
ORSANCO Fish Population	Ohio River, 18 sites	Fish population and biotic conditions surveys	1957-, annual	Yes/Yes*	Yes**	Ohio River Valley Water Sanitation Commission (ORSANCO)
D. Remote sensing-based estimates of ecosystem health proxies						
#Land Disturbances	Continental United States, 30m	Multispectral sensors on satellites and ground-truth land disturbance	1988-, annual	No/No	No	Qiu et al. (2025)
Aboveground biomass density	Global, 100m	LiDAR (laser imaging, detection, and ranging) sensors on satellites	10 years between 2007–2022, annual	Yes/No	No	Santoro et al. (2024)

Note: Table presents a survey of biodiversity data that can be used to assess firm impact on local biodiversity. The table is not exhaustive, and we exclude products with spatial resolution insufficient for local biodiversity impact analysis (coarser than 0.25°, approximately 27km at equator, or products only available at the country level). # = Used in this study. † = Does not provide abundance or richness metrics, but provide species-specific data (which can be aggregated to calculate richness), and capture abundance by species-specific risk of extinction. *=Provides species-specific abundance, can be aggregated to obtain species richness and other biodiversity metrics (e.g., Shannon's Diversity). **=Provides species-specific data, can be weighted with rarity. IUCN = International Union for Conservation of Nature, ORSANCO = Ohio River Valley Water Sanitation Commission.

science submissions of bird observations to estimate species-specific trends in population and in their range (Fink et al., 2020, 2023). They overcome well-known challenges in using citizen-science data (Johnston et al., 2023) by focusing on research-grade observations and by explicitly taking into account observer effort in modeling species abundance–resulting in 3km to 27km grid-level estimates of bird species' population and their trends. Similarly, TreeMap (Riley et al., 2022) provides 30m pixel-level estimate of tree species composition and other forest characteristics (e.g., biomass per area) using decades-long ecological surveys from the United States Forest Service.

Unlike model-based predictions, such survey-based gridded products provide a more direct measureme of biodiversity. This is because their species-level data can be used to compute well-known metrics of species biodiversity, such as the Shannon-Wiener Index, Simpson's Index, and Gini coefficients, and can also be used to assess heterogeneous impacts of firm activity across different species. Nevertheless, they are often limited in their temporal resolution (e.g., generated every 2-4 years for TreeMap) and in their taxa coverage. Such data sets are hence useful when variations in the measured taxon's biodiversity sufficiently capture the effect of the conservation policy in question.

In a similar vein, the third type of data (panel C) provide spatially constrained yet temporally extensive snapshots of local biodiversity, with many data sets spanning several decades. A careful empirical strategy that compares within-site, intertemporal variation in exposure to firm activities (e.g., firm pollution) to that of outcomes observed in the fixed sites could reveal the biodiversity impact of land-use conservation.

The fourth type of data (panel D) provide *proxies* of ecosystem health, through remote-sensing results from airborne or spaceborne sensors targeting, for example, forest biomass density. While such measures do not directly measure biodiversity, they can provide important information on local trends in factors that drive biodiversity *loss*, such as land-use change.

Lastly, we note that raw data on species presence and expert-based species-specific range estimates (e.g., eBird raw observation data) provide essential data on presence of different species across the globe. Carefully combined with data sets on the biotic and abiotic conditions of the reported locations, the species presence data can be used to construct species distribution models (SDMs) which capture the suitability of locations to individual species (Araújo et al., 2019). However, species presence data require considerable data cleaning (Zizka et al., 2019), and the data by definition do not include non-presence; the absence of records cannot be interpreted as true absence of the species. The number of observations *per se* also cannot be treated as an unbiased estimate of abundance, as evidenced in the "data voids" in the tropics (Meyer et al., 2015).

3 Data

3.1 Conservation Banks

We obtain conservation banking Data comes from the Regulatory In-lieu Fee and Bank Tracking System (RIBITS), which provide comprehensive information on the different conservation banks that have been approved by the USFWS, the number of credits issued, acres involved, and their approval and credit generation timelines. While the RIBITS shows 192 conservation banks have been approved by the USFWS,[4], spatial boundaries are only available for 111 of them.[5] Given that precise spatial joins and calculations are foundational to all our empirical exercises, we focus our analysis on this refined subset of 111 banks to ensure data accuracy.

3.2 Bird Biodiversity

3.2.1 North American Breeding Bird Survey

We use the North American Breeding Bird Survey ("BBS," Ziolkowski et al., 2025) to assess the impact of CBs on local bird communities. Initiated in 1966, the BBS provides one of the longest-running and most systematically collected datasets on bird populations in North America. The survey consists of approximately 4,000 routes, each approximately 24.5 miles in length, along which trained observers conduct standardized point counts at 50 equidistant stops, recording all birds seen or heard (Sauer et al., 2017). The core BBS sampling protocol has remained largely unchanged since the survey's inception in 1966, allowing for consistent comparisons over time.

Using the species-specific count data for each route-year, we calculate species richness, total abundance (i.e., total number of birds observed), and species evenness (using equation (3)). We also join the route-year level data with weather data from the BBS data set, which provide information on the exact date and duration of the survey, along with the temperature, cloud cover, wind speed over the survey.

3.2.2 Importance of Bird Biodiversity

Beyond the unparalleled temporal coverage and granularity of the BBS, it is worth emphasizing why bird diversity is itself a meaningful outcome of interest. Firstly, birds carry "existence value" (the inherent value that comes from the existence of the species) as a species–a consideration embedded in the ESA itself and the broader framework motivating conservation banking. Beyond this, birds provide a host of important ecosystem services including pest control from

[4]To the extent that RIBITS data on banks for not only ESA but also the Clean Water Act, they flag conservation banks by "species" in their column "Credit Types," In practice, the CBs included in these projects generate not only species credits but also habitat credits for ESA.

[5]To be precise, RIBITS provides boundary data for 135 banks, but 24 of these boundaries are too large compared to the number of credits generated–at least three times larger. We hence drop these 24 banks from the data set.

insectivores (Mols and Visser, 2002; Greenberg et al., 2000), seed dispersion (Howe and Smallwood, 1982), waste management from scavengers (Frank and Sudarshan, 2024), and pollination by roughly 900 different species of birds (Nabhan and Buchmann, 1997).

Furthermore, bird biodiversity provides significant ecosystem services, as birdwatching represents a significant sector of recreational spending, with total economic output estimated at $279 billion in 2022 (USFWS, 2024). Lastly, birds serve as sensitive "bioindicators" of broader ecological conditions. The well-documented collapse of bird populations under DDT exposure (and their subsequent recovery following the 1972 ban) provides a canonical example of how avian populations can reveal otherwise invisible environmental stressors. Consequently, bird diversity is reflective of changes in habitat quality, pollution, and land-use dynamics.

As such, the increases in species richness and population evenness we document are informative not only about avian communities themselves, but also about the underlying ecological conditions that conservation banks are intended to maintain.

3.3 Gridded Ecological Metrics

Land Disturbance Data. We use Qiu et al. (2025) for a 30m-resolution data on the "disturbance" of land-use practices, from 1988 to 2024. The Qiu et al. (2025) stands out, among other aspects, for its classification of disturbed pixels into their agents associated with the disturbances. We discuss the characteristics of the data set in grater detail below.

Species Threat Abatement and Restoration (STAR) Metric. STAR was developed by Mair et al. (2021) and has two different, though related, metrics: STAR_T and STAR_R. STAR_T measures the potential contribution of threat abatement in grid cell i to reducing global species extinction risk while STAR_R quantifies the potential contribution of habitat restoration at location i. We obtain STAR_T from the Integrated Biodiversity Assessment Tool (IBAT), which calculates it using species on the IUCN Red List at a 5 km resolution according to:

$$STAR_i = \sum_{t=1}^{N_t} \sum_{s=1}^{N_s} W_s \cdot \frac{A_{s,i}}{G_s} \cdot C_{s,t} \tag{4}$$

where N_t and N_s are the number of threats and species respectively, W_s is a conservation weight based on species s's IUCN Red List classification, $A_{s,i}$ is the area of habitat for species s in grid cell i, G_s is the total area of habitat globally for species s, and $C_{s,t}$ is the relative contribution of threat t to the extinction risk of species s. To the extent that threats and species are fixed between grid cells, variation in STAR_T across grid cells is driven by differences in the share of each species' global range contained within the cell.

Mean Species Abundance (MSA). MSA compares observed abundances of all species in a pixel

to their abundances in an "undisturbed" reference state.

$$MSA = \frac{1}{N} \sum_{i=1}^{N} \frac{A_i}{A_{i,ref}}$$

where N is the number of species in the pixel's reference state and A_i and $A_{i,ref}$ denote the current and reference abundances respectively. Importantly, A_i is capped at $A_{i,ref}$ to avoid intactness being inflated by generalist species that benefit from habitat disturbances. Furthermore, only species present in the reference state are included, so newly introduced species do not contribute to the metric. As a result, MSA is bounded above by 1. We obtain MSA from Schipper et al. (2020), which calculates the MSA within GLOBIO 4. In this framework, MSA is not calculated directly from species-level abundance data, but instead inferred using empirically derived "pressure–impact" relationships between MSA and major drivers of biodiversity loss, including climate change, nitrogen deposition, land use, road construction, and hunting. These relationships are combined with spatial data on the corresponding pressures to produce global estimates of MSA at approximately 300 m resolution.

Rarity-weighted Species Richness (RWR). Rarity-weighted species richness is calculated in a grid cell using the following formula:

$$RWR = \sum_{i=1}^{N} \frac{1}{c_i}$$

where N is the total number of species in the cell and c_i is the number of cells containing species i in the study region (e.g. state, continent, globe, etc.). We obtain RWR from IBAT which calculates this metric globally at a ~10km resolution using rasterized range maps for mammals, birds, amphibians, crabs, crayfishes, and shrimps. Higher values of RWR indicate that a cell contains a large number of species and/or that the species contained in the cell have small ranges. Importantly, because RWR is a reweighted measure of species richness, it too fails to incorporate information on species abundances. Nonetheless, it is commonly used in conservation prioritization, as it highlights areas that disproportionately support range-restricted and endemic species.

4 Empirical Strategy and Results

We now bring high-resolution biodiversity data (Section 2) to bear to a three-step analysis on the effect of conservation banks (CBs) on ecological outcomes. First, we showcase how model-based global biodiversity data (Type A, Table 1) can be used to assess the cross-sectional variation in ecological conditions inside and outside the conservation banks, at a fixed point

in time. Second, we apply modern event-study methods (Callaway and Sant'Anna, 2021) to satellite-based estimates of ecological damage (Type D, Table 1) to evaluate the dynamic causal effect of CBs on suppressing habitat degradation. Lastly, we use long-difference (Burke and Emerick, 2016) to two decades of bird survey (Sauer et al., 2017) to evaluate the long-run effect of CBs on observed bird biodiversity (Type C, Table 1), which we use as a proxy for overall ecosystem biodiversity. Combined together, the analysis sheds light on whether CBs can suppress biodiversity loss and improve observed biodiversity.

4.1 Conservation Banks: Cross-sectional evidence from gridded biodiversity metrics

As previously discussed, gridded biodiversity metrics (Type A, Table 1) provide cross-sectional measures of richness and abundance based on a set of modeling assumptions. Here, we explore how three well-known cross-sectional biodiversity metrics (RWR, MSA, and STAR, Section 3.3) can be utilized to provide a nuanced picture of the processes driving the impact of CBs on local biodiversity.

In utilizing the cross-sectional biodiversity metrics for evaluating the impact of CBs, it is crucial that we rely on pixels that are exposed to similar ecological pressures and habitat characteristics. To this end, we take a localized approach of comparing pixels that adopt CBs versus those that don't, calculate the mean value within the boundaries of each conservation bank ("in-bank mean") versus the mean within a 10 km buffer surrounding the bank (outside-bank mean). We then conduct pairwise t-tests comparing the two.

Panel A of Table 2 presents the result of this comparison, for all CBs. The relatively small, albeit statistically significant, differences between RWR inside and outside the banks suggest that (rarity-weighted) species richness is broadly comparable across these areas. Put differently, the overall number of species found in the banks versus directly outside of them is largely similar.

The similarity in species richness provides important context in interpreting the STAR metric values, as the values are significantly higher in the bank than outside. Across areas with very similar species composition and overall environmental pressures (e.g., pollution, climate), differences in STAR metric are primarily driven by the size of the habitats provided to the species ($A_{s,i}$ in equation (4)). The higher STAR values within banks thus indicate that banks encompass a greater area of critical habitat for the species.

Further, under near-constant species richness across space, differences in MSA (Mean Species Abundance) translate to differences in anthropogenic threats to biodiversity. The higher MSA value found inside CBs (row 3, Table 2) point to lower overall pressure to areas within the bank.

All in all, the panel A results across RWR, STAR, and MSA point to the areas within CBs

Table 2. Placement of conservation banks: evidence from gridded ecological metrics

Metric (resolution)	(1) Number of in-bank pixels	(2) In-bank mean (SD)	(3) Outside-bank mean (SD)	(4) Mean pairwise difference (SE)
A. All conservation banks (111 banks)				
RWR (10km)	175	2.455	2.492	-0.037*
		(1.559)	(1.562)	(0.021)
STAR (1km)	443	2.203	1.611	0.592**
		(3.580)	(1.493)	(0.262)
MSA (300m)	4,709	39.772	36.516	3.255***
		(20.409)	(17.069)	(1.065)
B. Conservation banks approved after 2015 (43 banks)				
STAR (1km)	177	1.867	1.602	0.265
		(3.138)	(1.788)	(0.310)
MSA (300m)	1,945	42.877	43.840	-0.963
		(25.034)	(22.585)	(1.618)
C. Sold-out conservation banks (14 banks)				
RWR (10km)	22	2.551	2.532	0.019
		(1.251)	(1.277)	(0.040)
STAR (1km)	45	4.089	1.998	2.091
		(6.650)	(1.492)	(1.552)
MSA (300m)	431	37.258	30.655	6.603**
		(13.097)	(6.484)	(2.488)

*$p < 0.10$,** $p < 0.05$,*** $p < 0.01$

Notes: Table presents ecological indexes inside and outside conservation banks, across different gridded ecological estimates (Data type A, Table 1). Column 1 presents the number of grid pixels within the conservation bank boundaries, while columns 2 and 3 show summary statistics of different indexes within the banks and outside (up to 10km distance) the banks, respectively. Column 4 presents pairwise t-test results of comparing the ecological indexes across banks. Panel A covers all 111 conservation banks with known boundaries, while panel B covers 14 banks whose credits are in high demand (i.e., who have been "sold out"). Panel C focuses only on projects approved after 2015, which is the evaluation period for STAR and MSA. All summary statistics multiplied by 100 for legibility. See main text for definitions of different ecological indexes and their interpretation. STAR = Species Threat Abatement and Restoration metric, RWR = Rarity-weighted species richness metric, MSA = Mean Species Abundance.

being exposed to lower levels of anthropogenic pressure and housing a higher concentration of critical habitat for different species. However, to the extent that the gridded data sets are purely cross-sectional, the panel A estimates cannot disentangle the impact of selection bias (i.e., CBs

being placed in high-STAR, high-MSA regions) from the true treatment effect of CBs.

To overcome this identification challenge and to distinguish selection bias from treatment effect, we exploit the fact that STAR and MSA metrics capture the ecological status of areas as of 2015. If we see differences in STAR and MSA metrics for CBs established *after* 2015, then this is a very strong proof that the USFWS and landowners are prioritizing high-MSA, high-STAR locations over their neighbors. Put differently, if banks are systematically sited in higher-quality areas, we would expect positive differences in this subsample.

Panel B hence restricts attention to conservation banks approved after 2015. Interestingly, the estimates in Panel B are small and statistically insignificant across the two metrics, indirectly suggesting that selection bias is small in post-2015 banks. Taken together, this pattern indicates that selection alone is unlikely to fully account for the differences observed in the full sample, in panel A.

Further, while panel A results were focused on all CBs, panel C investigates whether the market discriminates the CBs following their ecological characteristics. Specifically, we assess whether "sold-out" banks whose credits have all been purchased exhibit superior biodiversity profiles. This analysis tests the hypothesis of market sorting, wherein credits from higher-quality banks are preferentially acquired. We find that RWR does not significantly vary by sale status, but areas within sold-out banks are characterized by markedly higher, though noisy, STAR and MSA values relative to their surroundings (column 4 values)–with the across-space differences being much larger than those in all CBs. This provides indirect evidence that the market may prioritize credits from sites with higher intactness and habitat relevance.

4.2 Conservation Banks and Habitat Degradation: Evidence from satellite imagery

Habitat degradation *via* land-use change is one of the leading drivers of rapid biodiversity loss (Semenchuk et al., 2022; Eyres et al., 2025). Recent advances in satellite imagery analysis have made wide-scale monitoring of land-use patterns possible, which use spatiotemporal variations in the multispectral surface reflectance (i.e., radiation reflected from the Earth surface across the electromagnetic spectrum) to detect deforestation and agricultural expansion.

In particular, we use a 30m-resolution "Land Disturbance data set" from Qiu et al. (2025) to assess the dynamic effect of CB establishment on land-use change. The Land Disturbance data set is based on a suite of machine learning models trained to detect ground-truthed abrupt changes in land-use practices. Crucially, the machine learning models are specifically trained to not only *identify* but also *classify* the sources of such disturbances (e.g., water stress, wildfire, agricultural conversion, logging). The data set hence provides an important step forward compared to traditional land-use data, which focus on specific forms of disturbance (e.g., deforestation, Hansen et al., 2013) or were agnostic to the sources of disturbance (e.g.,

Kennedy et al., 2010).

We further account for two empirical challenges in evaluating the causal effect of CBs on land-use change. First, we note that despite the failure to find significant differences in cross-sectional characteristics (panel B, Table 2)–there still is the possibility that such failures are due to statistical imprecision and that the CBs differ systematically from non-CB pixels in their baseline characteristics. Such "cross-sectional endogeneity" means that areas that were "never treated" to CBs are not a reliable source of counterfactual scenarios. We rule out such sources of selection bias by focusing solely on pixels that are eventually registered as CBs.

Further, even when such selection bias is controlled for, there is a possibility that landowners of CBs anticipate the designation of their land and engage in preemptive degradation activities ("dynamic endogeneity"), a behavior that has been documented for other land use-based interventions such as voluntary carbon offset programs (Garcia and Sanford, 2026). We thus adopt the event-study approach (Callaway and Sant'Anna, 2021) and assess whether land disturbance increases sharply in frequency prior to the CB approval.

We construct the CB-year level balanced panel data set of land disturbance as follows. For each CB and year, we assign a value of 1 to all pixels in CBs that were flagged as "disturbed for human-related causes," with 0 otherwise. The average of this value for each CB-year represents the unconditional expected probability of a pixel in the CB being disturbed, for that year. We evaluate whether this probability (i.e., the mean of land disturbance indicator variable) changes significantly following the establishment of CB. The event-study equation is thus:

$$Y_{ct} = \sum_{k=-10, k\neq -1}^{k=20} \beta_k \mathbb{1}[\text{CBApproved}]_{c,t-k} + \alpha_c + \delta_t + \varepsilon_{ct} \tag{5}$$

where Y_{ct} is the probability of human-related land disturbance for conservation bank c, in year t. We follow the definition of Qiu et al. (2025) to define human-driven disturbances as disturbances from logging, construction, and agriculture. We cluster standard errors at the CB level. Lastly, while our primary analysis focuses on human-driven land disturbances, we use non-human driven land disturbance (from wind damage, pest outbreaks, and wildfire) as a placebo test–as CBs are not meant to reduce risks of nature-driven losses.

Figure 2 presents the results of the event study regression (5). The results suggest a persistent drop in the probability of disturbance following CB approval. Overall, an approval is associated with a 3.82% point drop in the likelihood of disturbance, significant at the 95% confidence level. In contrast, the estimates for non-human disturbances are considerably noisier and the average treatment effect for treated (ATT) overall is not significant. This is consistent with the purposes of CB (targeting human-driven habitat loss) and confirms that it is indeed the policy requirements

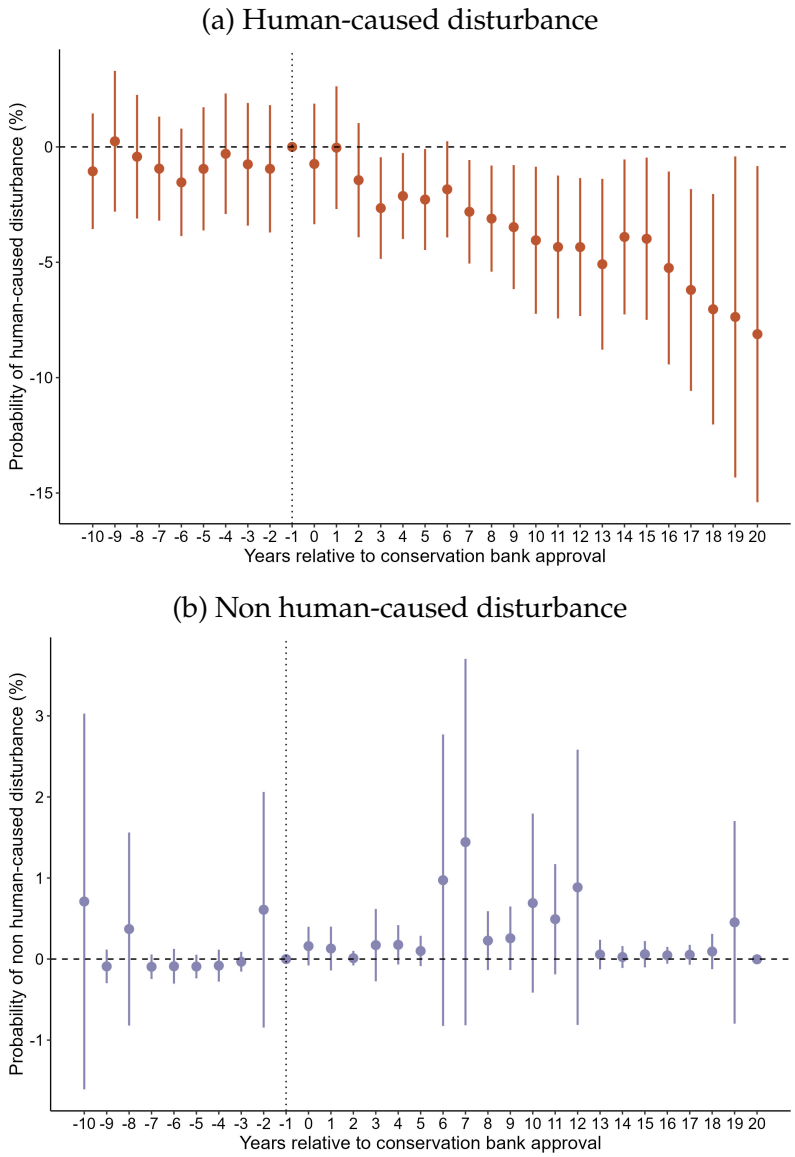


Figure 2. Impact of conservation banks on likelihood of land disturbance

Notes: Figure illustrates the estimates of the event-study regression (5), which evaluates the dynamic casual effect of conservation bank approval on the probability of land disturbance. The outcome is defined for each conservation bank-year, as the share of conservation banking sites that are flagged as "disturbed," in the Qiu et al. (2025) data set. Figure 2a uses as the outcome the ratio of human-caused disturbance pixels to total number of pixels, versus non-human cause disturbance pixels for Figure 2b. Human-caused disturbances are defined as those from logging, construction, and agricultural expansion, while non-human caused disturbances are driven by pest breaks, wind damage, and wildfire.

of CB that are driving the suppression of degradation. We do not see a clear pre-trend of disturbance, both human or non-human caused, prior to having the land declared as CB.

Why do landowners not engage in strategic degradation prior to their CB approval? One

potential explanation lies in the extensive monitoring involved in the CB approval process. In fact, landowners who wish to register their land for CBs are mandated to closely cooperate with their USFWS field office leading up to the filing of CBs. Such processes likely discourage landowners from degrading the habitat prior to their approval.

To the extent that there are three different components to human-driven disturbance, we break down the disturbance to different categories and compute the probability of each. The results, shown on Appendix Figures A1 and A2, suggest that the effects of CB in Figure 2a are driven by suppressing agricultural development (rather than building construction and logging activities).

Further, while the definition of Y_{ct} in equation (5) considers disturbance to be a "flow" variable, one can also redefine the dummy variable to be a cumulative, staggered indicator of "ever human-disturbed" taking value =1 if it has been disturbed at least once since the start of the data set (1988).[6] The results from using such a "stock" variable, shown in Appendix Figure A3, are analogous to Figure 2a.

All in all, the event-study estimates point to conservation banks successfully suppressing anthropogenic pressure on wildlife habitat. However, while such results do point to the suppression of biodiversity loss, it remains unclear whether such habitat preservation is linked with long-run improvements in real biodiversity. We thus turn to systematic ecological surveys to evaluate the long-run effect of CB adoption on local biodiversity.

4.3 Conservation Banks and Bird Biodiversity

In general, raw ecological survey data require substantial caution in their use, as results from different surveys are not comparable to one another due to differences in sampling methods and survey protocols (Zizka et al., 2019; Johnston et al., 2023). In contrast, the North American Breeding Bird Survey (BBS) compiles observations spanning six decades and $\approx 4,000$ routes using uniform survey protocols–providing a unique opportunity to assess long-run trends in bird population and biodiversity (e.g., Rosenberg et al., 2019), which are in turn excellent metrics of overall biodiversity (Section 2).

We apply the long-difference approach (Burke and Emerick, 2016) to assess the long-run impact of CBs on bird biodiversity. Intuitively, the approach regresses *within-unit* changes in *moving averages* of the outcome against the same variation in the treatment policy variable. The approach, originally developed to capture the long-run impact of climate change, has been applied to understand the impact of land-use policies in different contexts (Taylor and

[6] Contrary to the original regression, we add the "share of ever-disturbed pixels in the CB prior to the approval" as a control variable. This is because increasing the ever-disturbed pixel for a 95% ever-disturbed land, for example, is vastly different from doing the same for a 5% land.

Druckenmiller, 2022; Grosset-Touba et al., 2024).

For each route-year surveyed, we compute the species richness (number of unique species observed), total abundance (total number of birds observed), and species evenness (equation (3)). We then take the average of such outcomes over the 1990-1999 period and the 2010-2019 period. Regressing the changes in the decadal average across the two decades against the changes in the average number of conservation banks yields the long-difference equation:

$$\Delta Y_r = \beta_1 \Delta \text{CBs}_{<5\text{km},r} + \beta_2 \Delta \text{CBs}_{5-20\text{km},r} + \boldsymbol{\delta}' \Delta \mathbf{X}_r + \gamma_{j(r)} + \varepsilon_r \tag{6}$$

where ΔY_r is the within-route change in the long-run average of the biodiversity outcomes (species richness, abundance, and evenness), for route r. $\Delta \text{CBs}_{<5\text{km},r}$ is the change in the number of conservation banks in the 0-5km distance from route r, where 0km distance signifies a CB being installed in the route's path. $\Delta \text{CBs}_{5-20\text{km},r}$ is the same but for 5-20km distance. We also control for changes in the survey conditions $\mathbf{X}_r$ (temperature, cloud conditions, windspeed, duration, and day of year). We control for region-specific trends in bird biodiversity by using EPA level 2 ecoregion-fixed effect $\gamma_{j(r)}$.[7] For ε_r, we allow spatial spillovers using Conley standard errors of cutoff 50km, which constitutes the upper bound of home range of most breeding birds native to California. To the extent that not all routes are sampled every year, we weight the routes by the total number of observations throughout the sample period (1990s and 2010s).

The parameters of interest are β_1 and β_2, which capture the direct effect and "spillover" effects of a CB on bird biodiversity outcomes, respectively. The first-difference nature of the equation (6) accounts for all route-fixed characteristics that drive the *levels* of bird biodiversity and CB count.

The identification strategy relies on the plausibly exogenous variations in the number of new conservation banks across space. Such assumptions are plausible for two reasons. First, the routes surveyed for bird biodiversity under BBS are fixed well in advance of, and independently from, the establishment of conservation banks. This plausibly rules out non-random selection of survey sites following CB approvals or the lack thereof. Second, our empirical estimates using cross-sectional ecological data (panel B, Table 2) indirectly suggest that absent treatment effects from the CB *per se*, lands included in the CB and those in the neighborhood are similar in baseline characteristics. This suggests that at a local scale, the baseline features of a BBS route that receives an additional CB at a 5km distance should be similar to those that do not.

One potential source of identification challenges is reverse causality, where a drop in across-species biodiversity ΔY_r may be driving increases in the number of CBs, ΔCBs_r. We argue,

[7] EPA level 2 and level 3 ecoregions are designed to provide "national and subcontinental overviews of ecological patterns." There are 50 L2 ecoregions across North America, with 5 in California.

Table 3. Conservation Banks and Bird Biodiversity: Long-Difference Estimates

	Biodiversity Outcome of Interest:				
	Richness	Overall abundance	Evenness	Shannon's Diversity	Simpson's Diversity
	(1)	(2)	(3)	(4)	(5)
	A. Including all bird species				
Δ CBs$_{<5km}$	0.67***	−30.87***	1.13***	5.50***	0.49**
	(0.24)	(11.61)	(0.19)	(0.88)	(0.22)
Δ CBs$_{5-20km}$	−0.46	5.12	−1.34	−5.41	−0.80
	(0.83)	(55.96)	(0.91)	(3.70)	(0.76)
R-squared	0.12	0.09	0.14	0.10	0.09
Y_i mean at baseline (1990s)	47.23	782.62	79.57	301.59	91.03
Y_i SD at baseline (1990s)	16.26	728.65	8.23	52.62	6.70
	B. Excluding CB-targeted species				
Δ CBs$_{<5km}$	0.62***	−30.82***	1.15***	5.42***	0.48**
	(0.22)	(11.58)	(0.20)	(0.83)	(0.21)
Δ CBs$_{5-20km}$	−0.56	5.46	−1.31	−5.56	−0.80
	(0.84)	(55.98)	(0.90)	(3.59)	(0.75)
N	168	168	168	168	168
Weighted by Obs. frequency	Yes	Yes	Yes	Yes	Yes
R-squared	0.12	0.09	0.14	0.10	0.10
Y_i mean at baseline (1990s)	47.06	781.57	79.55	301.10	90.97
Y_i SD at baseline (1990s)	16.39	727.50	8.26	53.33	6.81

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Table evaluates the long-run effect of conservation banks on bird biodiversity outcome, as obtained from North American Breeding Bird Survey. Column 1 takes as the outcome species richness, the total number of unique species found in the survey routes. Column 2 assess the changes in total number of birds observed throughout the surveys, and column 3 is the same but for species evenness (equation (3)). Columns 4 and 5 evaluate changes in Shannon's Diversity index (equation (1)) and Simpson's Diversity Index (equation (2)). All columns include controls for changes in survey conditions (weather, time of day, and day of year). All specifications include EPA level 2 ecoregion-fixed effects. We use Conely standard errors with cutoff 50km. Columns 3 to 5 coefficients and SEs are multiplied by 100 for legibility. See Section 2 for definitions of different biodiversity outcomes.

however, that such effects are less likely, as the establishment of CBs are driven primarily by *individual* species, rather than species-wide trends in abundance and diversity. We test the robustness of our results to the biodiversity outcomes after excluding the bird species that are targeted by the CBs: burrowing owl, Swainson's hawk, California gnatcatcher, Bell's vireo, and Le Conte's thasher.

Table 3 presents the results of estimating the long-difference equation (6). Panel A shows the coefficient estimates when the different biodiversity outcomes are computed across all species, while Panel B's outcomes are computed after dropping the CB-targeted species.

Column 1 results suggest that increases in the number of nearby conservation banks are associated with increases in species richness, or the number of unique species found in the route–with one more CB being linked with 0.67 more species. The similarity of panels A and B coefficients strongly suggest that this increase is not driven by the CB-targeted species finding habitat in the banks, but rather by other non-targeted species settling in the CB-impacted route.

Contrary to the increase in species richness, column 2 coefficients suggest that CB establishments are associated with *reductions* in the total number of bird individuals observed (overall abundance), at around 4% (30.87/727.50) of the baseline standard deviation. Nevertheless, the trends in Pielou's species evenness index (equation (3)), shown in column 3, point to the abundance loss being focused on the species that were previously dominant–as the population across species are becoming more even.

Columns 4 and 5 provide additional nuance to the impact of CBs, where we see increases being more precise and larger in size for Shannon's diversity index (10% of baseline SD) than in Simpson's diversity index (7% of baseline SD). To the extent that Shannon's Index is more sensitive to rare species (versus Simpson's Index highlighting common species), the results point to the increases in diverstiy being driven by rarer, less common species.

Throughout all outcomes, we see very similar results for panels A and B. This strongly suggests that the increases in species richness, evenness, and diversity indexes are enjoyed by bird species that are not specifically targeted by the CBs. We also do not find significant effects from CBs being established outside of the 5km radius, hence pointing to the localized effects of conservation.

Taken together, the results point to significant and substantial changes in the inter-species distribution of population within the routes, following new CB establishments. The direction of the inter-species relative population change–characterized by overall increases in richness and in evenness–is associated with improvements in ecosystem services provision, under substitutability of species in providing ecosystem services (*à la* Giglio et al., 2024). We note, however, that such effects will be offset by the small but significant losses in total abundance.

5 Conclusion

Combining administrative data, ecological surveys, satellite imagery, and gridded biodiversity metrics, we provide the first empirical analysis of the effectiveness of biodiversity offsets. Focusing on the oldest biodiversity program in the world, we find cross-sectional evidence that the offset projects suppress anthropogenic pressure on ecosystems. This is corroborated by event-study estimates using four decades of satellite imagery of land-use change. The offsets projects have important local spillovers on bird populations, with species diversity significantly increasing in neighboring areas.

Two key elements of the specific empirical context of our analysis–USFWS-regulated conservation banking programs–provide important lessons for future biodiversity offset markets. First, the USFWS mandates that ecosystems only be substituted in close proximity to the sites of biodiversity loss–a crucial element considering the spatial heterogeneity of ecosystems. Two, USFWS exercises strong oversight across the credit generation processes and verification of credits prior to their ability to be purchased. We believe that these elements are very likely critical for creating a biodiversity offset market that is both effective and ecologically credible.

There are several refinements to our empirical approach that we plan to pursue in future work. In particular, we plan to incorporate additional species-level population trend data from eBird Trends (Fink et al., 2023), and explore the usage of event-study methods to the BBS data set, along with a barrage of additional robustness tests on all three components of our empirical analysis. Analyses on the heterogeneous effects of different conservation banks (e.g., those with and without habitat preservation credits) are likely of great interest.

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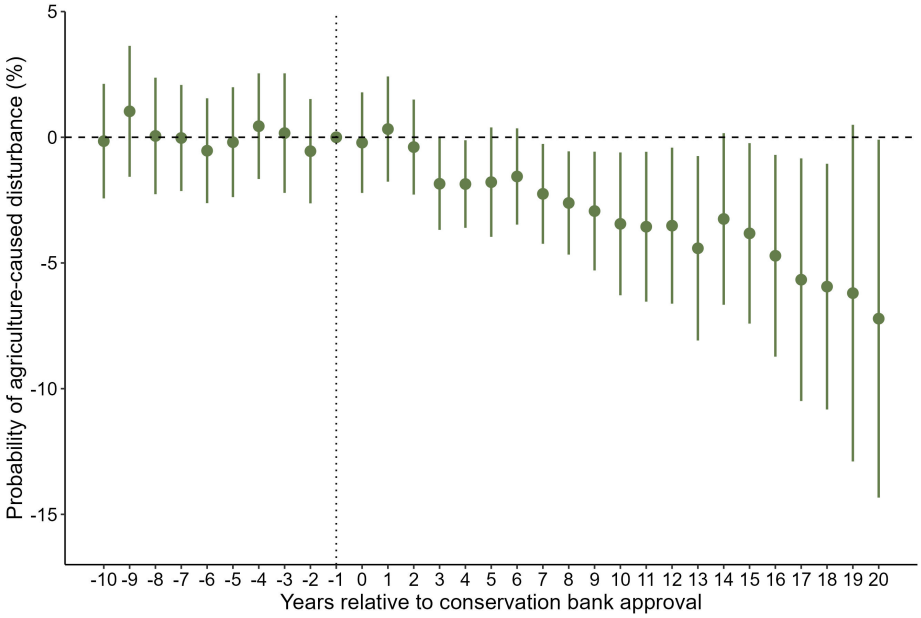
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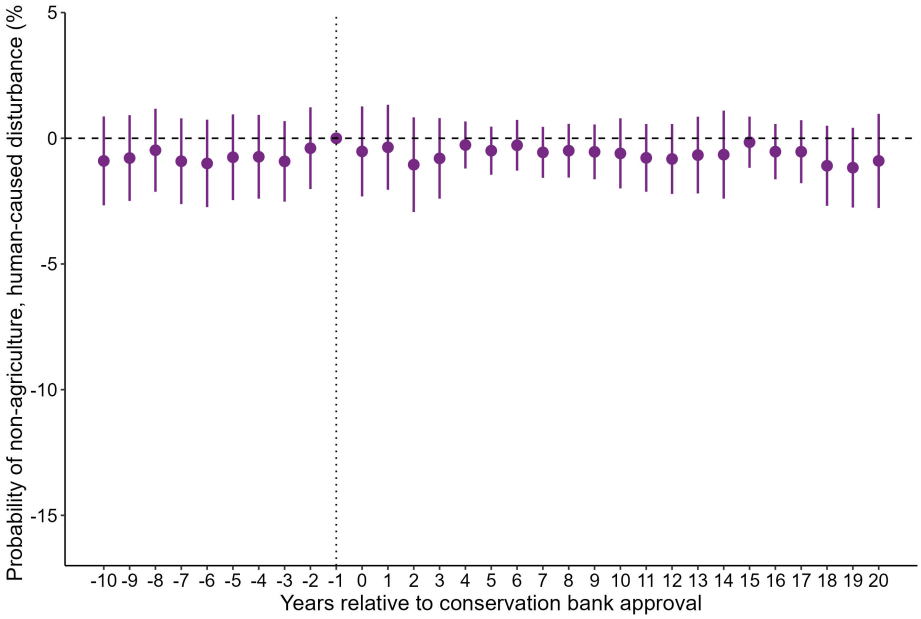
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Appendix

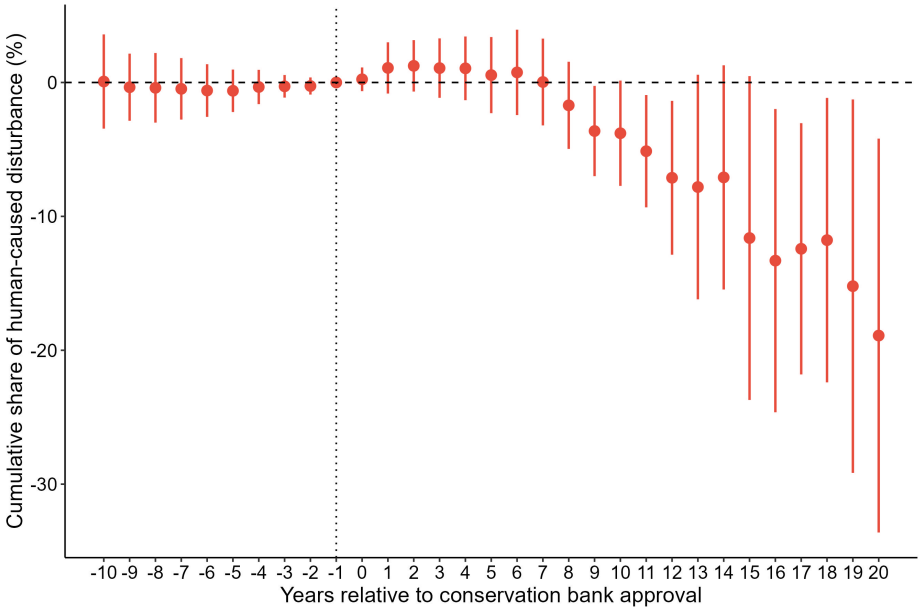
A Additional Figures



Appendix Figure A1. Event-study estimates: Probability of agriculture-caused disturbance



Appendix Figure A2. Event-study estimates: Probability of non-ag, human-caused disturbance



Appendix Figure A3. Event-study estimates: Probability of cumulative human disturbance

Appendix Table A1. Conservation Banks, Protected Areas, and Bird Biodiversity: Long-Difference Estimates

	Biodiversity Outcome of Interest:							
	Species Richness		Species Evenness		Overall abundance		log(Overall abundance)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Conservation Banks (2010s versus 1990s)							
Δ $CBs_{<5km}$	0.39**	0.72***	1.16***	1.16***	−41.72***	−31.74***	−4.48***	−3.52***
	(0.15)	(0.13)	(0.06)	(0.12)	(2.54)	(7.51)	(0.54)	(0.54)
Δ CBs_{5-20km}	−0.11	−0.23	−0.31	0.01	48.98***	20.17	6.55**	2.73
	(1.19)	(0.88)	(1.22)	(1.03)	(13.43)	(37.04)	(2.15)	(2.85)
	B. Protected Areas (2010s versus 1990s)							
Δ $PAs_{<5km}$	0.31	0.31	0.41***	0.39***	−27.95*	−23.99	−2.55	−2.10
	(0.47)	(0.55)	(0.08)	(0.08)	(13.85)	(19.99)	(1.94)	(2.76)
Δ PAs_{5-20km}	0.05	0.06	−0.01	−0.00	8.96**	8.28**	0.72	0.65
	(0.12)	(0.12)	(0.02)	(0.02)	(2.99)	(3.39)	(0.41)	(0.51)
Control for survey conditions		X		X		X		X
N	97	97	97	97	97	97	97	97
R-squared	0.04	0.15	0.07	0.11	0.07	0.12	0.06	0.14
Y_i mean at baseline (1990s)	52.67	52.67	79.96	79.96	946.23	946.23		
Y_i SD at baseline (1990s)	16.16	16.16	8.26	8.26	944.23	944.23		

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

Notes: Table evaluates the long-run effect of conservation banks and protected areas on bird biodiversity outcome, as obtained from North American Breeding Bird Survey. Columns 1 and 2 take as outcome the change in species richness, with column 2 including controls for changes in survey conditions (weather, time of day, and day of year). Columns 3 and 4 are the same but for species evenness. Columns 5 and 6 and 7 and 8 assess the changes in total number of birds observed throughout the survey and the changes of their log-transformations. All specifications include EPA level 2 ecoregion-fixed effects. Standard errors clustered at the EPA level 3 ecoregion level. Columns 3, 4, 7, 8 coefficients and SEs are multiplied by 100 for legibility. See Section 2 for definitions of different biodiversity outcomes.