Seung Min Kim

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Education

Columbia University, New York, USA — Sep 2023 -

Ph.D., Sustainable development
- Fields: Environmental economics, public economics, sustainable finance

Yale University, New Haven, USA — Sep 2021 - May 2023

MESc., Environmental economics
- Research Advisor: Robert Mendelsohn

Seoul National University, Seoul, South Korea — Mar 2015 - Aug 2021

B.A., *summa cum laude*, Economics (Minor in Atmospheric Sciences)

Publications

* Lead-authored/Co-lead authored. † Lightly refereed publications.

Economics journals

2. *"Climate Change and Fractional Outcomes: A Long-Run Panel Study of Crop Failure and Pasture Rates" (with Robert Mendelsohn). 2025. *Journal of Environmental Economics and Management* 130:103116.

1. *"Air Pollution and Solar Energy: Evidence from Wildfires" (with Kenneth Gillingham). 2025. *Journal of the Association of Environmental and Resource Economists* 12(2):493-526.

Earth & environmental sciences journals

5. "Well-water Arsenic Mitigation in Bangladesh: Benefits outweighing risks of sharing private data" (with Lex van Geen, Kazi Matin Ahmed, Mahfuz Khan, Prabhat Barnwal *et al.*). 2025. *Environmental Science & Technology.*

4. *"Estimating Spring Frost Risk in Apple Farms from Crop Insurance Data" (with Kwansoo Kim and Jeongha Hwang). 2025. *Weather and Climate Extremes.*

3. †"Measuring the impacts of air pollution" (with Robert Mendelsohn). 2023. *Science* 382: 878-879.

2. *"Climate change to increase crop failure in US" (with Robert Mendelsohn). 2023. *Environmental Research Letters* 18 (1): 014014.

1. *"A Panel Analysis on the Locality of Paddy Rice Yield's Response to Temperature Conditions: The case of South Korean municipalities" (with Jeongha Hwang, Jiwan Han, and Kwansoo Kim). 2020. In Korean. *Journal of Climate Change Research* 11:597-607.

Working Papers

*"Climate change and firm exposure to political risk". *R&R. Management Science.*

*"Bureaucracy and Political Bias: Evidence from Floods" (with Hannah Farkas). CEEP Working Paper.

*"Drivers of Cost-Effectiveness for Forest Carbon Projects in Compliance Offset Markets" (with Luke Sanford).

*"The Impact of Temperature on Mortality" (with Robert Mendelsohn)

Works in Progress

*"Improving state effectiveness in environmental risk mitigation: Experimental evidence from Bangladesh" (with Prabhat Barnwal, Michael Best, Md. Ahasan Habib, Lex van Geen, and Jack Willis). AEA Registry.

*"Climate, Biodiversity, and Environmental Damage" (with Jessie Lu)

*"Biodiversity Offsets" (with Sean Reese)

*"Ancient River Valley Networks Revealed by the Modern Distribution of Groundwater Arsenic in Bangladesh" (with Austin Chadwick, Lex van Geen *et al.*)

Awards & Honors

*Known number of awardees in parentheses ( ). All awards competitive.

2026	*ARCS Best Paper Award	(1, conference-wide)
2024-2028	*Ilju Fellowship	(<10, nation-wide)
	– $120,000 in stipend support & research funding (no strings attached).	
2021-2023	*Kwanjeong Fellowship	(<20, nation-wide)
2023	Dean's Scholarship, Yale School of the Environment	
2021	*Best Undergraduate Thesis Award, SNU	(1, departmental)
2015-2019	*Merit scholarships (5 times), SNU	(<5%, university-wide)
2015	*Top Freshman Award, SNU	(<0.5%, university-wide)
	– For top 10 incoming undergraduates at SNU.	

Research Grants

2026	Center for Political Economy Graduate Student Grant	$12,000
	– "Firm Ownership and Pollution: Evidence from Space"	
2025	Weiss Special Window for USAID Research (Student Co-PI, PI: Jack Willis)	$77,000
	– "Nolkup: an app to access low arsenic water in Bangladesh"	
2022	Jubitz Family Research Grant (*via* Yale School of the Environment)	$4,300
2020	SNU Undergraduate Research Grant	$7,300
2016, 2020	SNU ARE Overseas Undergraduate Research Support Program	$13,700

Academic Presentations

2026	ARCS Annual Conference; ARCS PhD Workshop; BIOECON XXVII; Camp Resources XXXII; Columbia IPWSD; Columbia SIRI Practicum (Guest Lecture); MPSA Annual Meeting; NBER Climate Finance PhD Workshop; University of British Columbia (FRE Lab Meeting)
2025	Columbia IPWSD; NBER Climate Finance PhD Workshop; Northeast Workshop on Energy Policy and Environmental Economics (Yale); Virtual SusDev Seminar
2024	Columbia IPWSD; Columbia Lamont-Doherty; Seoul National University
-2023	AAEA Annual Meeting; Northeast Workshop on Energy Policy and Environmental Economics (Cornell); Yale Carbon Offset Workshop; Yale Environmental Economics Seminar

Teaching Experience

2026S	Intermediate Macroeconomics (Columbia, undergrad 200+, TA)
2025F	Data Analysis for Policy Research (Columbia, Master's 40+, TA)
2025S, 2026S	Financial Economics of Climate and Sustainability (Columbia+, PhD 100+, TA)
2022F	Economics of Natural Resources (Yale, undergrad 130+, Head TA)
2021F	Economics of Natural Resources (Yale, undergrad 120+, TA)

Research Assistantships

Columbia	RA for Prof. Caroline Flammer (System-level investing)	2024-25
	RA for Profs. Michael Best, Lex van Geen, Jack Willis, and Prabhat Barnwal (Information and environmental risk: Experimental evidence from Bangladesh)	2023-
Yale	RA for Prof. Luke Sanford (Forest carbon offset projects)	2023
	RA for Prof. Robert Mendelsohn (Temperature and mortality)	2023
	RA for Prof. Kenneth Gillingham (Solar manufacturing employment)	2022
SNU	RA for Prof. Kwansoo Kim (Crop insurance policy)	2021
	RA for Profs. Kwansoo Kim & Donghwan An (Climate change policy)	2019-2020

Core Coursework

* Received highest grade. All PhD-level courses.

Economics	(Columbia) Micro I/II, Macro I, *Econometrics III, Environment & Resource Economics, *Political Economy I, *Public Economics and Development, *Topics in Micro Development Economics, *Topics in Organizational Economics (Yale) Econometrics *I/*II, *Environmental and energy economics, *Machine Learning and Causal Inference
Finance	(Columbia) Asset Pricing I, Climate Finance, Empirical Corporate Finance, Financial Economics of Climate and Sustainability
Earth Sciences	(Columbia) Atmospheric Radiation, *Aquatic Chemistry, Biodiversity Data Analysis I, Climate Data Science, Environmental Physicochemical Processes (Yale) Climate Dynamics (SNU) *Ecosystem Remote Sensing, Atmospheric Chemistry, Pollutant Dynamics

Skills

Statistical analysis	*R*, MATLAB, Python, Stata
Geospatial analysis	Google Earth Engine, QGIS
Other softwares	LaTeX, WRF numerical weather prediction model
Language	Korean (Native), English, French (Fluent)

Sean Reese

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EDUCATION

Expected 2029 Ph.D. in Sustainable Development, Columbia University
2023 M.P.P in Environmental Policy and Program Design and Evaluation, UC San Diego
2022 B.S. in Environmental Systems (Ecology, Behavior, Evolution), UC San Diego (*magna cum laude*)
2022 B.A. in Economics-Public Policy, UC San Diego

RESEARCH INTERESTS

Renewable natural resource management, biodiversity conservation, natural capital, climate change impacts, international cooperation, theoretical ecology

PUBLISHED PAPERS

Polonik, Pascal, Katharine Ricke, **Sean Reese**, and Jennifer Burney. "Air quality equity in US climate policy." Proceedings of the National Academy of Sciences 120, no. 26 (2023): e2217124120. doi:10.1073/pnas.2217124120

WORK IN PROGRESS

Reese, Sean. **"Fishery-Induced Evolution in Alaska Groundfish"**
Reese, Sean. **"Which 30?: Strategic Conservation Planning for the United States"**
Reese, Sean. **"Keystone Species Collapse and Fishery Productivity"**
Kim, Seung Min and Sean Reese. **"Biodiversity Offsets"**

TEACHING ASSISTANT EXPERIENCE

Columbia:
Undergraduate: Natural Science for Sustainable Development (Head TA), Globalization and its Risks, Challenges of Sustainable Development
Graduate: Fundamentals of Environmental Economics, Fundamentals of Ecology, Urban Ecology

UC San Diego:
Graduate: GIS and Spatial Data Analysis, Fundamentals of Energy Systems and Innovation, Policy Analysis and Decision Theory

AWARDS, FELLOWSHIPS, GRANTS, AND HONORS

Grants and Fellowships:
Triton Research & Experiential Learning Scholars (TRELS) Scholarship Recipient, 2022

Awards and Honors:
ARCS Best Paper Award, 2026
Phi Beta Kappa, 2022
Ernest C. Mort Leadership Excellence Award, 2019

Biodiversity Offsets*

Seung Min Kim Sean Reese†

September 26, 2026

Abstract

Accelerating biodiversity loss has intensified the pressure on firms to offset their ecological impacts. We present the first comprehensive evaluation of one of the world's oldest biodiversity offset policies: compensatory mitigation under the U.S. Endangered Species Act. By combining four decades of satellite land-use imagery with citizen science data, we find that highly regulated offset projects ("conservation banks") yield positive ecological spillovers and curb anthropogenic land-use pressure, but less supervised offsetting projects ("permittee-responsible mitigation") do not. Despite these localized gains, conservation banks are poorly sited across space. Using a stylized model of optimal bank placement, we demonstrate that conservation banks are systematically located in areas with minimal threats of development, calling into question their additionality. This inefficiency stems from a core policy design flaw: offset creation operates strictly on the extensive margin, generating offsets based on land area while failing to discriminate based on threat level or habitat quality. As voluntary and regulatory biodiversity markets expand worldwide, these results emphasize that offset frameworks must incorporate conversion risk to ensure additionality.

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1 Introduction

Rapid biodiversity loss is one of the defining features of the 21st century. During this period, vertebrate extinction rates have risen to up to 100 times their historic baseline, 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–are at risk of facing 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. As of 2022, the CB program conserved 260,000 acres of critical habitat for 57 endangered and threatened species (USFWS, 2022). Globally, biodiversity offsets and credits constitute the largest source of private biodiversity finance, channeling 7.1 out of 23.4 billion USD (30.1%) as of 2023 (United Nations Environment Programme, 2026). Nevertheless, there exists very little theoretical and empirical analysis on the effectiveness and efficiency of biodiversity offsets.

We provide the first comprehensive empirical analysis of biodiversity offset projects' effectiveness. Our objectives are twofold. First, we assess the effectiveness of conservation banks (CBs) using a novel data set that integrates administrative data, gridded ecological metrics, citizen science data, and satellite-based measures of land-use change. We then apply modern econometric methods to assess the long-run causal impact of USFWS-overseen CBs on local biodiversity and its drivers. This multidimensional approach is essential in light of the multifaceted nature of ecosystem functioning (Bull et al., 2013; Giglio et al., 2024). Second, we assess the spatial efficiency of conservation banking by developing a stylized theoretical model of optimal bank siting and testing its comparative statics against realized bank locations across California. To empirically test these predictions, we construct a fine-scale spatial dataset combining the footprints of banks with, machine-learning estimates of conservation costs, historical

land conversion rates, and MaxEnt species distribution models for six focal species.

We first assess whether CBs reduce anthropogenic pressure on local ecosystem using four decades of satellite imagery. Because spatial sorting invalidates the use of "never treated" neighboring lands as a reliable control group, we restrict our identification strategy to a sample of "ever-treated" units which removes the placement bias by strictly relying on the future evolution of land-use change in "not-yet treated" units to form our counterfactual scenario. Applying modern event-study methods (Callaway and Sant'Anna, 2021), we find that areas within CBs experience fewer disturbances from human-driven causes (e.g., intensive agriculture). Such effects are sustained over more than 20 years and are economically and statistically significant– and are not found for a similar conservation policy with less regulatory oversight (permittee responsible management), highlighting the importance of policy monitoring. The results are robust to alternative definitions of "disturbance," and 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.

Building on such results on the areas *within* CBs, we then assess whether the suppression of habitat loss translates to improvements in actual, observed biodiversity in the broader local ecosystem. Motivated by the role of bird population changes as "bioindicators" of overall biodiversity loss (Morrison, 1986; Butchart et al., 2010), we combine the footprints of CBs with a gridded data set of bird population estimates from Fink et al. (2023). While overall bird population has been in sharp decline across the North America, our results suggest that CBs are capable of dampening such negative trends, with an average CB being linked with 1.5% increase in bird population over a ten-year period. The results are robust to alternative definitions of bird population trends, and a separate empirical strategy that relies on plausibly exogenous variations of species listing in Endangered Species Act (ESA) to construct a Bartik instrument for the variations in CB areas.

Nevertheless, such results should not be interpreted as evidence of unalloyed success of the CB policy. For one, the relatively small size of the CBs compared to the sheer scale of biodiversity loss (e.g., an average effect of 1.5% over ten years for birds, versus 29% loss in population over 48 years, Rosenberg et al., 2019) suggest that biodiversity offset, in its current scale, cannot counter the rapid loss of nature and biodiversity in the 21st century. Further, the event-study estimates strongly suggest that the effects of CBs are limited to suppressing land disturbances at the intensive margin (e.g., reducing intensive tillage), but not at the extensive margin (i.e., preventing land type conversions).

Following these analyses, we pivot to assessing the spatial efficiency of where conservation banks are established across California. Grounding our analysis in a stylized spatial opti-

mization model, our framework contrasts a "discriminate" policymaker—who minimizes total cost to achieve a regional offset target weighted by habitat quality (S_i) and conversion threat (E_i)—with a decentralized market operating under unweighted, acre-for-acre credit rules (the current policy under the USFWS). While both regimes prioritize cheap (R_i) and ecologically suitable (S_i) land, they diverge sharply on conversion threat: a discriminate planner targets highly threatened land, whereas an unweighted market treats high conversion risk as an uncompensated opportunity cost penalty, driving conservation toward low-threat areas. To empirically test these predictions, we combine administrative bank footprints from RIBITS with machine-learning land value estimates, historical land-cover transitions, and fine-resolution MaxEnt species distribution models for six focal species across California. Consistent with our market model, we find that while bank sponsors target high-quality habitat and avoid expensive land, they systematically avoid areas facing high conversion risk (E_i). Consequently, existing offset markets operate functionally like an indiscriminate regulator, steering conservation toward low-threat areas where baseline habitat loss was unlikely to occur anyway. Taken together, our results deliver a unified policy message: while conservation banks are effective at suppressing local land disturbance and dampening biodiversity loss, their aggregate conservation yield is hindered by spatial misallocation driven by an unweighted regulatory design.

The 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 *transition risk* (i.e., the risk from potential government conservation efforts), we focus on the ecological effectiveness of the projects funded by biodiversity finance.

We also contribute to the rich ecological literature on the efficacy of place-based conservation. Our 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. Our results also 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.

Lastly, our paper builds on the more narrow literature on the effectiveness of biodiversity offsets. As opposed to the rich and active discussion on the philosophical and theoretical merits of biodiversity offset projects (Bull et al., 2013; Karlsson and Edvardsson Björnberg, 2021), empirical analysis of such projects have been focused on the targeted species' habitat conservation (Sonter et al., 2019) and land-use patterns (zu Ermgassen et al., 2023). By contrast, our multidimensional array of outcomes is focused on species-wide impact of biodiversity offset projects, as captured in the gridded ecological indexes and in the species diversity data from bird surveys. Such results provide an albeit partial evidence on the potential of biodiversity offset measures to deliver "no net loss" in ecosystem functions and biodiversity–an objective of critical importance, considering that biodiversity offsets are predicated on anthropogenic nature loss (Wauchope et al., 2024).

The remainder of the paper is structured as follows. Section 2 provides the institutional background on conservation banks. Section 3 explores our data, and Section 4 presents our empirical analysis of the effectiveness of conservation banks. Section 5 explores the allocative efficiency of banks; Section 6 concludes.

2 Institutional Background

As alluded to above, this paper aims to evaluate the efficiency and effectiveness of one of the oldest forms of biodiversity offsets–conservation banking (CB). To this end, we discuss in depth the institutional characteristics that define the CB policy. To the extent that CB constitutes a market-based mitigation of environmental impact, we focus on the *demand* and *supply* of the CB market.[1]

[1]The contents of this section build largely on extensive discussions with numerous entities in the compensatory mitigation industry, including those inside and outside the USFWS. We are greatly indebted to their extremely valuable insights on the CB market and to their patience.

2.1 Conservation Banks: Demand

Source of demand for conservation banks. Our land-use policy of interest, CB, is adopted and enforced under the framework of the U.S. federal Endangered Species Act (ESA) of 1973.[2] 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 (Supreme Court of the United States, 1995). Under Sections 7 and 10 of the ESA, federal and non-federal developers who intend to engage in projects that will result in the "take" of protected species must consult a federal conservation agency *before* initiating their projects (see Section 5.1 for further discussion on the definition of "take"). Empirical studies point to significant costs and constraints to business activities from the ESA regulations (Ferris and Frank, 2021).

This ESA permit process is the source of demand for CBs. Throughout the permit approval procedure, the United States Fish and Wildlife Services (USFWS), which oversees the implementation of ESA for land and freshwater species,[3] can mandate the project developers to carry out "compensatory mitigation" in order to offset their adverse impacts. CBs constitute one of three mechanisms through which such compensatory mitigation can be achieved. Under the CB system, developers purchase credits from pre-approved "conservation banking sites" that are "permanently protected land that is managed for endangered, threatened, or other at-risk species" (p. 7, USFWS, 2013). Importantly, the conservation activities that lead to the generation of credits ("credit releases") occur *prior* to the pollution and biodiversity loss. The liability for habitat and species impact is completely transferred to the bank "sponsor"–who manages the CB and its conservation activities.

This element of timing (i.e., mitigation activities precede pollution) and liability transfer distinguish CBs from the two remaining compensatory mitigation mechanisms, proponent-responsible mitigation (PRM) and in-lieu fee (ILF) programs. Under PRM, developers assume responsibility, and the ultimate liability, for implementing and managing mitigation on their own sites. Such PRM activities mostly occur through "turnkey" mitigation measures, where the permittees purchase a land and record it as conservation easement–a legal device blocking the use of the land for development. Clearly, under PRM the mitigation does not precede the habitat loss, and the liability is not transferred. ILF programs, by contrast, allow the transfer

[2]Note that the ESA is not the only policy that incurs the demand for compensatory mitigation. State-level conservation laws, such as California's Endangered Species Act (CESA), require developments affecting state-listed species (e.g., burrowing owls) to fully mitigate their ecological impacts.

[3]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.

of liabilities–but require developers to pay into a publicly administered fund that finances mitigation projects. The programs are hosted by non-governmental organizations (NGOs) and governmental wildlife agencies, and the mitigation activities take place *after* the habitat loss.[4]

We focus on CBs out of the three mechanisms for two reasons. First, ILF programs are very rarely used for compensatory mitigation purposes in the U.S.; nationwide, there are only 7 programs that generate credits for ESA compliance, compared to more than 200 CBs. This is explained by a strong preference from USFWS for CBs: its 2023 Mitigation Policy document from USFWS, which precisely guides the decisions of USFWS bureaucrats (USFWS, 2023b), clearly notes that "... [the USFWS] should recommend that projects proponents implement compensatory mitigation measures before the impacts of an action occur (Section 5(h))," and that it "prefers compensatory mitigation measures that are implemented in advance of project impacts (Section 6.7.1)."[5] Second, contrary to CBs–where footprints of most approved banks can be easily identified through a centralized system–PRMs' footprints are not systematically compiled and no known data for USFWS PRM footprint exist.[6] While we take specific steps to identify potential PRMs to the best of our capacity, our primary empirical focus is on CBs due to their robustness to measurement errors.

Policy-imposed market segmentation: species and space. During the CB approval process (see below), the USFWS field office sets a specific "service area" for each bank. These service areas are set to ensure that credits are only used to offset impacts within spatially delineated zones that are deemed ecologically comparable to the habitat protected by the bank itself. These zones are known as "service areas." A service area defines the geographic market for a bank's credits, limiting their use to areas where impacts are expected to affect the same species, populations, or ecological functions that the bank was established to protect. Service areas are typically based on biological or hydrological boundaries such as species ranges, soil types, watersheds, or ecoregions, but administrative boundaries like state borders can also play a role (USFWS, 2003). Furthermore, banks with more than one type of credit may have different service areas designated for each different type of credit.

Such spatial market segmentation is designed to ensure that compensatory mitigation is ecologically relevant rather than allowing habitat protection in one region to offset losses in a substantially different ecological context. For instance, a credit from a Burrowing Owl conser-

[4]The only exception is the "advance" ILF credits, where ILF sponsors in their "compensatory planning framework" (i.e., the framework agreement that enables the adoption of ILF programs) lay out mitigation activities that they will carry out and release credits in return.

[5]Another driver is that many species that invoke the ESA take clause are not amenable to the projects funded by ILFs (e.g., vaccination of vulnerable populations). These species are instead better addressed by land area-based approaches procuring safe habitats–a type of conservation approach that CBs excel at.

[6]Based on discussions with a USFWS field biologist and field supervisor.

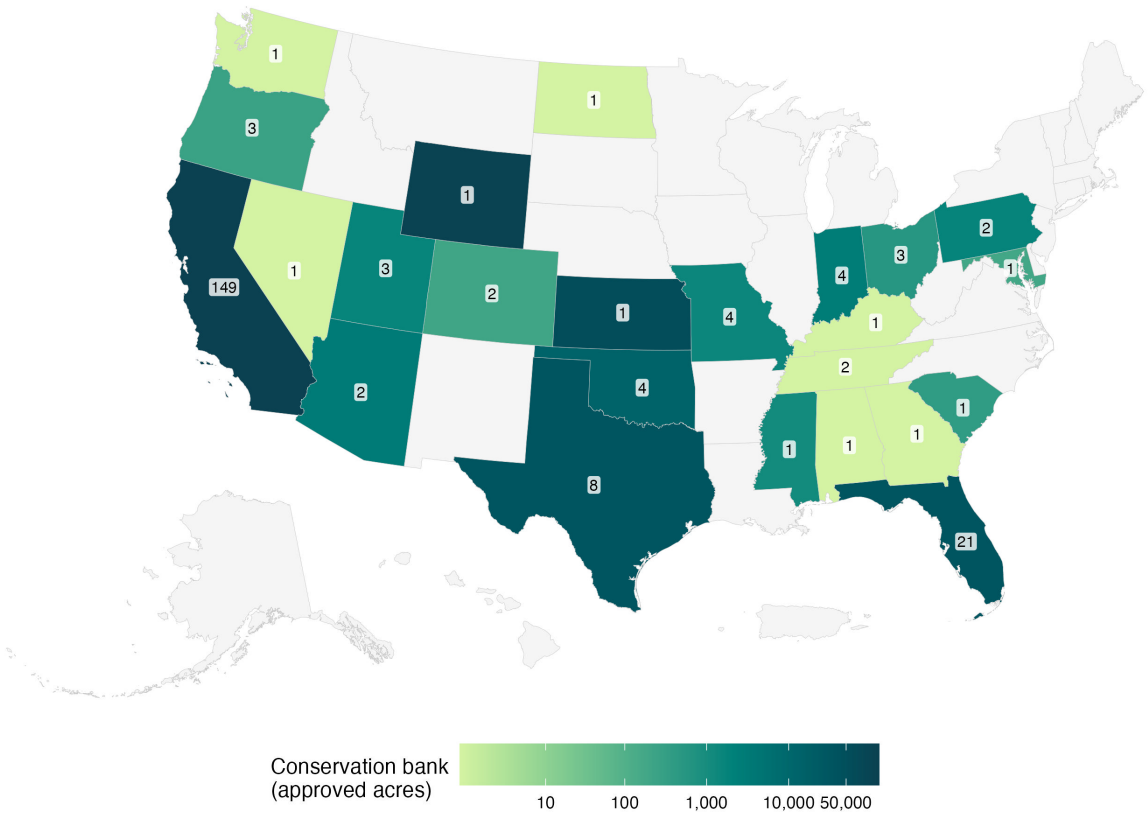


Figure 1. Spatial distribution of conservation banks in the U.S.

Notes: Figure shows the number of USFWS-approved conservation banks and their acreage in the U.S. Darker fill represents larger CB acreage, and the number of approved banks is shown in text. States without any approved CBs shown in grey.

vation bank in Sacramento county, CA, cannot be used to offset a Burrowing Owl habitat loss in Kings county, CA.

Two additional points on the use of CB credits are in order. First, all CB transactions–both their generation and their use for compliance–are species-specific. A "take" on Desert Tortoise habitat, for example, cannot be compensated by credits from a Burrowing Owl credit. Second, the CB market is an entirely compliance offset market: private polluters cannot purchase the credits for voluntary mitigation purposes. USFWS, upon clearing the retirement of credits from the offset market ("credit withdrawal"), is mandated to attach a relevant ESA document–a PBO or HCP[7]–that mandated their purchase and use. This policy element, combined with the spatial perimeters adopted by CBs *via* service areas, allow us to attribute revealed patterns of CBs to CB market-specific forces.

[7]PBO is used for Section 7 (federal) projects, versus HCP for Section 10 (non-federal/private) projects. See Section 5.1 for details.

Spatial distribution of conservation banks and its pricing. The revealed spatial pattern of CBs, shown in Figure 1, strongly present California as the leader of CB in the U.S. This is driven by both market aspects (frequent "take" clause invocations, from high density of ESA-listed species combined with economic development) and institutional aspects. The latter element pertains to the vivacity of the CB market in California, driven by its historical role in the evolution of the CB policy (where nation's first CB, the Coles levee Ecosystem Preserve, was developed in the state). This historical path dependence is combined with the existence of state-level legislation (California ESA) that also mandates compensatory mitigation–hence resulting in permittees presenting compensatory mitigation in their initial ESA consultations.

Regarding the pricing of CB credits, discussions with stakeholders reveal that the prices are highly variable depending on the species involved and the tightness of the market within the segmented market. This high variability makes the pricing data highly sensitive–and there is no known publicly available data set of its prices. Nevertheless, Poudel and Pokharel (2021), which used extensive interviews to collect the pricing data of a limited subset of CBs, found an average price of \$6,014.72/acre for an average credit (median of \$553.65/acre). Such per-acre price is substantially larger than that found in other environmental offset markets (e.g., voluntary carbon offset markets, where an average carbon credit is priced at \$6/ton CO_2e, Ecosystem Marketplace, 2025)[8], and points to the importance of CBs and the compensatory mitigation policy in driving conservation demand.

2.2 Conservation Banks: Supply and regulatory oversight

Generation of credits: Two activities. CBs support two different types of conservation activities. First, CB credits may be used for habitat "creation" purposes, where bank sponsors create specific habitats housing the affected species. Such banks are used when the ESA-listed species being affected have very little viable habitats left to be protected (e.g., giant garter snakes) and where a non-USFWS partnering agency (e.g., US Army Corps of Engineer) has a strong propensity for creation projects. For example, for a vernal pool fairy shrimp credit, a CB sponsor could fund projects that form temporary and seasonal wetland in a site that previously belonged to a paddy rice field.

In contrast, "preservation" CB credits are given for activities that preserve an existing habitat. When a specific ESA-listed species is found in a site, a landowner and a conservation corporate can apply for specific measures that protect the existing habitat. For example, a cow rancher in California may apply for a project building fences surrounding the habitat–therefore receiving a credit. In the parlance of forest-based carbon offsets, creation CBs are akin to afforestation

[8] An average forest carbon offset project issues carbon credits amounting to approximately 25-50 ton CO2e/acre.

projects, and preservation CBs to avoided conversion projects.

CB credit generation, or "credit release," is subject to USFWS approval and is carried out in tranches following the achievement of predetermined ecological milestones, called "credit evaluation and release schedule." The schedule is a subject of intensive USFWS oversight and is highly bank dependent. For example, a preservation CB's milestones mostly consist of proper provision of funds for constructing fences, while creation CB's milestones may require a fixed number of individuals found on the premises. Both CBs are subject to annual site visits from regulatory agencies (see below).

Joint production of credits and the acre-to-acre norm. How exactly does an acre of land translate into CB credits? In practice, there are cases where a given land hosts habitats and species for multiple ESA-listed species. Importantly, these credits cannot be subdivided to satisfy separate mitigation requirements across projects; the full bundle must be purchased as a whole.

To the extent that individual sites will differ in the distribution of species and habitats enclosed, a single CB 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 2). The site has three forms credits that can be generated: credits for Coastal Sage Scrub (CSS, green)[9], credits for Burrowing Owl (BUOW, orange), and 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. Nevertheless, a permittee purchasing a credit from both CAGN and CSS credits (e.g., the centermost acre) can only use the acre once to satisfy either one of its CAGN or CSS compliance requirements. Once purchased, the CB credit is permanently retired and cannot be resold to other permittees.

While a given acre of land can in principle be used to release more (or less) than one credits, such practice has fallen out of fashion after the first few years of CB initiation (in 1995). Nowadays, a single acre of CB is almost always leading to a single credit–a trend borne out in the credit release data (Appendix Figure B1), where 76% of transactions involve banks where the credit-to-acre ratio is exactly 1.

Further, a given CB can also contain credits that can be sold for non-ESA regulatory compliance. For example, CB activities for vernal pool fairy shrimps involve the creation of wetlands and streams–both of which can be used to be sold as wetland credits under the Clean Water Act.

[9]Note that the CSS is a "habitat conservation banking" credit, compared to the "species conservation banking" credits for California Tiger Salamanders.

Under such circumstances, the bank project is subject to oversight from all relevant agencies (e.g., US Army Corps of Engineer for wetland credits) and consequently a heightened regulatory oversight. Upon retirement for wetland credits, the bank credits cannot be used for ESA compliance purposes.

Bank oversight by USFWS. Very importantly, the federal CB policy stands out 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 USFWS. The role of USFWS starts even before a single bank credit has been released–it openly elicits draft proposals from prospective bank sponsors and provide preliminary reviews for the banks in return. Upon actual receipt of bank proposal from a landowner–which must include the proposed activities, proposed service area, proposed credit evaluation and release schedule, and biological surveys showing species presence–the USFWS decides whether to move ahead with the proposal.

Under USFWS authorization, the bank proponent and the agency goes through a series of negotiations to develop "bank-enabling instruments," an arduous process often spanning several years. The meetings culminate in an instrument that always includes a map of the proposed site, conservation plans, credit release and evaluation schedules, and very importantly, endowment funding plans. The endowment is meant to 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, 2023a). The finalization of the bank-enabling instrument leads to the establishment of the bank. Even after the bank establishment, however, USFWS retains the ultimate discretion in judging that the milestones for credit generation (called performance standards) are reached. Such decision is supported by an annual visit and monitoring of the bank sites–the parameters of which are already detailed in the instrument.

Comparison of conservation banking with wetland mitigation banking. The compensatory mitigation policy of ESA emulates that of the Clean Water Act (CWA)–and share similar structures and terminologies (e.g., "mitigation banks" are the equivalent of CBs under the CWA). As in CBs, wetland mitigation banks provide a potent avenue for gains from trade, where high-abatement cost polluters can compensate low-cost abaters for mitigating the impact on their behalf (Aronoff and Rafey, 2026).

Nevertheless, the two policies differ in one very important aspect. While CWA specifically dictates that the goal of the compensatory mitigation policy is to result in "no net loss"–whereby the total acreage of wetlands in a watershed has to remain the same compared to the baseline

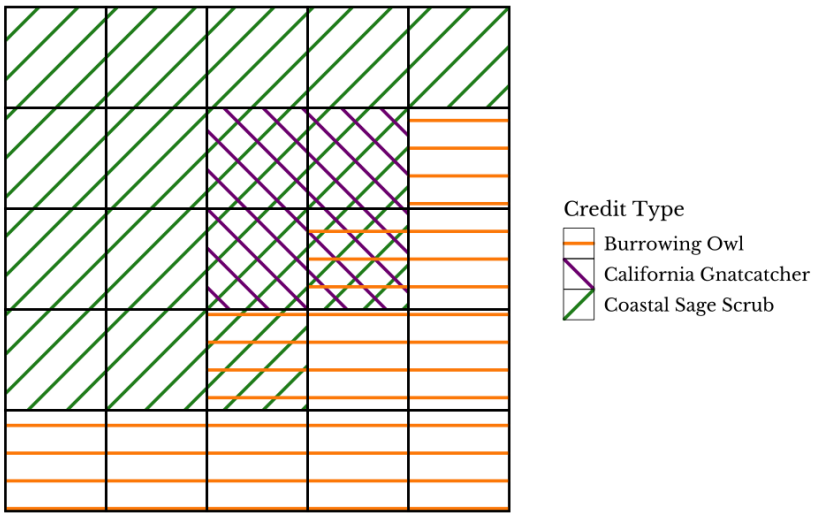


Figure 2. Creation of credits: Example Conservation Bank

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.

period–no such statutory requirements exist for ESA. This means that ESA bureaucrats cannot mandate permittees to fully compensate their ecological damage, and that the ultimate amount of compensatory mitigation mandated is up to significant discretion. This also potentially explains the spatial pattern of CBs shown in Figure 1.

3 Data

3.1 Conservation Banks and potential PRM sites

We obtain conservation banking data 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,[10], spatial boundaries are only available for 111 of them.[11] 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.

[10]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.

[11]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.

While PRM footprint data are not publicly available, we exploit the fact that most PRMs are required to register the land as conservation easements to identify the potential PRM sites using the California Conservation Easement Database (GreenInfo Network, 2026). We drop entries with missing establishment years and those not mentioning "conservation" or "wildlife" in its establishment purpose. We also drop the parcels that belong to CBs.

3.2 Bird Biodiversity

3.2.1 eBird Trends

We use gridded species-level bird population data set from Fink et al. (2023). The data set uses citizen science-based reports of bird identification from research-grade submissions to model, for each 27km grid, (1) the changes in species *occurrence*, and (2) changes in species *count*, conditional on occurrence. The double machine learning model, extended from Chernozhukov et al. (2018), use predictors capturing observation effort and survey environment to control for spurious variations in detection of bird species (and the reported counts thereof) driven by differences in observation effort.

The final data set provides 27km level estimates of bird population trend, over a 10-year period. The outcomes are either % of population lost (or, in case of positive estimates, gained) per year or the raw number of population changes. While the method can in principle compute population trends for multiple seasons (e.g., breeding versus migration season), in practice the computations are done for a single season, with the great majority of species having their population calculated for their breeding season.

3.2.2 The Importance of Bird Biodiversity

Beyond the unparalleled temporal coverage and granularity of the eBird data set, 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 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 Additional data

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.

National Land Cover Database (NLCD). While Qiu et al. (2025) identifies the changes in land-use practices at the intensive margin (e.g., intensive tillage of cropland), we use transitions in NLCD classifications to identify land-use changes at the extensive margin. We use annual NLCD data from 1985 to 2024.

4 Effectiveness of Compensatory Mitigation measures

We now bring high-resolution biodiversity data to bear to a two-part analysis on the effect of conservation banks (CBs) on ecological outcomes. First, we apply modern event-study methods (Callaway and Sant'Anna, 2021) to satellite-based estimates of ecological damage to evaluate the dynamic causal effect of CBs on suppressing habitat degradation. Estimates from this event-study analysis will demonstrate whether CBs can reduce anthropogenic pressure on local biodiversity, *within* the targeted areas themselves. We motivate the event study by comparing the ecological characteristics of pixels within CBs versus those outside, using gridded cross-sectional biodiversity products.

Second, we assess whether the CBs affect the overall *observed* biodiversity observed in areas adjacent to the banks themselves. In particular, we apply long-difference methods (Burke and Emerick, 2016) to gridded bird species-level population trend data to evaluate the long-run effect of CBs on observed bird biodiversity, which we use as a proxy for local biodiversity. Taken together, the two-part analysis will shed light on whether CBs can suppress biodiversity loss and improve observed biodiversity.

4.1 Conservation Banks and Habitat Degradation: Evidence from satellite imagery

4.1.1 Empirical strategy

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, the results from our preceding cross-sectional analysis (Section A.2, Table A1) strongly suggest meaningful differences in the ecological characterstics of CB-included pixels and their service areas. 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:

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

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 assess whether CBs can also suppress non-human driven land disturbance (from wind damage, pest outbreaks, and wildfire, following the definition of Qiu et al. (2025)).

We compare the effects of CBs with PRMs by identifying potential PRM sites and estimating the model (1). The only difference is that we use the year of PRM site establishment, not CB approval year. The results will assess whether PRMs, which are subject to much weaker regulatory scrutiny, also confer the same amount of performance compared to the.

We complement the Land Disturbance data set, which focuses on "intensive margin" changes in land-use practices, with National Land Cover Database (NLCD). The transitions of NLCD types from one type to another point to an "extensive margin" conversion that directly affects the habitat of the species within the banks. In particular, we use transitions of NLCD coverage from "nature" land-use types to "non-nature" types. The "nature" types are defined as deciduous/evergreen/mixed forests, shrub/scrub, grassland/herbaceous, woody wetlands, and emergent herbaceous wetlands. Non-nature types are pasture/hay, cultivated crops, and developed lands containing human-constructed materials.

4.1.2 Empirical results

Figure 3 presents the results of the event study regression (1). 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) but also suggests that the conservation benefits of CBs do not extend to non-human caused disturbances. We do not see a clear pre-trend of disturbance, both human or non-human caused, prior to having the land approved as CB.

How do we exactly interpret the 3.82% point drop in the outcome? Recall that the outcome variable represents the "share of conservation bank disturbed," hence capturing the uncondi-

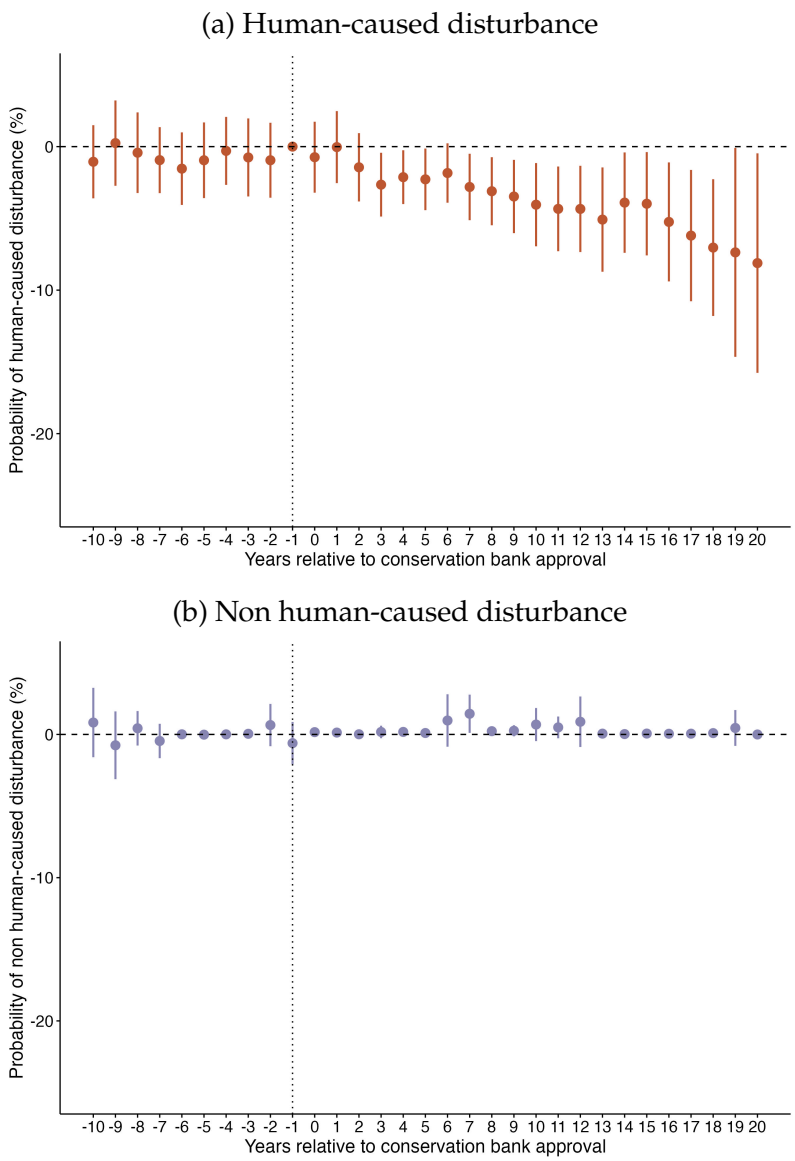


Figure 3. Impact of conservation banks on likelihood of land disturbance

Notes: Figure illustrates the estimates of the event-study regression (1), 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 3a uses as the outcome the ratio of human-caused disturbance pixels to total number of pixels, versus non-human cause disturbance pixels for Figure 5b. 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.

tional probability of disturbance occurrence. In practice, land disturbances are relatively rare events–where a given bank-year has a 34.8% probability of experiencing a non-zero human-driven disturbance (prior to bank approval). Nevertheless, *conditional on* non-zero disturbance

occurrence, a given bank-year has on average 6.5% of its land being exposed to disturbances. Combined, this leads to an average baseline disturbance of 2.26% (34.8% × 6.5%) in the banks prior to their approval. The 3.82% point drop is thus consistent with the protection and creation CBs suppressing the occurrence of disturbances and reducing its intensity–compared to counterfactual levels, constructed from not-yet-treated banks.

Nevertheless, this interpretation raises the possibility that the results in Figure 3a are driven by several not-yet-treated areas that experience an intense disturbance event. Appendix Figure B5 suggests that the results are robust to the removal of high-intensity disturbance events.

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 B2 and B3, suggest that the effects of CB in Figure 3a are driven by suppressing agricultural development (rather than building construction and logging activities). Similarly, we find that the effects are much larger in conservation banks that had a higher baseline share of agricultural land (Appendix Figures B6 and B7).

Further, while the definition of Y_{ct} in equation (1) 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).[12] The results from using such a "stock" variable, shown in Appendix Figure B4, are analogous to Figure 3a.

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–with many bank proposals spanning several years prior to their approval. Such processes likely discourage landowners from degrading the habitat prior to their approval.

The suppression of human disturbances in CBs raises the question: does this lead to spillover effects in neighboring areas that are purchasing the credits? The distinct feature of CBs, where the purchases of credits can only originate from within its "service area," allow us to evaluate such spillover effects by estimating the event-study model for pixels within service areas. The resulting estimates, shown in Figure 4a, are highly noisy. This is consistent with the effect of *service area* formation (the estimand of Figure 4a) being very noisy and spread across multiple years, as banks' credits are not immediately sold upon their installation. The diffusion of habitat

[12]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.

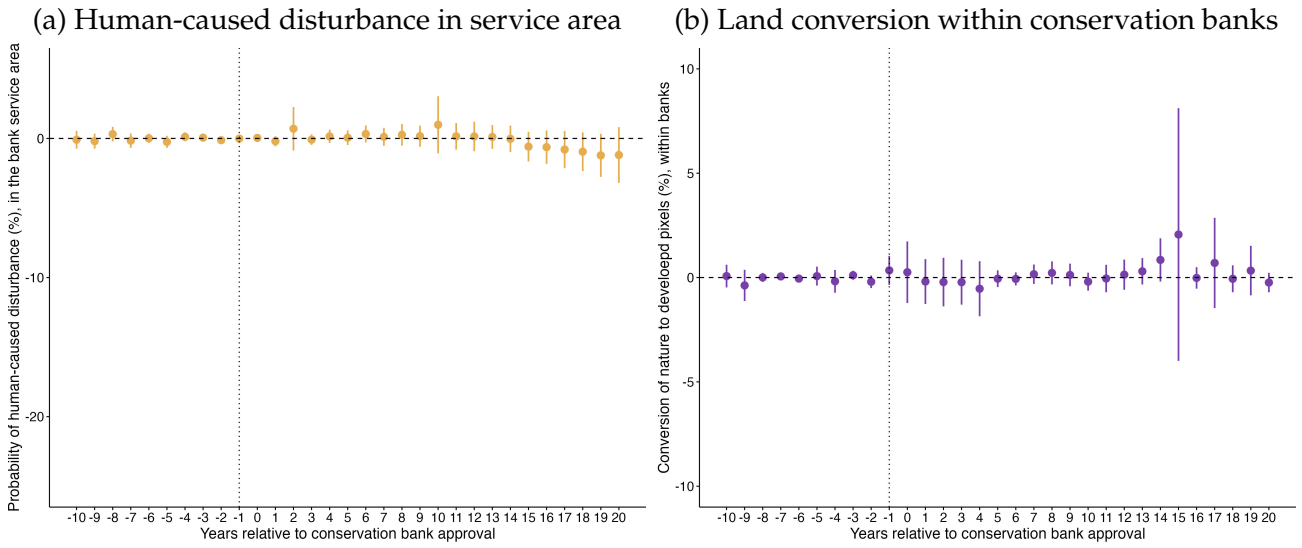


Figure 4. Conservation Banks: Spillover effects and impact on land-use conversion

Notes: Figure explores potential spillover of land disturbance and the extensive-margin effect of conservation banks. Figure 4a illustrates the impact of the banks in their *service area*, where the demand for bank credits originate. Figure 4b takes as the outcome variable the probability of land-use conversion from nature to "developed" pixels, in the NLCD data set.

pressure also occurs across

Further, while Figure 3a suggests that CBs suppress habitat loss at the intensive margin–largely driven by reductions in intensive agricultural practices–Figure 4b results suggest that such positive effects do not follow through for land-use *conversions*. That is, the CBs do not meaningfully suppress the conversion of natural land to developed areas.

Lastly, we note that the disturbance-suppression properties of conservation banks are not shared by permitte-responsible mitigation (PRM), which are an alternative to CBs subject to substantially weaker regulatory oversight (Section 2). The coefficient estimates for PRMs are substantially smaller than that of CBs, for both human- and non-human disturbances (Figure 5). This is consistent with the extensive policy oversight from USFWS being a strong driver of CB performance.

All in all, the event-study estimates point to conservation banks successfully suppressing anthropogenic pressure on wildlife habitat–at the intensive margin. Such effects do not follow through for extensive margin, land-use conversions. However, it remains unclear whether such mixed effect on habitat preservation will be linked with long-run improvements in real biodiversity. We thus turn to citizen science data to evaluate the long-run effect of CB adoption on local biodiversity.

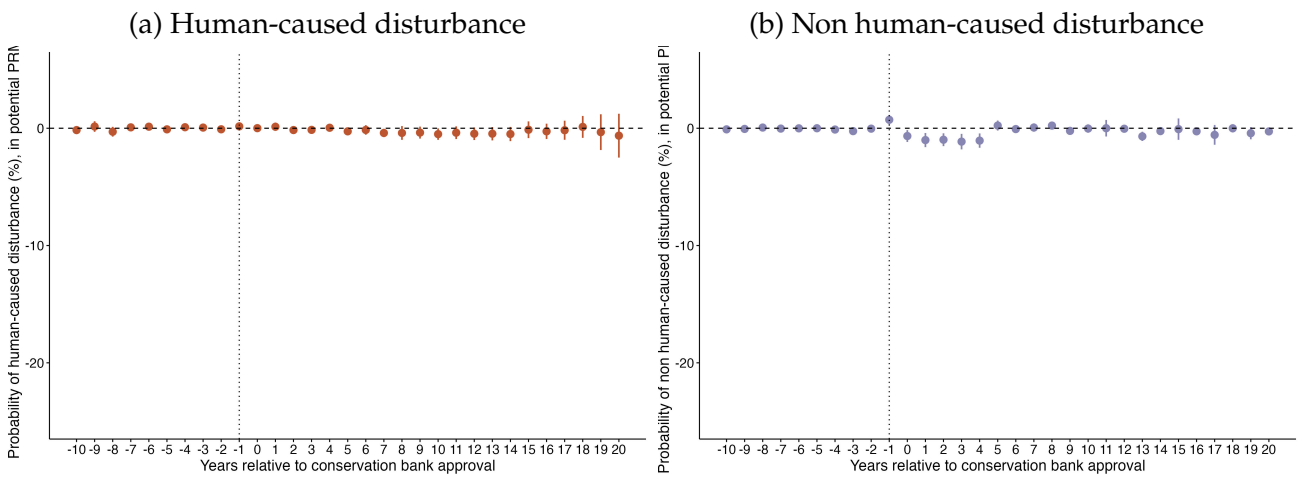


Figure 5. Impact of potential PRMs on likelihood of land disturbance

Notes: Figure repeats the event-study analysis, shown in Figure 3, but uses potential permittee-responsible mitigation (PRM) sites. The PRM sites are obtained from "conservation easement" data bases.

4.2 Conservation Banks and Bird Biodiversity: Evidence from Citizen Science

While systematic ecological surveys, such as the Breeding Bird Survey (BBS), provides unparalleled temporal coverage of bird biodiversity data (spanning four decades), its spatial coverage is inherently limited to the routes and the observation conditions of the day in which the surveys are conducted. In contrast, citizen science-based gridded data sets compile data from high-quality citizen observations to generate wall-to-wall "snapshots" of population estimates, at fixed time periods. Recent studies (e.g., Fink et al., 2020; Teng et al., 2023) have combined machine learning methods with citizen science observations from eBird (a leading platform for citizen science on bird observation) to predict bird species occurrence and presence at high spatial resolution.

In particular, Fink et al. (2023) use cutting-edge methods in machine learning-based causal inference (Chernozhukov et al., 2018) to evaluate the changes in different bird species' "relative abundance" between 2012 and 2022, at 27km grid level.[13] Relative abundance is defined as the product of probability of species occurrence and the expectation of species abundance conditional on its occurrence (see Section 3.2.1). The trend estimates for species-level relative abundance, combined with the changes in CB areas over the same period, can be used to estimate a long-difference model (Burke and Emerick, 2016). To the extent that the gridded population estimates are species-specific, one can also include species fixed effects that control for global shocks to the bird species' abundance. We can also estimate the spillover effects from

[13]In practice, there are several species for which the start and end years are not precisely 2012 and 2022. In such rare cases, we calculate the overlap of CBs for the species-specific start and end years.

the existence of CBs in neighboring grid cells by including their exposure as an independent variable, *à la* Miguel and Kremer (2004).

To be precise, for each grid cell c in the Fink et al. (2023) data set, we calculate its overlapping area with CBs in years 2012 and 2022. The within-grid intertemporal variation in such overlapping CB area is defined as $\Delta\text{CBAreaInGrid}_c$. We calculate the same change in overlapping area but for the grids neighboring grid c, defined as $\Delta\text{CBAreaInNeighborGrid}_c$. The unit of area is square kilometers (km^2). The combination of the two variables leads to our reduced-form equation of interest:

$$\Delta Y_{sc} = \tilde{\beta}_1 \Delta\text{CBAreaInGrid}_c + \tilde{\beta}_2 \Delta\text{CBAreaInNeighborGrid}_c + \alpha_{s,j(c)} + \varepsilon_{sc} \tag{2}$$

where ΔY_{sc} is the change in relative abundance of species s in grid cell c. $\alpha_{s,j(c)}$ is the species-by-ecoregion fixed effect that controls for species-specific shocks common to the ecoregion. To focus on breeding birds native to North America, we focus only on bird species that are found in the BBS and use EPA level 2 ecoregions fixed effects. We also limit our samples to "eventually treated" grids experiencing non-zero increases in overlapping CB area, both in the grid cells themselves and in their neighbors. The error term ε_{sc} is clustered at the species level, to account for arbitrary correlation of errors across space.

The use of species-by-ecoregion fixed effects $\alpha_{s,j(c)}$, combined with our focus on "eventually treated" units, implies that our right-hand side variables are driven by within-species-ecoregion differences in the *intensity* of CB establishment. Put differently, the β coefficients capture the extent to which bird population in a high-CB density location is on a different trajectory to those with low-CB density location, compared to the population in the *same* ecoregion *and* species. For the coefficients to be still endogenous, the area of conservation banking area would have to be correlated with other factors that are not controlled by the $\alpha_{s,j(c)}$ fixed effect.

While such usage of species-and-location specific fixed effect accounts for many sources of endogeneity, we also test the robustness of using a shift-share Bartik instrument. In particular, for each grid cell, we calculate the area of the cell designated as "critical habitat" for species listed as "endangered" or "threatened" under the ESA, in years 2012 and 2022. The sum of areas can be understood as a shift-share instrument, where the individual loadings on "share" are the sizes of the species' habitat in the cell, and "shift" is a global vector of values -1, 0 or 1 (0 if status unchanged, 1 if newly listed, and -1 if delisted).

Our identification strategy for the Bartik instrument relies on the capacity of such critical habitat area changes to improve the suitability of the cell to the installation of CBs, all the while the listing and delisting of species are likely exogenous from the individual cells' location and

their shocks. We thus instrument for the change in the conservation banking area with the changes in such overlap area. The identification for such shift-share approach comes from the exogeneity in the timing of species listing (i.e., the "shift" element, *à la* Borusyak et al., 2022).

Fink et al. (2023) provide the ΔY_{sc} trend estimates in two different formats: absolute population change per year, and percentage population change per year. While our preferred outcome variable is the latter normalized measure due to its inter-species comparability, we test the robustness of our results to the absolute trend estimates. We also test the robustness of our results to controlling for baseline population of the species, and to dropping all grid cells with statistically insignificant ΔY_{sg} estimates. We also test the heterogeneous effect of CBs by dividing species into those that are less common in each grid cell c and assess the heterogeneous effect of CB establishment for the less-common and more-common species. We also test the robustness of our results to dropping CB-targeted species, to account for potential reverse causality in the designation of species.

The headline results, shown in Table 1, point to the overall positive effect of conservation banks on bird population (abundance). Column 1 results suggest that a 1km^2 increase in conservation bank area in a 27km grid cell is linked with an improved population trend per year (0.04% increase in population per year). To the extent that the Fink et al. (2023) estimates are obtained over a ten-year period, an average-sized conservation bank (3.66km^2) is linked with 1.5% (3.66×0.4×10) increase in population over the ten-year period. The impact on neighboring cells, captured in the ΔCBAreaInNeighborGrid$_c$ coefficient estimates, is smaller and noisier.

The 10-year effect of CBs compare to the result from a recent analysis of bird population in North America, which estimate a 29% loss in overall abundance over the last 48 years (Rosenberg et al., 2019). The results suggest that biodiversity offset projects can play a small yet important role in mitigating the rapid loss in bird biodiversity observed globally (Matthews et al., 2024).

Column 2 evaluates the heterogeneity of the effect of conservation banks, as a function of whether a species is less common in each grid cell (defined as possessing a below-median abundance compared to other species in the grid cell). The results suggest that indeed, the positive effects of CBs are driven by their influence on less-common species (ΔCBAreaInNeighborGrid$_c$ $\mathbb{1}$[LessCommon$_{sc}$]).

Column 3 strengthens the identification strategy by focusing on cells that experience an increase in ESA-listed species' critical habitat area, and using this change as an instrument for the CBAreaInNeighborGrid$_c$ variable. While the subsetting of cells with critical habitat change greatly reduces the sample size, the results are still consistent with our headline (column 1) estimates. The stronger point estimates imply that conservation banks' effects are stronger when

Table 1. Conservation Banks and Bird Biodiversity: Citizen Science-based estimates

	Biodiversity Outcome of Interest:					
	% change in population per year			Raw change in population per year		
	(1)	(2)	(3)	(4)	(5)	(6)
ΔCBAreaInGrid$_c$	0.04***	0.01	0.32***	0.26***	−0.01	3.48***
	(0.01)	(0.01)	(0.09)	(0.09)	(0.10)	(1.08)
ΔCBAreaInGrid$_c \mathbb{1}$[LessCommon$_{sc}$]		0.06***			0.59***	
		(0.02)			(0.15)	
ΔCBAreaInNeighborGrid$_c$	0.01	0.01**	0.25***	0.08	0.07*	2.83***
	(0.01)	(0.00)	(0.08)	(0.06)	(0.05)	(0.97)
ΔCBAreaInNeighborGrid$_c \mathbb{1}$[LessCommon$_{sc}$]		−0.00			0.02	
		(0.01)			(0.10)	
Specification	OLS	OLS	2SLS	OLS	OLS	2SLS
Min. first stage F-statistic			78.19			78.19
Num. Obs.	2547	2547	283	2547	2547	283
R-squared	0.73	0.74	0.79	0.72	0.73	0.73
Y_i mean	−0.64	−0.64	−0.72	−2.77	−2.77	−3.98
Y_i SD	2.80	2.80	2.66	28.64	28.64	26.51

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

Notes: Table evaluates the long-run effect of conservation banks on bird population, using the long-difference method (2). The outcome data are from Fink et al. (2023), which uses machine learning analysis of citizen science reports to estimate per-year loss in population over a ten-year period for different bird species. Columns 1 to 3 use relative change in abundance (i.e., population) per year, in percentages, as the outcome, while columns 4 to 6 use absolute changes in abundance per year as the outcome variable. ΔCBAreaInGrid$_c$ and ΔCBAreaInNeighborGrid$_c$ represent the square kilometers of conservation banking area change in the cell c over the ten-year period. Columns 2 and 5 evaluate whether the effect of conservation banks are larger for species that are less common in the cell ($\mathbb{1}$[LessCommon$_{sc}$]). Columns 3 and 6 use Bartik instruments, obtained from the changes in Endangered Species Act (ESA)-listed critical habitat area, to account for potential endogeneity. All specifications include species-by-ecoregion fixed effect. See Appendix for additional analyses and robustness checks.

driven by an overall increase in the regulatory importance of the location, as captured in the changes in the listed critical habitat. The first-stage F-statistic support the first-stage relevance of our instrument, suggesting that changes in critical habitat are indeed strong drivers of CB area increase.

The effects of CBs remain robust when we use raw change in population per year as the outcome variable (columns 4 to 6). In particular, an average CB is associated with 9.51 ($3.66 \times 0.26 \times 10$) increase in population for an average bird species over the 10 years. The results are still stronger for less common species, and the Bartik instrument estimates are consistent with the OLS estimates (column 6 versus column 4).

A series of additional analyses and robustness checks provide important nuances to the results. First, the results are robust to including baseline abundance and changes in ecologically protected areas as control variables (column 2, Appendix Table B4), suggesting that the results are not driven by baseline differences in abundance and concomitant time-varying changes in conservation policies. Further, the results remain significant when we drop species that are targeted by the conservation banks[14], and to cells with statistically significant trends (columns 3 and 5). In fact, the estimates become noisier when we focus on CB-targeted species, likely due to the reduction in sample size–originating from the rarity of the species themselves. Lastly, dropping $\Delta\text{CBAreaInNeighborGrid}_c$ and $\Delta\text{CBAreaInGrid}_c$ terms produce estimates that are largely consistent with those of Table 1 (columns 6 and 7, Appendix Table B4).

Further, a subsample analysis of the same specification for different "guilds" of bird species, where the guild classifications are obtained from Carroll et al. (2024), suggest that the impact of CBs are not equally distributed across species (Appendix Table B5). In particular, it is primarily the "habitat generalists" with large ranges rather than small ranges that gain from the CBs, and the residents whose trend estimates that are taken over their breeding season (for Fink et al., 2023), that drive the positive effects of CBs. In contrast, habitat specialists have a weaker and noisier benefits from CB establishment.

All in all, the results on citizen science data from eBird strongly suggest positive long-run impacts from CB establishment, with the impacts being particularly larger for habitat generalists and for less-common species. Nevertheless, the benefits from an average CB–1.5% increase in population over 10 years–dwarf in comparison sheer size of the bird population loss in North America (29% over 48 years), suggesting that biodiversity finance from private investments consist a partial solution to the rapid biodiversity loss of the Anthropocene.

[14]These are: Burrowing Owl, California Gnatcatcher, Florida Scrub-Jay, Le Conte's Thrasher, Bell's Vireo, Swainson's Hawk, Golden-cheeked warbler, Tricolored blackbird, Greater sage-grouse, Lesser prairie-chicken, and Black-capped vireo.

5 Efficiency of Conservation Banks

5.1 Additional Policy Background

Under the ESA, compensatory mitigation is generally required whenever a proposed activity is likely to result in unavoidable "take" of a listed species. Historically, "take" included not only direct killing or injuring of animals but also significant habitat modification that resulted in actual injury or death.[15] To determine if ”take” is unavoidable, the USFWS assesses proposed impacts and determines compensatory mitigation requirements through standardized regulatory frameworks—primarily Programmatic Biological Opinions (PBOs) or Habitat Conservation Plans (HCPs). Within both PBOs and HCPs, the USFWS translates physical land impacts into specific credit obligations using quantitative weighting mechanisms and functional assessments. These frameworks scale mitigation demands according to ecological quality, threat levels, and spatial connectivity—frequently applying tiered replacement ratios, such as a 3:1 ratio for critical habitat versus a 1:1 ratio for marginal habitat. This ensures that credit duties reflect actual functional loss rather than raw acreage alone.

Importantly, ESA compensatory mitigation is not designed as a universal "no net loss" policy, distinguishing it from Clean Water Act Section 404 wetland regulations. Under the ESA, mitigation serves as a targeted mechanism solely to offset authorized take and minimize species impacts to the extent practicable, rather than enforcing a broad mandate to preserve net ecological baselines.

5.2 Efficient allocation of conservation banks: Model and empirical analysis

To this end, once take is authorized the central question becomes one of spatial allocation: which lands should be set aside for conservation? Consider a landscape divided into a continuum of spatial units (pixels) $i \in \{1, \ldots, P\}$ within region r. Each pixel i is characterized by three exogenous parameters:

- $E_i \in [0, 1]$: Baseline probability of pixel i being converted to non-natural habitat (representing the threat of land loss);
- $R_i > 0$: Net transaction value or economic return generated when pixel i is converted to development;
- $S_i \in [0, 1]$: Species-specific habitat suitability or ecological quality score.

[15] A September 14, 2026 USFWS guidance memorandum instructed staff to narrow the interpretation of take, asserting that prohibited "take" is limited to actions intentionally and purposefully directed at a listed animal. This fundamentally changed the scope of the ESA and has raised concerns in the industry about the impacts it will have on credit demand.

We assume these parameters are spatially homogeneous within a given pixel i but vary across space. We argue that welfare-maximizing regulator must simultaneously account for all three when choosing where to site conservation. To formalize the problem, we consider a "discriminate" regulator who seeks to equalize the marginal cost per unit of additionality-weighted ($S_i E_i$) functional habitat preserved across all sites. Seeking to offset the regional authorized take, N_r, at minimal total social cost, the discriminate policymaker operates according to the following optimization problem:

Definition 1 (Objective Function of the Discriminate Regulator)**.** For a given region r, the regulator chooses the vector of conserved land allocations $\{A_i\}_{i=1}^{P}$ to solve:

$$\min_{\{A_i\}} \sum_{i=1}^{P} [C_i(A_i, R_i, S_i) + E_i R_i A_i] \quad \text{s.t.} \quad \sum_{i=1}^{P} S_i E_i A_i \geq N_r \tag{3}$$

In Equation (3), N_R represents the aggregate functional habitat offset target mandated for region r. The objective function incorporates two distinct cost components: direct conservation and land management costs, $C_i(A_i, R_i, S_i)$, and the expected opportunity cost of foregone development, $E_i R_i A_i$. In the constraint, the product $S_i E_i$ captures additionality-weighted ecological gain, ensuring that credit is awarded only for suitable habitat (S_i) that was genuinely at risk of conversion (E_i). Equation (3) is solved independently for each region r and assuming interior solutions ($A_i^{**} > 0$), the theoretical equilibrium is characterized as follows:

Theorem 1 (Equilibrium under the Discriminate Regulator)**.** Under Equation (3), the optimal allocation of conserved land A_i^{**} for interior solutions satisfies the first-order condition:

$$E_i R_i + MC_i(A_i^{**}, R_i, S_i) = \lambda S_i E_i \tag{4}$$

where $MC_i(A_i^{**}, R_i, S_i) \equiv \frac{\partial C_i}{\partial A_i}$ is the marginal cost of conservation management, and λ is the shadow price of the regional target N_R.

Equation (4) directly recovers the spatial equimarginality result of Muller and Mendelsohn (2009). The condition says that the regulator equalizes the total marginal cost per unit of weighted habitat quality ($S_i E_i$) across all pixels with partial conservation. In other words, the regulator spends money to conserve area where it yields the most effective habitat quality per dollar, balancing expenditures until the marginal cost of additional conservation is uniform across all spatial units. Corner solutions occur when a unit's marginal cost per effective unit exceeds λ even at zero protection ($A_i = 0$), leaving it entirely unconserved, or remains below λ up to full capacity ($A_i = 1$), making full conservation optimal before equality can be reached.

5.2.1 Empirical Predictions

To map this stylized model onto empirical predictions, we assume the following properties of the marginal cost function:

Definition 2 (Assumptions #1: Marginal cost)**.** The cost function of conservation activities $C_i(A_i, R_i, S_i)$ is twice differentiable, and the marginal cost function $MC_i(A_i, R_i, S_i)$ satisfies the following :

$$MC_A \coloneqq \frac{\partial MC(A_i, R_i, S_i)}{\partial A_i} > 0, MC_R \coloneqq \frac{\partial MC(A_i, R_i, S_i)}{\partial R_i} > 0, MC_S \coloneqq \frac{\partial MC(A_i, R_i, S_i)}{\partial S_i} < 0$$

These assumptions state that the cost function is strictly convex with respect to A_i, the marginal cost function is an increasing function of R_i (i.e., the higher the land value the more costly the conservation) and the marginal cost function is a decreasing function of S_i (i.e., the more suitable the habitat is at baseline, the less costly it is to conservation). Under these assumptions, the discriminate objective function, and its associated FOC (4), we have:

Theorem 2 (Comparative statics of A_i^{**}, under discriminate equilibrium)**.** Under Definition (2), interior solutions have the following comparative statics

$$\begin{aligned} S_i : \frac{\partial A_i^{**}}{\partial S_i} &= \frac{\lambda E_i - MC_S}{MC_A} > 0 \\ R_i : \frac{\partial A_i^{**}}{\partial R_i} &= \frac{-(E_i + MC_R)}{MC_A} < 0 \\ E_i : \frac{\partial A_i^{**}}{\partial E_i} &= \frac{\lambda S_i - R_i}{MC_A} > 0 \end{aligned} \tag{5}$$

These comparative statics align with intuitive spatial targeting principles, areas that are more suitable, cheaper, and at greater risk should be prioritized for conservation. Together, these theoretical conditions establish verifiable empirical predictions for evaluating whether observed regulatory offsets reflect discriminate spatial targeting.

5.2.2 Methods and Results

To examine whether the realized distribution of conservation banks reflects these comparative statics, we estimate empirical models at a 1 km pixel resolution across California using both

species-level and pooled multi-species specifications:

$$\text{Species Level: } A_i = \beta_1 E_i + \beta_2 R_i + \beta_3 S_i + \alpha_{r(i)} + \epsilon_i$$
$$\text{Pooled: } A_{si} = \beta_1 E_i + \beta_2 R_i + \beta_3 S_{si} + \alpha_{r(i),s} + \epsilon_{si}$$

where the dependent variable, A_i (or A_{si} for species s in pixel i), measures the area of established conservation bank footprints sourced from RIBITS aggregated to the 1 km grid. County fixed effects, $\alpha_{r(i)}$, and county-species fixed effects, $\alpha_{r(i),s}$, in the species-specific and pooled models respectively, absorb unobserved regional and region-by-species heterogeneity.

5.2.3 Data

Land conversion risk (E_i) is measured as the proportion of land that transitioned from natural to developed within each pixel between 1985 and 2000, calculated using 30 m resolution raster data from the National Land Cover Database (NLCD). Private development returns (R_i) are measured using fair market private land values from Nolte (2020), constructed for 2010 at a 480 m resolution via a machine-learning framework trained on over six million arms-length property sales.

To operationalize site-specific habitat quality (S_{si}) across California, we construct fine-resolution species distribution models for six target focal species: the Burrowing Owl (*Athene cunicularia*), California Tiger Salamander (*Ambystoma californiense*), California Red-Legged Frog (*Rana draytonii*), Desert Tortoise (*Gopherus agassizii*), Giant Garter Snake (*Thamnophis gigas*), and San Joaquin Kit Fox (*Vulpes macrotis mutica*). Models are estimated using Maximum Entropy (MaxEnt) machine learning algorithms implemented via the maxnet and ENMeval frameworks in R. All spatial predictors and output suitability rasters are standardized to a 30 arc-second resolution ($\approx$ 1 km pixel size) across the state of California.

Species presence records were compiled from the Global Biodiversity Information Facility (GBIF) and subjected to spatial thinning to mitigate sampling bias arising from opportunistic reporting. To ensure that multiple records in heavily sampled areas did not artificially distort model fitting, occurrence points were deduplicated at the grid-cell level so that each 30 arc-second pixel contained at most a single presence observation. Background pseudo-absence points were randomly sampled across the terrestrial extent of California to characterize the broader environmental domain available to each species.

We compiled a comprehensive suite of environmental covariates capturing climate, terrain, land cover, soil composition, and hydrologic connectivity. Climate metrics were derived from WorldClim bioclimatic variables, supplemented by topographic indices—elevation, slope, and

terrain ruggedness—calculated from high-resolution digital elevation models. Physical soil properties from SoilGRIDS, including bulk density, sand, and clay content, were integrated alongside categorical land-cover classes from the National Land Cover Database. For species with specialized life-history dependencies, we derived continuous spatial distance measures to critical habitat features, such as vernal pool systems and surface water bodies identified in the California Aquatic Resource Inventory. To eliminate multicollinearity, candidate continuous predictors were filtered to remove collinear variables that exceeded standard inflation thresholds.

Model tuning and evaluation were conducted using spatial block cross-validation, partitioning the landscape into geographically independent blocks to prevent spatial autocorrelation from inflating performance metrics. For each species, we systematically evaluated candidate models across varying feature combinations and regularization penalties to prevent overfitting. Optimal model configurations were selected by maximizing out-of-sample predictive performance, assessed via the continuous boyce index (CBI) and spatial area under the curve (AUC). All models perform well on these metrics, with no model achieving a CBI below .75 and AUC below .8. Final model predictions were projected using the complementary log-log transformation, producing a continuous index of relative habitat suitability ($S_{si} \in [0, 1]$) for each species s and spatial unit i.

Table 2 presents the parameter estimates for both individual species and the pooled specification. Across all models, the empirical estimates for private development returns (R_i) and habitat suitability (S_{si}) strongly align with theoretical predictions under both regulatory benchmarks. The coefficient on land value (R_i) is uniformly negative, confirming that conservation banks systematically avoid high-value land where foregone development opportunity costs are steep. Conversely, the coefficient on habitat suitability (S_{si}) is consistently positive and statistically significant across most specifications, including the pooled model. This indicates that bank sponsors successfully target ecologically high-quality sites.

However, the empirical estimates for expected conversion risk (E_i) reveal a clear breakdown in spatial targeting relative to the discriminate benchmark. While a social planner seeking additionality prioritizes high-threat land, our empirical estimates for E_i are overwhelmingly negative across individual species and in the pooled specification. Rather than concentrating protection on imperiled sites at immediate risk of conversion, conservation banks are disproportionately located in low-threat areas. This empirical result directly rejects the discriminate benchmark.

The sole departure from this negative pattern occurs in the model for the Giant Garter Snake (GGS), which yields a small positive point estimate on E_i. This exception is ecologically and

Table 2. Empirical Test of Spatial Targeting Comparative Statics

	BUOW	CTS	RLF	SJKF	DT	GGS†	Pooled
Expected Conversion (E)	-0.72*	-0.53**	-0.36	-0.46**	-0.028	0.020	-0.067*
(per 100)	(0.38)	(0.24)	(0.24)	(0.21)	(0.024)	(0.075)	(0.027)
Development Benefit (R)	-0.0095	-0.031*	-0.024	-0.014	-0.0014	-0.017	-0.0020
(per \$1,000/ha)	(0.016)	(0.016)	(0.016)	(0.017)	(0.0029)	(0.011)	(0.0014)
Suitability (S)	0.56**	0.99**	0.80	0.47*	0.045	0.22*	0.11**
	(0.24)	(0.50)	(0.68)	(0.27)	(0.034)	(0.12)	(0.036)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	No
County × Species FE	No	No	No	No	No	No	Yes
Bank Counties Only	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Conley SE (10 km)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Banks	18	28	8	14	10	5	50
Number of Treated Pixels	158	207	106	162	58	21	712
Observations	65,910	32,225	16,812	44,115	61,112	7,817	2,241,486

Standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. BUOW: Burrowing Owl, CTS: California Tiger Salamander, RLF: Red-Legged Frog, SJKF: San Joaquin Kit Fox, DT: Desert Tortoise, GGS: Giant Garter Snake. † See text for caveats.

institutionally revealing. Unlike the other focal species whose credit generation relies primarily on preserving existing natural habitat in rural hinterlands, GGS mitigation relies heavily on wetland creation and restoration integrated with agricultural water infrastructure (such as rice fields and irrigation canals) in the Sacramento Valley. Because GGS habitat requires these specific hydrologic features, which sit directly on the expanding urbanizing agricultural fringe, and because regulatory frameworks often require local in-kind wetland restoration within impacted basins, GGS bank sponsors are institutionally constrained to locate in higher-threat zones, counteracting the standard opportunity cost penalty ($E_i R_i$).

5.3 Market Model

Why does the existing policy framework fail to incentivize conservation on threatened land? In reality, the spatial allocation of conservation banks is determined through decentralized market transactions rather than centralized regulatory mandate. Consider the following model of an unweighted conservation banking market, where credits are traded on a simple acre-for-acre basis without ecological or additionality scaling.

There is one landowner per each pixel i and each landowner can conserve a percentage,

$A_i \in [0,1]$, of land in their pixel. The remainder of the pixel $1 - A_i$ is kept at business as usual. Under this market, the regulator decides an amount of take that is authorized in a region and announces that each landowner in that region is assigned A_i^0 amount of conservation to carry out (where the A_i^0 are set such that they sum to N_r). Importantly, this amount can be lowered by buying credits from others (A_{bij}), and can be increased by saying that the landowner will abate on behalf of others (A_{si}). Given this constraint, the landowner decides the A_i, A_{si}, A_{bij} such that the costs of compliance with the regionally-mandated level of conservation is minimized.

Formally, this set-up is given as follows:

$$\begin{aligned} \min_{A_i, A_{si}, A_{bij}} \quad & \underbrace{E_i A_i R_i}_{(1)} + \underbrace{C(R_i, S_i, A_i)}_{(2)} - \underbrace{P\left(A_{si} - \sum_{j \neq i} A_{bij}\right)}_{(3)} \\ \text{s.t.} \quad & A_i \geq A_i^0 + A_{si} - \sum_{j \neq i} A_{bij}, \\ & A_i \in [0,1], \quad A_{si} \geq 0, \quad A_{bij} \geq 0. \end{aligned} \tag{6}$$

where (1) is the expected loss of future cash flow from having signed up A_i amount of land to conservation, (2) is the total cost of abatement, given abatement amount A_i, gains from conversion R_i, and habitat suitability S_i, and (3) is the net losses from trade where A_{si} is the amount of conservation the landowner is doing for others (hence earning PA_{si} in the offset market) and A_{bij} is the amount of offsetting the landowner i purchases from j (hence spending $P \sum_{j \neq i} A_{bij}$ in the offset market). The budget constraint says that the landowner has to offset the amount that it was ordered to do A_i^0, plus any abatement that it promised to do for others A_{si}, minus any abatement that they ordered others to do A_{bij}.

Theorem 3 (Market equilibrium under conservation banking market)**.** The market equilibrium is as follows: Under interior solutions ($A_i^* \in (0,1)$),

$$E_i R_i + MC(R_i, S_i, A_i^*) = P$$

For corner solutions,

$$A_i^* = \begin{cases} 0 \text{ if } E_i R_i + MC(R_i, S_i, A_i = 0) > P \\ 1 \text{ if } E_i R_i + MC(R_i, S_i, A_i = 1) < P \end{cases}$$

This has the same interpretation as Theorem 4, with the key difference being that P is no longer weighted by $S_i E_i$. For pixels with very low abatement costs, they abate everything

($A_i^* = 1$) with the opposite being true ($A_i^* = 0$) for very high abatement cost pixels. For pixels within these bounds, they reach the equimarginal principle with respect to P (rather than $S_i E_i P$).

5.3.1 Parallels with an Indiscriminate Policymaker

This result is precisely the same result one obtains by considering an "indiscriminate" regulator who doesn't internalize the suitability or conversion threat of a pixel. The indiscriminate policymaker operates according to the following optimization problem, where the only difference from the dsciriminate policymaker is in the constraint:

$$\min_{\{A_i\}} \sum_{i=1}^{P} [C_i(A_i, R_i, S_i) + E_i R_i A_i] \quad \text{s.t.} \quad \sum_{i=1}^{P} A_i \geq N_r \tag{7}$$

Theorem 4 (Equilibrium under the Indiscriminate Regulator)**.** Under Equation (7), the optimal allocation of conserved land A_i^* for interior solutions satisfies the first-order condition:

$$E_i R_i + MC_i(A_i^*, R_i, S_i) = \lambda \tag{8}$$

where $MC_i(A_i^*, R_i, S_i) \equiv \frac{\partial C_i}{\partial A_i}$ is the marginal cost of conservation management, and λ is the shadow price of the regional target N_R.

Interpretation of this objective function is the same as (3), except for the fact that areas are no longer weighted by their suitability or conversion risk. Under the assumptions of Definition (2), the indiscriminate objective function, and its associated FOC (8), we have:

Theorem 5 (Comparative statics of A_i^*, under indiscriminate equilibrium)**.** Under the assumptions in Definition (2), interior solutions have the following comparative statics

$$\begin{aligned} S_i &: \frac{\partial A_i^*}{\partial S_i} = \frac{-MC_S}{MC_A} > 0 \\ R_i &: \frac{\partial A_i^*}{\partial R_i} = \frac{-(E_i + MC_R)}{MC_A} < 0 \\ E_i &: \frac{\partial A_i^*}{\partial E_i} = \frac{-R_i}{MC_A} < 0 \end{aligned} \tag{9}$$

Importantly, the major divergence between the two sets of comparative statics is that E_i has the opposite sign in the indiscriminate case. The economic intuition underlying this divergence centers on how conversion threat enters the decision problem. In the indiscriminate framework, every conserved unit yields an identical shadow price λ (or market credit price P), independent

of the site's baseline risk or suitability. However, enrolling land with higher conversion risk (E_i) increases the expected opportunity cost of foregone development ($E_i R_i$), and this additional loss goes uncompensated. Because an unweighted framework fails to credit the additionality generated by protecting threatened habitat, higher conversion risk acts as a pure cost penalty. Consequently, conservation is systematically directed away from high-risk sites toward low-threat, low-opportunity-cost parcels.

This theoretical result provides a direct explanation for our empirical findings in Table **??**. While the discriminate social planner prioritizes high-threat sites ($\frac{\partial A_i^{**}}{\partial E_i} > 0$), our empirical estimates consistently yield negative coefficients on E_i across individual species and in the pooled specification. This empirical alignment with Equation (9) demonstrates that existing conservation banking markets operate functionally like an indiscriminate regulator. By failing to denominate credits in terms of weighted habitat, current policy rules inadvertently steer conservation banks toward low-threat land, generating systematic spatial misallocation relative to the social optimum.

6 Conclusion

Combining administrative data, satellite imagery, and citizen-science observations, we provide the first empirical analysis of the effectiveness of biodiversity offsetting. Focusing on the oldest biodiversity program in the world, we find evidence that the offset projects suppress anthropogenic pressure on ecosystems using four decades of satellite imagery of land-use disturbances. The offset projects also have important local spillovers on bird populations, with species diversity significantly increasing in neighboring areas.

While these banks have demonstrated clear local ecological efficacy, we show that their systemic policy impact is constrained by spatial misallocation in site selection. By combining machine-learning land value models, historical land cover transitions, and fine-resolution species distribution models across California, we evaluate whether bank siting reflects efficient spatial targeting across habitat quality (S), land cost (R), and conversion threat (E). We find that while bank sponsors successfully target ecologically suitable habitat and avoid high-cost land, they systematically avoid conservation on parcels facing high conversion risk. This empirical pattern confirms our theoretical prediction that unweighted, acre-for-acre credit trading forces offset markets to operate like an indiscriminate regulator—penalizing landowners who protect threatened land and steering conservation toward low-risk areas where additionality is minimal.

Lastly, two key elements of the specific empirical context of our analysis (USFWS-regulated conservation banking programs) provide important lessons for future biodiversity offset mar-

kets. 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.

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Appendix

A Cross-sectional Evidence Using Gridded Ecological Metrics

A.1 Gridded Ecological Metrics

Species Richness (S): Species richness represents the total number of native species within a defined geographic area. We measure this using the Areas of Conservation Emphasis (ACE) dataset, which integrates species ranges, habitat preferences, and landcover maps to estimate native species richness across a continuous hexagonal grid spanning California (CDFW, 2018). To calculate species richness at the conservation bank level, we intersect the spatial footprint of the bank with the ACE grid. We assign each intersecting cell a weight based on its overlapping area, yielding the area-weighted sum:

$$S = \sum_{i=1}^{N} w_i * S_i$$

where N is the total number of intersecting hexagons, S_i is the richness score of hexagon i, and w_i is the fraction of the bank's total area covered by hexagon i.

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:

$$STAR_i = \sum_{t=1}^{N_t} \sum_{s=1}^{N_s} W_s \cdot \frac{A_{s,i}}{G_s} \cdot C_{s,t} \tag{A1}$$

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.

A.2 Conservation Banks: Cross-sectional evidence from gridded biodiversity metrics

As previously discussed, gridded biodiversity metrics (Type A, Table **??**) provide cross-sectional measures of biodiversity based on a set of modeling assumptions. However, because they are not time variant, we 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. In order to squarely focus

on the former element (selection bias), we leverage three widely used metrics (Species Richness, MSA, and STAR; Section A) to evaluate the baseline conditions as of the CBs' establishment. We exploit two different features of the gridded ecological metrics and the CB policy to do this.

First, using the fact that the metrics were developed to capture the status of the biodiversity as of year 2015, we restrict our analysis to banks approved after 2015. This implies that any observed differences in biodiversity metrics reflect difference sin pre-existing conditions rather than CB-induced ecological improvements. Second, in utilizing the cross-sectional biodiversity metrics, it is crucial that we rely on pixels that are exposed to similar ecological pressures and habitat characteristics. We achieve this by restricting our comparison group to the specific, legally defined service area of each bank–defined by the USFWS upon the CB establishment. To mitigate the risk of spatial spillovers, we apply a 10 km exclusion buffer around all existing protected areas and CBs, erasing these overlapping footprints from the service areas. We then compare the mean biodiversity score within the strict boundaries of each bank ("in-bank mean") against the mean of this refined service area ("outside-bank mean"). To evaluate whether these spatial differences are statistically significant, we estimate pairwise t-tests.

Panel A of Table A1 presents the results of this comparison for the national sample of 30 conservation banks approved after 2015. We observe clear evidence of spatial sorting: conservation banks are systematically sited in areas with higher baseline biodiversity than their surrounding service areas. This difference is most pronounced for MSA, which is 5.075 points higher inside the banks. This magnitude is both statistically significant and ecologically meaningful, signifying that in-bank habitats are approximately 5% more ecologically intact relative to pre-disturbance baselines compared to their surrounding service areas. While the STAR metric also indicates a positive in-bank bias, the difference is not statistically distinguishable from zero.

Panel B restricts the sample to the 19 post-2015 banks in California, allowing us to leverage higher-resolution taxonomic richness data. The California results corroborate the national trend of positive spatial selection, driven primarily by localized habitat suitability for specific taxa. Amphibian and reptile richness are significantly higher inside the banks (by 0.147 and 0.087 species respectively) which aligns with the fact that many of these banks are established to generate credits for habitats or species of these types (e.g. vernal pools, california tiger salamander, california red-legged frog, giant garter snake, desert tortoise, etc.). Differences for more highly mobile taxa (birds and mammals), as well as the aggregate MSA and STAR metrics, are not statistically significant in this smaller geographic subset.

From an empirical standpoint, this non-random placement strongly implies that the usage of "never treated" locations (i.e., pixels that are not exposed to any CB establishment) are

Appendix Table A1. Placement of conservation banks: evidence from gridded ecological metrics

Metric (resolution)	(1) Number of in-bank pixels	(2) In-bank mean (SD)	(3) Service Area mean (SD)	(4) Mean pairwise difference (SE)
A. Conservation banks approved after 2015 (30 banks)				
STAR (1km)	149	1.035	0.889	0.146
		(1.057)	(0.749)	(0.147)
MSA (300m)	1,771	47.090	42.016	5.075**
		(25.727)	(25.478)	(2.071)
B. Conservation banks approved after 2015 in California (19 banks)				
Amphibian Richness (3km)	156	3.659	3.186	0.147*
		(2.795)	(2.276)	(0.081)
Reptile Richness (3km)	156	22.058	20.302	0.087**
		(6.813)	(7.050)	(0.036)
Bird Richness (3km)	156	99.198	99.453	-0.005
		(49.862)	(47.893)	(0.057)
Mammal Richness (3km)	156	36.051	35.725	0.010
		(4.297)	(4.657)	(0.016)
Non-Plant Richness (3km)	156	160.966	158.666	0.011
		(47.704)	(44.324)	(0.031)
STAR (1km)	74	1.396	1.122	0.275
		(0.960)	(0.511)	(0.232)
MSA (300m)	871	54.495	52.717	1.779
		(27.844)	(28.162)	(1.526)

$^{*}p < 0.10,^{**} p < 0.05,^{***} p < 0.01$

Notes: Table presents ecological indexes inside and outside conservation banks, across different gridded ecological estimates (Data type A, Table **??**). 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 the banks (the service area with all conservation banks and protected areas buffered to 10 km removed) respectively. Column 4 presents pairwise t-test results of comparing the ecological indexes inside the bank and in the service area. Panel A includes the 30 conservation banks with known boundaries and service areas that were approved after 2015, while panel B subsets this to those exclusively in California. STAR and MSA are multiplied by 100 for legibility. See main text for definitions of different ecological indexes and their interpretation. STAR = Species Threat Abatement and Restoration metric, MSA = Mean Species Abundance.

vulnerable to endogeneity. This motivates our strict focus on "ever treated" units in the analysis of the "additionality" of CBs in the following section (Section 4.1).

However, from a policy perspective, this spatial selection bias is an intended feature of the conservation banking program rather than a programmatic flaw. The fundamental goal of

compensatory mitigation is to offset development impacts in degraded zones by protecting, managing, and connecting high-quality habitats. Finding that banks are deliberately placed in areas with superior pre-existing biodiversity confirms that the program's ecological targeting is functioning exactly as designed. Put differently, in the general equilibrium, the CBs' establishment–even when they entail equivalent losses in habitat acreage in the service area–may have positive effects on the overall health of the ecosystem. This motivates our usage of ecological surveys and gridded population metrics (Sections **??** and 4.2), to capture the general effect of CB establishments on the local ecosystem.

B Additional Tables and Figures

Appendix Table B1. 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)

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

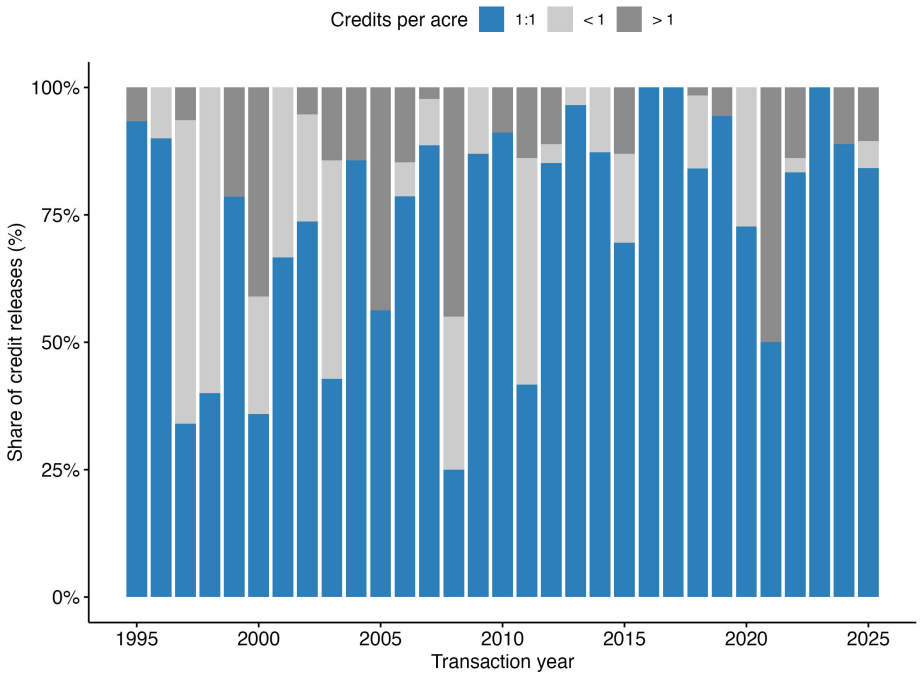
Notes: Table presents ecological indexes inside and outside conservation banks, across different gridded ecological estimates (Data type A, Table **??**). Column 1 presents the number of grid pixels within the conservation bank boundaries, while columns 2 and 3 show summary statistics of different indexes 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.

Appendix Table B2. Placement of conservation banks: evidence from gridded ecological metrics

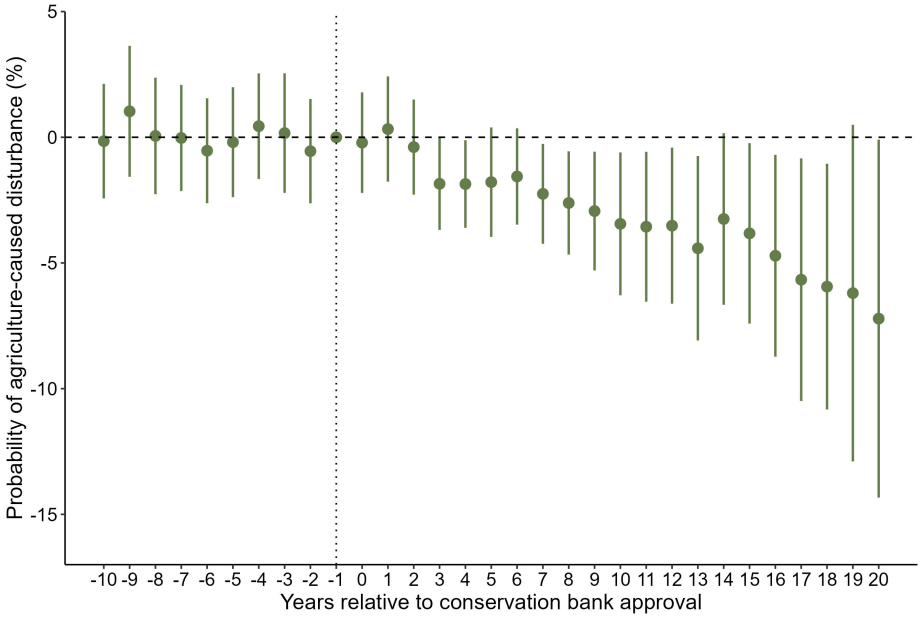
Metric (resolution)	(1) Number of in-bank pixels	(2) In-bank mean (SD)	(3) Service Area mean (SD)	(4) Mean pairwise difference (SE)
A. Conservation banks approved before 2015 (42 banks)				
STAR (1km)	181	2.535	1.424	1.111*
		(4.149)	(0.854)	(0.651)
MSA (300m)	1,974	36.501	27.702	8.799***
		(16.954)	(11.409)	(1.939)
B. Conservation banks approved after 2015 (30 banks)				
STAR (1km)	149	1.035	0.889	0.146
		(1.057)	(0.749)	(0.147)
MSA (300m)	1,771	47.090	42.016	5.075**
		(25.727)	(25.478)	(2.071)

$^{*}p < 0.10,^{**}p < 0.05,^{***}p < 0.01$

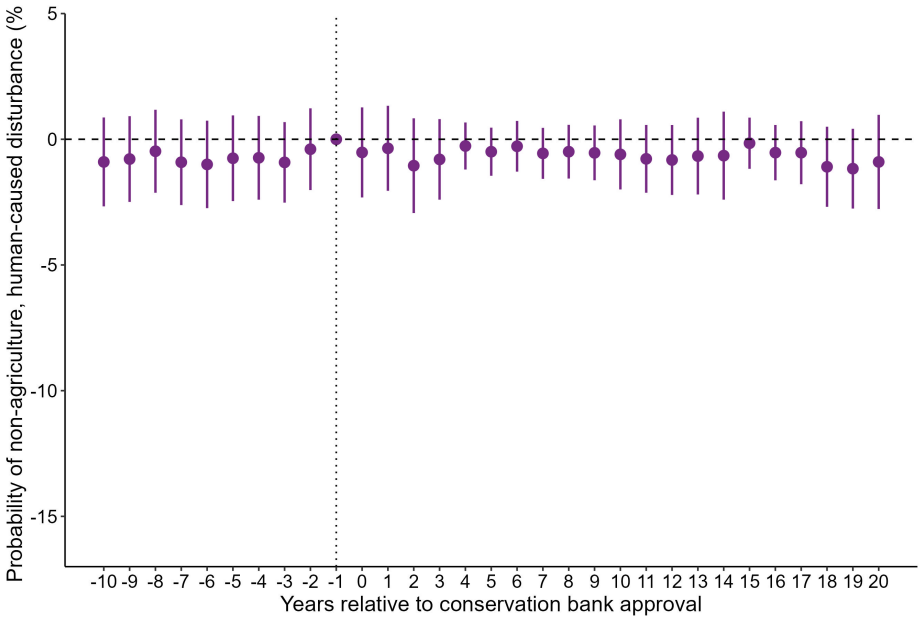
Notes: Table presents ecological indexes inside and outside conservation banks, across different gridded ecological estimates (Data type A, Table **??**). Column 1 presents the number of grid pixels within the conservation bank boundaries, while columns 2 and 3 show summary statistics of different indexes within the banks and outside the banks (the service area with all conservation banks and protected areas buffered to 10 km removed) respectively. Column 4 presents pairwise t-test results of comparing the ecological indexes inside the bank and in the service area. Panel A includes the 42 conservation banks with known boundaries and service areas that were approved prior to 2015, while panel B includes the remaining 30 banks that were approved after 2015.. 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.



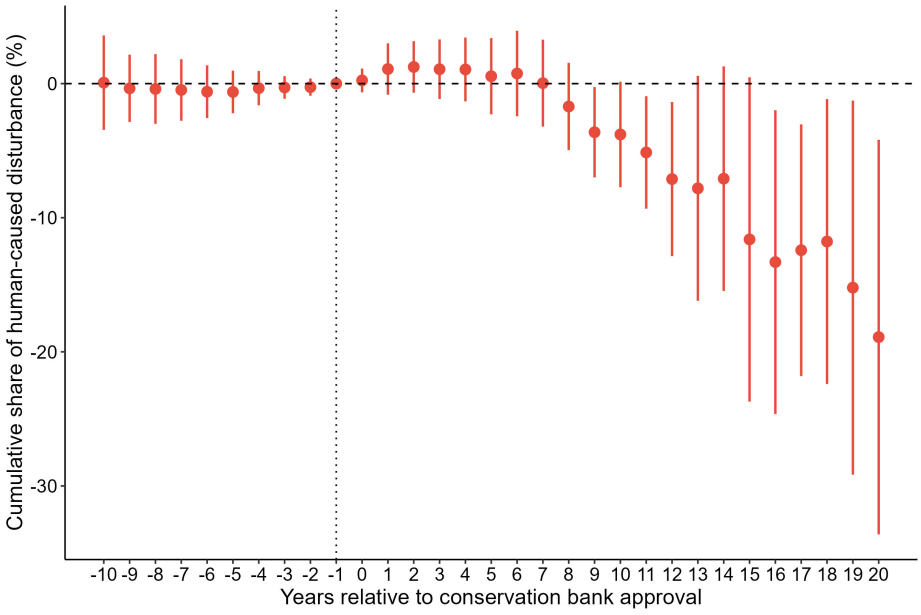
Appendix Figure B1. Number of credits issued per acre, across transaction yera



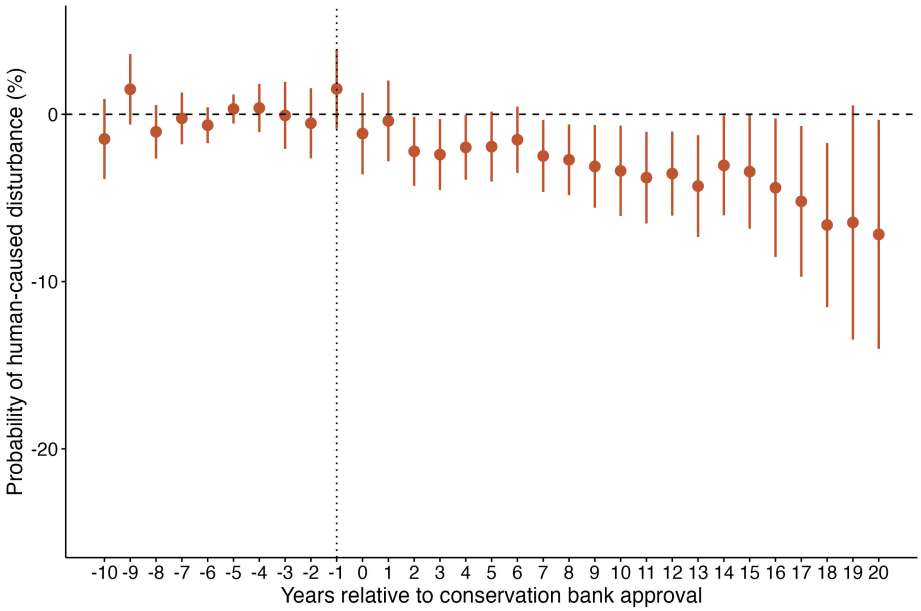
Appendix Figure B2. Event-study estimates: Probability of agriculture-caused disturbance



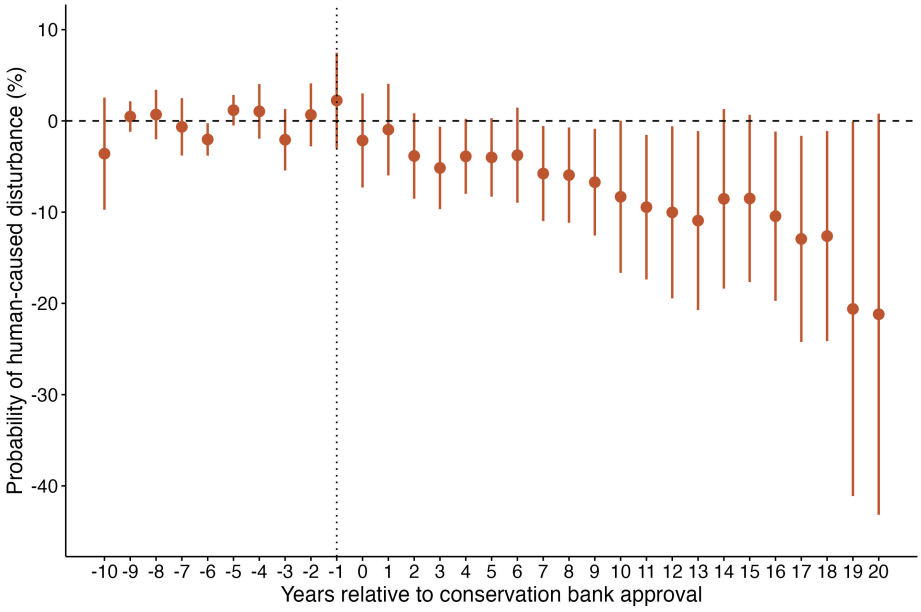
Appendix Figure B3. Event-study estimates: Probability of non-ag, human-caused disturbance



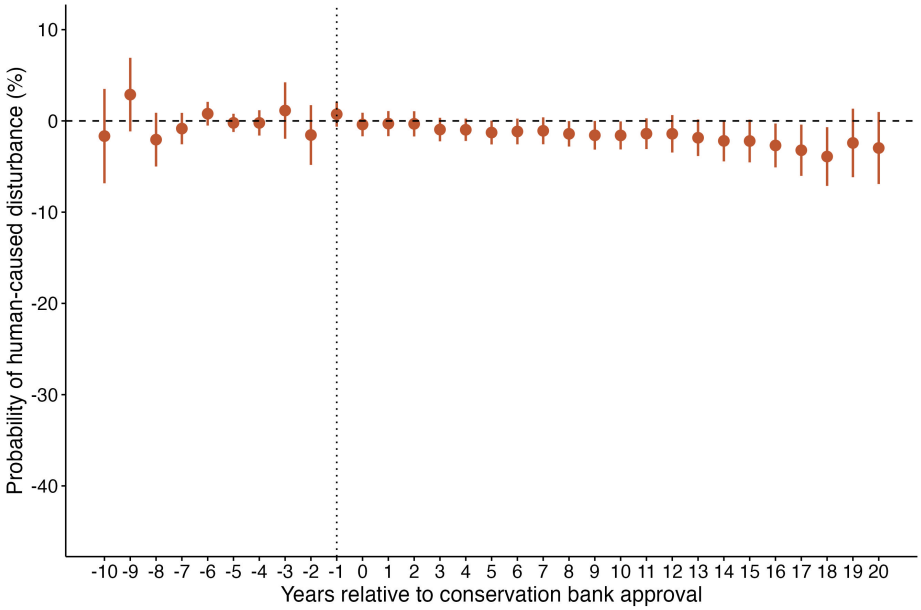
Appendix Figure B4. Event-study estimates: Probability of cumulative human disturbance



Appendix Figure B5. Event-study estimates: Probability of human-caused disturbance, dropping extreme disturbances (>80% of land disturbed)



Appendix Figure B6. Event-study estimates: Probability of human disturbance, for high-agriculture banks



Appendix Figure B7. Event-study estimates: Probability of human disturbance, for low-agriculture banks

Appendix Table B3. Conservation Banks, Protected Areas, and Bird Biodiversity: Estimates from Breeding Bird Survey

	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.

Appendix Table B4. Conservation Banks and Bird Biodiversity: Citizen Science-based estimates, robustness check

	(1)	(2)	(3)
ΔCBAreaInGrid$_c$	0.04***	0.04***	0.03***
	(0.01)	(0.01)	(0.01)
ΔCBAreaInNeighborGrid$_c$	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
Num. Obs.	2547	2547	2498
R-squared	0.73	0.73	0.73
Y_i mean at baseline (Baseline)	−0.64	−0.64	−0.64
Y_i SD at baseline (Baseline)	2.80	2.80	2.76
Model	Main	Main, with controls	Main
Sample	Full	Full	Drop CB-targeted species

	(4)	(5)	(6)	(7)
ΔCBAreaInGrid$_c$	0.08	0.06***	0.03***	
	(0.05)	(0.02)	(0.01)	
ΔCBAreaInNeighborGrid$_c$	−0.01	0.01		0.00
	(0.02)	(0.01)		(0.01)
Num. Obs.	49	979	2547	2547
R-squared	0.77	0.87	0.73	0.73
Y_i mean at baseline (Baseline)	−0.38	−1.25	−0.64	−0.64
Y_i SD at baseline (Baseline)	4.41	3.87	2.80	2.80
Model	Main	Main	Drop neighbor CB	Drop self CB
Sample	CB species	Stat. significant trends	Full	Full

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

Notes: Table evaluates the robustness of Table 1 results. Column 1 is the main result from column 1, Table 1. Column 2 includes controls of baseline abundance, protected area (PA) changes in the grid cell self and its neighbors. Column 3 drops conservation banking-targeted species from the sample, while column 4 solely focuses on them. Columns 5 and 6 include own CB area change and neighbors' CB area change.

Appendix Table B5. Conservation Banks and Bird Biodiversity: Sub-sample analysis

	(1)	(2)	(3)	(4)	(5)	(6)
ΔCBAreaInGrid$_c$	0.04***	0.04***	−0.02	0.00	0.01	0.05***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.04)	(0.01)
ΔCBAreaInNeighborGrid$_c$	0.01	0.02***	−0.03	0.01	−0.01	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
Num. Obs.	2547	1198	328	611	121	1718
Bird guilds	Full	Large range	Small range	Forest-specialized	Grassland-specialized	Full
Trend season	All	All	All	All	All	Breeding season
R-squared	0.73	0.76	0.72	0.77	0.75	0.75
Y_i mean at baseline (Baseline)	−0.64	−0.52	−0.30	0.27	−1.38	−0.65
Y_i SD at baseline (Baseline)	2.80	2.61	3.17	2.78	3.63	2.80

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

Notes: Table evaluates the heterogeneous effect of conservation banks on bird biodiversity, by subsampling the analysis to bird species based on their guilds (obtained from Carroll et al. (2024)).