

Job Impacts of the U.S. Endangered Species Act

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Abstract

The U.S. Endangered Species Act (ESA) provides some of the strongest habitat protections for imperiled species in the world. Critics argue these protections are costly to local economies, often pointing to highly publicized job losses in a few controversial species listing contexts. We use causal inference methods to test whether the ESA has impacted local labor markets for 128 terrestrial species subject to the full regulatory scope of the ESA, both listing and critical habitat designations, covering a much larger set than prior work has analyzed. We obtain the universe of employment in the U.S. over a 31-year period and use large language models to link the threats of individual species to relevant economic sectors, pinning our analysis directly to the mechanisms of the Act. We estimate a distribution of the ESA's impact on jobs across species and economic sectors at the ZIP-code level, complemented by a pooled county-level analysis. We find little evidence that the ESA affects jobs in most species-specific settings, with effects concentrated among three cases in the tail of our distribution that exhibit meaningful sector-specific impacts (13-47% job declines). Our county-level analysis reveals additional evidence of job declines in the oil, gas, and mining sector of a similar magnitude. We find no evidence of total job impacts in either analysis. Our primary estimates imply direct impacts of the ESA on the order of 6,000 jobs, aggregated across three decades for over one hundred species listing contexts. This is far fewer than the commonly referenced individual species setting of the northern spotted owl, whose impacts ranged from 16,000-32,000 jobs.

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1 Introduction

Environmental laws in the U.S. have become increasingly controversial and politically charged in recent decades, as they often create unequally distributed benefits and costs across different groups in society. A prominent example is the United States Endangered Species Act (ESA), which regulates land use on imperiled species habitat to protect and recover their populations. The ESA is widely regarded as the strongest, and most controversial, conservation policy in the nation — evidenced by a history involving hundreds of lawsuits and recent congressional hearings such as the *ESA at 50: The Destructive Cost of the ESA* (U.S. House Committee on Natural Resources, 2023). Much of its controversy stems from highly publicized economic impacts, such as job losses, among a small set of individual settings such as the listing of the northern spotted owl that affected tens of thousands of timber-related jobs in the Pacific Northwest (Ferris and Frank, 2021). However, little is known about the distribution of these impacts across the rest of the country, with direct implications for the current rollbacks being made to species protections under the ESA in the name of “economic growth and American prosperity” (U.S. Department of the Interior, 2026).

This paper estimates the magnitude and distribution of the ESA’s impact on local job outcomes for a much larger set of species than has been analyzed to date. Our focus is on the habitat of 128 terrestrial species that were affected by both regulatory layers of the ESA – listing and critical habitat designations – to capture the impacts of the full regulatory extent of the Act. We link the universe of jobs in the conterminous U.S. between 1989-2020 to the regulatory histories of these species at the ZIP-code tabulated area (ZCTA) level, and use causal inference methods to estimate a distribution of the ESA’s impact on jobs across different species contexts and economic sectors. Large language models (LLMs) are used to identify the sectors most likely to be regulated by the ESA for each species by using information in individual species listing documents, which ties our analysis directly to the mechanisms of the Act using information ex-ante to the regulations themselves. We provide additional pooled analyses which test for total employment effects, and a complementary county-level analysis which re-analyzes these impacts at a different scale.

We find little evidence of job declines in the majority of the species settings we analyze, even in our design focused on sectors most likely to be regulated by the ESA. The exceptions are three species-sectors in the tail of our overall distribution which exhibit large and precisely estimated job declines in particular industries (13-47% declines). These include the Mexican spotted owl in the forestry sector ($\approx 1,100$ jobs impacted), the Gunnison sage-grouse in the development sector (≈ 840 jobs), and the Sierra Nevada yellow-legged frog in the develop-

ment sector ($\approx 1,030$ jobs). In our complementary, county-level analysis, we find additional evidence of job declines among species pooled together and linked to the oil, gas, and mining economic sector of a similar magnitude (31% decline, or 3,040 jobs).¹ We find no evidence of job impacts in other sectors at either scale, and no evidence of total employment declines in ESA-regulated areas.

These estimates imply direct impacts on the order of 6,000 jobs across all species analyzed—highlighting that the economic impacts of the ESA do exist, but are concentrated in a few settings and are far smaller in aggregate than the individual cases often cited in policy discussions (e.g., the 32,000 timber jobs attributed to the northern spotted owl in U.S. House Committee on Natural Resources, 2023). These effects are also small relative to the total jobs in these areas, where sector-specific impacts range from 0.09–2.2% of total local employment across these cases. Our results suggest that current, blanket reforms to species protections may be poorly matched to the highly specific contexts in which the ESA’s economic costs are concentrated.

Our empirical approach considers variation in ESA regulations over space and time as a series of natural experiments. We estimate the impacts of the ESA on jobs by comparing trends in employment outcomes in areas regulated by the ESA (treated group) to otherwise similar areas that were not regulated (control group) before and after the regulations occurred. Under the *parallel trends* assumption that employment outcomes would have trended similarly between these groups in the absence of ESA “treatment”, we can credibly recover a causal estimate of the ESA’s impact on jobs. Our treated group comprises ZCTAs regulated by both the ESA listing rule and critical habitat designation for our focal species. We define the control set of ZCTAs on a species-by-species basis, as those that lie within the same states as the species range, but outside of the range area itself. This approach isolates the combined effect of both regulatory layers of the ESA. It also creates a spatial buffer between the treated and control groups by removing ZCTAs which are immediately adjacent to the treated ones, which can alleviate concerns about employment spillovers (Ferris and Frank, 2021). This is our baseline approach for each species-economic sector we analyze.

We conduct our analyses using a series of causal inference tools. We apply difference-in-differences (DD) as our primary estimation strategy, and condition our results on passing pre-trend diagnostic tests from their corresponding event studies (Rambachan and Roth, 2023). One potential concern may be that ESA regulations are not randomly assigned, such that nearby control ZCTAs may differ in labor market trends relevant to the DD analysis.

¹The county-level analysis detects this effect with greater precision than the corresponding ZCTA-level estimates, which are of a similar magnitude but imprecisely estimated.

We address this by applying 12 distinct matching algorithms to select different combinations of control ZCTAs with similar pre-treatment labor market characteristics to treated ZCTAs for each species (Ferraro and Miranda, 2017). Another concern may be that ESA regulations correlate in space and time with other macroeconomic shocks, which we address by incorporating an additional control group: employment in non-ESA relevant sectors (e.g., finance) in ESA-regulated ZCTAs, which we operationalize using a triple difference (DDD) approach (Olden and Møen, 2022). Our results are robust to these specifications, as well as a series of additional robustness tests we include that vary treatment boundaries and include additional covariates, among others.

This analysis makes several contributions to the literature. First, we provide a more holistic perspective on the labor market costs of the ESA, covering a much larger set of species and longer time period than prior work. Two prior studies have used causal inference methods to estimate the impacts of individual species listing settings under the ESA on labor markets, to which we make explicit comparisons. These include the listing of the northern spotted owl in the Pacific Northwest, in which 16,000-32,000 timber-related jobs were impacted (Ferris and Frank, 2021), as well as the lesser prairie-chicken in the Southern Great Plains that impacted 5,000-6,000 total jobs (Melstrom et al., 2018). Using other methods, Duffy-Deno (1997) provides an analysis showing little evidence of ESA-related job impacts for species listed in the American West between 1980-1990. Together, these analyses cover a minority of the settings and economic sectors potentially impacted by ESA regulations, and we contribute by filling in these estimates from 1989-2020 for 128 terrestrial species.

Another novelty of our approach is that we explicitly consider heterogeneous effects at the species and economic sector level, where sectors are determined by LLMs to be tied to species threats using regulatory document filings. In doing so, we isolate the causal mechanisms of the regulation in a way that analyses on total impacts may miss. In the context of the ESA and species related analyses, this extends prior work which assesses heterogeneity at coarse groups such as taxa (e.g., Mamun et al., 2024).

Our work also complements another vein of ESA literature focused on quantifying the average treatment effect of ESA listing and critical habitat designations on private land markets across the U.S., which similarly finds little overall effect (Frank et al., 2025a; Melstrom, 2021; Mamun et al., 2024), with significant heterogeneity at the individual species level (Wietelman and Melstrom, 2017; Klick and Ruhl, 2020; Auffhammer et al., 2020; List et al., 2006). Unlike these studies, our analyses cover potential economic impacts which may transpire on public lands as well. More generally, our study contributes to a better understanding of the labor

market impacts of U.S. federal environmental laws (e.g., Walker, 2013; Curtis, 2020; Sheriff et al., 2019; Ferris et al., 2014), as well as a growing literature on the economic impacts of land protection policies (Walls et al., 2020; Sims et al., 2019; Cheng et al., 2023; Jakus and Akhundjanov, 2018; Chen et al., 2016; Xu et al., 2023; Grupp et al., 2026).

The rest of the paper proceeds as follows. Section 2 provides background information on the history of the ESA and its relevant regulatory mechanisms. Section 3 outlines the data used in this analysis, and Section 4 describes the empirical approach in greater detail. Section 5 summarizes the results. Section 6 contextualizes the findings in this analysis, provides a discussion of their policy relevance, and concludes.

2 ESA Background & Regulatory Mechanisms

The ESA was enacted in 1973 in the U.S. with the goals of preventing species extinctions and recovering imperiled species populations (U.S. Congress, 1973). The ESA’s functional success is often debated, with an excellent track record in preventing extinctions (Greenwald et al., 2019), but very poor performance in recovering species populations (Evans et al., 2016). The mechanisms through which the ESA implements these goals are Sections 4, 7, and 9 of the Act, which are administered by the U.S. Fish & Wildlife Service (USFWS) for terrestrial species, the focus of this analysis.² Section 4 of the Act outlines the process through which species at risk of extinction are afforded regulatory protections. Importantly, there are *two* regulatory layers of the ESA which are enacted at the species level – listing and critical habitat designations – which vary across space and time.

The listing rule applies to the entire range area of a listed species after a species receives a warranted finding through the ESA listing process. The listing process can be initiated by a citizen petition, after which USFWS has 90 days to conduct an internal review and then 12 months to perform a status review to determine whether listing is warranted, not warranted, or warranted but precluded. If a species receives a warranted finding, a proposed listing rule is published, after which USFWS may take another 12 months to publish a final listing rule, withdraw the rule, or delay another 6 months. A 60-day public comment period is to be issued before a final listing rule. In practice, the time periods over which species receive listing rules vary dramatically, spanning decades in some cases (Puckett et al., 2016), as USFWS will often determine a “warranted but precluded” finding which places the species on a candidate list to be reconsidered for official listing annually. USFWS may

²The National Oceanic and Atmospheric Administration (NOAA) is responsible for marine and anadromous species.

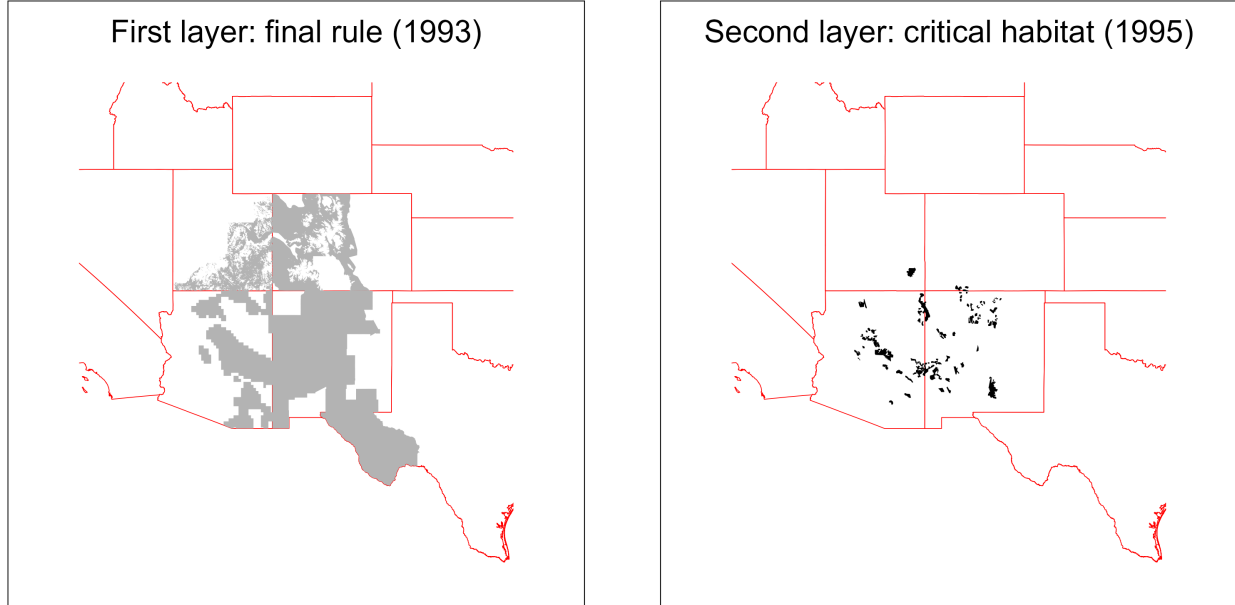
also initiate their own listing proposal which has no designated timeline (Langpap, 2022), creating additional uncertainty about when and which species will receive a listing rule. The listing process is to be conducted on the basis of the best scientific data available.

The mechanisms through which the ESA can limit economic activity to protect endangered species are the Act’s Section 7 interagency consultation and Section 9 no-take clauses. Section 7 regulates land uses involving the federal nexus, such as any economic activity that occurs on public lands or requires any permit from a federal agency, which must be shown not to jeopardize the continued existence of a listed species. Section 9 makes it illegal to “take” a listed species, defined as actions which “harass, harm, pursue, hunt, shoot, wound, kill, trap, capture, or collect” the species (U.S. Congress, 1973). For over four decades the regulatory definition of harm included significant habitat modification that injures or kills a listed species (Powell, 1995); this definition was recently rescinded (U.S. Fish and Wildlife Service and National Marine Fisheries Service, 2026). Section 9 applies across the species range, including on private lands. These provisions require businesses and private actors to obtain authorization from USFWS, through Section 7 consultation or a Section 10 incidental take permit, demonstrating that their actions will not jeopardize the continued existence of endangered species, potentially limiting the scope of some operations (e.g., timber harvesting, development; Epanchin-Niell and Boyd, 2020). In practice, however, Section 7 consultations very rarely result in jeopardy findings (Malcom and Li, 2015).

The second layer of ESA regulation is critical habitat designations, which typically apply to subsets of species range areas deemed crucial to the survival of the species (e.g., nesting grounds) and are designated after or simultaneously with a species listing rule. We provide an example of how these two regulatory layers vary over space and time in Figure 1 for the Mexican spotted owl. Under section 4 of the ESA, USFWS is to designate critical habitat “to the maximum extent prudent and determinable” for listed species (U.S. Congress, 1973). Despite this, many species have not received a critical habitat designation, often due to the limited funding that USFWS receives relative to the workload required to adequately list and designate critical habitat (Jesup, 2012). The designation of critical habitat involves an explicit consideration of economic impacts in determining habitat boundaries.

The pathways whereby critical habitat may restrict local economic activity are the same as the listing rule. However, it is generally the case that a higher standard must be met to clear Section 7 consultation for activities in these areas, which must not “result in the destruction or adverse modification of habitat of such species which is determined by the Secretary ... to be critical” (U.S. Congress, 1973). This language surrounding critical habitat may be

Figure 1: Two Regulatory Layers of the ESA



Notes: The range area (left) of the Mexican spotted owl, the geographic extent regulated by the first layer of the ESA, and the critical habitat boundary (right) regulated as the second layer.

enforced more stringently in court (Kendrick, 2021), and it also serves as a spotlight on sensitive wildlife areas, which may trigger lawsuits from environmental activists or additional regulatory actions by local regulators (Auffhammer et al., 2020; Kendrick, 2021). The designation and revision of critical habitat has been contentious throughout the ESA’s history, with many lawsuits being filed for and against their designations by environmental NGOs and businesses respectively (Parenteau, 2005; Langpap, 2022). In some cases, USFWS publishes predicted impacts of critical habitat, in terms of revenue and job impacts, alongside its designation (Plantinga et al., 2014).

After a species has received both regulatory layers of the ESA, the spatial extent of these critical habitat designations may change significantly over time. For instance, some species are delisted altogether such that they are no longer protected under the Act. Further, after an initial critical habitat designation, USFWS “may, from time-to-time thereafter as appropriate, revise such designation[s]” (U.S. Congress, 1973). As an extreme example, we visualize how these boundaries have been revoked and revised over time for the Mexican spotted owl in the Appendix Figure A1, illustrating how these regulations turn on and off in given areas over time. We provide a simplified flow chart in the Appendix Figure A2 of the listing and critical habitat process for a given species, with all of the possible regulatory statuses a species may receive through time.

3 Data

Listed Species Data

We download information for all species that have been listed under the ESA from the USFWS Environmental Conservation Online System (ECOS) on 8/2/2023 (U.S. Fish and Wildlife Service, 2023). We extract species-specific information such as the timing of listing and critical habitat rulings, taxa, and region using the USFWS API. We directly download all spatial data on species range and critical habitat boundaries available from USFWS ECOS on the same date (U.S. Fish and Wildlife Service, 2023). We focus on terrestrial species (i.e., excluding fish, clams, crustaceans) within the conterminous U.S. that were regulated within the time frame of our labor market data, 1990 - 2020. Our main analyses cover 128 species that received both a listing and critical habitat designation within this time frame.

USFWS provides spatial data for all current critical habitat boundaries, but omits historic boundaries for rulings that were revised, revoked, or for species that were delisted. These areas are important to our analysis, so we cross-reference the USFWS API and critical habitat boundary data to identify all historic critical habitat cases among our focal species. We digitize these historic critical habitat boundaries in ArcGIS Pro using maps available in the final critical habitat Federal Register documents available on the ECOS species profile pages. We identified 63 terrestrial species with historic critical habitat boundaries, which we visualize in the Appendix Figure A3 to contrast areas with revised/revoked critical habitat designations to those that have been permanent over time.

By referencing the USFWS API, spatial data, species-profile pages, and action timelines provided by the Center for Biological Diversity, we are able to identify the listing and critical habitat histories among all focal species in our analysis. This includes a handful of corrections to dates of regulations that are missing or inconsistent (e.g., a critical habitat ruling is assigned to a species on a given date, for which the ruling states no critical habitat is to be assigned). We also treat batch listings as a singular regulatory event, i.e., cases where multiple species are regulated on the same day in the same document in the same region for both layers of the ESA (see Appendix Figure A4 for an example). In the rare instance that critical habitat shapefiles are outside of the boundary of the species range shapefile, we consider the union of both to be the species range.

Labor Market Data

We obtain the universe of business establishments with employment data between 1989-2020 in the U.S. from the National Establishment Time Series (NETS) database. These data are

collected annually by Dun & Bradstreet, a private company specializing in business data and analytics, who assign a unique D-U-N-S number to each active U.S. firm to be tracked over time. These data are collected from a variety of sources such as company filings, court records, and government registries, among many others. These data are used by banks in high-stakes financial settings such as company credit scoring (Neumark et al., 2007; Currie et al., 2010) and have been used in a variety of peer-reviewed academic studies as well (Walls et al., 2020; Currie et al., 2010; Lester, 2014; Joiner et al., 2025; Rossi-Hansberg et al., 2021; Zeballos and Dong, 2022). These are proprietary data subject to a nondisclosure agreement that were purchased from the data curators Walls & Associates.

We use NETS to create a panel dataset of employment across the conterminous U.S. at the ZCTA level between 1989 - 2020 for distinct economic sectors. We do so by aggregating employment numbers from over 87 million establishments in NETS, including for firms that moved, by year for all ZCTAs. We map ZIP-code level data in NETS to ZCTAs using several crosswalks (U.S. Department of Housing and Urban Development, 2024; Census Reporter, 2019). We group employment data by economic sector according to several classifications such as the SIC division code level and a broader classification outlined in Table A1 that matches Section 7 consultation classifications from Malcom and Li (2015). We provide more information about NETS in the Appendix Section A.1.1.

We collect county-level employment from two sources to provide a complementary panel dataset to that of NETS for this analysis. The first is a harmonized version of County Business Patterns (CBP) provided in Eckert et al. (2020). Using linear programming methods, the authors leverage information available on state level industry employment, county-level total employment, and uncensored firm size information by county-year-industry to impute employment in county-industry-years which are otherwise suppressed. This provides a balanced county-level panel of employment values for the key economic sectors needed for this analysis (e.g., forestry, oil and gas and mining), which are provided using NAICS codes. We map the SIC version of our focal sectors to the NAICS codes at the 3 digit level in Table A1.³ The data are provided for all years of this analysis up until 2018. Unless otherwise stated, we drop 42 counties in which there are missing employment values from this CBP data. We supplement the CBP by collecting farm employment data from the Bureau of Economic Analysis (BEA; U.S. Bureau of Economic Analysis, 2023), a sector not provided by CBP, to add agricultural employment to the panel over the timeframe of the analysis.

³Because of the reclassifications made between the SIC and NAICS vintages, in which oil & gas and mining are combined (i.e., in terms of their support activities), we decide to group oil, gas, and mining together as one focal sector for the county-level panel (rather than risk double counting).

Census, Land Use, and Commuting Zone Data

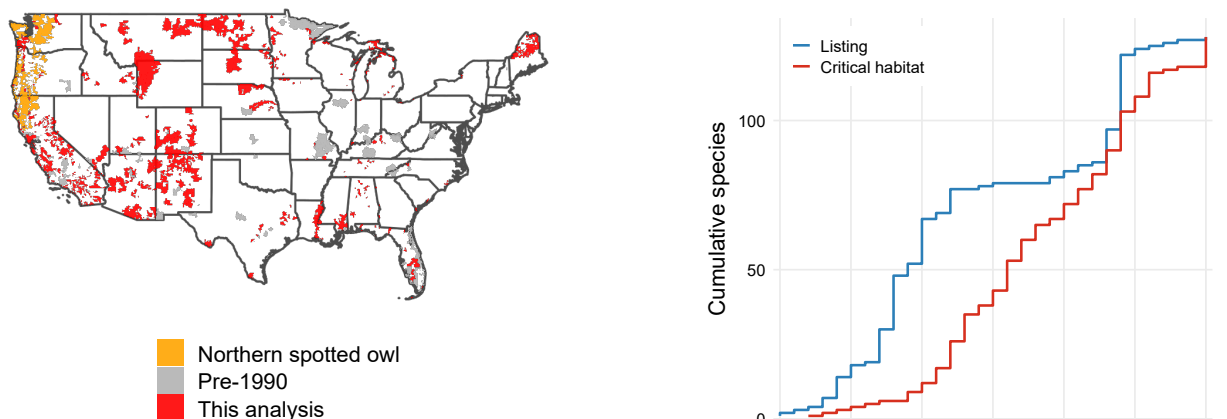
We obtained shapefiles of U.S. ZCTA spatial boundaries from the U.S. Census Bureau (U.S. Census Bureau, 2023), and annual land use data by year from U.S. Geological Survey’s Land Change Monitoring, Assessment, and Projection data product V1.3 (U.S. Geological Survey, 2023). We calculate land use by ZCTA-year, such as proportion forest cover, which we merge to our final panel dataset. We use a crosswalk between commuting zones and counties (which we further map to ZCTAs) available from Autor and Dorn (2013) as well.

4 Methods & Empirical Strategy

Defining Treatment & Descriptive Information

We define treated ZCTAs for each terrestrial species as those that are newly regulated by both regulatory layers of the ESA (i.e., spatial areas regulated by the *initial* critical habitat designation for a species, at the time of listing). We drop ZCTAs already regulated by critical habitat at the beginning of our panel in 1989. We also drop ZCTAs which are confounded by multiple critical habitat designations in the post-treatment period for any of our analyses (but re-include these areas as a robustness check). Figure 2 displays the ZCTA boundaries considered treated in any of the analyses below, as well as the cumulative distribution of the timing of the listing and critical habitat designations for our 128 focal species. We elaborate on our choice to focus on critical habitat boundaries in the Appendix Section A.1.2.

Figure 2: Descriptive Information



Notes: All treated ZCTAs (left panel) in red, defined as those regulated by both the listing rule and critical habitat designation for the focal species in our analysis, as well as those impacted by the critical habitat boundary of the northern spotted owl. The right panel plots the cumulative number of species listings and initial critical habitat designations over the study period.

We focus solely on terrestrial species in this analysis. We do so because our empirical strategy relies on determining a treated group of ZCTAs before and after ESA regulations occur in a consistent manner across species. This approach is less amenable to aquatic species because their threats often relate to water quality and quantity issues that occur upstream from critical habitat. Further, some aquatic species have ESA regulations that are not consistent through time, such as limiting water withdrawals intra-annually or during drought years. It is unlikely that the causal inference approach used in this paper is appropriate for these aquatic species, and we leave quantifying these impacts to future research.

Classifying Economic Sectors and Linking to ESA Mechanisms

We develop a crosswalk of economic sectors for our main analysis, based primarily on the [SIC division structure](#), with a few changes to map more directly to the regulatory mechanism of the ESA. Specifically, we rely on the extensive data collection effort of Malcom and Li (2015), who code the economic sector of ESA Section 7 consultations completed by USFWS between 2008 and 2015. This is one of the key regulatory mechanisms of the Act, requiring federal agencies to consult with USFWS before authorizing activities that may jeopardize listed species or adversely modify critical habitat. Following their classifications, we use “Development” as one of our focal sectors to include real estate along with the SIC construction division. We similarly create a “Forestry” group which groups the Lumber and Wood Products SIC 2 code, which includes logging, to the Forestry SIC 2 code which is consistent with the sub-groupings of the Forestry category in Malcom and Li (2015). We separate out an “Oil and Gas” category from the “Mining” SIC division level to analyze each separately, again matching these groupings and sub-groupings. Lastly, we retain “Agriculture” according to the SIC division groupings, which aligns with the agriculture category of Malcom and Li (2015). We present a crosswalk of this classification in Table [A1](#).

We use LLMs to identify which economic sectors are likely to be regulated in each context, emphasizing species-level heterogeneity rather than coarser groupings such as taxa. For instance, the ESA’s regulatory bite for an endangered owl under threat from logging on public forest land may be very different than that of a frog with wetland habitat adjacent to growing housing developments. We do so by obtaining URLs for the final listing rules for each of our focal species published in the Federal Register from the USFWS API, downloading them, and scraping all of the text in sections A, B, and E of the “Summary of factors affecting the species” sections. USFWS is authorized to write this section, which describes threats to species, for all species listed under the ESA. This gives us a consistent way to identify threats to the focal species in our analysis.

We develop a prompt that asks LLMs to identify the threats for each species from the text pulled from their listing rule, and then identify the economic sectors most likely to be linked to each threat for each species. This provides a non-arbitrary way to identify the economic sectors that are most likely to be regulated by the ESA for each species. This approach also has the advantage of using information preceding regulation for a species, rather than being conditional on impacts of the regulation itself.

In our prompt, we include a list of economic sectors at the SIC 2 level as well as a broader classification scheme outlined in Table A1 to perform the economic sector-threat linking. We send the same prompt to an API for both ChatGPT-4o mini and Claude 3.5 Haiku, and keep the economic sector-threat linkage for a given species if both LLMs agree with each other. We perform a manual coding for 22 focal species ($N = 396$ species-sectors) and confirm a 91% agreement rate between our choices and those of the LLMs. We also provide results for our analysis where we ignore this approach altogether, showing results for all species-focal economic sectors regardless of threat linkage. We note that because LLMs are not deterministic, we save all responses from the LLMs to make our results reproducible. If desired, this process can be reproduced for no more than \$10-15 using these LLMs (if they remain available from OpenAI and Anthropic). Figure A5 plots the distribution of economic sectors linked to threats faced by our focal species, and the taxa of our focal species.

Analysis 1: Individual Species Impacts

Our first analysis focuses directly on the mechanisms of the ESA by analyzing the job impacts of the Act at the individual species-economic sector level. One challenge with this approach is that many focal species in our analysis have critical habitat designations that intersect very few treated ZCTAs, and, therefore, lack sufficient statistical power to be analyzed individually (Alvarez et al., 2025). We choose a cutoff of 20 treated ZCTAs for this individual species-sector analysis (MacKinnon et al., 2023) and pool the remaining treated ZCTAs by threat-linked sector described in the following section for Analysis 2.⁴ This gives us 23 species-economic sector pairings that we analyze individually. We note that two of these cases represent “batch listings” where multiple species are listed together, which we describe further in the Appendix Section A.1.3.

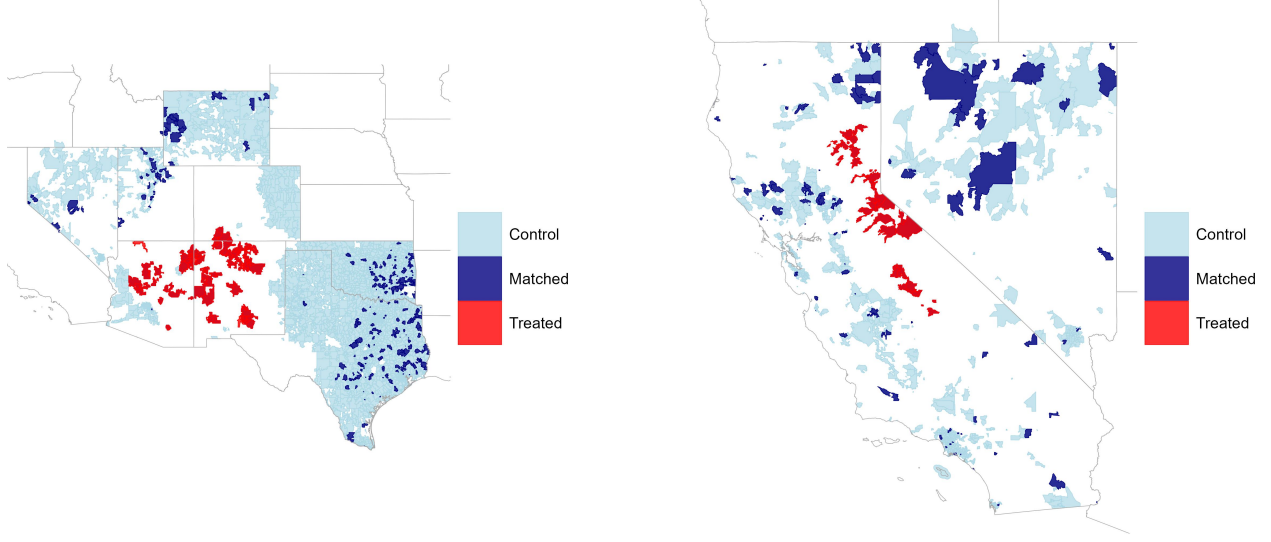
⁴Varying this cutoff to 15 or 25 ZCTAs does not meaningfully affect conclusions.

Control Group: Matching

For each species-sector, we define 13 distinct control groups for the analysis to assess the internal validity of our findings. The full candidate control set of ZCTAs is defined for each species as those which are in the same states as the species range area, but outside of this range area itself. This confirms that control units are in similar regions as the treated ones and subject to similar macroeconomic shocks; but not immediately adjacent, to mitigate the potential for affected employment to spillover between the two groups after ESA regulations occur. We also test a specification which varies the candidate control set to ZCTAs in the same state as the treated ZCTAs, but in different commuting zones.

As additional robustness checks, we use 12 versions of Mahalanobis nearest neighbor matching to select different sets of the candidate control group with similar labor market characteristics to our treated ZCTAs before treatment occurs. These combinations vary by 1:1, 2:1, and 3:1 control-to-treated group matching, matching with and without replacement, and matching with and without 1 standard deviation calipers on each of the supplied labor market characteristics (Ferraro and Miranda, 2017). There is a bias-variance tradeoff among these choices (Ho et al., 2007; Smith and Todd, 2005; Ferraro and Miranda, 2017), so we use pairwise combinations of each as robustness checks to each other. All matching is done for treated and the full candidate control set of ZCTAs using pretreatment data for the following variables: total employment, changes in total employment, changes in employment in the focal sector, total establishments in the focal sector, and proportion of establishments in each focal sector classified as small (<10 employees), medium (10-99 employees), and large (≥ 100 employees). For any case where we consider forestry as an economic sector, we also match on the proportion of forested area. An example of this design is presented for two individual species analyzed in Figure 3.

Figure 3: Treated and Control ZCTAs for Two Focal Species



Notes: Treated ZCTAs (red), full candidate control ZCTAs (light blue), and one example of matched control group (dark blue) for two focal species: the Mexican spotted owl (left) and the Sierra Nevada yellow-legged frog (right).

Two-Way Fixed Effects DD

We apply a DD model with two-way fixed effects (TWFE) for our individual species Analysis 1, which controls for unobserved time-invariant ZCTA characteristics (e.g., geography) and year-specific shocks common to all units (e.g., recession year). We estimate the model using a Poisson quasi-maximum likelihood estimator (QMLE), which is most appropriate for count outcome variables such as jobs that can equal zero (Chen and Roth, 2024; Wooldridge, 2023; Gourieroux et al., 1984):

$$E(Y_{i,t}|\cdot) = \exp \left[\gamma_t + \lambda_i + \delta^{DD}(D_i \cdot POST_t) \right] \quad (1)$$

where $Y_{i,t}$ is employment in a given ZCTA i and year t . We include fixed effects for year (γ_t) and for ZCTA (λ_i) which performs a double-demeaning by area and time to control for unobserved confounding effects. Our coefficient of interest is δ^{DD} , which captures the causal effect of ESA regulations on employment outcomes, where D_i is equal to one if a ZCTA is treated and $POST_t$ is equal to one in the post-treatment period. The transformation $\exp(\delta^{DD}) - 1$ is the precise proportional effect on jobs. We cluster our standard errors at the ZCTA level with no matching, at the matched group level when we match without

replacement (Abadie and Spiess, 2022), and at both the matched level and at the ZCTA by year level when we match with replacement (Dechezleprêtre et al., 2023; Colmer et al., 2024). We conduct several robustness checks where we replace year with state-by-year fixed effects, as well as include a time-varying covariate $X_{i,t}$ to control for changes in the number of other species listing rules at the ZCTA-year level (e.g., listing rule for a nearby species that did not receive a critical habitat designation). We outline the procedure to choose the panel timeframe T for individual species in the Appendix Section A.1.4, which applies to each species consistently.

There are several assumptions under which $\hat{\delta}^{DD}$ is a reliable estimate of the ESA’s causal effect on jobs. First, we assume the stable unit treatment values assumption holds, meaning that changes in employment outcomes in treated ZCTAs do not affect employment outcomes in control ZCTAs. The prevailing approach in the literature to satisfy this assumption is to create a buffer around the treated area of interest (Ferris and Frank, 2021; Walls et al., 2020; Frank, 2024; Walker, 2013), which is built into our analysis by design. Second, we follow the assumption of prior work that ESA listings are exogenous shocks (Melstrom et al., 2018; Ferris and Frank, 2021), such that firms are not preemptively laying off workers or moving their locations in anticipation of ESA listing rules, which is plausible given the uncertainty regarding the ESA listing timeline. Third, we assume that the treated and control ZCTAs would have trended similarly in their employment outcomes in the absence of ESA regulations, which we cannot test directly. However, we can provide evidence that this parallel trends (in ratios) assumption is likely to hold by estimating a dynamic “event study” form of DD:

$$E(Y_{i,t}|\cdot) = \exp \left[\gamma_t + \lambda_i + \sum_{\tau \neq t_{list}} \delta_{\tau}^{DD} (\mathbf{1}\{t = \tau\} \cdot D_i) \right] \quad (2)$$

where all notation is identical to Equation 1, except that we now wish to estimate δ_{τ}^{DD} , which can be interpreted as the differences in employment outcomes between treated and control ZCTAs in every year τ relative to the omitted baseline year t_{list} . This allows the post-treatment period to capture effects from the listing rule and subsequent effects from critical habitat. By estimating $\hat{\delta}_{\tau}^{DD}$ before ESA regulations occur, we can visually assess and formally test the plausibility of the parallel trends assumption using pretreatment data.

DDD

The triple difference (DDD) model extends the two-way fixed effects estimator by incorporating a third “control” group, economic sectors that are never linked by our manual coding to species threats. We aggregate all employment in sectors not represented in Table A1 to the ZCTA-year level to provide this additional source of variation for our analysis. The purpose of this approach is to additionally control for macro-level economic trends that happen to correlate with listing and critical habitat designations in space and time. The key identifying assumption is an expanded version of the parallel trends assumption similar to the DD model (Olden and Møen, 2022). One threat to this identifying assumption is that within-ZCTA spillovers in treated areas may occur (i.e., jobs lost in the treated sector gained in a non-treated sector), which would bias our results. We therefore use the DD model as our preferred specification in this analysis, with the DDD model being a robustness check. We estimate the following DDD model:

$$E(Y_{s,i,t}|\cdot) = \exp \left[\delta^{DDD} (D_i \cdot \text{POST}_t \cdot \text{THREAT}_s) + \theta_{i,t} + \gamma_t \cdot \text{THREAT}_s + \lambda_i \cdot \text{THREAT}_s \right] \quad (3)$$

as well as the event study form:

$$E(Y_{s,i,t}|\cdot) = \exp \left[\sum_{\tau \neq t_{list}} \delta_{\tau}^{DDD} (\mathbf{1}\{t = \tau\} \cdot D_i \cdot \text{THREAT}_s) + \theta_{i,t} + \gamma_t \cdot \text{THREAT}_s + \lambda_i \cdot \text{THREAT}_s \right] \quad (4)$$

which have a similar notation to Equations 1-2, with the added binary indicator THREAT_s which is equal to one if a sector s is identified as a threat to a given species (zero otherwise), as well as ZCTA by year fixed effects $\theta_{i,t}$. $\hat{\delta}^{DDD}$ is the estimated coefficient of interest, which captures the causal effect of ESA regulations on labor market outcomes that evolve differentially between both treated sectors and non-treated sectors, and between treated ZCTAs and non-treated ZCTAs. In the Appendix Section A.1.5, we describe an additional DDD specification which creates a “fake” treated group, in the same focal sectors, as an additional falsification test that we visualize in Figure A6.

Pretrend Diagnostics

The empirical approach of Analysis 1 recovers many estimates across multiple species, sectors, matched control groups, and across the DD and DDD models, making it infeasible to rely on event studies on a case-by-case basis to confirm the plausibility of the parallel trends

assumption. We instead apply recently developed pretrend diagnostic tools for DD, which allow us to systematically test whether each statistically significant effect is robust to potential violations in the parallel trends assumption. Specifically, we condition each statistically significant result on being robust to an $M > 0$ deviation in a linear extrapolation of the pre-period employment trends using the smoothness restriction method of the HonestDiD R package (Rambachan and Roth, 2023). In other words, this approach avoids attributing causal effects to estimates which are driven by control and treated ZCTAs having differences in employment outcomes regardless of ESA regulations. We present an example of a case that would not pass this pretrend test in the Appendix Figure A7.

Analysis 2: Pooled, Small-Regulated-Area Species Impacts

We pool the remaining species-sector pairings with critical habitat designations that span small areas (<20 ZCTAs) to increase statistical power. This is mutually exclusive to the individual species-sectors of Analysis 1, and we do so by the LLM threat-linked economic sector level (e.g., all ZCTAs regulated by the ESA for species with forestry-linked threats). The estimated impacts are representative of a small-regulated-area species linked to each of these sectors. We define treated and control ZCTAs the same way as in Analysis 1 for the individual species, where matching is done by treated cohort in the pooled setting. Table 1 provides a brief overview of the number of ZCTAs and scope of the individual and pooled analyses. An example of the design is illustrated in the Appendix Figure A8.

Table 1: Summary of Individual and Pooled Species Analyses

	Individual species	Pooled species
Panel timeframe	5 years post critical habitat or until reversal	Full panel
Estimation method	TWFE	ETWFE
N ZCTAs	623 (59%)	429 (41%)
ZCTAs with reversals	Yes	No
Matching	Yes	Yes

Extended-Two-Way Fixed Effects

The canonical TWFE model can introduce estimation bias in settings where treated units come into treatment differentially over time (Callaway and Sant’Anna, 2021; Goodman-Bacon, 2021), such as for this pooled analysis. Among newly developed estimators that correct for this bias in staggered treatment settings (De Chaisemartin and d’Haultfoeuille, 2020; Callaway and Sant’Anna, 2021), the extended-TWFE (ETWFE) approach of Wooldridge

(2023) is the most appropriate in our analysis as it allows for non-linear estimation techniques such as Poisson QMLE that accommodate zero-valued observations in an otherwise log-linear model. Formally, the ETWFE model that we use can be written (Wooldridge, 2023; Rios-Avila et al., 2022):

$$E(Y_{i,t}|\cdot) = \exp \left[\alpha + \sum_{g \in G} \sum_{t=t_0}^{g-1} \theta_{g,t}^{pre} D_{i,g,t} + \sum_{g \in G} \sum_{t=g}^T \theta_{g,t}^{post} D_{i,g,t} + \xi_g + \xi_t \right] \quad (5)$$

for an outcome $Y_{i,t}$ (jobs) which varies by ZCTA i and year t , with t_0 representing the first year of the panel, and each ZCTA belonging to a treatment cohort g . $D_{i,g,t}$ is the interaction between year indicators, treatment cohort indicators, and a time-varying treatment indicator (equal to zero for the pre-regulation omitted reference year, and 1 otherwise). Included is an intercept term α as well as fixed effects for treated cohort groups ξ_g and year ξ_t . T represents all panel years and G represents the full set of treated cohort group years. The coefficients of interest are $\theta_{g,t}^{pre}$, which we can use as an indirect test of the parallel trends assumption, and $\theta_{g,t}^{post}$ which can be interpreted as the treatment effect for a given treated cohort g at time t compared to never treated control ZCTAs. We estimate this model using pooled Poisson QMLE, which is numerically equivalent to ETWFE under the “no reversibility” assumption (Wooldridge, 2023). We drop all ZCTAs with reversals from this analysis.

Rather than estimate a single treatment by time interaction (as in Equation 1), the ETWFE model is saturated with interactions between treated cohort groups, time, and treatment (Wooldridge, 2023). The intuition is that we now estimate a multitude of group-time treatment effects, which we can aggregate to an overall, or dynamic, treatment effect using the appropriate marginal effects command (McDermott, 2024). This approach recovers the causal effect of the ESA on local employment outcomes under the same assumptions as Equation 1 in the staggered setting.

Our preferred specification uses three-year indicator variables for g and t . Our panel covers a 32-year period, so we necessarily set t_0 to be a two-year grouping to cover all years. We modify these groupings slightly to avoid cases where very few ZCTAs (e.g., 1-2) are treated in a given treatment cohort g across the different pooled species-economic sectors we analyze (Wooldridge, 2023). We re-estimate a variant form of this model to include one time-varying covariate $X_{i,t}$ which controls for changes in other species listings at the ZCTA-year level as a robustness check. To apply the DDD to the ETWFE framework, we use $THREAT_s$ as the binary indicator that separates groups into the treated sector or not, and interact it with

everything in the model. The coefficients on $D_{i,g,t} \cdot THREAT_s$ are the DDD analogue of the $\theta_{g,t}^{pre}$ and $\theta_{g,t}^{post}$ from the DD case.

Analysis 3: Total Employment Effects

As a distinct analysis, we pool treated ZCTAs among all focal species covered over the timeframe of our panel and analyze whether there are any effects of the ESA on overall employment trends in regulated areas. This includes the northern spotted owl’s listing (whose sector specific impacts were already analyzed in Ferris and Frank (2021)), and drops ZCTAs with reversals. We apply the ETWFE DD estimator for this setting where there is staggered treatment timing (Wooldridge, 2023), and otherwise follow the same methodological steps as described above, where our outcome variable is now total employment in all sectors.

Analysis 4: County-Level Analysis

We provide an additional analysis which re-applies the same methodological procedure as the baseline approach above using county-level data from the CBP (Eckert et al., 2020) and BEA data on agricultural employment. We do so to assess whether applying our approach to data sources with a different scale and data generating process from NETS arrives at meaningfully different conclusions regarding the ESA’s effect on local labor markets.

We define treatment in the same way at the county level as we did ZCTAs in the main analysis: those which are newly regulated by critical habitat (in space), after the ESA final listing rule (in time). We similarly drop already treated counties in 1989 and counties with aquatic critical habitat designations (though, we again allow the latter to confound treatment for our focal species in a robustness check). Counties, which are about an order of magnitude bigger than ZCTAs, create two additional challenges that prevent this analysis from being a 1:1 comparison with our main results. The first is that dropping already treated areas removes a larger set of species than were identified at the ZCTA level. Second, the number of treated units per species critical habitat area is much smaller, leaving us underpowered to try to estimate effects on individual species as we did at the ZCTA level. We instead opt to pool all focal species from both the individual and pooled versions of our main analyses to increase power and more reliably estimate effects, and apply the same ETWFE procedure outlined above.⁵ For these reasons, we consider this to be a complementary analysis in providing a holistic picture of the ESA’s impact on local labor markets.

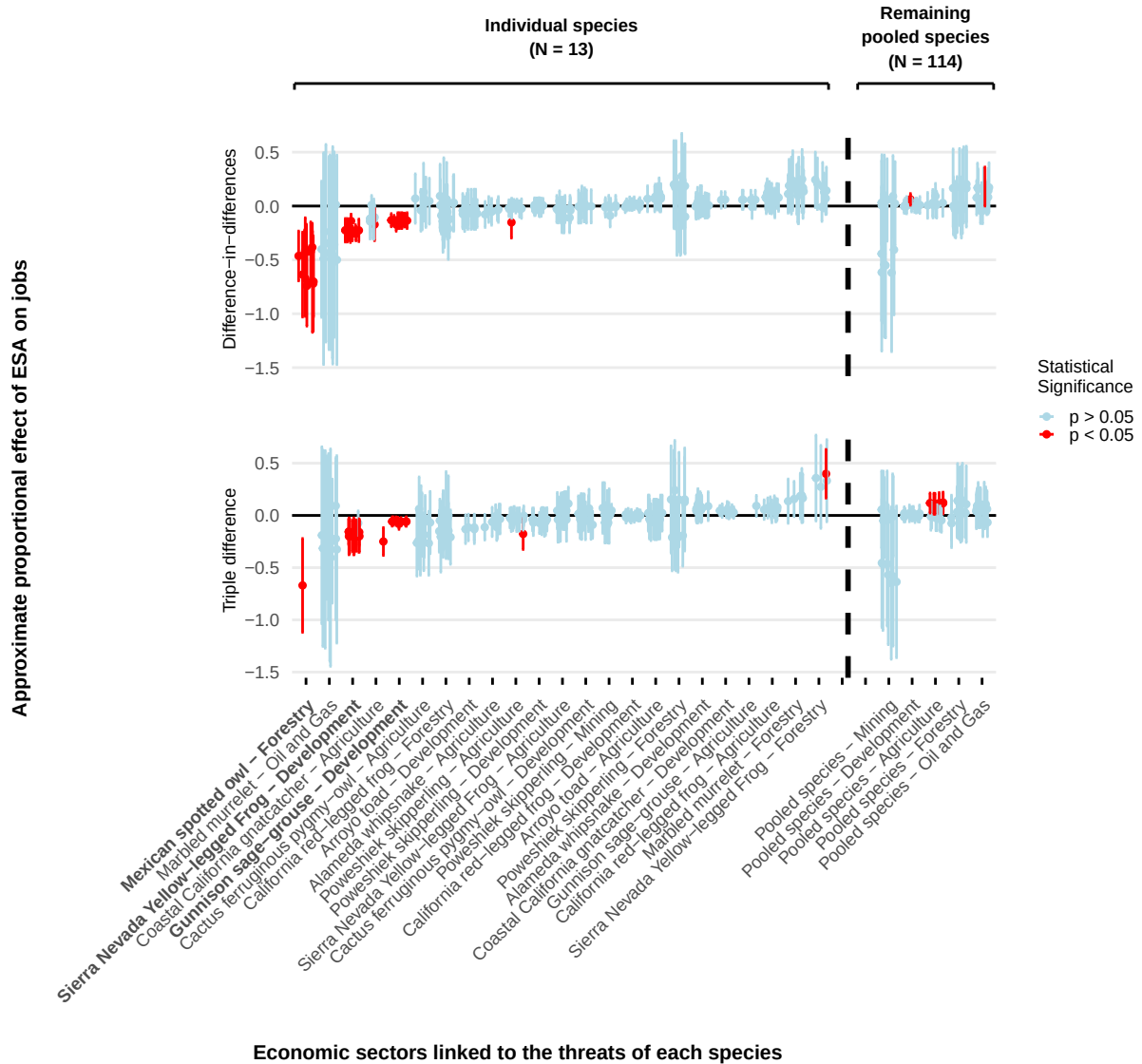
⁵The one exception we make is for the Mexican spotted owl, whose first critical habitat designation spans 16 counties, which is just above the lowest threshold of 15 treated units used at any point in Analysis 1.

5 Results

Distribution of Estimated Effects

We find no statistically significant effect of the ESA on jobs in 25 of the 28 species-sectors we analyze, including both the individually estimated species and the remaining species pooled by sector, which we illustrate in Figure 4.

Figure 4: Distribution of ESA Job Impacts Across Species and Economic Sectors

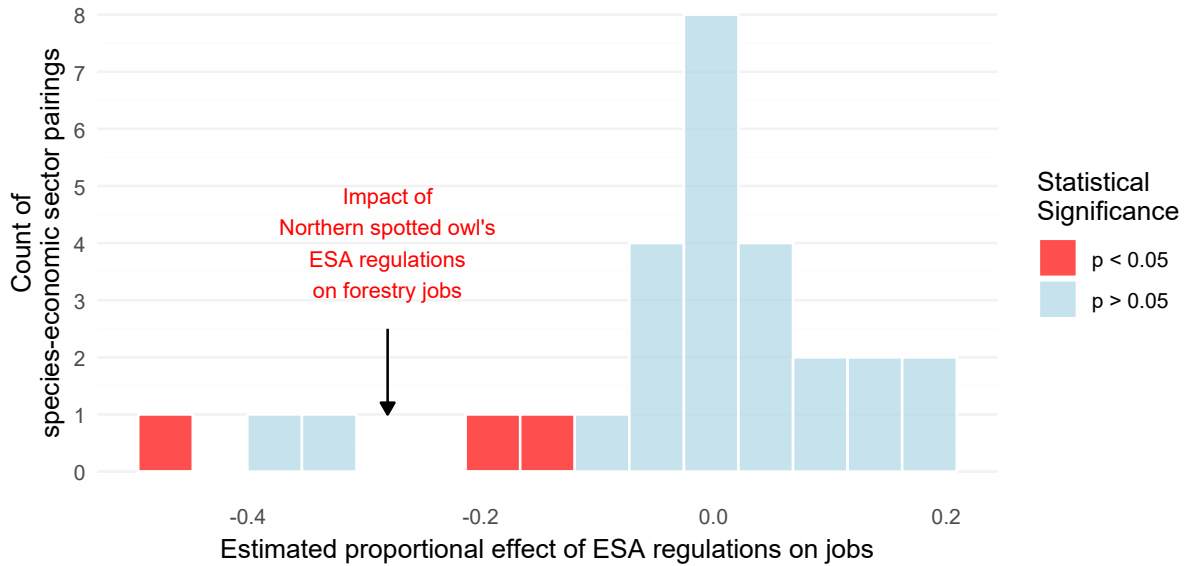


Notes: Distribution of coefficients from the DD and DDD models representing the causal effect of both regulatory layers of the ESA on jobs. Species-economic sector pairings are determined by using LLMs to identify the economic sectors most likely to be regulated in each species context. 23 of these pairings are for the individual species analysis (left of dashed line) and 5 are for the small-regulated-area pooled analysis (right of dashed line). Species in **bold** represent statistically significant effects which are robust to multiple specifications. We present coefficients for 13 control groups, and remove statistically significant results which are not robust to violations in pretrend diagnostics.

The three exceptions are individual species settings which exhibit large, precisely estimated job impacts that are robust to multiple specifications: the Mexican spotted owl in the forestry sector (a 47% decline in the baseline model; 32–52% across the 12 matched control groups), the Sierra Nevada yellow-legged frog in the development sector (13% decline in the baseline model; 20–23% across the 12 matched control groups), and the Gunnison sage-grouse in the development sector (15% decline in the baseline model; 12–13% across the 12 matched control groups).

Figure 5 summarizes the median DD effect for each species-sector as a histogram, with the northern spotted owl estimate from Ferris and Frank (2021) shown for comparison. Together, Figures 4 and 5 display the overall distribution of treatment effects of the ESA on local job outcomes for our focal species, in which we find little evidence of job impacts outside of three cases in the tail of this distribution. We exercise caution in interpreting the minority of species-sectors whose statistical significance depends on the control group or estimator used, such as the Poweshiek skipperling in the agricultural sector.

Figure 5: Histogram of Proportional ESA Job Impacts by Species-Sector



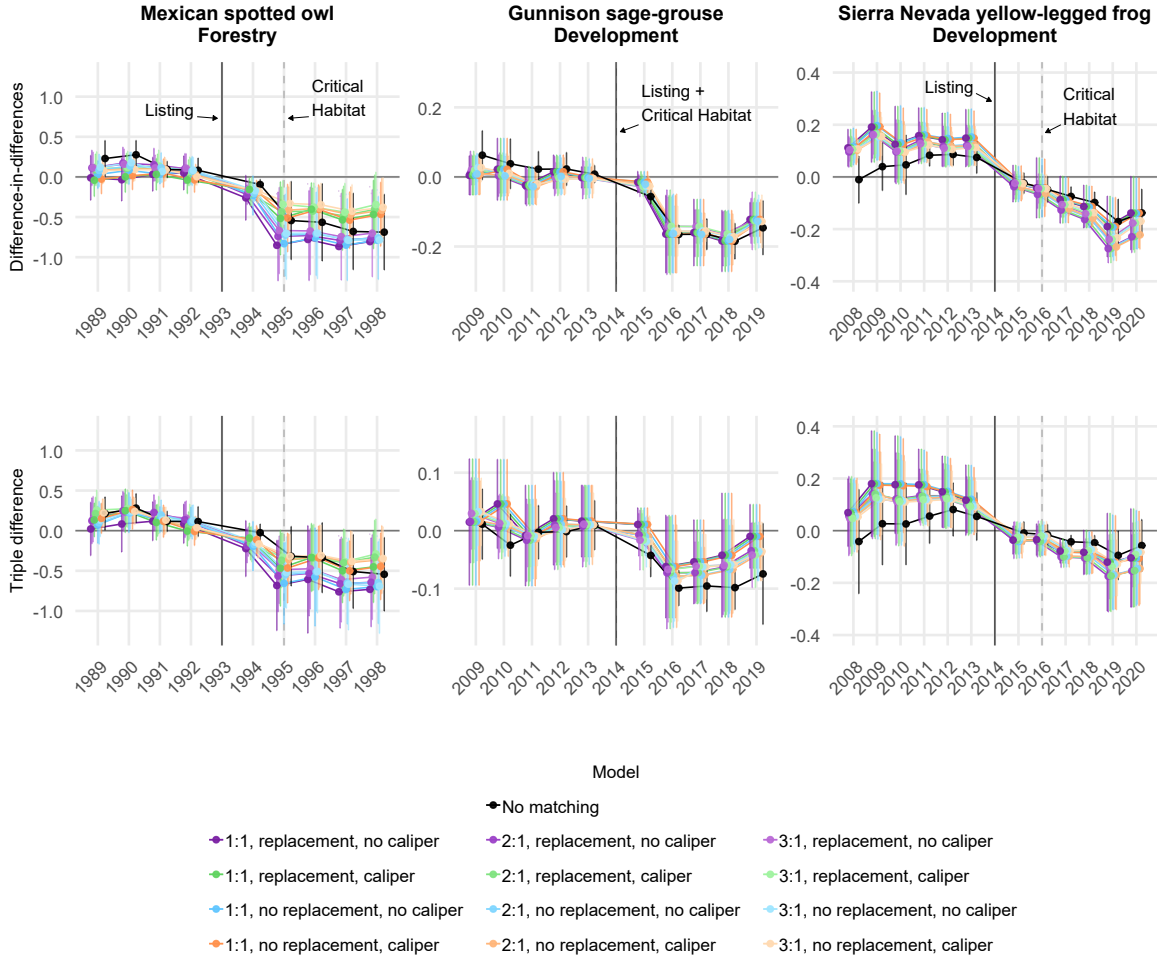
Notes: Histogram of the proportional impact of both regulatory layers of the ESA (i.e., listing and critical habitat) on jobs for each species-economic sector pairing. The plotted effects are the median coefficient from the DD models for each species-sector transformed to represent the exact proportional impact on jobs. We plot $N = 28$ coefficients, including the 23 individual species-sectors of Analysis 1 and 5 pooled species-sectors of Analysis 2. The latter serve as a “representative species” linked to each of our five focal sectors for the cases with very small critical habitat areas. We display where the estimated effects for the northern spotted owl’s impact on the forestry sector (Ferris and Frank, 2021) fall on our distribution.

We subject our estimates to a battery of robustness checks that we present in the Appendix Figures A9 through A16. Examples of these alternative specifications include controlling for changes in other species listings (Figure A10), using a 10 kilometer buffer to define treatment around critical habitat (Figure A12), including all species-focal sector pairings regardless of LLM linkage (Figure A13), using state-by-year fixed effects for Analysis 1 (Figure A16), among several others. We continue to find strong evidence for job impacts in the three previously identified species-sectors, with little evidence of statistically significant results elsewhere. We provide information about the number of observations and compare the effect size to the standard error for the estimated effects from our baseline model (full control set) of Analysis 1 in the Appendix Figures A17 and A18. We find no evidence of a pattern between effect sign and magnitude and precision of estimation in our analysis, suggesting our approach is not biased against finding job losses where they exist. Lastly, we plot the estimated coefficients of Analysis 1 against landscape and species level covariates to explore heterogeneous impacts in the Appendix Figure A19.

Figure 6 presents event study versions of the DD and DDD models for the three species-sectors with consistently negative employment effects. For the DD event studies, we find statistically significant job declines in years following ESA regulations relative to the omitted listing year, particularly following critical habitat designations.⁶ We find similar, albeit noisier, effects for the DDD event studies. The flat trends between treated and control ZCTAs before ESA regulations support the parallel trends assumption critical to our estimation strategy. The estimated effects for these species-sectors are robust to the sensitivity analyses of Rambachan and Roth (2023), providing additional support for the parallel trends assumption.

⁶We also attempted to isolate the effect of critical habitat above and beyond the listing rule by using ZCTAs within the species range but outside critical habitat as the control group. Too few such control units exist for some species to apply matching, so we treat these results as suggestive. In this design, job declines for the Mexican spotted owl in the forestry sector persist, and we find no evidence of effects for the remaining individual species (Appendix Figures A31 and A32).

Figure 6: Event Studies for Species-Sectors with Statistically Significant Effects



Notes: Event study analysis of the effect of the ESA on local employment among our three species-sectors with statistically significant effects robust to multiple specifications. The coefficients for the difference-in-differences (DD) event study capture the differences in employment outcomes between treated and control ZCTAs in years before and after ESA regulations, relative to the omitted pre-regulation baseline year. The triple difference (DDD) event study coefficients capture a similar effect, incorporating employment outcomes in economic sectors not linked to species threats as an additional control group in each year. We use the flat pre-regulation differences in trends as indirect evidence that the *parallel trends* assumption is likely to hold for each species-sector. We note that the pre-regulation differences are statistically positive for some models for the Sierra Nevada yellow-legged frog, which we address in Appendix Figures A11 and A21.

For each of these three statistically significant species, we provide a map of the design, matching balance figures, and alternative event study and DD results in the Appendix Figures A20 through A22. Our balance figures display the absolute standardized mean difference before and after 3:1 matching, with replacement, and no calipers as an example. We present alternative event study specifications that use a one-year lag to define treatment, which accounts for potential anticipation (e.g., for the case of the Sierra Nevada yellow-legged frog, in which some pre-regulation differences in employment trends are statistically higher in the treated

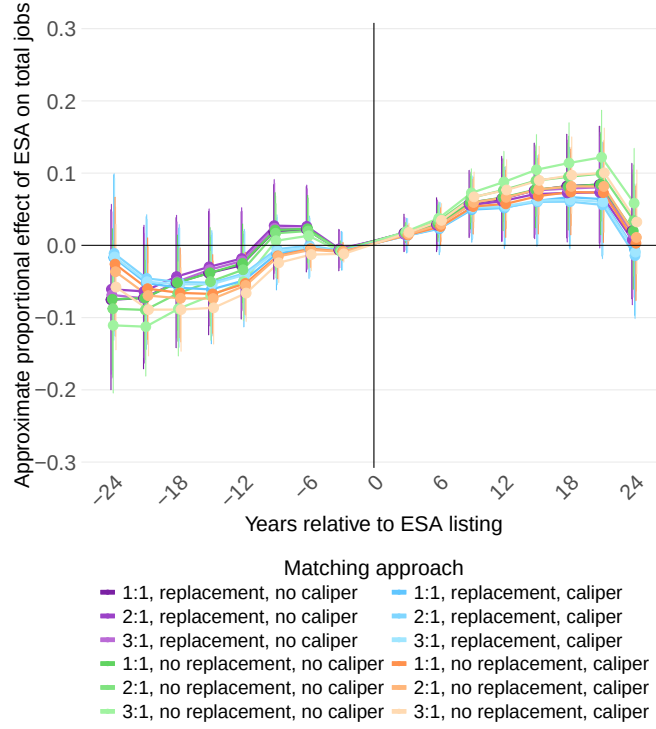
vs. control ZCTAs), and for the SIC division code grouping of the focal economic sector in each case. We also show DD coefficients for our baseline model applied to the main focal sector, other sectors linked to species threats, total employment, as well as placebo tests including sectors unlikely to be impacted by ESA listings (e.g., finance) and a “time placebo” which reruns the base model using an alternative (incorrect) time period as treatment. We continue to see strong evidence of job impacts for these three species-sectors, particularly after critical habitat designations, in the event studies for these robustness checks. We present the event studies for the statistically insignificant results presented in Figure 4 in the Appendix Figures A23 and A24, and the coefficients and event studies from an additional DDD falsification test in Appendix Figures A25 and A26.

Total Employment Effects

The event studies in Figure 7 demonstrate that there is no discernible effect of the ESA, regardless of timeframe, on total employment for all focal species in this analysis pooled together ($N = 126$; dropping ZCTAs with treatment reversals). In fact, the estimated coefficients show that there is job growth in areas eventually designated as critical habitat relative to matched control ZCTAs both before and after ESA regulations occur, with no evidence of a downward trend after treatment. In other words, areas destined for critical habitat designation have higher job growth in aggregate, and this differential growth is unaffected by ESA regulations, implying that there may be an association between areas with eventual species endangerment and overall economic job growth. This result holds across all models where we match on observable labor market characteristics.⁷ In none of these models do we detect negative impacts of the ESA on total employment. Importantly, the presence of an upward pre-trend prior to ESA regulation, combined with no clear kink or jump in this trend after treatment, rules out an alternative hypothesis that ESA regulations are a net “job creator” (Wooldridge, 2023; Rambachan and Roth, 2023).

⁷We omit the event study using the full candidate control group, which illustrates this trend even more strongly.

Figure 7: Event Study of ESA Effects on Total Employment

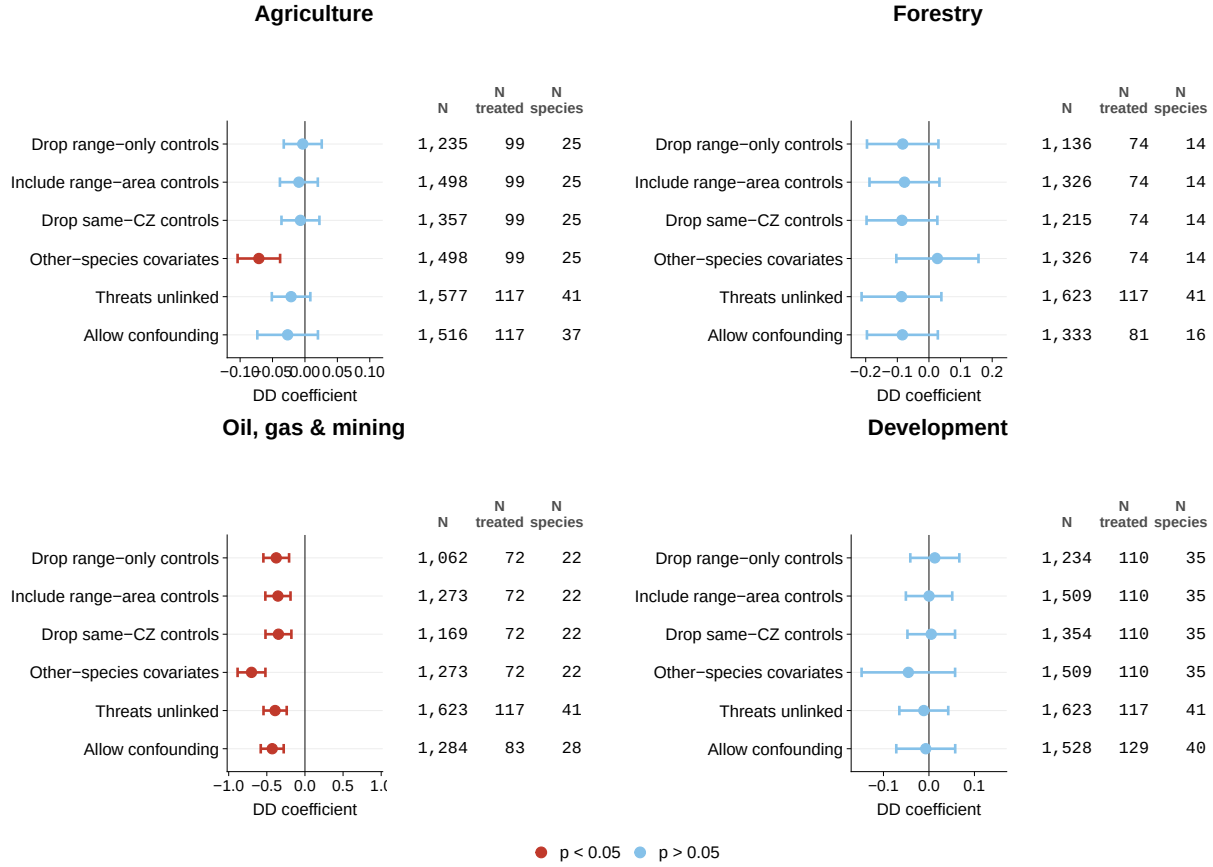


Notes: Event study analysis of the long-run effects of both regulatory layers of the ESA on total jobs in affected ZCTAs. Event study coefficients capture the proportional differences in employment outcomes between treated and control ZCTAs in years before and after ESA regulations, relative to the omitted pre-regulation baseline year. We compare treated ZCTAs to 12 distinct matched control groups. We find evidence of a similar upward trend in job growth in critical habitat areas both before and after ESA regulations, implying no causal effect.

County-level Analysis

We present the estimated DD coefficients from the county-level version of the analysis for each of our four focal sectors in Figure 8. This includes our baseline specification, along with several other robustness checks. Similar to the ZCTA-level analysis, we find little evidence of job declines following ESA regulations in agriculture, forestry, or development sectors across nearly all specifications. We do find, however, statistically significant and precisely estimated job declines in the oil, gas, and mining sector which are robust to different specifications. Most of these estimated coefficients imply a 29-35% decline in employment in this sector. We note this is of a similar magnitude to the pooled species-mining estimates found in ZCTA-level Analysis 2 (Figure 4), which are more noisily estimated. In the Appendix Figure A27, we present an event study and the design for the Mexican spotted owl in the forestry sector, in which we continue to find statistically significant declines that corroborate our ZCTA-level findings.

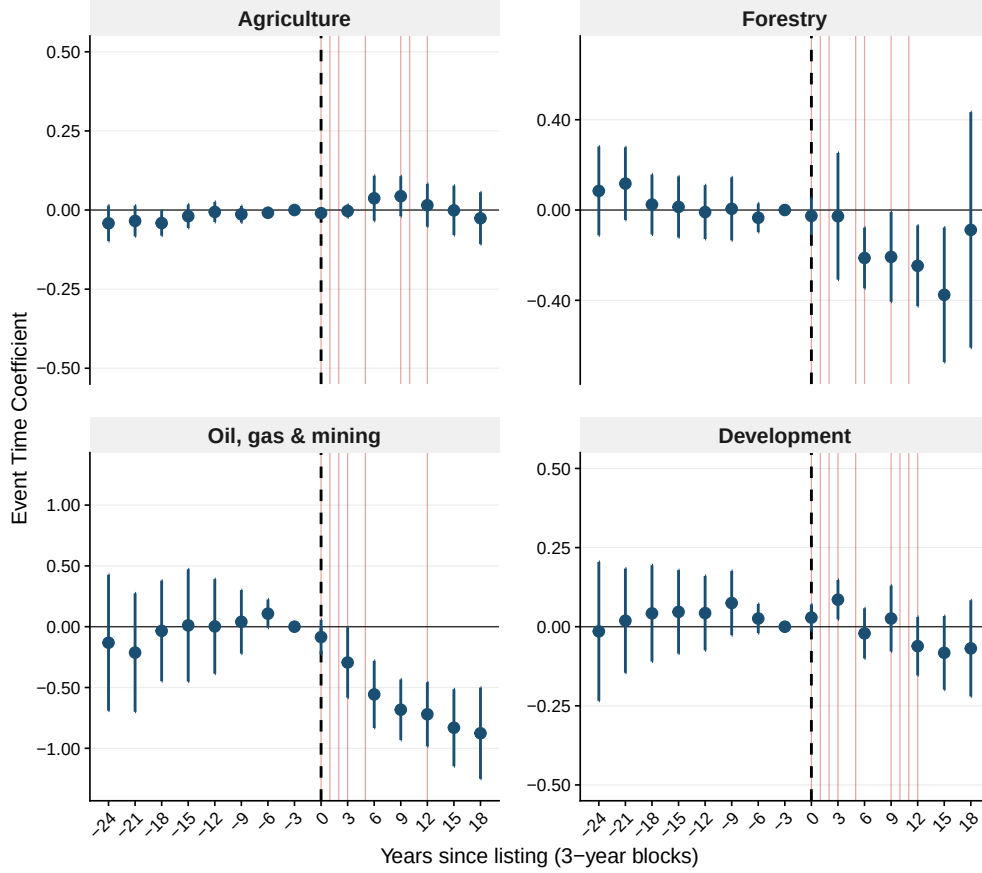
Figure 8: County-Level DD Estimates by Focal Sector Across Specifications



Notes: Each panel reports the DD coefficient and 95% confidence interval for one focal sector under six specifications: (i) comparing treated counties to same-state counties outside the species' range, (ii) including each species' range area in the control group, (iii) dropping controls in the same commuting zone as treated counties, (iv) adding other species listings as a time-varying covariate, (v) using all species regardless of LLM-defined threat linkages, and (vi) allowing confounding from other species' critical habitat in the post-period. Columns to the right of each panel report the number of counties, treated counties, and focal species behind each estimate. Red markers are significant at the 5% level; blue are not. The control group is never-treated counties throughout.

We present the event studies from the baseline specification for these estimates in Figure 9. These display generally flat estimated coefficients throughout, except for the effects in the oil, gas, and mining sector which experience significant post ESA-listing declines. In the Appendix, we present maps of the treated and control counties used in these analyses in Figure A28, all remaining event studies by pooled sector in Figure A29 and a total employment version of the county-level analysis in Figure A30.

Figure 9: County-Level Pooled Event Studies by Focal Sector



Notes: Event study coefficients and 95% confidence intervals for each focal sector using control counties in the same states as the species range but outside the range itself. Treatment timing is the final listing rule for each species (black dashed line), and thin red lines indicate the ensuing timing of each species' critical habitat designation.

6 Discussion

This analysis shows that the ESA is not slowing overall job growth in areas regulated by both layers of the ESA between 1990-2020, complementing prior work showing similar results for a subset of species regulated between 1980-1990 in the American West (Duffy-Deno, 1997). However, total employment growth may swamp impacts in particular economic sectors that are directly tied to the mechanisms of ESA regulations. We test this by recovering a distribution of treatment effects of the ESA on labor markets at the species-sector level, by linking species threat information to the exact economic sectors likely to be regulated by the ESA in each setting. Despite this best-case scenario for uncovering an effect, we find no evidence of sector-specific job impacts in the majority of ESA listing contexts in our analysis. Our work provides a broader and more representative view of the impacts of the ESA on

local economies, establishing that high-profile individual-species cases, such as the northern spotted owl, along with several additional cases in this analysis, are outliers relative to the distribution of overall ESA impacts on local economies. While understanding these tail cases is important, they should not be mistaken as representative of the typical impacts of ESA listings and critical habitat designations.

Magnitude and Interpretation of Estimated Effects

Three of the species-sectors that we analyze have statistically and economically significant employment declines following the rollout of ESA regulations. The percentage impacts for these cases range from 13% job declines for the Sierra Nevada yellow-legged frog in the development sector to 47% for the Mexican spotted owl in the forestry sector using our baseline model, which are similar to the 28% job impacts estimated for the northern spotted owl (Ferris and Frank, 2021). We confirm that these effects remain statistically and economically significant for these cases by performing a variety of robustness checks which vary the control group (Figure 4) and alter the design in a variety of ways (Appendix Figures A9 through A16).

We estimate the total number of jobs impacted in these three species-sector cases by multiplying the estimated proportional effect by the pre-treatment mean across treated ZCTAs and by the total number of ZCTAs treated in each setting. This procedure implies effects between 745 to 1,640 jobs impacted for the Mexican spotted owl in the forestry sector (1,100 in baseline approach), between 620 to 1,010 jobs impacted for the Gunnison sage-grouse in the development sector (840 in baseline approach), and between 920 to 1,805 jobs impacted for the Sierra Nevada yellow-legged frog in the development sector (1,030 in baseline approach) across the different DD model specifications. In the complementary, county-level analysis, we find additional evidence of labor market declines in the oil, gas, and mining sector which range from 2,980-5,540 jobs (3,040 in baseline approach).⁸

Using our baseline specification, we estimate around 6,000 jobs impacted in aggregate, which covers a 31-year period and over 100 species listing contexts. Our most conservative estimates imply job impacts of approximately 5,260 and our least conservative estimates imply impacts no greater than 10,000 jobs. This is far fewer than the 16,000-32,000 forestry jobs impacted by the listing of the northern spotted owl alone, whose regulations are often pointed to in policy discussions to make statements about the costs of the ESA (U.S. House Committee on Natural Resources, 2023). The estimated total job impacts in this analysis along with prior

⁸These effects are similar in magnitude to those found in the ZCTA analysis, which is more noisily estimated in this sector.

work (Duffy-Deno, 1997; Melstrom et al., 2018; Ferris and Frank, 2021) rule out the extremely large job impacts that are sometimes claimed for existing or potential ESA regulations, such as over 175,000 jobs for the Coastal California gnatcatcher (Natural Resources Defense Council et al. v. United States Department of the Interior et al., 2002) or upwards of 130,000 jobs for the northern spotted owl (Bonnett and Zimmerman, 1991), a claim that was dispelled in Ferris and Frank (2021).

Assessing Costs Relative to Benefits of the Act

Evaluating the performance of the ESA requires an understanding of the costs and benefits of the Act. Our analysis focuses on one dimension of cost: the direct, local employment impacts of ESA regulations. Our results show that the job impacts are low in the overwhelming majority of cases, with a handful of exceptions concentrated in particular areas and economic sectors. Though jobs and property values (Frank et al., 2025a) are often focal economic indicators, other dimensions of cost to be considered for ESA regulations include revenue impacts to firms, potential cost pass-through to consumers, opportunity costs from engaging with permitting processes, and direct expenditures on conservation and recovery actions by the USFWS. Further, we do not observe general equilibrium spillover effects which may take several forms. For instance, impacted workers may go on to earn higher or lower wages elsewhere (Walker, 2013). These are areas that future research can engage with more thoroughly by collecting and analyzing such data.

A critical need for future research is a better understanding of the benefits of conservation policies such as the ESA. While costs can be more easily quantified using available market indicators such as prices or employment numbers, quantifying the benefits of the ESA regulations is much more challenging as many of these values are not priced directly in the market, but are also not zero. Large existence values and willingness to pay estimates for the conservation of endangered species have been elicited from stated preference work (Moore et al., 2022; Richardson and Loomis, 2009). Similarly, quasi-experimental work has used sharp changes in the population numbers of particular species (e.g., local extinctions, reintroductions of species) to reveal large, and often hidden, economic benefits annually provided by bats (Frank, 2024; Manning and Ando, 2022) and wolves (Raynor et al., 2021) in the U.S. context, and vultures (Frank and Sudarshan, 2024) and sparrows (Frank et al., 2025b) in other settings. Avoiding such extinctions is a primary goal of the ESA, and can serve to preserve the option value of restoring ecosystem services linked to imperiled species as well as protect benefits from the preservation of genetic diversity. Additional work to quantify such benefits is needed to truly understand the balance of costs and benefits from the ESA.

Quantifying the benefits of species recovery, beyond just avoiding extinctions, will also be an important area of future work. This will require tracking species population levels and range areas consistently over time, which may be more reliably achieved with recent technological advancements in monitoring such as eDNA (Çevik and Çevik, 2025), bioacoustic monitoring (Wood et al., 2023), and big data becoming available from citizen science platforms (Johnston et al., 2025) which can help with near real-time monitoring of species populations (Fischman et al., 2023). More work is needed to quantify these changes in terms of economic benefits.

Other Implications for Future Research and Policy

There are multiple explanations for the statistically insignificant effect of the ESA on jobs in the majority of the cases we analyze. One explanation may simply be the case that the USFWS is highly motivated to manage economic tradeoffs through the ESA policy process. USFWS can and does consider economic impacts when drawing critical habitat boundaries (Frank et al., 2025a), and they have approved the vast majority of Section 7 consultations they have received to allow economic activity to continue in regulated areas (Malcom and Li, 2015). Indeed, USFWS processed over 88,000 Section 7 consultations between 2008 through 2015 and approved nearly all of them with little to no modification (Malcom and Li, 2015). While possibly benefiting local economic actors, this can create a “death by a thousand cuts” situation wherein species habitats are not protected adequately to move beyond merely avoiding extinction to actually promoting recovery, a goal of the ESA that has not been effectively met (Gerber et al., 2018; Haines et al., 2021). A better understanding of the universe of Section 7 and Section 10 incidental take permits approved by the USFWS, the location of such activity, and their relation to both local economic productivity and species recovery is an important future area of research. Another possible explanation for the negligible job impacts of ESA regulation is that critical habitat is sited in specific areas that, intentionally or not, are not likely to experience much threat from future economic activity. This is consistent with the finding of Nelson et al. (2017), who find no change in land cover over time in areas regulated by critical habitat compared to surrounding areas, leading to questions of the on-the-ground effectiveness of critical habitat designation for actually promoting species recovery.

While our analysis demonstrates that job losses from ESA regulation are rare, this does not mean that there is not a need for policy innovation to more effectively recover species while managing the overall economic costs and local community impacts of conservation. One approach to this challenge may be preemptive conservation strategies (Treacle et al., 2023; Stanley et al., 2024; Langpap and Wu, 2017), whereby the USFWS works with local

economic actors to provide conservation for species *before* they are listed under the Act. For instance, Candidate Conservation Agreements with Assurances (CCAAs) programs allow economic actors to provide upfront conservation actions for candidate species in exchange for assurances that their activities won't be regulated by the ESA if that species is listed. CCAAs provide flexibility and potential financial benefits to firms if upfront costs of conservation are less than future compliance costs under the ESA (Epanchin-Niell and Boyd, 2020). Targeting species for conservation earlier on is likely cost-effective relative to the status quo under the ESA, where imperiled species populations remain unprotected during lengthy listing timelines and do not receive protections until their population numbers have dwindled further. This has contributed to a backlog of conservation-reliant endangered species whose small population numbers are “logistically, economically, and politically overwhelming” for managers to try to recover (Scott et al., 2010). Other approaches, such as direct payments for habitat protections in settings where economic costs are shown to be concentrated, may also be effective (e.g., larger critical habitat boundaries in rural areas; Figure A19). As the results in this analysis highlight, targeting preemptive conservation or reactive payment mechanisms to particular settings may be more efficient than blanket approaches that treat all species-settings homogeneously.

Conclusion

Narratives about the costs of the Endangered Species Act have directly shaped U.S. conservation policy over the past several decades. These narratives, particularly those related to jobs, have been grounded in a few individual species settings with little known about the overall magnitude and distribution of the Act's economic impacts. This study shows that, across 128 terrestrial species and three decades of ESA regulations, job effects have been concentrated in a small minority of settings. These job impacts are large within the specific settings in which they occur, suggesting that policy responses which account for this distribution of costs may be effective at balancing species conservation with local economic conditions. This is in contrast to the blanket rollbacks of species protections currently being implemented under the ESA. Overall, our analysis provides a holistic and empirically grounded picture of the ESA's impact on local labor markets, showing that the large effects found in a handful of settings are not representative of the typical ESA listing—an important distinction for policymakers evaluating the Act's performance and considering any reforms to the Act.

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A Appendix

A.1 Supporting Text

A.1.1 NETS Data

The NETS database offers several important advantages in this study context over other employment data sources. Critically, NETS tracks the economic sector of each firm according to its SIC/NAICS codes and provides high-resolution location information for each firm (e.g., ZIP-code level). This is in direct contrast to other publicly available employment datasets, such as the Quarterly Census of Employment and Wages (QCEW), which have high rates of data censorship among specific economic sectors and provide much coarser, county-level data. Because the ESA is intuitively linked to certain resource-extractive sectors, access to these sector-specific data is key to our research question, at the spatial resolution at which critical habitat designations occur. NETS is also preferred to the U.S. Census Bureau’s Longitudinal Business Database (LBD), another employment database with sector-level data, for three reasons. First, one of the key sectors likely to be affected by ESA regulations is agriculture, which is present in NETS but completely omitted in the LBD. Second, the NETS database has higher coverage of small firms, which are important for analyses such as this one focused on rural areas (Walls et al., 2020). Third, for confidentiality reasons, the Census Bureau does not approve projects that may re-identify firms, which is more likely in projects such as this one focused on particular sectors in small rural areas (Walls et al., 2020). NETS does not have these restrictions.

Several studies have made comparisons between the NETS data and other administrative sources. One of the first was Neumark et al. (2007), who compare employment trends in California in 1997-2000 with the Quarterly Census of Employment and Wages (QCEW), the Current Employment Statistics (payroll) survey (CES), and the Size of Business data (SOB). The authors generally find strong evidence of agreement between these data sources with NETS by county-industry employment levels and three-year changes, using 1-digit SIC codes to define industries. They do highlight some evidence of measurement error of employment in NETS, such as rounding of employment (which is largely random), and they generally recommend using three-year intervals at a minimum in analyses of employment changes. A second, more recent analysis (Barnatchez et al., 2017) again compares NETS to the QCEW, the County Business Patterns (CBP), and Nonemployer Statistics (NES) using national data from 1992-2014. These authors similarly find “strikingly high” correlations for employment at the county-level between NETS and other administrative sources. The authors do highlight some areas where divergences exist, such as among smaller establishments, in the education

sector broadly, and in post-2000 trends for mining, construction, and manufacturing. Finally, Crane and Decker (2019) provide an additional comparison between NETS and the U.S. Census Bureau’s Longitudinal Business Database (LBD) using national data between 1990-2014. These authors *exclusively* rely on single-year growth patterns in establishment level employment for their analysis, finding less evidence of agreement on this time scale with other administrative sources, and flagging the same discrepancies as in Barnatchez et al. (2017). Throughout, the authors highlight inherent challenges in making comparisons between NETS and other data such as differences in scope (e.g., NETS includes proprietors and contractors), as well as general difficulties in defining sector classifications (Barnatchez et al., 2017).

Our analyses account for these known discrepancies (i.e., potential mismeasurement in our outcome variable) by i) always conducting analyses that make comparisons within the same sector, ii) matching on known correlates of potential mismeasurement in NETS (i.e., proportion small establishments), iii) confirming our results are robust to several DDD specifications, and iv) re-testing our approach at the county-level with different data. Further, we show that NETS qualitatively reproduces the large employment declines following the listing of the northern spotted owl, which we present in Figures A33 and A34. Conditional on our matching and same-sector comparisons, the relevant consequence of mismeasurement in our outcome variable would be inflated standard errors. We find no evidence of a relationship between sign, magnitude, or statistical significance with the size of our standard errors (Figure A18). We also find that the statistically insignificant estimated coefficients in this study are distributed fairly evenly around zero. ↪ [Back to the data section](#).

A.1.2 Choosing Critical Habitat as Treatment

We focus on areas newly regulated by both layers of the ESA, rather than just the listing rule, for several reasons. First, it allows us to examine the effects of the full regulatory extent of the ESA on local job outcomes. Second, as described above, critical habitat designation is the layer more likely to be enforced, as indicated by: precedent in court rulings (Kendrick, 2021), expected costs as published by USFWS (Plantinga et al., 2014), regulatory pressure from lawsuits (Parenteau, 2005; Langpap, 2022), and pressure from local regulators and environmental activists (Auffhammer et al., 2020). There is anecdotal evidence from USFWS themselves who claim critical habitat forces actors to take the ESA “more seriously” (Owen, 2012), and complementary empirical work shows that the ESA has impacts on property values around critical habitat boundaries but not range area boundaries (Frank et al., 2025a). Third, endangered species range areas map almost the entirety of the United States (Frank et al., 2025a), and it is unrealistic to assume that the chronically underfunded USFWS is

able to monitor and enforce the ESA’s regulations across such great areas (Jesup, 2012). Despite this, we know that USFWS are out monitoring critical habitat areas even before they are designated as the agency draws and proposes these boundaries, hence our choice to set the post-treatment period to years after the listing rule for a given species in areas designated as critical habitat. [↪ Back to the defining treatment section.](#)

A.1.3 Batch Listings

When possible, our analysis is conducted at the species level. An exception we make is for “batch listings”, or cases where a group of species receive ESA regulations in the same document, published on the same date for both regulatory layers, in the same region. We group these ZCTAs together in our analysis as one singular listing and critical habitat set, and use one species as the representative name for the setting. There are two such cases in our individual species Analysis 1 – the Sierra Nevada yellow-legged frog (which was regulated simultaneously with the Mountain yellow-legged frog and Yosemite toad), as well as the Poweshiek skipperling (which was regulated simultaneously with the Dakota skipper). We visualize the ZCTAs regulated by each species’ critical habitat for the case of the Sierra Nevada yellow-legged frog in Figure A4. All batch listings are grouped together by design in our pooled analyses. [↪ Back to the Analysis 1 section.](#)

A.1.4 Panel Timeframes for Analysis 1

We apply an algorithmic approach to choose the number of years before and after ESA regulations occur to include in the panel timeframe T for each individual species setting, with an emphasis on accommodating cases where critical habitat was revised or revoked. For these cases, we include all years up to and including the revised critical habitat year. For species with no reversals, we include up to 5 years post-critical habitat in T to capture long-run effects of both layers of the ESA, or no more than double the pre-period years to account for cases with few pretreated years. Because we utilize the pre-trend diagnostic tools (Rambachan and Roth, 2023) to make inferences, which rely on extrapolating pre-trend years from the event studies, we drop species with fewer than 3 pre- or post-period years for this analysis. [↪ Back to the TWFE section.](#)

A.1.5 Additional Falsification: Same Sector DDD

We present one more robustness check which leverages employment trends in the same sector, in neighboring states, as an additional control group. Specifically, we first match ZCTAs in the neighboring states of each species’ range to our treated ZCTAs using the

same pre-treatment covariates as the main analysis (using 3:1 matching with calipers and replacement). We consider this to be a pseudo-treated group that is similar on pre-ESA regulation characteristics to our actual treated group. We assign a fake ESA treatment at the same time as our focal treated ZCTAs to these ZCTAs, and compare differences in trends between these fake-treated ZCTAs and the rest of the unmatched ZCTAs in these neighboring states. This creates a second difference that we operationalize in a DDD model for our main specification. In other words, we compare the difference-in-differences in employment between our treated ZCTAs and control ZCTAs (in the same states as the species range, outside of the species range), where we net out the effect of an additional difference-in-differences in employment in matched ZCTAs in neighboring states and other ZCTAs in the same economic sector. The design is visualized in Figure A6. The model is:

$$E(Y_{i,t}|\cdot) = \exp \left[\delta^{DDD} (P_i \cdot POST_t \cdot INSTATE_i) + \alpha_i + \gamma_t \cdot INSTATE_i + \gamma_t \cdot P_i \right] \quad (6)$$

where $Y_{i,t}$ is employment in ZIP-code i in year t . Binary indicators for treatment (or pseudo-treatment) P_i , post-listing treatment $POST_t$, and in the actual critical habitat treated state $INSTATE_i$ are defined. Included are interacted fixed effects for year γ_t with either dummy variable $INSTATE_i$ and P_i to capture pairwise interactions, as well as ZCTA fixed effects α_i which absorb the remaining interaction. The coefficient of interest is δ^{DDD} and standard errors are clustered at the ZCTA level. [↪ Back to the DDD section.](#)

A.2 Supporting Tables

Table A1: Groupings of focal and other economic sectors linked to species threats. The bolded portion of each NAICS code indicates the 2-digit NAICS sector at which the grouping is identified. NAICS codes are used for county-level analysis by necessity.

Grouping	SIC Code	NAICS 3-digit Code
Agriculture (Focal)	SIC 1: Agricultural Production - Crops SIC 2: Agricultural Production - Livestock and Animal Specialties SIC 7: Agricultural Services	Not collected by CBP
Forestry (Focal)	SIC 24: Lumber and Wood Products, Except Furniture SIC 8: Forestry	NAICS 321 : Wood Product Manufacturing NAICS 113 : Forestry and Logging NAICS 115 : Support Activities for Agriculture and Forestry
Oil and Gas (Focal)	SIC 13: Oil and Gas Extraction	NAICS 211 : Oil and Gas Extraction

Continued on next page

Table A1 continued

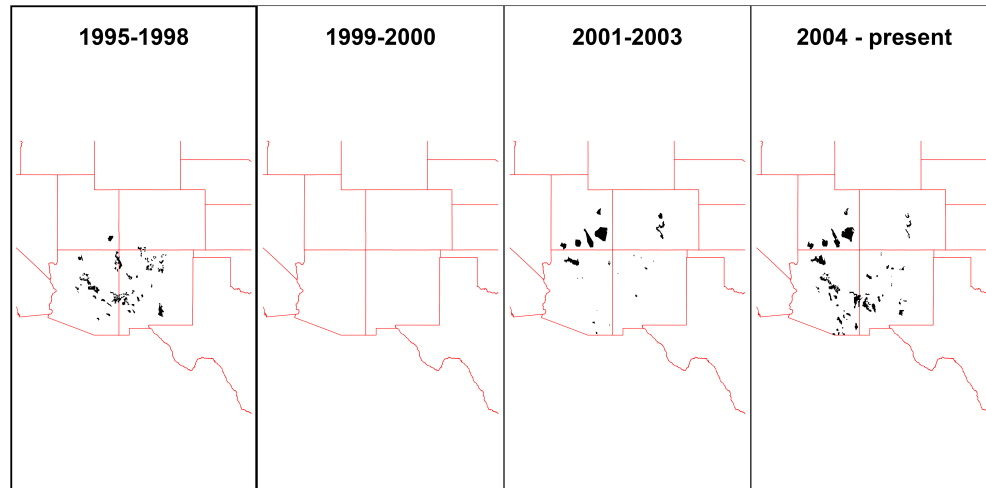
Grouping	SIC Code	NAICS 3-digit Code
	SIC 29: Petroleum Refining and Related Industries	NAICS 212 : Mining (except Oil and Gas)
	SIC 46: Pipelines, Except Natural Gas	NAICS 213 : Support Activities for Mining
		NAICS 324 : Petroleum and Coal Products Manufacturing
		NAICS 486: Pipeline Transportation
Mining (Focal)	SIC 10: Metal Mining	<i>Grouped with Oil and Gas (NAICS 21); see above</i>
	SIC 12: Coal Mining	
	SIC 14: Mining and Quarrying of Nonmetallic Minerals, Except Fuels	
Development (Focal)	SIC 15: Construction - General Contractors & Operative Builders	NAICS 236 : Construction of Buildings
	SIC 16: Heavy Construction, Except Building Construction, Contractor	NAICS 237 : Heavy and Civil Engineering Construction
	SIC 17: Construction - Special Trade Contractors	NAICS 238 : Specialty Trade Contractors
	SIC 65: Real Estate	NAICS 531 : Real Estate
Fishing or hunting or trapping	SIC 9: Fishing / hunting / trapping	NAICS 114 : Fishing, Hunting and Trapping
Transportation	SIC 40: Railroad Transportation	NAICS 481 : Air Transportation
	SIC 41: Local & Suburban Transit & Interurban Highway Transportation	NAICS 482 : Rail Transportation
	SIC 42: Motor freight transportation	NAICS 484 : Truck Transportation
	SIC 43: United States Postal Service	NAICS 485 : Transit and Ground Passenger Transportation
	SIC 45: Transportation by Air	NAICS 487 : Scenic and Sightseeing Transportation
	SIC 47: Transportation Services	NAICS 488 : Support Activities for Transportation
Electric gas and sanitary services	SIC 49: Electric gas and sanitary services	NAICS 221 : Utilities
Recreation	SIC 79: Amusement and Recreation Services	NAICS 711 : Performing Arts, Spectator Sports, and Related Industries
	SIC 58: Eating and Drinking Places	NAICS 712 : Museums, Historical Sites, and Similar Institutions
	SIC 70: Hotels, Rooming Houses, Camps, and Other Lodging Places	NAICS 713 : Amusement, Gambling, and Recreation Industries
		NAICS 721 : Accommodation
		NAICS 722 : Food Services and Drinking Places

Notes: We include support activities at the 2 digit level for the majority of these groupings as well. One exclusion is 31- which covers all manufacturing (NAICS 31–33), which is too broad for the forestry and oil and gas sectors (i.e., both at 32 level specifically). Because NAICS does not separate mining from oil and gas extraction at the 2-digit level (both fall under NAICS 21 with a common “support activities” grouping), the Mining and Oil and Gas groupings are combined on the NAICS side. → [Back to the sector classification section.](#)

A.3 Supporting Figures

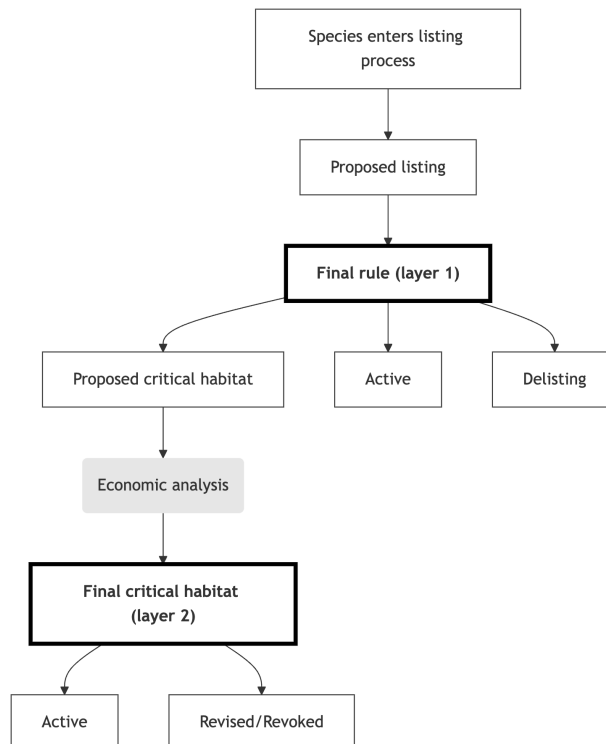
Descriptive Figures

Figure A1: Revoked and Revised Critical Habitat for the Mexican Spotted Owl



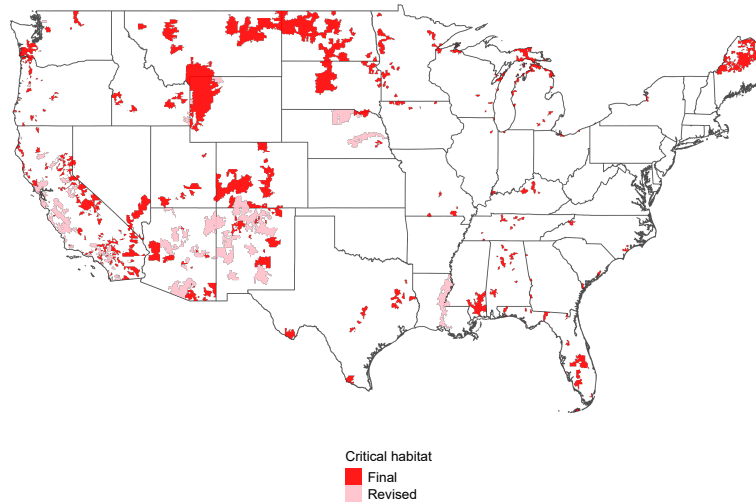
Notes: The spatial extent of critical habitat designations, revocations, and revisions over time for the Mexican spotted owl, illustrating how ESA regulations turn on and off in given areas. [↔ Back to the background section.](#)

Figure A2: Timeline of the ESA Listing and Critical Habitat Process



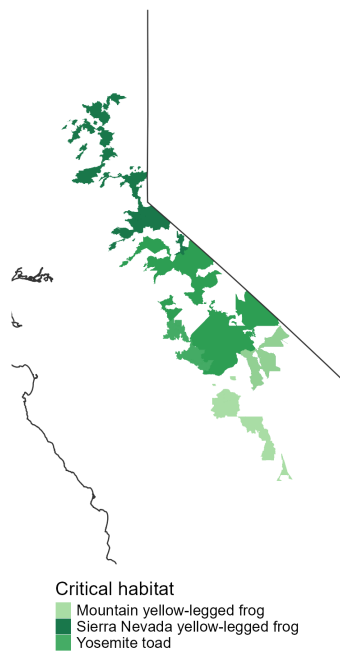
Notes: Simplified flowchart of the listing and critical habitat process for a given species, showing all possible regulatory statuses a species may receive over time. [↔ Back to the background section.](#)

Figure A3: Permanent and Revised Critical Habitat ZCTAs



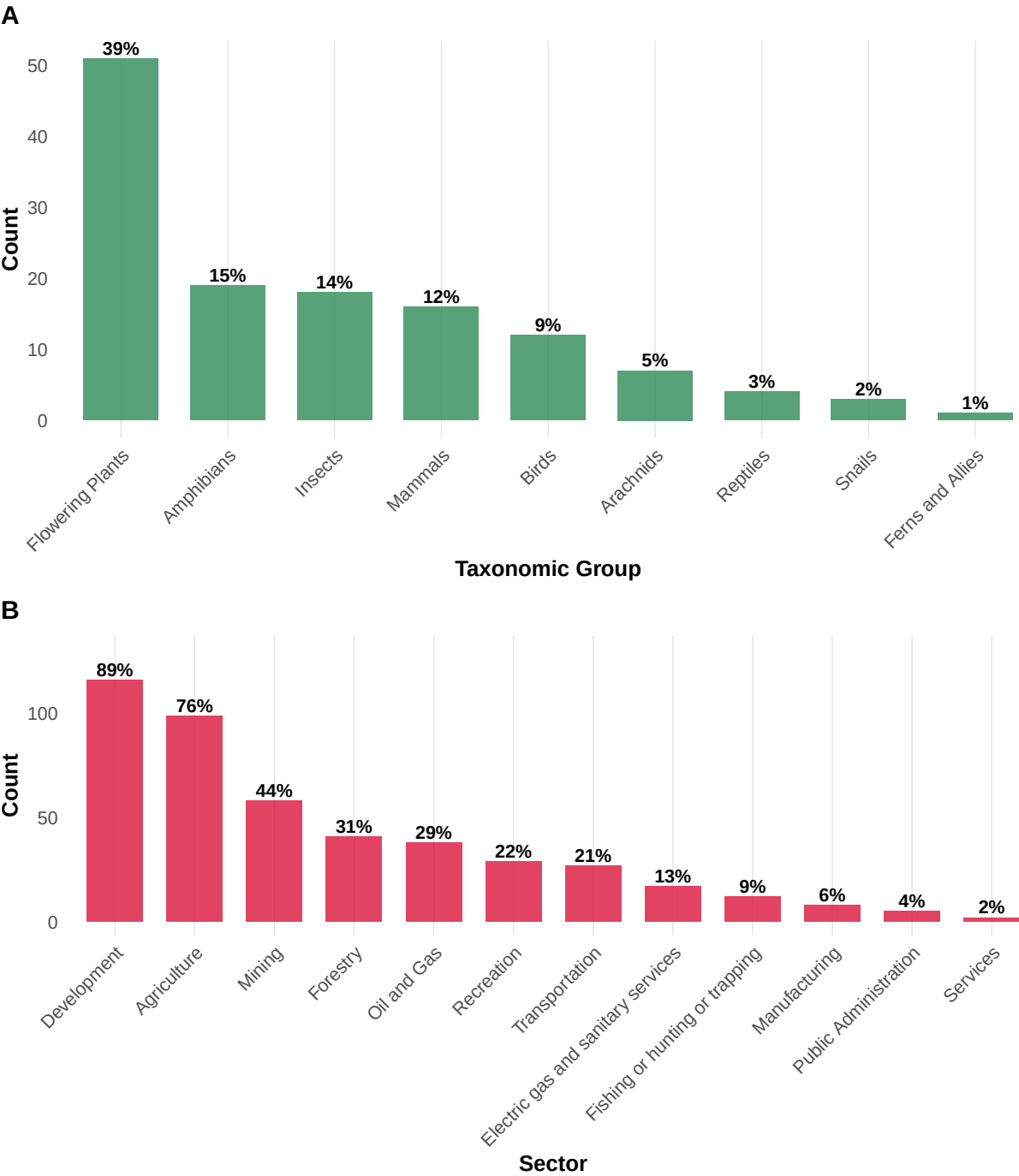
Notes: Map of all ZCTAs regulated by critical habitat across our analysis, distinguishing between cases that are permanent and cases where USFWS revised or revoked the critical habitat regulation at some point between 1990 and 2020. Some species included in our analysis have ZCTAs excluded here that already had critical habitat designated for another species, which we omit from our analysis. [↔ Back to the data section.](#)

Figure A4: Batch Listing Example



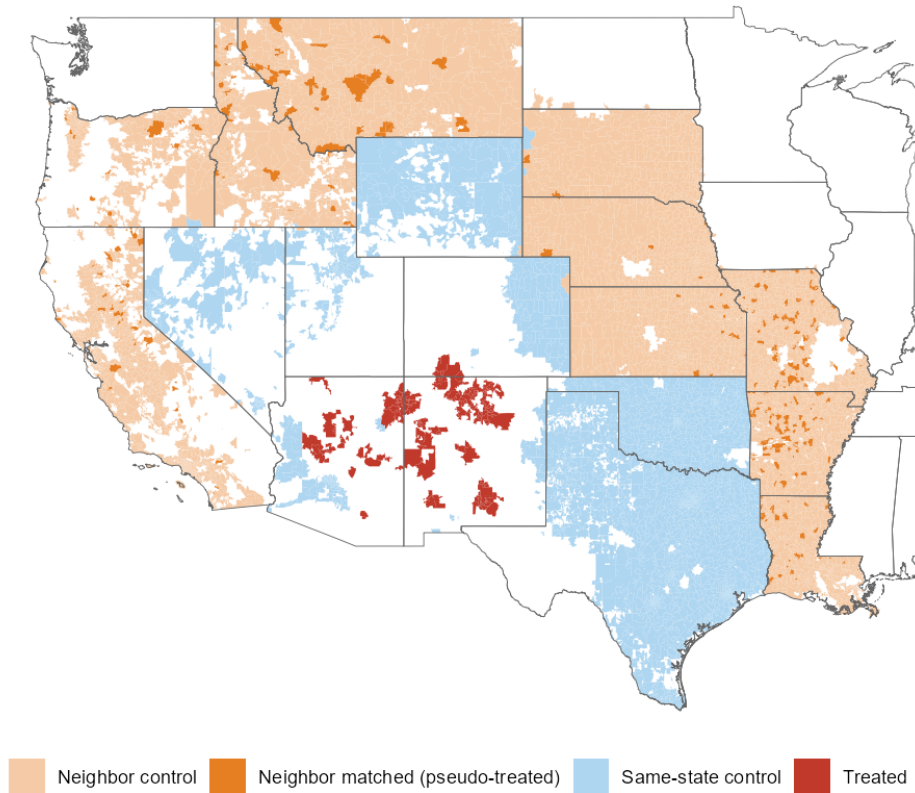
Notes: Map of all ZCTAs intersecting critical habitat for the Sierra Nevada yellow-legged frog, Yosemite toad, and Mountain yellow-legged frog, which were batch listed together, meaning all three species received their listing and critical habitat rulings on identical dates. We group all ZCTAs together as one listing event for our analysis, using the Sierra Nevada yellow-legged frog as the representative species. [↔ Back to the data section.](#)

Figure A5: Distribution of Species Taxa and Threat-Linked Economic Sectors



Notes: Panel A shows the distribution of taxa across all species considered in the analysis. Panel B shows the distribution of economic sectors linked to species threat information. For our main analyses we focus on the top five economic sectors linked to threats that affect at least a quarter of all species considered (Development, Agriculture, Mining, Forestry, and Oil and Gas). We do not consider Manufacturing, Public Administration, or Services to be linked to species threats, as these sectors were never identified as such in our manual coding. [↪ Back to the LLM methods section.](#)

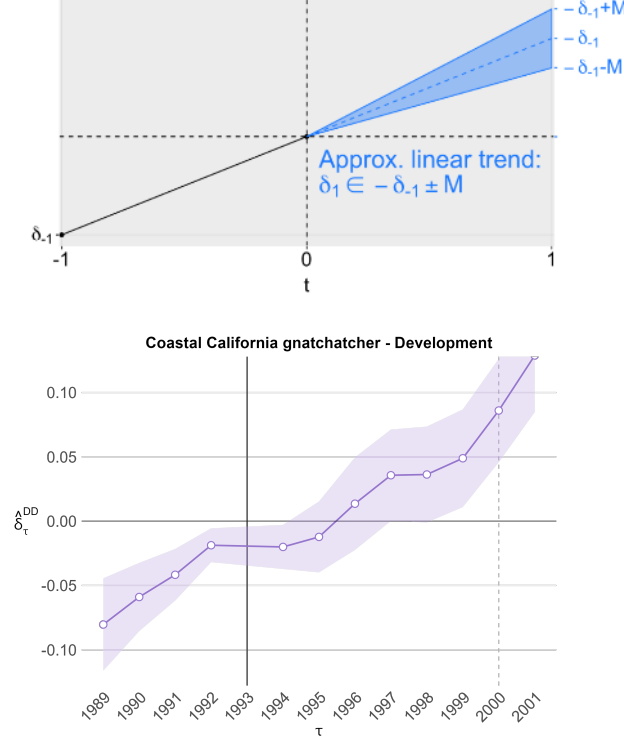
Figure A6: Neighboring-State Pseudo-Treatment DDD Design



Notes: Design of the DDD using matched ZCTAs in neighboring states as a pseudo-treated group. The identification tests the difference-in-differences between the treated group (red) and the control group within the same states as the species range (light blue), net of the difference-in-differences between the pseudo-treated group (dark orange; determined by matching on pre-treatment employment covariates) and the additional control group (light orange). Example shown: Mexican spotted owl. [↔ Back to the DDD section.](#)

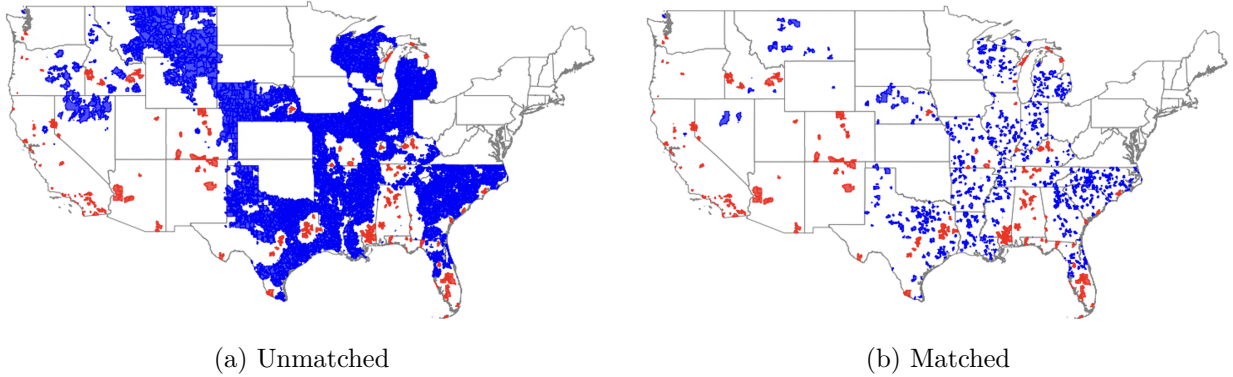
Figure A7: Pre-Trend Sensitivity Diagnostics

- **Smoothness restriction:** Bound how far δ_1 can deviate from a linear extrapolation of the pre-trend: $\delta_1 \in [-\delta_{-1} - M, -\delta_{-1} + M]$



Notes: Example of the smoothness restriction method we apply to our statistically significant results (Rambachan and Roth, 2023). The top panel visualizes the intuition of the approach (Roth, 2024). The bottom panel provides an example of a statistically significant event study we recover which is not robust to violations in pre-trends. We exclude such cases from our results to avoid attributing causal effects to estimates that are driven by pre-existing differences in employment trends between treated and control ZCTAs. [↪ Back to the pretrend diagnostics section.](#)

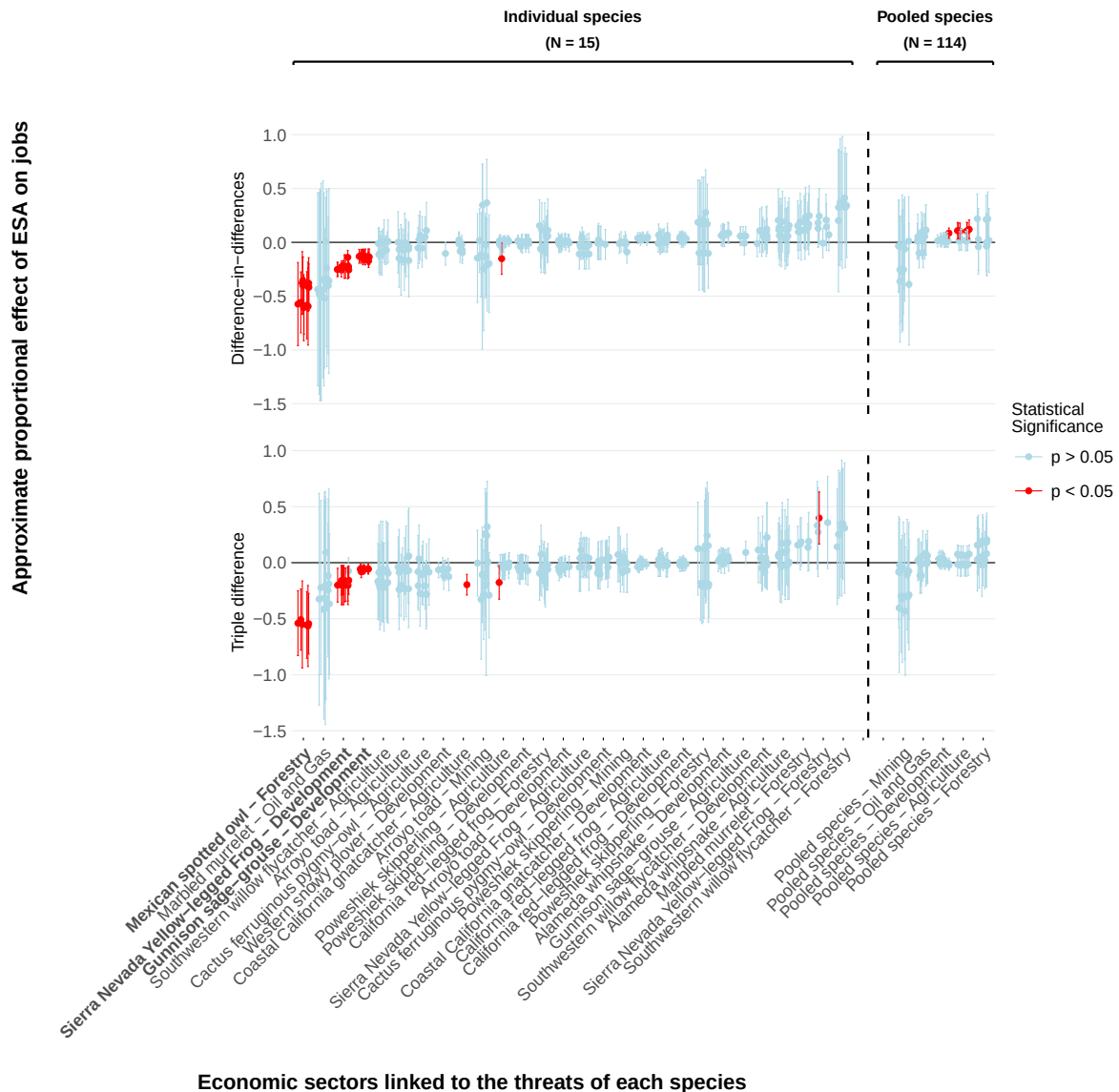
Figure A8: Example Design for Pooled Small-Regulated-Area Species



Notes: Map of treated and control ZCTAs for the pooled species analysis in the development sector, using the full control set (left) and the matched control set (right). [↪ Back to the Analysis 2 methods section.](#)

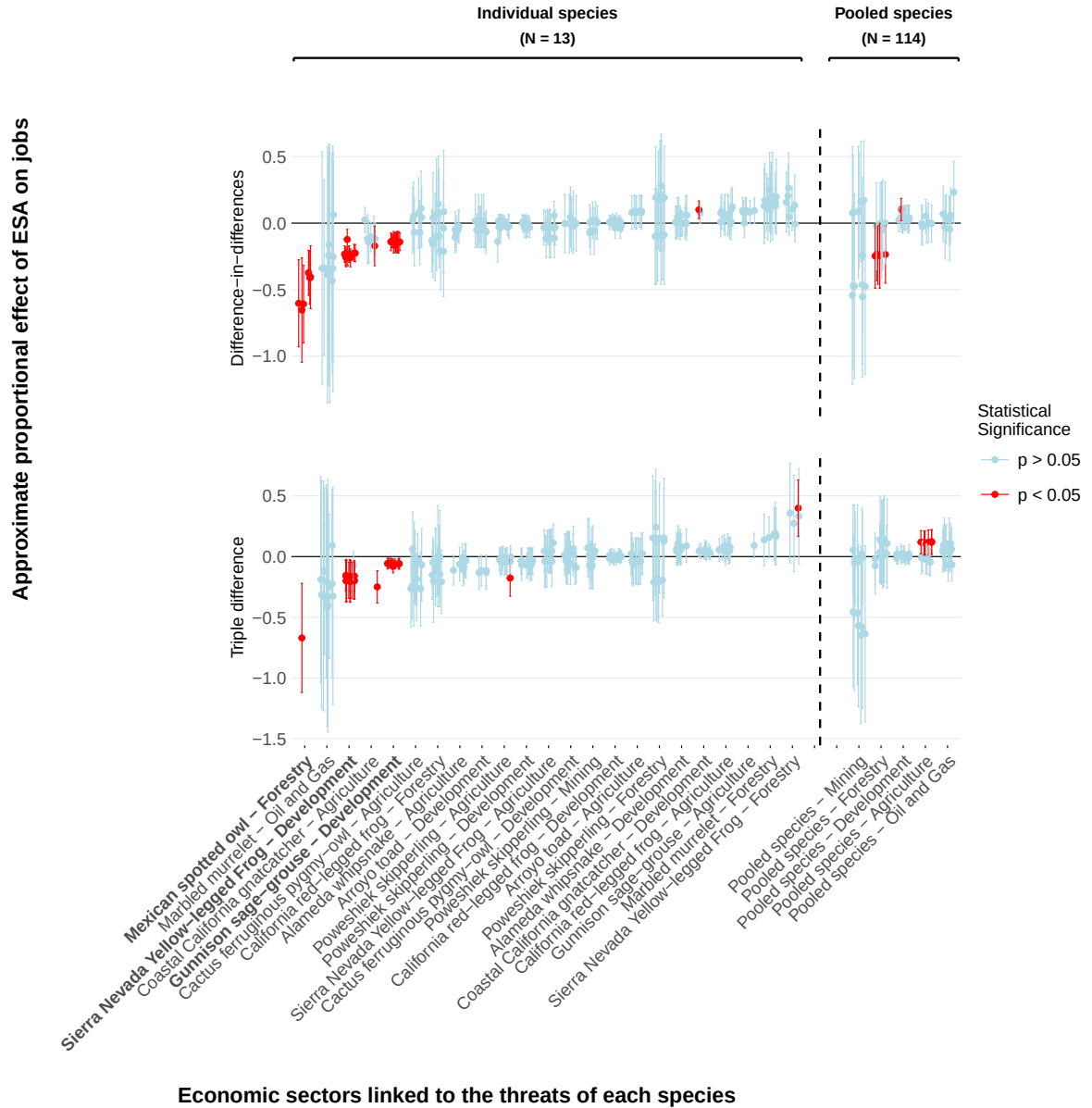
Robustness Checks: Full Distribution of Estimated Impacts

Figure A9: Retaining ZCTAs with Multiple Critical Habitat Designations



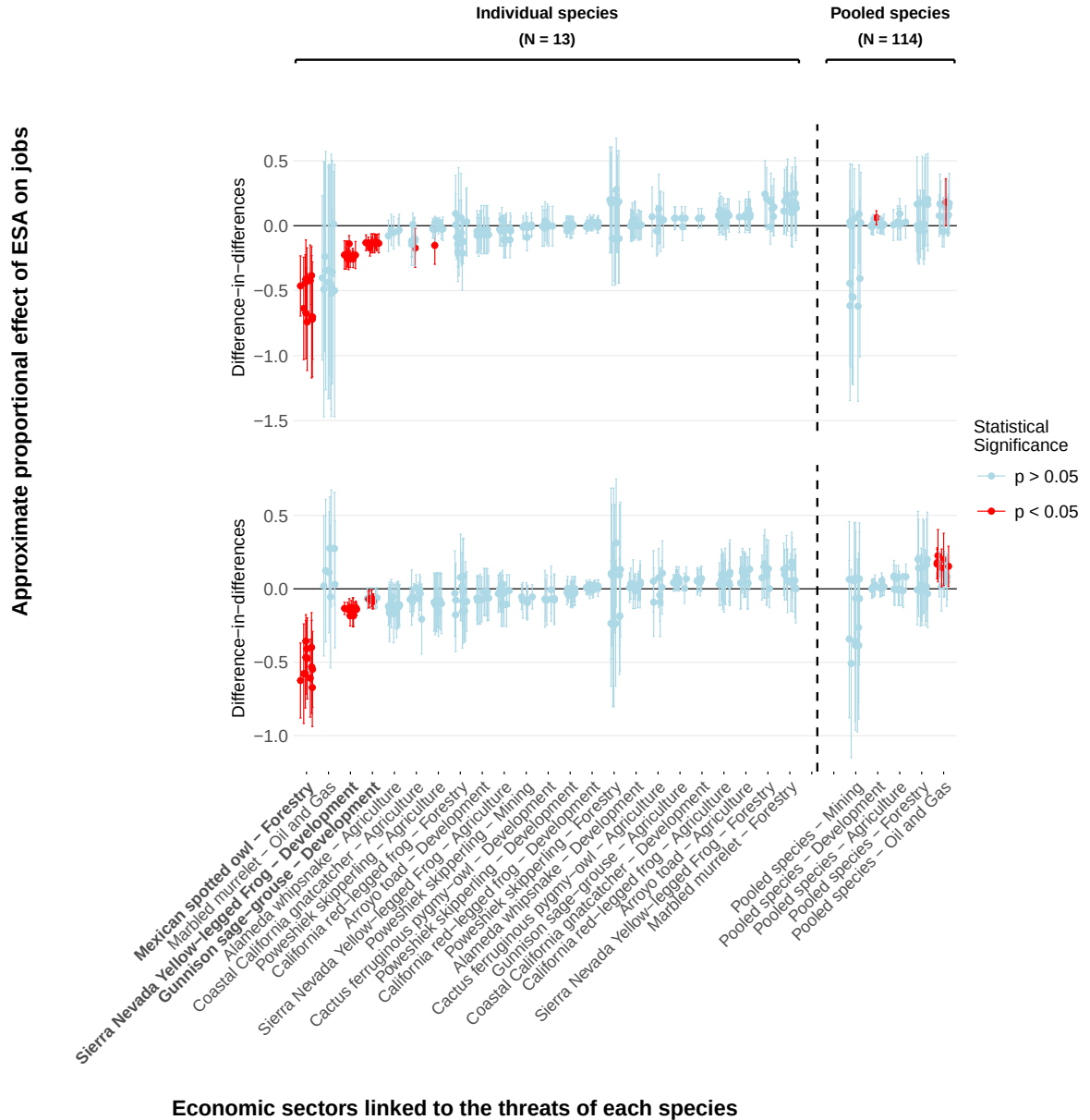
Notes: Robustness check for the distribution of estimated impacts of both regulatory layers of the ESA on local employment in affected ZCTAs, not dropping ZCTAs in which there is more than one critical habitat designation in the post period for each species-sector. Species in **bold** represent statistically significant effects which are robust to a multitude of specifications. We remove statistically significant results which are not robust to violations in pretrend diagnostics. Note that because the number of observations increases among treated ZCTAs for species in this case, we include two more species-economic sectors in Analysis 1 with enough non-zero entries per sector (≥ 20 ZCTAs) to be analyzed. These species, however, are linked to other threat sectors still below this threshold and are thus included in Analysis 2 as well (i.e., Analyses 1 and 2 are mutually exclusive with respect to species-sectors, not species themselves). [↪ Back to the Analysis 1-2 results section.](#)

Figure A10: Controlling for Other Species Listings



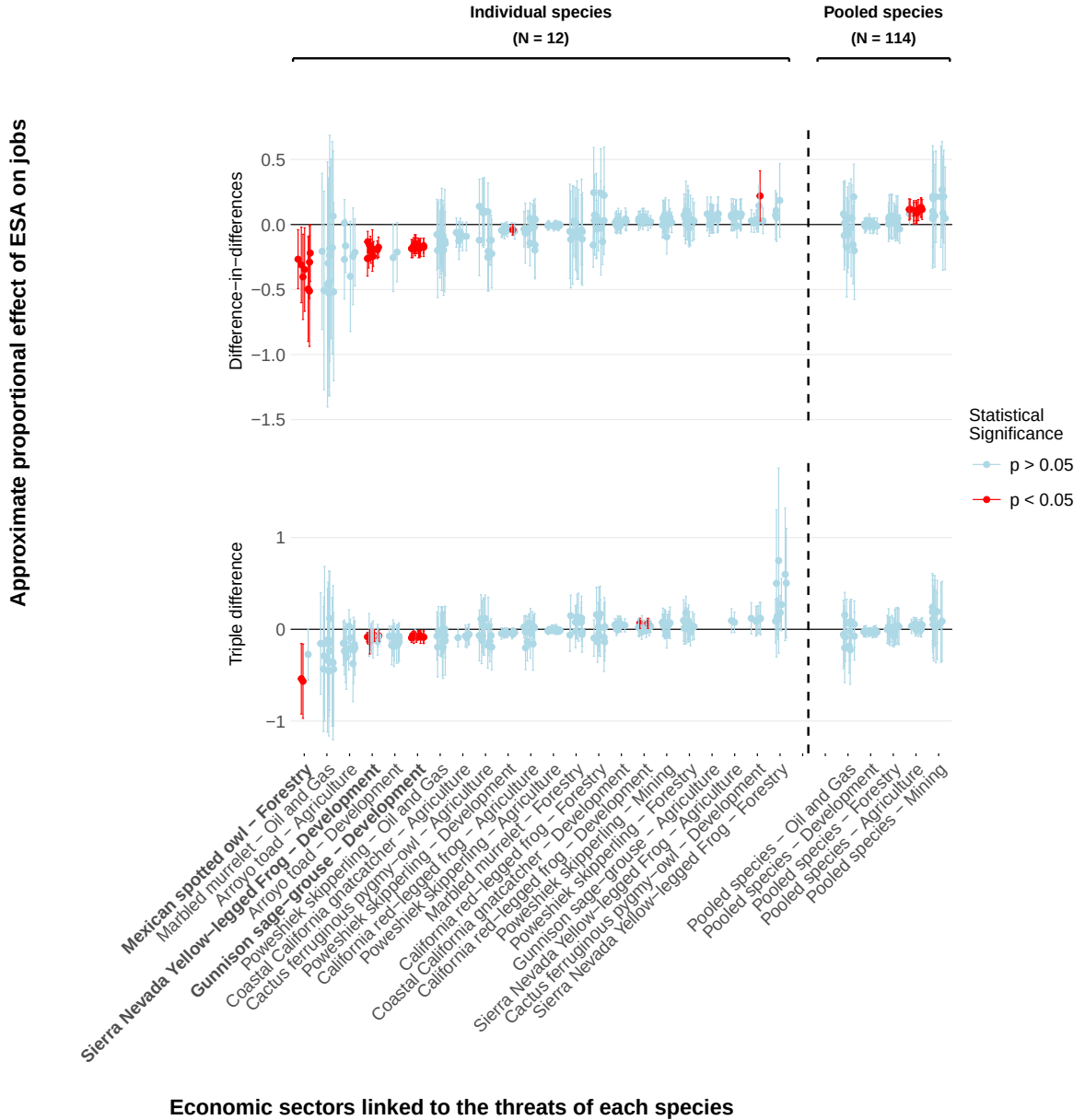
Notes: Robustness check for the distribution of estimated impacts of both regulatory layers of the ESA on local employment in affected ZCTAs, adding one time-varying covariate to control for changes in other species listings by ZCTA and year. Species in **bold** represent statistically significant effects which are robust to a multitude of specifications. We remove statistically significant results which are not robust to violations in pretrend diagnostics.
[↪ Back to the Analysis 1-2 results section.](#)

Figure A11: One-Year Lag in Treatment Timing



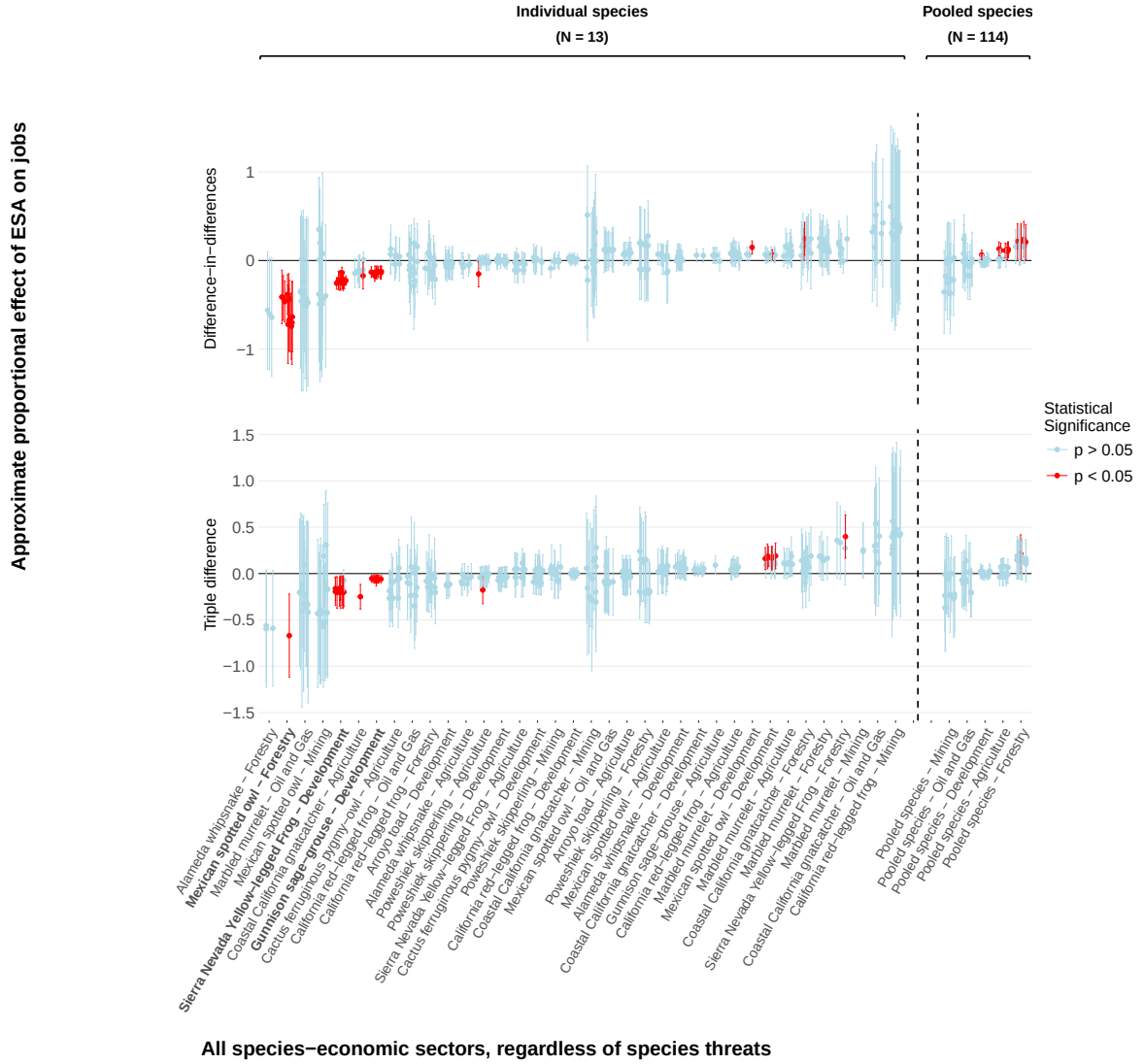
Notes: Robustness check for the distribution of estimated impacts of both regulatory layers of the ESA on local employment in affected ZCTAs, comparing the DD model when using a one-year lag (bottom panel) of the true listing year as treatment. Species in **bold** represent statistically significant effects which are robust to a multitude of specifications. We remove statistically significant results which are not robust to violations in pretrend diagnostics.
[↪ Back to the Analysis 1-2 results section.](#)

Figure A12: Treatment Defined with a 10 km Buffer Around Critical Habitat



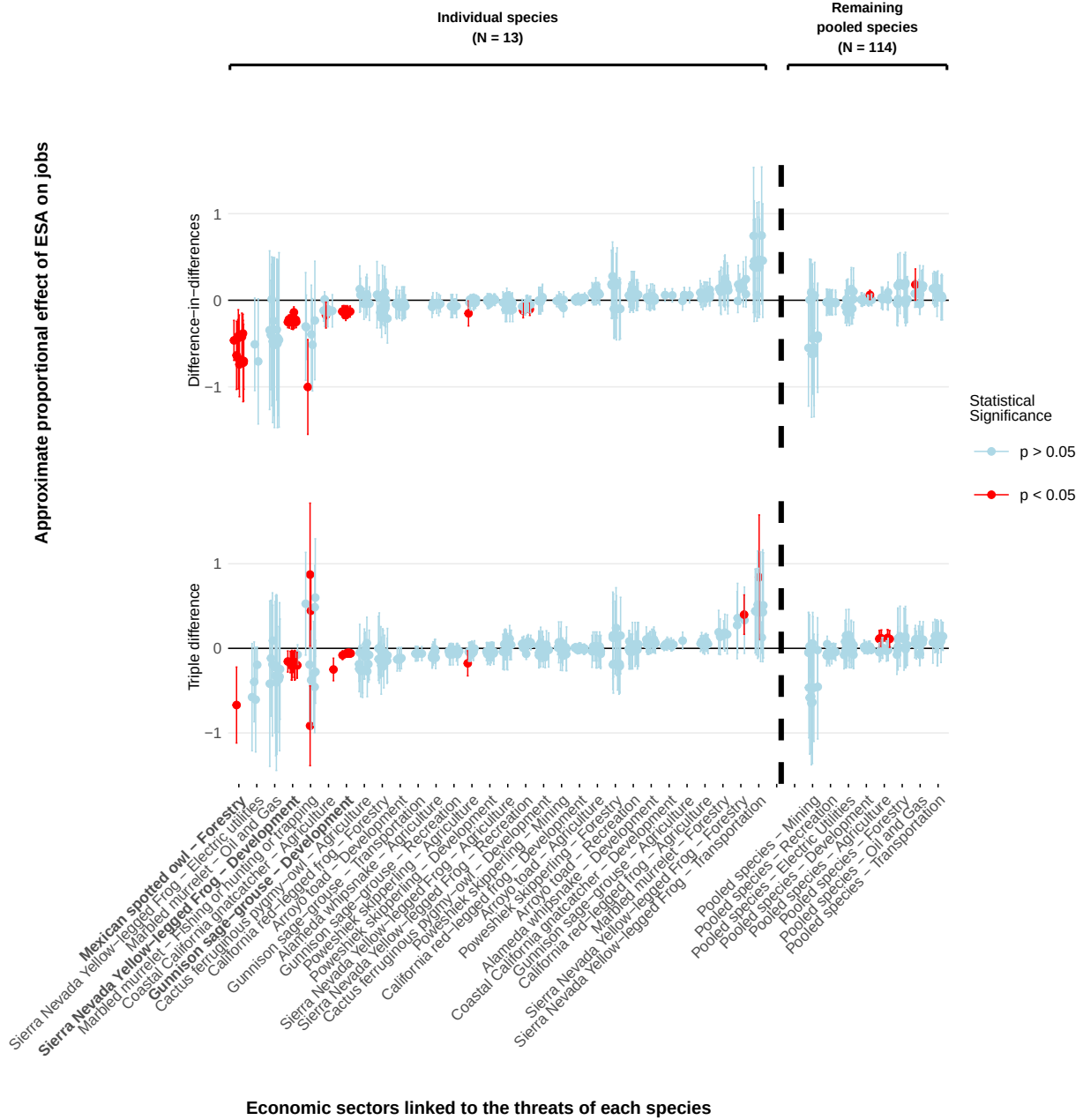
Notes: Distribution of estimated impacts of both regulatory layers of the ESA on local employment in affected ZCTAs plus all ZCTAs within a 10 km buffer of critical habitat. Species in **bold** represent statistically significant effects which are robust to a multitude of specifications. We remove statistically significant results which are not robust to violations in pretrend diagnostics. Because we redefine treatment as ZCTAs within 10 km of critical habitat, we remove additional confounding ZCTAs from other species in this approach, and one species-sector drops below our threshold of ≥ 20 treated ZCTAs in Analysis 1 and is included in the pooled species analysis of Analysis 2. [↪ Back to the Analysis 1-2 results section.](#)

Figure A13: All Focal Sectors Regardless of Threat Linkages



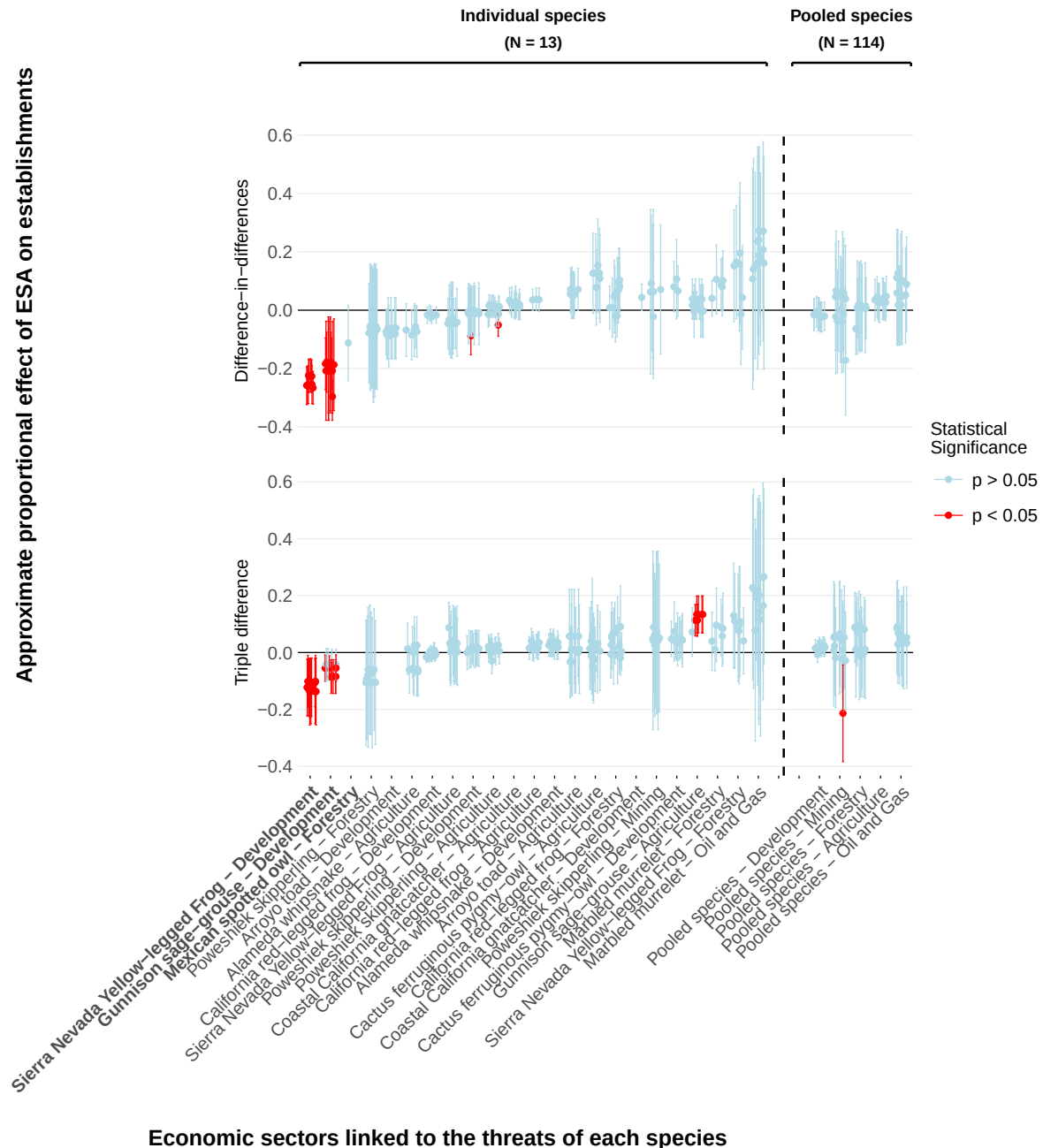
Notes: Distribution of estimated impacts of both regulatory layers of the ESA on local employment in affected ZCTAs, using all possible species-sectors among our five focal sectors, regardless of threat linkages. Species in **bold** represent statistically significant effects which are robust to a multitude of specifications. We remove statistically significant results which are not robust to violations in pretrend diagnostics. [↪ Back to the Analysis 1-2 results section.](#)

Figure A14: All Threat-Linked Sectors Beyond the Five Focal Sectors



Notes: Distribution of estimated impacts of both regulatory layers of the ESA on local employment in affected ZCTAs, using all species-sectors linked to species threat information beyond our five focal sectors. Species in **bold** represent statistically significant effects which are robust to a multitude of specifications. We remove statistically significant results which are not robust to violations in pretrend diagnostics. [↪ Back to the Analysis 1-2 results section.](#)

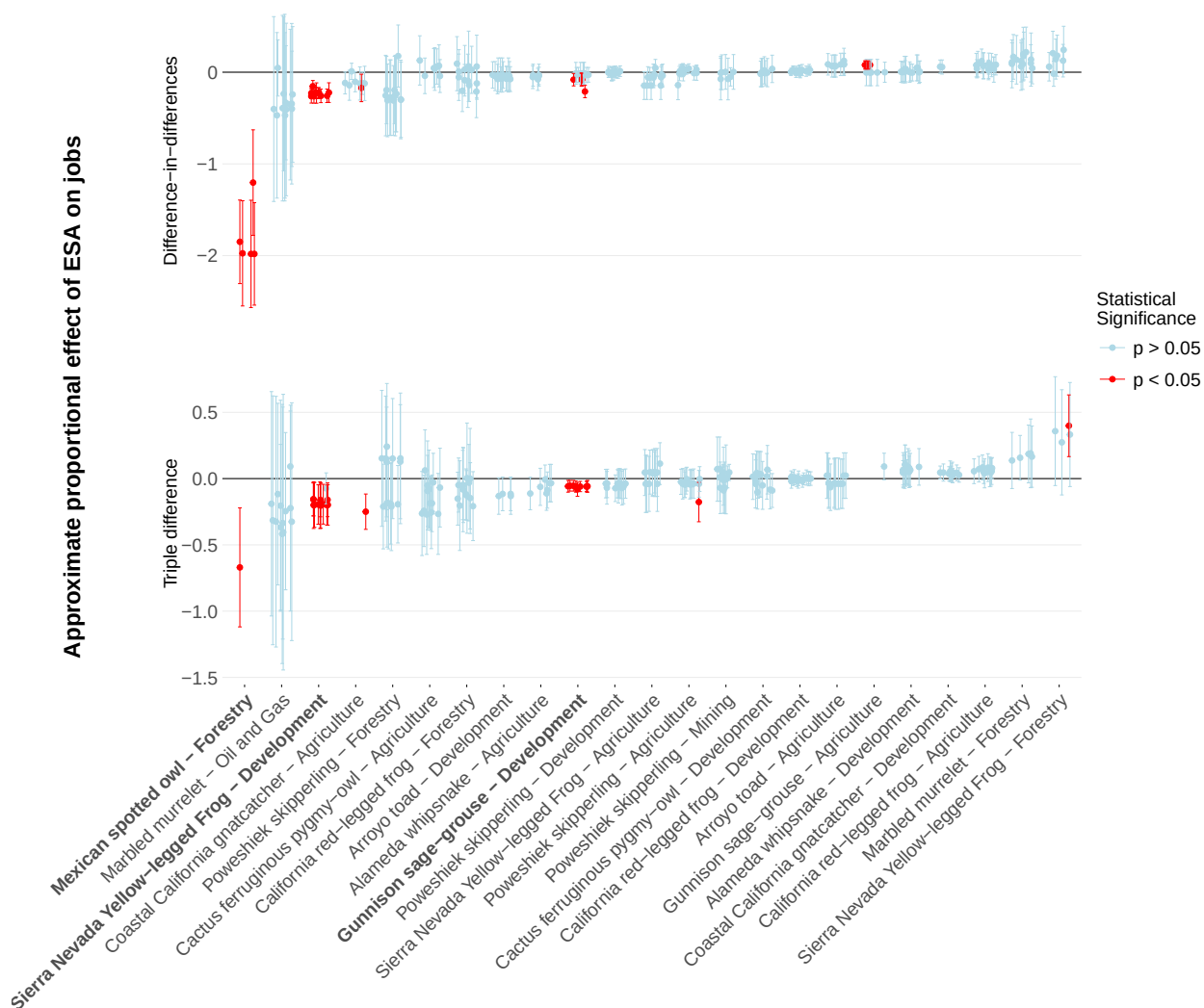
Figure A15: Number of Establishments as the Outcome Variable



Notes: Distribution of estimated impacts of both regulatory layers of the ESA on the number of establishments in affected ZCTAs, using establishments rather than employment as the outcome variable. Species in **bold** represent statistically significant effects which are robust to a multitude of specifications. We remove statistically significant results which are not robust to violations in pretrend diagnostics. [↪ Back to the Analysis 1-2 results section.](#)

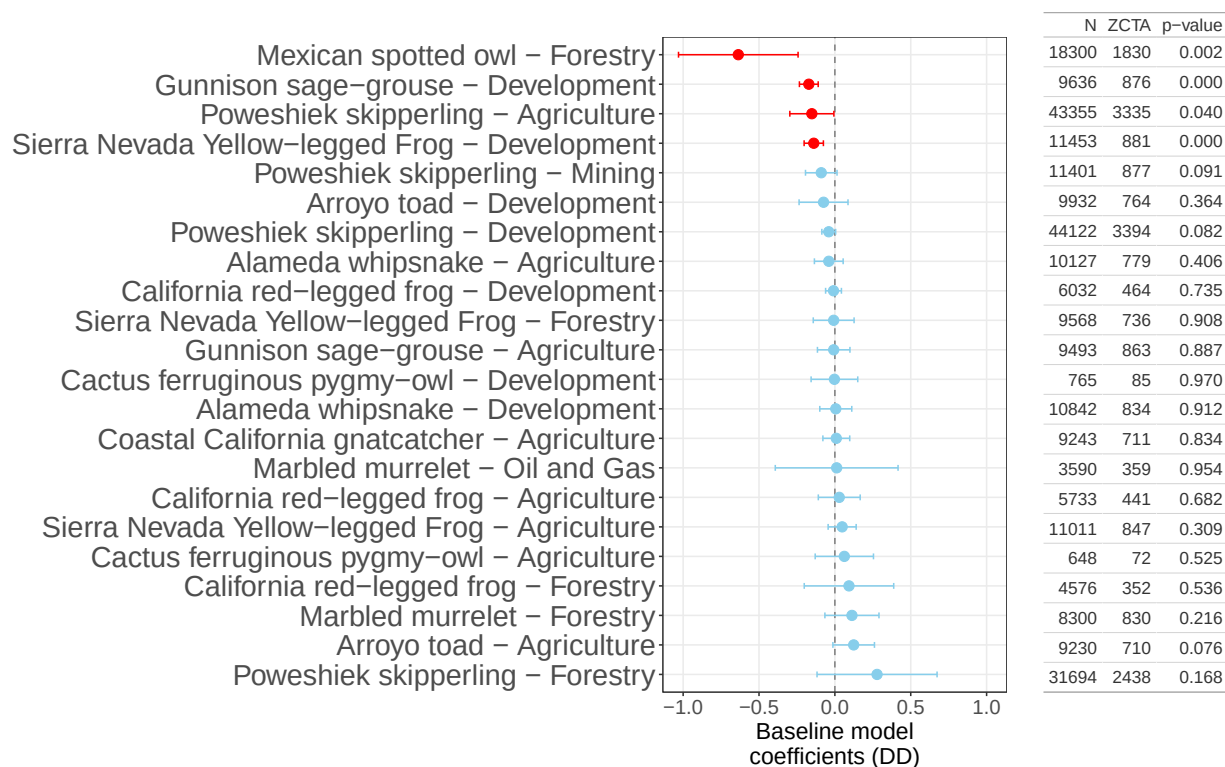
Robustness Checks: Individual Species

Figure A16: State-by-Year Fixed Effects



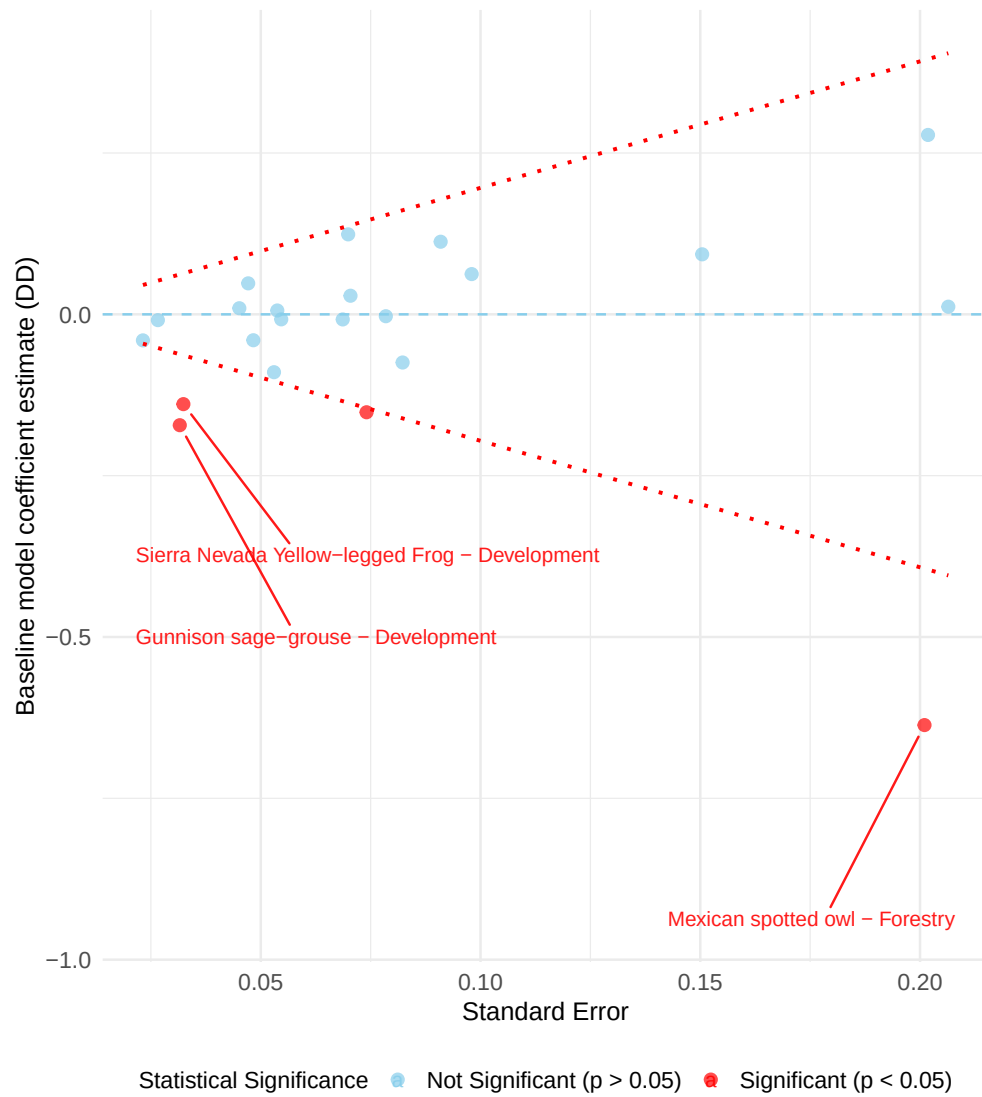
Notes: Distribution of estimated impacts of both regulatory layers of the ESA on jobs in affected ZCTAs, using state-by-year fixed effects instead of year fixed effects for the DD model of Analysis 1. This approach controls for unobserved time-varying confounders within each U.S. state. Species in **bold** represent statistically significant effects which are robust to a multitude of specifications. We remove statistically significant results which are not robust to violations in pretrend diagnostics. [↪ Back to the Analysis 1-2 results section.](#)

Figure A17: Baseline Model Estimates with Sample Sizes and p-values



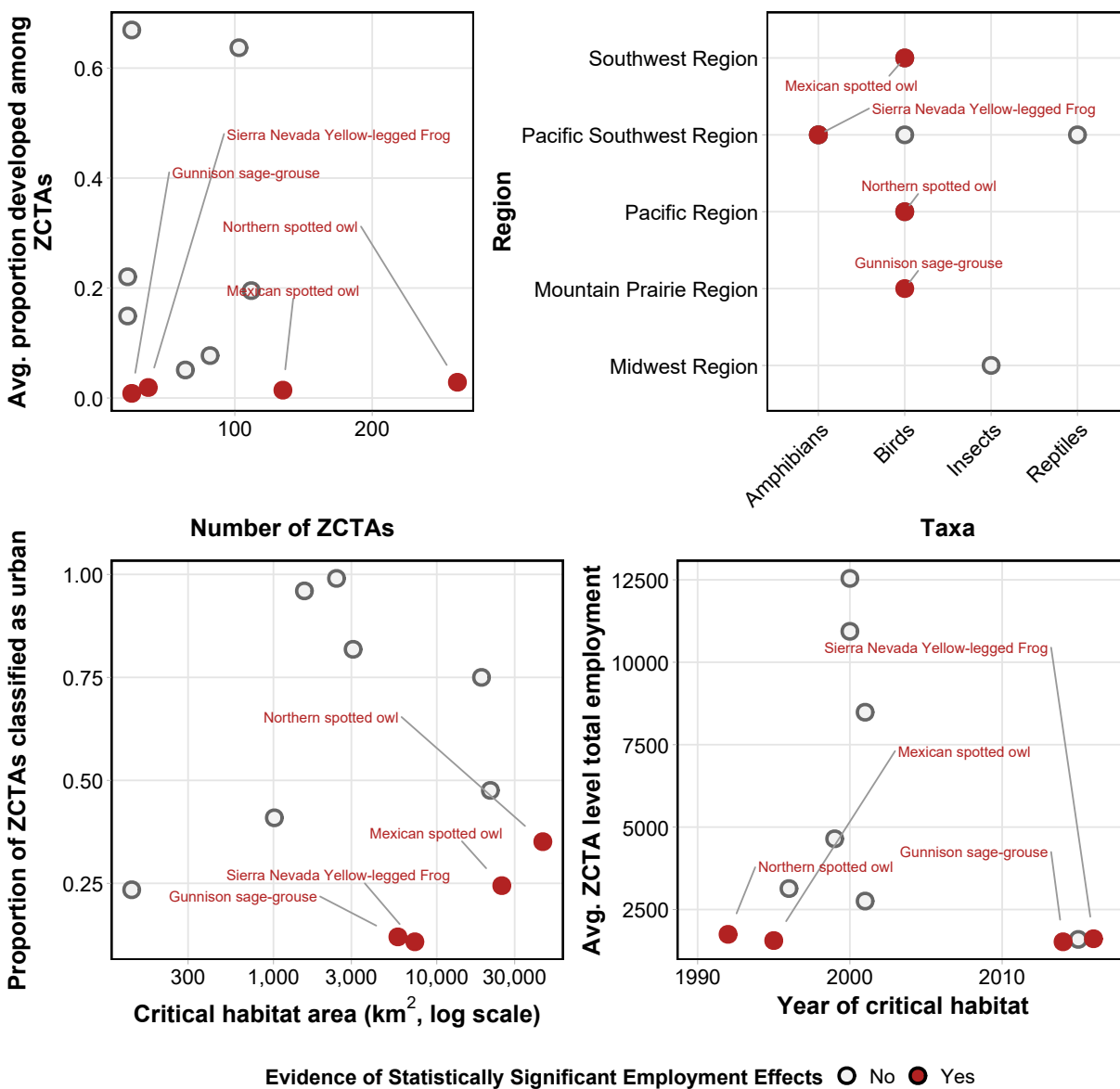
Notes: Distribution of estimated impacts of both regulatory layers of the ESA on local employment in affected ZCTAs from the baseline model for Analysis 1 (i.e., using the full control set of ZCTAs). We include the number of observations and p-values along with these estimated effects. We remove statistically significant results which are not robust to violations in pretrend diagnostics. [↔ Back to the Analysis 1-2 results section.](#)

Figure A18: Coefficients Versus Standard Errors from the Baseline Model



Notes: Coefficients from the baseline model (i.e., using the full control set of ZCTAs) plotted against their standard errors. Lines indicate regions of statistical significance at an alpha level of 0.05. We remove statistically significant results which are not robust to violations in pretrend diagnostics. [↔ Back to the NETS appendix section.](#) [↔ Back to the Analysis 1-2 results section.](#)

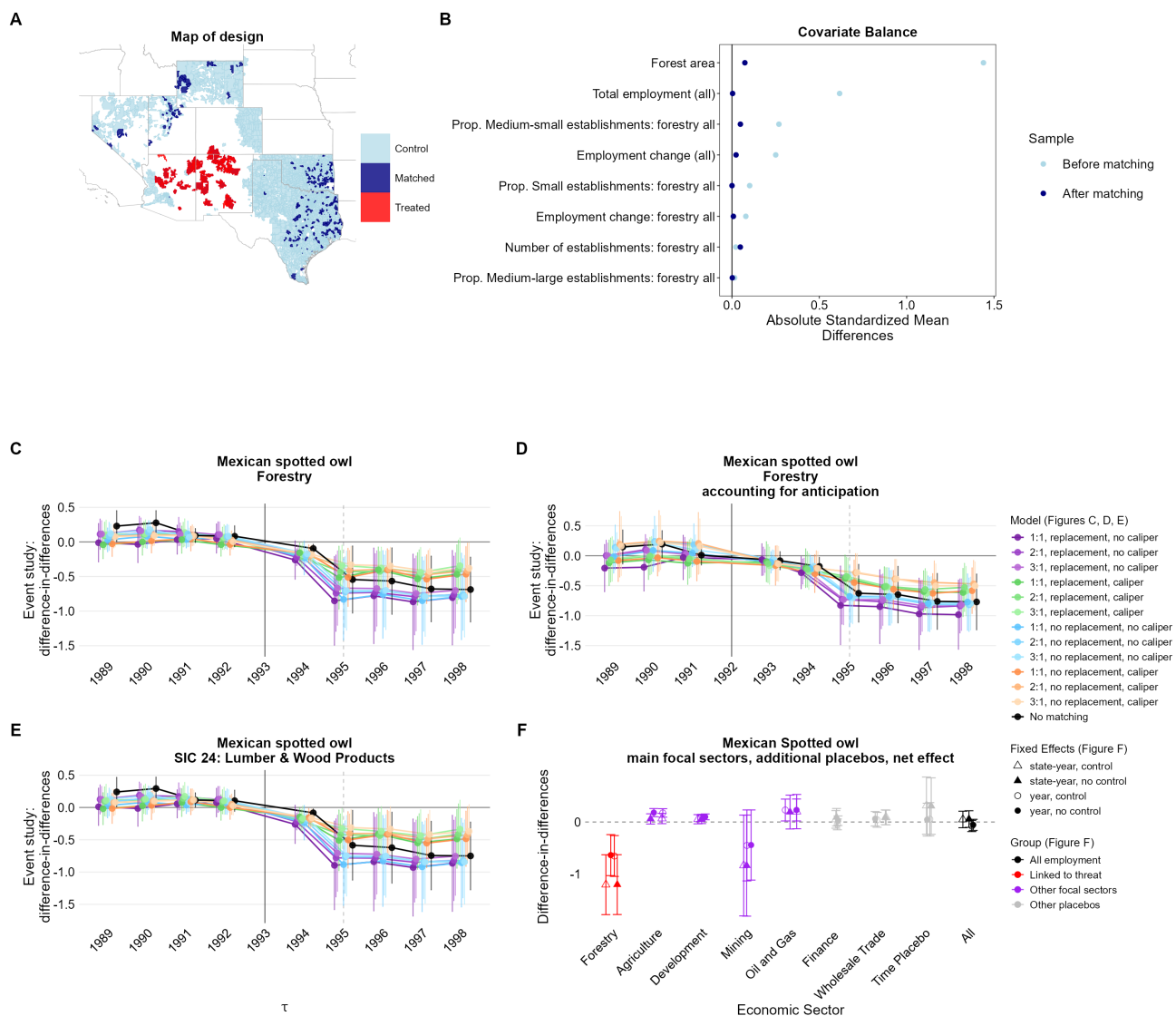
Figure A19: Species Characteristics by Statistical Significance of Effects



Notes: Examples of characteristics associated with individual species for which we did and did not recover statistically significant effects on local labor markets, along with the effect found in Ferris and Frank (2021) for the northern spotted owl. Pooled species-sectors are excluded. → [Back to the Analysis 1-2 results section.](#)

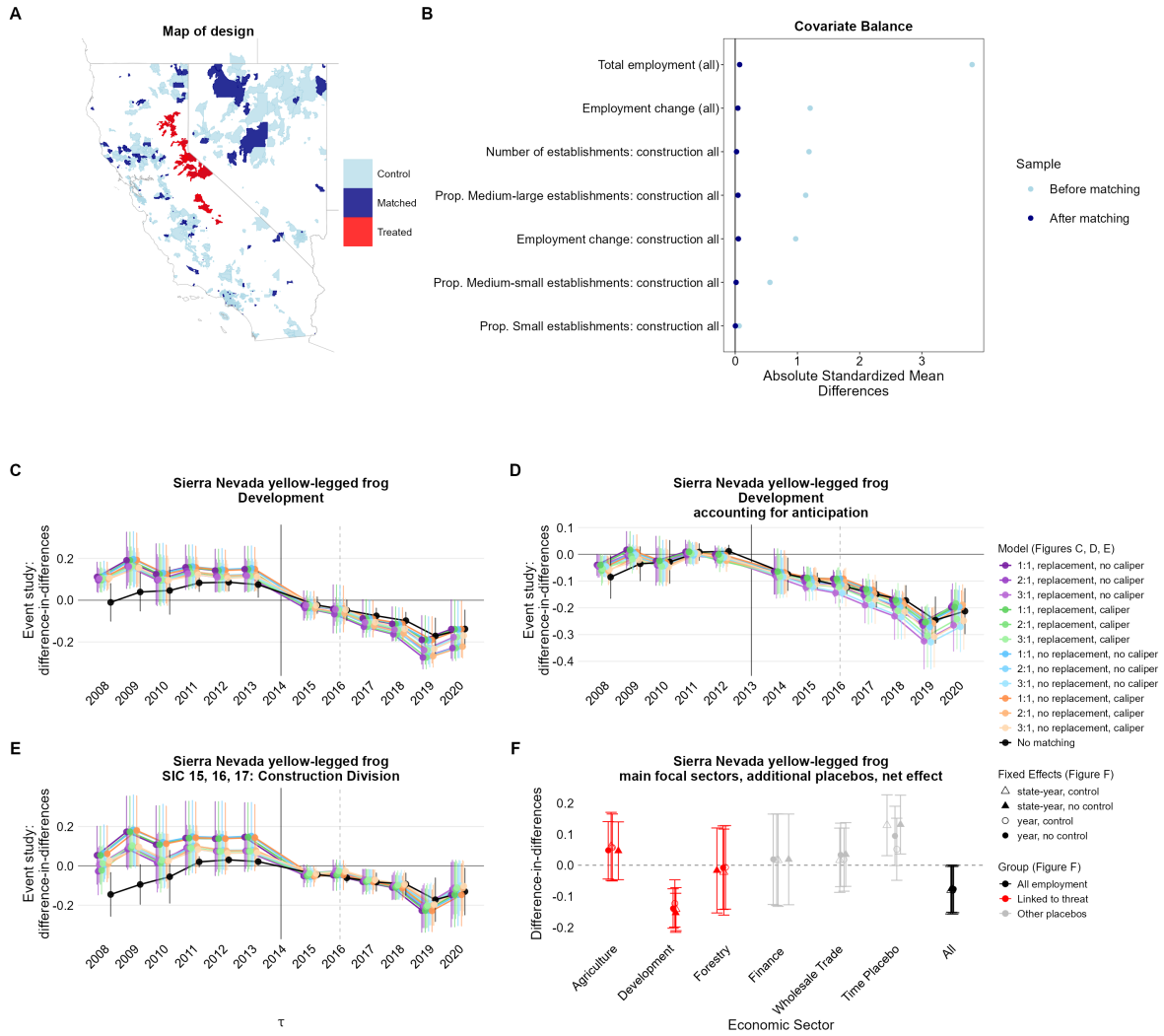
Statistically Significant Species-Sectors

Figure A20: Mexican Spotted Owl – Forestry



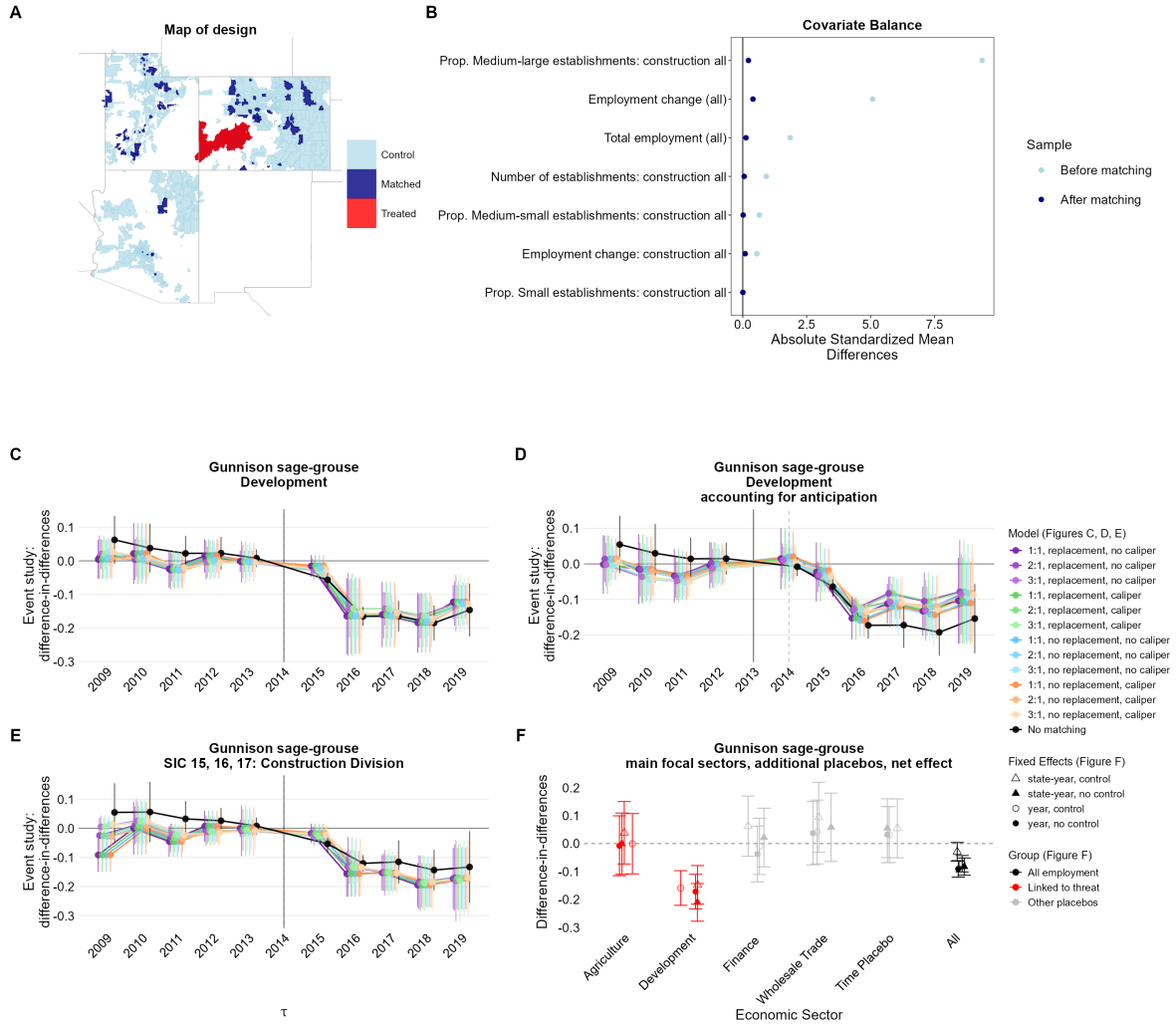
Notes: Additional results for the statistically significant effect of ESA regulations for the Mexican spotted owl on the forestry sector in Analysis 1. We present a map of the design (Panel A), covariate balance with matching (B), event study (C), event study with one-year lag in treatment (D), event study using SIC division classification for employment (E), and DD coefficients from the baseline model for focal sectors, additional DD placebos, and total employment (F). [↔ Back to the Analysis 1-2 results section.](#)

Figure A21: Sierra Nevada Yellow-Legged Frog – Development



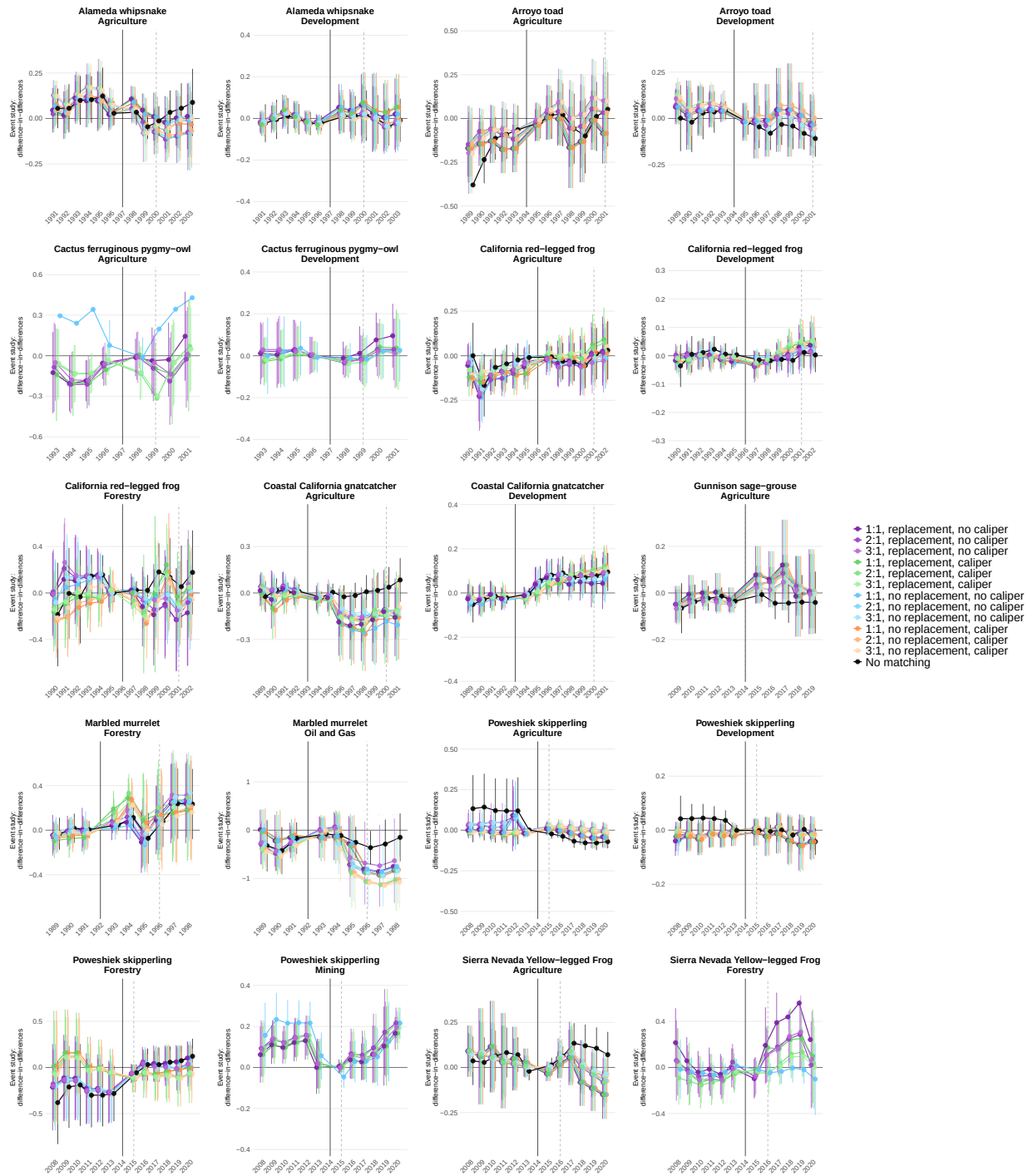
Notes: Additional results for the statistically significant effect of ESA regulations for the Sierra Nevada yellow-legged frog on the development sector in Analysis 1. We present a map of the design (Panel A), covariate balance with matching (B), event study (C), event study with one-year lag in treatment (D), event study using SIC division classification for employment (E), and DD coefficients from the baseline model for focal sectors, additional DD placebos, and total employment (F). Some sectors have too few treated ZCTAs with any variation (e.g., oil and gas) and are thus omitted from Panel F. [↪ Back to the Analysis 1-2 results section.](#)

Figure A22: Gunnison Sage-Grouse – Development



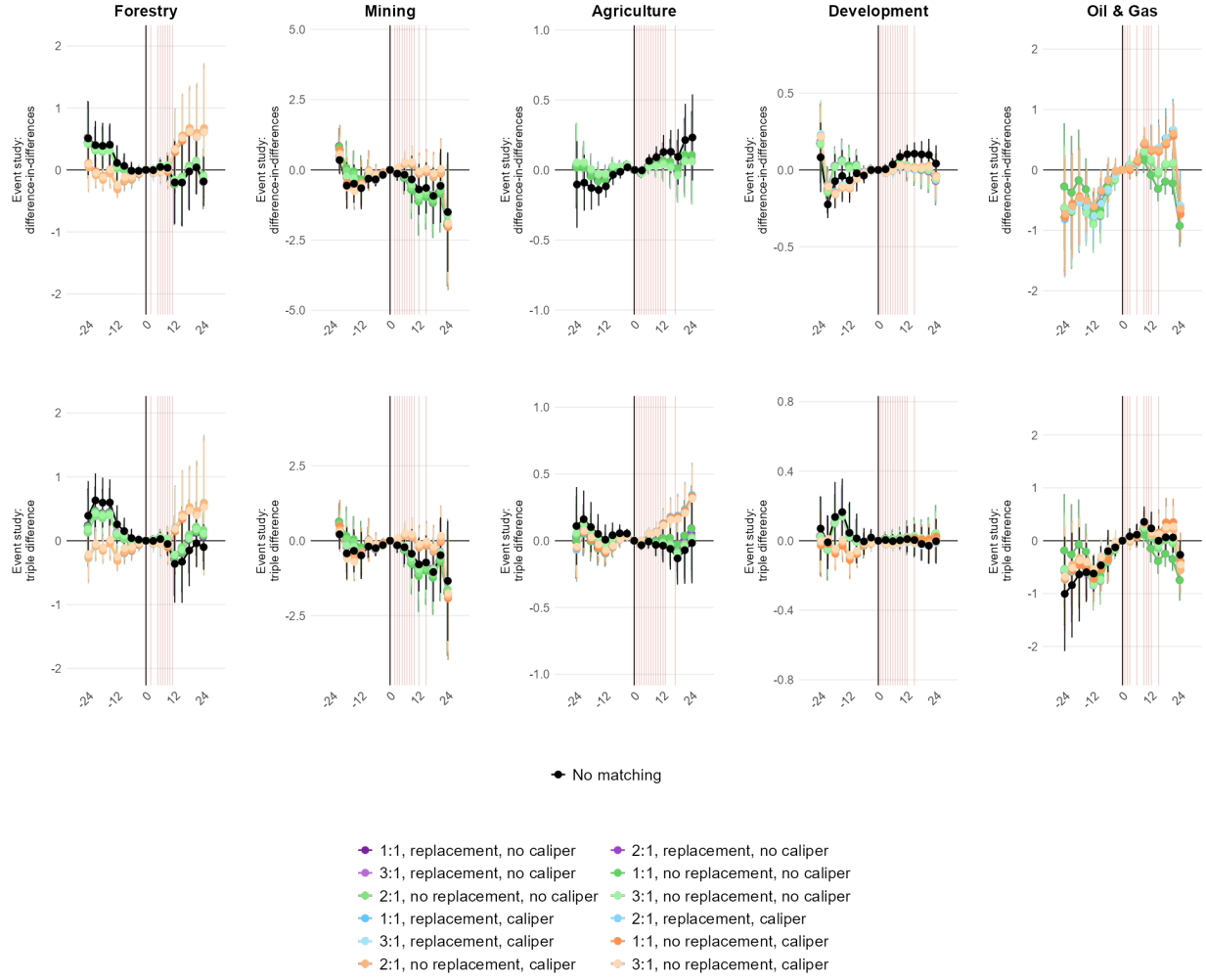
Non-statistically Significant Individual Species

Figure A23: Event Studies for Statistically Insignificant Individual Species-Sectors



Notes: Event studies for all coefficients presented in Figure 4 among individual species-sectors with statistically insignificant effects in Analysis 1. [↪ Back to the Analysis 1-2 results section.](#)

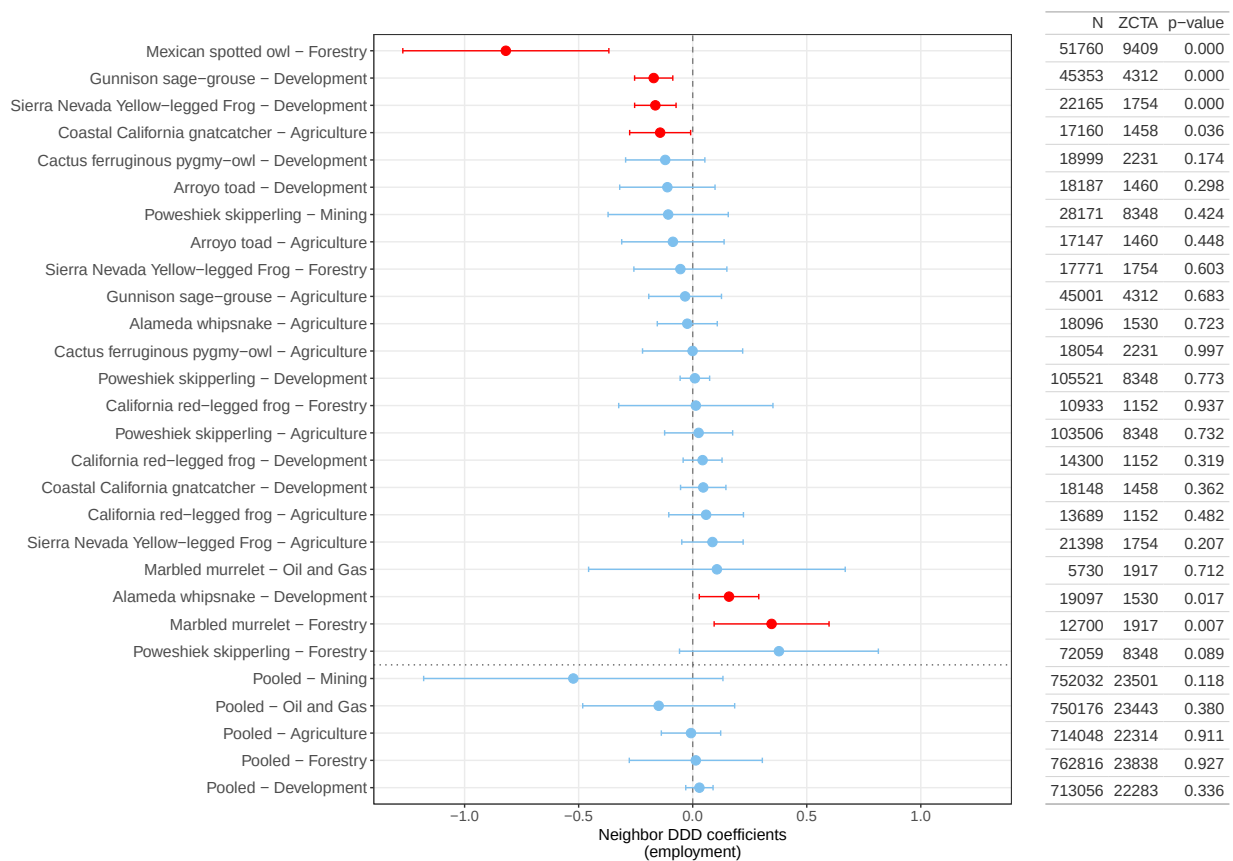
Figure A24: Event Studies for Pooled Species-Sectors



Notes: Event studies for all coefficients presented in Figure 4 among pooled species-sectors of Analysis 2. Red lines indicate ensuing critical habitat designations among focal species in the pooled analysis, after their listings (treatment). We remove statistically significant results which are not robust to violations in pretrend diagnostics. [↪ Back to the Analysis 1-2 results section.](#)

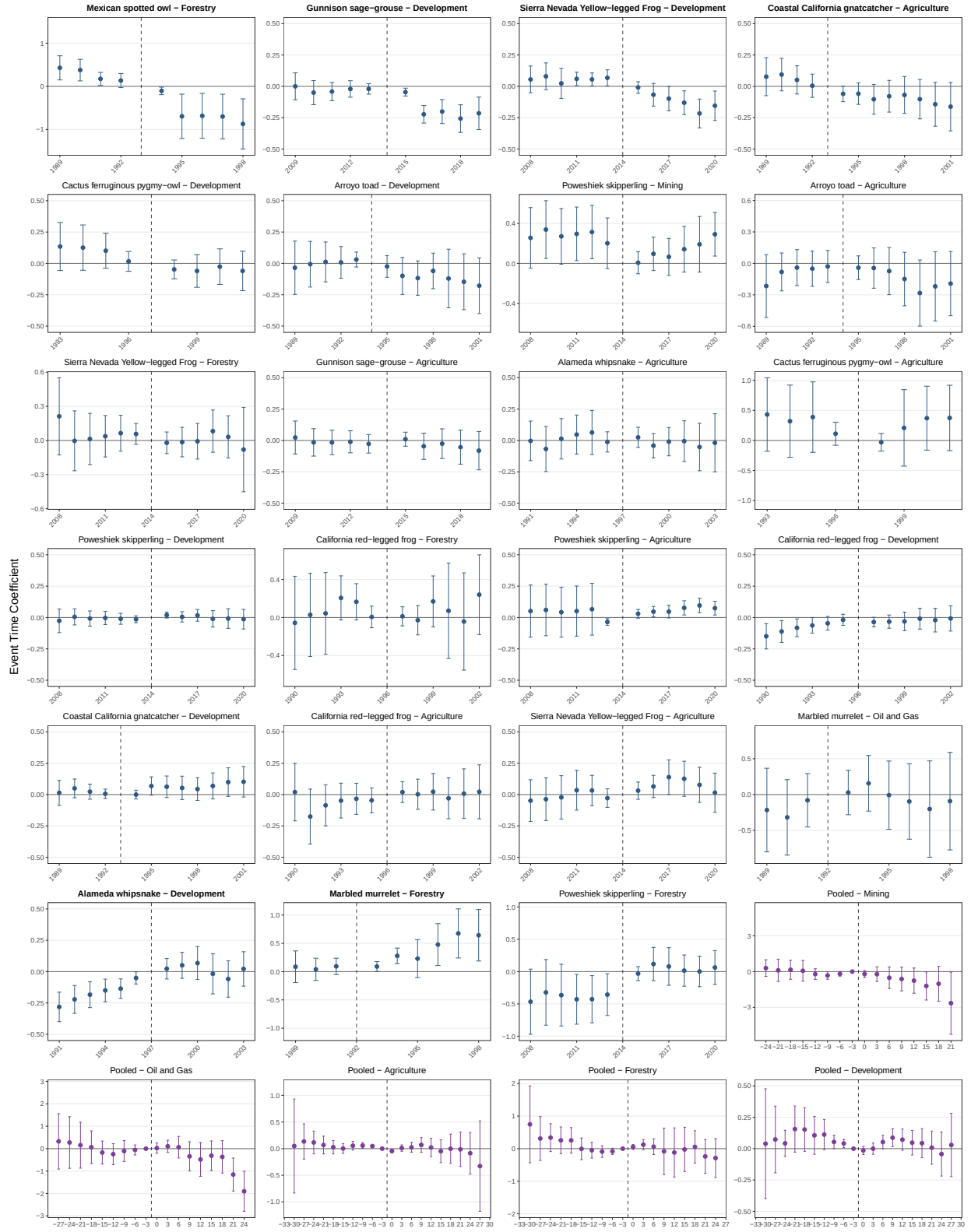
Additional Falsification: Same Sector DDD

Figure A25: Neighboring-State DDD Estimates by Species-Sector



Notes: Estimated effects ($\hat{\delta}^{DDD}$) on employment in threat-linked sectors for our individual species and pooled analyses using the neighboring-state, pseudo-treatment DDD approach. [↪ Back to the Analysis 1-2 results section.](#)

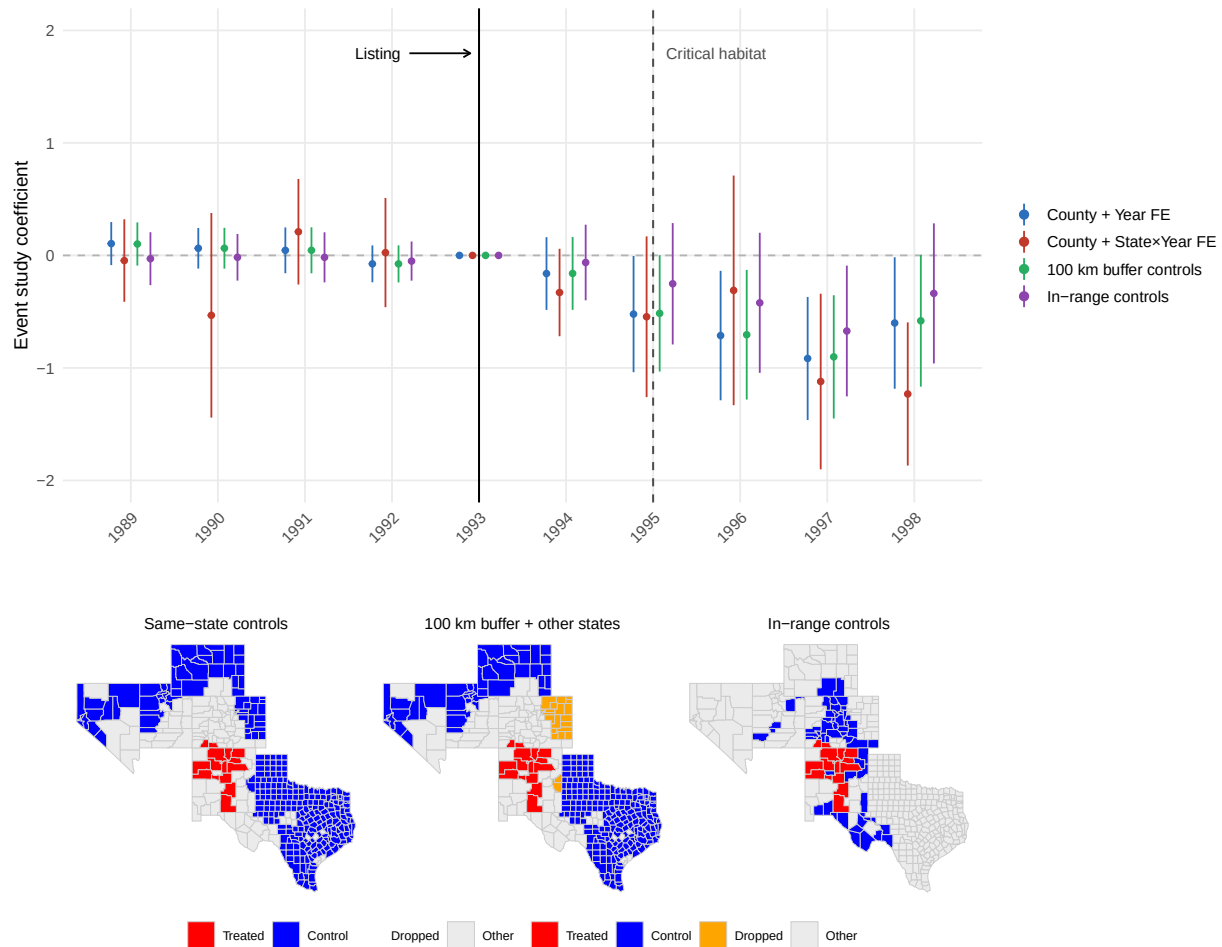
Figure A26: Neighboring-State DDD Event Studies by Species-Sector



Notes: Event study coefficients for dynamic employment effects of ESA regulations on threat-linked sectors for our individual species and pooled analyses using the neighboring-state, pseudo-treatment DDD approach. [↔ Back to the Analysis 1-2 results section.](#)

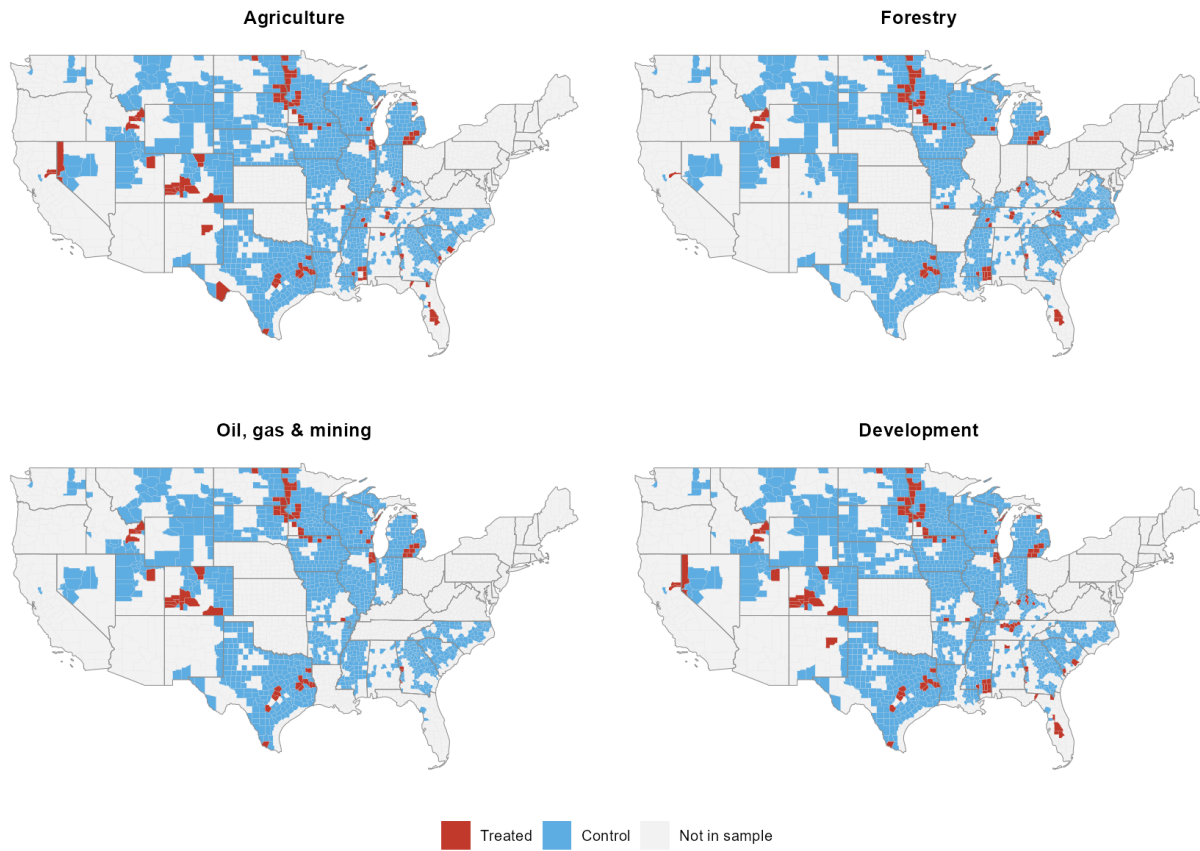
County-Level Analysis

Figure A27: Mexican Spotted Owl: County-Level Analysis



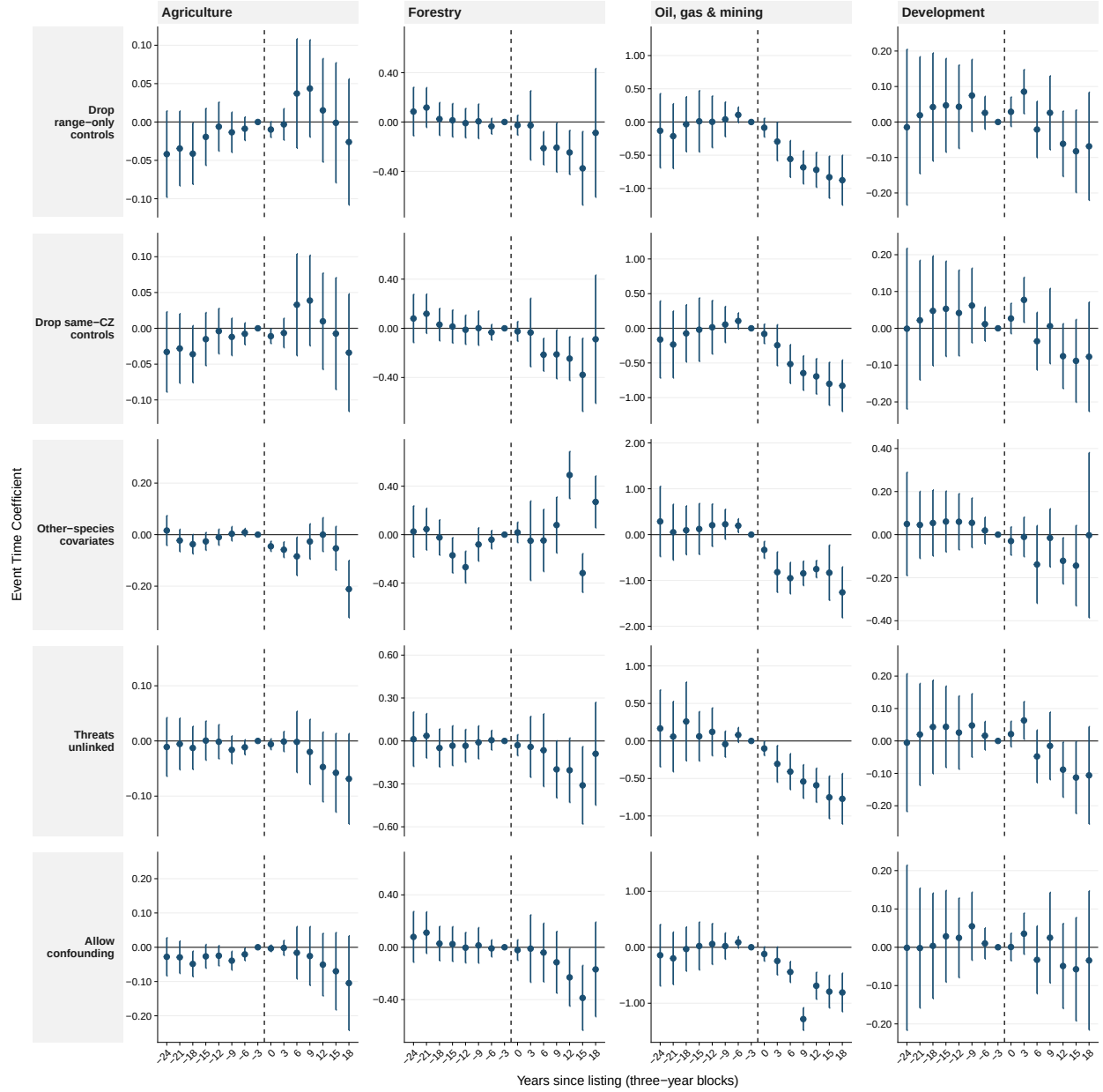
Notes: Event study coefficients from the Poisson TWFE model, estimating dynamic impacts of the ESA listing and ensuing critical habitat designation of the Mexican spotted owl on local forestry employment (top panel). Effects are estimated for the three control groups visualized in the bottom panel, plus a specification using state-by-year instead of year fixed effects for the same-state controls model. Bars are 95% confidence intervals, clustered by county. [↪ Back to the county-level results section.](#)

Figure A28: County-Level Treated and Control Units



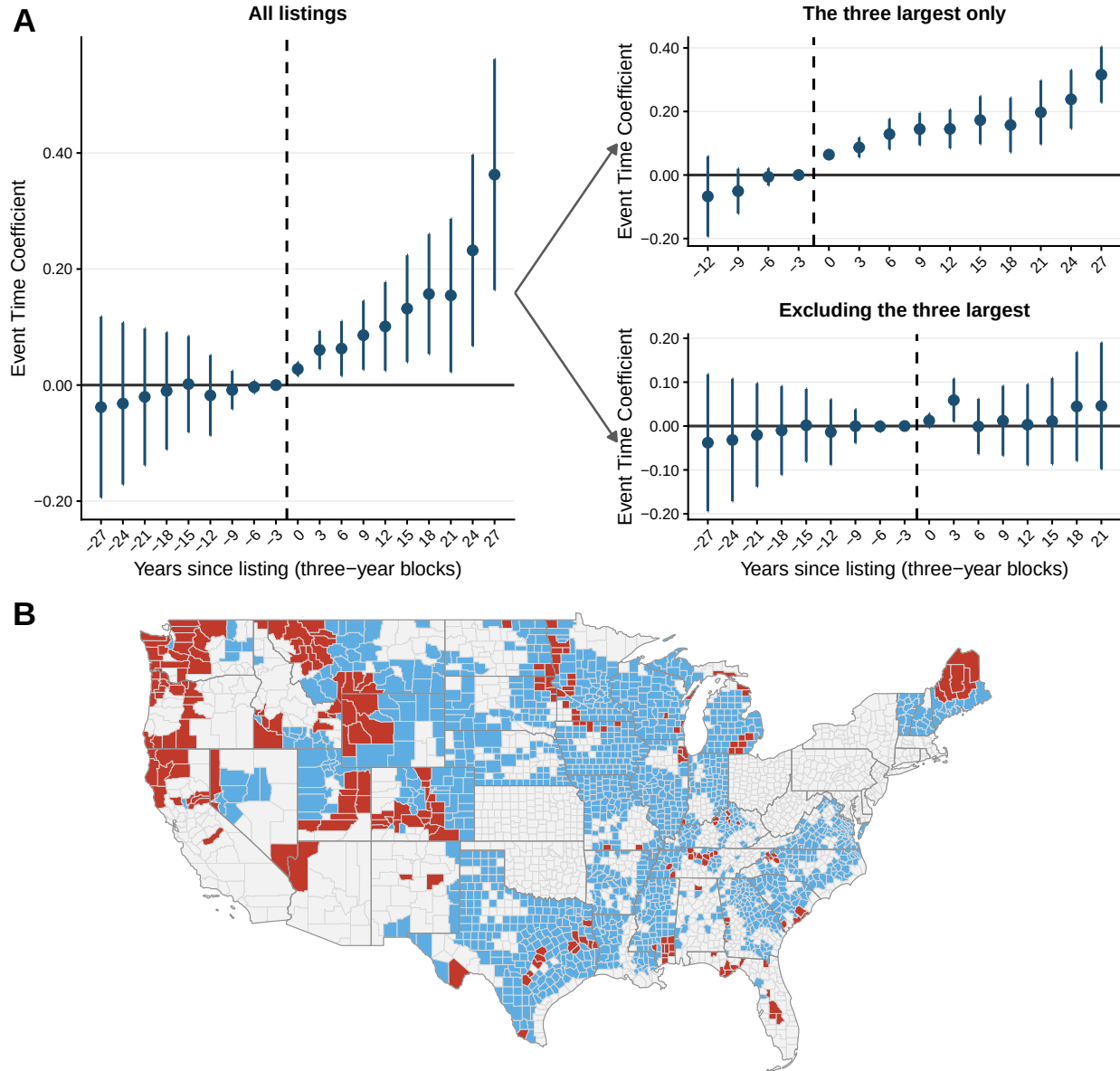
Notes: Treated counties (red) are those in which at least one focal species was linked via LLMs to the focal sector. Candidate control counties (blue) are never-treated counties in the same states as the species range. The baseline specification drops all counties within these species ranges as well. [↪ Back to the county-level results section.](#)

Figure A29: Employment Event Studies Across Sectors and Specifications



Notes: Event study coefficients and 95% confidence intervals for employment in agriculture, forestry, oil, gas and mining, and development (columns) under five specifications (rows): dropping range-only controls, dropping same-commuting-zone controls, adding other-species covariates, unlinking threats from sectors, and allowing confounding designations. Controls are never-treated counties. Event time is measured in three-year blocks relative to listing; the dashed line marks the last pre-treatment block. The longest lead and lag are omitted from each panel, as each is identified off a single cohort. The vertical axis is scaled independently in each panel and centred on zero. → [Back to the county-level results section.](#)

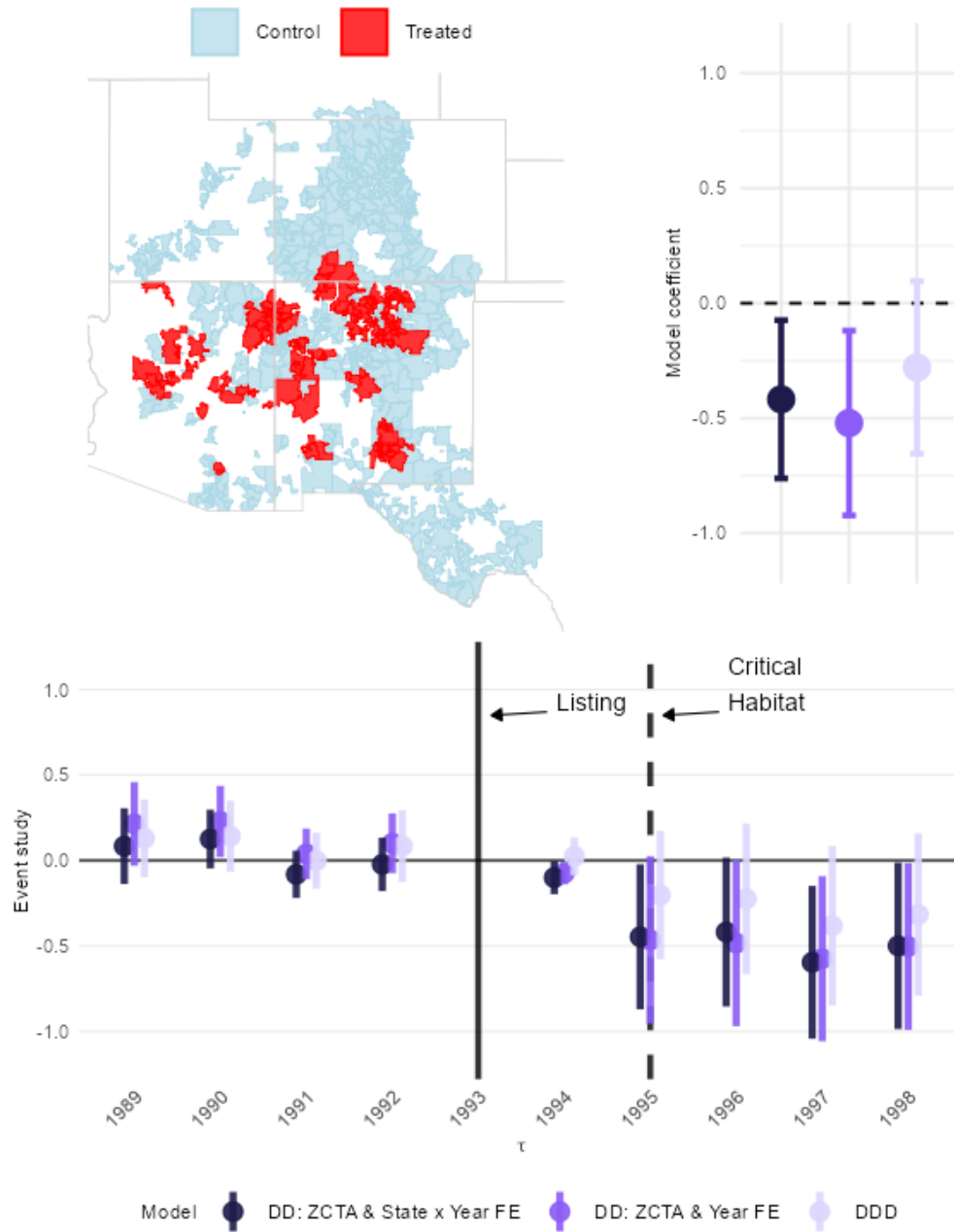
Figure A30: Total Employment Event Study, Decomposition, and Treated Areas



Notes: Panel A shows event study coefficients and 95% confidence intervals for total county employment when pooling all species with ESA listings and critical habitat designations (including non-initial designations) over the timeframe of the analysis. The decomposition estimates effects on two samples: species with uncharacteristically large treated areas (Canada lynx, Mexican spotted owl, and northern spotted owl) and all other species. All event studies show some sign of upward relative trends in employment before treatment, such that post-listing increases in employment cannot be interpreted causally. Panel B shows the total employment estimation sample: treated counties in red, never-treated control counties in blue. [↪ Back to the county-level results section.](#)

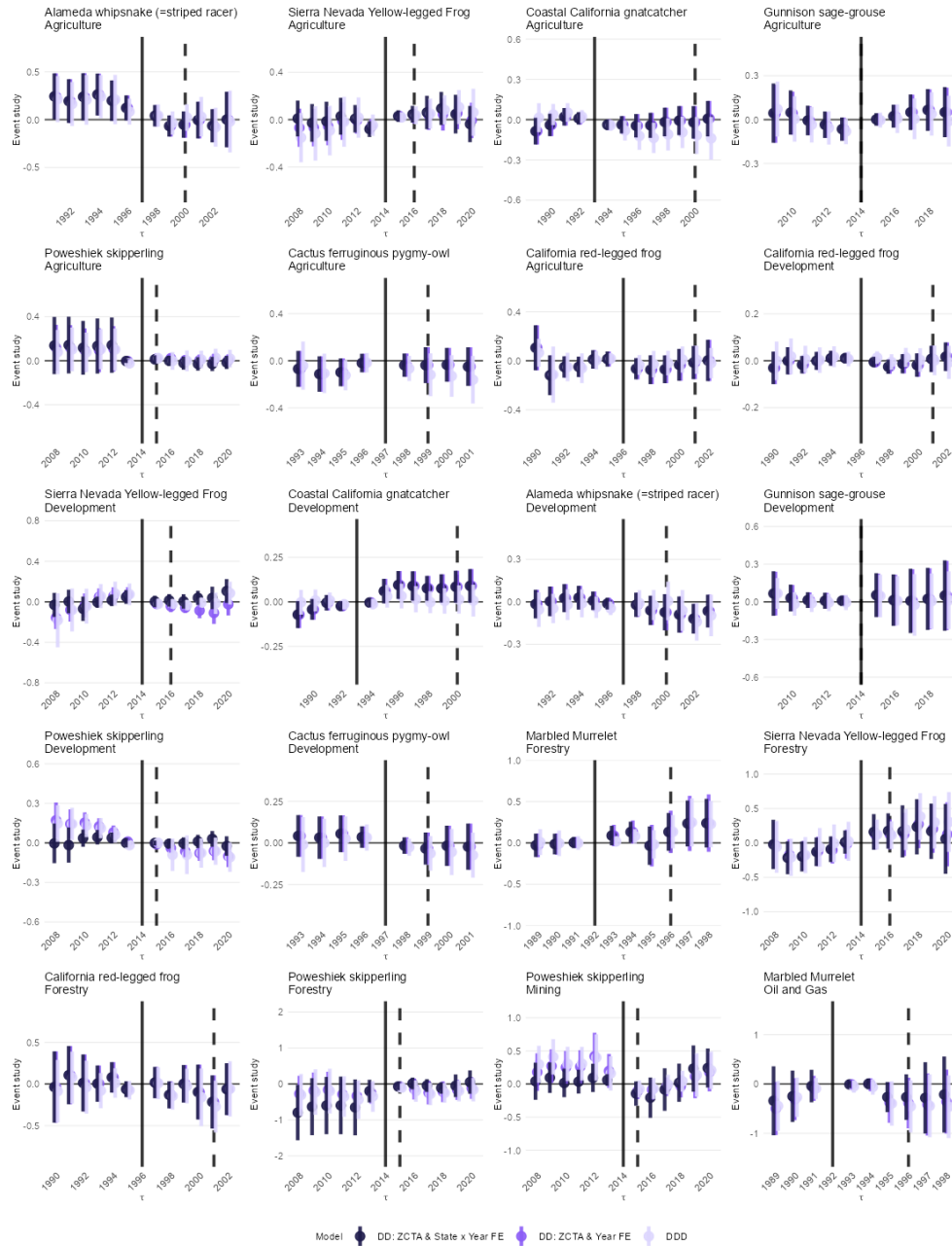
Critical Habitat Above-and-Beyond Listing Rule

Figure A31: Mexican Spotted Owl – Forestry: Critical Habitat Above and Beyond Listing



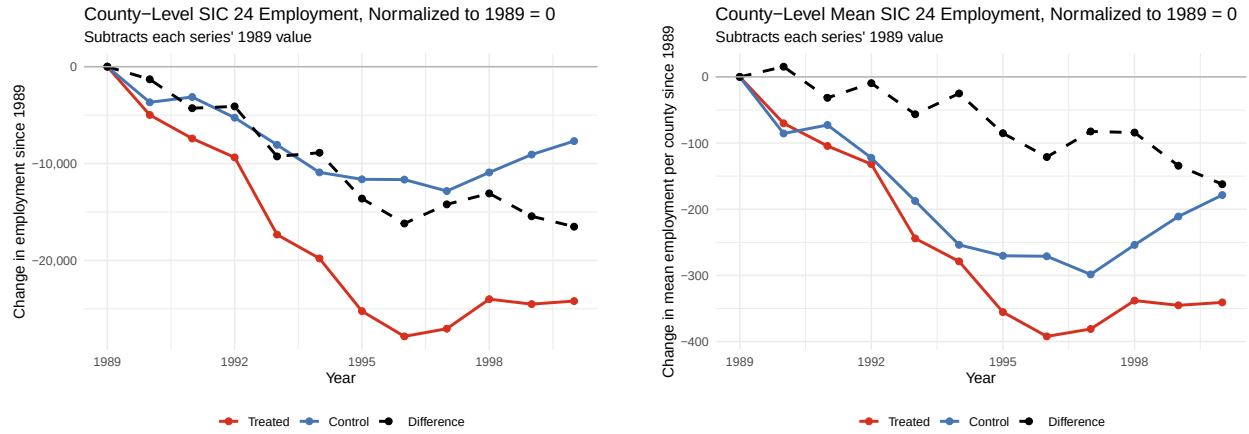
Notes: Map of the design, coefficients from the DD and DDD models, and associated event studies for the Mexican spotted owl in the forestry sector, using the range area as the control group. [↪ Back to the results section.](#)

Figure A32: Remaining Event Studies: Critical Habitat Above and Beyond Listing



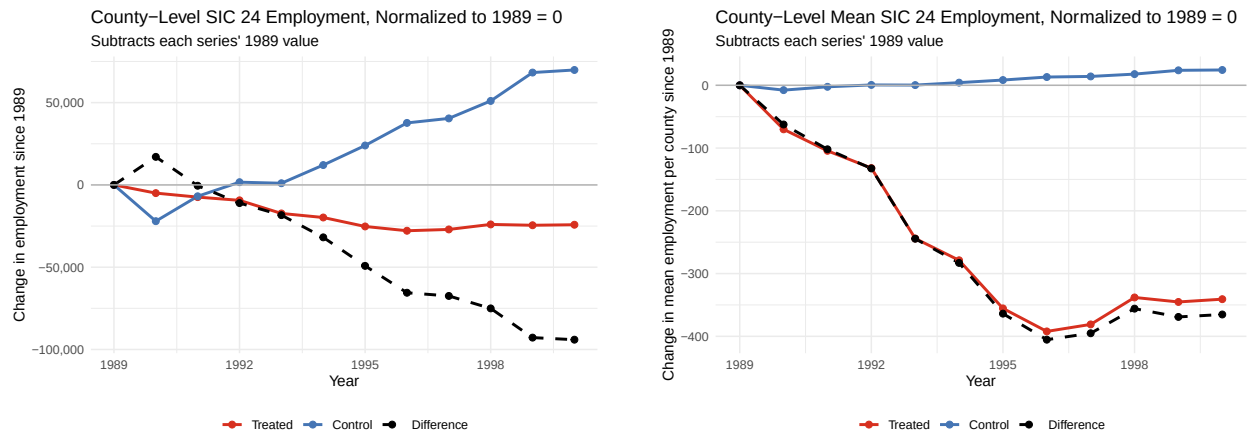
Notes: Remaining event studies for species and their threat-linked economic sectors, estimating the effects of critical habitat on employment above and beyond the listing rule. [↔ Back to the results section.](#)

Figure A33: NETS Comparison to Regional Control Counties from Ferris and Frank (2021)



Notes: Time series comparison of treated counties to the regional control group from Ferris and Frank (2021) using NETS data for SIC 24. Each panel normalizes total (left) and mean (right) SIC 24 employment to the year 1989 and visualizes the differential trends in these outcomes. → [Back to the NETS appendix section.](#)

Figure A34: NETS Comparison to National Control Counties from Ferris and Frank (2021)



Notes: Time series comparison of treated counties to the national control group from Ferris and Frank (2021) using NETS data for SIC 24. Each panel normalizes total (left) and mean (right) SIC 24 employment to the year 1989 and visualizes the differential trends in these outcomes. → [Back to the NETS appendix section.](#)