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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. Despite such trends, causal evidence for economic drivers of biodiversity loss and effective policy responses remains sparse. Here we study the relationship between economic production and biodiversity using a novel panel dataset that contains detailed and consistently reported information on the types and quantities of wildlife at thousands of locations across the United States between 1960 and 2015. Exploiting quasi-experimental variation in local economic output due to national military buildups, we find that economic production substantially reduces the total abundance of wildlife, reduces the diversity of species, and changes the composition of species in a local ecosystem even holding the number of species constant. We provide new causal evidence that air pollution, an externality caused by economic production, is an important driver of biodiversity declines. We show that air quality regulations preserve biodiversity and provide policymakers with another lever for conservation efforts.

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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, what are the mechanisms? Are there environmental or conservation policies that can serve to mitigate biodiversity declines? In this paper, we provide some of the first causal evidence for the link between economic production and biodiversity. We show that air pollution is a key channel underlying the relationship, and that federal ambient air quality regulations in the United States help preserve biodiversity.

The central obstacle that has impeded attempts to empirically study the economic determinants of biodiversity is the lack of data. Generally, biodiversity data collection faces a trade-off between fine-scale precision and representativeness across spatial scales (König et al., 2019). Commonly used existing datasets either provide only cross-sectional information on the geographic extent of species as in the International Union for Conservation of Nature Red List of Threatened Species (IUCN, 2021), or they provide panel data but only for a single taxonomic class, as in the North American Breeding Bird Survey (USGS, 2014). These limitations hamper the data's usefulness in establishing causal relationships 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, subject to confounding factors (Newbold et al., 2015); or is focused on a specific taxon, and so might not reflect broader biodiversity impacts across different taxa or biomes (e.g., Liang et al., 2020; Cole et al., 2021).

A primary contribution 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

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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).

useful for studying the causal link between economic development and biodiversity at broad scales. First, all the included studies have consistent sampling protocols within each location over time. This means that the year-over-year variation in biodiversity metrics at the same sampling location reflects genuine changes in underlying biodiversity conditions, rather than changes in sampling methods that may be driven by economic factors. This consistency criterion allows us to use fixed effects estimators to address unobservable differences in sampling methodology across different studies that otherwise would bias our results. 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 alleviates taxonomic biases – for example, collectors focus more on charismatic groups – which is often a major limitation of biodiversity datasets, and it 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 examines how year-over-year changes in economic output in the United States relate to biodiversity outcomes at a given location. Our focal measure of economic output is local (state-level) 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 and captures the stability of the composition of species. Our findings are robust to using county-level income per capita data to capture production, as well as using alternative biodiversity metrics from the ecology literature, such as the Gini diversity, Shannon diversity, and Sorensen similarity indices.

Our baseline analysis is a fixed effects model with one of the biodiversity metrics as the outcome variable, GDP per capita as the regressor, and a set of location-taxon fixed effects and year fixed effects. This exercise reveals a strong, negative association between economic production and biodiversity outcomes. The ordinary least squares (OLS) estimates for the GDP elasticity of the different metrics are -3.6 for abundance, -1.6 for richness, and -0.1 for similarity. The adverse effects of economic development appear 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 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. However, one may be concerned about omitted factors that drive both biodiversity and output, such as local extreme weather. We strengthen the econometric design and credibility of the estimates by exploiting U.S. military buildups, which are heavily influenced by geopolitical factors and unexpected military events, as a quasi-experimental source of variation in local GDP. 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 instrumental variable (IV) estimates show that increased local economic production deteriorates biodiversity outcomes with GDP-elasticities of -4.5 for abundance, -2.8 for richness, and -0.5 for similarity.

Next, we explore channels underlying the GDP-biodiversity relationship. First, we study urbanization and habitat loss, a widely acknowledged and studied driver in biodiversity declines (IUCN, 2021). We find that this channel holds in our study setting: areas where more nearby land is urbanized tend to have lower biodiversity. Second, we turn to an understudied mechanism: air pollution. We test the impact of pollution on biodiversity using remote sensing data that allow us to track atmospheric pollution levels nearby the sampling sites over a long period of time. Following our approach with the GDP-biodiversity analysis, we first use a fixed effects model to show that pollution is positively associated with GDP, and negatively associated with all three biodiversity measures. We then use an IV strategy to recover causal effects. 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,

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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.

and competitive effects of this policy (e.g., Becker and Henderson, 2000; Greenstone, 2002; Greenstone et al., 2012; Walker, 2013). Our IV estimates suggest that the pollution elasticity of biodiversity is -5.7 for abundance, -3.4 for richness, and -0.4 for similarity. All three are similar in size to their GDP-elasticity IV counterparts.

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; Cole et al., 2021), temperature changes (Antão et al., 2020), agricultural activities (Li et al., 2020; Noack et al., 2021; Strobl, 2021), and industrial pollution (Liang et al., 2020). To the best of our knowledge, this research 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). One of our primary contributions is highlighting the critical role of air pollution. Air pollution has well-established negative economic and health impacts, and here we show that it also is a major factor in ecological degradation. This new finding indicates that there are additional policy levers at our disposal for enhancing conservation efforts, and also that the benefits of air pollution regulations are substantially underestimated by ignoring the non-market ecological benefits.

This research also builds on prior literature on the ecological and economic importance of biodiversity. 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). Our finding that the negative impact of GDP is largest in the least-biodiverse areas emphasizes this important feature at a large spatial and taxonomic scale.

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). The simultaneous relationship between biodiversity and economic activity reinforces the importance of exploiting natural experiments for measuring causal effects on biodiversity.

The paper is organized as follows: Section 2 describes the data. Section 3 presents the baseline panel data estimation. Section 4 presents the mechanisms analysis. Section 5 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.2). 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.

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.3). 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). In Appendix Table A.3, we also provide empirical tests showing economic conditions are not explanatory of sampling efforts as proxied by study duration, study beginning/ending years, or years with missing observations. 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 in a given taxon, 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 in a given taxon, 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 in a given taxon, 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 in taxon j and location c, and let $n(\cdot)$ denote the cardinality of a set. The Jaccard similarity index is given by:

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

the number of species in taxon j 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 $J_{cjt} = 0$, there are no

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[3] BioTIME also includes 30 reptile 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.

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.

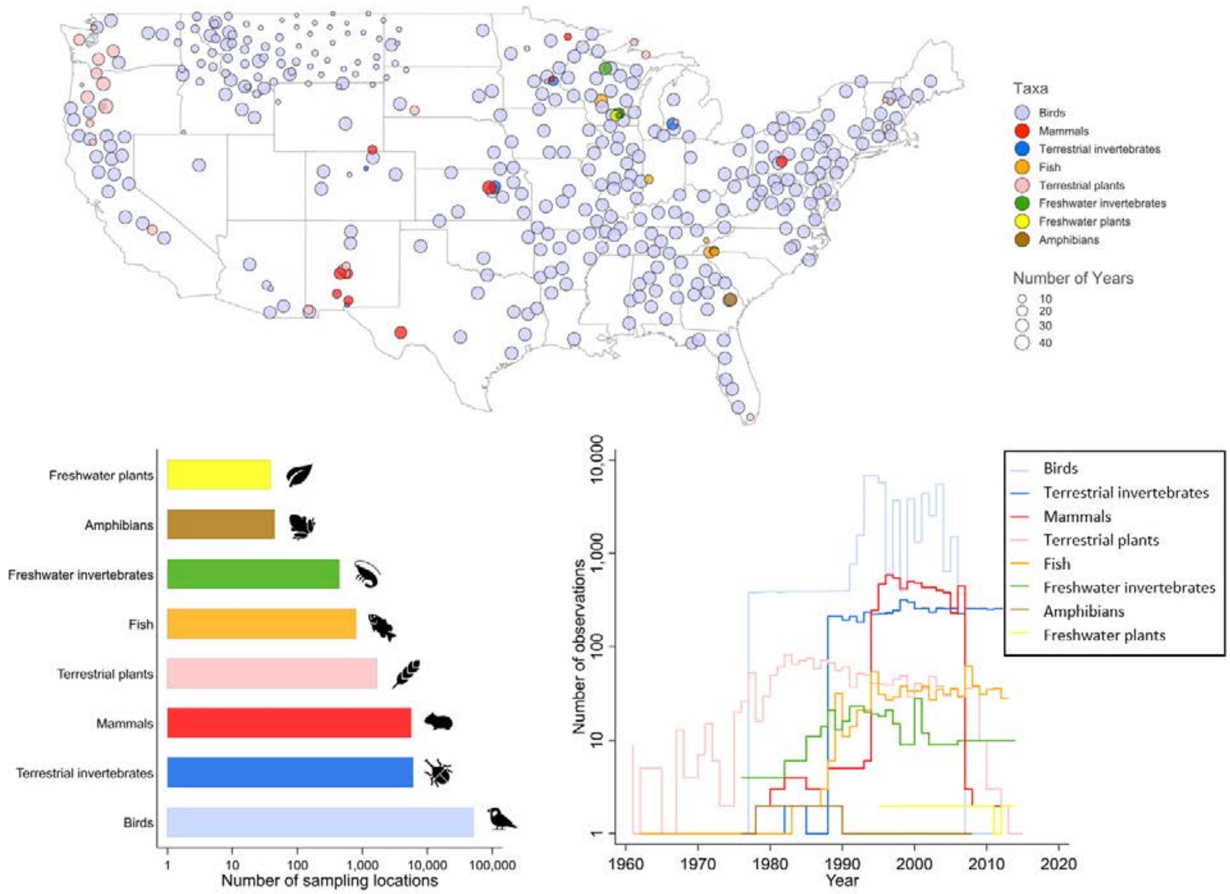
Table 1: Summary Statistics

	(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.3. 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.2, 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. The lower right panel of Figure 1 shows that an increasing number of studies are conducted in more recent years. To assess the concern that earlier studies may adopt less modern sampling practices (and thus potentially provide lower-quality biodiversity measurements) which may cause attenuation of our estimates, in Table A.4 we report a robustness exercise where we estimate our main models separately by the first and second half of the study period.

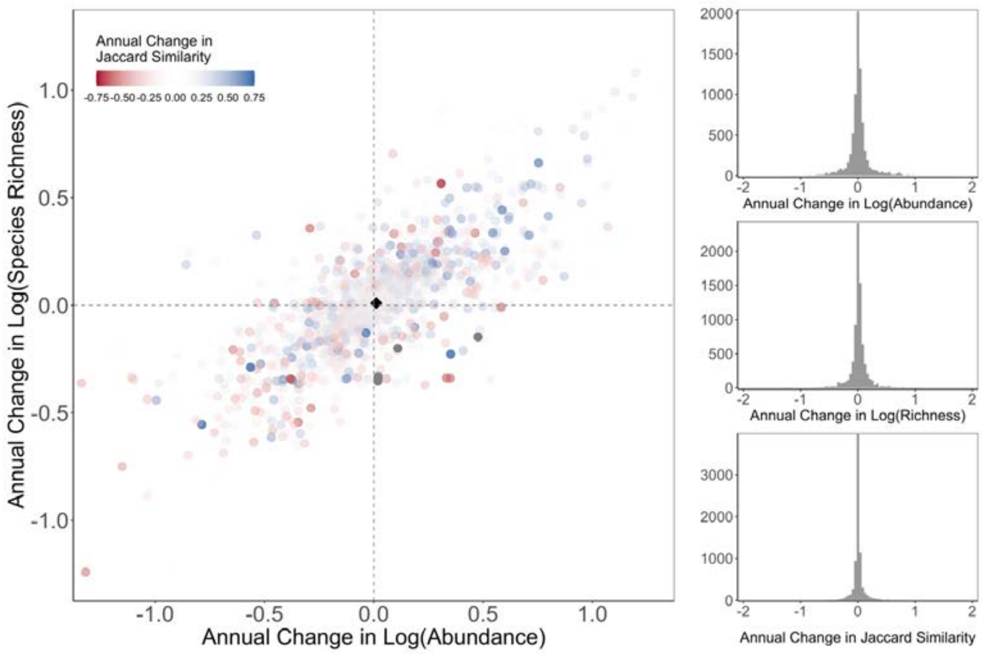
Figure 1: Sampling Locations and Observations



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 (BEA) 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. In several robustness specifications, We use county-level income from BEA in place of state GDP.

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.

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). 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. 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 or 100-km radius, or the county of the BioTIME sampling site.

Pollution Pollution data come from the MERRA-2 reanalysis dataset, where satellite and ground-based measurements of aerosol optical depth (AOD) – a measure of the amount of particles in a column of air between the top-of-atmosphere and the ground – are assimilated into Earth system modeling (product ID: M2I3NXGAS Version 5.12.4). MERRA-2 provides a measure of AOD on a 30km-by-30km grid, approximately the same area as the average county.

An alternative source of pollution measurement is provided by the U.S. Environmental Protectoin Agency's Air Quality System (AQS). AQS is a network of ground monitoring stations that monitors counties' compliance with the U.S. Clean Air Act. Because ground-level air pollution is only measured at a selected set of locations, many tend to be nearby urbanized population centers, we use MERRA-2 AOD in lieu of the AQS measurement as our primary pollution measure.[5] We test robustness of our results using the AQS pollution measure, in which we focus on counties with ground pollution monitoring data available.

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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] Remote sensing-based pollution measures are increasingly used in economics to circumvent issues with the sparsity of the pollution monitoring network (e.g. Fowlie et al., 2019; Zou, 2021).

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. Figure 6 plots the location of nonattainment areas as of year 2019.[6]

3 The Effect of Economic Production on Biodiversity

3.1 Ordinary Least Squares

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

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

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 $\log GDP_{st}$, which is the logged per capita real GDP for the state-year. 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 (i.e., we are not comparing trees to birds or ants to mice). 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. A given ecological study may have multiple sampling locations. The North American Breeding Bird Survey (Section 2.1, example study 1), for

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[6] 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.

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 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 time series of location-taxon data in our dataset depends on changes in sampling protocols and the overall study duration. If the sampling methodology changed during the course of the study, a new ID is assigned so it is treated as a new observational unit. Our final estimation data are thus an unbalanced, annual panel of sampling locations by taxon.

Selection into sampling One potential concern with our setting is that economic conditions may affect whether a study starts, stops, or is paused at a particular location. For example, one may conjecture that ecological studies are more likely to be conducted in years with strong GDP growth due to funding availability, but that studies may be interrupted in recessions. The impact of this type of selection on our estimates is largely ambiguous and depends on the non-linearity of the impact of GDP.[7] 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.

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 every year throughout the lifetime of the study (defined as the period in-between the first and the last sampling year); among the locations not sampling every year, biodiversity metrics are available on average 63.2% of the time. In Appendix Table A.3, we further present various "zero-stage" regres-

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[7] In principle, oversampling periods of high GDP, or undersampling periods of 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.

sions 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 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.

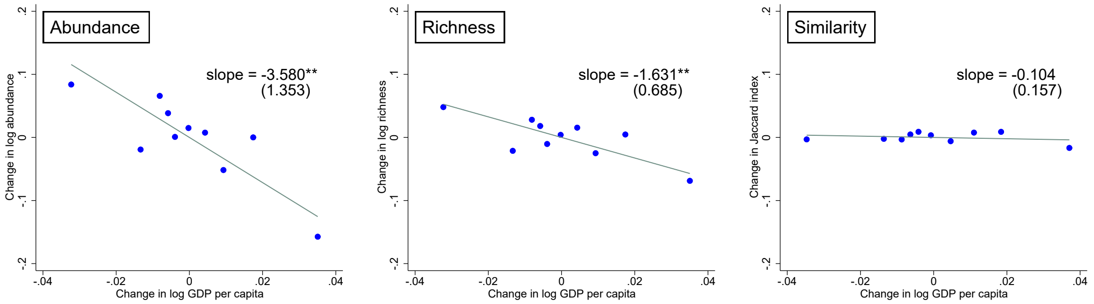
Results Figure 3, Panel A reports the estimation results from equation (1). The three columns correspond to species abundance, species richness, and Jaccard similarity. We residualize the biodiversity metrics and log GDP with the fixed effects, and then plot one against the other using a decile binscatter. 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 analyses, we report both full-sample results, and a sub-sample version that excludes birds.

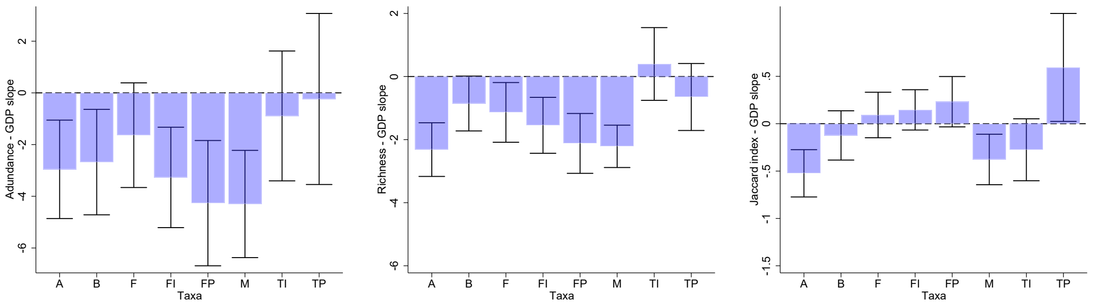
Panel C of Figure 3 shows elasticity estimates by quintiles of the sampling area's average (1966-2015) GDP per capita. We find that the GDP-biodiversity elasticities do not vary substantially across *overall levels* of GDP. Thus, there is thus limited evidence within our study scope that the GDP-biodiversity 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

Figure 3: The Biodiversity - GDP Relationship

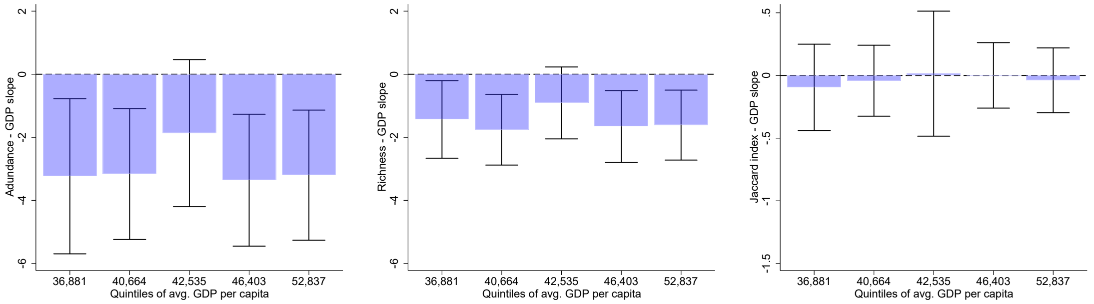
Panel A. Average effect



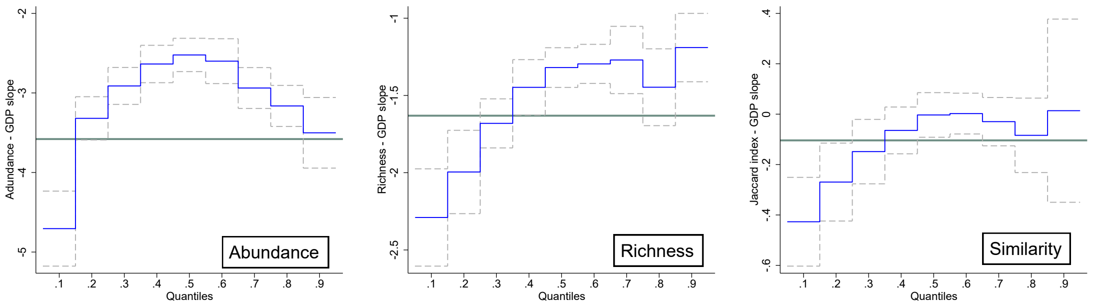
Panel B. By taxa



Panel C. By sample-average GDP per capita



Panel D. By regression quantiles



Notes: Panel A plots decile binscatter of biodiversity 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.

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 residualized 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 higher levels of biodiversity may increase resilience to adverse shocks to the ecosystem.

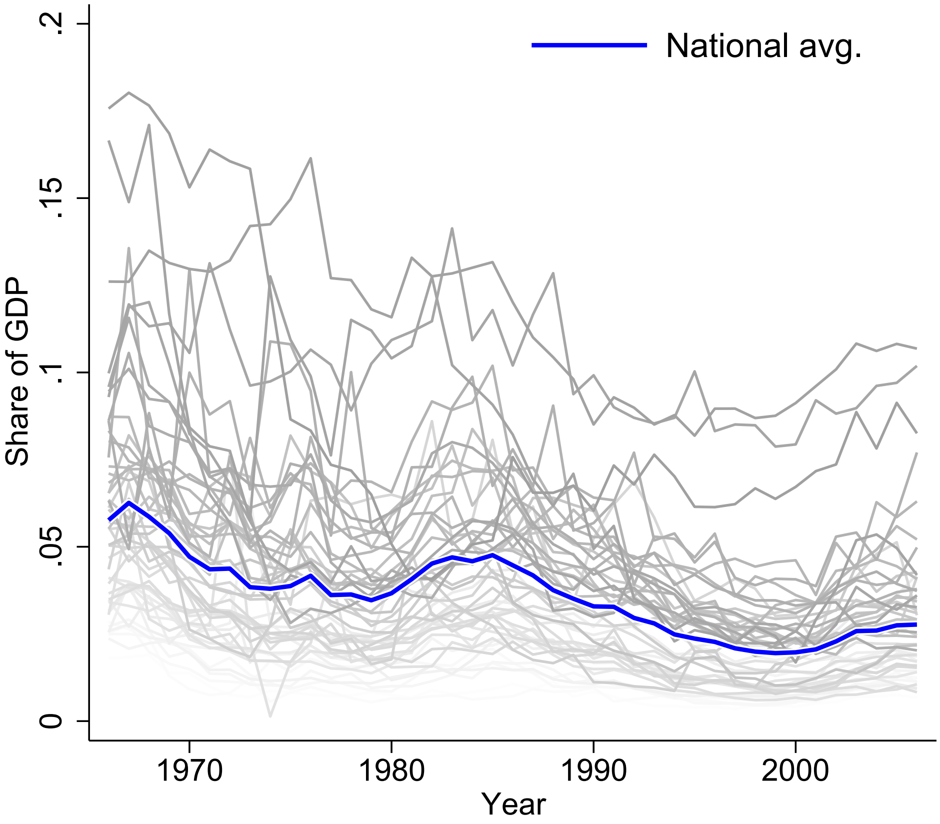
3.2 Instrumental Variables

The OLS approach reveals a general negative association between biodiversity and economic production, 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 a plausibly exogenous shock to economic output that is tied to policy changes. We then leverage this quasi-experimental research design to derive causal GDP-biodiversity elasticity estimates using the instrumental variable (IV) approach.

Our causal IV design exploits shocks to state GDP from changes in national military buildups. This strategy has been widely used 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

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.

leads to greater military spending in some states than in others. Figure 4, adapted from Nakamura and Steinsson (2014), plots each 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 repair and maintenance of military facilities, strongly influence construction and manufacturing outputs; these sectors are associated with substantial environmental externalities, and may 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

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

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).[8] As shown in 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. We provide more discussions on channels in Section 4.

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

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[8] 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 A.7.

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 (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.

3.3 Robustness Checks

Overall, Figure 3 and Table 2 suggest a strong, negative, and pervasive relationship between biodiversity and GDP. We report several extensions of the panel estimation in the Appendix.

First, Appendix Table A.5 presents a dynamic specification where we include a lead and a lag term of GDP in addition to current year's GDP. We find the "placebo", lead coefficients to be statistically insignificant and in general an order of magnitude smaller than the main GDP effect size; evidence on a lagged effect of GDP is inconclusive.

To test more explicitly for potential lagged impacts in the longer run, in Appendix Table A.6, we report alternative specifications where we replace the logged GDP variable with various forms of GDP *growth*, including current growth rate, five-year moving average rate, and/or five-year moving maximum rate. Even conditional on the effect of current growth, we find large, negative effects of sustained trend of growth in the past years on biodiversity (columns 2, 5, and 8) , which is partially explained by years with a burst of growth (columns 3, 6, 9). While we view these specifications as less well-identified than the simple OLS regressions of equation (1), they provide suggestive evidence that biodiversity is influenced by the trajectory of economic growth in addition to year-over-year shocks.

Table 2: Military Spending 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							
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. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Appendix Table A.7 reports a series of robustness checks on the IV results. 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 replaces state-level GDP with county-level income as the right-hand-side measure of economic production. Overall, the results are stable across these specification checks.

Throughout the paper, we use abundance, species richness, and the Jaccard similarity index as our focal outcome variables, but there are 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 species in $\mathbb{S}_{ct}$, then species richness, Gini diversity, and Shannon diversity all yield the same value. For example, if there is an equal share of 2 species in $\mathbb{S}_{ct}$, then all three indices will be 2. 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.9 repeats both our OLS and IV estimation using these three alternative biodiversity measures. We find that the results are largely the same regardless of which biodiversity metric we use.

4 Channels

We now turn toward unpacking the mechanisms behind the negative GDP-biodiversity relationship. Using our setting, we first revisit a major factor in biodiversity trends related to economic production: land use and urbanization. We then provide evidence for the role of air pollution.

4.1 Land Use and Urbanization

Habitat losses are widely accepted as major determinants of biodiversity decline (IUCN, 2021), and increased economic development and urbanization may result in destruction of habitat. Here we establish this relationship in our study context.

Urbanization We first explore increasing urbanization of land as a potential driver of biodiversity losses. This exercise leverages the fact that high-resolution satellite observations of urbanization became available during the second half of our study period (post-2001). We use NASA's Moderate Resolution Imaging Spectroradiometer (MODIS) land cover data (Section 2.3) which allows us to directly measure the degree of urbanization near the sampling sites in the BioTIME dataset, unlike GDP which is reported at a larger spatial scale. Our primary measure of urbanization is the log amount of land within 50 kilometers of a sampling site that falls under the MODIS urban classification. Figure A.4 shows that this measure of urbanization is positively associated with GDP. We also test the robustness of our results using urbanization measured within 100 km of the site or within the county of the site.[9] We then estimate the effect of urbanization on biodiversity outcomes using the identical approach outlined in equation (1) where the variable of interest is the log land area that is classified as urban in MODIS.

Table 3 shows our results. The first row shows the urbanization elasticity of biodiversity when focusing within a 50 kilometer radius, the second row is for a 100 kilometer radius, and the third row is within the entire county. All elasticities are large for the measures of urbanization within 50 or 100 kilometers of the sampling site. The magnitudes of the estimates

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[9] The average county has an area equivalent to a circle with a radius of about 30 kilometers.

Table 3: Urbanization and Biodiversity Outcomes

	(1) Abundance	(2) Richness	(3) Similarity	(4) Abundance	(5) Richness	(6) Similarity
	Panel A. All species			Panel B. Non-bird species		
Urbanization (50-km radius)	-11.91***	-6.39**	-2.26	-16.67**	-10.53**	-5.24***
	(4.01)	(2.38)	(1.54)	(6.94)	(3.71)	(1.69)
Urbanization (100-km radius)	-11.59***	-5.15***	-3.94***	-13.79***	-7.48***	-4.47***
	(2.29)	(1.53)	(1.40)	(2.87)	(2.23)	(0.99)
Urbanization (county)	-1.73	-0.69	-0.29	-16.14***	-8.59***	-4.04
	(1.36)	(0.66)	(0.38)	(4.18)	(1.56)	(2.35)
Observations	19,611	19,611	17,188	6,830	6,830	6,752

Notes: Each cell corresponds to a regression. Outcome variables are in logs except for Similarity which is a ratio (columns 3 and 6). Independent variables are logged urban areas within 50-km radius of the sampling location (first row), logged urban areas within 100-km radius of the sampling location (second raw), and logged urban areas of the county (third row). Columns 1-3 reports full sample estimation. Columns 4-6 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. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

shrink slightly going from the 50 kilometer measure to the most aggregate 100 kilometer measure, consistent with urbanization near the sampling site being a more important determinant of biodiversity. The estimates at the county-level are smallest, potentially because of measurement error: sampling sites may be near county boundaries and not the county centroid, and counties do not necessarily have regular shapes. Overall, the evidence suggests that increased urbanization is negatively associated with our three measures of biodiversity, consistent with an extensive literature showing land use change and habitat destruction is a major driver of biodiversity trends.

Land Use Policies In Appendix A, we report another piece of evidence on the relevance of land use in the GDP-biodiversity relationship. We examine whether protective land use policies – specifically, conservation protected areas that limit or ban industrialization within their borders – can mitigate the negative effects of GDP. We find that having a larger share of nearby land as protected areas reduces the negative impact of economic production on biodiversity. We also find evidence that the physical geography of how the protected area is arranged matters: the same amount of protected area has a smaller protective effect if the area is broken up into more discontiguous areas of land.

Table 4: Sector-Specific 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	-0.504**	-0.366***	-0.021	-1.505***	-0.677***	-0.009
	(0.198)	(0.091)	(0.023)	(0.343)	(0.154)	(0.068)
Mining	-0.063	-0.008	-0.012	-0.274	0.090	-0.138***
	(0.045)	(0.025)	(0.011)	(0.188)	(0.071)	(0.045)
Timber and Logging	-0.021	-0.014	0.002	-0.287**	-0.138**	-0.007
	(0.035)	(0.021)	(0.002)	(0.114)	(0.051)	(0.008)
Agriculture	-0.002	-0.012	0.009	0.638***	0.126**	0.073***
	(0.063)	(0.023)	(0.008)	(0.158)	(0.057)	(0.017)
Construction	0.172	0.134	0.025	0.754	0.139	-0.075
	(0.356)	(0.090)	(0.059)	(0.628)	(0.206)	(0.132)
Services	-0.187	-0.289	-0.031	0.278	0.099	-0.087
	(0.558)	(0.205)	(0.060)	(1.462)	(0.372)	(0.298)
Observations	59,651	59,651	46,746	13,809	13,809	12,613

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

4.2 Air Pollution

We begin by revisiting the GDP-biodiversity link, replacing overall GDP measure in equation (1) with sector-specific income. We focus on six sectors. Two are well known to cause significant amounts of pollution: manufacturing (air pollution) and mining (water pollution); two that physically alter the landscape: agriculture and logging; and two that are related to economic activity within urban areas: construction and mining. Table 4 presents the results. Our results show large and consistent negative associations between manufacturing income – indicative of greater manufacturing production – and biodiversity. We also find a negative correlation between logging-related income and biodiversity metrics for non-bird species, and a positive association for agriculture. This evidence suggests that air pollution emitted as a byproduct of economic production may be a key driver of biodiversity trends.

Next, we directly test whether air pollution reduces biodiversity. Because ground-level air pollution is only measured at a selected set of locations in the US, and those locations tend to be nearby urbanized population centers, we use remote sensing-based reanalysis measurements of Aerosol Optical Depth (AOD) from MERRA-2. Figure A.4 shows that AOD is positively associated with GDP.

We first estimate the association between air pollution and biodiversity by estimating equation (1) with AOD in place of GDP. The first row of Table 5 shows results from estimating the effect of log AOD on biodiversity using equation (1). Across all measures and both groups of all species and non-bird species, we find strong negative associations with larger elasticities for non-bird species.

As with GDP, there may be omitted factors driving variation in both pollution and biodiversity such as extreme heat.[10] To more formally test whether pollution drives the biodiversity-GDP relationship we find, and to also determine whether there are policy levers for mitigating the relationship, we consider variation induced by 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 established national criteria for outdoor air quality, targeting six widespread air pollutants that harm public health.

A key component of the CAA program is its annual designation of compliance and noncompliance 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}, ozone (O_3), sulfur dioxide (SO_2), carbon monoxide (CO), and lead (Pb) – and/or for failing to meet one or more of the versions of the standards for a given pollutant.[11] 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.[12] Figure 6 plots the location of nonattainment counties and the

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[10] For example, hotter temperatures and more sun provide better conditions for ozone formation.

[11] 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).

[12] There are usually years of lag between the times when a pollutant standard was promulgated and when

Table 5: Air Pollution and Biodiversity Outcomes

	(1) Abundance	(2) Richness	(3) Similarity	(4) Abundance	(5) Richness	(6) Similarity
	Panel A. All species			Panel B. Non-bird species		
AOD (OLS)	-0.737*** (0.223)	-0.332*** (0.118)	-0.061** (0.027)	-2.298*** (0.426)	-1.152*** (0.260)	-0.065** (0.025)
$\hat{\text{AOD}}$ (Clean Air Act IV)	-5.702*** (1.791)	-3.370*** (1.056)	-0.436 (0.450)	-5.803*** (0.753)	-3.293*** (0.521)	-0.589*** (0.077)
Kleibergen-Paap F-stat.	7.74	7.74	7.23	14.9	14.9	14.9
Observations	53,248	53,248	40,827	12,526	12,526	11,416

Notes: Each cell corresponds to a regression. Outcome variables are in logs except for Similarity which is a ratio (columns 3 and 6). Independent variables are county's annual logged Aerosol Optical Depth (AOD) level. The first row reports OLS regression estimates. The second row reports IV regression estimates, using county's nonattainment status (number of pollutant standards the county was in violation of) as the instrumental variable for logged AOD. The Kleibergen-Paap F-statistics of the first stages are reported at the bottom of the table. Columns 1-3 reports full sample estimation. Columns 4-6 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. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

number of standards being violated in each county as of year 2019.

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; Hollingsworth et al., 2022) while effectively reducing air pollution (e.g. Chay and Greenstone, 2005; Sanders et al., 2020; Hollingsworth et al., 2022).

Here we use the same IV approach as our military spending setting, but instead with the number of nonattainment designations instrumenting for AOD. The second row of Table 5 shows our results. All estimates indicate that increases in air pollution reduce biodiversity. The elasticities are all larger than the OLS estimates which is consistent with measurement error in AOD.

In Table A.8, we conduct a set of robustness checks similar to those shown in Table A.7. 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 overidentified model with 12 excluded instruments, each indicating nonattainment status for a separate pollution standard as shown in Figure 5. We report the limited information

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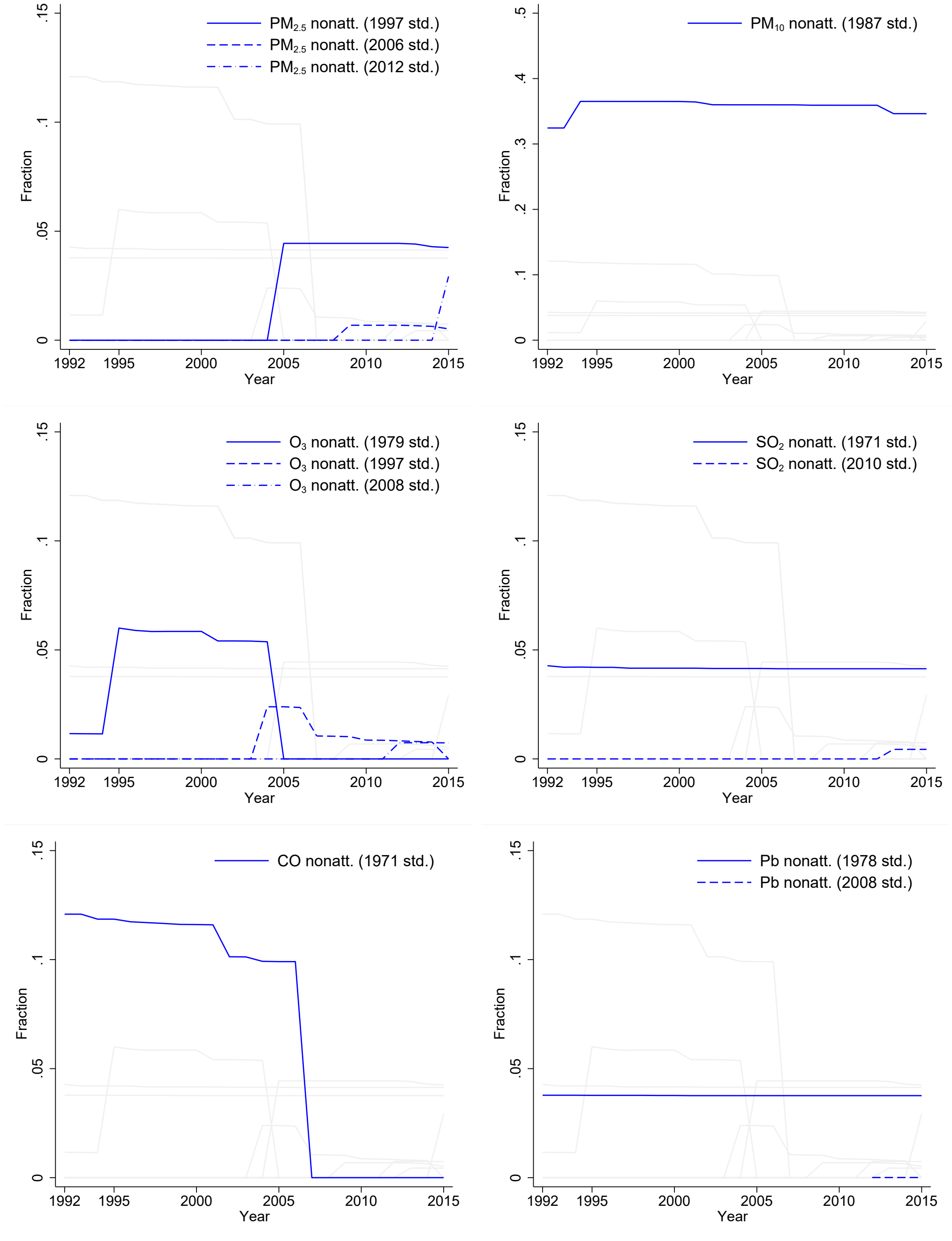
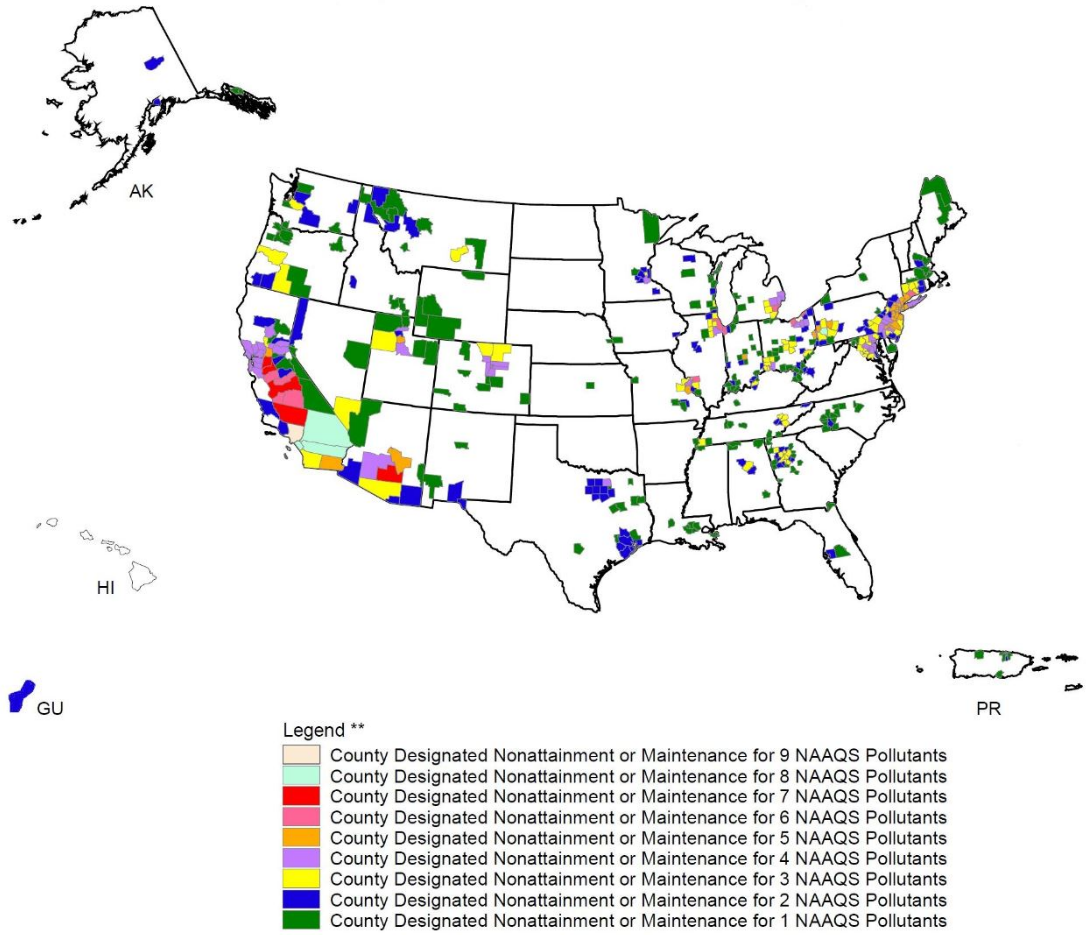
the nonattainment designation actually occurred. For example, as shown in Figure 5, the designation of nonattainment status with respect to the 1997 $\text{PM}_{2.5}$ standard did not occur until the year 2005.

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.

Figure 6: 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.

maximum likelihood (LIML) estimator for this model.[13] In Panel C, we control for Census Division-specific decadal trends in additional to the location-taxa and year fixed effects. Panel D restricts to a subsample where ground-level fine particulate matter ($PM_{2.5}$) measurement from the U.S. Environmental Protection Agency (EPA) are available, and we repeat the IV estimation using the *in situ* pollution measure in place of the remote-sensing AOD measure. The results are robust to the specification changes.

5 Conclusion

This paper provides one of the first estimates on the causal effect of economic production on biodiversity. One innovation of our paper 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 are strongly negatively affected by local economic production. One of our main contributions is identifying a novel channel for how economic activity affects biodiversity: air pollution. We find that air pollution is negatively associated with all of our biodiversity measures and that air pollution regulations can serve as conservation policy and provide ecological co-benefits in addition to the benefits they provide to humans.

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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[13] The main tradeoff with the overidentified model is potentially increasing bias from using weak instruments in order to improve efficiency (Wooldridge, 2010). LIML estimates are median-unbiased with weak instruments.

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Appendix

A Protected Areas and GDP

One interpretation of our overall 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. Here we leverage existing policies to speak to such a possibility. We focus on 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.

There is an extensive economics literature on the economic costs of various forms of environmental protection — such as air quality regulation, protected areas, and endangered species listings (e.g. Walker, 2013; Walls et al., 2020; Ferris and Frank, 2021) — which are aimed at guarding the environment from the negative effects of growth.[14] There is also burgeoning complementary literature on the effectiveness of protected areas.Destruction of habitat is one of the primary drivers of species decline (IUCN, 2021), but the literature has generally found that protected areas — which cover nearly 15% of the Earth's land and 10% of its water — have had mixed results due to management issues, funding, resource exploitation, and ecological connections to areas outside of the protected area that may be degrading (Leverington et al., 2010; Laurance et al., 2012; Watson et al., 2014; Di Marco et al., 2019; Geldmann et al., 2019).

Since early 1990s, adoption of conservation protected area policies has grown rapidly (Frank and Schlenker, 2016).[15] 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 marine and terrestrial protected areas. The database is in the form of a shapefile that outlines

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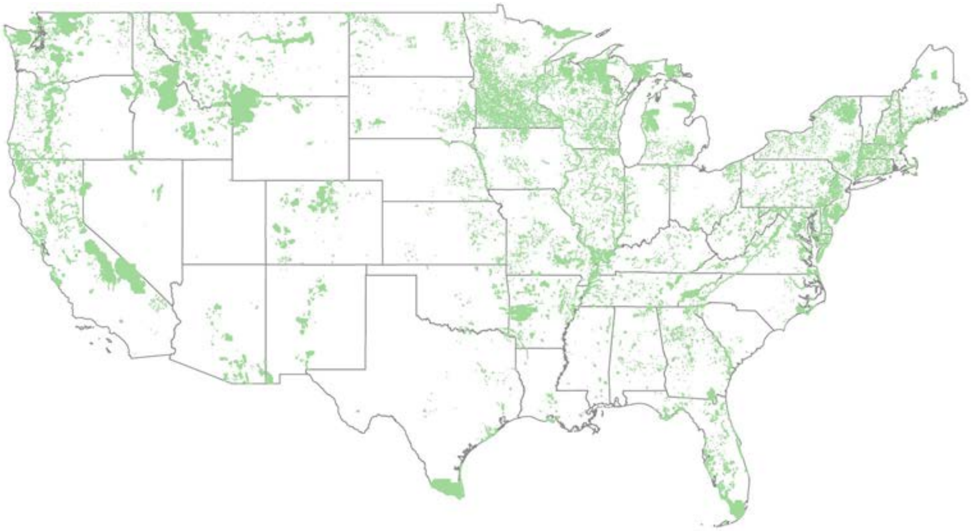
[14] Endangered species listings may have costs exceeding billions of dollars for a single species (Montgomery et al., 1994), and in some cases, it can even backfire and lead to habitat destruction (Lueck and Michael, 2003).

[15] 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 A.1: Protected Areas Within 50 Kilometers of a Sampling Location



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.

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 A.1 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 A.1 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 land within 50 kilometers that is within a protected area. Columns 2, 4, and 6 include additional interaction terms between log GDP and the number of discontiguous protected areas within 50 km.[16] Columns 1 and 2 show that the abundance-GDP relationship is attenuated by an increase in the amount of nearby land that

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[16] 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).

Table A.1: Protective Policy and the Biodiversity - GDP Relationship: Protected Areas

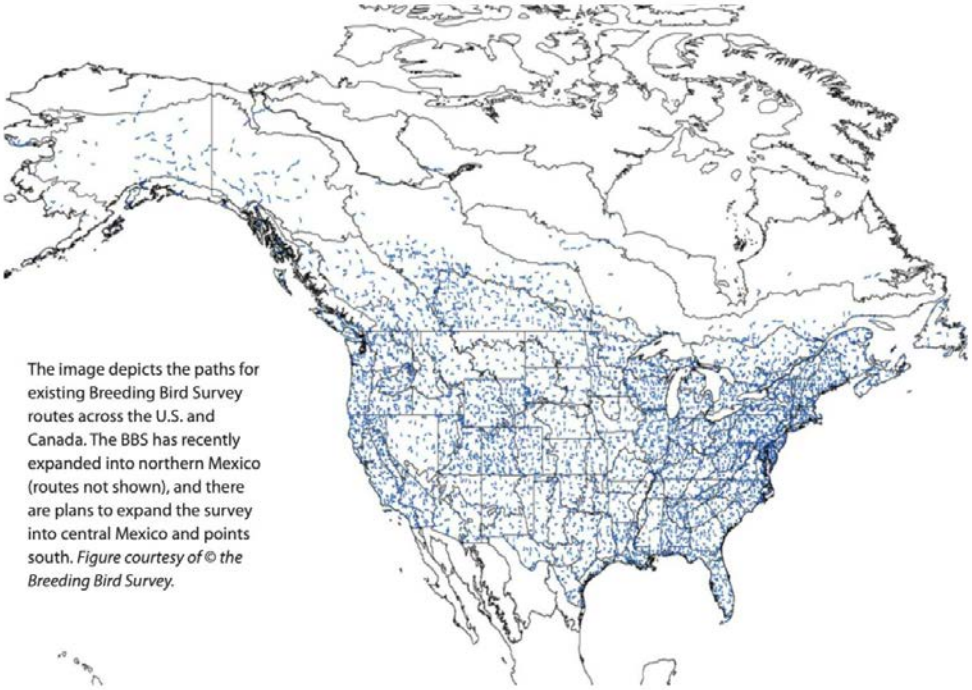
	(1)	(2)	(3)	(4)	(5)	(6)
	Abundance		Richness		Similarity	
Panel A. All species						
GDP	-3.798*** (1.341)	-3.410*** (1.142)	-1.721** (0.684)	-1.490*** (0.611)	-0.219 (0.147)	-0.255* (0.140)
GDP × %Areas protected	1.765* (1.023)	2.028* (1.158)	0.732 (0.500)	0.892 (0.555)	0.890*** (0.252)	0.864*** (0.237)
GDP × #Fragmented areas	- -	-0.206* (0.108)	- -	-0.144 (0.088)	- -	0.023 (0.015)
Observations	54,907	54,907	54,907	54,907	42,426	42,426
Panel B. Non-bird species						
GDP	-6.510*** (0.787)	-4.229*** (0.813)	-3.277*** (0.261)	-2.339*** (0.436)	-0.652*** (0.158)	-0.754*** (0.087)
GDP × %Areas protected	7.484 (4.812)	13.976** (6.080)	-0.263 (0.938)	1.805 (1.269)	3.217** (1.237)	3.520** (1.286)
GDP × #Fragmented areas	- -	-0.731* (0.418)	- -	-0.147 (0.139)	- -	-0.115 (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. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

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). Columns 5 and 6 show that protected areas tend to reduce the negative effect of GDP on species turnover, but we do not detect any effect of changing the number of areas. We note that interpreting these findings as causal should be taken with a grain of salt. Protected areas are not adopted randomly but may in fact be targeted at areas with high levels of biodiversity to begin with, or areas that are seeing increasing developmental pressures.

B Additional Tables and Figures

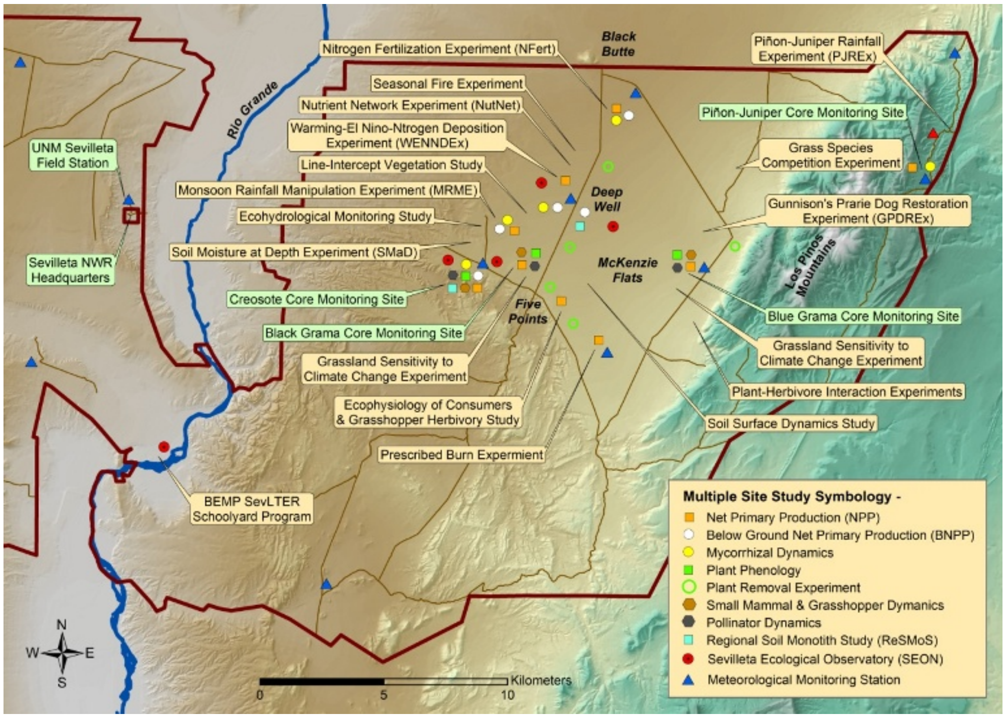
Figure A.2: Breeding Bird Survey routes across the US and Canada



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.*

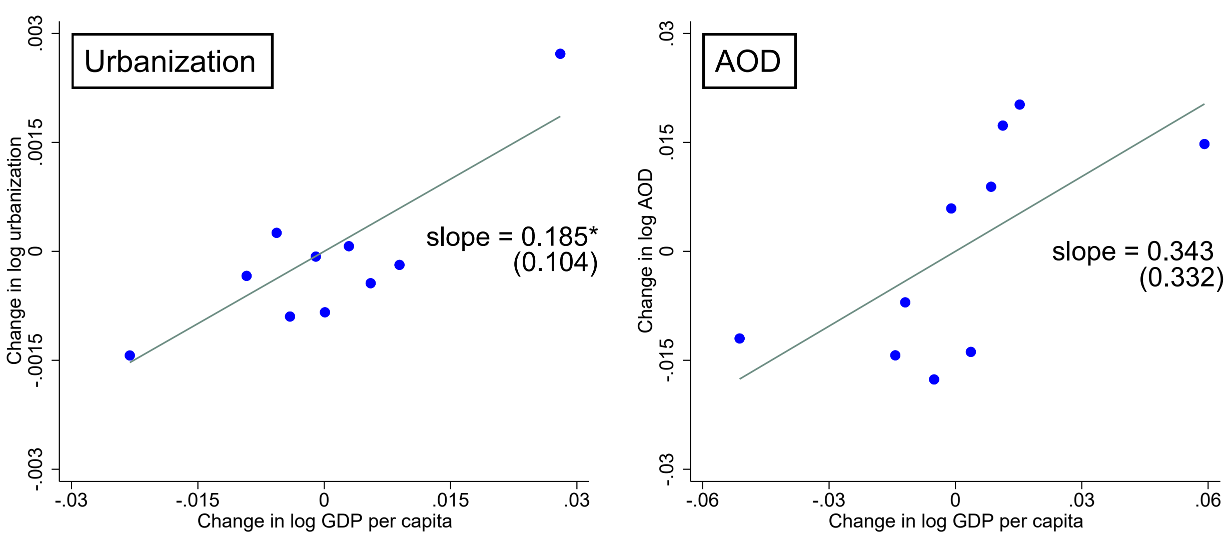
Note: This figure is from Ziolkowski Jr et al. (2010). It shows the sample collecting routes in the North American Breeding Bird Survey (BBS), which is one of the studies in the BioTIME database. The BBS is a long-term and large-scale avian monitoring program that tracks the status and trends of North 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.3: 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.4: Association Between GDP and Urbanization and AOD



Notes: Panel A plots a decile binscatter of urbanization 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). Standard errors are clustered at the state level. Panel B plots a decile binscatter of AOD and log GDP.

Table A.2: 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.3: GDP and Biodiversity Sampling in BioTIME Dataset

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Log(study duration)	$\mathbb{1}$(start year)		$\mathbb{1}$(end year)		$\mathbb{1}$(missed year)	
GDP growth (%)	0.013	-	-	-	-	-	-
	(0.054)	-	-	-	-	-	-
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)
$\text{GDP}_\text{t-1}$	-	-	-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.4: The Biodiversity - GDP Relationship: Older and Newer Studies

	(1) Abundance	(2) Richness	(3) Similarity
Panel A. By year of sampling			
GDP (1961-1997)	-3.311**	-1.100	-0.227
	(1.316)	(0.918)	(0.303)
GDP (1998-2015)	-3.042***	-1.421***	-0.163
	(0.901)	(0.509)	(0.174)
Observations (1961-1997)	22,603	22,603	12,683
Observations (1998-2015)	31,360	31,360	28,256
Panel B. By year when study began			
GDP (1961-1993)	-3.617***	-1.943***	0.014
	(1.027)	(0.531)	(0.111)
GDP (1994-2013)	-3.358	-1.054	-0.074
	(2.015)	(1.079)	(0.140)
Observations (1961-1993)	14,535	14,535	14,208
Observations (1994-2013)	40,352	40,352	28,198

Notes: Each cell represents a separate regression per equation (1). Each column corresponds to a different biodiversity metric. Panel A reports separate regressions by before and after median year of sampling. Panel B reports separate regressions by before and after median year of a study's first year of sampling. 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.5: 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)
$\mathrm{GDP}_{t\text{-}1}$	-	-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)
$\mathrm{GDP}_{t\text{-}1}$	-	-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.6: Biodiversity - GDP Growth Relationship

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Abundance			Richness			Similarity		
Panel A. All species									
GDP growth	-3.00	-2.89*	-2.48*	-2.01	-1.98	-1.64	0.16	0.17	0.15
	(2.30)	(1.65)	(1.35)	(1.52)	(1.36)	(1.12)	(0.31)	(0.38)	(0.38)
Avg. GDP growth		-11.39*	-3.60		-2.93	3.53		-1.09	-1.56
(last 5-y)		(6.23)	(6.35)		(2.83)	(3.83)		(0.79)	(1.15)
Max. GDP growth			-7.68***			-6.36**			0.44
(last 5-y)			(2.16)			(2.46)			(0.43)
Observations	37,644	37,644	37,644	37,644	37,644	37,644	33,789	33,789	33,789
Panel B. Non-bird species									
GDP growth	-6.24**	-3.92***	-2.49**	-5.06***	-3.98***	-3.32***	0.32***	0.67**	0.37*
	(2.40)	(1.26)	(0.90)	(1.39)	(0.92)	(0.79)	(0.07)	(0.25)	(0.21)
Avg. GDP growth		-26.10***	-10.26**		-12.14***	-4.87**		-4.16***	-7.77***
(last 5-y)		(4.57)	(3.75)		(1.53)	(1.74)		(0.98)	(1.38)
Max. GDP growth			-9.83***			-4.51***			2.28***
(last 5-y)			(2.59)			(1.30)			(0.52)
Observations	11,236	11,236	11,236	11,236	11,236	11,236	10,443	10,443	10,443

Notes: Outcome variables are in logs except for Similarity which is a ratio (columns 7-9). “GDP growth” is annual GDP per capita growth rate. “Avg. GDP growth ” is the average GDP per capita growth rate for the past 5 years, from t-5 to t-1. “Max. GDP growth” is the maximum annual GDP per capita growth rate in the past 5 years. 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.7: 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
County-level income	-5.189***	-3.102***	-0.587**
	(1.174)	(0.755)	(0.241)
Kleibergen-Paap F-stat.	4.634	4.634	4.953
Observations	57,362	57,362	44,310

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.8: Environmental Protection and Biodiversity Outcomes: IV Robustness

	(1) Abundance	(2) Richness	(3) Similarity
1(any nonatt. status) as IV	-7.695***	-4.944***	0.467*
	(1.659)	(0.943)	(0.242)
Kleibergen-Paap F-stat.	5.325	5.325	5.010
Observations	53,248	53,248	40,827
All nonatt. status as IVs	-4.925***	-2.736***	-0.405
(LIML)	(1.388)	(0.752)	(0.357)
Kleibergen-Paap F-stat.	108.190	108.190	201.410
Observations	53,248	53,248	40,827
Census Division decadal trends	-3.902***	-2.788***	-0.625
	(1.111)	(0.878)	(0.611)
Kleibergen-Paap F-stat.	9.604	9.604	6.594
Observations	53,248	53,248	40,827
Ground-level particulate matter	-1.198**	-0.721*	-0.400*
	(0.482)	(0.414)	(0.208)
Kleibergen-Paap F-stat.	24.304	24.304	26.796
Observations	25,040	25,040	22,665

Notes: Each panel corresponds to an alternative IV specification where the outcome variable is a biodiversity measure (as indicated by the column header) and the endogeneous regressor is logged pollution. See text for more details. Standard errors are clustered at the state level. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.

Table A.9: Other Measures of Biodiversity: Robustness

	(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)
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)

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. *: $p < 0.10$; **: $p < 0.05$; ***: $p < 0.01$.