Canaries in the Coal Mine: Firm Response to Biodiversity Policy Risk *

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Abstract

We study whether firms respond to local biodiversity policy risk and whether those adjustments spill over to other regions through their plant networks. Using a novel measure that links endangered species habitats to firm establishments, we find that a conservation-oriented policy announcement leads exposed firms to cut toxic releases and reduce presence in ecologically sensitive areas. Importantly, these changes improve local vegetation and bird diversity. However, firms reallocate production and toxic releases to non-sensitive areas, though this reallocation is imperfect. Thus, while conservation policy improves priority habitats, it may simultaneously intensify environmental harm in regions not covered by protections.

Keywords: Biodiversity Policy, Reallocation, Toxic Releases, Endangered Species, Ecological Outcomes

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I. Introduction

Biodiversity underpins essential ecosystem services including pollination, water purification, and climate regulation, and its continued erosion[1] is expected to impose substantial economic costs–estimates suggest a reduction in global GDP of more than 2% per year by 2030 (Johnson et al., 2021). Recognizing these risks, governments and international bodies are increasingly proposing and adopting biodiversity protection measures, such as land-use restrictions, habitat restoration programs, and conservation finance mechanisms. The most prominent example is the "30 by 30" initiative with the goal of conserving 30% of the planet's land and oceans by 2030 ("30 by 30") (Dinerstein et al., 2019) which the United States joined the effort in 2021 via Executive Order 14008.[2]

Although prior work shows that investors price firms' biodiversity regulatory risk (Garel et al., 2024; Xiong, 2023; Coqueret et al., 2025), far less is known about how firms respond to these risks. Moreover, the existing literature neglects the inherently spatial nature of biodiversity risks and instead focuses on firm-aggregate output measures. Instead, we argue that financial materiality stems from a firm's proximity to endangered biodiversity and its operations in habitats likely to face regulations. This perspective is natural given that frameworks such as the Endangered Species Act (ESA) are geographic in design: endangered species are listed, critical habitats are designated, and federal agencies restrict activities that may damage those locations.[3]

Using the introduction of "30 by 30" in the United States as a policy shock, we study

[1] Extinction rates are now estimated to be 10–100 times higher than the historical baseline over the past 10 million years (Marques et al., 2019).

[2] Subsequent initiatives under the Biden administration, including the Infrastructure Investment and Jobs Act, Executive Order 14072, the Bureau of Land Management's 2024 Public Lands Rule, and the Inflation Reduction Act, further allocated substantial resources to biodiversity-related initiatives.

[3] Ecologically sensitive areas are widely recognized as priorities for conservation policy (Carroll and Noss, 2022; Pulido-Chadid et al., 2023; Allan et al., 2022).

whether firms reallocate their toxic releases in response to heightened biodiversity conservation risk and examine the real spillover effects of these adjustments. Our spatial approach allows us to assess how firms respond in ecologically sensitive areas, whether firms shift pollution to less exposed plants in the firm's internal network, and whether such responses benefit biodiversity in the most vulnerable areas. In doing so, our study sheds light on how firms interact with their local ecological environment when faced with land-conservation regulations, and provides evidence relevant to policymakers for evaluating the effectiveness of conservation policy.

To define ecologically-sensitive areas, this paper introduces a novel, spatially based measure of exposure to endangered biodiversity areas lacking formal protections. The measure adapts tools from the environmental science literature to finance, building on Hamilton et al. (2022), who combine information on species rarity, habitat range, and existing legal protections to construct Protection-Weighted Range-Size Rarity (PWRSR) scores for every 990m $\times$ 990m grid in the U.S.[4] They further classify grid cells meeting a PWRSR threshold as Areas of Unprotected Biodiversity Importance (AUBIs). We extend this by linking AUBI areas to establishment-level data from Dun & Bradstreet[5] and the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI).

We validate that our measure captures biodiversity policy risk by examining its effects in financial markets. Firms with high AUBI exposure in locally nature-dependent sectors exhibit significantly higher implied volatility following the launch of "30 by 30."' In addition, long–short portfolios that buy high-exposure firms and short low-exposure firms earn

[4]For each grid cell and each of 2,216 endangered species, they assess the likelihood of presence, weight it by the species' total habitat size and degree of protection, and then aggregate across species to obtain a PWRSR score.

[5]Firm-level exposure measure calculated by aggregating across establishments using employment weights.

negative cumulative abnormal returns (CARs) after EO 14008—an effect that reverses following the 2024 election.[6] These results are reassuring: the firms most dependent on local natural resources and most exposed to endangered, unprotected biodiversity experience the strongest adverse market reaction. Investors therefore perceive conservation-oriented policy as detrimental to expected firm performance, with substantial heterogeneity linked to spatial exposure.

Using detailed data on plant-level production, toxic releases, and abatement activities from the EPA's TRI merged with our biodiversity measures,[7] we show that firms adjust their behavior in response to anticipated conservation policy. Relative to less exposed facilities, those in unprotected, endangered areas report significantly lower toxic releases following the launch of "30 by 30" in 2021. Using a difference-in-differences approach, we find a one–standard deviation increase in PWRSR is associated with a 1.4% decline in total toxic releases at the facility level in the post-announcement period. Our dynamics demonstrate no pre-trends and our specifications include facility-by-chemical fixed effects, parent company-by-chemical-by-year fixed effects, and state-by-chemical-by-year fixed effects to control for time-invariant facility characteristics, firm-specific shocks, and local policy or economic trends.

Our economic hypothesis is that, anticipating that toxic releases near endangered biodiversity may attract regulatory action, firms engage in reallocations emissions away from sensitive areas. Profit-maximizing firms can do this through two broad channels: (i) facility-level source reduction and (ii) reallocation, either within a facility or across the firm's network of establishments.

[6] Returns are adjusted for the Fama–French four factors and a green-minus-brown factor (Pástor et al., 2022).

[7] Our primary dataset covers 14,313 manufacturing facilities operated by 4,143 firms from 2018 to 2024.

At the facility level, firms may lower production, invest in abatement technologies, or improve waste-treatment abilities. While these mechanisms reduce toxic releases for a given unit of output, they also impose short-run economic costs. Consistent with this, we find that a one–standard deviation increase in PWRSR is associated with a 1.2% decline in facility production, but no evidence of investment in abatement or waste treatment. We view this pattern as validating: "30 by 30"–and most biodiversity-oriented policies under the Biden administration—relies on monitoring and conservation incentives rather than punitive regulation. Firms therefore appear reluctant to undertake costly, irreversible technological upgrades, instead temporarily scaling back production to reduce releases.

Firms may also respond through reallocation. At the facility level, plants can shift chemical waste from on-site disposal to off-site removal; at the firm level, production and emissions can be moved from ecologically sensitive to non-sensitive facilities. While we estimate positive effects on off-site disposal, the results are not significant. Following Giroud and Mueller (2015, 2019), we examine within-firm spillovers and find strong evidence of network reallocation: toxic releases at a given facility increase when other facilities owned by the same firm are more exposed to unprotected biodiversity. This pattern indicates that conservation policy aimed at sensitive areas induces displacement of pollution toward less sensitive ones. Our CAR results suggest that markets view these reallocations as imperfect and financially costly for firms.

We also observe contractions in manufacturing presence in the most exposed counties following the policy announcement. Counties in the top 5% of PWRSR exposure experience a 3.2% decline in facility presence relative to baseline counties, with the contraction increasing to 5.2% among counties in the top 2.5%. These results indicate that firms respond not only by reducing toxic releases at existing sites but also by exiting—or avoiding entry into—counties with the highest concentration of unprotected, endangered biodiversity when conservation policy risk rises.

Crucially, we ask whether the shifts observed after Biden's "30 by 30" translate into meaningful ecological improvements. To evaluate real environmental consequences, we bring in two novel, high-resolution ecological datasets: NASA's MODIS Enhanced Vegetation Index (EVI), which measures vegetation health, and the North American Breeding Bird Survey (BBS), an indicator of avian biodiversity. Leveraging these datasets, we show that areas surrounding high-exposure facilities experience measurable ecological gains following the policy announcement.[8] Specifically, vegetation density increases and local bird diversity rises significantly in the post-policy period. These results demonstrate that conservation policy not only reshapes firm behavior but also yields tangible improvements in local ecosystems—an important validation that biodiversity policy can produce ecological benefits.

Importantly, we exploit an additional source of variation: President Trump's re-election on November 5, 2024. Given his vocal opposition to environmental regulation–and the Biden administration's limited record of punitive enforcement–one would expect a reversal of the trends we document under the "30 by 30" policy regime.[9] Consistent with this prediction, we observe a clear shift in both financial markets and firm behavior. The long–short nature-dependent portfolio earns positive CARs following the election, reversing the negative returns experienced earlier. Similarly, our dynamic difference-in-differences estimates show that the decline in on-site toxic releases among high-PWRSR facilities emerges in 2021–2023 but dissipates in 2024, coinciding with the election outcome. The

[8]We find that it is high-polluting facilities driving this result. High-polluting facilities are defined as the average total releases across facility-chemicals in the three years preceding the policy announcement. High-exposure facilities are those that are in the top tercile based on PWRSR.

[9]President Trump rescinded Executive Order 14008 on his first day in office, January 20, 2025.

combination of negative production and market responses to regulatory risk and subsequent reversal following a deregulatory signal provides confirmation of our proposed channels and exposure measure.

Overall, while our findings demonstrate meaningful ecological gains in the most sensitive areas, they also reveal that these improvements come with important trade-offs. The spillover effects induced by the "30 by 30" policy shock are not uniformly positive: firms strategically use their internal networks to reallocate toxic releases away from ecologically sensitive facilities toward those located in less sensitive counties. This segregation of environmentally harmful economic activity from conservation-priority areas is a novel and policy-relevant insight, highlighting that conservation policy can successfully protect vulnerable ecosystems while unintentionally intensifying pollution elsewhere. As biodiversity loss worsens and policy increasingly concentrates on areas with remaining endangered habitats, these dynamics become more salient. At the limit, they point toward a future where conservation policy preserves high-value habitats but concentrates environmentally harmful activity in less regulated areas, an outcome that underscores both the promise and the limits of targeted biodiversity policy.

II. Related Literature

We contribute to the nascent but growing literature on biodiversity policy risks in finance. Despite rising attention from policymakers and investors, biodiversity remains largely absent from leading finance journals (Karolyi and Tobin-de la Puente, 2023). Recent work has begun to fill this gap. For example, Garel et al. (2024) introduce a measure of corporate biodiversity footprint (CBF), which captures both direct and indirect biodiversity losses due to land use, greenhouse gas (GHG) emissions, water pollution, and air pollution using data from Iceberg Data Lab (IDL). They show that high-CBF firms experience lower realized returns following major policy announcements, but higher implied costs of capital (a proxy for expected returns) around significant policy events, suggesting that investors anticipate new regulations or litigation targeting these firms. Similarly, Coqueret et al. (2025) construct a biodiversity factor from IDL data and find that it is not subsumed by carbon emissions or standard Fama–French factors. Xiong (2023) use MSCI data augmented with corporate biodiversity incidents and highlight the importance of land use in biodiversity transition risk. Finally, Giglio et al. (2023) employ textual analysis to construct aggregate and firm-level biodiversity risk measures and show that returns on sorted portfolios covary with innovations in their aggregate measure.

Our work is closely related to this literature but differs in several key respects. First, while prior measures emphasize firms' pollution or biodiversity footprints, we highlight that policy risk also depends on a firm's geographic proximity to endangered biodiversity that is likely to become a conservation priority. Most existing biodiversity-finance work mirrors climate-finance methods, relying on non-spatial aggregate measures such as emissions, land-use, or pollution footprints. We agree that intensity of usage is a defining characteristic of a firm's exposure to biodiversity policy risk but in this paper we emphasize the spatial dimension of a firm's exposure. Greenhouse gas emissions have similar effects regardless of location; biodiversity impacts depend critically on where they occur. An identical industrial project may have negligible direct consequences in a barren desert but severe consequences in an endangered rainforest. Second, we extend the scope of analysis well beyond equity returns, presenting evidence that biodiversity policy affects options markets and firm behavior. And third, we show that biodiversity policy generates positive real environmental effects in surrounding ecosystems, underscoring the tangible consequences of biodiversity policy and exposure.

Our paper also contributes to the literature on the propagation of economic shocks and their spillover effects through firms' internal networks (Giroud and Mueller, 2015, 2019; Giroud et al., 2024). More specifically, we add to the subset of this literature that examines how firms reallocate emissions in response to regulatory or political pressure (Ben-David et al., 2021; Bartram et al., 2022; Bisetti et al., 2022). While existing work documents reallocation under carbon regulation or political scrutiny, we show that similar patterns arise in a biodiversity policy context and that they occur broadly across firms—not only among those facing financial constraints. Moreover, we provide evidence that, despite inducing spillovers, conservation policies remain effective at safeguarding biodiversity in the most sensitive areas.

Further, we contribute to the literature on sustainable finance and ESG investing, with a focus on the role of environmental risks in financial markets. A large body of work shows that climate-related risks are increasingly priced and influence firm and investor behavior. For example, climate policy uncertainty is priced in equity markets (Bolton and Kacperczyk, 2021; Zhang, 2025), affects option-implied volatility and slope (Ilhan et al., 2021), raises credit spreads (Seltzer et al., 2022), alters investment and innovation (Basaglia et al., 2025), shapes bank lending decisions (Delis et al., 2019), and reallocates capital in venture capital markets (Noailly et al., 2022). Firms also adjust their activities in anticipation of regulation: Barnett (2024) document preemptive responses to expected policy changes. Our study extends this literature by examining biodiversity as a distinct but related environmental risk. Our framing builds on Krueger et al. (2020) and Stroebel and Wurgler (2021), who emphasize the financial materiality of environmental regulatory risks.

III. Background and Data

This section provides essential background on biodiversity conservation and the 30 by 30 Initiative, followed by a description of the datasets used in our analysis.[10] Our empirical strategy requires assembling data at two complementary levels of analysis. At the firm level, we construct measures of biodiversity importance by aggregating establishment-level exposures and merging these with standard financial datasets. At the facility level, we combine information on annual toxic releases with static biodiversity exposure measures, geospatially matched vegetation indices observed at a monthly frequency, and bird observation . Together, these datasets allow us to evaluate both financial market and real economic responses to biodiversity policy.

A. Biodiversity and the 30 by 30 Initiative

Biodiversity refers to the variety of life forms on Earth, including ecosystems, species, and genetic diversity. It can be measured on various levels, from the genetic differences within a species to the number of species in a specific area. In simple terms, biodiversity is often understood as the richness of species within an ecosystem.

The Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) has reported that human activity now threatens more species with global extinction than ever before (Díaz et al. (2019), Marques et al. (2019)). Nearly one-quarter

[10] Table IA.A.1 summarizes variable definitions, and Table IA.A.4 details datasets that are well established in the literature.

of animal and plant species face extinction, while local extinctions within specific ecosystems are becoming more widespread. A report by the World Wildlife Fund (Fund (2020)) revealed a staggering 69% decline in the monitored wildlife on earth between 1970 and 2018.

This profound loss of biodiversity is likely to impact billions of people as the degradation of natural systems presents a significant risk to quality of life. Additional studies have supported these findings (Jones et al. (2018), Pereira et al. (2024), Allan et al. (2022), Senior et al. (2024)), showing that biodiversity loss can have serious economic consequences (Blarel et al. (2023), WEF (2020)). Recent evidence shows that biodiversity loss can have direct and measurable human and economic costs, as seen in the collapse of vultures in India leading to higher mortality and sanitation costs (Frank and Sudarshan, 2024) and the decline of bats in North America increasing insecticide use, health risks, and crop losses (Frank, 2024). Biodiversity loss could also lead to an increased risk of future pandemics (Daszak et al. (2020)). To address accelerating biodiversity loss, the 30 by 30 initiative, which aims to conserve 30% of the Earth's land and marine areas by 2030, was first proposed at the 2014 IUCN World Parks Congress and later championed by the High Ambition Coalition for Nature and People. It has since been endorsed by over 100 countries and was formally codified as Target 3 of the Kunming-Montreal Global Biodiversity Framework, adopted at the 2022 COP15 conference, often described as the "Paris Agreement for Nature."

In addition to 30 by 30, the Biden administration has enacted several policy measures that impact land conservation and biodiversity protection in the last few years. Executive actions include Executive Order 14008 on January 27, 2021 (30 by 30) and Executive Order 14072 issued in 2022 which focuses on forest conservation and promoting biodiversity.

As of the end of 2021, less than 13% of the United States is permanently protected and primarily managed to support biodiversity (U.S. Geological Survey (2021)). Panel A of Figure 1 shows these protected areas color-coded by ownership types, such as federal, state, regional agencies, NGOs, and private entities.

Legislative actions such as the Inflation Reduction Act and the Bipartisan Infrastructure Law have allocated substantial funding to conservation programs and habitat restoration, increasing compliance costs for businesses operating in sensitive ecological areas.[11] Identifying which firms[12] may be exposed to these policy and transition risks requires understanding which regions are most likely to be designated as conservation areas under 30 by 30 or future environmental regulation.

B. Environmental Data

In this section, we describe the environmental datasets that underpin our analysis. These come from three sources. First, we draw on NatureServe, which provides geographically precise, science-based information on species distributions, ecosystem vulnerability, and climate exposure. These data allow us to construct establishment-level measures of biodiversity policy risk and associated climate controls. Second, we rely on NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) satellite products, which provide consistent, high-frequency vegetation indices used to assess real ecological outcomes. And lastly, we rely on data from the U.S. Geological Survey's (USGS) North American Breeding Bird Survey (BBS), which track the status and trends of North American bird populations.

[11] See here for Executive Order 14008; here for Executive Order 14072; here for Inflation Reduction Act; here for Bipartisan Infrastructure Law; here for Bureau of Land Management Regulation; here for ESA Regulations; here for America the Beautiful Initiative.

[12] Firms have increasingly highlighted their commitments to biodiversity conservation in annual reports. Table IA.A.2 presents a subset of disclosures.

Together, these sources enable us to link firm activity to biodiversity policy exposure and to measure environmental responses on the ground.

B.1 Biodiversity Data and Habitat Modeling

NatureServe plays a central role in biodiversity conservation by modeling the habitat ranges of imperiled species and assessing ecosystem vulnerability. We incorporate these data into our firm-level and facility-level biodiversity policy exposure measures, described in more detail below.

NatureServe is a nonprofit organization dedicated to advancing biodiversity conservation by providing high-quality, science-based data on species and ecosystems. Through its expertise in species distribution, conservation status assessments, and ecosystem analysis, NatureServe addresses critical data gaps that government agencies alone often cannot fill. It collaborates with over 60 governmental and non-governmental organizations across North America, working with a network of 1,000 conservation scientists to gather and analyze biodiversity data. By offering detailed biodiversity data, NatureServe supports conservation planning and policy, thus assisting researchers, policymakers, and businesses in identifying high-priority areas for biodiversity protection.

To categorize species, NatureServe uses a system of conservation status ranks, ranging between GH (possibly extinct), G1 (critically imperiled), G2 (imperiled), G3 (vulnerable), G4 (apparently secure), and G5 (secure). This ranking system has been used by U.S. agencies as a valuable tool for identifying species and ecosystems at risk and for shaping both policy decisions and practical conservation strategies.[13]

While the Endangered Species Act (ESA) similarly addresses at-risk species, federal

[13] It also aligns closely with international standards, such as the IUCN Red List, ensuring consistency in global biodiversity risk assessments.

limitations in staff and resources prevent comprehensive assessments for all species NatureServe considers at risk. NatureServe therefore supplements federal listings by providing a broader set of observations for assessing the health of additional species and ecosystems at various scales. These ranks also supply critical status information for species that have not yet been listed or are under evaluation for listing under the ESA.

Traditional biodiversity assessments typically rely on "coarse-range" maps, which depict broad species distribution ranges. While informative at a general scale, these maps lack the spatial precision needed to capture specific habitat features and environmental variations critical to accurately identifying high-priority conservation areas. This limitation is particularly significant for rare or at-risk species, which often inhabit smaller, specialized environments that coarse mapping cannot adequately represent. To overcome these limitations, Hamilton et al. (2022)[14] employ habitat suitability models (HSMs) enhanced by machine learning. HSMs predict suitable habitats by analyzing environmental variables such as climate, land cover, and soil types, to identify areas that best support a species' survival and reproduction. Machine learning enables accurate habitat suitability estimates even in data-sparse regions and produces finely detailed habitat suitability maps.

The study specifically focuses on 2,216 imperiled species from four taxonomic groups: vertebrates, vascular plants, freshwater invertebrates (such as mussels and crayfish), and pollinators (including bumble bees, butterflies, and skippers). Only species classified as critically imperiled (G1) or imperiled (G2) by NatureServe, or listed as endangered under the U.S. Endangered Species Act, were included. By concentrating on these high-priority species, the assessment identifies regions with urgent conservation needs, aligning with

[14] Although not formally published by NatureServe, the top three coauthors of this study are affiliated with NatureServe, underscoring the organization's involvement in developing the methodology.

our research goal to evaluate policy risks for areas likely to receive protection under initiatives like 30 by 30.

B.2 Climate Exposure Data

We utilize two geographical climate datasets from NatureServe: the Climate Change Exposure Score and the Habitat Climate Change Vulnerability Index (HCCVI) score. These variables are included to emphasize that our biodiversity exposure measure captures a risk distinct from physical climate risks. The Climate Change Exposure Score evaluates the stress induced by climate change on ecosystem-specific processes, focusing on changes in temperature and precipitation patterns. This score incorporates baseline climate conditions, historical climate variability, and future climate projections, emphasizing deviations from historical norms. It is based on two measures of climate vulnerability: Climate Departure, which predicts shifts in temperature and precipitation between mid-20th-century averages and future 21st-century estimates, and Climate Sensitivity, which evaluates changes in modeled habitat suitability over time.

The Habitat Climate Change Vulnerability Index (HCCVI) score assesses the climate change vulnerability of various habitats and ecosystems within a hexagonal spatial unit. The Climate Change Exposure Score serves as a critical input to the HCCVI framework, which provides average scores across 99 habitat types. Higher HCCVI scores reflect lower vulnerability (high resilience or low exposure), while lower scores indicate greater vulnerability (low resilience or high exposure). Both datasets include two temporal assessments: mid-to-late century and near-century projections, offering insights into the evolving impacts of climate change on natural habitats.

We perform the same steps as how we calculate firm-level biodiversity policy risk measures to obtain firm-level climate change exposure score and HCCVI score. The maps of these scores are plotted in Figures IA.A.1 and IA.A.2. In our regressions, we include three climate-related controls: the Climate Change Exposure Score for both mid-to-late century and near-century projections, and the Habitat Climate Change Vulnerability Index (HCCVI) for the mid-to-late century. We omit the HCCVI near-century score because it is a linear combination of the other three variables.

B.3 Vegetation Indices

For our analysis of the real effects of biodiversity policy, we rely on vegetation data from NASA's Moderate Resolution Imaging Spectroradiometer (MODIS). MODIS produces vegetation indices at 16-day intervals and multiple spatial resolutions, enabling consistent temporal and spatial comparisons of vegetation canopy greenness across the globe. These indices synthesize spectral reflectance in the red, near-infrared, and blue bands to capture composite properties of vegetation, such as leaf area, chlorophyll concentration, and canopy structure.

MODIS produces the Enhanced Vegetation Index (EVI), which corrects for canopy–soil background noise, incorporates atmospheric resistance coefficients, and leverages the blue band to reduce distortions from aerosols. The resulting index provides robust detection of vegetation changes across a wide range of ecological conditions. The EVI is calculated as:

$$\mathrm{EVI} = G \times \frac{(\mathrm{NIR} - \mathrm{R})}{(\mathrm{NIR} + C_1 \times \mathrm{R} - C_2 \times \mathrm{B} + L)},$$

where NIR, R, and B denote near-infrared, red, and blue reflectance values, respectively; L is a canopy background adjustment factor; C_1 and C_2 are aerosol resistance coefficients;

and G is a gain factor.[15] We implement these data through Google Earth Engine, filtering to retain only pixels with VI quality assurance flags ≤ 1[16] and aggregating 16-day composites to monthly means at the facility level using establishment coordinates.

B.4 Breeding Bird Survey

To measure ecological responses to biodiversity policy, we rely on avian population data from the North American Breeding Bird Survey (BBS), a long–running multinational monitoring program coordinated by the U.S. Geological Survey in collaboration with Canada and Mexico. The BBS provides the primary source of large-scale, long-term information on breeding-season bird populations across the continent, supplying annual indices of abundance and species richness for more than 700 bird species.

Each year during the peak breeding season, skilled volunteer observers conduct standardized roadside surveys along fixed 25-mile routes. Each route contains 50 point counts, and at each point an observer records all birds seen or heard within a 0.25-mile radius during a 3-minute interval. More than 4,800 routes span the continental United States, Canada, and northern Mexico, and route boundaries do not cross state lines.

For each route-year observation, the BBS provides measures of abundance (the total number of individual recorded across all point counts) and diversity (the number of unique species observed). These metrics form the outcome variables in our ecological analyses.

To link ecological conditions to firm activity, we spatially join manufacturing facilities to the nearest BBS route. We construct a 50-kilometer radius around each route's starting

[15] See here and here for more details.

[16] The MODIS VI Quality Assurance (QA) bits categorize pixel reliability: 0 indicates highest quality, 1 indicates marginal quality, and values ≥ 2 represent snow/ice or clouds. We retain pixels with QA ≤ 1 following standard practice.

point and assign a facility to the closest route whose starting point lies within this radius. Routes are state-specific and do not cross borders.

The BBS has been instrumental in documenting long-term declines in North American bird populations, identifying species of conservation concern, and informing regional and national management actions. In our context, the breadth and temporal consistency of the data enable credible measurement of ecological changes surrounding manufacturing facilities exposed to biodiversity policy.

IV. Measures of Biodiversity Importance

Hamilton et al. (2022) introduce three distinct measures to capture different aspects of biodiversity importance: Range-Size Rarity (RSR), Protection-Weighted Range-Size Rarity (PWRSR), and Areas of Unprotected Biodiversity Importance (AUBI). In this study, we employ PWRSR and AUBI to analyze how biodiversity policy risks influence firms' financial outcomes, behavior, and their environmental impact. Below, we introduce each measure in detail.

Range-Size Rarity (RSR). Range-Size Rarity (RSR) is designed to quantify the rarity of species within a given geographic area. The measure is calculated in two steps: first, the inverse of the modeled habitat area is computed for each species, e, and second, these values are summed across all species within the geographical area, g, to obtain the RSR score at the geographical level.

$$RSR_g = \sum_e RSR_{eg} = \sum_e \frac{1}{Habitat\ Area_{eg}}$$

A higher range-size rarity indicates that a species has a smaller habitat, making it more vulnerable to threats. By highlighting areas with greater ecological sensitivity, RSR serves as a critical tool for identifying biodiversity hotspots. The data for RSR are available at a resolution of 990 meters, enabling fine-grained spatial analysis across the continental United States.

Protection-Weighted Range-Size Rarity (PWRSR). Protection-Weighted Range-Size Rarity (PWRSR) extends the RSR metric by incorporating the extent of habitat protection for each species. Protected areas, as defined in the study, are those classified with GAP Status 1 or 2 in the Protected Areas Database for the United States, which are areas mandated for biodiversity conservation. For each species, e, the PWRSR score is calculated as the product of its RSR score and the proportion of its habitat that remains unprotected. These scores are then summed across all species within a geographic area, g, to produce the PWRSR score at the geographical level.

$$PWRSR_g = \sum_e PWRSR_{eg} = \sum_e \frac{1}{Habitat\ Area_{eg}} \times Percentage\ Unprotected_g$$

Overall, protection-weighted Range-Size Rarity (PWRSR) signifies the vulnerability of a species based on its habitat range and the degree to which its habitat remains unprotected. A higher PWRSR score indicates a species with a small, rare habitat that is largely unprotected, making it especially susceptible to extinction risks. Thus, this measure identifies not only regions with ecologically rare species but also those where such species face significant conservation gaps. By integrating protection data, PWRSR highlights regions with high biodiversity risks due to inadequate conservation measures. Like RSR, PWRSR is computed at a 990-meter resolution, providing detailed insights into biodiversity vulnerabilities at the local level. Panel B of Figure 1 overlays PWRSR onto protected areas.

Areas of Unprotected Biodiversity Importance (AUBI). Areas of Unprotected Biodiversity Importance (AUBI) is a binary measure derived from PWRSR score. A region is classified as AUBI if its summed PWRSR score equals or exceeds a threshold of 0.0005; otherwise, it is assigned a value of 0. This PWRSR value of 0.0005 corresponds to a single species with a 500 km^2 range that is 25% unprotected, a species with a smaller range of 20 km^2 that is 1% unprotected, or multiple co-occurring species with lower individual PWRSR values. This binary classification pinpoints regions where biodiversity risks are both significant and unprotected, making them priorities for conservation efforts.

AUBIs spanned 510,521.3 km^2, or 6.3% of the contiguous United States (CONUS). These AUBIs often included habitats for multiple threatened species: 86% of AUBIs contained more than one imperiled species, with an average of 4.8 species (σ = 3.21) predicted in each area. Overall, habitats for 2,124 species, representing 96% of all modeled species, were expected to occur within AUBIs. California stands out with the highest percentage of land area designated as AUBIs (27.6%), while Florida, Georgia, and Tennessee each had nearly 20% of their land overlapping with AUBIs. Except for Rhode Island, every state included AUBIs, with 90% of the CONUS population residing within 50 kilometers of one. These three measures, RSR, PWRSR and AUBI, cover the entire continental United States at a resolution of 990 meters. Figure 2 plots these measures.

The biodiversity layers are treated as time-invariant over our sample. This reflects both data limitations and the slow-moving nature of habitat suitability, species distributions, and protection status. Our measures draw on extensive historical information on ranges, habitat characteristics, and conservation actions, capturing long-run ecological conditions rather than short-term land-use changes. We use the 2020 spatial surface as a representative baseline throughout the sample. Accordingly, these measures should be interpreted as a forward-looking proxy for structural, geography-based exposure to biodiversity regulation, not as a real-time reflection.

A. Firm-Level AUBI Exposure

Building on the biodiversity risk measures above, we construct a firm-level proxy for exposure to Areas of Unprotected Biodiversity Importance (AUBIs). *Employee-Weighted AUBI Exposure*, captures the share of a firm's workforce located within AUBIs.[17]

We obtain establishment-level data for US public firms from Dun & Bradstreet, which provides detailed information on firm establishments, including the parent company name, establishment name, location and number of employees. Using Google Maps API, we geocode each establishment's coordinates and match these locations to a grid from NatureServe which has RSR, PWRSR, and AUBI scores.

Employee Weighted AUBI Exposure. We assign a binary value of 1 to establishments located in an AUBI and 0 otherwise. To account for the relative size of each establishment, we weigh the biodiversity policy risk exposure by the number of employees at each establishment. For example, suppose Caterpillar, Inc has two establishments: one with 400 employees located in an AUBI, and another with 600 employees outside such areas. In this case, the weighted average biodiversity policy risk exposure for Caterpillar, Inc

[17] Using establishment-level presence to measure environmental risk exposure is consistent with prior work in climate finance. Acharya et al. (2022) use establishment-level geographic distribution data to estimate firm exposure to regional heat stress.

would be 0.4, reflecting the proportion of its workforce in an AUBI region.

We merge the resulting dataset with CRSP-Compustat. The merge is performed using a combination of firm names and geographic proximity. Specifically, we geocode firm headquarters from CRSP and match them to public company establishments in the Dun & Bradstreet NETS database. Our final sample includes 1,039 public firms, each assigned a fixed AUBI exposure score based on 2021 employment footprints and 2020 spatial biodiversity risk. We merge this with CRSP-Compustat and OptionMetrics data spanning 2016 to 2024 to construct the financial markets data used in our analyses. Figure 3 displays the geographic distribution of firm establishments overlaid on Areas of Unprotected Biodiversity Importance. We provide summary statistics of the final datasets[18] in Tables 1 and 2.

Locally Nature-Intensive and Nature-Dependent Firms. We categorize firms into two groups: those that are locally nature-intensive and nature-dependent, and those that are not. Locally nature-intensive and nature-dependent firms are those whose core operations rely directly on exploiting land and natural capital in sensitive areas. This concept is closely related to land usage, but with two important distinctions: we define it locally—excluding upstream or downstream supply-chain effects—and we emphasize the firm's reliance on the surrounding natural environment. For example, consider an oil drilling firm and a technology firm with facilities in an AUBI region. If conservation policy restricts industrial activity in such areas, the oil firm would face substantial operational disruptions or compliance costs because its activity both, depends on, and exploits the local natural resources, whereas the technology firm would face far less risk. Financial materiality

[18] Summary statistics for less pertinent datasets are detailed in Table IA.A.5.

arises both from proximity to endangered biodiversity and from relying on activities near sensitive habitats that are likely to be deemed harmful and subject to regulatory constraint.

To capture this heterogeneity, we classify firms based on their primary industry. While this industry-level segmentation is coarse, our aim is to demonstrate the importance of location-based policy exposure rather than to finely measure sectoral intensity. Specifically, we define locally nature-dependent firms as those classified under two-digit NAICS[19] code ≤ 33, which includes Agriculture, Forestry, Fishing, and Hunting; Mining, Quarrying, and Oil & Gas Extraction; Utilities; Construction; and Manufacturing. These industries depend heavily on land use, resource extraction, and proximity to natural ecosystems, making them especially sensitive to local environmental regulation. Firms in other sectors are assumed to be less reliant on physical geography and thus less exposed to direct biodiversity policy. We maintain this distinction throughout our validation and report counts for each sectoral category in Table IA.A.3.

Although our definition of nature-dependent industries is intuitive, we validate it statistically using the ENCORE database of ecosystem service dependencies. Specifically, we perform a principal components analysis (PCA) of industry-level dependence on ENCORE's 25 ecosystem services, treating "Not Applicable" as zero following Garel et al. (2025). Because ENCORE is based on ISIC classifications, we map our NAICS-defined sectors to their ISIC counterparts: A (Agriculture, forestry, fishing), B (Mining), C (Manufacturing), D (Utilities), E (Water and waste management), and F (Construction). Figure

[19]We classify firms using the North American Industry Classification System (NAICS), a standardized framework developed by U.S., Canadian, and Mexican statistical agencies to categorize businesses by economic activity. Each firm is assigned a NAICS code ranging from two to six digits, where additional digits denote increasing specificity. For instance, the 2-digit code 23 refers broadly to the Construction sector, 236 to Construction of Buildings, 2362 to Nonresidential Building Construction, and 236210 to Industrial Building Construction. This hierarchy illustrates that finer-grained codes often reflect more specialized but closely related operations, suggesting diminishing within-sector heterogeneity beyond the 2-digit level.

IA.B.1 shows industry loadings on the first two principal components. The ISIC groups corresponding to our nature-dependent industries (red dots) cluster tightly in the upper-right quadrant, distinct from most other sectors (gray dots), providing reassurance that our chosen industries are indeed naturally grouped and nature-dependent.[20]

A.1 Predictability of Firm-level AUBI Exposure

We assess whether AUBI exposure could have been predicted using pre-2020 firm-level data, in order to evaluate the empirical novelty of our measure and establish that it captures a distinct regulatory risk channel. Since the underlying NatureServe biodiversity data were released in 2020, we construct our AUBI exposure measure by linking firm establishments to spatial biodiversity risk data that were not publicly available before 2020. This raises the question: to what extent could firm-level AUBI exposure have been anticipated using observable firm characteristics prior to the release of the NatureServe data?

To address this, we regress AUBI exposure on a broad set of pre-2020 observables, using firm-level averages from 2016-2019. We estimate these regressions separately for nature-dependent industries and all other sectors. For each group, we estimate four specifications: (1) physical climate risk only, using NatureServe's Climate Change Exposure Scores; (2) climate transition risk, using Scope 1, 2, and 3 emissions; (3) financial fundamentals, including total assets, leverage, investment intensity, and profitability; and (4) a pooled model with all covariates. All regressions include 2-digit NAICS industry fixed effects to account for sectoral differences that may be correlated with both geography and regulation.

As shown in Table 3, explanatory power is uniformly low across all specifications and

[20] A nearby cluster of gray dots corresponds to pharmaceuticals, which are resource-dependent but not necessarily locally nature-dependent.

industry segments. Even in the fully saturated models (Columns 4 and 8), adjusted R^2 values remain below 5.8% for nature-dependent firms and are negative for most specifications among other firms. Most individual coefficients are statistically insignificant and economically small. These patterns suggest that AUBI exposure is not simply a function of firm size, capital expenditures, emissions, or proximity to climate-vulnerable ecosystems. It is orthogonal to standard firm-level observables, uncorrelated with traditional measures of physical and transition climate risk, and exhibits minimal within-industry predictability. This supports our interpretation of AUBI as a novel, spatially-rooted channel of biodiversity-related policy risk and distinct from the climate channels explored in prior work (e.g., Acharya et al., 2022; Bolton and Kacperczyk, 2021).

V. Measure Validation

The central question we test in this section is whether our measure is viewed as financially material by investors. This is not obvious: in climate finance, greenhouse gas emissions are systematically reported and widely accessible through public and private data providers, making them straightforward inputs for investors. By contrast, endangered biodiversity exposure data are fragmented, difficult to construct at high resolution, and have not been available in any financial context. Moreover, climate risk often becomes salient through extreme weather events that draw intense media attention (Choi et al., 2020), whereas biodiversity loss lacks a similarly catastrophic and attention-grabbing counterpart. These features make it an open question whether investors recognize and respond to biodiversity policy through this exposure channel. We show below that they do, validating our measure in option and equity markets.

A. Option-Implied Volatility

Implied volatility reflects the market's forward-looking uncertainty regarding a firm's future cash flows and risk exposure, and is therefore a natural proxy for investor-perceived policy risk.[21]

We implement a difference-in-differences framework that compares changes in implied volatility for firms with high exposure to Areas of Unprotected Biodiversity Importance (AUBI) to changes for low-exposure firms, before and after the announcement. Our primary outcome variable is 30-day and 365-day at-the-money (ATM) implied volatility, averaged across puts and calls at the firm-day level.

We estimate the following regression:

$$\mathrm{IVOL}_{it} = \beta_0 + \beta_1 \cdot (\mathrm{Post}_t \times \mathrm{HighAUBI}_i) + \beta_2' X_{i,t-1} + \gamma_{jt} + \delta_i + \lambda_t + \epsilon_{it} \tag{1}$$

where IVOL_{it} denotes the implied volatility of firm i on day t; $\mathrm{Post}_t \times \mathrm{HighAUBI}_i$ is an interaction term equal to one for firms in the top tercile of employee-weighted AUBI exposure in post-policy periods; $X_{i,t-1}$ is a vector of lagged firm-level controls including size, leverage, profitability, investment, past return volatility, and momentum; γ_{jt} captures industry-by-day fixed effects; δ_i denotes firm fixed effects; and λ_t captures day fixed effects. The coefficient β_1 measures the differential change in implied volatility for high-AUBI firms relative to low-AUBI firms following the policy announcement.

Table 4 reports the results of the implied volatility difference-in-differences analysis. The sample spans from January 2020 to December 2021, covering the year prior to and following the "30 by 30" Executive Order. In our specification we control for firm and 4-digit

[21] Both Hassan et al. (2019) and Sautner et al. (2023) use implied volatility to confirm their measures capture firm-level risks.

industry-by-day fixed effects. For Columns (1) and (3) the interaction term β_1 is positive and highly statistically significant, indicating a consistent increase in perceived risk for firms highly exposed AUBIs. This suggests that, following the "30 by 30" announcement, firms with high AUBI exposure experienced significantly larger increases in short-term implied volatility relative to their low-exposure counterparts.[22]

B. Cumulative Abnormal Returns of Sorted Portfolios

To illustrate the differential market response to biodiversity regulatory shocks, we construct an equal-weighted long-short portfolio that buys firms in the top tercile of AUBI exposure and shorts those in the bottom tercile.[23] Figure 4 presents cumulative abnormal returns (CARs) for our long-short portfolios around the January 27, 2021 executive order. We report results for three groups of firms: the full sample, a subset of nature-dependent sectors, and a residual group comprising all other sectors. Solid lines correspond to estimates from the FFC4 model, dotted lines include controls for the green-minus-brown (FFC4 + G) portfolio, and dashed lines additionally control for carbon (FFC4 + G + C) portfolios sorted by emissions intensity. These specifications demonstrate robustness to broader green and carbon transition risks.

Following the executive order we observe a pronounced divergence in returns. Specifically, the long-short nature-dependent portfolio experiences an immediate and sustained negative CAR. This indicates significant underperformance by high-AUBI firms relative to

[22]Our results are robust to several alternative specifications. Table IA.C.1 repeats the analysis excluding the period between the 2020 U.S. presidential election and the "30 by 30" announcement to rule out confounding election-related factors. Table IA.C.2 conducts a placebo test around the U.S. withdrawal from the Paris Climate Agreement and finds no significant effects.

[23]Firms in our sample have zero exposure up to roughly the 36th percentile, so the short leg effectively captures the bottom 36% of the distribution.

low-AUBI firms, consistent with investors rapidly repricing biodiversity policy risks associated with the 30 by 30 initiative. In contrast, differential CARs in non-nature-dependent industries exhibit only mild movements, remaining relatively flat overall.[24]

VI. Firm Response and Reallocation

Having established the financial materiality of exposure to biodiversity policy, we next examine how firms adjust their behavior in response to policy signals. Specifically, we study changes in facility-level toxic releases following the issuance of Executive Order 14008. We draw on the Environmental Protection Agency's (EPA) Toxic Release Inventory (TRI) and restrict the analysis to manufacturing facilities.

A. Facility Toxic Releases

If firms anticipate heightened constraints in areas of high biodiversity importance, they may reduce their releases accordingly. To test this hypothesis, we implement a difference-in-differences design and dynamic event-time regressions, using Protection-Weighted Range-Size Rarity (PWRSR)[25] as a continuous measure of facility-level exposure to endangered species habitats.

We estimate the following difference-in-differences specification:

[24] We further test a set of placebo policy dates, including President Trump's first election and inauguration, the U.S. withdrawal from the Paris Climate Accord on June 1, 2017, and President Biden's 2020 election. Figure IA.D.1 presents CARs around each of these placebo events. We do not observe any meaningful separation between the two portfolios for any event.

[25] AUBI is defined as an indicator for firms with PWRSR exposure greater than 0.0005. At the firm level, we relied on this threshold to construct a continuous measure, while at the facility level we use the underlying continuous PWRSR directly.

$$\log(\text{Releases}_{kt}) = \beta_0 + \beta_1 \cdot (\text{Post}_t \times \text{PWRSR}_k) + \delta_{kc} + \theta_{ict} + \epsilon_{kct} \tag{2}$$

where $\log(\text{Releases}_{kt})$ denotes the natural logarithm of toxic releases (on-site, off-site, or total) reported by facility k in year t; PWRSR_k is the facility's exposure to unprotected endangered species habitats, and Post_t is an indicator equal to one for years after 2020. The coefficient β_1 captures whether releases decline more significantly post-policy among facilities with higher biodiversity exposure. The specification includes facility-by-chemical fixed effects (δ_{kc}), and parent firm-by-chemical-by-year fixed effects (θ_{ict}). In some specifications, we also include state-by-year fixed effects. Standard errors are clustered at the facility level.

Table 5 reports the results using a sample of 2018-2023 sample. Columns (1) and (2) focus on on-site releases; Columns (3) and (4) on off-site releases; and Columns (5) and (6) on total releases. In columns (7) and (8) we change the dependent variable to be the natural logarithm of on-site/off-site emissions. In each pair, the first column excludes state-by-year fixed effects, while the second includes them. Across all specifications, we find that facilities with greater PWRSR exposure significantly reduce on-site and total toxic releases after 2020. The coefficients for on-site releases range from −6.780 to −5.974 (both significant at the 1% level), for off-site releases range from 1.309 to 1.878, and for total releases from −6.538 to −6.104 (significant at 1%). Under our tightest specification, a one standard deviation increase in facility PWRSR ($\sigma = 0.00222$) corresponds to a 1.32% decline in on-site releases, a 0.29% increase in off-site releases (though this is not significant), and a net reduction of 1.35% in total releases. These findings suggest both within-facility and across-facility reallocation. Within facilities, firms reduce on-site releases while increasing off-site transfers, indicating a shift in how pollution is managed rather than a pure reduction. Across facilities, multi-plant firms reduce toxic releases at high-PWRSR locations, effectively decreasing the relative contribution of these ecologically sensitive sites to overall firm-level releases after 2020.

To assess the dynamics of these responses and test for pre-trends, we estimate a dynamic version of the baseline specification by interacting year indicators (relative to 2020) with the continuous PWRSR exposure measure. This event-study framework allows us to trace how releases evolved before and after the 30 by 30 Executive Order, using the full 2016–2023 sample. The regressions are estimated at the facility-chemical-year level, and include facility-by-chemical fixed effects and parent firm-by-chemical-by-year fixed effects.[26] Standard errors are clustered at the facility level. Figure 5 plots the estimated dynamic coefficients, which capture the differential change in releases for facilities with higher PWRSR exposure in each year relative to 2020. Panel A displays the dynamic effects for on-site releases, Panel B for off-site releases, and Panel C for total releases. We observe no discernible trend in the pre-policy period, suggesting parallel trends. In the years following the 2021 Executive Order, we find a sharp and statistically significant decline in the effect of PWRSR exposure on both on-site and total releases, particularly in 2022 and 2023. These results corroborate the static DiD estimates and reinforce the interpretation that firms in biodiversity-sensitive areas responded to the policy signal by reducing local releases.

[26]Figure IA.E.1 plots the dynamics including state-by-year fixed effects while Figure IA.E.2 runs the dynamics with the independent variable now defined as an indicator variable if PWRSR is greater than 0.0015. Interpretations of results are largely the same.

B. Within Firm Reallocation

Building on prior work on firm networks and spatial reallocation (Giroud and Mueller, 2015, 2019; Bartram et al., 2022; Bisetti et al., 2022), we investigate whether firms use their internal production networks to shift environmentally harmful activity away from ecologically sensitive locations. Our hypothesis is that, when faced with heightened biodiversity conservation risk, firms strategically reallocate toxic releases from highly exposed facilities to less sensitive ones within the same corporate network in order to limit potential regulatory exposure.

Following Giroud and Mueller (2019), we construct a measure of how vulnerable other facilities within a network are relative to a facility. For each parent company, this measure is constructed by summing the PWRSR values of all other facilities owned by the same parent, explicitly excluding the focal facility's own PWRSR. This variable captures the broader exposure of the parent firm's network outside of the focal facility.

We estimate the following difference-in-differences specification:

$$\log(\text{Releases}_{kct}) = \beta_0 + \beta_1 \cdot \left(\text{Post}_t \times \text{PWRSR}_i^{-k}\right) + \delta_{kc} + \theta_{cst} + \epsilon_{kct}, \tag{3}$$

where $\log(\text{Releases}_{kct})$ denotes the natural logarithm of toxic releases (on-site or total) reported by facility k for chemical c in year t; $\text{PWRSR}_{i(k)}^{-k}$ is a leave-one-out measure of parent-level exposure to unprotected endangered species habitats, constructed as the sum of PWRSR values across all other facilities owned by parent firm i, excluding facility k itself. Post_t is an indicator equal to one for years 2021 and onward. The coefficient β_1 captures whether releases decline more sharply after 2020 among facilities whose parent firms have greater biodiversity exposure elsewhere in their internal network. The specification includes facility-by-chemical fixed effects (δ_{kc}) and chemical-by-county-by-year fixed effects (θ_{cst}). In some specifications, we don't include chemical-by-county-by-year fixed effects and opt for either county-by-year or chemical-by-year fixed effects.

Table 6 reports the estimates. Columns (1)-(3) examine on-site releases, while Columns (4)-(6) use total releases as the dependent variable. Across both outcomes, our most stringent specification—which includes facility-by-chemical fixed effects, county-by-year-by-chemical fixed effects, and clusters standard errors at the county level—yields statistically significant estimates of β_1 at the 10% level for on-site releases and the 5% level for total releases (Columns 1 and 3, respectively).

The magnitude of the estimated coefficients is economically meaningful. A one-standard-deviation increase in ex-facility parent-level PWRSR exposure ($\sigma = 0.01664$) is associated with a 1.85% increase in on-site toxic releases and a 2.48% increase in total releases after 2020. These results indicate that facilities belonging to parents whose other facilities are more exposed to endangered biodiversity areas exhibit relatively larger increases in emissions, consistent with within-firm reallocation of environmentally harmful activity.

Such reallocation behavior can limit the effectiveness of biodiversity policy in reducing total environmentally harmful activity. However, unlike the conclusion reached by Bartram et al. (2022), reallocations in a biodiversity context still yield important positive outcomes. In contrast to climate policy, where the geographic location of emissions is largely irrelevant for the ultimate environmental impact, limiting releases near endangered biodiversity provides meaningful benefits. Shifting pollution away from high-value habitats can therefore represent a desirable outcome, even if aggregate releases do not fall.

C. Reduction Mechanisms

Following Akey and Appel (2021); Bisetti et al. (2022), we investigate three primary mechanisms by which facilities can reduce toxic releases; the firm can reduce production, invest in new abatement technologies to reduce emissions from the production process, or the firm could increase its post-production treatment and recycling activity.

We estimate the following difference-in-differences specification:

$$\text{Mechanism}_{kt} = \beta_0 + \beta_1 \cdot (\text{Post}_t \times \text{PWRSR}_k) + \delta_{kc} + \theta_{ict} + \epsilon_{kct} \tag{4}$$

where Mechanism_{kt} denotes the mechanism of specific interest (Production Ratio, Log of Cumulative Production, Abatement, or Post-Production Reduction Ratio) reported by facility k in year t; PWRSR_k is the facility's exposure to unprotected endangered species habitats, and Post_t is an indicator equal to one for years after 2020. The specification includes facility-by-chemical fixed effects (δ_{kc}), and parent firm-by-chemical-by-year fixed effects (θ_{ict}). Standard errors are clustered at the facility level.

Table 7 reports how facilities adjust different toxic-release reduction mechanisms in response to biodiversity policy risk. Column (1) examines changes in the production ratio, a measure of how much the production process that generates a given toxic chemical increases or decreases year-over-year. We find a large and statistically significant decline in production among high-PWRSR facilities after 2021, consistent with exposed plants scaling back activity in ecologically sensitive areas. Column (2) turns to cumulative production, constructed as the multiplicative accumulation of prior production ratios and normalized to one in the first year of our sample. The estimates indicate substantial reductions in overall output among exposed facilities, reinforcing the view that firms curtail operations in sensitive locations following conservation-oriented policy. Further, Table IA.E.1 reruns Table 6 with the natural log of cumulative production as the dependent variable. We find evidence that production is reallocated away from sensitive areas in a firm's network.

Column (3) analyzes abatement activities, defined by the EPA TRI as source reduction or pollution-prevention actions that eliminate or reduce the use of chemicals or the creation of chemical waste. These activities include raw material substitution, reformulation or redesign of technology, and process modifications. The coefficient on Post $\times$ PWRSR is small and statistically insignificant, suggesting that firms do not increase on-site abatement in response to heightened biodiversity risk. Finally, Column (4) studies post-production activities, defined as the share of total generated waste that is diverted into recycling, treatment, or energy recovery rather than released. Consistent with the abatement results, we find no evidence that exposed facilities expand end-of-production mitigation strategies. Taken together, the evidence suggests that firms facing biodiversity conservation risk primarily reduce pollution by scaling back production rather than by adopting additional internal pollution-control measures.

D. Counties and Facilities

We next examine whether biodiversity policy exposure influences firms' decisions about the geographic footprint of their operations. Specifically, we test whether the number of facilities contracts in counties with high exposure to unprotected endangered biodiversity following the policy announcement.

To do so, we use EPA TRI facility data merged to county boundaries and construct an annual panel of facility counts by county for the entire contiguous United States. Importantly, we include all counties, not only those with TRI activity, so that our analysis captures both the entry and exit margins of facility presence across space. The dependent variable is the number of active facilities in county c and year t. For each county, we calculate the average share of land area overlapping with Areas of Unprotected Biodiversity Importance (AUBI). We then classify counties into "High AUBI" categories based on their percentile in this distribution (e.g., top 10%, top 5%, top 3.33%, top 2.5%).

We then estimate a Poisson regression of the form:

$$\text{Count}_{ct} = \beta_0 + \beta_1(\text{Post}_t \times \text{HighAUBI}_c) + \gamma_c + \lambda_{st} + \varepsilon_{ct},$$

where γ_c are county fixed effects, λ_{st} are state-by-year fixed effects, and β_1 captures whether facility presence contracts more sharply in high-AUBI counties following the policy announcement.

Table 8 presents the results across different thresholds of high exposure. We find no significant effect for counties in the top 10% of AUBI exposure, but stronger evidence of contraction at more stringent thresholds. The coefficients indicate counties in the top 5% experience a statistically significant 3.1% decline in facility presence, counties in the top 3.33% exhibit a 4.1% decline, and counties in the top 2.5% exhibit a 5.1% decline.[27] These results suggest that firms are more likely to exit, or avoid entry into, counties with the highest concentration of unprotected, endangered biodiversity once policy risk increases.

[27] Although the 2.5% cutoff may appear restrictive, it is important to note that nearly 30% of counties have zero facilities across all years. Moreover, the top 2.5% of counties account for roughly 3.1% of total facilities, the top 3.33% for about 4%, the top 5% for about 7%, and the top 10% for about 14%. Given the sunk costs of fixed investments, we would not expect meaningful relocation effects except in counties with the very highest levels of unprotected, endangered biodiversity exposure.

VII. Real Effects

In the prior section, we showed that firms both decrease toxic releases and, in aggregate, reduce facility presence in high-exposure counties. In this section, we examine whether these adjustments in firms' environmental footprint translate into measurable ecological benefits. We draw on satellite imagery from NASA's MODIS program and the USGS's Breeding Bird Survey (BBS).[28] Although we would ideally measure changes in endangered species abundance directly, such data are unavailable at sufficient spatial and temporal resolution. Instead, we use vegetation and avian data as proxies of biodiversity.

A. Vegetation Indices

We first consider vegetation as captured by NASA, which provides global coverage at a 250m $\times$ 250m resolution. Vegetation is a core component of biodiversity, and increases in vegetation health are indicative of improved habitat suitability.

To focus on the real effects of facilities with double materiality, those that are both highly polluting and located in areas of high exposure to unprotected endangered biodiversity, we define two categorical variables. High Polluters are facilities in the top tercile of toxic releases by weighted averaged across chemicals during the three years prior to Executive Order 14008, while High PWRSR are facilities in the top tercile of exposure to unprotected endangered biodiversity.

We estimate regressions of the form:

[28] See the Data and Background section for further details.

$$EVI_{kt} = \beta_0 + \beta_1(\text{Post}_t \times \text{HighPWRSR}_k) + \beta_2(\text{Post}_t \times \text{HighPolluter}_k) + \beta_3(\text{Post}_t \times \text{HighPWRSR}_k \times \text{HighPolluter}_k) + \delta_k + \theta_{st} + \varepsilon_{kt}. \quad (5)$$

where EVI_{kt} measures vegetation health in the vicinity of facility k at time t, δ_k are facility fixed effects, and θ_{st} are state-by-month fixed effects. The coefficient β_1 captures the post-policy change in vegetation around facilities with high PWRSR exposure, β_2 captures the post-policy change for facilities classified as high polluters, and β_3 captures the additional effect for facilities that are both high PWRSR and high polluters.

Table 9 presents the results. We are most interested in the triple interaction in Column (3), which shows that facilities facing double materiality are the ones for which meaningful ecological effects emerge. The coefficient on the triple interaction is positive and statistically significant, indicating that vegetation health improves in the vicinity of these facilities following the policy announcement. Column (1) shows that, taken on its own, high PWRSR exposure does not predict any systematic change in vegetation. Column (2) suggests that facilities classified as high polluters are associated with improvements in vegetation health, but this effect is absorbed once we account for joint exposure to biodiversity risk. In Column (3), the triple interaction dominates, highlighting that the observed ecological benefits are concentrated precisely where facilities are both environmentally intensive and located near vulnerable, unprotected ecosystems. These findings reinforce our argument that policy is most consequential when firms overlap with conservation-priority biodiversity and simultaneously exert substantial local environmental pressure.

B. Avian Responses

To complement our vegetation analysis, we examine whether biodiversity policy is associated with changes in local bird populations. We draw on the North American Breeding Bird Survey (BBS). The BBS provides the primary source of large–scale, long–term information on breeding–season bird populations across the continent, supplying annual indices of abundance and species richness for more than 700 species.

We spatially link manufacturing facilities to the nearest BBS route whose starting point lies within a 50–kilometer radius. Consistent with our vegetation analysis, we focus on facilities subject to double materiality risk–those that are both highly polluting and located near unprotected areas of endangered biodiversity. We define High PWRSR routes as those in the top tercile of pre–2021 average PWRSR exposure, and we define High Polluter as a continuous measure indicating how many top-tercile, high-polluting facilities fall within a 50km of the starting route.[29]

We estimate regressions of the form:

$$
\begin{aligned}
Y_{rt} = \beta_0 + \beta_1(\text{Post}_t \times \text{HighPWRSR}_r) + \beta_2(\text{Post}_t \times \text{HighPolluter}_r) \\
+ \beta_3(\text{Post}_t \times \text{HighPWRSR}_r \times \text{HighPolluter}_r) + \delta_r + \theta_{st} + \varepsilon_{rt}, \quad (6)
\end{aligned}
$$

where Y_{rt} is either Abundance (the total number of birds recorded on a route) or Richness (the number of unique species observed), δ_r denotes state–route fixed effects, and θ_{st} are state–by–year fixed effects. The coefficient β_1 captures post–policy changes in bird populations surrounding routes exposed to high biodiversity risk, β_2 measures changes around routes heavily influenced by high–polluting facilities, and β_3 identifies whether

[29] We run robustness regarding the quantile and present the results in Table IA.E.2.

ecological responses are amplified or attenuated in locations characterized by both high PWRSR exposure and high pollution intensity.

Table 10 presents the results for avian abundance and species richness. Across all columns, we estimate both Poisson and OLS specifications and find that the results are highly consistent across forms: the sign and relative magnitude of each interaction term are similar regardless of whether outcomes are modeled in levels or logs. This robustness provides confidence that the underlying ecological patterns are not driven by distributional assumptions.

We do not detect statistically significant changes in overall bird abundance following the policy announcement. While the coefficients in Columns (1)–(3) are directionally positive for the triple interaction, they are imprecisely estimated. This muted response may reflect greater measurement error in abundance counts, which depend on total individual detections and are more sensitive to observer conditions, weather, and species detectability. Nonetheless, the signs are encouraging and point in the expected direction: abundance tends to increase most in routes facing both high biodiversity exposure and high pollution intensity.

In contrast, the results for species richness in Columns (4)–(6) show a clear and statistically significant ecological response. The triple interaction between Post, High PWRSR, and the High Polluter Count is positive and significant across all specifications, indicating that the number of unique bird species increases most substantially in areas where highly polluting facilities are located near unprotected biodiverse ecosystems. Moreover, the magnitude of the triple-interaction coefficient rises with the number of high-polluting facilities mapped to a route, implying that the strongest ecological gains occur precisely where both environmental pressure and biodiversity exposure are greatest.

The signs on the lower-order terms are fully consistent with our conceptual framework. Routes that are heavily polluted but not located in biodiversity-sensitive areas tend to experience declines in richness after 2021, suggesting ecological degradation in locations lacking conservation priority.

VIII. President Trump's Re-Election

In Figure 6, we replicate our event-study analysis around November 5, 2024, the date of President Trump's re-election. President Trump has consistently expressed opposition to federal environmental regulation, and, as noted earlier, rescinded Executive Order 14008 on his first day in office in January 2025. If our AUBI- and PWRSR-based measures genuinely capture exposure to conservation-oriented policy, we should observe a reversal of the valuation effects documented around the 2021 "30 by 30" announcement.

Consistent with this prediction, we observe an opposite response to the 2024 election. Long–short portfolios that hold high-exposure firms and short low-exposure firms generate positive cumulative abnormal returns following President Trump's victory. The differential CARs for nature-dependent firms rise immediately after the election and remain positive throughout the post-event window, in sharp contrast to the negative CARs observed after the 2021 policy launch. These results indicate that investors anticipate weaker enforcement, reduced conservation efforts, and a diminished likelihood of future biodiversity regulation under the new administration.

To examine whether firm behavior also responds to this deregulatory signal, we extend our dynamic toxic-release analysis through the 2024 reporting year and present the results in Figure 7. The difference-in-differences estimates reveal a clear pattern: the decline in on-site toxic releases among high-PWRSR facilities, evident throughout 2021–2023, dissipates in 2024. We observe similar reversion patterns for total releases. These dynamics closely mirror the behavior of financial markets and provide compelling evidence that firms adjusted production and release decisions in anticipation of a less stringent regulatory environment.

Taken together, the 2024 election results strengthen our identification strategy and strengthen the interpretation of our exposure measure. Financial markets and facility behavior both react systematically to changes in the expected regulatory regime, implying that firms view biodiversity policy as financially material and adjust their environmental decisions accordingly. The fact that these effects reverse when policy expectations shift in the opposite direction provides an important validation: the responses we document are tightly linked to changes in anticipated conservation policy.

IX. Conclusion

This paper provides the first evidence on how firms adjust real environmental behavior in response to emerging biodiversity conservation policy, and whether those adjustments translate into observable ecological benefits. We document that firms meaningfully alter production and release decisions when operating near ecologically sensitive habitats. High-exposure facilities reduce toxic releases and scale back production following the policy announcement, while we find little evidence of costly investments in abatement or waste-treatment technologies. These responses are consistent with firms managing short-run regulatory risk rather than committing to long-run technological upgrades in an environment with limited enforcement.

At the same time, our results reveal important within-firm spillovers. Firms strategically reallocate pollution away from sensitive locations toward less exposed facilities in their internal networks. Using high-resolution satellite vegetation data and the North American Breeding Bird Survey, we show that vegetation health and species richness increase significantly around high-exposure, high-polluting facilities after 2021. These results strengthen the interpretation that "30 by 30" meaningfully improved ecological conditions in conservation-priority habitats, even as it shifted environmental burdens to less sensitive regions.

Finally, the reversal of our documented patterns following President Trump's 2024 election—both in financial markets and in facility-level toxic releases—provides an important validation of our identification strategy. When the incoming administration signaled a deregulatory shift, the negative market valuations of high-exposure firms ameliorated, and the decline in on-site releases among PWRSR-exposed facilities reverted to pre-policy levels. This dynamic response underscores that firms and investors interpret biodiversity regulation as financially material, and that policy durability plays a central role in shaping investment, production, and environmental decisions.

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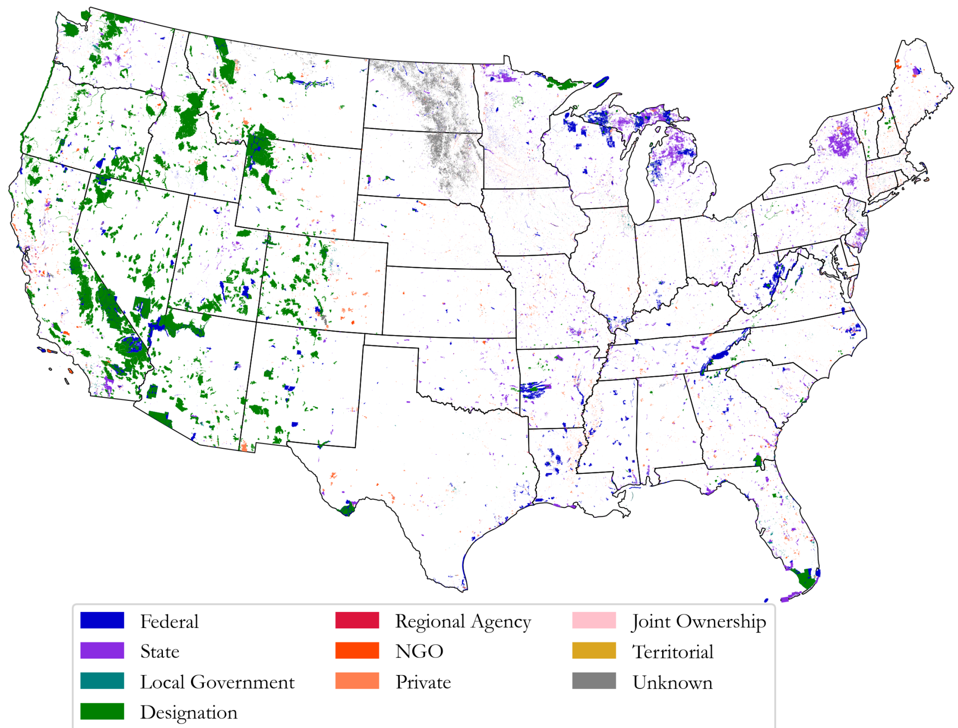
Figure 1: Protected Areas

This figure shows the areas that are permanently protected for biodiversity conservation. Panel A shows the protected areas. Protected areas are those classified with GAP Status 1 or 2 in the Protected Areas Database for the United States, which are areas mandated for biodiversity conservation. The areas are colored by the type of agency that owns the land. Panel B shows both the protected areas and the main continuous measure of biodiversity risk, Protected Weighted Range Size Rarity (PWRSR). Note, Designation here demonstrates territory that is not owned in the traditional sense, instead, they are lands protected by designation rather than explicit ownership.

Panel A: Protected Areas by Ownership Type



Panel B: Protected Areas and PWRSR

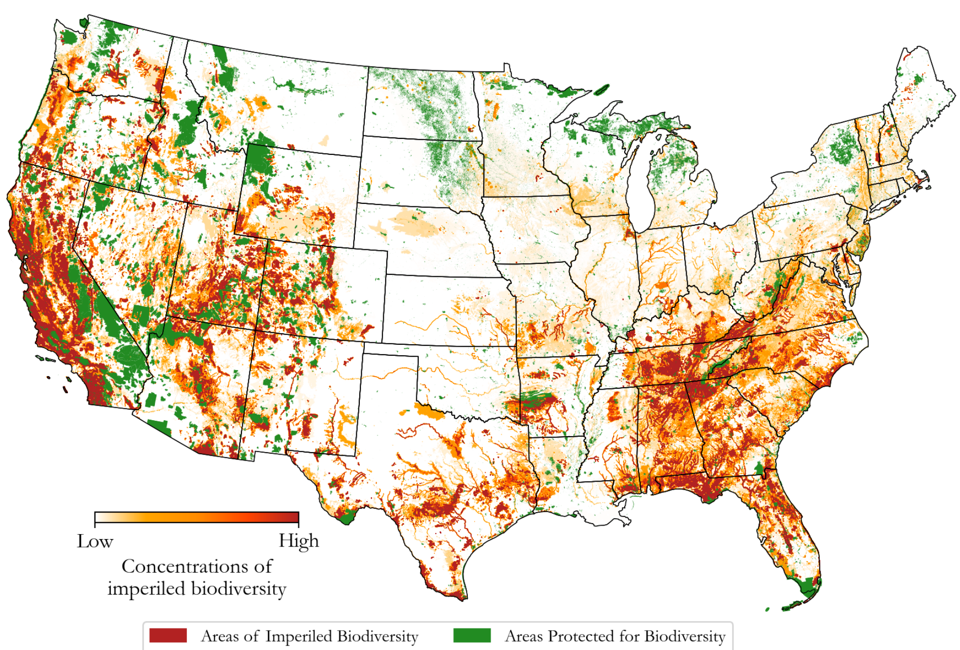
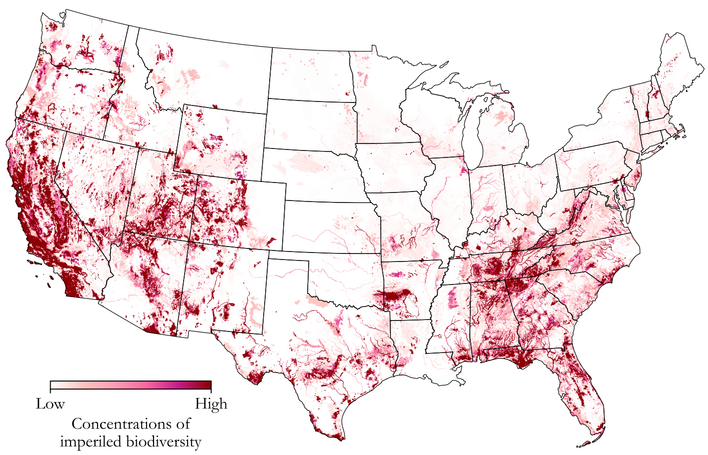


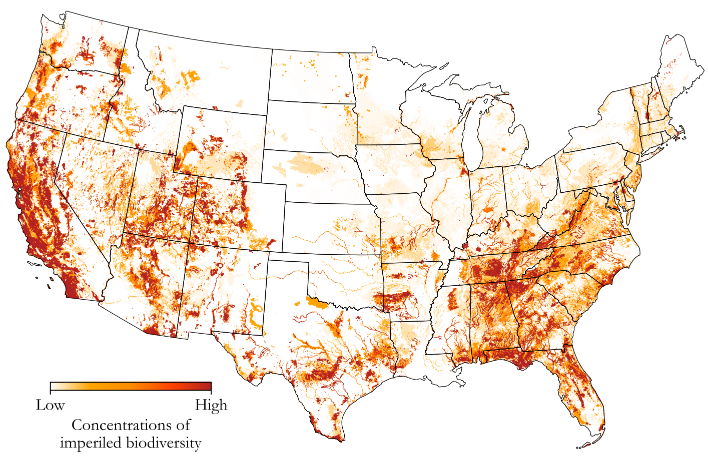
Figure 2: Measures of Endangered Biodiversity

This figure shows the primary measures of biodiversity risk that we adopted from NatureServe. Panel A shows the main continuous measure, Protection-weighted Range-size Rarity (PWRSR). Panel B shows range-size rarity, which is the inverse of the modeled habitat area. Panel C shows the main binary measure, which is the Areas of Unprotected Biodiversity Importance (AUBIs). For each species, PWRSR is the product of two components: range-size rarity and the percentage of this habitat that lies outside protected areas. AUBIs are all map pixels with a summed PWRSR of 0.0005 or greater—a threshold set to identify areas with notable conservation importance. This PWRSR value of 0.0005 corresponds to a single species with a 500 km² range that is 25% unprotected, or a species with a smaller range of 20 km² that is 1% unprotected, or even multiple co-occurring species with lower individual PWRSR values. Both PWRSR and AUBI metrics are determined at a resolution level of 990 meters, providing a detailed spatial scale for biodiversity risk.

Panel A: Range Size Rarity (PSR)



Panel B: Protected Weighted Range Size Rarity (PWRSR)



Panel C: Areas of Unprotected Biodiversity Importance (AUBIs)

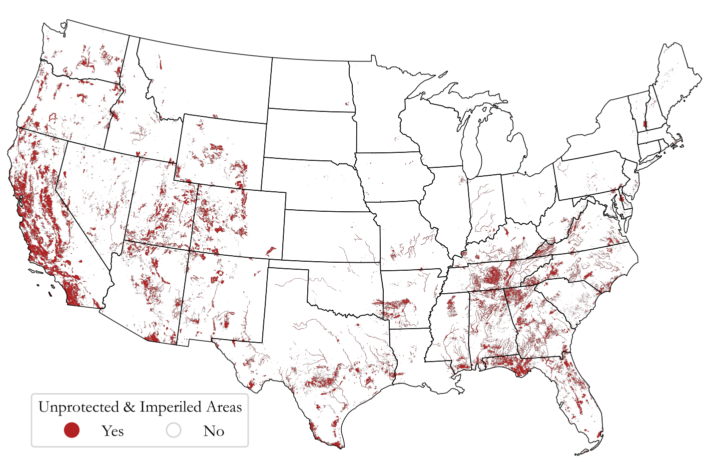
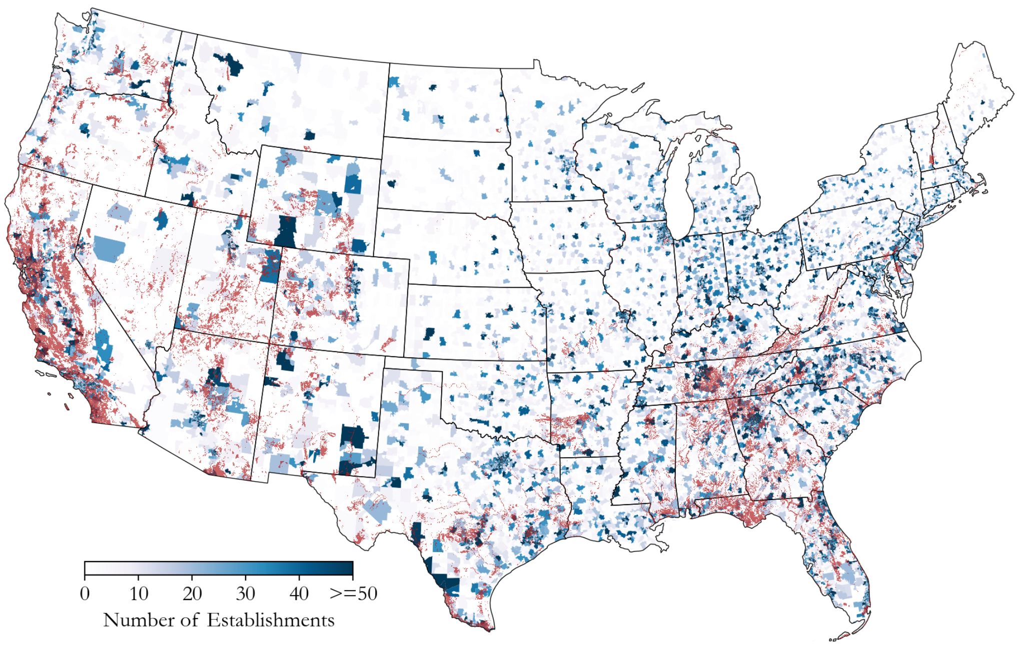


Figure 3: Establishments and Employees by County

This figure illustrates the geographical distribution of public firms' establishments in the sample, overlaid with the main binary measure of biodiversity risk, the Areas of Unprotected Biodiversity Importance (AUBIs). Panel A displays the number of establishments per county, where darker blue shades indicate higher concentrations of establishments. Panel B shows the number of employees per county, with darker blue shades representing counties with a larger employee count. In both panels, regions in red indicate areas where the AUBI measure equals one.

Panel A: Number of Establishments by County



Panel B: Number of Employees in the Establishments by County

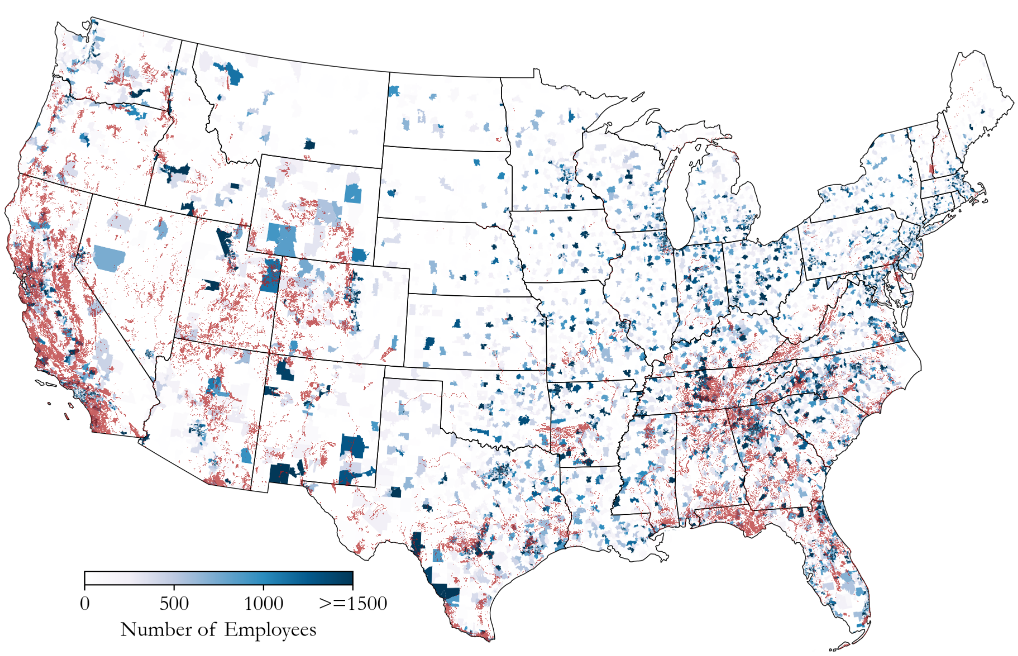
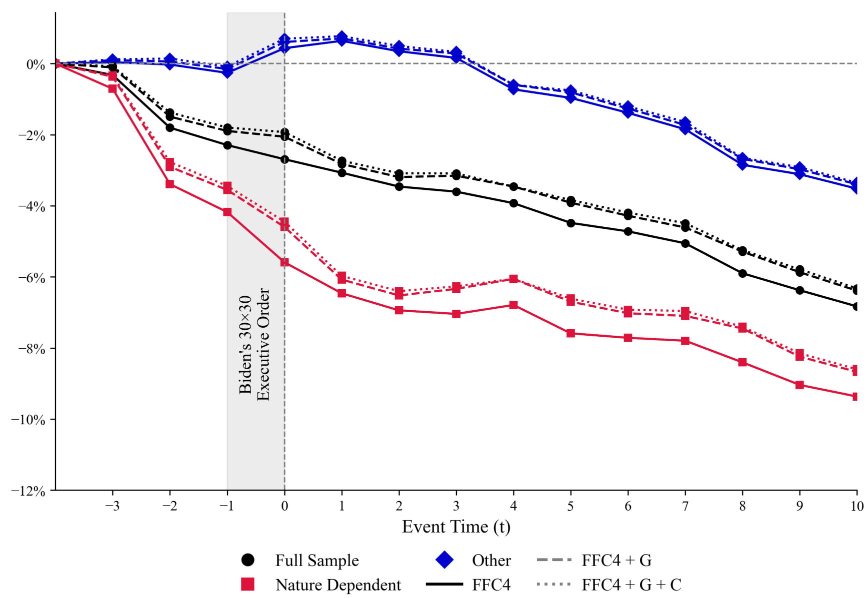


Figure 4: Cumulative Abnormal Returns around 30 by 30

This figure presents the cumulative abnormal returns (CARs) of an equal-weighted long-short portfolio that takes long positions in firms within the top tercile of AUBI exposure and short positions in firms within the bottom tercile around January 27, 2021. Expected returns are obtained from factor model predictions, where factor loadings are estimated using a 100-trading-day window ending 10 days before the event window. Panel A covers the event window from $t = -3$ to $t = 10$; Panel B extends this window to $t = 90$. The dashed vertical line represents $t = 0$, January 27, 2021. CARs are computed using the Fama-French-Carhart four-factor (FFC4) model, controlling for a daily GMB factor (FFC4 + G), and Scope 1, 2, and 3 Carbon Intensity portfolios (FFC4 + G + C) when specified. The figure plots the CAR for three long-short portfolios: black lines represent the full sample, red lines correspond to location and nature-dependent firms (Mining, Utilities, Oil & Gas, Manufacturing, or Construction), and blue lines represent other firms.

Panel A: Event Window $t = [-3, 10]$



Panel B: Event Window $t = [-3, 90]$

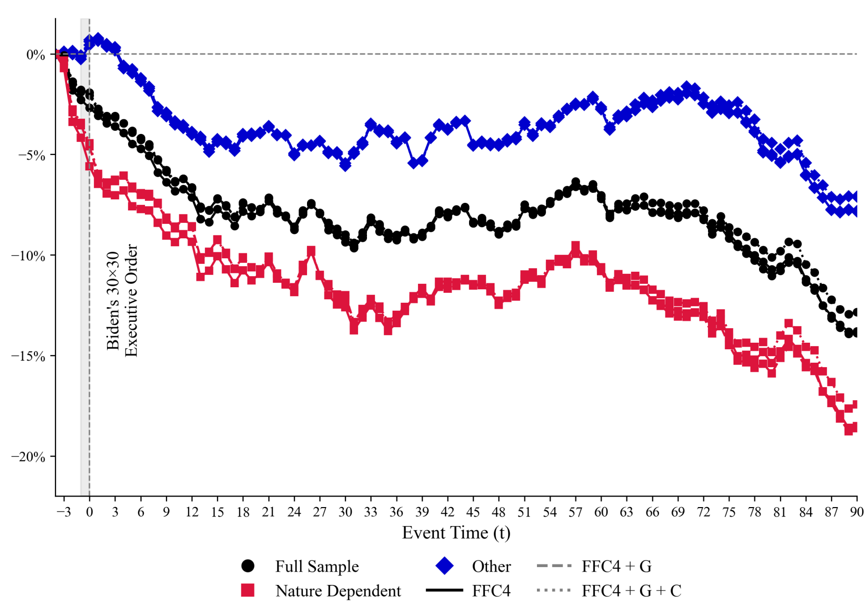
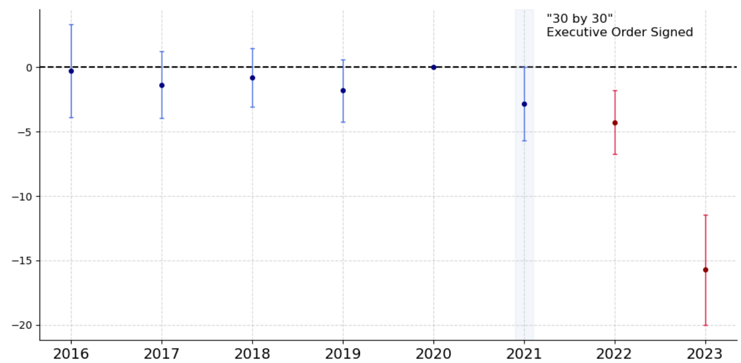


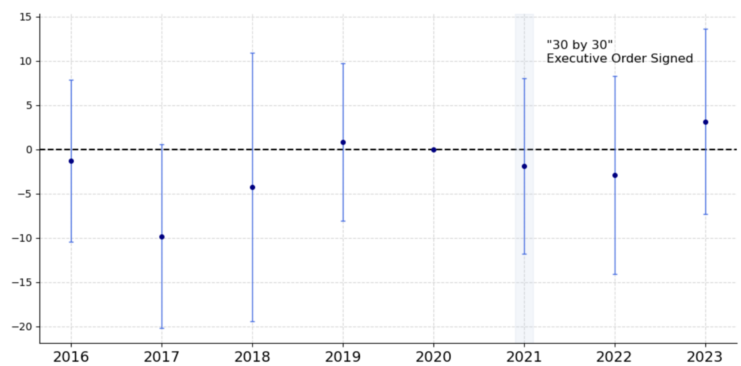
Figure 5: Dynamic Effects on Firm Toxic Releases

This figure plots year-by-year coefficients from a regression of logged toxic releases on interactions between year dummies (relative to 2020) and a continuous measure of facility-level exposure to endangered species, proxied by Protection-Weighted Range-Size Rarity (PWRSR). Regressions are estimated at the facility-year level using high-dimensional fixed effects (facility × chemical and parent company × chemical × year), and standard errors are clustered at the facility level. The coefficients represent the marginal effect of PWRSR exposure on toxic releases in each year, relative to 2020. Error bars indicate 95% confidence intervals, with red markers denoting statistically significant coefficients at the 5% level. The shaded region highlights the timing of President Biden's January 27, 2021 "30 by 30" Executive Order. Panel A plots results for on-site toxic releases, Panel B shows off-site toxic releases, and Panel C shows total releases.

Panel A: On-Site Releases



Panel B: Off-Site Releases



Panel C: Total Releases

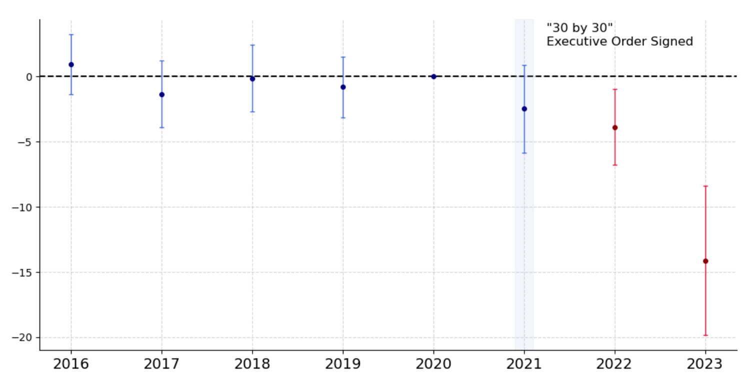
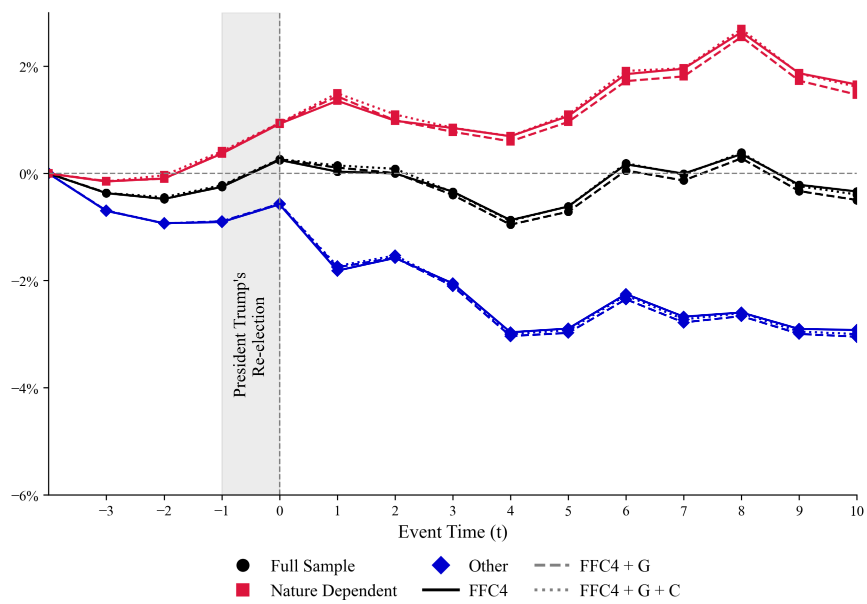


Figure 6: Cumulative Abnormal Returns around Trump's Re-Election

This figure presents the cumulative abnormal returns (CARs) of an equal-weighted long-short portfolio that takes long positions in firms within the top tercile of AUBI exposure and short positions in firms within the bottom tercile around November 5, 2024. Expected returns are obtained from factor model predictions, where factor loadings are estimated using a 100-trading-day window ending 10 days before the event window. Panel A covers the event window from $t = -3$ to $t = 10$; Panel B extends this window to $t = 90$. The dashed vertical line represents $t = 0$, November 5, 2024. CARs are computed using the Fama-French-Carhart four-factor (FFC4) model, controlling for a daily GMB factor (FFC4 + G), and Scope 1, 2, and 3 Carbon Intensity portfolios (FFC4 + G + C) when specified. The figure plots the CAR for three long-short portfolios: black lines represent the full sample, red lines correspond to location and nature-dependent firms (Mining, Utilities, Oil & Gas, Manufacturing, or Construction), and blue lines represent other firms.

Panel A: Event Window $t = [-3, 10]$



Panel B: Event Window $t = [-3, 30]$

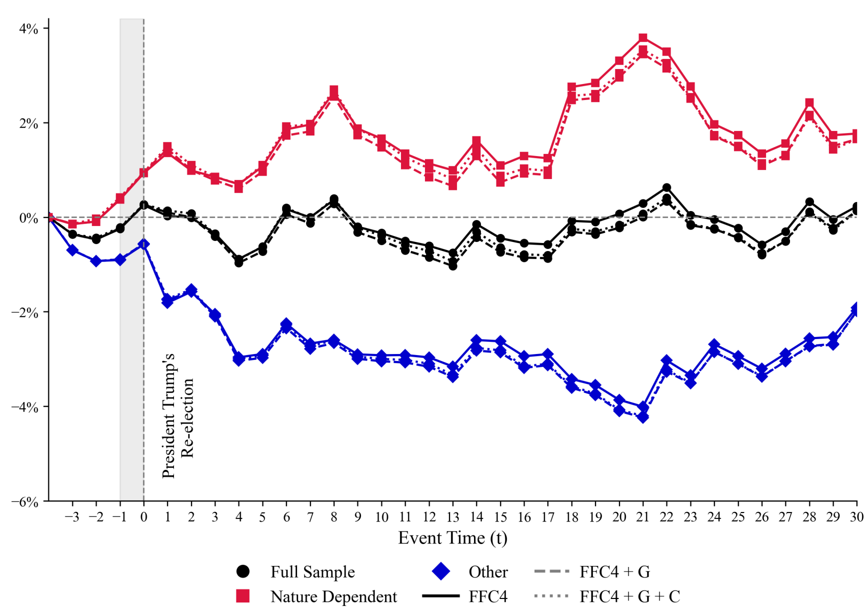
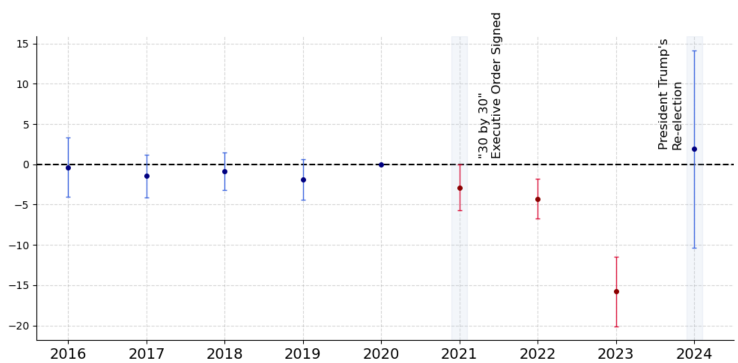


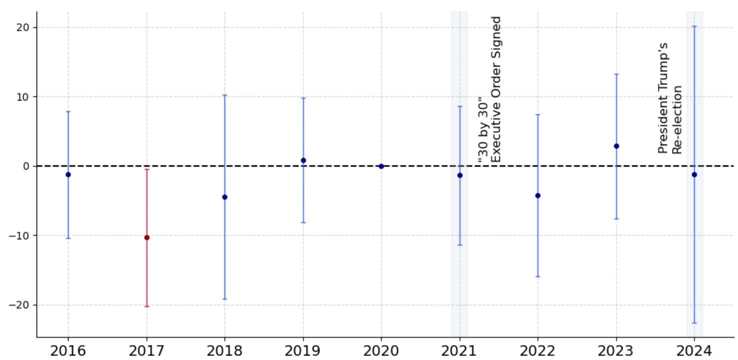
Figure 7: Dynamic Effects on Firm Toxic Releases Including 2024

This figure plots year-by-year coefficients from a regression of logged toxic releases on interactions between year dummies (relative to 2020) and a continuous measure of facility-level exposure to endangered species, proxied by Protection-Weighted Range-Size Rarity (PWRSR). Regressions are estimated at the facility-year level using high-dimensional fixed effects (facility × chemical and parent company × chemical × year), and standard errors are clustered at the facility level. The coefficients represent the marginal effect of PWRSR exposure on toxic releases in each year, relative to 2020. Error bars indicate 95% confidence intervals, with red markers denoting statistically significant coefficients at the 5% level. The first shaded region highlights the timing of President Biden's January 27, 2021 "30 by 30" Executive Order while the second highlights the re-election of President Trump on November 5, 2024. Panel A plots results for on-site toxic releases, Panel B shows off-site toxic releases, and Panel C shows total releases.

Panel A: On-Site Releases



Panel B: Off-Site Releases



Panel C: Total Releases

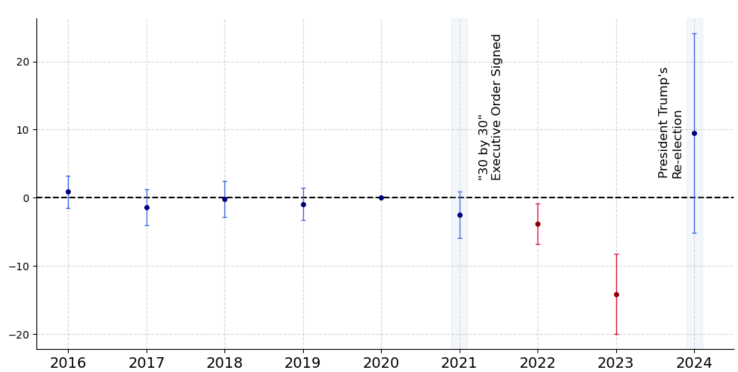


Table 1: Financial Summary Statistics

This table presents the summary statistics for the variables used in the paper. Panel A presents the statistics for the set of firms that are nature dependent, which are defined as firms in Mining, Utilities, Oil & Gas, Manufacturing, or Construction, while Panel B shows the statistics for the rest of the firms. The sample period is from 2020-2023. The Implied Volatility observations are at the daily level, Employee Weighted AUBI Exposure, Employee Weighted PWRSR Exposure, Employee Weighted RSR Exposure, Employee Weighted Distance AUBI Exposure, Climate Change Exposure Near Century, Climate Change Exposure Mid to Late Century, Habitat Climate Change Vulnerability Score Near Century are at the firm level, volatility and momentum are at the monthly level and remaining variables are at the annual level.

	Number of Obs.	Mean	Std Dev	p5	p25	Median	p75	p95
Panel A: Location & Nature Dependent Firms								
Monthly Returns	23254	1.70	22.65	-21.38	-7.34	0.07	8.42	27.71
Asset growth	23254	0.12	0.44	-0.23	-0.03	0.05	0.15	0.66
Sales growth	23254	0.60	9.71	-0.36	-0.06	0.07	0.22	0.80
Ln(Total assets)	23254	7.10	2.22	3.40	5.66	7.22	8.67	10.83
Leverage	23254	0.24	0.17	0.00	0.08	0.23	0.35	0.56
Capex/Total assets	23254	0.03	0.04	0.00	0.01	0.02	0.04	0.11
PPE/Total assets	23254	0.25	0.21	0.03	0.10	0.19	0.33	0.75
Ln(Market cap)	23254	7.29	2.42	3.27	5.62	7.44	8.89	11.13
Book-to-market	23254	0.57	0.55	0.07	0.22	0.42	0.72	1.58
ROA	23254	-0.01	0.26	-0.47	-0.03	0.04	0.10	0.21
Realized Volatility	23254	15.80	15.39	6.38	9.18	12.64	18.11	32.17
Momentum	23254	1.72	6.53	-5.67	-1.13	1.10	3.65	10.24
Employee Weighted AUBI Exposure	522	0.13	0.28	0.00	0.00	0.01	0.09	0.99
Employee Weighted PWRSR Exposure	522	0.00086	0.00482	0.00000	0.00002	0.00009	0.00029	0.00292
Employee Weighted RSR Exposure	522	0.00107	0.00642	0.00000	0.00002	0.00010	0.00032	0.00381
Climate Change Exposure Near Century	494	0.75	0.11	0.58	0.70	0.76	0.82	0.91
Climate Change Exposure Mid to Late Century	494	0.62	0.13	0.39	0.55	0.62	0.69	0.83
Habitat Climate Change Vulnerability Score Near Century	494	0.59	0.05	0.51	0.56	0.59	0.62	0.67
365day ATM Implied Volatility	438339	0.56	0.42	0.23	0.32	0.44	0.64	1.31
30day ATM Implied Volatility	235801	0.70	0.73	0.22	0.34	0.49	0.75	1.93
Panel B: Other Firms								
Monthly Returns	23096	1.53	19.84	-19.34	-6.41	0.59	8.06	24.06
Asset growth	23096	0.13	0.81	-0.17	-0.02	0.05	0.15	0.54
Sales growth	23096	0.28	7.97	-0.27	-0.03	0.08	0.19	0.53
Ln(Total assets)	23096	7.93	2.09	4.46	6.70	7.91	9.13	11.46
Leverage	23096	0.32	0.22	0.01	0.12	0.30	0.49	0.71
Capex/Total assets	23096	0.03	0.04	0.00	0.00	0.02	0.04	0.10
PPE/Total assets	23096	0.24	0.25	0.00	0.04	0.12	0.40	0.76
Ln(Market cap)	23096	7.71	2.24	3.75	6.30	7.79	9.16	11.29
Book-to-market	23096	0.68	0.94	0.06	0.20	0.45	0.87	1.85
ROA	23096	0.03	0.16	-0.14	0.00	0.04	0.08	0.19
Realized Volatility	23096	13.74	13.20	6.24	8.64	11.40	15.54	25.49
Momentum	23096	1.48	5.83	-4.81	-0.94	1.07	3.28	8.62
Employee Weighted AUBI Exposure	517	0.07	0.17	0.00	0.00	0.03	0.07	0.34
Employee Weighted PWRSR Exposure	517	0.00036	0.00117	0.00000	0.00002	0.00012	0.00028	0.00112
Employee Weighted RSR Exposure	517	0.00042	0.00137	0.00000	0.00003	0.00014	0.00033	0.00145
Climate Change Exposure Near Century	511	0.78	0.09	0.64	0.73	0.77	0.83	0.91
Climate Change Exposure Mid to Late Century	511	0.65	0.12	0.46	0.59	0.65	0.73	0.87
Habitat Climate Change Vulnerability Score Near Century	511	0.60	0.04	0.53	0.58	0.60	0.63	0.67
365day ATM Implied Volatility	566534	0.45	0.26	0.23	0.30	0.38	0.51	0.87
30day ATM Implied Volatility	303495	0.56	0.48	0.22	0.32	0.44	0.61	1.24

Table 2: Production and Outcome Summary Statistics

This table presents the summary statistics for the prodction, vegetation, and bird variables used in the paper. The sample period is from 2018-2023. The EPA Production observations are at the annual level, EVI is at the monthly level, and birds observation are at the monthly level.

	Number of Obs.	Mean	Std Dev	p5	p25	Median	p75	p95
On-site Release Total	188464	27726.00	306268.16	0.12	8.74	207.00	3200.00	63577.92
Off-site Release Total	90628	16090.34	171617.21	0.21	8.92	188.00	2232.00	40426.65
On-site / Off-site Ratio	72869	18609.99	1866890.63	0.00	0.02	0.43	10.73	1663.96
Total Release	206223	32409.51	315832.91	0.24	22.00	508.00	5740.88	83440.37
Production Ratio	240089	1.04	0.36	0.63	0.90	1.00	1.09	1.51
Cumulative Production	238556	7.65	793.26	0.50	0.87	1.00	1.04	1.66
On-site Emissions Intensity	197917	13158776.93	5732373141.97	0.14	8.93	205.59	3401.00	69772.68
Abatement Activities	263367	0.04	0.23	0.00	0.00	0.00	0.00	0.00
Post-Prodction Ratio	155746	0.81	0.31	0.04	0.76	0.98	1.00	1.00
EVI	2444138	0.2147	0.1220	0.0604	0.1225	0.1904	0.2842	0.4521
Abundance	6039	1413.70	713.55	612.00	984.00	1310.00	1700.00	2522.20
Richness	6039	111.12	24.35	68.00	96.00	114.00	128.00	148.00

Table 3: Determinants of Firm-Level AUBI Exposure

This table reports firm-level regressions where the dependent variable is Employee-Weighted AUBI Exposure. The sample spans 2016-2019, and all explanatory variables are constructed as firm-level averages over this period. Regressions are estimated separately for firms in locally nature-intensive industries—Mining, Oil & Gas, Utilities, Construction, and Manufacturing (Columns 1-4)—and for all other industries (Columns 5-8). Columns (1) and (5) contain climate risk exposures, namely Climate Change Exposure Near Century and Climate Change Exposure Mid to Late Century. Columns (2) and (6) include log-transformed Scope 1, Scope 2, and Scope 3 carbon emissions. Columns (3) and (7) incorporate firm financial characteristics, including the log of total assets, leverage (debt-to-assets), investment ratios (capital expenditures and property, plant, and equipment, each scaled by total assets), return on assets, log market capitalization, and the book-to-market ratio. Columns (4) and (8) include all of the aforementioned controls as well as the share of a firm's establishments located in urban areas. All regressions include 2-digit NAICS industry fixed effects. Robust Standard Errors are given in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Nature-Dependent				Others			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Climate Change Exposure Near Century	0.042			0.147	0.205			0.152
	(0.213)			(0.224)	(0.151)			(0.166)
Climate Change Exposure Mid to Late Century	0.011			-0.055	-0.118			-0.086
	(0.176)			(0.187)	(0.092)			(0.116)
Ln(Scope 1 Emissions)		-0.016		0.011		-0.009*		-0.006
		(0.013)		(0.013)		(0.005)		(0.006)
Ln(Scope 2 Emissions)		0.022		0.013		-0.004		-0.009
		(0.020)		(0.021)		(0.009)		(0.011)
Ln(Scope 3 Emissions)		-0.019		-0.031		0.004		-0.003
		(0.015)		(0.020)		(0.008)		(0.012)
Ln(Total assets)			-0.042	-0.068			-0.010	-0.010
			(0.026)	(0.043)			(0.012)	(0.018)
Leverage			-0.087	0.005			0.003	0.011
			(0.078)	(0.083)			(0.042)	(0.048)
Capex/Total assets			-0.834*	-0.130			0.021	-0.069
			(0.447)	(0.393)			(0.189)	(0.156)
PPE/Total assets			-0.053	-0.148			-0.016	-0.017
			(0.091)	(0.112)			(0.034)	(0.040)
Ln(Market cap)			0.043	0.085**			0.011	0.019
			(0.026)	(0.035)			(0.013)	(0.015)
Book-to-market			-0.027	0.098			0.002	0.017
			(0.041)	(0.067)			(0.015)	(0.018)
ROA			-0.069	-0.060			0.019	0.048
			(0.065)	(0.113)			(0.031)	(0.064)
Share of Urban Establishments				0.102				0.093
				(0.110)				(0.076)
R-squared	0.0462	0.0679	0.0952	0.103	0.0216	0.0509	0.0223	0.0682
Adj. R-squared	.0301	.0481	.0715	.0577	-.0123	.00729	-.0216	-.00244
Within R-squared	.000392	.022	.057	.0759	.00412	.0153	.00443	.034
Obs.	482	432	511	396	508	388	513	384
Ind FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Difference-In-Differences Option Validation of AUBI Exposure

This table reports difference-in-differences regressions testing whether firms with higher AUBI exposure respond differently to biodiversity-related policy shocks. Columns (1) and (2) use daily 30-day at-the-money implied volatility as the dependent variable, while Columns (3) and (4) repeat the analysis using daily 365-day at-the-money implied volatility, both measured over January 2020–December 2021 and centered on the Biden administration's January 27, 2021 Executive Order on biodiversity conservation. The key explanatory variable is the interaction of a post-event indicator with a top-tercile AUBI exposure dummy. Results are presented separately for nature-dependent industries (Columns 1 and 3) and all other industries (Columns 2 and 4). "Financial Controls" include log total assets, leverage, Capex/Assets, PPE/Assets, ROA, log market capitalization, book-to-market ratio, asset growth, sales growth, volatility (36-month return standard deviation), and momentum (12-month average return). "Physical Climate Controls" include firm-level exposures to Climate Change Near Century, Climate Change Mid to Late Century, and the Habitat Climate Change Vulnerability Score. Specifications vary in the inclusion of firm and industry × time fixed effects as indicated. Standard errors are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	30d Tenor		365d Tenor	
	Nature-Dependent (1)	Others (2)	Nature-Dependent (3)	Others (4)
Post × Top Tercile AUBI Exposure	0.110**	0.005	0.048**	0.003
	(0.043)	(0.038)	(0.023)	(0.016)
Adj. R-squared	0.749	0.715	0.813	0.841
Obs.	122,692	118,237	122,692	118,237
Financial Controls	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes
4-digit Ind × Day FEs	Yes	Yes	Yes	Yes

Table 5: Biodiversity Exposure and Toxic Releases

This table examines the relationship between reported Releases under the EPA Toxics Release Inventory (TRI) and facility-level exposure to unprotected endangered species. The dependent variables are the natural log of on-site, off-site, total releases, and on-site to off-site ratio reported by facilities to the EPA TRI. The sample period spans 2018–2023 and is restricted to manufacturing sectors (NAICS 31–33). The key independent variable is a continuous interaction term between a post-2021 indicator and the facility's Protection-Weighted Range-Size Rarity (PWRSR) exposure. Columns (1)–(2) report regressions for on-site releases, Columns (3)–(4) for off-site releases, Columns (5)–(6) for total releases, and Columns (7) and (8) for on-site to off-site ratios . All specifications include parent company × chemical × year and facility × chemical fixed effects, while even-numbered columns additionally control for state × year fixed effects. Standard errors are clustered at the facility level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	On-site		Off-Site		Total		On-site / Off-site Ratio	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × PWRSR	-6.780***	-5.974***	1.878	1.309	-6.538***	-6.104***	-7.584*	-7.736*
	(1.696)	(1.665)	(4.239)	(4.216)	(1.639)	(1.706)	(4.487)	(4.371)
Adj. R-squared	0.9505	0.9505	0.8685	0.8694	0.9262	0.9262	0.8750	0.8759
Obs.	113,614	113,614	48,156	48,156	125,697	125,697	36,854	36,853
Facility × Chemical FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FEs	No	Yes	No	Yes	No	Yes	No	Yes
Firm × Chemical × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Toxic Release Reallocation Within Firm Network

This table examines the relationship between facility-level emissions reported to the EPA Toxics Release Inventory (TRI) and parent-level exposure to unprotected endangered species. The dependent variables are the natural logarithm of on-site toxic releases and the natural logarithm of total releases. The sample spans 2018–2023 and is restricted to manufacturing facilities classified under NAICS 31–33. The key independent variable is a continuous interaction between a post-2021 indicator and a leave-one-out measure of parent-level Protection-Weighted Range-Size Rarity (PWRSR) exposure. For each parent company, this measure is constructed by summing the PWRSR values of all other facilities owned by the same parent, explicitly excluding the focal facility's own PWRSR. Columns (1)–(3) report regressions using on-site releases as the dependent variable, while Columns (4)–(6) present results for total releases. Within each outcome, the three specifications progressively introduce richer fixed effects: all models include facility × chemical fixed effects; Columns (2) and (5) additionally include county × year fixed effects; and Columns (3) and (6) further include county × year × chemical fixed effects. Standard errors are clustered at the county level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	On-site			Total		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Other PWRSR	1.2848**	1.0221*	1.1012*	1.2155*	0.7715	1.4738**
	(0.6448)	(0.6063)	(0.6563)	(0.6450)	(0.6578)	(0.6920)
Adj. R-squared	0.9521	0.9535	0.9347	0.9237	0.9256	0.9031
Obs.	182,797	181,909	89,702	200,121	199,288	102,397
Facility × Chemical FEs	Yes	Yes	Yes	Yes	Yes	Yes
Chemical × Year FEs	Yes	No	-	Yes	No	-
County × Year FEs	No	Yes	-	No	Yes	-
County × Year × Chemical FEs	No	No	Yes	No	No	Yes

Table 7: Toxic Release Reduction Mechanisms

This table examines the relationship between facility-level exposure to unprotected endangered species and a set of toxic-release reduction mechanisms reported under the EPA Toxics Release Inventory (TRI). The dependent variables include: (1) the annual production ratio, (2) the log of cumulative production, (3) total on-site abatement activities, and (4) the post-production recycling and treatment ratio, defined as the share of total produced waste diverted into recycling, treatment, or energy recovery rather than released. The sample period spans 2018–2023 and is restricted to manufacturing establishments (NAICS 31–33). The key independent variable is a continuous interaction term between a post-2021 indicator and the facility's Protection-Weighted Range-Size Rarity (PWRSR) exposure. All specifications include parent company × chemical × year and facility × chemical fixed effects. Standard errors are clustered at the facility level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. All dependent variables are winsorized at the 1st and 99th percentiles.

	Prod. Ratio	Log Prod.	Abatement	Post-prod. Reduction Ratio
	(1)	(2)	(3)	(4)
Post × PWRSR	-2.628***	-5.190***	-0.015	-0.027
	(0.337)	(0.715)	(0.128)	(0.344)
Adj. R-squared	0.134	0.742	0.543	0.882
Obs.	159,953	154,880	169,572	136,712
Facility × Chemical FEs	Yes	Yes	Yes	Yes
Firm × Chemical × Year FEs	Yes	Yes	Yes	Yes

Table 8: High Exposure Counties and Toxic Releasing Facilities

This table reports facility–level Poisson regressions where the dependent variable is the number of operating facilities in a county–year. The sample spans 2018–2023. The key explanatory variables are interactions between a post-policy indicator (Post, equal to one for years 2021 and later) and binary indicators for counties in the top share of exposure to Areas of Unprotected Biodiversity Importance (AUBI). We vary the treatment threshold across columns: counties in the top 10%, the top 5%, the top 3.33%, and the top 2.5% of the AUBI distribution. The specification includes county and state-by-year fixed effects, and standard errors are clustered at the county level. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Post × Top 10%	-0.006			
	(0.013)			
Post × Top 5%		-0.032*		
		(0.017)		
Post × Top 3.33%			-0.042**	
			(0.021)	
Post × Top 2.5%				-0.052**
				(0.025)
Obs.	12,792	12,792	12,792	12,792
County FEs	Yes	Yes	Yes	Yes
State × Year FEs	Yes	Yes	Yes	Yes

Table 9: Vegetation, PWRSR Exposure, and High Polluting Facilities

This table reports facility-level regressions where the dependent variable is the Enhanced Vegetation Index (EVI), measured monthly from MODIS satellite data. The sample spans 2018–2023 and is restricted to manufacturing facilities (NAICS 31–33). The key explanatory variables are interactions between a post-policy indicator (Post, equal to one for years 2021 and later), a binary indicator for facilities in the top tercile of Protection-Weighted Range-Size Rarity (High PWRSR), and a binary indicator for facilities in the top tercile of pre-2021 toxic releases (High Polluter). All specifications include facility and state-by-month fixed effects, and standard errors are clustered at the facility level. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Post × High PWRSR	-0.0002		-0.0007
	(0.0004)		(0.0005)
Post × High Polluter		0.0010***	0.0006
		(0.0003)	(0.0004)
Post × High PWRSR × High Polluter			0.0014**
			(0.0007)
Adj. R-squared	0.782	0.782	0.782
Obs.	750,797	750,797	750,797
Facility FEs	Yes	Yes	Yes
State × Month FEs	Yes	Yes	Yes

Table 10: Birds, PWRSR Exposure, and High Polluting Areas

This table reports State–Route–level regressions examining how biodiversity responds to pollution exposure after 2021. The dependent variables are Abundance and Richness, along with their natural logarithms, measured annually from 2018–2023 using the North American Breeding Bird Survey. The key explanatory variables are interactions between a post-policy indicator (Post, equal to 1 for years 2021 and later), a binary indicator for State–Route segments in the top tercile of pre-2021 Protection-Weighted Range-Size Rarity (High PWRSR), and the pre-2021 count of facilities in the top tercile of toxic releases within each State–Route segment (High Polluter Count). The table presents Poisson specifications for level outcomes and OLS specifications for both levels and logs. All regressions include State × Route and State × Year fixed effects, and standard errors are clustered at the State × Route level. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Abundance			Richness		
	(1)	(2)	(3) Log	(4)	(5)	(6) Log
Post × High PWRSR	0.0049	10.9696	0.0162	-0.0009	-0.0624	0.0009
	(0.0166)	(22.2693)	(0.0174)	(0.0069)	(0.7902)	(0.0078)
Post × High Polluter Count	-0.0030	-4.6044	-0.00299	-0.00245**	-0.2648**	-0.00256**
	(0.00288)	(4.2832)	(0.00351)	(0.00104)	(0.1147)	(0.00107)
Post × High PWRSR × High Polluter Count	0.00269	3.9352	0.00277	0.00317**	0.3402**	0.00326**
	(0.00331)	(4.7844)	(0.00398)	(0.00124)	(0.1368)	(0.00133)
Adj. R-squared	-	0.9041	0.8839	-	0.8964	0.9075
Obs.	5,801	5,801	5,801	5,801	5,801	5,801
State × Route FEs	Yes	Yes	Yes	Yes	Yes	Yes
State × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Poisson	OLS	OLS	Poisson	OLS	OLS

Internet Appendix for:
"Canaries in the Coal Mine: Firm Response to Biodiversity Policy Risk"

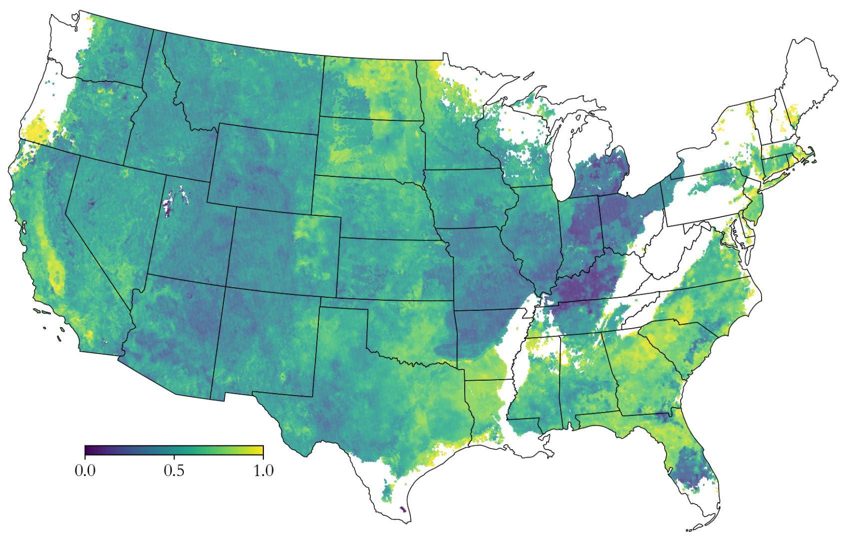
Ricardo Peña and Shikhar Singla

IA.A Descriptive and Summary Statistics

Figure IA.A.1: Climate Change Exposure

This figure shows the spatial distribution of climate change exposure, as measured by NatureServe's climate risk metrics, for mid to late century (Panel A) and near century (Panel B) scenarios across the continental United States. Climate change exposure represents the extent to which natural habitats are projected to experience significant changes in temperature and precipitation patterns, based on six key variables. Scores range from 0 (low exposure) to 1 (high exposure), where higher values indicate areas with greater sensitivity to climate shifts. Areas in white denote areas for which NatureServe does not have data.

Panel A: Climate Exposure Mid to Late Century



Panel B: Climate Exposure Near Century

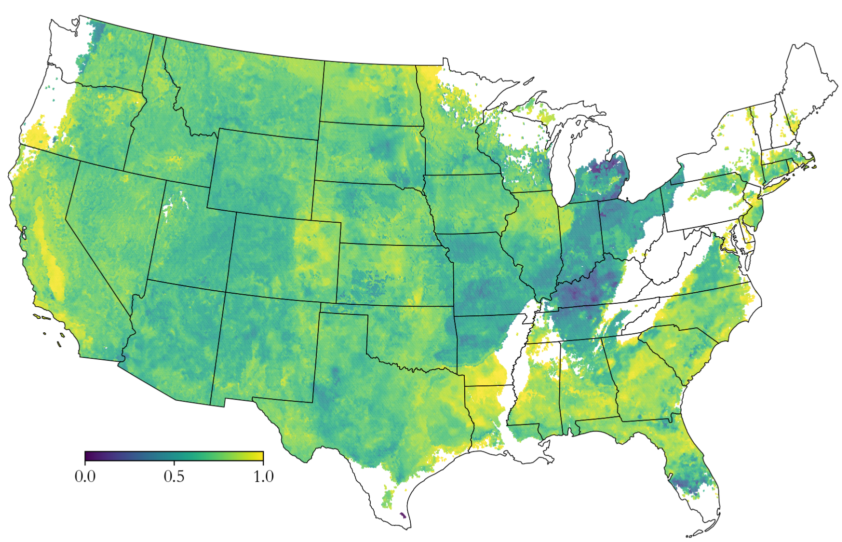
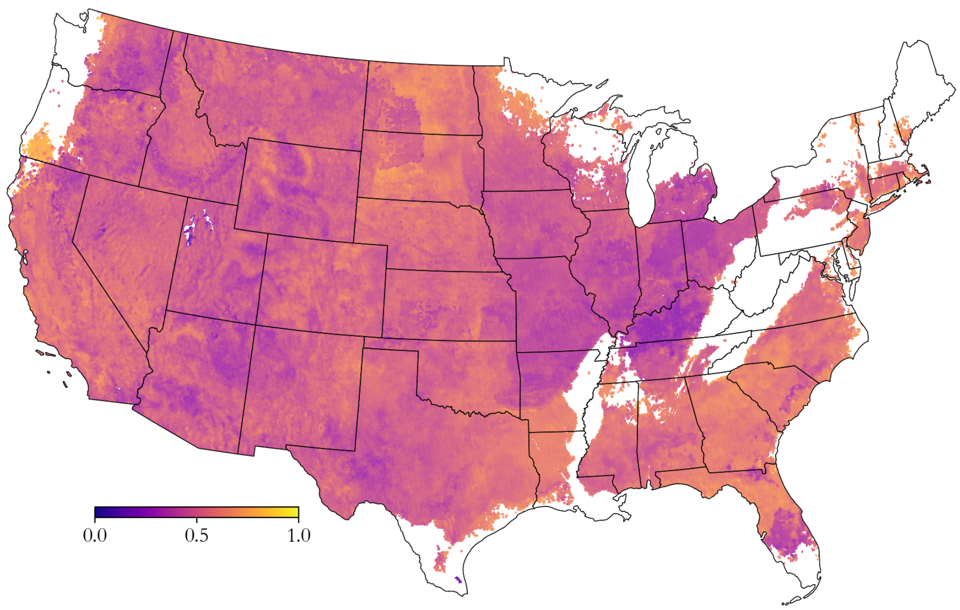


Figure IA.A.2: Habitat Climate Change Vulnerability Index (HCCVI)

This figure shows the spatial distribution of the Habitat Climate Change Vulnerability Index (HCCVI) scores for mid to late century (Panel A) and near century (Panel B) scenarios across the continental United States. The HCCVI score quantifies the vulnerability of natural habitats to climate change, accounting for factors such as exposure to climatic shifts, sensitivity of the habitat to those changes, and adaptive capacity of the ecosystem. Scores range from 0 (low vulnerability) to 1 (high vulnerability), where higher scores indicate areas more at risk of habitat degradation or loss due to climate change. Areas in white denote areas for which NatureServe does not have data.

Panel A: HCCVI Score Mid to Late Century



Panel B: HCCVI Score Near Century

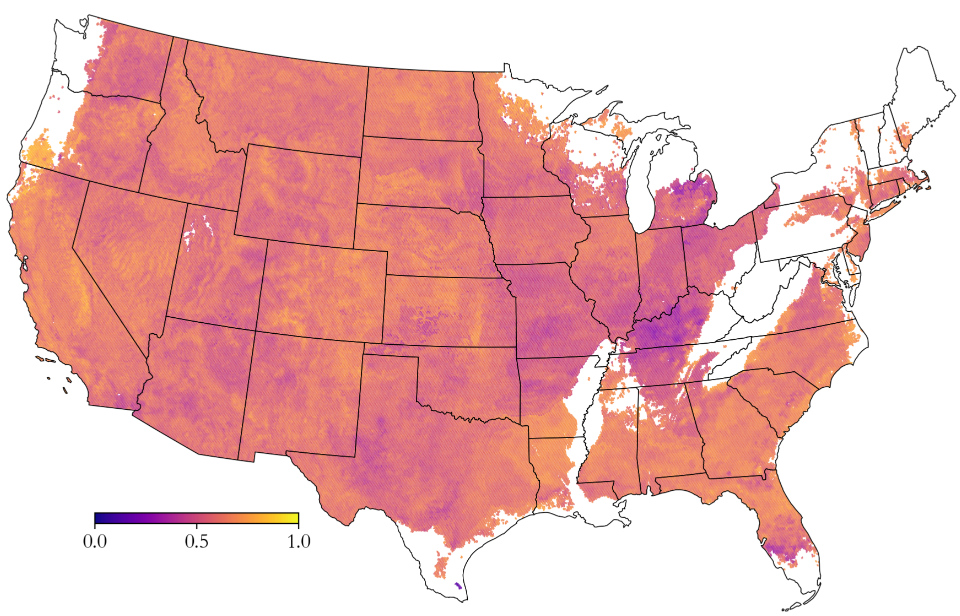


Table IA.A.1: Variable Definitions

Variables	Definitions	Sources
	Biodiversity-related Variables	
RSR	Range-size rarity. First, calculate the inverse of the modeled habitat area for each species. Second, sum these values across species to aggregate range-size rarity at the geographical level. Data are at a 990-meter resolution.	Hamilton et al. (2022)
PWRSR	Protection-weighted range-size rarity. First, calculate for each species as the product of its range-size rarity and the percentage of habitat outside protected areas. Second, sum these values across species to aggregate protection-weighted range-size rarity at the geographical level. Data are at a 990-meter resolution.	Hamilton et al. (2022)
AUBI	Areas of unprotected biodiversity importance. A binary variable equal to 1 if the summed PWRSR at the geographical level is $\geq$ 0.0005; otherwise, it equals 0. Data are at a 990-meter resolution.	Hamilton et al. (2022)
Employee-weighted RSR exposure	A firm-level measure calculated as the employment-weighted average of RSR scores across the firm's establishments.	Self-constructed
Employee-weighted PWRSR exposure	A firm-level measure calculated as the employment-weighted average of PWRSR scores across the firm's establishments.	Self-constructed
Employee-weighted AUBI exposure	A firm-level measure calculated as the proportion of the firm's total workforce located in establishments within AUBI.	Self-constructed
	Climate-related Variables	
CCE	Climate Change Exposure. Measures climate-induced stress on ecosystems within spatial units over 100 square kilometers. Scores range from 0.0 (highest stress) to 1.0 (lowest stress), with projections for near-century and mid-to-late-century timeframes.	NatureServe
HCCVI	Habitat Climate Change Vulnerability Index. Assesses habitat vulnerability based on exposure, sensitivity, and adaptive capacity within spatial units over 100 square kilometers. Scores range from 0.0 (highest vulnerability) to 1.0 (lowest vulnerability), with near-century and mid-to-late-century projections.	NatureServe
CCE (firm-level)	A firm-level measure calculated as the employment-weighted average of CCE scores across the firm's establishments.	Self-constructed
HCCVI (firm-level)	A firm-level measure calculated as the employment-weighted average of HCCVI scores across the firm's establishments.	Self-constructed
Scope 1/2/3 emissions intensity	The intensity of Scope 1, Scope 2, or Scope 3 GHG emissions. Annual data.	Trucost
Ln(Scope 1/2/3 emissions)	The natural logarithm of Scope 1, Scope 2, or Scope 3 greenhouse gas (GHG) emissions. Annual data.	Trucost

(Continued)

Table IA.A.1: Variable Definitions *(Continued)*

Variables	Definitions	Sources
	Stock Return Variables	
Monthly return (%)	Monthly stock return. We build total return using stock prices expressed in $ (prccd), adjustment factors (ajexdi), exchange rates (exratd), and total return factors (trfd). Monthly data.	Compustat
Volatility (%)	Standard deviation of the monthly returns over the 36 preceding months. Monthly data.	Compustat
Momentum (%)	Average monthly return over the twelve preceding months. Monthly data.	Compustat
	Firm Characteristic Variables	
Total assets	Total assets. Annual data.	Compustat
Book-to-market	Ratio of book equity to market capitalization. Annual data.	Compustat
Leverage	Total debt, divided by total assets. Annual data.	Compustat
Capex/Total assets	Capital expenditures, divided by total assets. Annual data.	Compustat
PPE/Total assets	Net property, plant, and equipment, divided by total assets. Annual data.	Compustat
ROA	Income before extraordinary items, divided by total assets. Annual data.	Compustat
Asset growth	Percentage change in total assets. Annual data.	Compustat
Sales growth	Percentage change in sales. Annual data.	Compustat
Market cap	Market capitalization. Monthly data.	Compustat
	Options Variables	
30-day ATM Implied Volatility	Daily firm-level implied volatility, computed as the average of the 30-day, 50-delta call and put option implied volatilities. Daily data.	OptionMetrics
365-day ATM Implied Volatility	Daily firm-level implied volatility, computed as the average of the 365-day, 50-delta call and put option implied volatilities. Daily data.	OptionMetrics

Table IA.A.1: Variable Definitions *(Continued)*

Variables	Definitions	Sources
	Toxic Releases Variables[30]	
On-Site Releases	Total pounds of toxic chemicals released directly to air, water, and land at the facility site. Includes stack and fugitive air emissions, surface water discharges, and land disposal. Annual Data.	EPA TRI
Off-Site Releases	Total pounds of toxic chemicals transferred off-site for disposal, treatment, or recycling. These releases occur at the receiving location, not at the reporting facility. Annual Data.	EPA TRI
Total Releases	Sum of on-site releases and off-site transfers, representing the total environmental release of toxic chemicals associated with the facility. Annual Data.	EPA TRI
Production Ratio	A ratio indicating how much the production process that generates the toxic chemical increased (or decreased) year over year. Annual Data.	EPA TRI
Cumulative Production	The multiplication of prior annual production ratios. We normalize to 1 based on the starting period of our sample to get a measure of facility-level production, similar to work done in Akey and Appel (2021). Annual Data.	EPA TRI
Abatement	Also known as source reduction or pollution prevention, these are activities that eliminate or reduce the use of chemicals and the creation of chemical waste. For example: substitution of raw materials, reformulation or redesign of technology, and process modifications. Facilities report newly implemented activities during the TRI reporting year. Annual Data.	EPA TRI
Post-Production Activity	The sum of emissions reduced through treatment, recycling, and energy recovery activities divided by the total gross waste of a plant. The releases variable excludes emissions reduced through post-production activities. Annual Data.	EPA TRI

Table IA.A.2: Corporate Biodiversity Commitments

This table showcases examples of how companies across various industries address biodiversity and 30 by 30 initiatives in their recent annual or sustainability reports.

Company	Industry	Excerpt	Source
3M Company	Manufacturing	The emergence of biodiversity and ecosystems as a new priority topic in 2022 has validated a category of work we've engaged in for years across all three pillars.	Global Impact Report 2023
BP P.L.C	Oil & Gas Supply Chain	Biodiversity and protected areas: Our biodiversity position builds on robust practices already in place to manage biodiversity across bp projects. We are committed to not operate any new oil or gas exploration or production activities inside natural or cultural UNESCO World Heritage sites, or in Strict Nature Reserves and Wilderness Areas as listed on 1 January 2020 and defined by the International Union for Conservation of Nature (IUCN).	Sustainability Report 2023
Caterpillar Inc.	Manufacturing	Over the past two decades, the Foundation's innovative approaches to nature-based solutions help create resilient, more sustainable communities that thrive in a rapidly changing world. In 2023, the Foundation supported 20 organizations in 21 countries in building basic infrastructure services, like water and energy, and restoring natural ecosystems to withstand natural disasters and environmental challenges.	Sustainability Report 2023
Enagas	Oil & Gas Supply Chain	A commitment to biodiversity is reaffirmed as one of Enagás' priority lines of action. For this reason, the company has joined the new Pact for Biodiversity and Natural Capital with the highest level of commitment. This initiative is backed by the Spanish Business and Biodiversity Initiative (IEEB).	Annual Report 2023
Endeavour Mining	Metals & Mining	Turning to ESG Reporting, we have become early adopters of the Task Force on Nature-related Financial Disclosures (TNFD), demonstrating industry leadership on the importance of nature, particularly biodiversity in our case.	Sustainability Report 2024
Heidelberg Materials	Metals & Mining	A study investigated the role that mining sites can play as alternative habitats for insects that are potentially endangered due to landscape changes. The project complements our measures to improve biodiversity management at our quarries.	Annual and Sustainability Report 2023
Newmont Corporation	Metals & Mining	Our commitment to No Net Loss of Key Biodiversity Values (KBVs) from mine-related activities is integral to our approach and essential for achieving positive nature outcomes. In 2023, we conducted audits of biodiversity risks at Ahafo South, Akyem and Boddington.	Sustainability Report 2023

Table IA.A.3: Firm Count by NAICS Sectors

This table displays the number of firms in our sample by two-digit NAICS sectors.

Code	Two-Digit NAICS Sectors	Number of Firms
11	Agriculture, Forestry, Fishing and Hunting	3
21	Mining, Quarrying, and Oil and Gas Extraction	39
22	Utilities	7
23	Construction	18
31	Manufacturing	46
32	Manufacturing	138
33	Manufacturing	271
42	Wholesale Trade	47
44	Retail Trade	23
45	Retail Trade	45
48	Transportation and Warehousing	30
49	Transportation and Warehousing	2
51	Information	88
52	Finance and Insurance	115
53	Real Estate Rental and Leasing	49
54	Professional, Scientific, and Technical Services	36
56	Administrative and Support and Waste Management and Remediation Services	21
61	Educational Services	6
62	Health Care and Social Assistance	21
71	Arts, Entertainment, and Recreation	6
72	Accommodation and Food Services	22
81	Other Services (except Public Administration)	4
Total		1039

Table IA.A.4: Description of Additional Datasets Used in the Analysis

Dataset	Description
Protected Areas	We obtain data on protected areas from the U.S. Geological Survey's (USGS) Protected Areas Database of the United States. This database provides comprehensive spatial data on protected lands across the U.S., including information on ownership type, conservation designation, and management intent. For this study, we focus on areas with GAP Status 1 and 2, as they are explicitly designated for biodiversity conservation. GAP Status 1 includes areas with the strictest protections, managed to maintain natural ecosystems with minimal human impact, prohibiting extractive activities entirely. GAP Status 2 areas are also managed for biodiversity conservation but may allow for limited human activities that do not degrade the ecological conditions. Figure 1 illustrates these protected areas. Panel A shows the protected areas color-coded by ownership type, such as federal, state, regional agencies, NGOs, and private entities. Panel B overlays these areas with the Protected Weighted Range Size Rarity (PWRSR) measure.
Carbon Emissions Data	To ensure our results are not driven by climate-related risks, we obtained firm-level carbon emission data from Trucost. Trucost is a leading carbon emission data provider and has been widely used in the literature. Trucost provides information on corporate Scope 1, Scope 2, and Scope 3 carbon emissions and other greenhouse gas emissions; merging with Trucost data led to a 23% reduction in observations. In our analysis, we control for both carbon emission levels and intensity. Specifically for our CAR event-study we construct a daily, value-weighted portfolios for Scope 1, 2, and 3 carbon emissions ranked on level, intensity, and year-over-year changes. We long firms the top tercile of carbon and short firms in the bottom tercile with monthly reweighting and sorting. Taking note from Zhang (2025), which finds corporate emissions data are published with delay, we construct portfolios using 0m, 6m, and 12m lags but focus on 12m lags to lower the amount of forward-looking sales bias. We still find statistical significance accounting for these portfolios, signaling biodiversity risk is being priced into equities.
Option-Implied Volatility	We obtain daily option-implied volatility data from the OptionMetrics Ivy DB U.S. database, covering the period from 2015 to 2024. OptionMetrics constructs implied volatility surfaces using exchange-traded option prices for all U.S. equity securities. For each firm-day, we extract implied volatilities at fixed maturities (30-day and 365-day) and delta levels, focusing primarily on at-the-money options (i.e., 50/-50 delta). These surfaces are interpolated using proprietary methods that ensure internal consistency across strike and maturity dimensions. This approach allows for a consistent forward-looking measure of firm-level uncertainty. Our use of implied volatility data follows the methodology employed in prior work such as Ilhan et al. (2021).

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Dataset	Description
EPA Toxics Release Inventory (TRI)	We incorporate facility-level releases data from the EPA's Toxics Release Inventory (TRI), a federally mandated program established under the Emergency Planning and Community Right-to-Know Act of 1986. TRI tracks annual releases of over 650 toxic chemicals across U.S. industrial facilities, including on-site releases and off-site transfers. Importantly, the dataset is at the facility-chemical-year level with facilities tracking data at the toxic chemical level. Facilities also report chemical waste management and source reduction activities. We spatially merge TRI records with high-resolution biodiversity exposure data to assign each facility a localized measure of regulatory vulnerability. This enables us to examine how facilities embedded in ecologically sensitive areas respond to shifts in policy salience. We focus on manufacturing facilities (NAICS 31–33) in the contiguous United States.

Table IA.A.5: Summary Statistics of Other Datasets

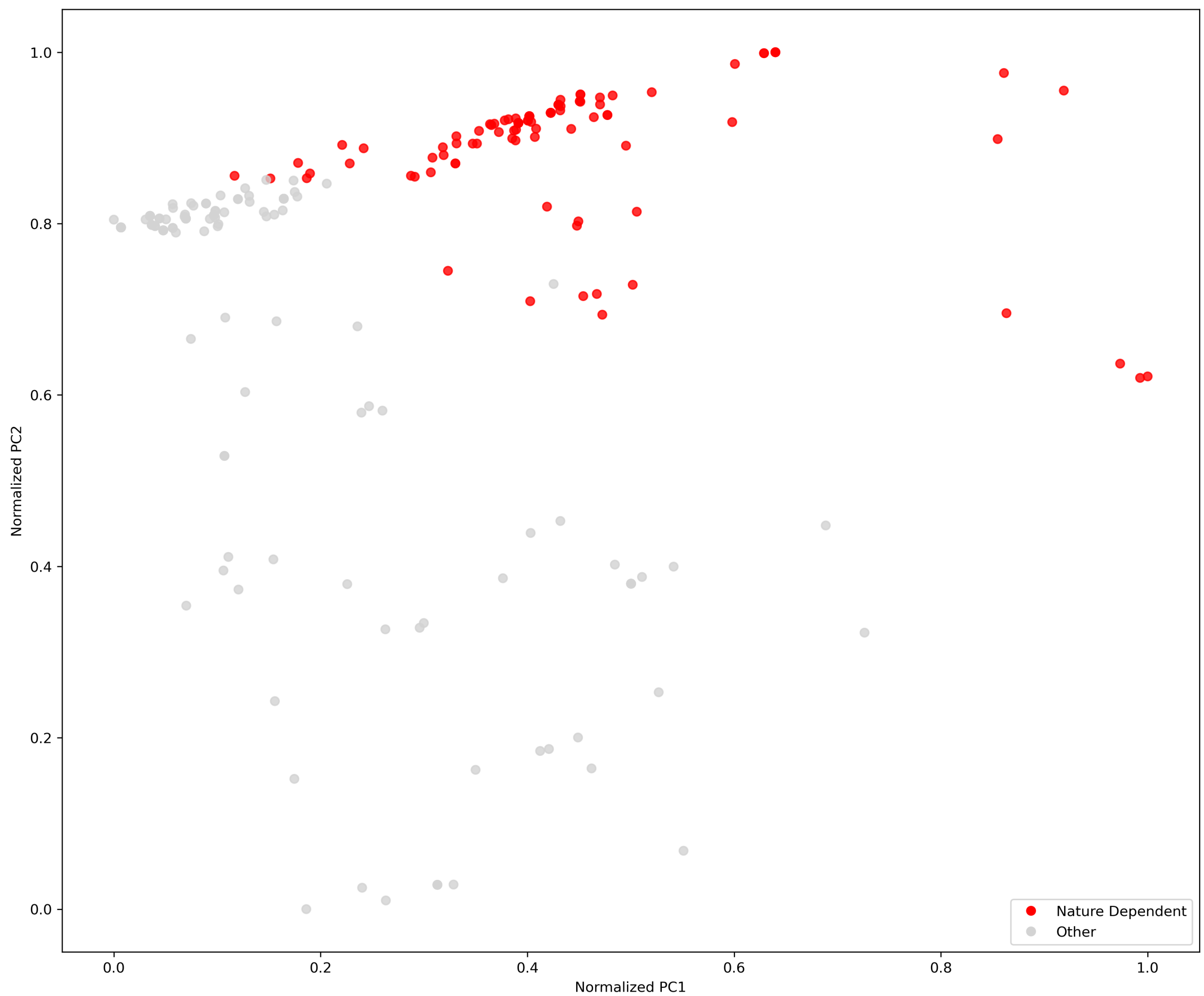
This table presents the summary statistics for the variables used in the other datasets in the paper. The sample includes all firms in the sample, and the sample period is from 2020 to 2023. Factor premiums are obtained from Fama-French Data Library. Carbon emission data are obtained from Trucost. Institutional ownership data are from Thomson Reuters 13F institutional holdings data. Mutual fund holdings are obtained from the CRSP Mutual Funds database.

	Number of Obs.	Mean	Std Dev	p5	p25	Median	p75	p95
Panel A: Trucost								
Scope 1 Emissions	34592	711237.17	3579630.80	276.00	3017.48	16426.78	87707.89	2365000.00
Scope 2 Emissions	34592	270038.04	983407.68	569.58	5858.57	25161.00	102425.00	1262328.00
Scope 3 Emissions	34592	1523096.03	5864799.35	4000.86	38826.21	171194.15	719451.72	5677346.23
Scope 1 Emissions Intensity	34592	87.01	357.74	0.38	3.79	12.18	23.55	305.22
Scope 2 Emissions Intensity	34592	30.96	115.80	1.71	7.04	14.95	29.56	90.97
Scope 3 Emissions Intensity	34592	139.16	154.13	22.94	45.04	88.03	182.76	396.29

IA.B Nature-Dependent Industries

Figure IA.B.1: PCA Analysis of Nature-Dependent Sectors

This figure presents the principal component analysis (PCA) of industry-level ecosystem dependence. Each point represents a ISIC group, which roughly corresponds to 3-digit NAICS industries. Red dots denote ISIC groups that belong to the following ISIC sections A (Agriculture, forestry and fishing), B (Mining and quarrying), C (Manufacturing), D (Electricity, gas, steam and air conditioning supply), E (Water supply; sewerage, waste management and remediation activities), and F (Construction). Gray dots indicate ISIC groups in other sections. PCA is conducted using ENCORE's 25 ecosystem service ratings for each ISIC group. The axes are first two principal components normalized to [0, 1] for replicability.



IA.C Implied Volatility Diff-in-Diff

Table IA.C.1: AUBI Exposure and 30d Implied Volatility without Biden's Election

This table replicates the baseline analysis of biodiversity policy risk and its effect on option-implied volatility, excluding the period between the U.S. presidential election (November 3, 2020) and the Biden administration's conservation executive order (January 27, 2021). The dependent variable is implied volatility, measured as the average 30-day at-the-money (ATM) implied volatility at the firm-month level. The sample period spans from January 2020 to December 2021, with the two-month election-to-executive order window excluded. Columns (1)–(4) restrict the sample to nature-dependent industries—Mining, Oil & Gas, Utilities, Construction, and Manufacturing (NAICS ≤ 33)—while Columns (5)–(8) include firms in all other sectors (NAICS > 33). The main explanatory variable is an interaction between a post-order dummy (equal to 1 for observations after January 27, 2021) and a binary indicator for firms in the top tercile of employee-weighted AUBI exposure. All regressions control for firm size (log of total assets), leverage, capital expenditures scaled by total assets (Capex/Total assets), property, plant, and equipment scaled by total assets (PPE/Total assets), valuation (log market cap and book-to-market ratio), profitability (ROA), asset and sales growth, return volatility (past 36 months), and momentum (past 12 months). Fixed effects vary across specifications: Columns (1) and (5) include firm and day fixed effects; Columns (2)–(4) and (6)–(8) absorb increasingly granular industry × day fixed effects at the 2-digit, 3-digit, and 4-digit NAICS level. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Mining, Oil, Utilities, Construction, Manufacturing				Others			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × Top Tercile Employee Weighted AUBI Exposure	0.109***	0.108***	0.124***	0.125***	0.046	0.039	0.019	-0.000
	(0.041)	(0.041)	(0.044)	(0.047)	(0.047)	(0.052)	(0.048)	(0.042)
Ln(Total assets)	-0.128	-0.101	-0.067	-0.090	0.081	0.128	0.063	0.231**
	(0.085)	(0.096)	(0.108)	(0.119)	(0.091)	(0.111)	(0.086)	(0.113)
Leverage	0.178	0.213	0.189	0.163	0.279	0.268	0.260	0.161
	(0.254)	(0.255)	(0.256)	(0.288)	(0.242)	(0.289)	(0.261)	(0.318)
Capex/Total assets	0.102	0.726	0.640	0.430	-0.299	-0.071	0.107	0.124
	(1.475)	(1.474)	(1.483)	(1.688)	(0.926)	(1.011)	(0.825)	(0.813)
PPE/Total assets	0.986	0.982	1.169	1.175	1.039	1.013	1.041*	0.778
	(0.717)	(0.689)	(0.722)	(0.720)	(0.684)	(0.680)	(0.623)	(0.561)
Ln(Market cap)	0.028	0.022	0.015	0.026	-0.053	-0.061	-0.066	-0.164**
	(0.073)	(0.074)	(0.078)	(0.079)	(0.102)	(0.112)	(0.081)	(0.079)
Book-to-market	-0.075	-0.102	-0.089	-0.074	0.202*	0.218**	0.249**	0.122
	(0.064)	(0.082)	(0.087)	(0.080)	(0.103)	(0.105)	(0.107)	(0.077)
ROA	-0.452	-0.409	-0.452	-0.479	-0.206	-0.218	-0.182	-0.310
	(0.384)	(0.359)	(0.371)	(0.402)	(0.271)	(0.264)	(0.237)	(0.248)
Asset growth	0.043	0.022	0.016	0.012	-0.018	-0.017	-0.006	-0.028
	(0.050)	(0.046)	(0.048)	(0.057)	(0.030)	(0.034)	(0.030)	(0.034)
Sales growth	0.001***	0.001***	0.001**	0.001**	-0.046	-0.064	-0.075	-0.059
	(0.000)	(0.000)	(0.000)	(0.000)	(0.044)	(0.053)	(0.064)	(0.065)
Volatility	-0.023***	-0.024***	-0.025***	-0.025***	0.011***	0.013***	0.014***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.003)
Momentum	-0.016***	-0.017***	-0.017***	-0.015***	-0.021***	-0.024***	-0.024***	-0.019***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.004)
Adj. R-squared	0.747	0.751	0.746	0.750	0.673	0.674	0.688	0.711
Obs.	120,454	120,454	119,110	109,117	119,731	119,506	117,314	104,973
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	-	-	-	Yes	-	-	-
Ind × Day FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes

Table IA.C.2: AUBI Exposure and 30d Implied Volatility around Paris Agreement Withdrawal

This table analyzes the impact of biodiversity policy risk on option-implied volatility, focusing on differences across firm-level exposure to Areas of Unprotected Biodiversity Importance (AUBIs). The dependent variable is implied volatility, measured as the average 30-day at-the-money (ATM) implied volatility at the firm-month level. The sample period spans from June 2016 to June 2018, centered around President Trump's announcement of U.S. withdrawal from the Paris Climate Agreement. Columns (1)-(4) restrict the sample to nature-dependent sectors—Mining, Oil & Gas, Utilities, Construction, and Manufacturing (NAICS $\leq$ 33)—while Columns (5)-(8) include all other sectors (NAICS > 33). The key explanatory variable is the interaction between a binary indicator for firms in the top tercile of employee-weighted AUBI exposure and a post-event dummy equal to 1 for observations after June 1, 2017. All regressions include an extensive set of control variables, including log total assets, leverage (total debt over total assets), capital expenditures scaled by total assets (Capex/Total assets), property, plant, and equipment scaled by total assets (PPE/Total assets), valuation measures (log market cap and book-to-market), profitability (ROA), asset and sales growth, return volatility (standard deviation over the prior 36 months), and momentum (average return over the prior 12 months). Columns differ in their treatment of fixed effects: Columns (1) and (5) include firm and date fixed effects; Columns (2)–(4) and (6)–(8) further absorb industry × day fixed effects at the 2-digit, 3-digit, and 4-digit NAICS level, respectively. Standard errors are clustered at the firm level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

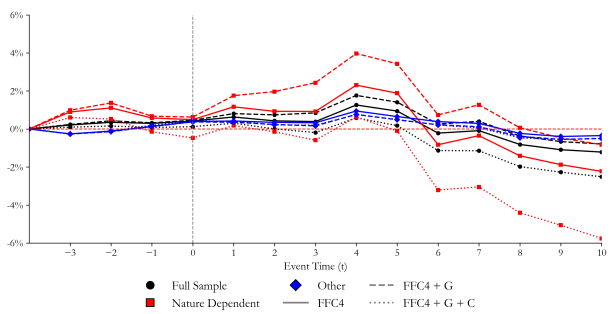
	Mining, Oil, Utilities, Construction, Manufacturing				Others			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post × Top Tercile Employee Weighted AUBI Exposure	0.042	0.043	0.055	0.073	-0.013	-0.039	-0.048	-0.035
	(0.037)	(0.040)	(0.046)	(0.057)	(0.022)	(0.031)	(0.032)	(0.030)
Ln(Total assets)	0.086	0.088	0.086	0.067	-0.009	0.009	0.009	0.142
	(0.105)	(0.107)	(0.118)	(0.146)	(0.171)	(0.167)	(0.173)	(0.111)
Leverage	0.154	0.145	0.147	0.149	-0.301*	-0.351**	-0.325**	-0.537***
	(0.178)	(0.175)	(0.180)	(0.197)	(0.178)	(0.173)	(0.162)	(0.206)
Capex/Total assets	0.013	0.156	0.235	0.235	0.122	0.117	0.083	0.028
	(0.197)	(0.185)	(0.211)	(0.216)	(0.228)	(0.226)	(0.265)	(0.337)
PPE/Total assets	-0.629	-0.685	-0.778	-0.885	-0.499*	-0.513	-0.477	-0.686**
	(0.448)	(0.488)	(0.531)	(0.589)	(0.300)	(0.311)	(0.311)	(0.338)
Ln(Market cap)	-0.092*	-0.100**	-0.106*	-0.107*	-0.107***	-0.112**	-0.125**	-0.175**
	(0.047)	(0.049)	(0.054)	(0.064)	(0.040)	(0.044)	(0.049)	(0.068)
Book-to-market	-0.075	-0.079	-0.080	-0.053	-0.078	-0.094	-0.103	-0.102
	(0.077)	(0.080)	(0.086)	(0.097)	(0.054)	(0.058)	(0.070)	(0.076)
ROA	-0.114*	-0.107*	-0.107*	-0.115	-0.342*	-0.339*	-0.330*	-0.311
	(0.062)	(0.060)	(0.062)	(0.070)	(0.177)	(0.178)	(0.179)	(0.203)
Asset growth	-0.036	-0.039	-0.044	-0.037	0.092	0.102	0.102	0.045
	(0.049)	(0.046)	(0.049)	(0.058)	(0.080)	(0.086)	(0.091)	(0.045)
Sales growth	0.022*	0.022*	0.022*	0.022	-0.139***	-0.137***	-0.140***	-0.141***
	(0.013)	(0.013)	(0.013)	(0.014)	(0.048)	(0.047)	(0.044)	(0.039)
Volatility	-0.016	-0.017	-0.017	-0.019	-0.004	-0.007	-0.008	-0.005
	(0.013)	(0.014)	(0.015)	(0.018)	(0.013)	(0.013)	(0.015)	(0.016)
Momentum	-0.018***	-0.018***	-0.019***	-0.018***	-0.015***	-0.015***	-0.014***	-0.014**
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Adj. R-squared	0.799	0.798	0.791	0.781	0.785	0.783	0.786	0.792
Obs.	125,117	125,116	122,921	111,695	123,899	123,563	120,549	107,878
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day FEs	Yes	-	-	-	Yes	-	-	-
Ind × Day FEs	No	Yes	Yes	Yes	No	Yes	Yes	Yes

IA.D Event CARs Analysis

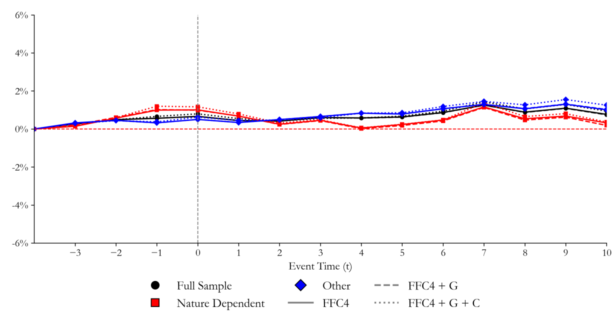
Figure IA.D.1: Cumulative Abnormal Returns around Key U.S. Political Events

This figure presents the cumulative abnormal returns (CARs) of an equal-weighted long-short portfolio that takes long positions in firms within the top tercile of AUBI exposure and short positions in firms within the bottom tercile around key U.S. political events. Expected returns are obtained from factor model predictions, where factor loadings are estimated using a 100-trading-day window ending 10 days before the event window. All panels cover the event window from $t = -3$ to $t = 10$. The dashed vertical line represents $t = 0$, corresponding to the event date. CARs are computed using the Fama-French-Carhart four-factor (FFC4) model, controlling for a daily GMB factor (FFC4 + G), and Scope 1, 2, and 3 Carbon Intensity portfolios (FFC4 + G + C) when specified. The figure plots the CAR for three long-short portfolios: black lines represent the full sample, red lines correspond to location and nature-dependent firms (Mining, Utilities, Oil & Gas, Manufacturing, or Construction), and blue lines represent other firms.

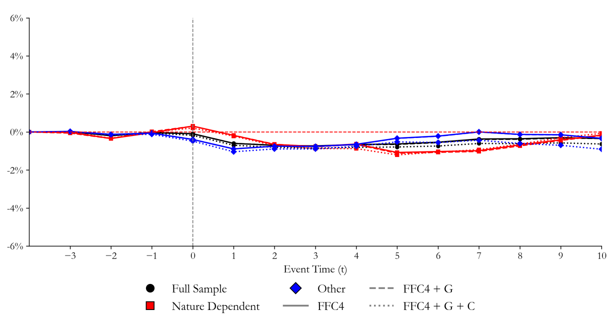
Panel A: President Trump's Election - November 08, 2016



Panel B: President Trump's Inauguration - January 20, 2017



Panel C: Paris Agreement Exit - June 01, 2017



Panel D: President Biden's Election - November 03, 2020

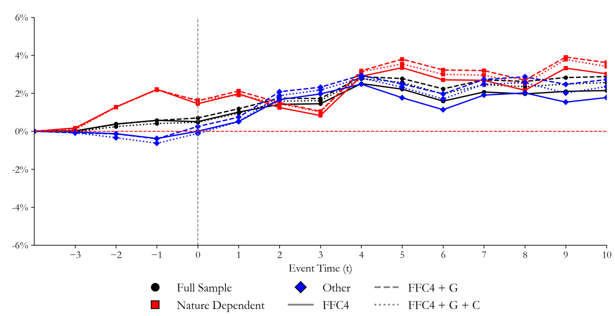


Table IA.D.1: AUBI Exposure and CARs: β_1 Estimates

This table reports the estimated betas from a regression of the form $CAR_{it} = \beta_0 + \beta_1 \cdot (TopTercileAUBI_i)$, around two key events: January 27, 2021, and November 5, 2024. Firm-level cumulative abnormal returns (CARs) are computed using a 100-trading-day estimation window ending 10 days before the start of the event window. We analyze three event windows: $t = [-3, 3]$, $t = [-3, 5]$, and $t = [-3, 10]$. The regressions are based on the Fama-French-Carhart four-factor (FFC4) model and, depending on the specification, additionally control for a daily Green-minus-Brown (GMB) factor (FFC4 + G) and Scope 1, 2, and 3 carbon intensity-sorted portfolio returns (FFC4 + G + C). Results are presented for three samples: the full sample, nature-dependent firms, and non-nature-dependent firms (denoted as "Other"). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: January 27, 2021

	FFC4			FFC4 + G			FFC4 + G + C		
Sample	[-3,3]	[-3,5]	[-3,10]	[-3,3]	[-3,5]	[-3,10]	[-3,3]	[-3,5]	[-3,10]
All									
	-3.064	-4.059**	-5.348***	-2.98	-3.99**	-5.244***	-2.854	-3.846*	-5.195**
	(2.09)	(1.987)	(2.041)	(2.078)	(1.976)	(2.018)	(2.075)	(1.982)	(2.042)
Other									
	-0.282	-0.914	-2.644	-0.128	-0.788	-2.452	-0.191	-0.779	-2.563
	(1.583)	(1.384)	(1.608)	(1.562)	(1.361)	(1.55)	(1.557)	(1.376)	(1.617)
Nature Dependent									
	-8.413*	-9.767**	-10.616**	-8.485*	-9.827**	-10.706**	-8.023	-9.437*	-10.32**
	(4.997)	(4.866)	(4.816)	(4.977)	(4.85)	(4.8)	(4.976)	(4.859)	(4.813)

Panel B: November 05, 2024

	FFC4			FFC4 + G			FFC4 + G + C		
Sample	[-3,3]	[-3,5]	[-3,10]	[-3,3]	[-3,5]	[-3,10]	[-3,3]	[-3,5]	[-3,10]
All									
	0.786	0.75	0.747	0.52	0.343	0.373	0.72	0.745	0.804
	(0.701)	(0.839)	(1.118)	(0.715)	(0.868)	(1.129)	(0.724)	(0.895)	(1.148)
Other									
	-0.507	-0.851	-1.226	-0.681	-1.117	-1.471	-0.674	-1.034	-1.428
	(0.804)	(0.928)	(1.256)	(0.808)	(0.925)	(1.224)	(0.803)	(0.939)	(1.252)
Nature Dependent									
	2.462*	2.744*	3.446	1.977	2.001	2.762	2.464*	2.865*	3.776*
	(1.287)	(1.564)	(2.108)	(1.326)	(1.661)	(2.189)	(1.364)	(1.734)	(2.206)

Table IA.D.2: AUBI Exposure and CARs: β_1 Estimates Across Events

This table reports the estimated betas from a regression of the form $CAR_{it} = \beta_0 + \beta_1 \cdot (TopTercileAUBI_i)$, around four major climate-related and political events: (A) President Trump's Election (November 8, 2016), (B) President Trump's Inauguration (January 20, 2017), (C) the U.S. exit from the Paris Agreement (June 1, 2017), and (D) President Biden's Election (November 3, 2020). Firm-level cumulative abnormal returns (CARs) are computed using a 100-trading-day estimation window ending 10 days prior to each event window. We analyze three event windows: $t = [-3, 3]$, $t = [-3, 5]$, and $t = [-3, 10]$. Regressions are estimated using the Fama-French three-factor model (FF3) and the Fama-French-Carhart four-factor model (FFC4). Results are presented for the full sample, nature-dependent firms, and non-nature-dependent firms (denoted as "Other"). ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: President Trump's Election - November 08, 2016

	FF3			FFC4		
Sample	[-3,3]	[-3,5]	[-3,10]	[-3,3]	[-3,5]	[-3,10]
All	0.65	1.223*	-0.681	0.39	0.941	-1.213
	(0.695)	(0.738)	(1.251)	(0.67)	(0.702)	(1.218)
Other	0.293	0.65	-0.41	0.321	0.681	-0.352
	(0.654)	(0.675)	(0.806)	(0.647)	(0.669)	(0.81)
Nature Dependent	1.746	2.8*	-0.493	0.934	1.919	-2.154
	(1.509)	(1.63)	(3.124)	(1.435)	(1.522)	(3.024)

Panel B: President Trump's Inauguration - January 20, 2017

	FF3			FFC4		
Sample	[-3,3]	[-3,5]	[-3,10]	[-3,3]	[-3,5]	[-3,10]
All	0.567	0.595	0.742	0.6	0.633	0.768
	(0.424)	(0.469)	(0.602)	(0.441)	(0.487)	(0.604)
Other	0.389	0.473	0.814	0.538	0.64	0.928
	(0.424)	(0.536)	(0.727)	(0.428)	(0.539)	(0.723)
Nature Dependent	0.737	0.474	0.474	0.619	0.343	0.384
	(0.893)	(0.881)	(1.061)	(0.948)	(0.944)	(1.077)

Panel C: Paris Agreement Exit - June 01, 2017

	FF3			FFC4		
Sample	[-3,3]	[-3,5]	[-3,10]	[-3,3]	[-3,5]	[-3,10]
All	-0.828**	-0.919	-0.158	-0.731*	-0.63	-0.339
	(0.378)	(0.578)	(0.786)	(0.382)	(0.588)	(0.783)
Other	-0.726*	-0.549	0.236	-0.595	-0.159	-0.008
	(0.417)	(0.480)	(0.643)	(0.423)	(0.497)	(0.640)
Nature Dependent	-1.134	-1.631	-0.838	-1.088	-1.495	-0.924
	(0.727)	(1.337)	(1.840)	(0.730)	(1.353)	(1.831)

Panel D: President Biden's Election - November 03, 2020)

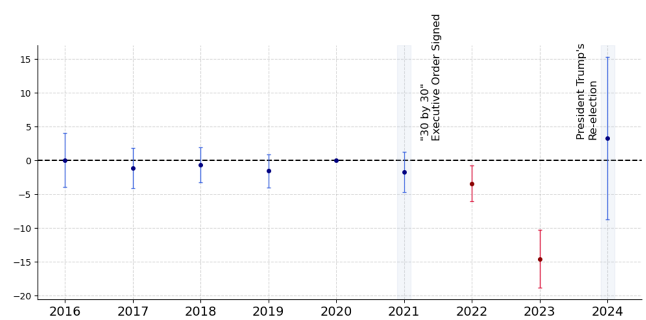
	FF3			FFC4		
Sample	[-3,3]	[-3,5]	[-3,10]	[-3,3]	[-3,5]	[-3,10]
All	1.424	2.096	2.024	1.45	2.219	2.146
	(0.991)	(1.34)	(1.48)	(1.004)	(1.391)	(1.515)
Other	2.009	1.389	1.447	1.979	1.244	1.303
	(1.378)	(1.695)	(1.758)	(1.401)	(1.848)	(1.9)
Nature Dependent	0.647	1.93	1.475	0.813	2.732*	2.274
	(1.263)	(1.486)	(2.026)	(1.265)	(1.54)	(2.036)

IA.E Firm Responses

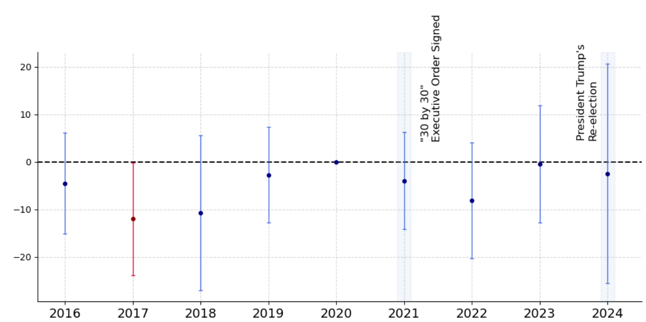
Figure IA.E.1: Dynamic Effects on Firm Toxic Releases–State×Year FEs

This figure plots year-by-year coefficients from a regression of logged toxic releases on interactions between year dummies (relative to 2020) and a continuous measure of facility-level exposure to endangered species, proxied by Protection-Weighted Range-Size Rarity (PWRSR). Regressions are estimated at the facility-year level using high-dimensional fixed effects (facility × chemical, parent company × chemical × year, and state × year), and standard errors are clustered at the facility level. The coefficients represent the marginal effect of PWRSR exposure on toxic releases in each year, relative to 2020. Error bars indicate 95% confidence intervals, with red markers denoting statistically significant coefficients at the 5% level. The first shaded region highlights the timing of President Biden's January 27, 2021 "30 by 30" Executive Order while the second highlights the re-election of President Trump on November 5, 2024. Panel A plots results for on-site toxic releases, Panel B shows off-site toxic releases, and Panel C shows total releases.

Panel A: On-Site Releases



Panel B: Off-Site Releases



Panel C: Total Releases

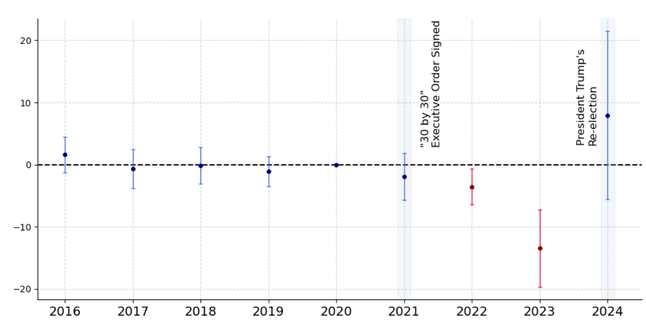
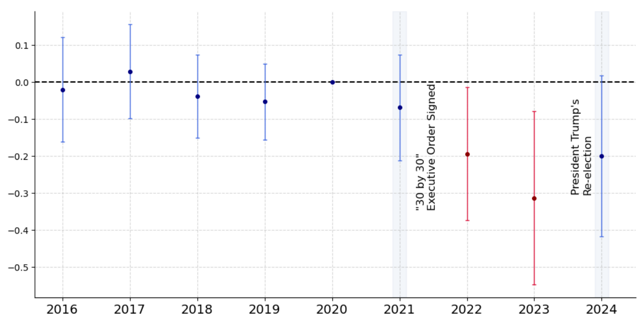


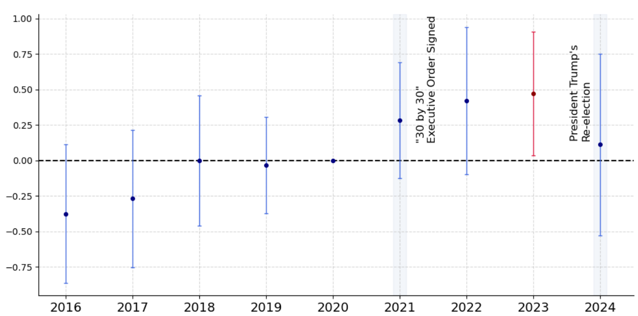
Figure IA.E.2: Dynamic Effects on Firm Toxic Releases–Discrete

This figure plots year-by-year coefficients from a regression of logged toxic releases on interactions between year dummies (relative to 2020) and a discrete measure of facility-level exposure to endangered species, proxied by Protection-Weighted Range-Size Rarity greater than 0.0015. Regressions are estimated at the facility-year level using high-dimensional fixed effects (facility × chemical, parent company × chemical × year, and state × year), and standard errors are clustered at the facility level. The coefficients represent the effect of PWRSR exposure on toxic releases in each year, relative to 2020. Error bars indicate 95% confidence intervals, with red markers denoting statistically significant coefficients at the 5% level. The first shaded region highlights the timing of President Biden's January 27, 2021 "30 by 30" Executive Order while the second highlights the re-election of President Trump on November 5, 2024. Panel A plots results for on-site toxic releases, Panel B shows off-site toxic releases, and Panel C shows total releases.

Panel A: On-Site Releases



Panel B: Off-Site Releases



Panel C: Total Releases

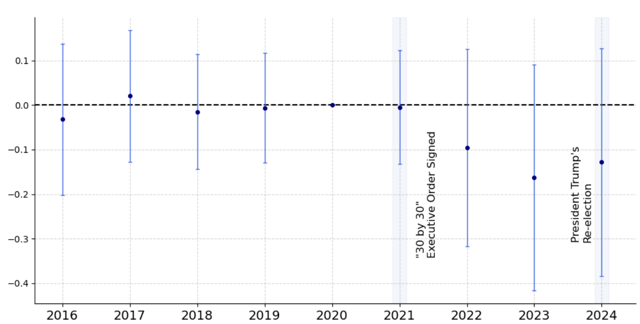


Table IA.E.1: Production Reallocation Within Firm Network

This table examines the relationship between facility-level production reported to the EPA Toxics Release Inventory (TRI) and parent-level exposure to unprotected endangered species. The dependent variable is the natural logarithm of total production-related toxic releases. The sample spans 2018–2023 and is restricted to manufacturing facilities classified under NAICS 31–33. The key independent variable is a continuous interaction between a post-2021 indicator and a leave-one-out measure of parent-level Protection-Weighted Range-Size Rarity (PWRSR) exposure. For each parent company, this measure is constructed by summing the PWRSR values of all other facilities owned by the same parent, explicitly excluding the focal facility's own PWRSR. All models include facility × chemical fixed effects. Column (1) additionally includes year × chemical fixed effects; Column (2) replaces these with county × year fixed effects; and Column (3) includes both county × year and chemical × year fixed effects. Standard errors are clustered at the county level and reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Post × Other PWRSR	0.6284**	0.6505**	0.6056*
	(0.2460)	(0.3006)	(0.3128)
Adj. R-squared	0.5148	0.5547	0.5569
Obs.	236,513	235,766	235,312
Facility × Chemical FEs	Yes	Yes	Yes
Year × Chemical FEs	Yes	No	Yes
County × Year FEs	No	Yes	Yes

Table IA.E.2: Birds, PWRSR Exposure, and High Polluting Areas–Higher Cutoff

This table reports State–Route–level regressions examining how biodiversity responds to pollution exposure after 2021. The dependent variables are Abundance and Richness, along with their natural logarithms, measured annually from 2018–2023 using the North American Breeding Bird Survey. The key explanatory variables are interactions between a post-policy indicator (Post, equal to 1 for years 2021 and later), a binary indicator for State–Route segments in the top quintile of pre-2021 Protection-Weighted Range-Size Rarity (High PWRSR), and the pre-2021 count of facilities in the top quintile of toxic releases within each State–Route segment (High Polluter Count). The table presents Poisson specifications for level outcomes and OLS specifications for both levels and logs. All regressions include State × Route and State × Year fixed effects, and standard errors are clustered at the State × Route level. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Abundance			Richness		
	(1)	(2)	(3) Log	(4)	(5)	(6) Log
Post × High PWRSR	0.0035	7.7089	0.0151	-0.0076	-0.7956	-0.00635
	(0.0187)	(24.9562)	(0.0198)	(0.0078)	(0.8638)	(0.00885)
Post × High Polluter Count	-0.00061	-1.3313	0.00028	-0.00234*	-0.2472*	-0.00250*
	(0.00296)	(4.2906)	(0.00335)	(0.00128)	(0.1389)	(0.00134)
Post × High PWRSR × High Polluter Count	-0.00114	-1.3621	-0.00202	0.00372***	0.39750***	0.00394***
	(0.00336)	(4.7587)	(0.00386)	(0.00141)	(0.1515)	(0.00149)
Adj. R-squared	-	0.8654	0.8370	-	0.8546	0.8702
Obs.	5,801	5,801	5,801	5,801	5,801	5,801
StateNum × Route FEs	Yes	Yes	Yes	Yes	Yes	Yes
StateNum × Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Poisson	OLS	OLS	Poisson	OLS	OLS