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ECONOMIC PRODUCTION AND BIODIVERSITY IN THE UNITED STATES

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ABSTRACT

Species extinctions and ecological degradation are accelerating to a degree unprecedented in human history. We present causal evidence on the economic drivers of biodiversity loss using a novel panel dataset on the types and quantities of wildlife at thousands of locations across the U.S. from 1960-2015. Exploiting fiscal and regulatory shocks to local economic output, we document large, negative impacts of GDP on abundance and diversity of species spanning multiple taxa. The adverse effects of production are mitigated by conservation and air emission abatement efforts, which points toward habitat losses and pollution as underlying contributors to contemporaneous biodiversity declines.

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1 Introduction

Economic development's various impacts on the environment – such as land use changes, natural resource extraction, and pollution – are widely seen as key drivers of ecological degradation and biodiversity loss, but empirical research on the economic roots of biodiversity trends is rare (Frank and Schlenker, 2016).[1] Little causal evidence exists on natural, first-order questions: Does economic development harm biodiversity and, if so, to what extent? Do conservation policies such as the creation of nature reserves protect biodiversity from the harms that may occur from development? Do environmental regulations designed to protect human health provide co-benefits to help conserve wildlife? In this paper, we provide some of the first causal evidence for the link between economic production and biodiversity, as well as the role of environmental policies.

The central obstacle that has impeded attempts to empirically study the economic determinants of biodiversity is the lack of data. Generally, existing datasets on biodiversity outcomes either provide only cross-sectional information (geographic extent of species), such as the International Union for Conservation of Nature Red List of Threatened Species (IUCN, 2021); or longitudinal information for a single taxonomic class, as is the case for the North American Breeding Bird Survey. These limitations hamper the data's usefulness in establishing causal inference and in studying the effects of economic development on biodiversity at broad scales. To the best of our knowledge, most existing evidence on the anthropogenic drivers of biodiversity loss is either correlational in nature and, hence, might be subject to confounding factors (Newbold et al., 2015); or is focused on a specific taxon, and so might not reflect biodiversity across different taxa or biomes (e.g., Liang et al., 2020).

A primary innovation of this paper is that we use a novel biodiversity database known as BioTIME that has only recently become available (Dornelas et al., 2018; Blowes et al., 2019). BioTIME is a database of hundreds of ecological studies that maintain *assemblage time-series*: academic research studies that measure the abundance (count or biomass) of relevant species in a particular area over time, with some studies spanning several decades. In total, BioTIME contains millions of records of species counts at the species-location (latitude and longitude)-year level at over 10,000 different locations, across many different biomes and types of organisms. Two key features of BioTIME make the data particularly useful for studying the link between economic development and biodiversity. First, all the included studies have consistent sampling protocols within the same sampling locations. This means

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[1] Traditionally, economics has focused on the economic value of biodiversity, an approach that started with the defining work of Weitzman (1992), and has since been advanced by many others (e.g., Metrick and Weitzman, 1998; Weitzman, 1998; Heal, 2000; Armsworth et al., 2004; Polasky et al., 2005; Freeman III et al., 2014; Dasgupta, 2021).

that the year-over-year variation in biodiversity metrics at the same location reflects genuine changes in underlying biodiversity conditions, rather than changes in sampling methods that may be driven by economic factors. Second, BioTIME allows us to observe significant fractions of the total number of species in different taxonomic classes, which we call taxa. For example, we observe 80 percent of the known bird species, 40 percent of mammals, 30 percent of amphibians, and 25 percent of freshwater fish. In addition, BioTIME records observations of thousands of unique plant species. The significant coverage of the dataset allows us to gain a broad understanding of how economic development affects biodiversity and ecosystems to an extent that previously was not possible.

With the longitudinal data provided by BioTIME, our analysis revolves around standard panel data methods that examine how year-over-year changes in economic output in the United States link to biodiversity outcomes at a given location. Our focal measure of economic output is local (state) GDP per capita. We examine three fundamental metrics of biodiversity: species *abundance*, which measures the total quantity of individuals that were observed at a given location in a given year; species *richness*, which measures the total number of unique species that were observed; and *Jaccard similarity*, which measures the share of common species between two adjacent years of a study. In the appendix, we report robustness checks using alternative biodiversity metrics that are commonly used in the ecology literature, such as the Gini diversity, Shannon diversity, and Sorensen similarity indices.

Our baseline analysis is a fixed effects model with a biodiversity metric as the outcome variable, GDP as the regressor, and a set of location-taxon fixed effects and year fixed effects. This exercise reveals a strong, negative correlation between economic production and biodiversity outcomes. The ordinary least squares (OLS) estimates for the elasticity of the different metrics are -3.6 for abundance, -1.6 for richness, and -0.1 for similarity (more on effect size below). The adverse effects of economic development appears to be pervasive. We find negative elasticities across multiple taxa – for amphibians, birds, fish, freshwater plants and invertebrates, and mammals. The effects emerge in areas with different levels of economic development: the negative elasticities are not statistically different across areas with the lowest, middle, or highest quintiles of sample-average GDP per capita.[2] The effects exhibit significant distributional heterogeneity: at the lowest decile of biodiversity, the negative effects of local economic production are almost twice as large as the average effects. This finding suggests that economic development exacerbates biodiversity losses

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[2] There is thus limited evidence within our study scope that the effect of economic production on biodiversity exhibits an Environmental Kuznets Curve (Grossman and Krueger, 1995). See, for example, Harbaugh et al. (2002) and Lin and Liscow (2013) for evidence in other settings.

to the greatest degree in areas where biodiversity is already low. It also suggests that biodiversity itself may increase resilience to adverse shocks to the ecosystem (Hautier et al., 2015).

The fixed effects regression results provide evidence of a general association between biodiversity and economic output. We then strengthen the econometric design by honing in on economic fluctuations that are tied to policy shocks that generate quasi-experimental variation in GDP. We exploit two distinct quasi-experiments that are known to have opposite effects on local economic output. We first consider government spending shocks that **expand** the local economy. We use U.S. military buildups, which are heavily influenced by geopolitical factors and unexpected military events, to create an exogenous source of variation in government spending. Military buildups have been widely leveraged in the empirical macroeconomics literature to estimate the causal effect of government spending on total economic output, i.e., the fiscal multiplier (e.g., Hall, 2009; Barro and Redlick, 2011; Ramey, 2011; Nakamura and Steinsson, 2018). We follow this literature and implement a shift-share design that exploits systematic heterogeneity in a state's receipt of federal military spending (and therefore in the state's output) in response to the national military shock (Nakamura and Steinsson, 2014). Our second research design exploits regulatory shocks that **contract** local economic production. We leverage a series of tightening of Clean Air Act environmental standards across U.S. states and counties since the 1990s. These provisions imposed sweeping emission abatement requirements on jurisdictions in violation of a set of outdoor air quality standards. A thorough environmental economics literature has examined the productivity, employment, and competitive effects of this policy (e.g., Becker and Henderson, 2000; Greenstone, 2002; Greenstone et al., 2012; Walker, 2013). We follow this literature and construct regulation shocks from annual listing (and de-listing) of jurisdictions in violation of such standards across the United States.

Using an instrumental variable (IV) approach, we show that the expansionary spending shock leads to a deterioration of biodiversity outcomes; by contrast, the contractionary regulation shock leads to biodiversity improvements. Though both quasi-experiments are drawn from distinct parts of the economics literature and differ substantially in context and scope, they nevertheless yield similar causal biodiversity-GDP elasticity estimates. Using the military spending (regulation) design, we estimate GDP elasticities of -5.9 (-4.5) for abundance, -3.2 (-2.8) for richness, and -0.54 (-0.52) for similarity. We also find similar results when both instruments are used simultaneously in an over-identified IV model. These estimates are statistically more precise than their OLS counterparts.

We are unaware of other published estimates on the biodiversity-GDP links at similar geographic and taxonomic scales, and so it is difficult to compare our effect sizes with those from any prior studies. In light of the difficulty in interpreting absolute effect sizes, we present two exercises that speak to relative effect sizes. We first consider habitat loss, which is widely accepted as one of the primary contributors to biodiversity loss (Pimm et al., 2014; Díaz et al., 2019). To use this as a comparison, we focus on the second half of our study period, when the advent of satellite technology makes it possible to take advantage of high-resolution measures of urbanization near sampling locations. We repeat the panel fixed effects estimation, but use urbanization as the regressor to compare against the effect size of GDP. We find that the two effect sizes are on par with each other, suggesting the total ecological effect measured by the GDP elasticity may be as important as other factors such as habitat loss that are conventionally thought of as first-order determinants of biodiversity. Second, we consider how our estimates line up with abundance changes in birds, the best known animal groups and one of the only taxa for which comprehensive data on historical population trends are available. Prior research has shown an alarming, 13 percent decline in North American bird populations between 1990 and 2015 (Rosenberg et al., 2019). Combining our estimates with GDP growth during this time span suggests that the effect of economic development may explain virtually the entire decline of bird population.

Readers may find our evidence painting a grim picture, given our findings on pronounced reductions in biodiversity resulting from increases in economic activity in a wealthy, low-density country, with an economy geared primarily toward services rather than toward the exploitation of the natural environment. Is economic development *necessarily* at odds with preserving biodiversity? In the final part of the paper, we examine whether two classes of protective policies – conservation protected areas, and regulation-induced adv ances in abatement technologies – play a role in mitigating the adverse effect of economic production. We find evidence that increasing the quantity of land that is protected from development helps dampen the negative effect of economic development, though not to an enormous extent. Our analysis finds that protecting 50 percent of the land within 50 kilometers around a sampling location, as compared to the absence of any such protections, would only reduce the negative effects of GDP by about 25 percent. Our results also show that the spatial distribution of the protected areas matters: conditional on the total area under protection, more fragmentation reduces the protected areas' ability to mitigate the negative effects of economic production. We also find that the negative impacts of GDP on biodiversity is muted in states that have experienced a fast decline of industrial emission intensity (pollution per unit of output) in the wake of the Clean Air Act Amendments of 1990. This evidence suggests environmental policies that are nominally designed to protect human health may provide conservation co-benefits as well. Though these results are based on cross-sectional comparison of effect sizes rather than using as-good-as-random variation in policy, they both point to the possibility that economic development is not necessarily at odds with biodiversity conservation once it is coupled with appropriate regulations.

Related Literature. The ecological and economic importance of biodiversity has been widely studied. Higher levels of biodiversity are associated with enhanced ecosystem stability and resilience, and can affect the physical environment such as local temperature (Tilman et al., 1996; Cottingham et al., 2001; Missirian et al., 2019). More diverse ecosystems also tend to have improved natural processes, such as nutrient recycling and biomass production (Cardinale et al., 2012). Biodiversity is also associated with numerous economic benefits (Brock and Xepapadeas, 2003). For example, restoration of biodiversity in the fisheries sector in recent decades has been associated with substantial increases in productivity (Worm et al., 2006); greater biodiversity in organisms such as pollinators is associated with enhanced crop yields (Dainese et al., 2019); higher plant species diversity helps mitigate households' income shocks from natural hazards such as droughts (Noack et al., 2019); biodiversity has critical value for pharmaceuticals where successful drug discovery hinges on molecular diversity (Simpson et al., 1996; Rausser and Small, 2000; Costello and Ward, 2006); nature and biodiversity preservation also have significant non-use and non-market value (Loomis and White, 1996; Kolstoe and Cameron, 2017).

Massive wildlife losses in recent decades highlight a pressing need to balance economic development and conservation (Polasky et al., 2005; Frank and Schlenker, 2016; Ando and Langpap, 2018; Dasgupta, 2021). Extinction rates are currently orders of magnitude higher than baseline, non-anthropogenic levels (Pimm et al., 2014), and species turnover rates are elevated as well (Dornelas et al., 2014). Our paper joins an emerging body of research that identifies specific anthropogenic determinants of biodiversity changes; such research has examined forest loss (Daskalova et al., 2020), temperature changes (Antão et al., 2020), agricultural activities (Li et al., 2020; Noack et al., 2021), and industrial pollution (Liang et al., 2020). Our work is among the first in economics and ecology to provide national-scale estimates on the GDP-biodiversity link across several different groups of plants and animals; this complements prior studies based on aggregated data (Dietz and Adger, 2003; Mills and Waite, 2009; Czech et al., 2012), correlational methods (Newbold et al., 2015), or simulation (Sumaila et al., 2019).

Our work also contributes to the literature on the costs and effectiveness of conservation programs (Montgomery et al., 1994; Lueck and Michael, 2003; Lewis et al., 2011; Laurance et al., 2012; Watson et al., 2014; Geldmann et al., 2019; Auffhammer et al., 2020; Ferris and Frank, 2021). The benefits derived from these programs will rely on both the economic value of biodiversity, and the degree to which biodiversity outcomes respond to policy making and economic changes. Despite the large size of the conservation policy literature, there is little evidence that these policies decrease the negative impacts of GDP and general economic pressures on biodiversity. We provide new evidence that protected areas mitigate negative effects of economic pressure, and that the spatial structure of the protected areas matters for their effectiveness.

Some qualifications of our analysis bear mention. First, because of the assemblage time-series nature of the BioTIME data, our study scope is restricted to the species covered by the underlying ecological studies. We are unaware of data sources that provide population-based, longitudinal information for multiple species at similar geographic and temporal scales. Second, a key finding of our paper is that economic development as measured by GDP harms biodiversity. We are, however, agnostic about the precise mechanisms through which these damages occur. That said, several pieces of evidence appear to consistently hint at an important role of pollution. Military shocks disproportionately boost manufacturing industries, which are a highly polluting economic sector (Section 4.1). Regulations that limit air pollution emissions reduce manufacturing activity and productivity (Sections 4.2 and 5). Although we focus on macro-/regional-scale economic and policy changes in this paper, the BioTIME database does include detailed geocoordinate information for each sampling location, making it a suitable source to study the determinants of biodiversity in more granular way and in specific contexts. We hope our analysis fosters future work on the topic.

The paper is organized as follows: Section 2 describes the data. Section 3 presents the baseline panel data estimation. Section 4 presents the instrumental variable analysis. Section 5 discusses mitigation policies. Section 6 concludes the paper.

2 Data

2.1 BioTIME Database

To help readers conceptualize the data structure, we begin with a brief description of two example studies included in BioTIME. We also use these examples at other points in the paper to provide conceptual references when helpful.

Example Study 1: North American Breeding Bird Survey (Birds). The North American Breeding Bird Survey (BBS) is a long-term and large-scale monitoring program that tracks the status and trends of North American bird populations (USGS, 2014). The BBS follows a regular and consistent sampling (observing) protocol. Skilled bird observers collect observation data at the same stops along the roadside survey routes during the avian breeding season every year (June for the most part of the United States). Each survey route is approximately 24.5 miles long, with stops situated about a half mile apart. At each stop, a three-minute point count is conducted. During the count, observers record every bird heard or seen within a 0.25-mile radius. Surveys start one and a half hours before local sunrise and take about five hours to complete. Over 4,100 survey routes are located across the continental United States and Canada (Figure A.1). BBS is perhaps the most widely used data source in the study of birds; as of this writing, it has been used in over 450 scientific publications, including Rosenberg et al. (2019), which is the major publication we use as a benchmark for bird population trends (Section 4.4). ■

Example Study 2: Sevilleta Long-Term Ecological Research (Mammals). Several studies included in BioTIME are conducted under the Sevilleta Long-Term Ecological Research (LTER) Program at the Sevilleta National Wildlife Refuge in central New Mexico (Figure A.2). The habitats, about 100,000 hectares in size, represent five regional biomes that extend through much of the central and western United States and northern Mexico. One example study in the program is its small mammals census, conducted from 1989 to 2008 (Friggens, 2008). In this study, permanent trapping stations were used to collect observational data about small mammals which were collected two to three times yearly across different seasons in multiple habitats within the refuge. During the sampling period, trapping webs, each consisting of 120 permanently marked trapping stations, were deployed for three consecutive nights. Sherman live traps (boxes that capture the animal without harming it) were placed at each station, with four traps placed at the center of the web. Upon capture, each individual is marked either permanently with tags or temporarily with Sharpies. There are 16,657 records for 27 distinct species covered in the study. The most commonly observed species is *Dipodomys merriami* (Merriam's kangaroo rat). ■

BioTIME has a number of features making it useful for causal analysis. First, the studies included in the dataset all maintained consistent sampling protocols over time, ensuring that within-study variation in outcomes does not stem from changes in how species are detected by the researchers (e.g., sighting versus trapping). Second, each study included in the panel dataset has at least two years of sampling, and some studies span multiple decades. This allows us to exploit within-study variation, and to control for any differences across studies in sampling protocols with location fixed effects. Third, the dataset contains information on about 40,000 unique species or genus at over 15,000 sampling locations, spanning a wide range of biomes and ecosystems. While such coverage is by no means "comprehensive" compared to the overall ecosystem (we observe 80 percent of the known bird species, 40 percent of mammals, 30 percent of amphibians, 25 percent of freshwater fish, among smaller coverage for other taxa), we believe the data let us gain by far the best understanding of which kinds of organisms and biomes are affected by economic production.

We make several sample restrictions. First, we focus on years after 1960 to line up with our economic data. Second, we include only studies from terrestrial or freshwater ecosystems, and exclude marine ecosystem studies, which often take place tens or hundreds of miles offshore and, thus, are difficult to link to measures of economic development. Third, we aggregate the raw species sampling observations to the taxon-location-year level. The included taxa are birds, fish, mammals, terrestrial invertebrates, freshwater invertebrates, terrestrial plants, and freshwater plants.[3] Fourth, we use only studies that report species abundance (i.e., counts of individuals), and exclude studies that only report total species biomass or species presence so that we have a unified measure of abundance. Last, we focus on studies in the United States. The United States accounts for about three-quarters of the total observations in the dataset; the next largest contributor, New Zealand, accounts for about 10 percent. Focusing on the United States also allows us to implement several well-understood quasi-experiments in the causal analysis. These sample restrictions give us a maximum of 66,418 taxon-location-year observations.

2.2 Measures of Biodiversity

Biodiversity is a multi-faceted concept. In this paper, we focus on three intuitive and important metrics: abundance, species richness, and the Jaccard similarity index. In the appendix, we report findings using other common measures of biodiversity.

Abundance is the total number of individuals observed at a given location in a given year. Abundance simply measures the pure quantity of individuals observed and is agnostic about the types of species in the sample.

Species richness is the total number of unique species present at a given location in a given year. This metric is agnostic about the composition of species or how the composition of species has changed. For example, if there is an equal loss of native species and introduction of invasive species, species richness will not change despite changes in the composition of the ecosystem.

Jaccard similarity is an inverse measure of the amount of year-to-year species turnover at a given location; thus, it provides a measure of compositional changes. Let $\mathbb{S}_{ct}$ be the set of species at some time t and location c, and let $n(\cdot)$ denote the cardinality of a set. The

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[3] BioTIME also includes 30 reptiles observations at one location, and one observation at a second location. The sparsity of the reptile data makes it impossible to credibly estimate the GDP effect for the taxon, and we therefore drop these observations from our estimation sample.

Jaccard similarity index is given by:

$$J_{ct} = \frac{n(\mathbb{S}_{ct+1} \cap \mathbb{S}_{ct})}{n(\mathbb{S}_{ct+1} \cup \mathbb{S}_{ct})},$$

the number of species present at location c in both times t and $t+1$ relative to the number of species present in either of the two times. The index is bounded between zero and one with lower values indicating some combination of loss of species, or the introduction of new species between times t and $t+1$. In the limiting case where $J_{ct} = 0$, there are no common species in times t and $t+1$ (but there still may be observed species at the location); on the other hand, a similarity index value of one indicates that the exact same set of species is present in times t and $t+1$ and there is no species turnover.

While our paper focuses on these three metrics, in the appendix, we show that the results are robust to alternative measures of biodiversity. For example, we repeated our analysis using a Gini diversity index (essentially a Herfindahl–Hirschman Index) and a Shannon diversity index (analogous to relative entropy), which account for relative abundances of different species, rather than indicating only whether a particular species was recorded. We also present results using a Sorensen index, a commonly used similarity index that is closely related to a Jaccard index but with a different formulaic specification.

We note three points here before proceeding to our summary statistics: First, we use log abundance and log species richness as our metrics. This allows us to interpret our coefficients as elasticities. We do not take a logarithm of the Jaccard similarity index since it is already a ratio. Second, for succinctness, from here on we refer to all three metrics together as biodiversity measures, although they are three distinct concepts. When referring to them individually, we make clear whether we are referring specifically to abundance, richness, or similarity. Third, we interpret declines in the three measures as worsening biodiversity outcomes; our reasoning is that declines in these measures indicate reductions in populations and/or changes in composition.

Summary Statistics. Table 1 reports summary statistics calculated based on taxon-location-year observations. Column 1 reports number of observations, which shows that roughly 80 percent of our observations are birds. To make sure that our results are not driven by a single taxon, we report two sets of results for our analyses: one uses the full estimation sample including all species, and the other uses a subsample that excludes birds.

Column 2 shows the mean and the standard deviation of abundance by taxa. The large differences in abundance across taxa partly reflect differences in study scope as well as sampling methods. For example, consider the North Temperate Lakes Long-Term Ecological

Research Program, a study that falls in the taxon category of “freshwater invertebrates.” The study samples zooplankton at the deepest location of lakes in Madison, Wisconsin, by pulling a conical net vertically through the water column, generating large abundance counts. By contrast, most studies on mammals use Sherman traps, which capture individual animals one at a time. For example, the small mammals study included in the Sevilleta Long-Term Ecological Research in central New Mexico (Section 2.1) reports only 27 unique species despite its 20-year time span. As previously noted, in all regression specifications we include taxon-by-location fixed effects to ensure the identifying variation comes from year-to-year changes in biodiversity outcomes and economic conditions, holding study protocols constant.

Columns 3 and 4 show the statistics for species richness and Jaccard similarity. Freshwater plants have the highest species richness, and mammals have the lowest richness. The average Jaccard similarity index is 0.425 among all species, indicating that around half of the species at a sampling location are observed in the next year of the study. The highest species turnover (or the lowest similarity) takes place among mammals; the lowest species turnover occurs among amphibians.

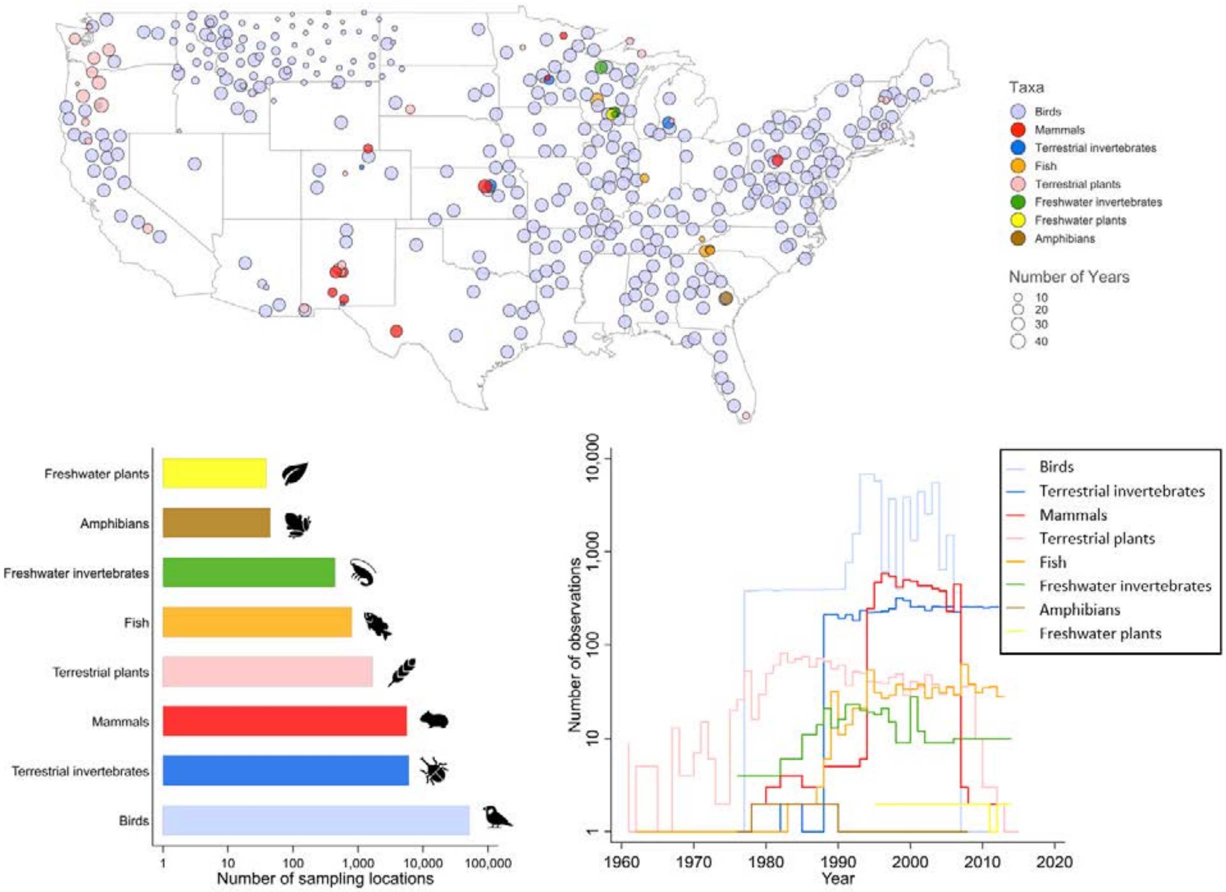
Table 1: Summary Statistics

	(1) Observations	(2) Abundance	(3) Richness	(4) Similarity
All species	66,418	39,132	15.44	0.425
		[1,203,156]	[19.62]	[0.269]
Amphibians	45	2,563	7.267	0.943
		[2,557]	[2.526]	[0.099]
Birds	51,695	216.8	18.43	0.419
		[1,967]	[20.5]	[0.252]
Fish	804	1,405	16.07	0.702
		[6,330]	[8.501]	[0.128]
Freshwater invertebrates	445	5,566,008	24.32	0.715
		[13,599,038]	[15.43]	[0.144]
Freshwater plants	39	2,747,857	83.87	0.470
		[1,193,869]	[11.56]	[0.045]
Mammals	5,658	21.18	1.91	0.316
		[174.2]	[1.958]	[0.339]
Terrestrial invertebrates	6,071	53.32	3.912	0.446
		[520.2]	[11.12]	[0.239]
Terrestrial plants	1,661	1,281	6.515	0.651
		[8,296]	[11.81]	[0.317]

Notes: Column 1 reports total number of observations in the estimation data that correspond to different taxa. For biodiversity outcomes (columns 2-4), numbers show the means, and standard deviations are in brackets.

Figures 1 and 2 further break down the summary statistics. Figure 1 shows, by taxa groups, the spatial distribution of sampling locations (upper panel), total number of sampling locations (lower-left panel), and number of taxon-location-year observations (lower-right panel). In practice, depending on the geographic scope of the study, many sampling locations may be close to each other but they may follow different sampling protocols; an example is given in the SLTER mammal study of Appendix Figure A.2. This explains why there appear to be many sampling locations but limited overall geographic coverage, especially for non-bird species. Because distinct sampling locations in the BioTIME data represent different study protocols, in our primary analysis we treat them as separate, cross-sectional units even if they are very close to each other. However, to address potential concern on spatial correlation, in Appendix Table A.1, we report the results from a series of robustness checks in which we "aggregate" the biodiversity outcomes using a spatial-binning approach. This exercise aggregates out spatial correlation at the cost of increased measurement errors that occur when samples collected using different protocols are simply "added up". We find that the results hold up qualitatively at various aggregation levels (3-km, 10-km, and 16-km hexagons) with the point estimates attenuate with coarser aggregation.

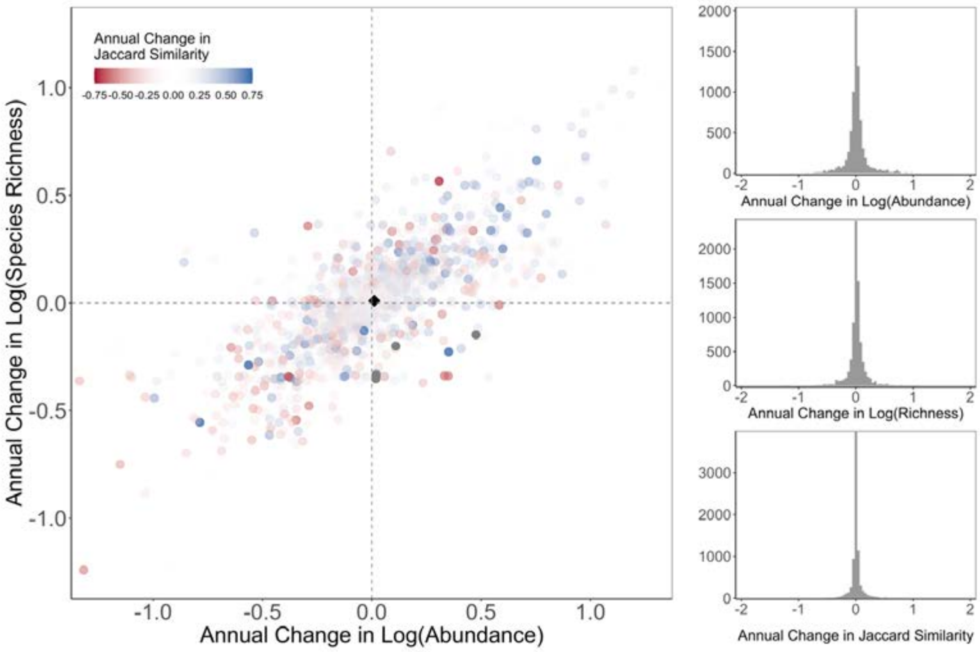
Figure 1: Sampling Locations and Observations



Notes: Upper panel plots sampling locations that are included in our main estimation sample. Location points are distinguished by taxa and are aggregated to a 95-by-95 km hexagon resolution to increase readability. Lower left panel reports number of sampling locations. Lower right panel reports total number of location-taxon observations in each year.

Figure 2 further summarizes annual *changes* in abundance, species richness, and Jaccard similarity. The scatterplot shows that changes in abundance and species richness are positively correlated; by contrast, their correlations with the change in the composition of species represented by the Jaccard similarity index can be of either sign.

Figure 2: Year-Over-Year Variation in Species Abundance, Richness, and Jaccard Similarity



Notes: All panels plot the coefficient estimates of our biodiversity metrics on a linear year time trend. The black point in the left panel is the location mean change in species richness and abundance. The right panels plot the marginal distributions of the time trend estimates for all three metrics.

2.3 Economic Data

Here we briefly describe the economic data. All data sources we use are in public domain.

Economic Output. We measure local changes in economic production using annual state level per capita GDP from the Bureau of Economic Analysis from 1966 to 2015. We use state-level output measures throughout the paper to capture overall economic changes in the area, so that our estimates do not reflect small-scale spatial displacement, for example, when individual animals move to a nearby location to avoid a rapid deterioration of the local environment. The state level measure also allows us to match geographic resolution of some key variables in the causal inference, such as the instrumental variable on state military contracting spending.

Military Spending. State level annual military spending and federal prime contracting data are from Nakamura and Steinsson (2014). The military spending data, sourced from the U.S. Department of Defense from 1966 to 2006, contain all types of military purchases such as purchase of aircraft and repairs of military facilities.[4] The federal prime contracting data identify locations where the majority of work was performed, so that one can attribute the economic production associated with the procurement to the states. The national average military spending accounts for around 3 percent of GDP; this share varies widely across states, from 10 percent in Virginia to 1 percent in Oregon.

Clean Air Act Nonattainment Designation. Annual designation of attainment and nonattainment areas are sourced from the U.S. Environmental Protection Agency (EPA) Greenbook for years 1992 to 2015. The data contain designation information for six criteria pollutants: $PM_{2.5}$, PM_{10}, O_3, SO_2, CO, and Pb. For a given pollutant, there may be multiple versions of standards that differ, for example, by the target metric (average or maximum concentration) or the year of initial promulgation (most pollution standards tighten over time). There are in total 12 standards during our study period. A jurisdiction (mostly county) can be in nonattainment with multiple standards in a given year. Appendix Figure A.3 plots the location of nonattainment areas as of year 2019.[5]

Land Cover. We measure urbanization between 2001 and 2015 using satellite data on land cover type from the Moderate Resolution Imaging Spectroradiometer (MODIS) platform maintained by the U.S. National Aeronautics and Space Administration (NASA). We use the yearly Land Cover Type product (product ID: MCD12C1), which classifies land cover into 17 types, such as urban and rainforest, at a spatial resolution of 0.05 degrees (about 5,600 meters). Our urbanization measure is the share of urban land within a 50-km radius of the BioTIME sampling site.[6]

Conservation Protected Areas. Spatial data on protected area are obtained from the World Database on Protected Areas (WDPA). The data are in the form of a shapefile that outlines the location of over 250,000 marine and terrestrial protected areas and the year that protective measures were put in place for each area. To capture conservation efforts in the vicinity of the sampling sites, we compute the share of land within a 50-km

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[4] These data are based on Department of Defense DD-350 military procurement forms that document all types of military purchases greater than a certain amount. In total, the data cover 90 percent of all military purchases in the United States.

[5] Each year, a jurisdiction's past three-year air quality metrics are calculated using data from *in situ* outdoor air pollution monitors within its administrative border. The calculated metrics, known as the "design values", are then compared with the national air quality standards. Nonattainment status is triggered when a design value exceeds the corresponding standard. Most designations occur at the county level, although nonattainment status can occasionally be assigned at a sub-county level or at a broader metropolitan-area level.

[6] The MODIS land-cover-type product is based on an ensemble-supervised classification algorithm (Friedl et al., 2010). The key inputs to the algorithm include satellite-based measurements of surface reflectance and surface temperature. The training data contain over 1,800 manually labeled sites (mostly obtained from Landsat satellite imagery) around the world.

radius of the sampling site that is under protection in each year. We also calculate the number of discontiguous protected areas within this radius to measure fragmentation of the conservation effort.

Technology Improvements. We measure state level improvements in abatement technologies using changes in emission intensity, i.e., industrial pollution emissions per unit of state GDP. We use data on air pollution emissions from the U.S. Environmental Protection Agency's Air Pollutant Emissions Trends Data, which contain state-by-year level total emissions of various criteria air pollutants and their precursors.[7]

3 Panel Estimates

3.1 Methods

We begin with a panel fixed effects regression model to estimate the within-location correlation between biodiversity outcomes and economic output. The workhorse regression equation is

$$Y_{cjt} = \beta \cdot \log GDP_{cjt} + \eta_{cj} + \eta_t + \varepsilon_{cjt} \tag{1}$$

Y_{cjt} is one of the three biodiversity metrics at sampling location c for taxon j in year t. For example, this may be the logged total number of birds observed at a particular sampling location in a given year. The regressor of interest is $\log GDP_{cjt}$, which is the logged per capita real output. η_{cj} are location-by-taxa fixed effects; these are the key panel fixed effects that ensure the identification is based on year-over-year changes in biodiversity and economic development for the same sampling location and within species in the same taxa. η_t denotes year fixed effects. ε_{cjt} is the error term. We cluster standard errors at the state level. The key parameter of interest is β, which measures the elasticity between GDP and our biodiversity metric of interest.

It is worth clarifying the unit of observation used in our panel estimation. The key geographic unit is a sampling location c. There may be multiple such locations in a given ecological study. The North American Breeding Bird Survey (Section 2.1, example study 1), for example, covers over 4,000 bird-observing "routes" that the researchers revisit every year;in BioTIME, each route is a sampling location identified uniquely by the route's centroid

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[7] These pollutants include CO, NH_3, NOx, $PM_{2.5}$, PM_{10}, SO_2, and VOC. The Air Pollutant Emissions Trends Data are aggregated from the National Emissions Inventory (NEI) database, which includes plant-level emissions information for plants in major ("Tier-1") sectors: biogenics, chemical and allied product manufacturing, fuel combustion sources, highway vehicles, metals processing, petroleum industries, solvent utilization, waste disposal and recycling, among other industries.

latitude and longitude. Some studies sample across multiple taxa at the same location, such as the Sevilleta Long-Term Ecological Research (LTER) Program (Section 2.1, example study 2), thus the cj subscripts. A key advantage of BioTIME data is that the study inclusion criteria ensure there are consistent study protocols used within each study conducted at the same sampling location. This means the year-over-year variation in biodiversity outcomes within the same location-taxon reflects genuine changes in underlying biodiversity measures, rather than changes in sampling methods. This feature of the data is important for our empirical estimation because, conditional on location fixed effects, it frees us from controlling for any changes in sampling practices that might be influenced by economic conditions across time.

Finally, the length of a study identified by a location-taxon depends on changes in sampling protocols and the overall study duration. If the sampling methodology changed during the course of the study, a new study ID is assigned. Our final estimation data are thus an unbalanced, annual panel of sampling locations by taxon. One potential concern with such panel structure is whether economic conditions may influence selections of biodiversity sampling in the first place. For example, one may conjecture that ecological studies are more likely to be conducted (interrupted) in years with good (bad) GDP due to funding availability. The impact of this type of selection on our estimates is largely ambiguous and depends on the non-linearity of the impact of GDP.[8] Alternatively, one might worry that a large economic boost in an area may distress the local environment so much so that the scientists give up the sampling location altogether; in this case, the sampling selection would cause us to understate the negative impact of GDP as the worst consequences are not observed.

These said, empirically, we do not find compelling evidence indicating that sampling activities respond to year-over-year changes in economic conditions. In fact, a majority, 62.7% of study locations in our estimation sample report biodiversity measures continuously throughout the study span (defined as the period in-between the first and the last sampling year); among the non-continuous locations, biodiversity metrics are available on average 63.2% of the time. In Appendix Table A.2, we further present various "zero-stage" regressions where we test if economic conditions influence sampling in any significant ways. First, in the cross section of study locations, we test if the average GDP growth rate at the location can predict the study span. Columns 1 shows the correlation is small: the point estimate suggests that each percentage point increase in the average GDP growth (or about 50 *percent* increase relative to the mean rate) at the study location is associated with 1.3 percent in the study

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[8] In principle, oversampling (undersampling) periods of high (low) GDP would only bias the average estimate when the "dosage" effect of GDP is nonlinear, i.e., the marginal effects of GDP differ at high vs. low levels. Figure 3, panel A shows some evidence that the effect of GDP is roughly linear for all three biodiversity outcomes.

duration; the coefficient estimate is statistically insignificant. Second, using the panel fixed effects regression framework outlined in equation 1, we test if year-over-year changes in GDP (as well as lagged GDP) can predict when a study starts sampling (columns 2 and 3), ends sampling (columns 4 and 5), and misses samplings (columns 6 and 7). We find no statistical evidence across the board that economic conditions can predict sampling activities.

3.2 Results

Figure 3, panel A reports the estimation results from equation (1). The three columns correspond to species abundance, species richness, and Jaccard similarity. We residualize the biodiversity metrics and log GDP with the fixed effects controls, and then plot one against the other using a decile binscatter. The slope of the fitted line thus represents the OLS estimate $\hat{\beta}$ of equation (1). Our results indicate negative, statistically significant, and roughly linear effects of GDP on both abundance (estimated elasticity = -3.580, SE = 1.353) and richness (estimated elasticity = -1.631, SE = 0.685). The effect of GDP on similarity is negative but imprecisely estimated (estimated elasticity = -0.104, SE = 0.157). A reduction in similarity implies that there are fewer species of the same type in a sampling location compared to the previous year, due to either a loss of species or newly introduced species.

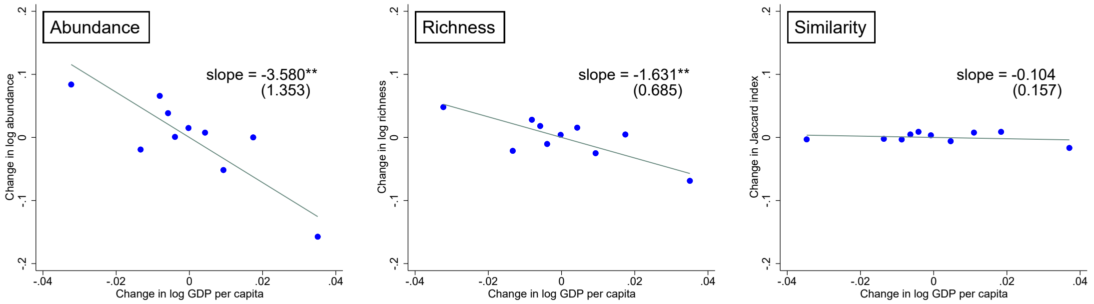
Panel B of Figure 3 shows elasticity estimates separately by taxon, where from left to right we report effects for amphibians, birds, fish, freshwater invertebrates, freshwater plants, mammals, terrestrial invertebrates, and terrestrial plants. We find that the negative associations with GDP emerge not only for birds (which comprise of 80 percent of our estimation sample), but for most of the taxon groups. Among amphibians and mammals, significantly negative effects of GDP are detected for all three biodiversity metrics. In following analysis, we report both full-sample results, and a sub-sample version that excludes birds.

Panel C of Figure 3 shows elasticity estimates by quintiles of the sampling area's average (1966-2015) GDP per capita. We find that the GDP-biodiversity elasticities do not vary substantially across *overall levels* of GDP. Thus, there is thus limited evidence within our study scope that the GDP-biodiversity elasticity follows an environmental Kuznets relationship (Grossman and Krueger, 1995; Andreoni and Levinson, 2001; Harbaugh et al., 2002); rather, the negative effects of GDP persist across different levels of economic development. Of course, a caveat here is that the range of average GDP per capita levels we examine is high because we focus on the United States.

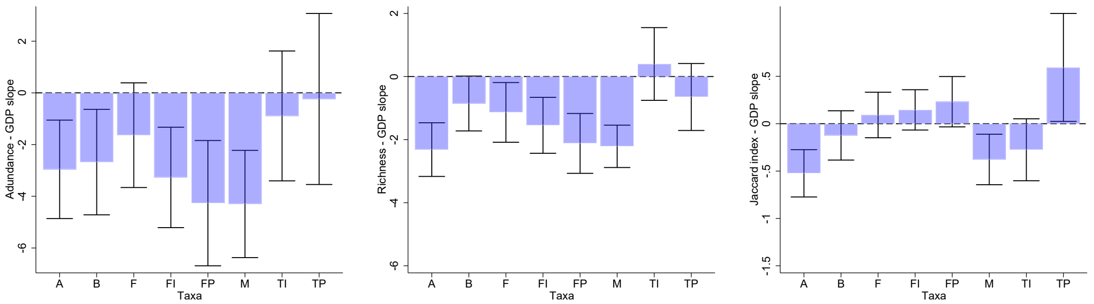
Panel D of Figure 3 investigates distributional heterogeneity, showing results from quantile regressions. We consider a fixed-effects-residualized version of equation (1), estimating regression quantiles using a residualized biodiversity metric as the outcome, and the resid-

Figure 3: The Biodiversity - GDP Relationship

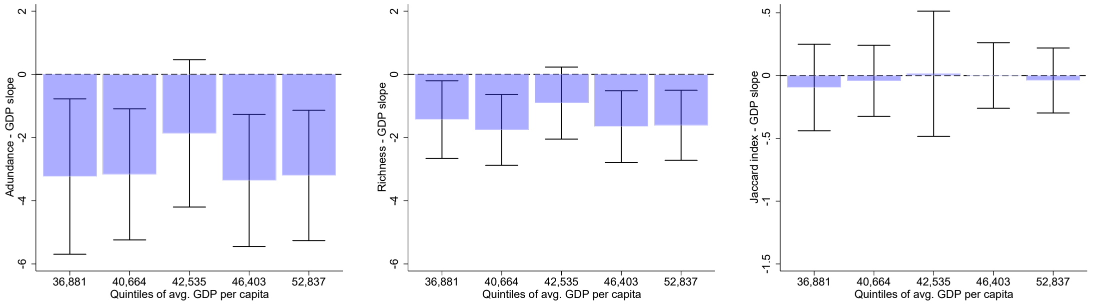
Panel A. Average effect



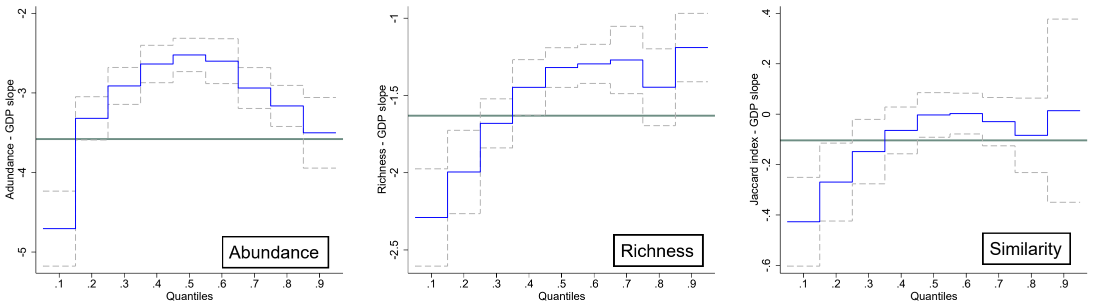
Panel B. By taxa



Panel C. By sample-average GDP per capita



Panel D. By regression quantiles



Notes: Panel A plots decile binscatter of bodiversity and log GDP, both residualized with location-by-taxa and year fixed effects. The slope of the fitted line represents the OLS estimate $\hat{\beta}$ of equation (1). Numbers in parentheses show standard errors clustered at the state level. Panel B/C/D reports heterogeneous OLS estimates by taxa/sample-average GDP per capita/regression quantiles. See text for more details.

ualized log GDP per capita as the explanatory variable. For each outcome, the horizontal line represents the average effect (i.e., the slope of the fitted line in panel A of Figure 3). For all three biodiversity outcomes, we find evidence that effects are negative or zero at all quantiles, and we find heterogeneity in the size of the effect; the negative effects of GDP are the largest at the lowest quantiles of the distributions of the biodiversity metrics. This pattern suggests that economic development exacerbates biodiversity losses in areas where biodiversity is already constrained. The heterogeneous effects also suggest biodiversity may increase resilience to adverse shocks to the ecosystem.

Overall, Figure 3 suggests a strong, negative, and pervasive relationship between biodiversity and GDP in a standard panel data setting. We report two extensions of the panel estimation in the Appendix. Appendix Table A.3 presents a dynamic specification where we include a lead and a lag term of GDP in addition to current year's GDP. We find limited evidence on a lagged effect of GDP; the "placebo", lead coefficients are statistically insignificant and in general an order of magnitude smaller than the main GDP effect size. Appendix Table A.4 presents an extension of the panel estimation results, replacing the GDP term with nine regressors representing (logged) industry income as measured by two-digit North American Industry Classification System (NAICS) code-levels. While the industry-specific estimates tend to be imprecise, negative correlations generally are observed for manufacturing, mining, retail, and transportation sectors. This evidence appears to hint at an important role played by industries with heavy environmental externalities. We explore related hypotheses in the next two sections.

4 Instrumental Variable Estimates

The panel data estimation approach reveals a general association between biodiversity and economic output, but it is subject to endogeneity concerns. One might worry that unobserved factors, such as local extreme weather, may correlate with both GDP and biodiversity (omitted variables); that noisily measured GDP and/or biodiversity outcomes may attenuate the elasticity estimates (measurement error); and that biodiversity may itself cause changes in economic output (reverse causality). In this section, we analyze how biodiversity outcomes respond to plausibly exogenous shocks to economic output that are tied to policy changes. We then leverage these quasi-experimental research designs to derive causal GDP-biodiversity elasticity estimates using the instrumental variable (IV) approach.

4.1 Research Design I: Economic Stimulus

Our first research design leverages positive shocks to state GDP through changes in national military buildups. This strategy has been widely leveraged in the empirical macroeconomics literature to estimate the fiscal multiplier, i.e., the effect of government spending on economic output (e.g., Hall, 2009; Barro and Redlick, 2011; Ramey, 2011; Nakamura and Steinsson, 2014, 2018). Here, we go a step further and ask how exogenous changes in economic output affect biodiversity outcomes.

Several features of military spending in the United States make it an attractive instrument for economic production in our setting. First, national military buildups are well known to be driven by geopolitical events such as the Vietnam War and Soviet invasion of Afghanistan; thus, the timing and magnitude of these events are plausibly exogenous to biodiversity changes in the United States. Second, because industries that produce military equipment are unevenly distributed across the country, national changes in military buildups leads to greater military spending in some states than in others. Figure 4, adapted from Nakamura and Steinsson (2014), plots state's military contract spending as a share of its GDP. Such variation helps us tease out regional changes in economic output that are attributable to national military spending shocks. Finally, military spending, such as repairs of military facilities, strongly influence construction and manufacturing outputs; these sectors are associated with substantial environmental externalities, and may conceivably influence biodiversity outcomes.

Nakamura and Steinsson (2014) use the cross-state variation associated with military buildups to estimate the effect of government spending on economic output. We adapt this approach as essentially our first stage in a two-stage least squares (2SLS) framework. We construct an instrumental variable that is the interaction between national military spending and states' historical average spending as a share of GDP. This shift-share instrument is then used to tease out the causal effect of GDP on biodiversity. The first-stage regression is

$$\log GDP_{cjt} = \theta \cdot \left(\frac{MS}{GDP}\right)_{state,1966-1971} \times MS_t + \eta_{cj} + \eta_t + \varepsilon_{cjt} \tag{2}$$

The excluded instrument is the variable $\left(\frac{MS}{GDP}\right)_{state,1966-1971} \times MS_t$, which is the initial (1966-1971 average) military contract spending (MS) a state receives as a share of GDP, interacted with annual, national per capita military spending shocks (MS_t).[9] As shown in

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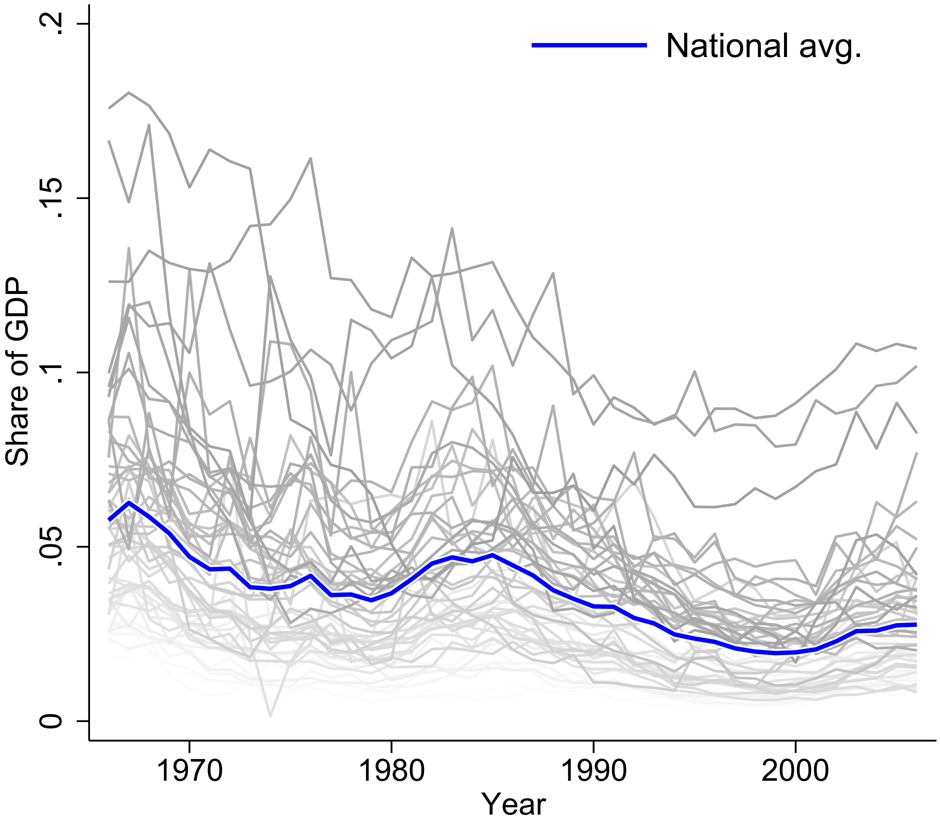
[9] The preferred IV design of Nakamura and Steinsson (2014) was an overidentified specification using national military spending MS_t interacted with state-specific dummies as the instrumental variables; the shift-share IV as in equation (2) was one of the robustness specifications, although we prefer it in our study context for the sake of its simplicity. We report results with alternative IV constructions in Appendix Table

Figure 4: Military Contract Spending as a Share of State GDP



Notes: Adapted from Nakamura-Steinsson (2014). This graph shows state's annual prime military contract spending as a fraction of its GDP. Each line represents a state. Darker lines indicate states with a higher average military/GDP share between 1966 and 1971, the base period used to construct the Nakamura-Steinsson (2014) shift-share instrument. The thick, blue line in the middle represents national average.

Figure 4, although the share of military spending to GDP changed over the years, the initial share over the 1966-1971 period still captures systematically different sensitivities of GDP to military spending shocks across states. We use this heterogeneity in sensitivity to identify the effect of military spending on GDP. The fixed effects variables are defined as in equation (1).

A central identifying assumption for the IV approach is that the exclusion restriction holds. That is, we assume that military spending shocks only affect biodiversity through their impacts on GDP. Our identification thus relies on the fact that the shock component of the instrument is as good as random (Borusyak et al., 2018). Here the shock component – states' relative differences in response to aggregate military buildups (which are themselves largely driven by geopolitical factors) – are unlikely to be correlated with unobservable determinants of local biodiversity. For example, the United States will not increase national military spending because states that receive larger military procurement contracts have less biodiversity. Because GDP is an overall measure of economic conditions, our IV estimates pick up on multiple mechanisms underlying economic development, such as changes in environmental pollution and land use.

Table 2 reports the IV results. We begin with panel A, which uses the full sample of all species. The first row ("Military spending") reports the effect of the military-spending IV on log GDP and biodiversity metrics. Column 1 is, hence, the first-stage estimate of θ in equation (2); it shows that an increase in the state shift-share IV increases state GDP by 0.3 percent. Columns 2 through 4 report the reduced-form effects of the instrument on biodiversity outcomes. We find that state military spending shocks lead to statistically significant decreases in abundance, richness, and similarity.

The IV GDP-biodiversity elasticity estimates are therefore the ratio of the reduced-form and the first-stage results. We find that increases in state GDP lead to large and precisely estimated declines in all three biodiversity metrics. Panel A, columns 5 and 6 show the GDP elasticities are -4.485 for the abundance measure (SE=1.594) and -2.753 for richness (SE=1.226). The corresponding first-stage Kleibergen-Paap F-statistics are about 7.4. Column 7 shows a coefficient of -0.535 for the similarity outcome (SE=0.183), which is a semi-elasticity estimate as the similarity metric is a ratio rather than a logarithm.

We find similar evidence on the negative effects of GDP on abundance, richness, and similarity for other taxa *excluding* birds. In panel B, we repeat the same estimation procedures focusing on non-bird observations (about 20% of full sample). In this subsample of the data, the predictive power of the IV on GDP is much stronger in the first-stage estimation

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A.5.

Table 2: Military Spending Shocks and Biodiversity Outcomes

	(1) First stage	(2)	(3) Reduced form	(4)	(5)	(6) IV	(7)
	GDP	Abundance	Richness	Similarity	Abundance	Richness	Similarity
Panel A. All species							
Military spending	0.299***	-1.341**	-0.823**	-0.164***	-	-	-
	(0.110)	(0.567)	(0.354)	(0.060)	-	-	-
GDP	-	-	-	-	-4.485***	-2.753**	-0.535***
	-	-	-	-	(1.594)	(1.226)	(0.183)
Kleibergen-Paap F-stat.	-	-	-	-	7.430	7.430	7.071
Observations	57,714	57,714	57,714	44,479	57,714	57,714	44,479
Panel B. Non-bird species							
Military spending	0.528***	-3.286***	-1.685***	-0.360***	-	-	-
	(0.087)	(1.075)	(0.624)	(0.057)	-	-	-
GDP	-	-	-	-	-6.225***	-3.193***	-0.638***
	-	-	-	-	(1.167)	(0.732)	(0.149)
Kleibergen-Paap F-stat.	-	-	-	-	37.05	37.05	34.46
Observations	11,861	11,861	11,861	10,335	11,861	11,861	10,335

Notes: Each panel-column is a separate regression. Outcome variables are in logs except for Similarity which is a ratio (columns 4 and 7). All outcome variables are multiplied by 100. Military spending shock is national per capita procurement interacted with state's 1966-1971 average military-GDP ratio. Columns 5 through 6 report IV estimates on the effect of GDP on biodiversity outcomes, using military spending shocks as the instrumental variable. Panel A reports full sample estimation. Panel B excludes observations that correspond to bird species. All regressions include location-by-taxa and year fixed effects. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

(Kleibergen-Paap F-statistic = 37). This is largely because the non-bird sampling locations are in states with higher military spending, and are thus more responsive to changes in national military buildups. In addition, as shown in Figure 1, non-bird observations are more evenly distributed across the entire study period, allowing us to better exploit temporal variation in economic changes. Panel B shows that we obtain similar IV elasticity estimates for the non-bird subsample.

Table A.5 reports a series of robustness checks on the IV estimation. In Panel A, we change the baseline period of the shift-share IV construction from an initial-period average (1966-1971) to a long-term average (1966-2006). In Panel B, we follow the primary research design of Nakamura and Steinsson (2014) and re-construct the IV variable as the fitted value of state spending on national spending, allowing different sensitivity for each state. In Panel C, we control for Census Division-specific decadal time trends in addition to the location-taxa and year fixed effects. Panel D reports the limited information maximum likelihood (LIML) estimates, which are median-unbiased with weak instruments. Overall, the results are stable across these specification checks.

4.2 Research Design II: Regulations

Having shown the effects of stimulus policies that boost the local economy, we now leverage regulatory policies to implement a "reverse" quasi-experiment in which local economic production experiences a negative shock. We consider the Clean Air Act (CAA), which is one of the first and most influential pieces of environmental legislation in the United States. The CAA regulates air quality at the state, local, and plant levels through a large number of individual programs. Our research design focuses on a major amendment of the CAA that was adopted in 1990, when the National Ambient Air Quality Standards (NAAQS) established national criteria for outdoor air quality, targeting six widespread air pollutants that harm public health.

A key component of the NAAQS program is its annual designation of compliance and non-compliance status. Jurisdictions (mostly counties) in compliance with the air quality standards are designated "attainment" areas, whereas those in violation with the standards are designated "nonattainment" areas. A nonattainment determination can be made for failing to achieve one or more of the pollutant standards ($PM_{2.5}$, PM_{10}, O_3, SO_2, CO, and Pb), and/or for failing to meet one or more of the versions of the standards for a given pollutant.[10] A nonattainment status triggers substantially elevated regulatory scrutiny; the state government is required to implement stringent regulations on the polluting industries. Such measures may include the installment of expensive pollution abatement technologies, and the use of emission permitting programs until air quality in the nonattainment area meets set standards. Figure 5 shows fraction of sampling locations in the BioTIME data that were in nonattainment areas with respect to each of the standards.[11]

We base our research design on two rich lines of environmental economics literature that document the economic costs and the environmental benefits of the nonattainment regulations. A nonattainment designation has been shown to reduce productivity and output, and impose considerable compliance and fiscal costs on the local economy (e.g., Greenstone, 2002; Greenstone et al., 2012; Walker, 2013; Blundell et al., 2020; Shapiro and Walker, 2020) while effectively reducing air pollution (e.g. Chay and Greenstone, 2005; Sanders et al., 2020). In a way, the NAAQS regulation research design explores a converse source of variation to that generated by the military-spending design: while military buildups increase economic

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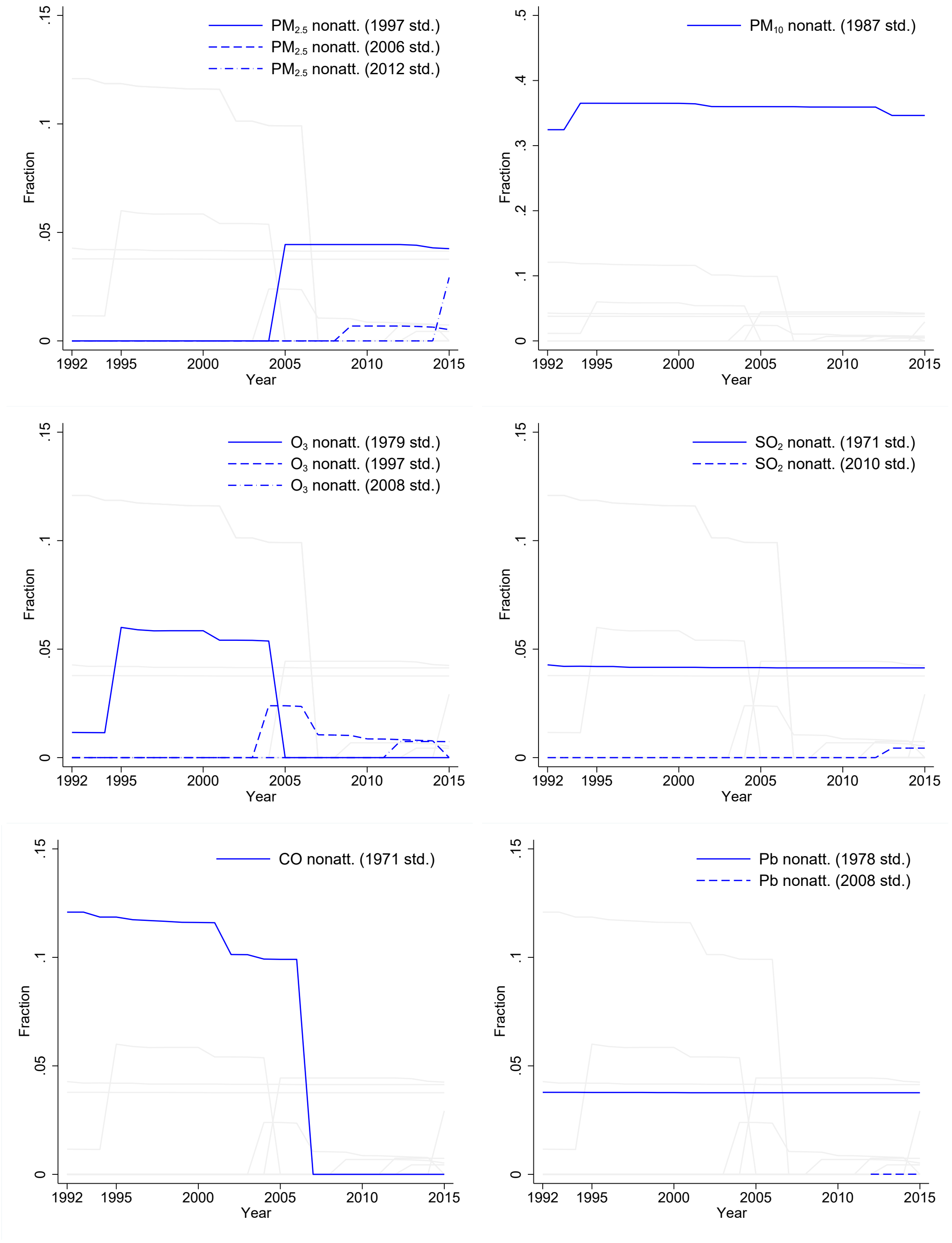
[10] Versions of standards reflect different target metrics or changes in regulatory stringency over time. For example, the 1997 $PM_{2.5}$ standard specifies an annual safety level of 15 ug/m^3, whereas the 2006 $PM_{2.5}$ standard specifies a 24-hour safety level of 35 ug/m^3; the 2008 O_3 standard (a daily maximum 8-hour concentration of 0.075 ppm) is a more stringent version of the 1997 O_3 standard (0.08 ppm).

[11] There are usually years of lag between the times when a pollutant standard was promulgated and when the nonattainment designation actually occurred. For example, as shown in Figure 5, the designation of nonattainment status with respect to the 1997 $PM_{2.5}$ standard did not occur until the year 2005.

Figure 5: Share of Sampling Locations in EPA Nonattainment Jurisdictions



Notes: This graph shows fraction of BioTIME sampling locations that were in counties designated by the U.S. Environmental Protection Agency as in “nonattainment” with respect to various air pollutants.

output and boost polluting industries, nonattainment regulations constrain economic production and reduce pollution.

The first-stage regression of the IV approach is

$$\log GDP_{cjt} = \theta \cdot Nonattainment_{county(c)t} + \eta_{cj} + \eta_t + \varepsilon_{cjt} \tag{3}$$

The excluded instrument $Nonattainment_{county(c)t}$ is the total number of nonattainment designations (across different pollutant standards) that were in place in the county of the sampling location c at year t.[12] Note that this estimation equation is analogous to equation (2) except for the change of the instrumental variable. We assume that the annual listing and de-listing of violating jurisdictions bring exogenous regulatory burdens; these shocks are borne by polluting firms in the area, which are ultimately reflected in changes of local GDP. The exclusion restriction of the IV estimation is that these policy-driven shocks would influence local ecosystem diversity only through environmental and economic changes that are captured by the overall measure of GDP.

Table 3 summarizes the results. Begin with the first row of panel A ("Nonattainment") which reports the effect of nonattainment status on GDP and biodiversity outcomes. Column 1 is the first-stage result corresponding to equation (3). It shows that one additional nonattainment designation reduces local GDP by about 3.8 percent. The magnitude of this estimate is consistent with prior evidence; for example, Greenstone et al. (2012) analyze production data from the 1972-1993 Annual Survey of Manufactures, and conclude that the NAAQS regulations have reduced total factor productivity (TFP) by 4.8 percent for manufacturing plants in nonattainment areas.

Columns 5 through 7 of Panel A show the GDP elasticities are -5.932 for the abundance measure (SE=0.624), -3.194 for richness (SE=0.268), and -0.519 for similarity (SE=0.532). The corresponding first-stage Kleibergen-Paap F-statistics are about 7.8. In Panel B, we repeat the same procedure using the non-bird subsample. Once again, we find similar evidence on the negative effects of GDP on biodiversity outcomes with a stronger first stage.[13]

In Table A.6, we conduct a set of robustness checks similar to those shown in Table A.5. In Panel A, we change the IV variable from *number* of nonattainment designations to an indicator variable for nonattainment of *any* pollutant standard. Panel B reports an

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[12] In robustness checks, we report alternative IV constructions such as using an indicator variable for the violation of *any* pollutant standard, or using multiple indicators for each pollutant standard separately.

[13] As we mention in Section 4.1, non-bird sampling locations tend to be in more industrialized states, which increases their exposure to environmental regulations. In addition, we find that, compared to bird sampling locations, a higher fraction of non-bird sampling locations are in counties that received a nonattainment designation at some point during the study period; this further increases the predictive power of the regulation IV.

Table 3: Environmental Regulation Shocks and Biodiversity Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	First stage	Reduced form			IV		
	GDP	Abundance	Richness	Similarity	Abundance	Richness	Similarity
Panel A. All species							
Nonattainment	-3.802***	22.55***	12.14***	2.015	-	-	-
	(1.358)	(7.989)	(4.623)	(1.795)	-	-	-
GDP	-	-	-	-	-5.932***	-3.194***	-0.519
	-	-	-	-	(0.624)	(0.268)	(0.532)
Kleibergen-Paap F-stat.	-	-	-	-	7.841	7.841	8.874
Observations	54,887	54,887	54,887	42,406	54,887	54,887	42,406
Panel B. Non-bird species							
Nonattainment	-5.323***	37.29***	19.33***	3.711***	-	-	-
	(0.749)	(3.813)	(2.524)	(0.676)	-	-	-
GDP	-	-	-	-	-7.005***	-3.631***	-0.704***
	-	-	-	-	(0.755)	(0.250)	(0.097)
Kleibergen-Paap F-stat.	-	-	-	-	50.570	50.567	49.56
Observations	13,331	13,331	13,331	12,161	13,331	13,331	12,161

Notes: Each panel-column is a separate regression. Outcome variables are in logs except for Similarity which is a ratio (columns 4 and 7). All outcome variables are multiplied by 100. Columns 5 through 6 report IV estimates on the effect of GDP on biodiversity outcomes, using nonattainment status (number of pollutant standards the county was in violation of) as the instrumental variable. Panel A reports full sample estimation. Panel B excludes observations that correspond to bird species. All regressions include location-by-taxa and year fixed effects. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

overidentified model with 12 excluded instruments, each indicating nonattainment status for a separate pollution standard as shown in Figure 5.[14] In Panel C, we control for Census Division-by-year trends in additional to the location-taxa and year fixed effects. Panel D reports estimates from the LIML estimator. The results are robust to the specification changes.

4.3 Other Robustness Checks

Although the CAA nonattainment exercise uses an entirely difference source and direction of GDP shocks compared to the quasi-experiment using military buildups, the biodiversity-GDP elasticity estimates in Table 3 are remarkably similar to those found in Table 2. In Appendix Table A.7 we further report the results obtained through overidentified models in which we use military spending shocks and nonattainment regulation shocks simultaneously as excluded instruments. We find that the results are, again, similar. This consistency increases our confidence that the quasi-experimental estimates represent the causal influences of economic development on biodiversity.

Throughout the paper, we use abundance, species richness, and the Jaccard similarity index as our focal outcome variables. Here we repeat our panel OLS and IV estimations with alternative measures of biodiversity that are also commonly used in the ecology literature. We first consider two alternative measures to species richness. Recall from Section 2.2 that $\mathbb{S}_{ct}$ is the set of species at location c and time t. Let n_{sct} be the abundance of species $s \in \mathbb{S}_{ct}$. We define relative abundance to be $r_{sct} = \frac{n_{sct}}{\sum_{j \in \mathbb{S}_{ct}} n_{jct}}$, the share of a particular species out of the total number of individuals. The Gini diversity index is given by

$$Gini_{ct} = \frac{1}{\sum_{s \in \mathbb{S}_{ct}} r_{sct}^2},$$

and the Shannon diversity index is given by

$$Shannon_{ct} = \exp\left(-\sum_{s \in \mathbb{S}_{ct}} r_{sct} \times \log r_{sct}\right).$$

Notice that the Gini diversity index is effectively an inverse Herfindahl–Hirschman index, whereas the Shannon diversity index is entropy. Unlike species richness, which considers only the total number of unique species presence, both Gini and Shannon diversity measures adjust for the relative abundance of species. If relative abundance is identical across all

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[14] The main tradeoff with the overidentified model is potentially increasing bias from using weak instruments in order to improve efficiency (Wooldridge, 2010).

species in $\mathbb{S}_{ct}$, then species richness, Gini diversity, and Shannon diversity all yield the same value.[15] If there is heterogeneity in relative abundance across locations, then the Gini diversity and Shannon diversity measures give a lower value than species richness.

As an alternative to the Jaccard similarity measure, we consider the commonly used Sorensen similarity index defined by

$$S_{ct} = \frac{2 \times n(\mathbb{S}_{ct+1} \cap \mathbb{S}_{ct})}{n(\mathbb{S}_{ct+1} \cup \mathbb{S}_{ct}) + n(\mathbb{S}_{ct+1} \cap \mathbb{S}_{ct})}.$$

Appendix Table A.8 repeats both the OLS estimation and the two IV research designs with these three alternative biodiversity measures. We find that the results are largely the same regardless of which biodiversity metric we use.

4.4 Effect Size

How economically and ecologically important are the estimated GDP-biodiversity elasticities? We face several challenges interpreting the effect sizes. First, as we noted, because the BioTIME data are assemblage time series (rather than population monitoring) in nature, the biodiversity measures we derive from the database need not coincide with population-wide abundance, richness, and similarity. Second, we are unaware of prior studies of the link between biodiversity and economic development at similar scales. Therefore it is difficult to compare our effect sizes with independent, pre-existing evidence. While interpretation of *absolute* effect sizes is difficult, here we present two benchmarking exercises that speak to *relative* effect sizes of GDP.

We first compare our effect sizes with those from habitat losses, which are widely accepted as major determinants of biodiversity decline (IUCN, 2021). We find these two effect are similar in magnitude. Our first exercise leverages the fact that, during the second half of our study period (post 2001), high-resolution satellite observation of urbanization became available. This allows us to examine the effect of changes in land use using the identical panel estimation setting as outlined in equation (1). Our urbanization measure comes from NASA's MODIS land cover data (Section 2.3). To capture habitat losses and development pressure, we focus on the amount of urban land near the sampling sites in the BioTIME dataset. We construct our measure of urbanization as the (centered) share of land within 50 kilometers of a sampling site that falls under the MODIS urban classification. We replace GDP in equation (1) with this variable to estimate the change in biodiversity outcomes due to urbanization. We then compare these regressions with the GDP results with the exact

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[15] For example, if there is an equal share of 2 species in $\mathbb{S}_{ct}$, then all three indices will be 2.

Table 4: Effect Sizes: Habitat Losses versus GDP

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Abundance			Richness			Similarity	
Panel A. All species									
%Urban land	-1.109***	-	-0.901***	-0.428**	-	-0.280	0.0038	-	0.007
	(0.379)	-	(0.333)	(0.166)	-	(0.171)	(0.086)	-	(0.095)
GDP	-	-1.624***	-1.555***	-	-1.128***	-1.106***	-	-0.022	-0.023
	-	(0.403)	(0.407)	-	(0.208)	(0.214)	-	(0.191)	(0.194)
Observations	20,721	20,721	20,721	20,721	20,721	20,721	17,944	17,944	17,944
Panel B. Non-bird species									
%Urban land	-3.194	-	2.522	0.212	-	3.636	-5.326**	-	-4.103
	(17.67)	-	(12.09)	(12.49)	-	(9.618)	(2.078)	-	(2.890)
GDP	-	-3.453***	-3.472***	-	-2.051***	-2.080***	-	-0.733**	-0.701**
	-	(0.557)	(0.539)	-	(0.437)	(0.468)	-	(0.283)	(0.273)
Observations	6,857	6,857	6,857	6,857	6,857	6,857	6,775	6,775	6,775

Notes: Each panel-column is a separate regression. Independent variables are demeaned percent urban land within 50 km^2 of the sampling site and demeaned per capita GDP. All regressions restrict to the 2001-2015 time period when satellite-based urban land measure is available. Outcome variables are in logs except for Similarity which is a ratio (columns 7 through 9). All regressions include location-by-taxa and year fixed effects. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

same specification (also using the post-2001 sample).

Table 4 summarizes the results. In the full sample estimation (Panel A), the effect of urbanization is similar to GDP for abundance and richness. When estimated separately, the urbanization elasticity is -1.109 (SE = 0.379) compared to a GDP elasticity of -1.624 (SE = 0.403) for abundance. For species richness, the estimated urbanization and GDP elasticities are -0.428 (SE = 0.166) and -1.128 (SE = 0.208), respectively. For both abundance and richness outcomes and in both separate and joint regressions, we cannot reject that the effects of urbanization and GDP are equal in magnitude. The effects on the similarity index are in general noisily estimated. Panel B shows that the estimates are less stable because we lose a large share of our observations when focusing on the non-bird subsample, and when concentrating exclusively on the period after 2001.

In a second exercise, we benchmark our abundance estimate with the decline of bird population. Recent work using the North American Breeding Bird Survey (Section 2.2) suggests a substantial decline in North American bird populations since the 1980s. Rosenberg et al. (2019) estimated that birds numbered around 8 billion in 1990, but had declined by about 1 billion by the end of 2015. To evaluate what fraction of such decline might be attributable to economic production growth during the time period, we estimate a modified version of equation (1) focusing on bird-related observations and with GDP per capita as the regressor; this estimation yields an estimated coefficient of -0.167 log units (representing a decline in the bird population) per \$10,000 increase of GDP per capita. Multiply this coefficient by the average growth of real GDP per capita between 1990-2015 suggests a decline of 1.04 billion birds. This implied effect on bird abundance is thus on par with the overall bird decline, suggesting again that economic development may be considered as a major contributor to abundance loss.

5 Protective Policies

One interpretation of our findings is that there is a trade-off between economic development and biodiversity, so that the goal of ecosystem preservation necessarily comes at the cost of economic slowdown. Alternatively, one could consider protective policies that mitigate the adverse effects of economic production. In this section, we leverage existing policies to speak to such possibility. Section 5.1 examines the standard, direct conservation approach of biodiversity protection, in which certain areas are protected by law from industrialization, providing ecological buffers from the influence of outside economic progress. Section 5.2 assesses the cleanup of U.S. production technologies, which have led to remarkable declines in pollution emissions per unit of economic output since the 1990s. We ask whether such technological advances, mainly driven by regulations intended to protect human health, have provided conservation *co-benefits* as well. Both of these policy tools have been extensively studied in their respective fields. Here we provide a first assessment of their protective roles in the context of biodiversity conservation.

5.1 Protected Areas

Destruction of habitat is one of the primary drivers of species decline (IUCN, 2021). Since early 1990s, adoption of conservation protected area policies has grown rapidly (Frank and Schlenker, 2016).[16] Protected areas now cover nearly 15% of the Earth's land (with U.S. accounting for a tenth of all protected land worldwide) and 10% of its water. Empirical assessments of protected area yield mixed results due to management issues, funding, resource exploitation, and ecological leakage to unprotected areas (Leverington et al., 2010; Laurance et al., 2012; Watson et al., 2014; Di Marco et al., 2019; Geldmann et al., 2019).

To study the effects of protected areas, we use the standard data source from the World Database on Protected Areas (WDPA). The WDPA is a geospatial database on over 250,000

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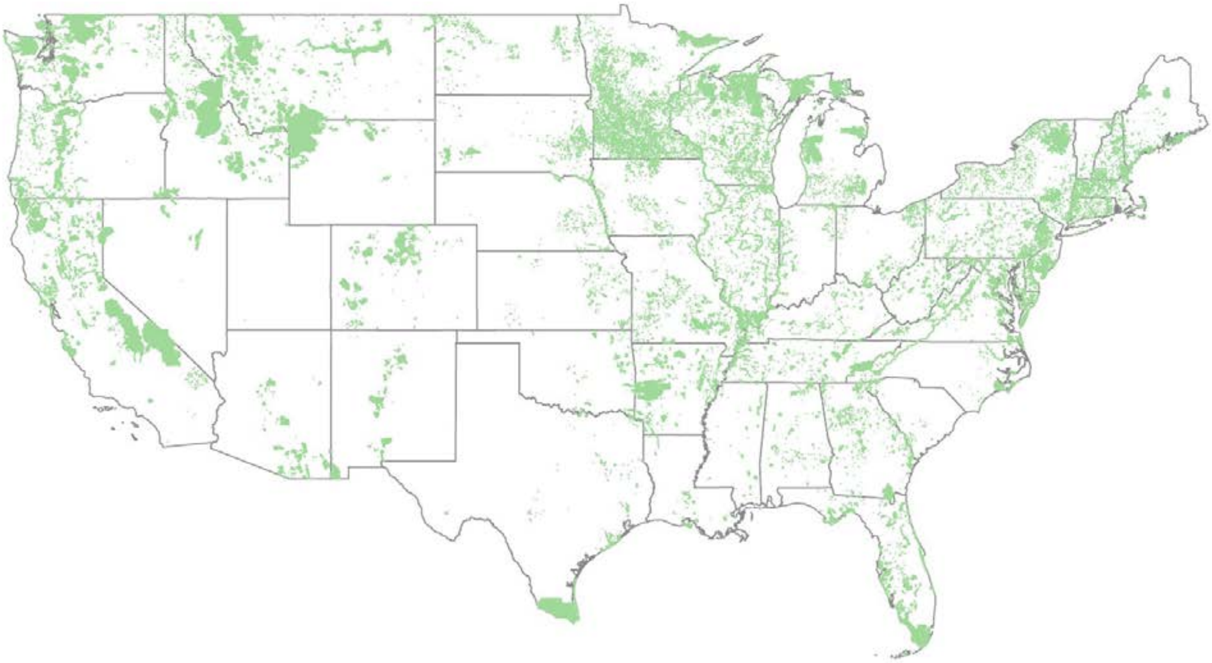
[16] According to IUCN, protected areas include national parks, wilderness areas, community conserved areas, nature reserves and so on. The areas are managed through legal or other effective means by both the federal and local authorities.

Figure 6: Protected Areas



Notes: Green represents areas that were protected any time in the World Database on Protected Areas (WDPA) sample and within 50 kilometers of a sampling location in BioTIME.

Table 5: Protective Policy and the Biodiversity - GDP Relationship: Protected Areas

	(1)	(2)	(3)	(4)	(5)	(6)
	Abundance		Richness		Similarity	
Panel A. All species						
GDP	-3.798***	-3.410***	-1.721**	-1.490***	-0.219	-0.255*
	(1.341)	(1.142)	(0.684)	(0.611)	(0.147)	(0.140)
GDP × %Areas protected	1.765*	2.028*	0.732	0.892	0.890***	0.864***
	(1.023)	(1.158)	(0.500)	(0.555)	(0.252)	(0.237)
GDP × #Fragmented areas	-	-0.206*	-	-0.144	-	0.023
	-	(0.108)	-	(0.088)	-	(0.015)
Observations	54,907	54,907	54,907	54,907	42,426	42,426
Panel B. Non-bird species						
GDP	-6.510***	-4.229***	-3.277***	-2.339***	-0.652***	-0.754***
	(0.787)	(0.813)	(0.261)	(0.436)	(0.158)	(0.087)
GDP × %Areas protected	7.484	13.976**	-0.263	1.805	3.217**	3.520**
	(4.812)	(6.080)	(0.938)	(1.269)	(1.237)	(1.286)
GDP × #Fragmented areas	-	-0.731*	-	-0.147	-	-0.115
	-	(0.418)	-	(0.139)	-	(0.088)
Observations	13,351	13,351	13,351	13,351	12,181	12,181

Notes: Outcome variables are in logs except for Similarity which is a ratio (columns 5 and 6). “%Areas protected” is the fraction of protected areas within a 50km radius of the sampling location. “#Fragmented areas” is the number (in 1,000s) of discontiguous protected areas within 50km radius of the sampling location. Smaller numbers of discontiguous areas indicate that each protected area is larger on average. All regressions include main effect terms, location-by-taxa fixed effects, and year fixed effects. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

marine and terrestrial protected areas. The database is in the form of a shapefile that outlines the location of each protected area and the year the protected area was implemented. In each location-year, we compute the total share of land and water within 50 km of the BioTIME sampling location that is within at least one currently implemented protected area. Figure 6 plots the location of these protected areas. We also compute the number of spatially discontiguous protected areas within 50 km. After conditioning on the share of protected land or water, this later variable helps us tease out the effect of protected areas fragmentation holding the quantity of protected area fixed. We include this variable following the recent conservation literature which has suggested that habitat fragmentation has significant negative effects on biodiversity and the local ecology (Haddad et al., 2015; Crooks et al., 2017; Newmark et al., 2017), implying that more fragmented configurations of protected areas may be less effective than contiguous networks.

Table 5 reports how protected areas modulate the effect of GDP on biodiversity outcomes. Columns 1, 3, and 5 use the same OLS specifications used in equation (1), but also interact log GDP with the share of nearby protected areas. Columns 2, 4, and 6 include additional interaction terms between log GDP and the number of discontiguous protected areas within 50 km.[17] Columns 1 and 2 show that the abundance-GDP relationship is attenuated by an increase in the amount of nearby land that is protected. On average across all species, if the share of protected land and water within 50 km goes from zero (no conservation areas) to 100 percent, the marginal effect of GDP halves. We estimate larger effects on non-bird species, where halving the marginal effect of GDP only requires having 15 percent to 50 percent of area in protection. Consistent with prior evidence on fragmentation, column 2 shows that having a more fragmented set of protected areas has the opposite effect. Columns 3 and 4 show that protected areas have a noisy relationship with species richness, although the signs of the effects are generally the same as for abundance. The results are overall similar for species turnover (columns 5 and 6).

5.2 Improvements in Abatement Technologies

Our results in Section 4 point to environmental pollution as a likely mechanism underpinning the GDP-biodiversity link. A natural question is whether advances in pollution abatement technologies, which reduce the emission footprint of economic production, may help dampen the adverse impacts on biodiversity. Our analysis builds on a prior literature on the remarkable cleanup of U.S. production technology since the 1990s. Panel A of Figure 7 shows that real output in the United States doubled between 1990 and 2019, and that, during the same period, industrial pollution emissions fell by half. Research using detailed data from the manufacturing sector suggests this cleanup was largely driven by technological improvements. That is, the intensity of emission per unit of output declined dramatically (Levinson, 2009) as a consequence of stringent environmental regulations (Shapiro and Walker, 2018).[18]

Panel B of Figure 7 presents cross-state heterogeneity in emission intensity trends. We regress state-year-pollutant level emissions on a set of pollutant fixed effects and state-specific year trends. We define states with faster advances in abatement technologies as those with a below-median (i.e., more downward-sloping) state-year trend coefficient.

Table 6 reports an augmented version of equation (1) that allows the GDP-biodiversity coefficient $\hat{\beta}$ to vary by states above and below median of pollution cleanup. We find that the adverse effects of GDP growth on abundance and species richness are smaller in locations

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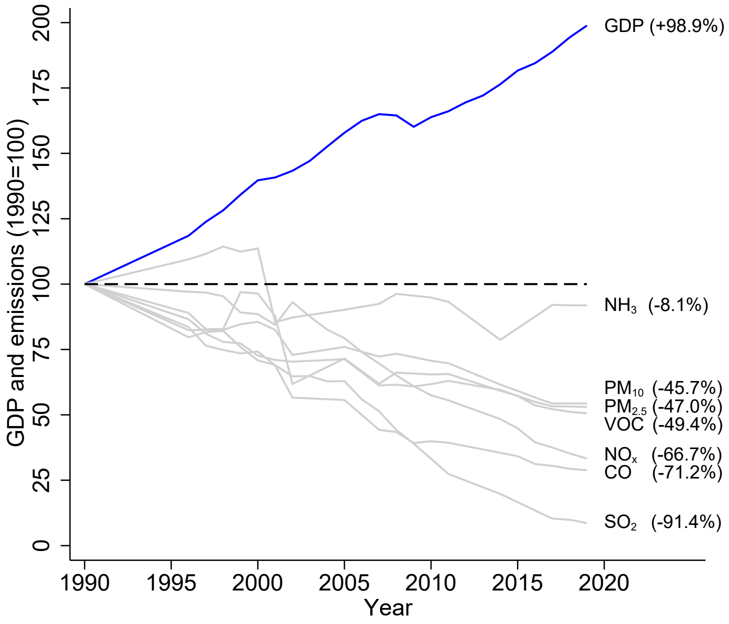
[17] Regressions also include the main effect terms for the share of protected area (columns 1, 3, 5) and, additionally, the number of discontinuous areas (columns 2, 4, 6).

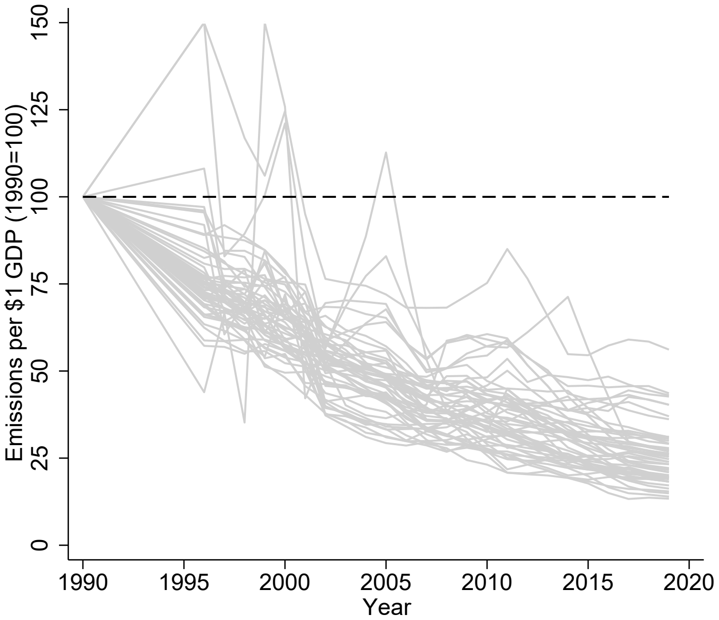
[18] A number of regulatory programs administered by the U.S. Environmental Protection Agency (EPA) have been shown to contribute to this trend. The NAAQS program we studied in Section 4.2 is one of them that targets areas with the highest pollution levels; other programs that reduced emission intensities include the Acid Rain Program (Barreca et al., 2017) and the NOx Budget Trading Program (Deschênes et al., 2017).

Figure 7: State Heterogeneity in Abatement Technology Advances

Panel A. Changes in national GDP and emissions



Panel B. Changes in state emissions-GDP ratio



Notes: Panel A shows percent changes in national annual real GDP and total air pollutants emissions according to the National Emissions Inventory. Panel B shows percent changes in state-level annual emissions-real GDP ratio. Each line represents a state trend which is the average across seven pollutant-specific trends.

with more stringent pollution cleanup; the effect on similarity is statistically inconclusive.

Table 6: Protective Policy and the Biodiversity - GDP Relationship: Emission Abatement

	(1) Abundance	(2) Richness	(3) Similarity
Panel A. All species			
GDP × 1(<median tech. advance.)	-5.065***	-2.636***	0.029
	(0.796)	(0.391)	(0.081)
GDP × 1(≥median tech. advance.)	-0.598	0.147	-0.186
	(0.649)	(0.542)	(0.153)
Observations	54,886	54,886	42,405
Panel B. Non-bird species			
GDP × 1(<median tech. advance.)	-4.069	-2.788**	0.531***
	(2.370)	(1.213)	(0.067)
GDP × 1(≥median tech. advance.)	-1.214	-1.595**	-0.198
	(2.521)	(0.619)	(0.324)
Observations	13,330	13,330	12,160

Notes: Outcome variables are in logs except for Similarity which is a ratio (column 3). To define state environmental stringency, we first estimate an OLS regression of state-year-pollutant emissions per real GDP on state-year time trends, pollutant-by-year fixed effects, and state fixed effects. States are then categorized into above ("1(≥median tech. advance.)") and below ("1(<median tech. advance.)") the median of the time trends coefficients times -1 (i.e., more negative trends implies higher environmental stringency). All regressions include main effect terms, location-by-taxa fixed effects, and year fixed effects allowed to vary by above/below median states. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

6 Conclusion

This paper provides one of the first estimates on the causal effect of economic production on biodiversity. Our primary innovation is the use of BioTIME, a novel database of hundreds of ecological studies that maintain assemblage time-series, which allows us to examine the economic production-biodiversity link in a longitudinal framework across many different taxonomic classes of wildlife. Using both fixed effects and instrumental variable strategies, we find that biodiversity outcomes respond strongly to local economic changes. In particular, our work highlights the importance of economic policymaking on ecosystem health which, in this paper, manifests as changes in local biodiversity as a consequence of national military buildups and industrial pollution control legislation. The magnitude of the effect we estimate rivals some well-recognized, direct determinants of biodiversity, such as habitat losses, which suggests economic production may indeed be considered as a major determinant of biodiversity during our study period. We also find evidence that protective policies such as protection areas and general environmental regulations may have helped dampen the negative effect of economic production. The BioTIME database we use in this paper allowed us to focus on well-known, macro-scale economic and policy changes, but we note that the database includes detailed, geocoordinate information for all sampling locations and across multiple species, attributes that make it a suitable source to study the determinants of biodiversity in more granular, specific contexts. We hope our analysis fosters future work on the topic.

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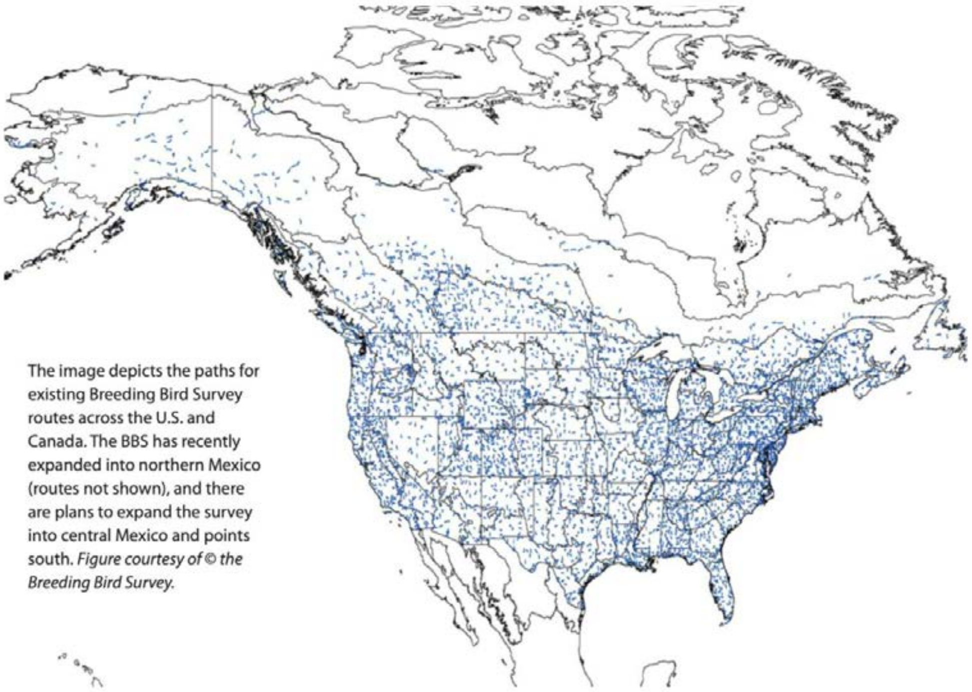
A Appendix

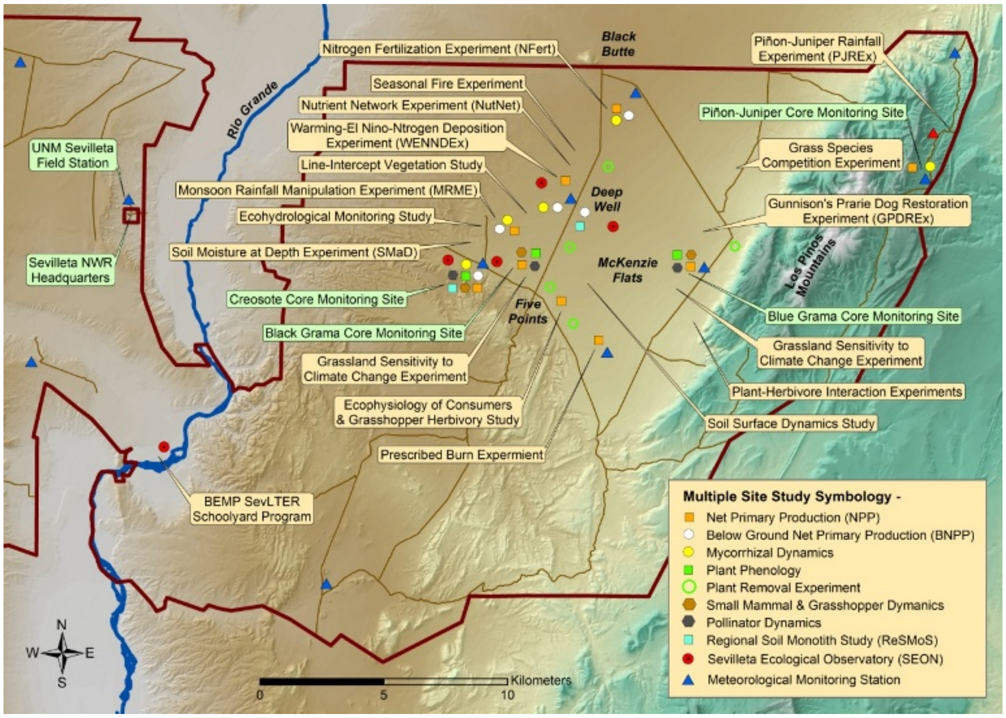
Figure A.1: Breeding Bird Survey routes across the US and Canada



The image depicts the paths for existing Breeding Bird Survey routes across the U.S. and Canada. The BBS has recently expanded into northern Mexico (routes not shown), and there are plans to expand the survey into central Mexico and points south. *Figure courtesy of © the Breeding Bird Survey.*

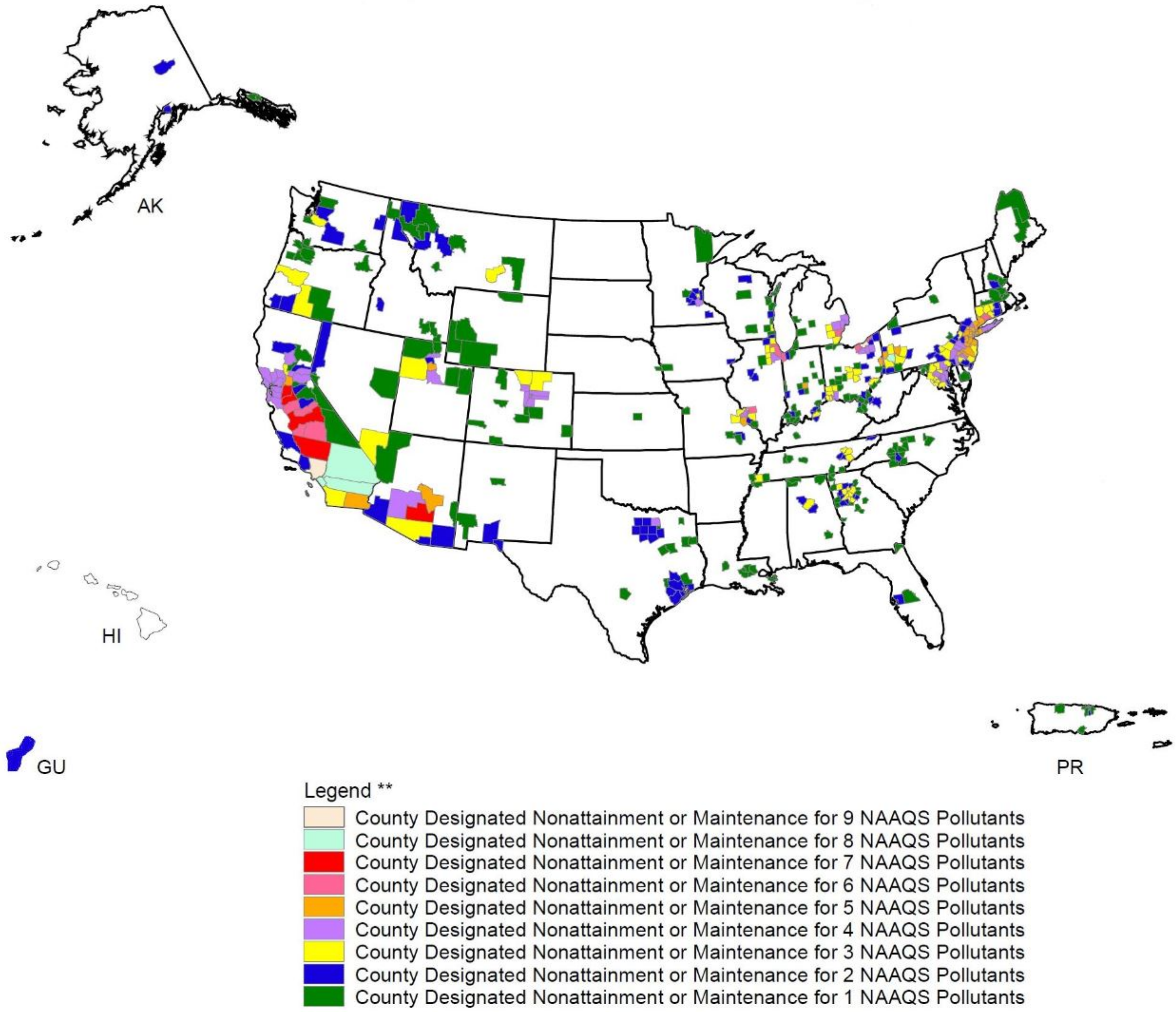
Note: This figure is from Ziolkowski Jr et al. (2010). It shows the sample collecting routes in the North American Breeding Bird Survey (BBS), which is one of the studies in the BioTIME database. The BBS is a long-term and large-scale avian monitoring program that tracks the status and trends of North American bird populations. Professional bird observers collect bird population data at the same stops along the roadside survey routes during the avian breeding season every year. Over 4100 survey routes are located across the continental US and Canada.

Figure A.2: Sevilleta Long Term Ecological Research (LTER) Program Map



Note: This figure is from the project overview for the Sevilleta Long Term Ecological Research (LTER) Program at http://sevlter.unm.edu/. As shown in this figure, several studies included in BioTIME are conducted under the Sevilleta Long Term Ecological Research (LTER) Program at the 100,000 hectare Sevilleta National Wildlife Refuge in central New Mexico. One study is the small mammals census from 1989 to 2008 (Friggens, 2008). There are 16,657 records for 27 distinct species covered in the study. Another study focuses on terrestrial plants in this wildlife refuge Muldavin (2001) collects 5,288 records for 123 distinct species.

Figure A.3: Counties Designated “Nonattainment” or “Maintenance”



Note: This map plots counties with Clean Air Act Nonattainment or Maintenance designations with respect to the National Ambient Air Quality Standards (NAAQS) as of year 2019. Source: https://www3.epa.gov/airquality/greenbook/map/mapnmpoll.pdf.

Table A.1: The Biodiversity - GDP Relationship: Hexagon Bin Aggregation

	(1) #Obs.	(2) Abundance	(3) Richness	(4) Similarity
Panel A. All species				
Aggregation: 3-km hex. bin.	11,915	-1.209*** (0.325)	-0.454*** (0.136)	-0.066 (0.062)
Aggregation: 10-km hex. bin.	9,881	-0.887** (0.377)	-0.288* (0.154)	-0.061 (0.059)
Aggregation: 16-km hex. bin.	8,896	-0.840** (0.379)	-0.206 (0.187)	-0.076 (0.055)
Panel B. Non-bird species				
Aggregation: 3-km hex. bin.	1,401	-1.699** (0.672)	-0.631** (0.271)	-0.261 (0.159)
Aggregation: 10-km hex. bin.	923	-1.719** (0.798)	-0.586 (0.354)	-0.145 (0.145)
Aggregation: 16-km hex. bin.	694	-1.417* (0.756)	-0.443 (0.518)	-0.132 (0.139)

Notes: This table reports the panel OLS estimation results (equation (1)) when the data are geographically aggregated up to hexagon bins of various resolution. Panel A reports full sample estimation. Panel B excludes observations that correspond to bird species. All regressions include grid-by-taxa and year fixed effects. Standard errors are clustered at the hexagon grid level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.2: GDP and Biodiversity Sampling in BioTIME Dataset

	(1) Log(study duration)	(2) $\mathbb{1}$(start year)	(3)	(4) $\mathbb{1}$(end year)	(5)	(6) $\mathbb{1}$(missed year)	(7)
GDP growth (%)	0.013	-	-	-	-	-	-
	(0.054)	-	-	-	-	-	-
$\mathrm{GDP_t}$	-	0.031	0.391	-0.213	-0.371	0.133	0.171
	-	(0.057)	(0.433)	(0.128)	(0.355)	(0.118)	(0.367)
$\mathrm{GDP_{t\text{-}1}}$	-	-	-0.408	-	0.169	-	-0.036
	-	-	(0.482)	-	(0.351)	-	(0.321)
Data structure	cross-section	panel	panel	panel	panel	panel	panel
Observations	15,735	409,838	394,075	409,838	394,075	409,838	394,075

Notes: Estimation data underlying column 1 is a cross section of study locations. Columns 2 through 7 are based on location-by-year panel data. Outcome variables are log number of years of a study location (column 1), an indicator for the study location's first sampling year (columns 2 and 3), an indicator for the study location's last sampling year (columns 4 and 5), and an indicator for nonsampling in the corresponding location-year (columns 6 and 7). GDP_{t-1} is the log of lagged one year GDP. All regressions include location-by-taxa fixed effects, and year fixed effects. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.3: The Biodiversity - GDP Relationship: Dynamic Specification

	(1)	(2)	(3)	(4)	(5)	(6)
	Abundance		Richness		Similarity	
Panel A. All species						
GDP_{t+1}	-	0.655	-	0.269	-	-0.106
	-	(0.848)	-	(0.607)	-	(0.120)
GDP_{t}	-3.580**	-3.705***	-1.631**	-2.246***	-0.104	0.271
	(1.353)	(1.199)	(0.685)	(0.671)	(0.157)	(0.271)
GDP_{t-1}	-	-1.006	-	0.417	-	-0.377
	-	(0.760)	-	(0.661)	-	(0.445)
Observations	54,887	54,176	54,887	54,176	42,406	41,729
Panel B. Non-bird species						
GDP_{t+1}	-	-0.229	-	-0.776	-	0.091
	-	(3.322)	-	(1.551)	-	(0.164)
GDP_{t}	-5.903***	-5.754	-3.302***	-4.043	-0.368	0.392*
	(0.990)	(4.809)	(0.271)	(2.448)	(0.262)	(0.206)
GDP_{t-1}	-	-0.420	-	1.752	-	-1.129**
	-	(1.364)	-	(1.191)	-	(0.415)
Observations	13,331	13,011	13,331	13,011	12,161	11,875

Notes: Outcome variables are in logs except for Similarity which is a ratio (columns 5 and 6). GDP_{t-1} is the log of lagged one year GDP. GDP_{t+1} is the log of GDP one year in the future. All regressions include location-by-taxa fixed effects, and year fixed effects. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.4: Industry income and biodiversity outcomes

	(1) Abundance	(2) Richness	(3) Similarity	(4) Abundance	(5) Richness	(6) Similarity
	Panel A. All species			Panel B. Non-bird species		
Manufacturing	-0.307**	-0.273***	-0.029	-0.913	-0.414*	-0.059
	(0.121)	(0.077)	(0.027)	(0.500)	(0.205)	(0.100)
Wholesale	-0.741*	-0.388**	0.168**	-1.960***	-1.021***	0.326***
	(0.376)	(0.171)	(0.069)	(0.621)	(0.286)	(0.043)
Mining	-0.078	-0.013	-0.014	-0.389	0.032	-0.142**
	(0.065)	(0.035)	(0.011)	(0.225)	(0.078)	(0.051)
Construction	0.352	0.206***	0.012	0.928	0.243	0.015
	(0.288)	(0.064)	(0.061)	(0.675)	(0.258)	(0.130)
Retail	-0.677	-0.211	-0.157**	-1.582	-0.881*	-0.415**
	(0.463)	(0.183)	(0.067)	(0.956)	(0.423)	(0.169)
Agricultural	0.057	0.016	0.003	0.834***	0.205***	0.044
	(0.077)	(0.031)	(0.008)	(0.239)	(0.068)	(0.038)
Transportation	-0.112	-0.080	-0.042	-0.473	-0.076	-0.105
	(0.254)	(0.067)	(0.042)	(1.060)	(0.252)	(0.162)
Finance	0.253	0.029	0.031	0.309	0.101	-0.060
	(0.262)	(0.068)	(0.023)	(0.352)	(0.164)	(0.055)
Service	0.353	0.173	-0.086	2.224	1.185**	-0.207
	(0.398)	(0.290)	(0.061)	(1.470)	(0.526)	(0.342)
Observations	60,211	60,211	47,140	13,085	13,085	12,066

Notes: Each column corresponds to a regression. Industry categorizations are based on 2-digit SIC and NAICS codes. Industry income data are from U.S. Bureau of Economic Analysis 1969 to 2016. Agriculture includes agriculture, forestry, and fishing. Transportation includes transportation, communications, electric, gas, and sanitary services. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.5: Military Spending Shocks and Biodiversity Outcomes: IV Robustness

	(1) Abundance	(2) Richness	(3) Similarity
IV with alt. base period (1966-2006)	-5.086**	-3.127*	-0.529***
	(2.175)	(1.649)	(0.190)
Kleibergen-Paap F-stat.	6.035	6.035	6.186
Observations	57,714	57,714	44,479
Pred. aggr. shock × state FEs as IV	-4.575**	-1.932*	-0.218
	(1.950)	(1.031)	(0.145)
Kleibergen-Paap F-stat.	1.794	1.794	2.168
Observations	57,714	57,714	44,479
Census Division decadal trends	-5.844***	-3.049*	-0.750***
	(2.050)	(1.554)	(0.226)
Kleibergen-Paap F-stat.	6.509	6.509	7.034
Observations	57,714	57,714	44,479
LIML	-4.485***	-2.753**	-0.535***
	(1.594)	(1.226)	(0.183)
Kleibergen-Paap F-stat.	7.430	7.430	7.071
Observations	57,714	57,714	44,479

Notes: Each panel corresponds to an alternative IV specification to equation (2). See text for more details. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.6: Environmental Protection and Biodiversity Outcomes: IV Robustness

	(1) Abundance	(2) Richness	(3) Similarity
1(any nonatt. status) as IV	-6.518***	-3.730***	0.267
	(1.246)	(0.552)	(0.254)
Kleibergen-Paap F-stat.	8.823	8.823	8.963
Observations	54,887	54,887	42,406
Multiple pollutants nonatt. IVs	-5.261***	-3.118***	-0.275
	(0.620)	(0.291)	(0.494)
Kleibergen-Paap F-stat.	4.448	4.448	4.624
Observations	54,887	54,887	42,406
Census Division year trends	-6.081**	-3.819***	-0.828
	(2.285)	(0.985)	(0.850)
Kleibergen-Paap F-stat.	9.715	9.715	10.311
Observations	54,887	54,887	42,406
LIML	-5.932***	-3.194***	-0.519
	(0.624)	(0.268)	(0.532)
Kleibergen-Paap F-stat.	7.841	7.841	8.874
Observations	54,887	54,887	42,406

Notes: Each panel corresponds to an alternative IV specification to equation (3). See text for more details. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.7: Overidentified IV Estimation with Both Instruments

	(1) Abundance	(2) Richness	(3) Similarity
Panel A. All species			
$\hat{\text{GDP}}$ (IV)	-4.999***	-2.937***	-0.407*
	(1.293)	(0.967)	(0.240)
Kleibergen-Paap F-stat.	5.095	5.095	5.581
Observations	57,714	57,714	44,479
Panel B. Non-bird species			
$\hat{\text{GDP}}$ (IV)	-5.496***	-3.052***	-0.438***
	(0.567)	(0.331)	(0.129)
Kleibergen-Paap F-stat.	108.9	108.93	118.5
Observations	11,861	11,861	10,335

Notes: Each column-panel represents a separate IV regression, where both military buildups (equation (2)) and nonattainment designations (equation (3)) are used simultaneously as instrumental variables for log GDP. Panel A reports full sample estimation. Panel B excludes observations that correspond to bird species. All regressions include location-by-taxa and year fixed effects. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.8: Other Measures of Biodiversity

	(1) Gini	(2) Shannon	(3) Sorensen
Panel A. All species			
GDP (OLS)	-1.845*	-2.175***	-0.214
	(0.946)	(1.021)	(0.197)
$\hat{\text{GDP}}$ (Military IV)	-3.745**	-3.800**	-0.659***
	(1.694)	(1.646)	(0.223)
$\hat{\text{GDP}}$ (Nonattainment IV)	-4.859***	-5.192***	-0.603
	(1.347)	(1.275)	(0.412)
Panel B. Non-bird species			
GDP (OLS)	-3.877***	-4.302***	-0.659**
	(0.630)	(0.666)	(0.270)
$\hat{\text{GDP}}$ (Military IV)	-4.621***	-4.901***	-0.853***
	(0.943)	(0.995)	(0.070)
$\hat{\text{GDP}}$ (Nonattainment IV)	-5.345***	-5.731***	-0.949***
	(0.270)	(0.277)	(0.147)

Notes: Each cell represents a separate regression. Each column corresponds to a different biodiversity metric: the Gini index (column 1), the Shannon index (column 2), and the Sorensen similarity index (column 3). Panel A reports full sample estimation. Panel B excludes observations that correspond to bird species. All regressions include location-by-taxa and year fixed effects. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.