

# **The Environmental Effects of Economic Production: Evidence from Ecological Observations**

April 2023

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# Motivation

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- Economists have long been interested in the impact of economic production on the **natural environment**
  - Ex: Biodiversity and economic prosperity (Weitzman, 1992, 1998; Arrow et al., 1995; Brown Jr and Shogren, 1998; Fullerton and Stavins, 1998; Heal, 2000; Brock and Xepapadeas, 2003).
- Empirical research centers on how externalities directly affect **human well-being**
  - Ex: production → pollution → health (Landrigan et al., 2018)
- Pollution and habitat destruction can disrupt a wide range of **wildlife**, reducing **ecosystem services**

# Motivation

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- **Biodiversity:** the variety of genes, species, or functional traits in an ecosystem
  - Enhances stability and resilience of ecosystems (e.g., Missirian et al., 2019)
- **Economic importance**
  - **Food sources:** fisheries (Worm et al., 2006), crop yields (Dainese et al., 2019), mitigate natural shocks (Noack et al., 2019)
  - **Medicine:** (Rausser and Small, 2000; Costello and Ward, 2006)
  - **Non-market values:** (Kolstoe and Cameron, 2017)
  - “**Coupling**” with human society: (Raynor, Grainger, Parker, 2021; Frank and Sudarshan, 2023)
  - Recent survey by Dasgupta (2021)
- **This paper**
  - Estimates the effect of economic production on biodiversity outcomes

# This Paper

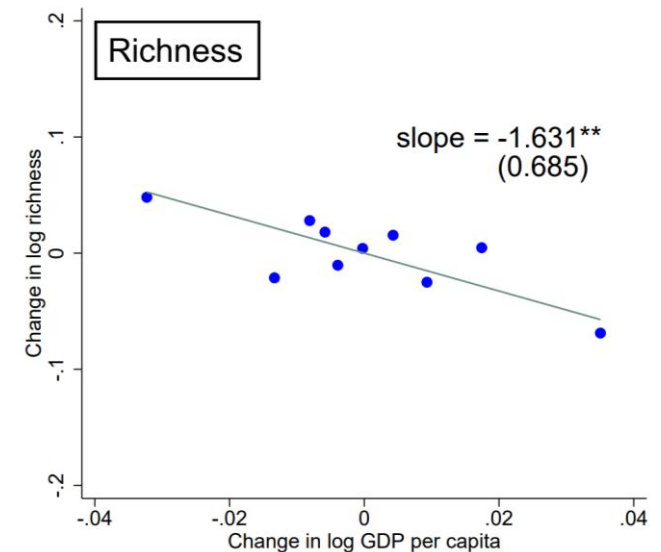
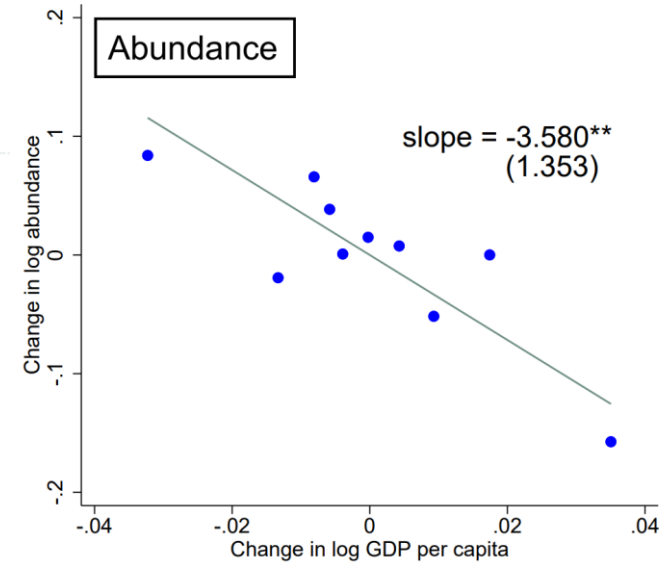
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1. Data: Use a compilation of ecological samplings to build panel measures of biodiversity
2. Correlation: Local economic production is negatively associated with biodiversity outcomes
3. Causality: Quasi-experimental design suggests the association is likely causal
4. Channel: Air pollution externalities can account for 1/3<sup>rd</sup> of the observed biodiversity-production link
5. Regulation: Pollution regulation generates conservation co-benefits



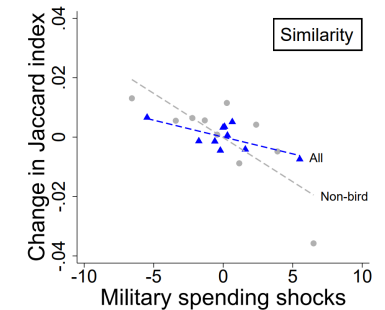
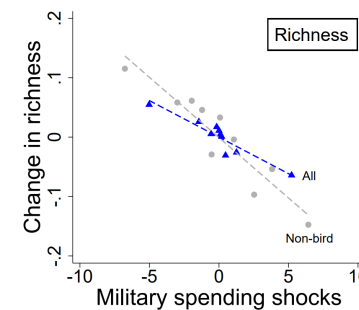
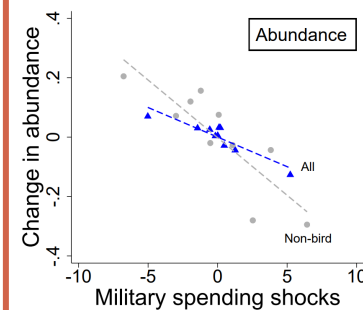
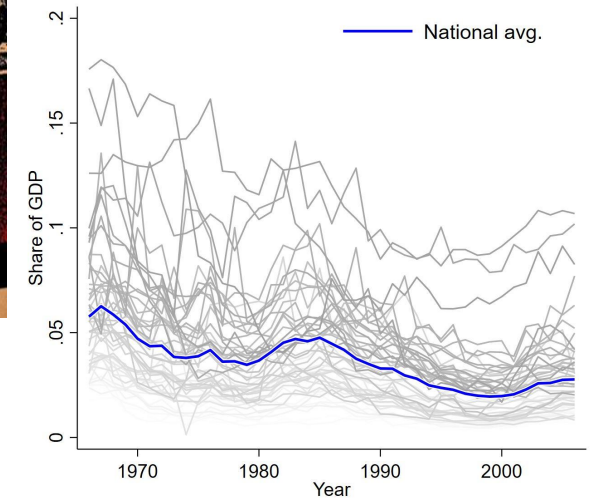
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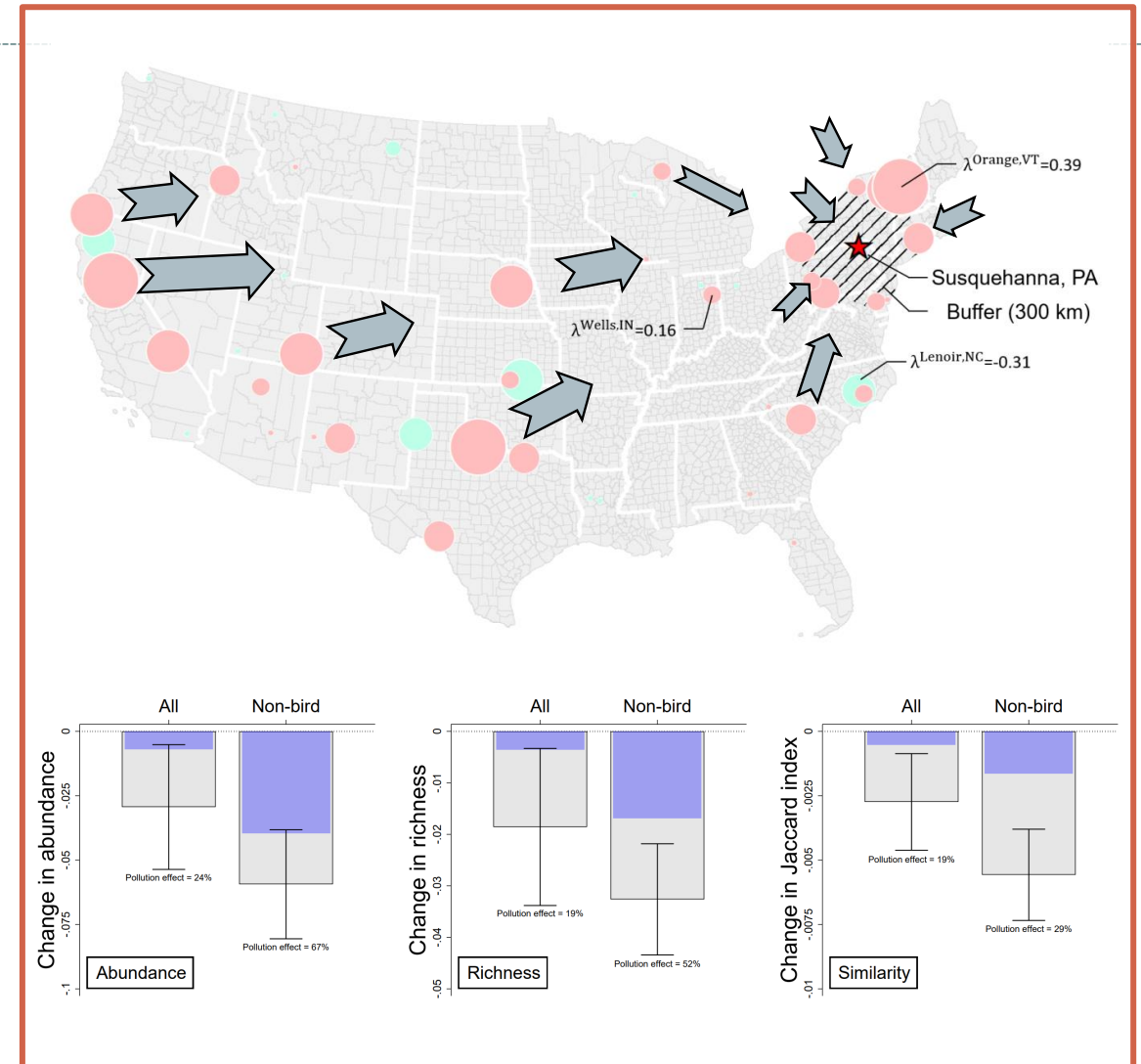
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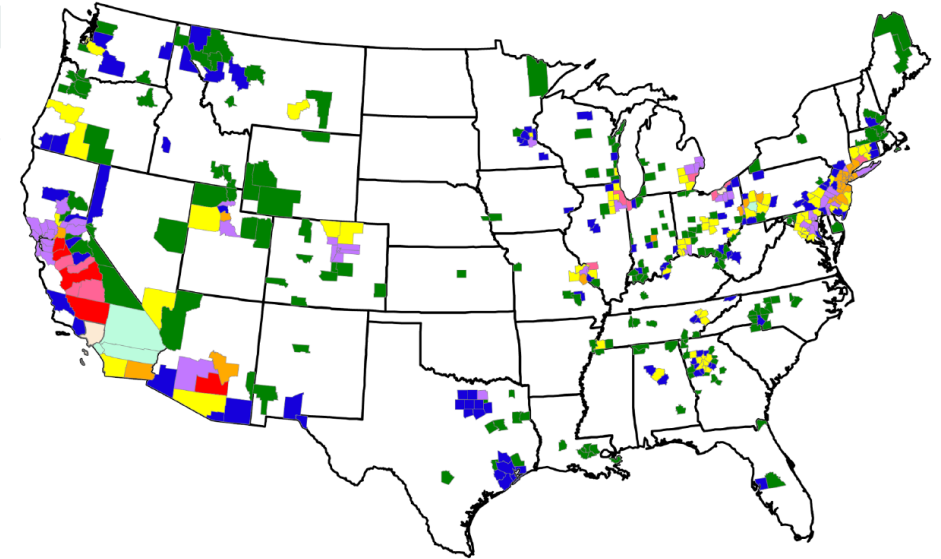
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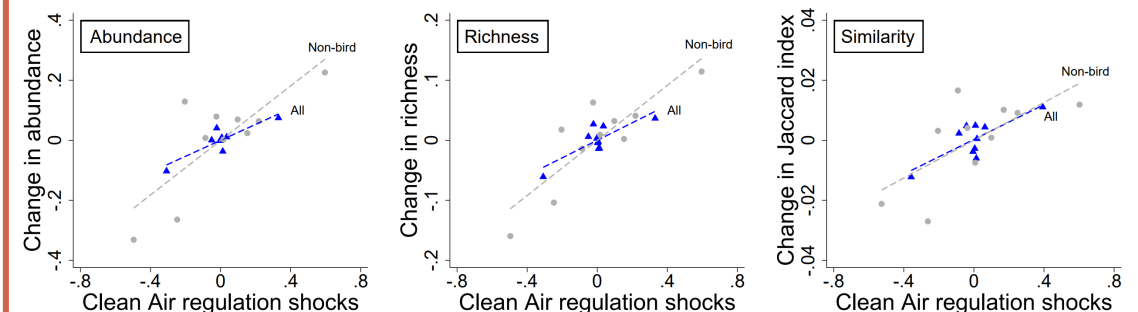
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Legend \*\*

- County Designated Nonattainment or Maintenance for 9 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 8 NAAQS Pollutants
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# Outline

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1. Measurement
2. Correlation
3. Causation
4. Channels
5. Regulations

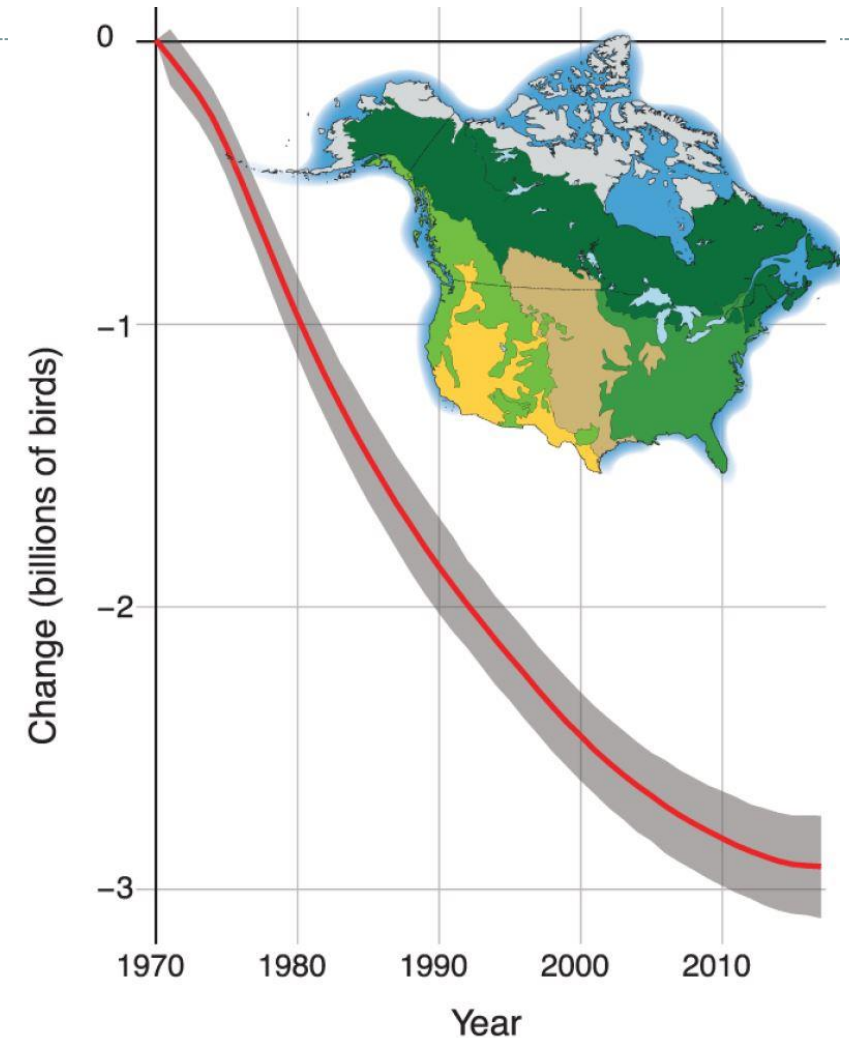
# BioTIME database



- <https://biotime.st-andrews.ac.uk/>
- A meta-dataset of 100s of ecological studies 1960-2015 (Dornelas et al., 2018)
- >12 million **study-species-lat-lon-year** abundance records
- Panel information over 10,000 sampling locations
- Studies conducted throughout time use **consistent sampling methodology**
- Good coverage: 40,000 unique species or genus, 8 broad taxa
  - Covers 80% known bird species, 40% mammals, 30% amphibians, 25% freshwater fish etc.
  - By far the best coverage that allows researchers to examine wide range of organisms and biomes

# Example Study: North American Breeding Bird Survey

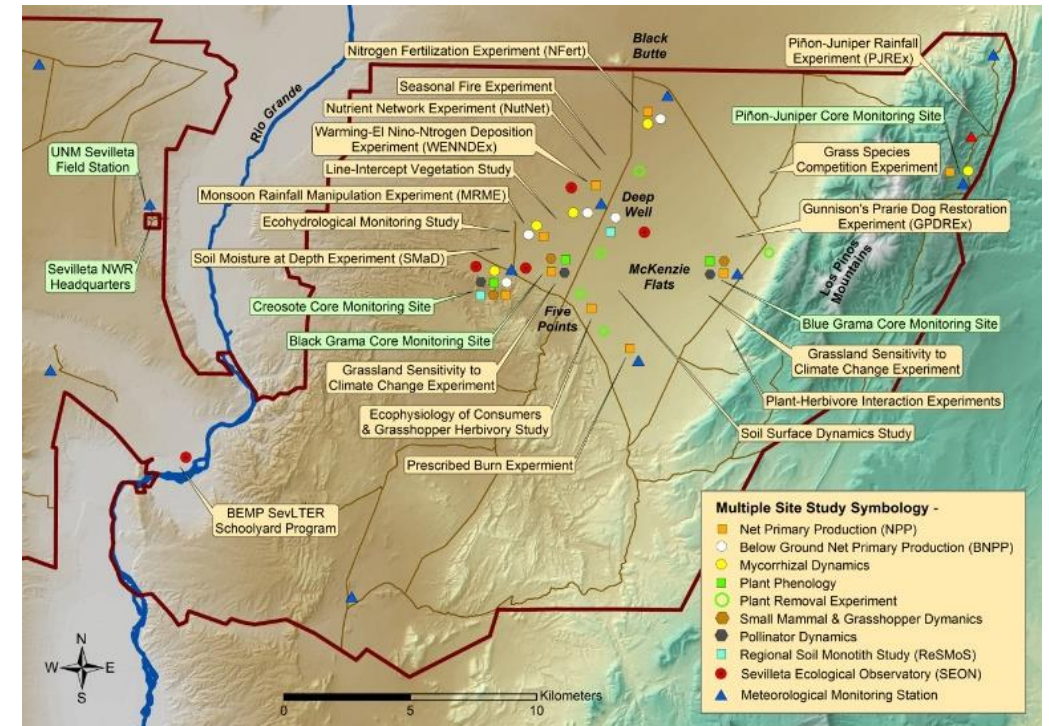
- From 1978 to present, avian breeding season every year (mostly June)
  - Professional bird observers collect observation data at the same stops along **>4100 roadside survey routes**
  - At each stop, conduct **3-minute point count** and record every bird heard or seen within a 0.25-mile radius



Source: Rosenberg et al. (2019)

# Example Study: Sevilleta Long Term Ecological Research Program

- A study on small mammals from 1989 to 2008 in New Mexico
  - multiple different locations, **3 trapping webs** at each location, each trapping web covers 3.14 ha
  - each trapping web is run **for 3 consecutive nights**
  - sampling locations span 5 different biomes

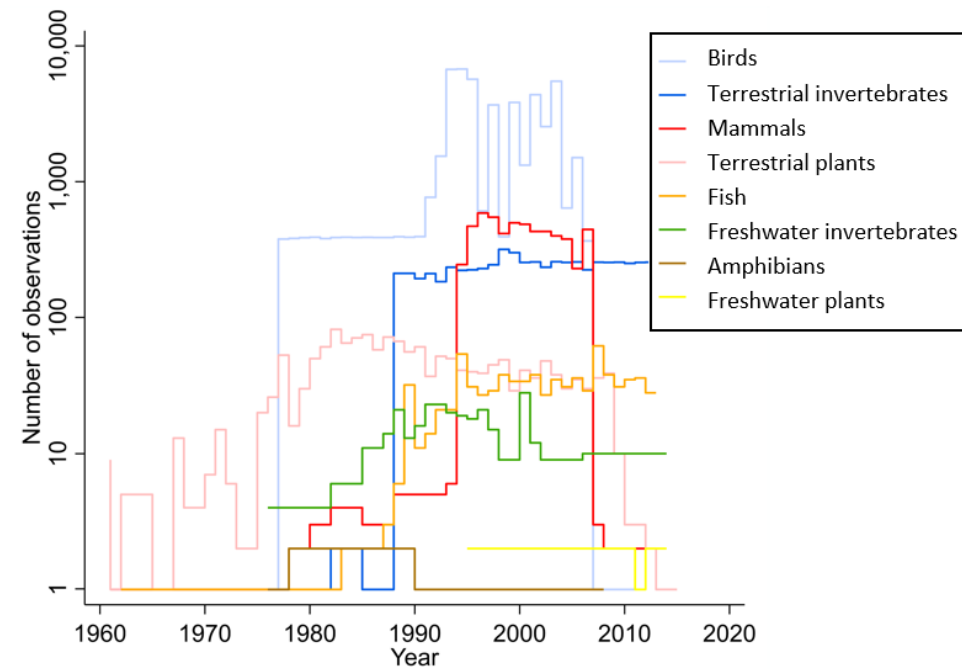
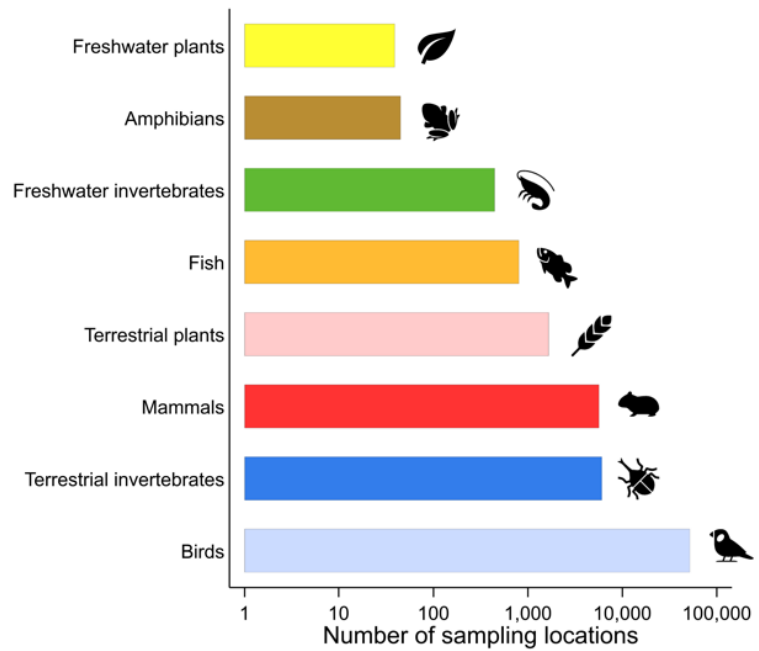
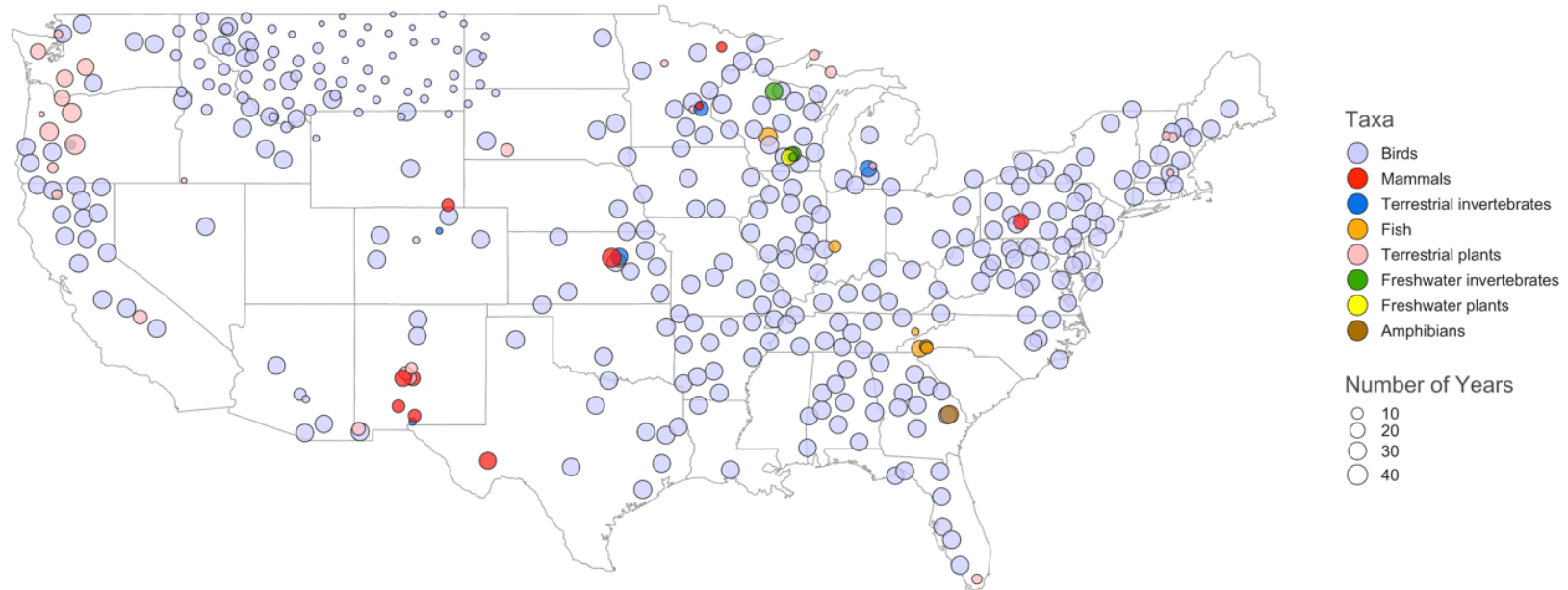


Source: <http://sevlter.unm.edu/>

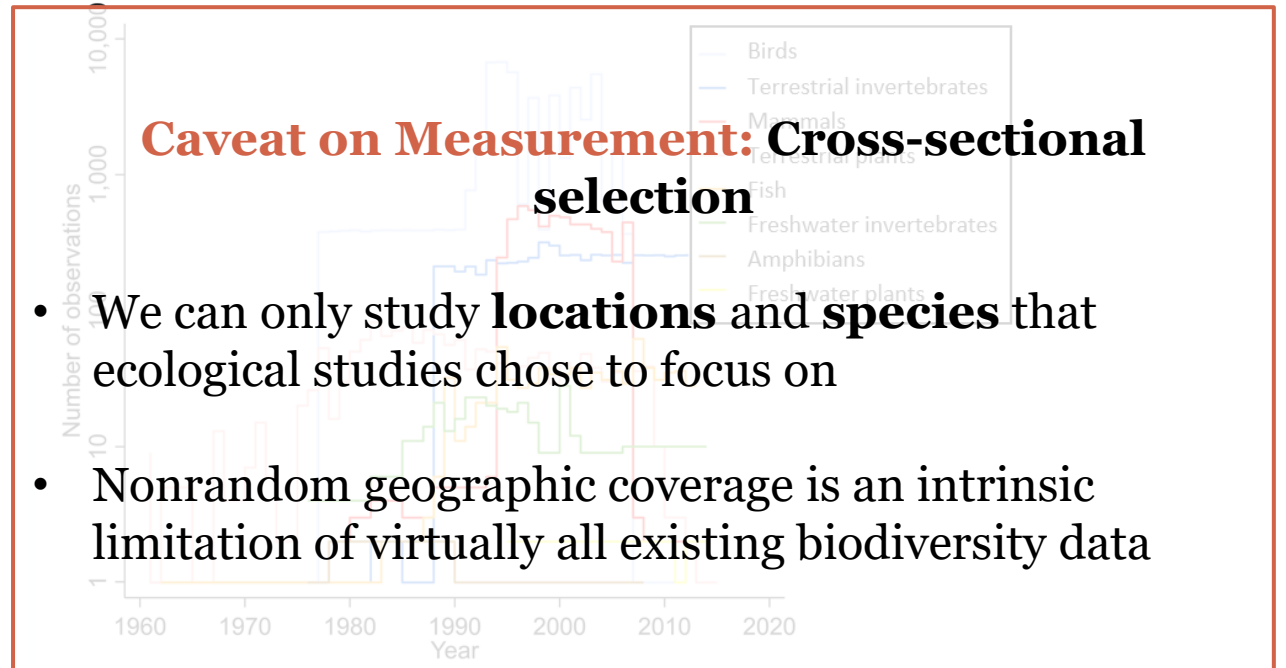
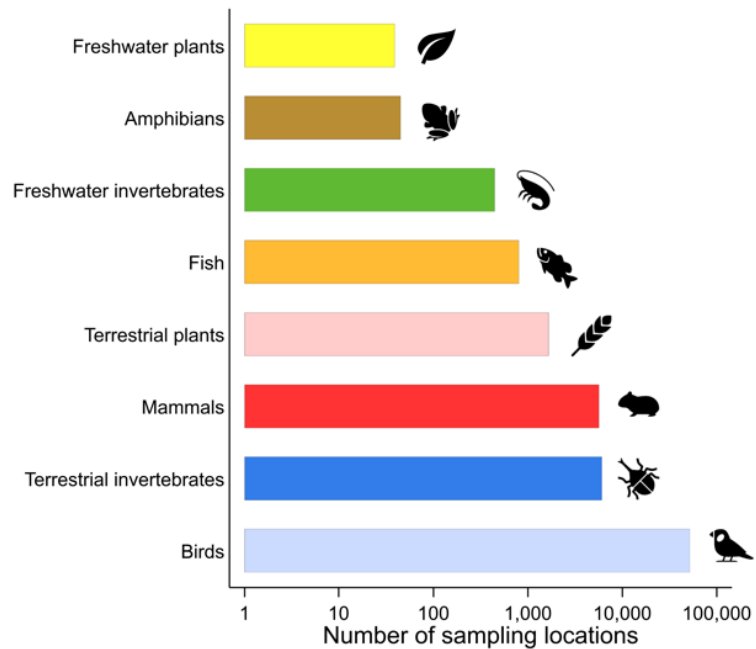
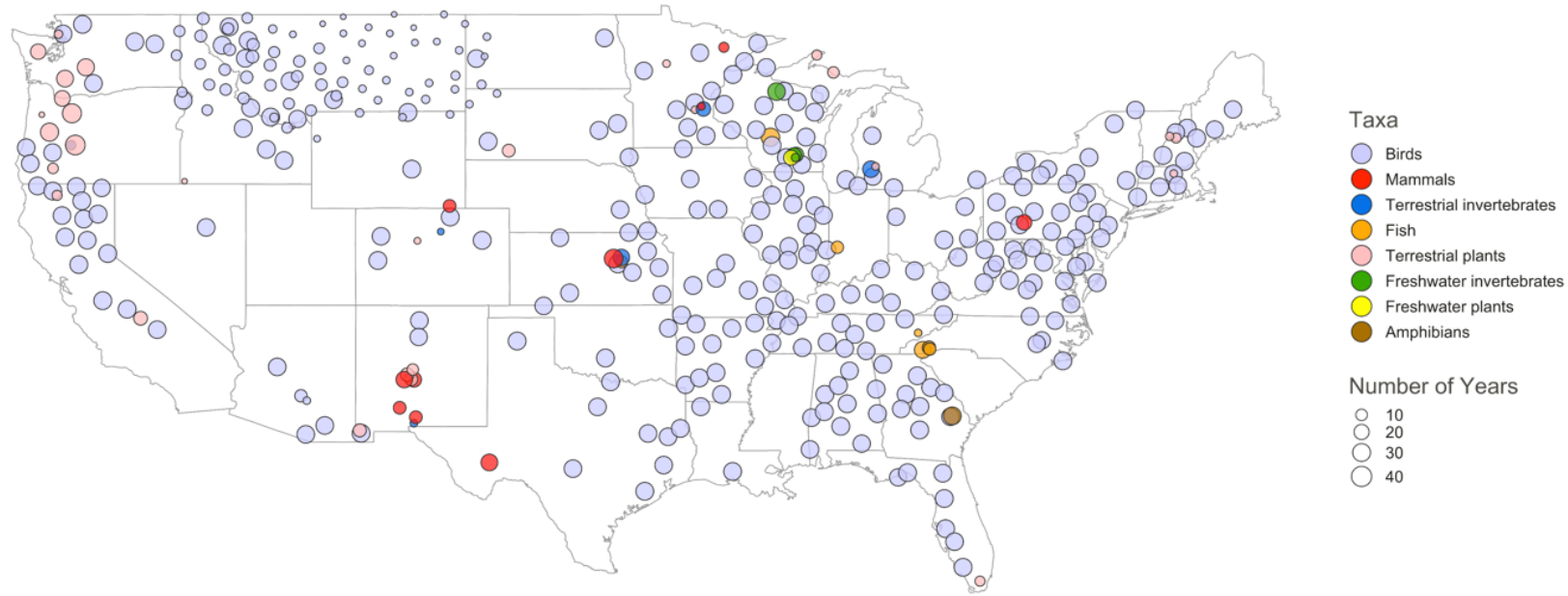




Source: <https://sevlter.unm.edu/small-mammals/>

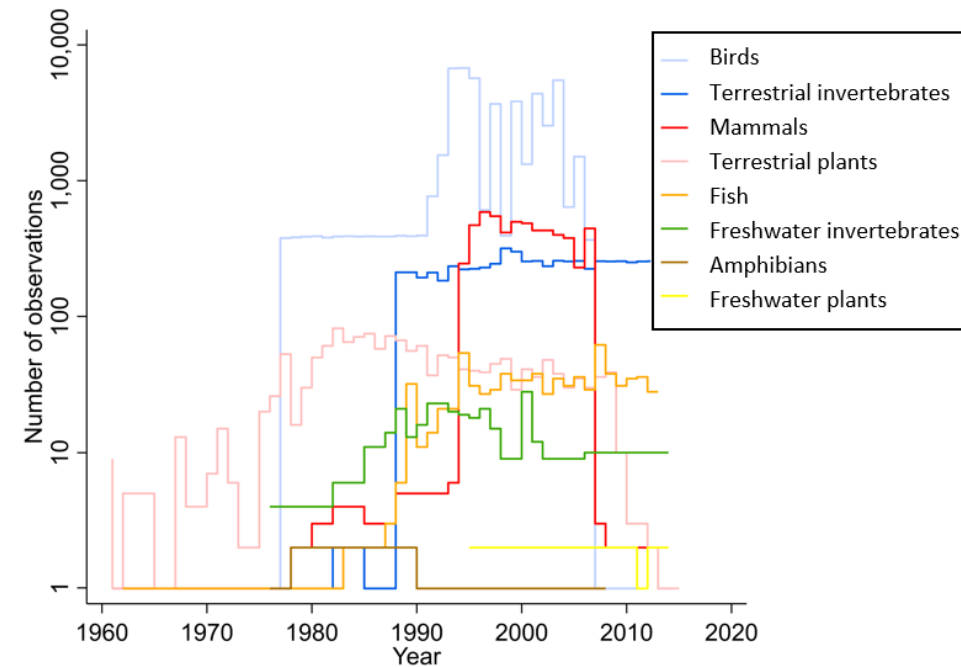
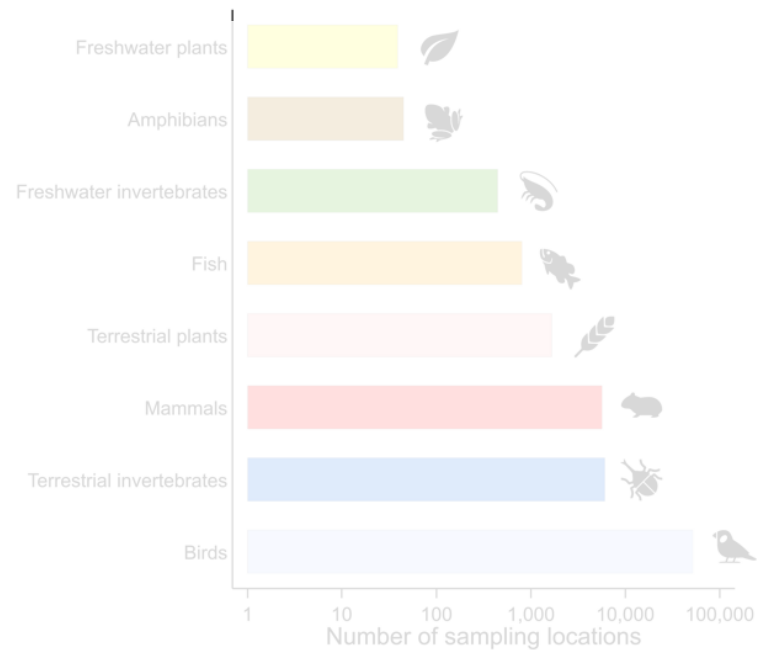






## Caveat on Measurement: Temporal selection

- We can only observe **years** when ecological studies chose to sample
- We assess endogenous sampling using standard attrition tests



### Taxa

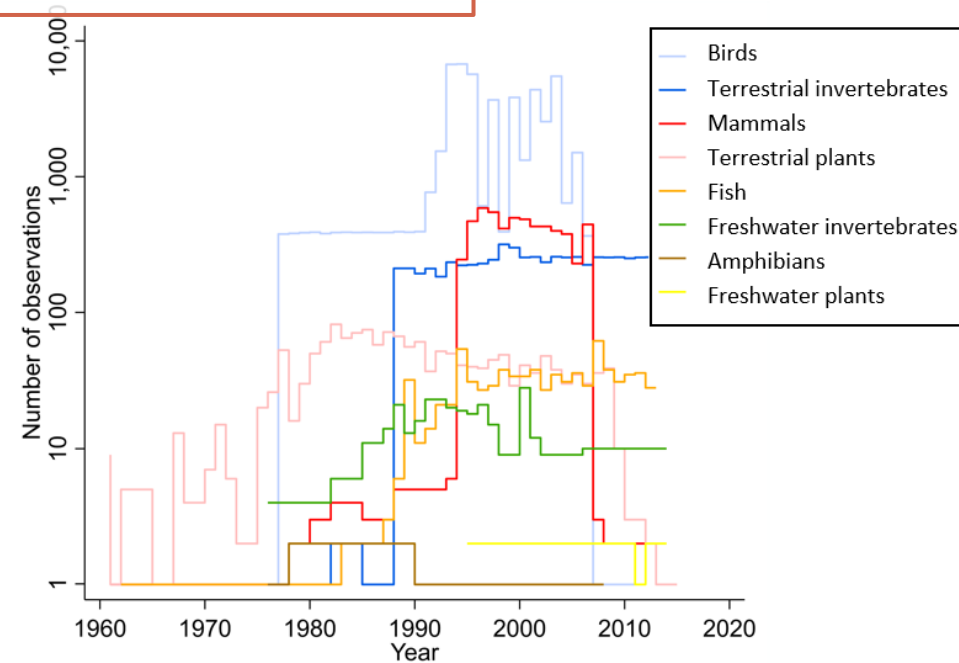
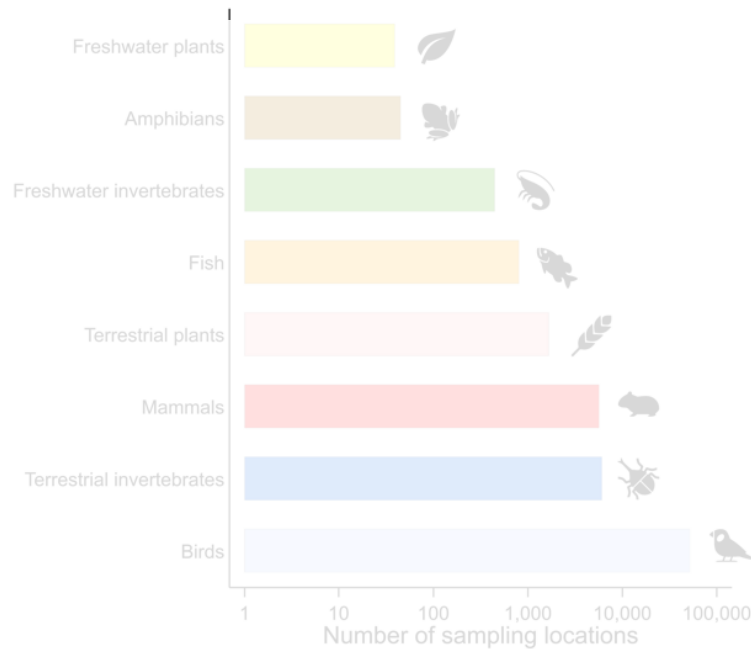


### Number of Years



## Caveat on Measurement: Change in sampling technology

- By construction, BioTIME only includes studies that adopted **fixed sampling protocols**
- But possible that sampling tech has improved over time
- We test stability of our estimates over time and across studies with different time span



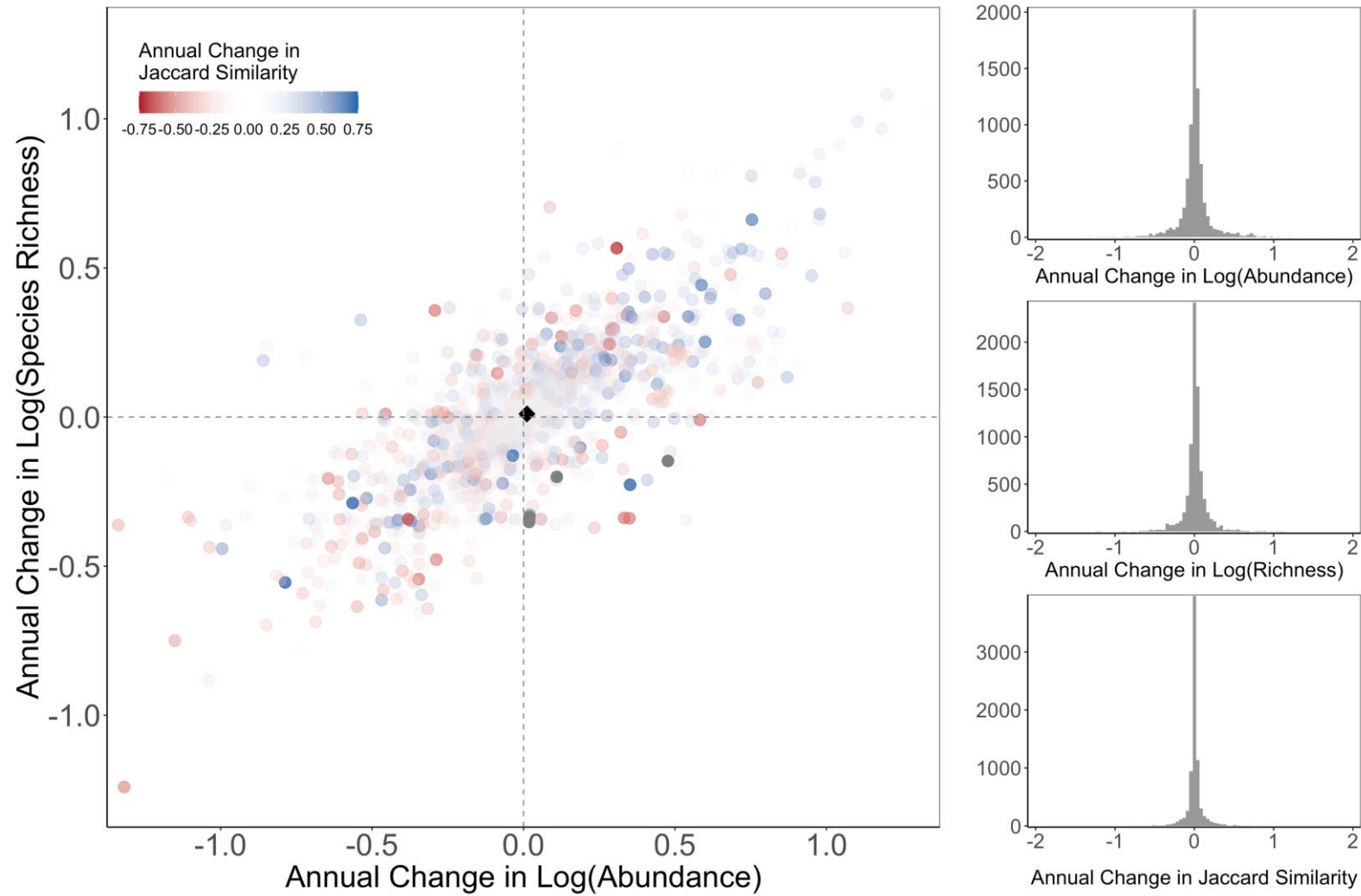
# Three Focal Biodiversity Measurements

1. **Abundance:** total number of individuals observed at a given location in a given year
2. **Richness:** total number of unique species present at a given location in a given year
3. **Similarity:** Jaccard index. Inverse of year-to-year species turnover at a given location

$$\text{Similarity}_{ct} = \frac{n(S_{ct+1} \cap S_{ct})}{n(S_{ct+1} \cup S_{ct})}$$

## Summary: Variation in biodiversity measures

Good / reasonable amount of year-over-year variation



Notes: Black point in the left panel is the location of mean changes in log richness and log abundance.

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# OLS Estimation

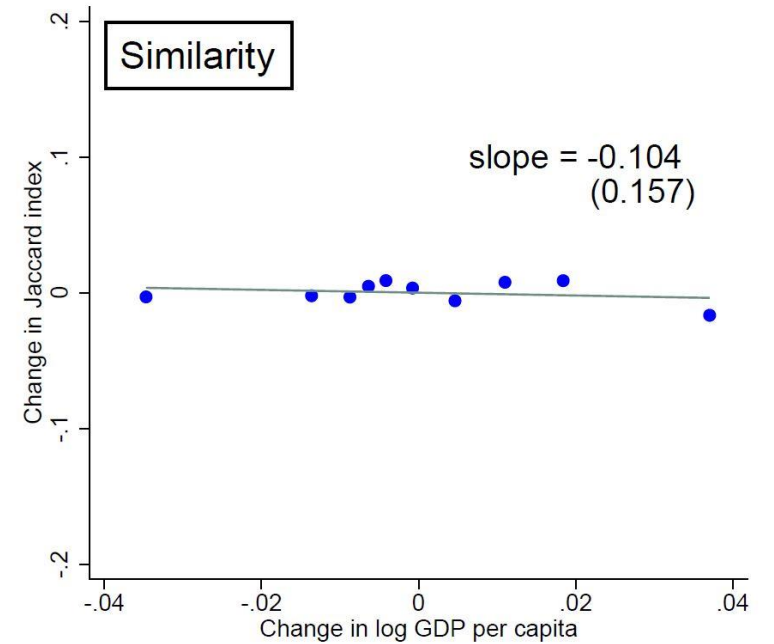
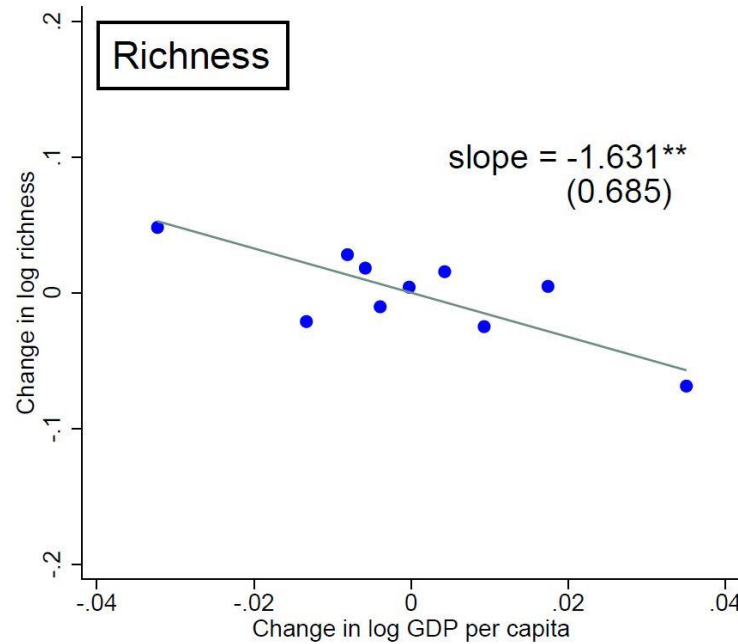
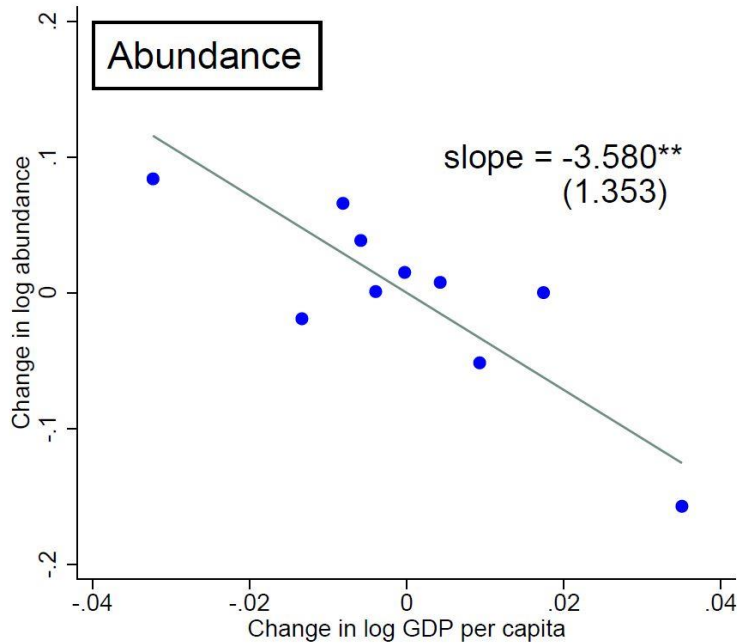
- Workhorse regression equation:

$$Y_{cjt} = \beta \cdot \log(\text{GDP}_{st}) + \eta_{cj} + \eta_t + \varepsilon_{cjt}$$

- $Y_{cjt}$  : biodiversity outcome log(abundance), log(richness), similarity index at location  $c$  for taxa  $j$  in year  $t$
- $\text{GDP}_{st}$  : log state annual real per capita GDP
- $\eta_{cj}$  : location-taxa fixed effects
- $\eta_t$  : year fixed effects
- Clustered standard errors at the state level

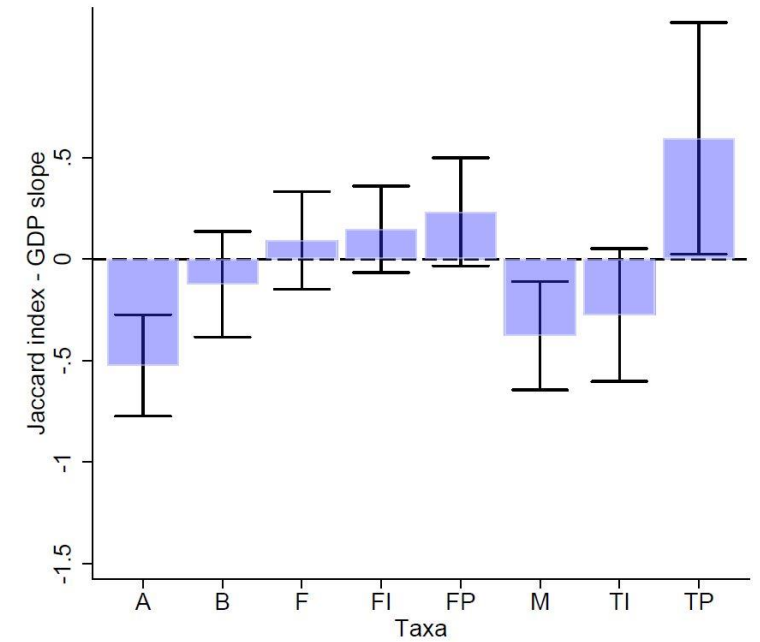
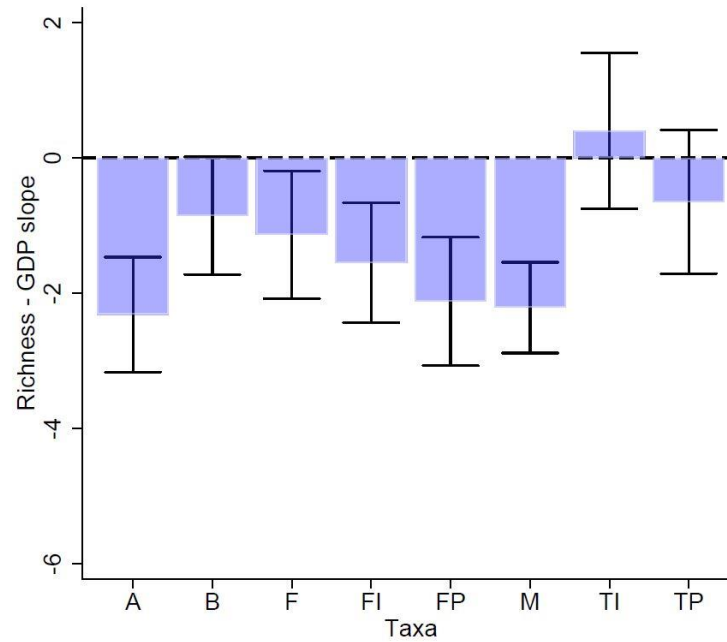
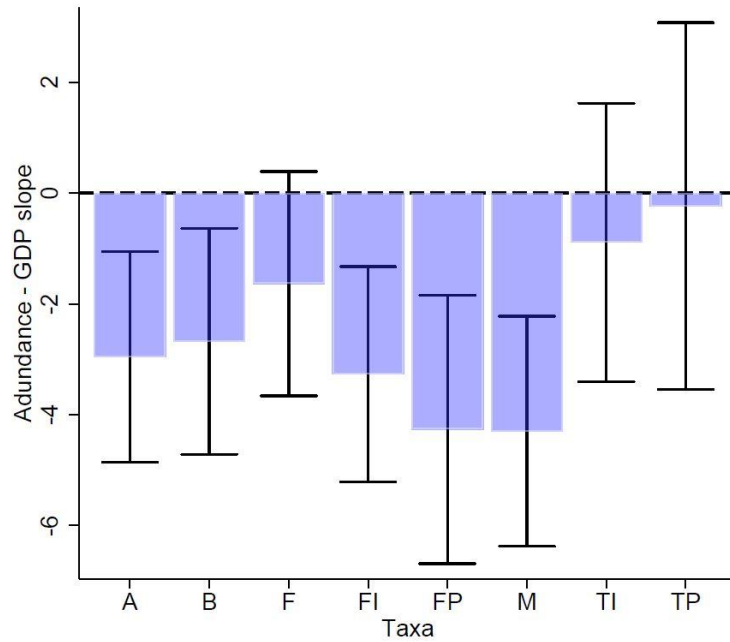


**Average effect: Negative association between production and biodiversity**  
Binscatter conditioned on location-taxon FEs, year FEs



Notes: Decile binscatter of FE-residualized biodiversity outcome against FE-residualized GDP. Slope of linear fit represents the OLS estimate.

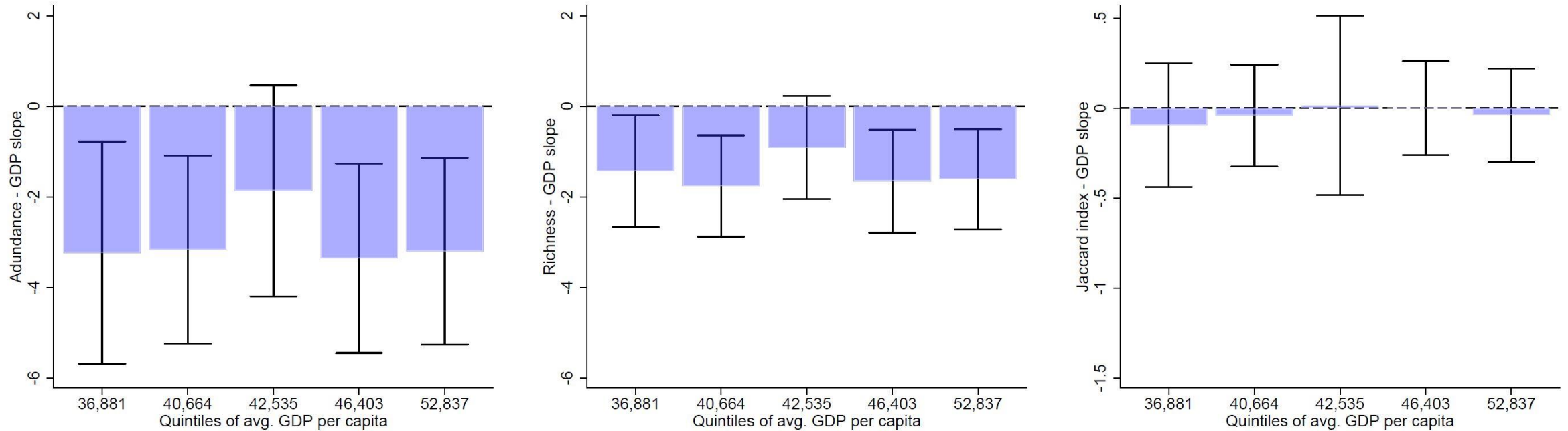
## Effect by taxa: Negative associations across the board



Notes: Estimation equation:  $Y_{cjt} = \sum \beta_j \cdot \log(\text{GDP}_{st}) \cdot 1(\text{taxa} = j) + \eta_{cj} + \eta_t + \varepsilon_{cjt}$ . Taxa main effects already absorbed by  $\eta_{cj}$ . Range bars show 95% CI using SEs clustered at the state level.

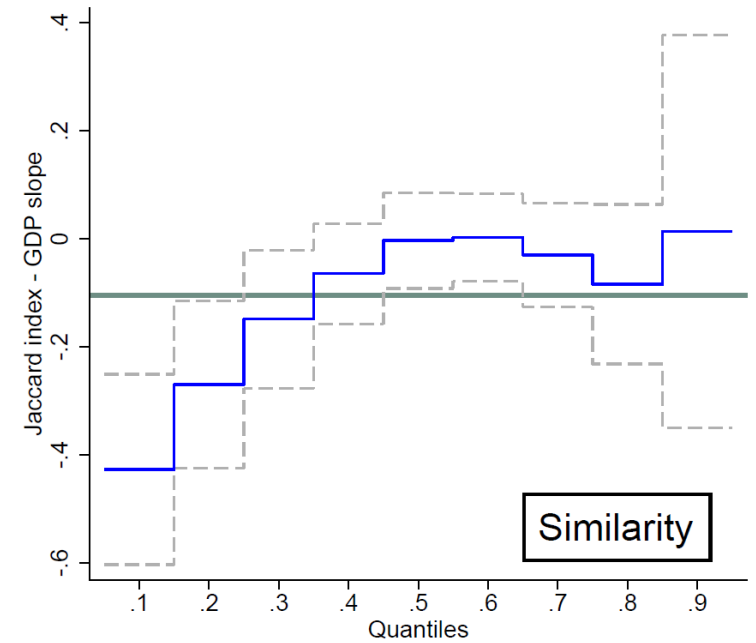
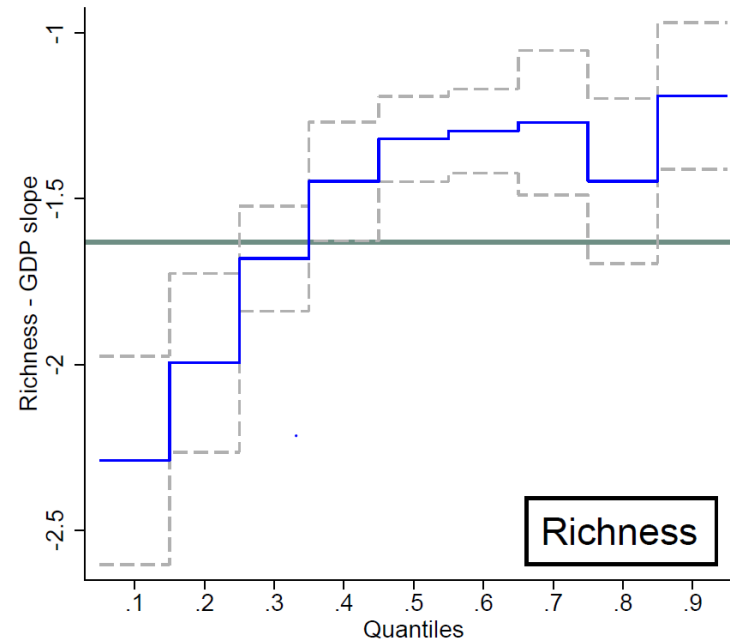
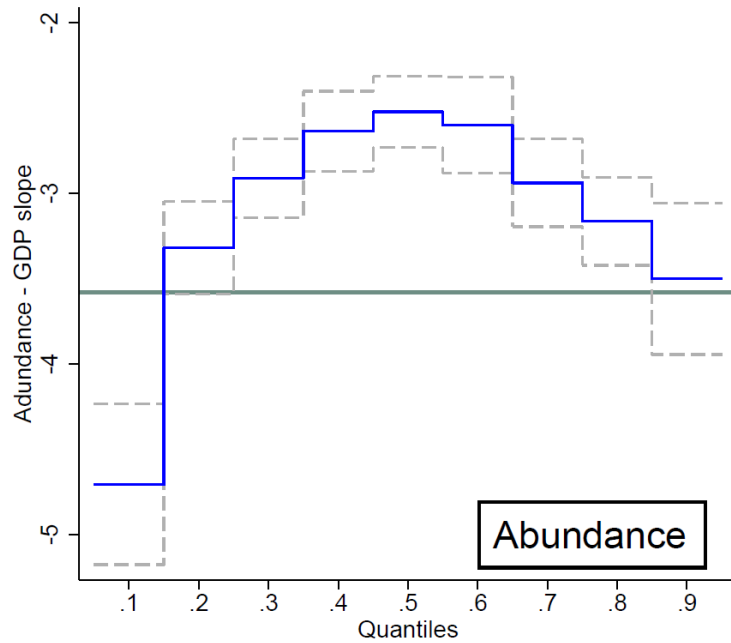
## Effect by average GDP : Similar across different levels of development

### Quintile bins of 1966-2015 per capita GDP



**Notes:** Estimation equation:  $Y_{cjt} = \sum \beta_g \cdot \log(\text{GDP}_{st}) \cdot 1(\text{GDP group} = g) + \sum \alpha_g \cdot 1(\text{GDP group} = g) + \eta_{cj} + \eta_t + \varepsilon_{cjt}$ .  
 Range bars show 95% CI using SEs clustered at the state level.

**By Regression quantiles: Effects are stronger in areas with worse metrics**  
Horizontal line is the average effect



Notes: Quantile regressions estimated using FE-residualized biodiversity outcome ~ FE-residualized log GDP.  
Dashed lines show 95% CI using bootstrapped SEs.

## Dynamic specification: Does last or *next* year's GDP matter?

*This year's GDP shock seems to matter the most*

	(1)	(2)	(3)	(4)	(5)	(6)
	Abundance		Richness		Similarity	
Panel A. All species						
GDP <sub>t+1</sub>	-	0.655	-	0.269	-	-0.106
	-	(0.848)	-	(0.607)	-	(0.120)
GDP <sub>t</sub>	-3.580**	-3.705***	-1.631**	-2.246***	-0.104	0.271
	(1.353)	(1.199)	(0.685)	(0.671)	(0.157)	(0.271)
GDP <sub>t-1</sub>	-	-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 <sub>t+1</sub>	-	-0.229	-	-0.776	-	0.091
	-	(3.322)	-	(1.551)	-	(0.164)
GDP <sub>t</sub>	-5.903***	-5.754	-3.302***	-4.043	-0.368	0.392*
	(0.990)	(4.809)	(0.271)	(2.448)	(0.262)	(0.206)
GDP <sub>t-1</sub>	-	-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<sub>t-1</sub> is the log of lagged one year GDP. GDP<sub>t+1</sub> 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.

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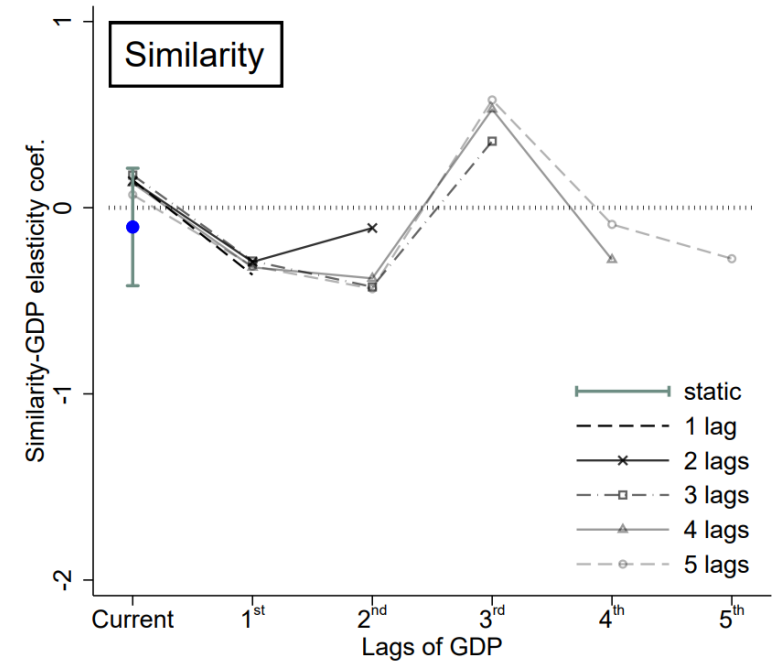
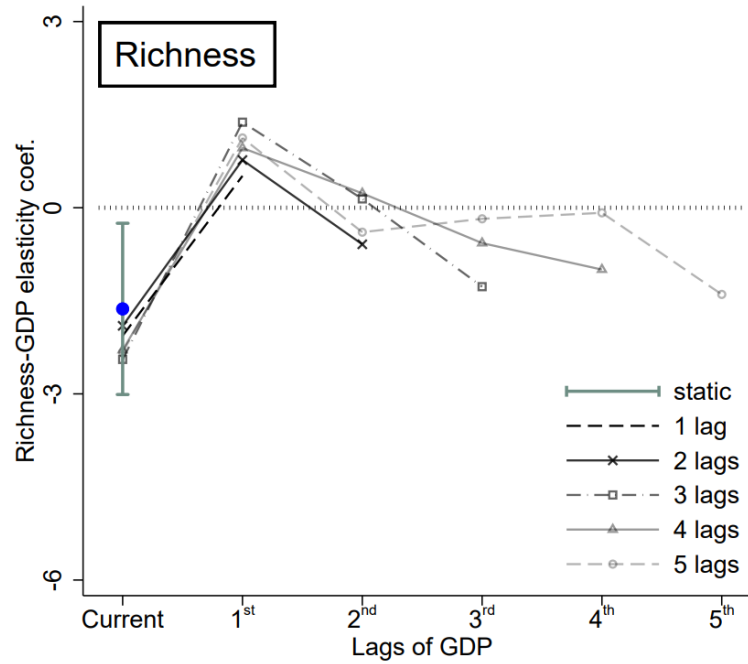
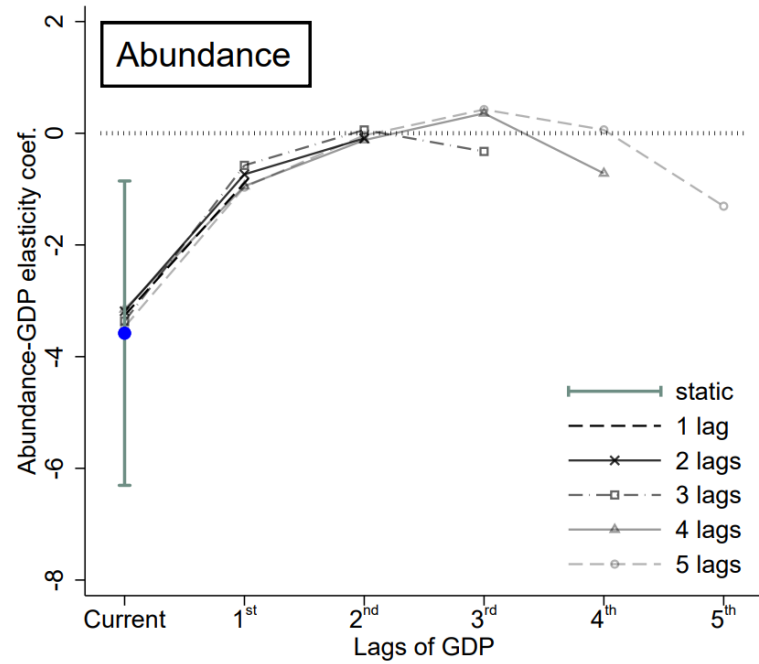
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## Dynamic specification: Distributed lag models

*This year's GDP shock seems to matter the most*



*Notes:* This figure plots coefficients when regressing biodiversity outcomes on the current and yearly lags of GDP. Each line represents a separate regression with different numbers of lags. For each outcome, the range bar shows point estimate and 95% confidence interval of the baseline, static specification with no lags of GDP. All regressions include location-by-taxa and year fixed effects. Standard errors are clustered at the state level..



# Panel Vector Autoregression (VAR)

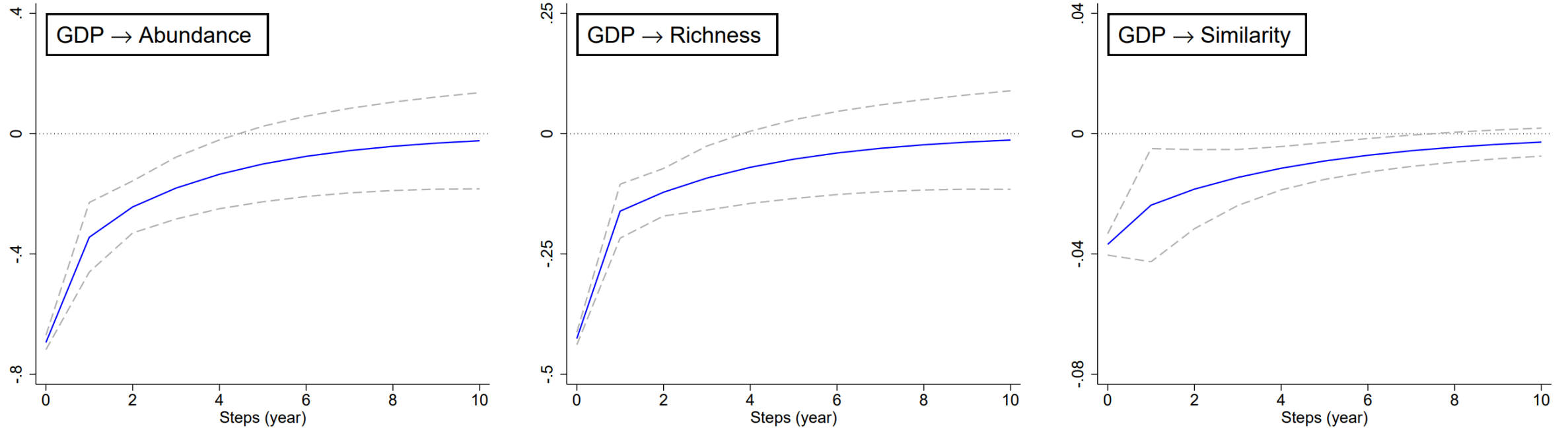
- We estimate bi-variate, first-order panel VARs with each of the three biodiversity outcomes and GDP as endogenous variables:

$$\mathbf{Y}_{cjt} = \mathbf{Y}_{cjt-1}\mathbf{A} + \mathbf{u}_{cj} + \mathbf{u}_t + \mathbf{e}_{cjt}$$

- $\mathbf{Y}_{cjt}$  : (1 x 2) vector of dependent variables (e.g., log abundance and log GDP per capita)
  - $\mathbf{u}_{cj}$  ,  $\mathbf{u}_t$  : (1 x 2) dependent-variable-specific location-by-taxa and year fixed effects
  - $\mathbf{A}$  : (2 x 2) matrix of homogeneous parameters
  - Clustered standard errors at the state level
- Derive impulse response functions (IRFs) for **biodiversity** → **GDP** and **GDP** → **biodiversity**; test Granger causality
  - Follows Love and Zicchino (2006)

## Dynamic specification: Panel VAR

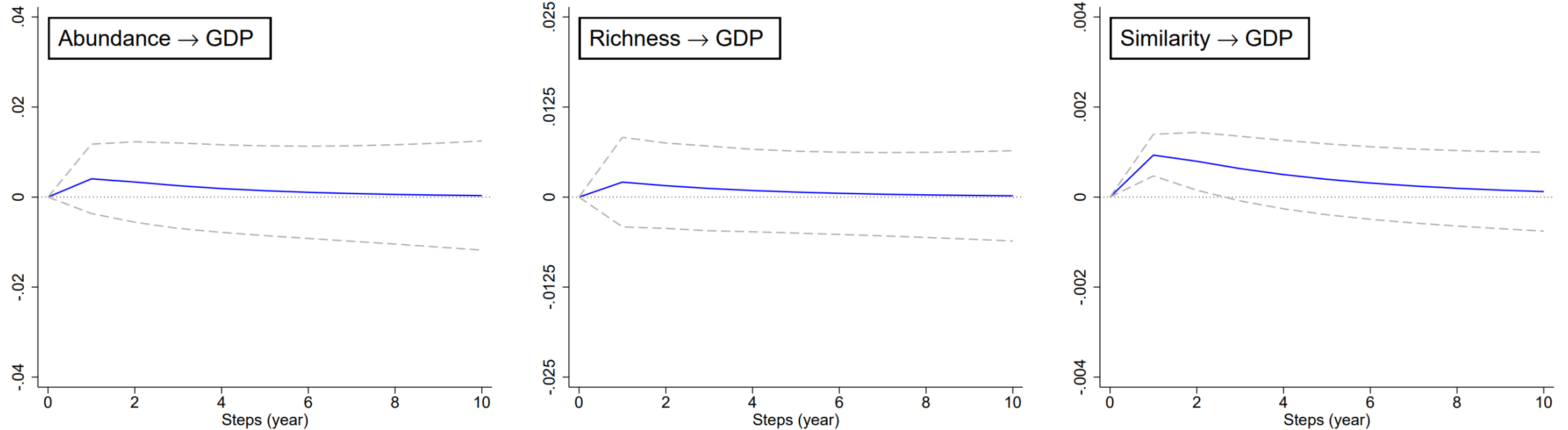
Impulse response functions for GDP → biodiversity outcomes



*Notes:* This figure plots orthogonalized impulse response functions from first-order panel vector autoregression (VAR). Three separate models are estimated for GDP and abundance (left), GDP and richness (middle), and GDP and Jaccard index (right). Location-taxa fixed effects and time fixed effects removed prior to estimation. Standard errors are clustered at the state level. The underlying panel Granger causality Wald test statistics are 13.6 ( $p < 0.001$ ), 22.2 ( $p < 0.001$ ), and 3.66 ( $p = 0.056$ ). Dashed lines show 95% confidence intervals constructed from 200 Monte Carlo simulations.

## Dynamic specification: Panel VAR

Impulse response functions for biodiversity outcomes → GDP



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## Industry-specific GDPs: Strongest correlation with manufacturing GDP

	(1) Abundance	(2) Richness	(3) Similarity	(4) Abundance	(5) Richness	(6) Similarity
	Panel A. All species			Panel B. Non-bird species		
Manufacturing	-0.504** (0.198)	-0.366*** (0.091)	-0.021 (0.023)	-1.505*** (0.343)	-0.677*** (0.154)	-0.009 (0.068)
Mining	-0.063 (0.045)	-0.008 (0.025)	-0.012 (0.011)	-0.274 (0.188)	0.090 (0.071)	-0.138*** (0.045)
Timber and Logging	-0.021 (0.035)	-0.014 (0.021)	0.002 (0.002)	-0.287** (0.114)	-0.138** (0.051)	-0.007 (0.008)
Agriculture	-0.002 (0.063)	-0.012 (0.023)	0.009 (0.008)	0.638*** (0.158)	0.126** (0.057)	0.073*** (0.017)
Construction	0.172 (0.356)	0.134 (0.090)	0.025 (0.059)	0.754 (0.628)	0.139 (0.206)	-0.075 (0.132)
Services	-0.187 (0.558)	-0.289 (0.205)	-0.031 (0.060)	0.278 (1.462)	0.099 (0.372)	-0.087 (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.

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Manufacturing	-0.504** (0.198)	-0.366*** (0.091)	-0.021 (0.023)	-1.505*** (0.343)	-0.677*** (0.154)	-0.009 (0.068)
Mining	-0.063 (0.045)	-0.008 (0.025)	-0.012 (0.011)	-0.274 (0.188)	0.090 (0.071)	-0.138*** (0.045)
Timber and Logging	-0.021 (0.035)	-0.014 (0.021)	0.002 (0.002)	-0.287** (0.114)	-0.138** (0.051)	-0.007 (0.008)
Agriculture	-0.002 (0.063)	-0.012 (0.023)	0.009 (0.008)	0.638*** (0.158)	0.126** (0.057)	0.073*** (0.017)
Construction	0.172 (0.356)	0.134 (0.090)	0.025 (0.059)	0.754 (0.628)	0.139 (0.206)	-0.075 (0.132)
Services	-0.187 (0.558)	-0.289 (0.205)	-0.031 (0.060)	0.278 (1.462)	0.099 (0.372)	-0.087 (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.

## Agricultural Sector GDP:

### Positive Correlation Partly Explained by Better Crop Farming and Conservation Spending

	(1) Abundance	(2) Richness	(3) Similarity	(4) Abundance	(5) Richness	(6) Similarity
	Panel A. All species			Panel B. Non-bird species		
<hr/>						
I. Subsectors of agriculture						
Agricultural income: crop & animal farming	0.049 (0.077)	-0.014 (0.027)	0.010 (0.008)	0.758** (0.304)	0.136 (0.102)	0.109** (0.044)
Agricultural income: fishing & hunting	0.011 (0.008)	0.003 (0.004)	-0.002 (0.003)	0.011 (0.042)	0.003 (0.019)	-0.015** (0.007)
Agricultural income: ag support	-0.048 (0.120)	-0.012 (0.036)	0.007 (0.015)	-0.495 (0.290)	-0.197* (0.101)	0.012 (0.027)
<hr/>						
II. Federal government conservation program spending						
Agricultural income	-0.019 (0.075)	-0.025 (0.030)	0.010 (0.010)	-0.214 (0.286)	-0.155 (0.100)	0.019 (0.020)
Gov conservation spending	0.056 (0.035)	0.024* (0.014)	0.003 (0.005)	0.382* (0.190)	0.222*** (0.070)	0.034 (0.030)

*Notes:* All income and spending variables are in log. In panel I, agricultural income is broken down to crop & animal farming (NAICS = 111-112), fishing & hunting (NAICS = 114), and ag support (NAICS = 115). In panel II, “Gov conservation spending” is federal government payments to the state-year under conservation programs including the Conservation Reserve Program, Agricultural Conservation Easement Program, Environmental Quality Incentives Program, Conservation Stewardship Program, Regional Conservation Partnership Program, and Conservation Technical Assistance. Data are sourced from USDA. Columns 1-3 reports full sample estimation. Columns 4-6 excludes observations that correspond to bird species. Standard errors are clustered at the state level. \*:  $p < 0.10$ ; \*\*:  $p < 0.05$ ; \*\*\*:  $p < 0.01$ .

# More Checks

- **Endogenous sampling?**
  - No evidence GDP predicts when sampling starts/ends/gaps (standard attribution tests)
  - No evidence local economy predicts overall length of the study
- **Outliers?**
  - Robustness to winsorizing extreme samples (1-99%, 2-98%, ...)
  - Robustness to dropping extreme deviations (+/- 4 S.D., +/- 3 S.D., ...)
- **Changes in measurement quality?**
  - Sub-sample analysis using older vs. newer samples or studies
- **Alternative biodiversity metrics?**
  - Robustness to using “fancier” indexes: Gini (HHI), Shannon (Entropy), ...
- **Alternative unit of analysis?**
  - Robustness to alternative geography: county, eco-region (U.S. EPA), hexagon bins of various resolutions



# Outline

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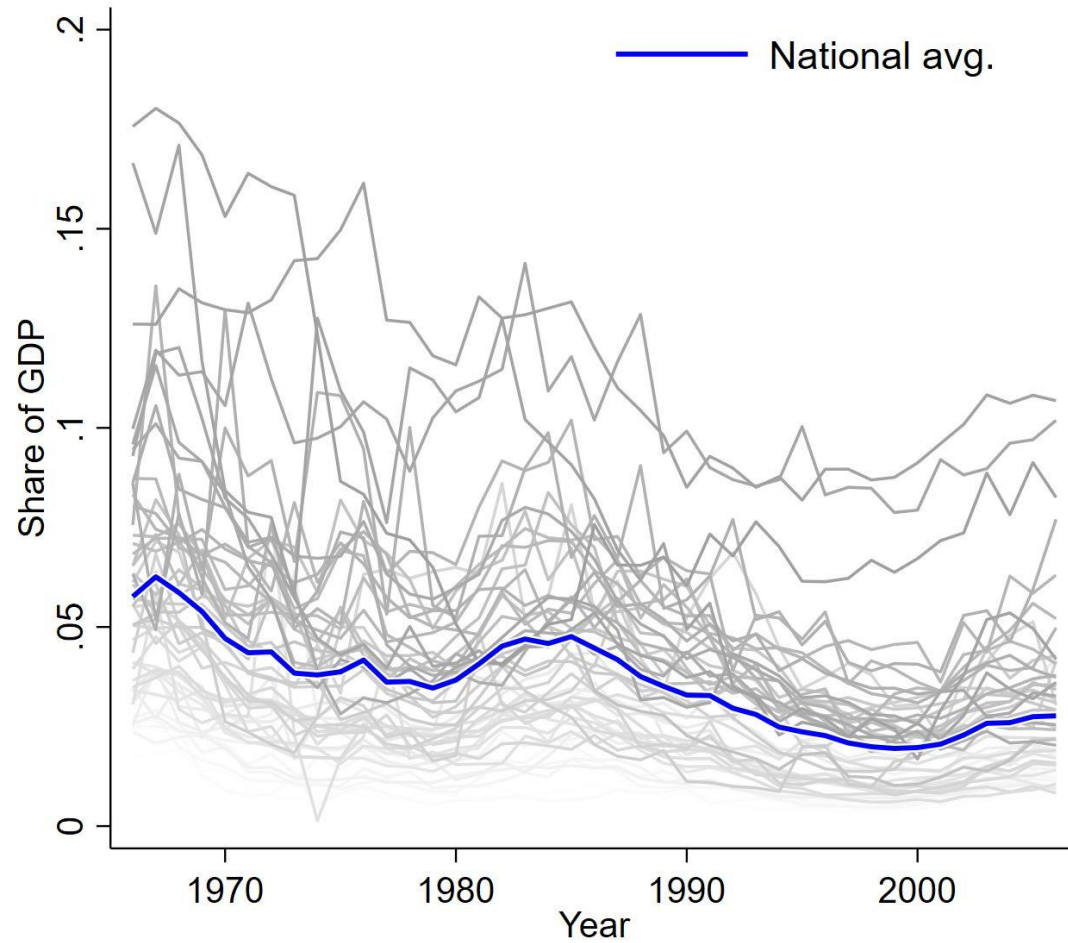
1. Measurement
2. Correlation
3. Causation
4. Channels
5. Regulations

# Economic Stimulus

- Examine state heterogeneity to **U.S. national military buildup**, which are largely associated with plausibly exogenous geo-political events
  - Ex: Vietnam War; Soviet invasion of Afghanistan
- Widely leveraged in empirical macro literature to estimate **fiscal multiplier** (e.g., Hall, 2009; Barro and Redlick, 2011; Ramey, 2011; Nakamura and Steinsson, 2014; 2018)
- **Data**: military spending and federal prime contracting data from U.S. Department of Defense DD-350 military procurement forms 1966-2006; covers >90% of all military procurements in the U.S. (Nakamura and Steinsson, 2014)

## Government policy: Military spending shocks

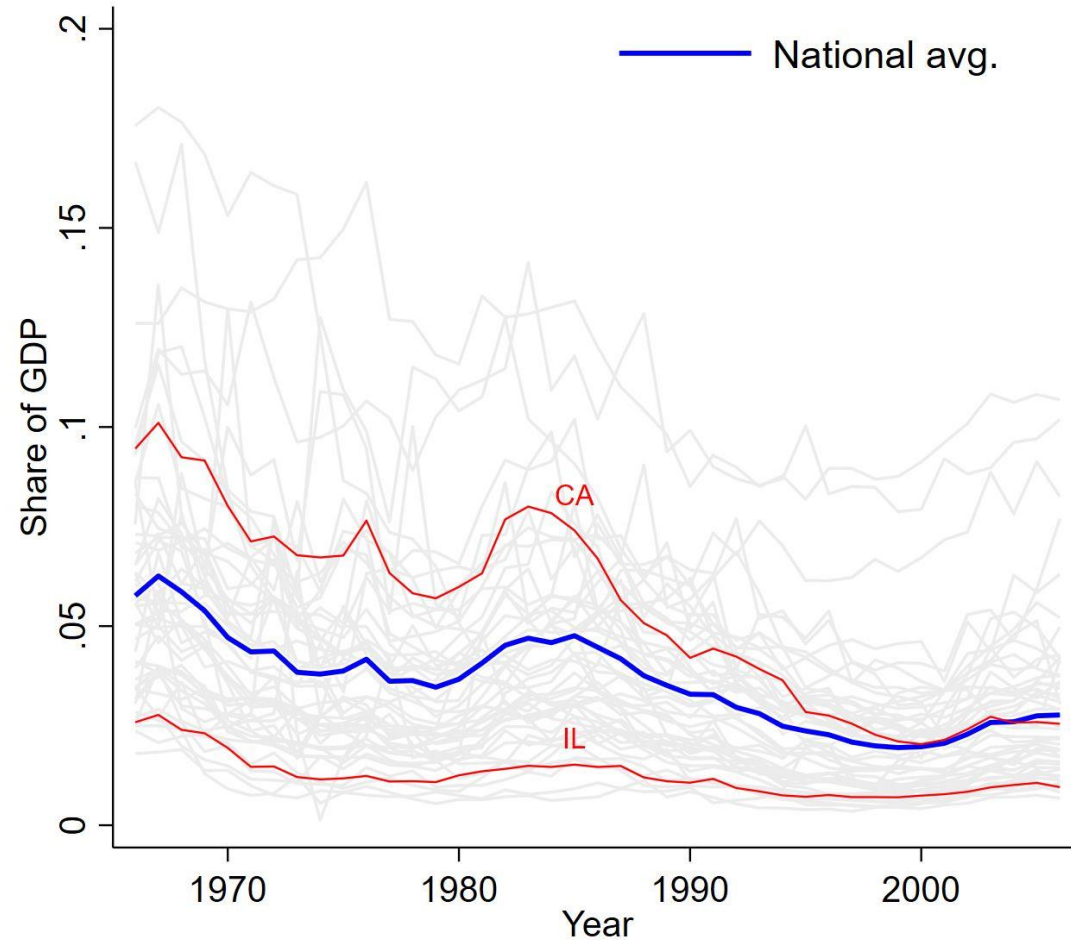
### Military contract spending as a share of state GDP



*Notes:* Each line represents a state. Darker lines indicate states with a higher average military/GDP ratio during 1966-1971. Blue line is national average.

## Government policy: Military spending shocks

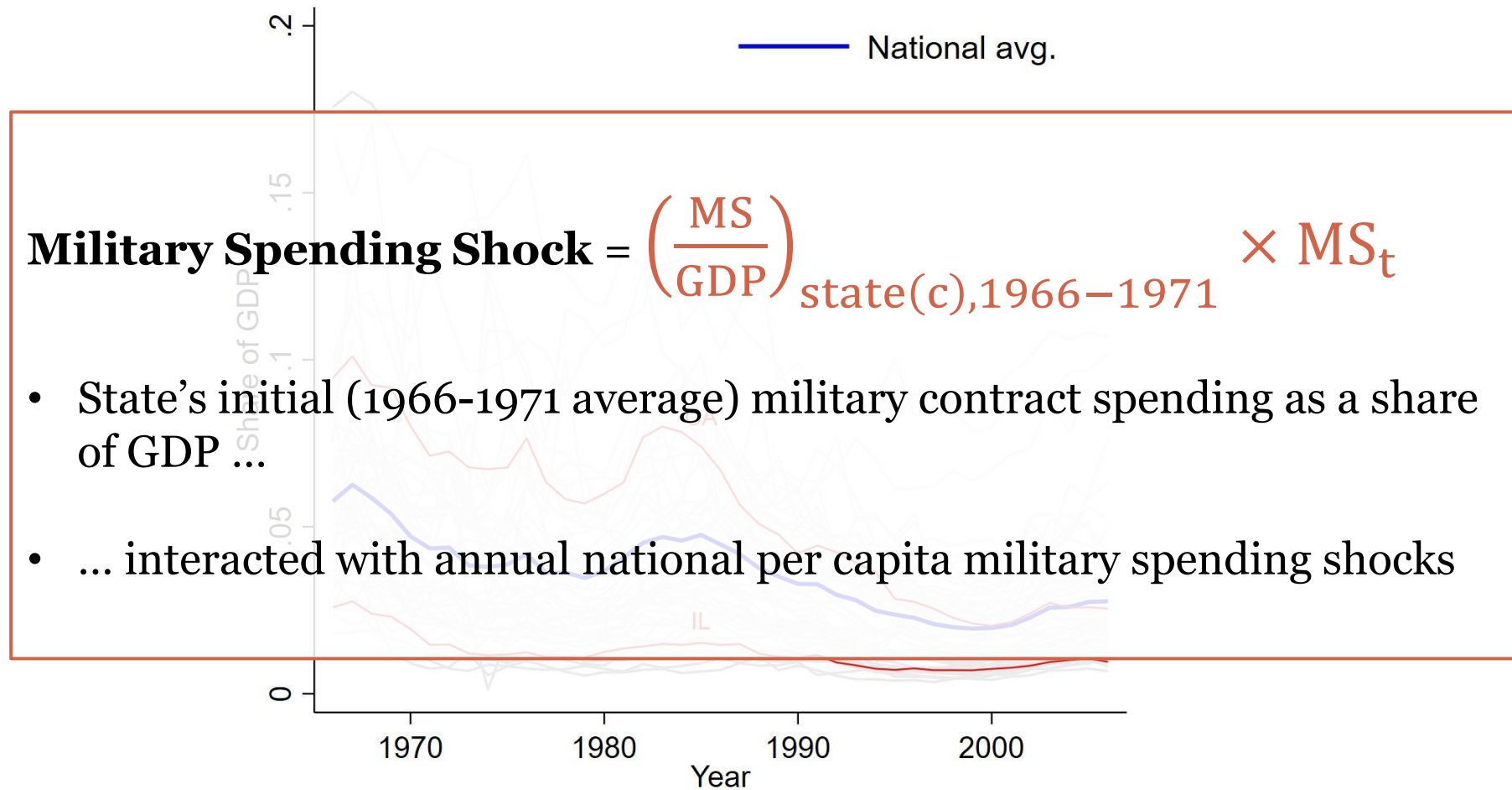
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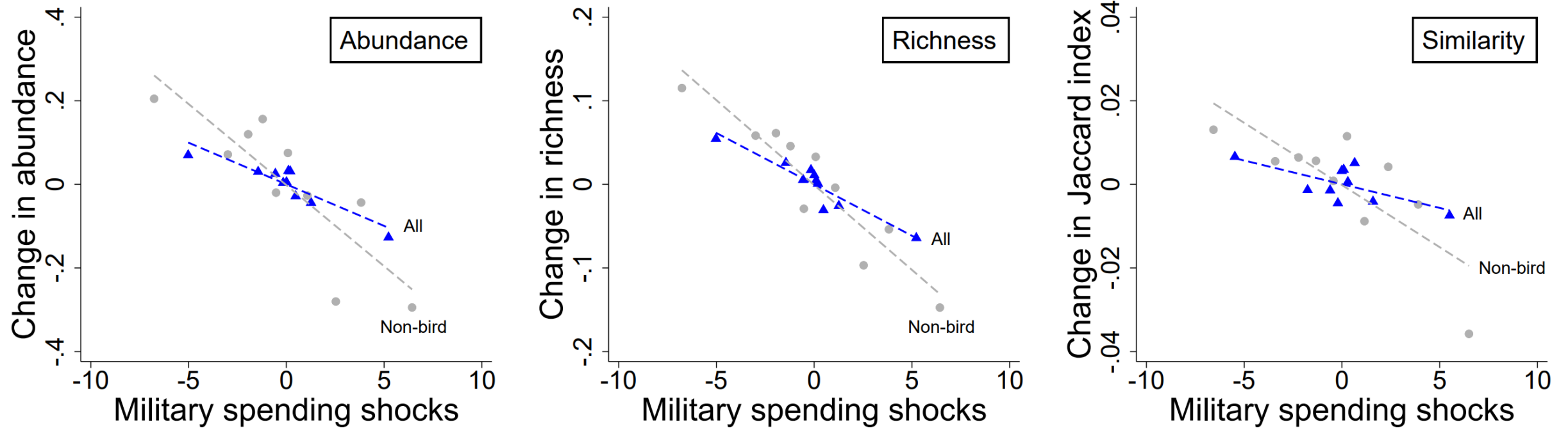
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## Government policy: Military spending shocks

The impact of military spending shocks on biodiversity outcomes



*Notes:* decile bin scatterplots of biodiversity and the military spending shock variable, both residualized with location-by-taxa and year fixed effects. The dashed blue line displays all-species results, and the dashed gray line displays subsample results with non-bird species.

## Military spending shocks and biodiversity outcomes

Policy shock = state's initial military spending share × national military shocks

	(1)	(2) (3) (4) Policy Effect			(5) (6) (7) Implied GDP Elasticity		
	GDP	Abundance	Richness	Similarity	Abundance	Richness	Similarity
<b>Panel A. All species</b>							
Military spending	0.299*** (0.110)	-1.341** (0.567)	-0.823** (0.354)	-0.164*** (0.060)	-	-	-
$\widehat{GDP}$	-	-	-	-	-4.485*** (1.594)	-2.753** (1.226)	-0.535*** (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
<b>Panel B. Non-bird species</b>							
Military spending	0.528*** (0.087)	-3.286*** (1.075)	-1.685*** (0.624)	-0.360*** (0.057)	-	-	-
$\widehat{GDP}$	-	-	-	-	-6.225*** (1.167)	-3.193*** (0.732)	-0.638*** (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:* All biodiversity and GDP variables in logs, except for Similarity which is already a ratio. All regressions include location-taxa and year FEs. SEs clustered at the state level.

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Policy shock = state's initial military spending share × national military shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Policy Effect				Implied GDP Elasticity		
	GDP	Abundance	Richness	Similarity	Abundance	Richness	Similarity
<b>These are estimated using 2SLS</b>							
• Endo var = GDP							
• IV = military spending shock							
$\widehat{GDP}$	-	-	-	-	-4.485***	-2.753**	-0.535***
	-	-	-	-	(1.594)	(1.226)	(0.183)
<b>Caution: “causal effect of GDP” ?</b>							
• GDP is an accounting concept					7.430	7.430	7.071
• Can't raise GDP <i>while holding everything else constant</i>					57,714	57,714	44,479
• Captures all underlying channels							
$\widehat{GDP}$	-	-	-	-	-6.225***	-3.193***	-0.638***
	-	-	-	-	(1.167)	(0.732)	(0.149)
<b>Next, focus on the air pollution channel which we can causally tease out.</b>							
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:* All biodiversity and GDP variables in logs, except for Similarity which is already a ratio. All regressions include location-taxa and year FEs. SEs clustered at the state level.

# Outline

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1. Measurement
2. Correlation
3. Causation
4. Channels
5. Regulations

# Pollution Channel

---

- Present **new evidence** that air pollution is a causal determinant of biodiversity
- Estimate the share of the total effect of stimulus shocks that is **due to pollution externalities**

## Pollution instrumental variable (IV): Finding exogenous variation in pollution

Transported pollution from upwind cities

- Instrumental variable:

$$IV_t = (1/3,000) \sum_{c \in \{1, \dots, 3000\}} \max\{0, \cos(\phi_{ct})\} \cdot \text{Pollution}_{ct} \cdot \left( \frac{1/\text{distance}_c}{1/\sum_i (1/\text{distance}_c)} \right)$$

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- $\text{Pollution}_{ct}$  : Air pollution of a donor city  $c$  on day  $t$

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- $\text{Pollution}_{ct}$  : Air pollution of a donor city  $c$  on day  $t$
- $\max\{0, \cos(\phi_{ct})\} \cdot \text{Pollution}_{ct}$  : The vector component of  $\text{Pollution}_{ct}$  that's expected to move toward Miami, given the wind direction  $\phi_{ct}$  in city  $c$  on day  $t$

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- ... take average across all donor counties  $c \in \{1, \dots, 3,000\}$ , inversely weighted by county  $c$ 's distance to Miami



## Pollution instrumental variable (IV): Finding exogenous variation in pollution

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  - ... take average across all donor counties  $c \in \{1, \dots, 3,000\}$ , inversely weighted by county  $c$ 's distance to Miami
- IV = “variation in Miami’s air pollution attributable to transported pollutants from upwind counties”

## Pollution instrumental variable (IV): Finding exogenous variation in pollution

Transported pollution from upwind cities

- Instrumental variable:

$$IV_t = (1/3,000) \sum_{c \in \{1, \dots, 3000\}} \max\{0, \cos(\phi_{ct})\} \cdot \text{Pollution}_{ct} \cdot \left( \frac{1/\text{distance}_c}{1/\sum_i (1/\text{distance}_c)} \right)$$

- To minimize endogeneity concerns, use all cities at least 300 km away from Miami as donors (~3000 counties)
- Using all 3000 counties can be inefficient  
Ex: Variation of air quality in Oregon is unlikely to be predictive of pollution in Miami

## Pollution instrumental variable (IV): Finding exogenous variation in pollution

Transported pollution from upwind cities

- Instrumental variable:

$$IV_t = (1/3,000) \sum_{c \in \{1, \dots, 3000\}} \max\{0, \cos(\phi_{ct})\} \cdot \text{Pollution}_{ct} \cdot \left( \frac{1/\text{distance}_c}{1/\sum_i (1/\text{distance}_c)} \right)$$

- Selection of donor cities:

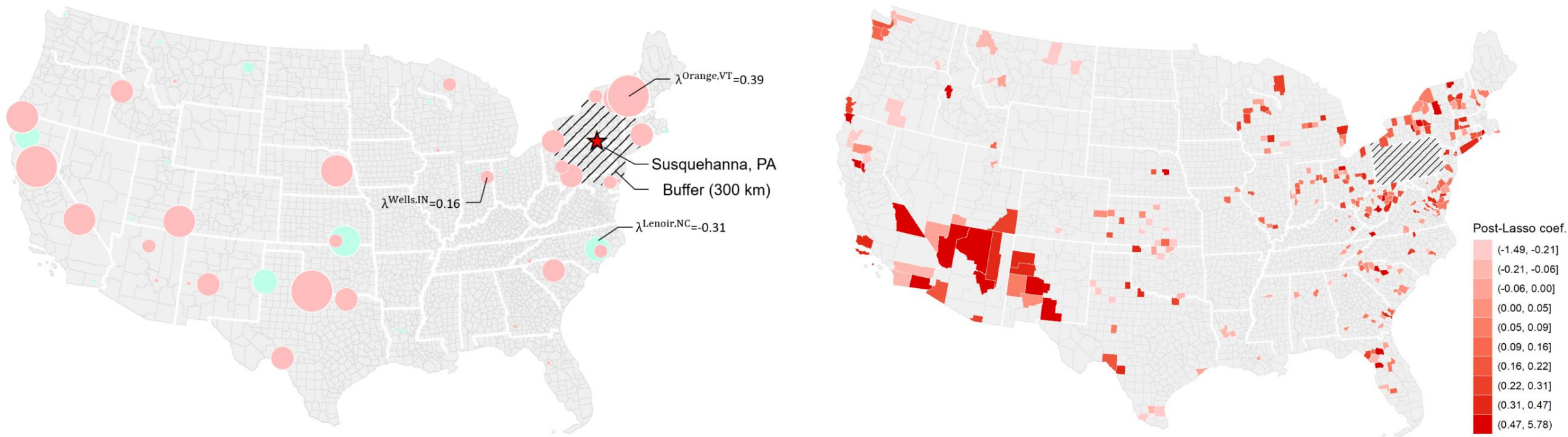
$$IV_t = (1/\#\mathbf{S}) \sum_{c \in \mathbf{S}} \max\{0, \cos(\phi_{ct})\} \cdot \text{Pollution}_{ct} \cdot \left( \frac{1/\text{distance}_c}{1/\sum_i (1/\text{distance}_c)} \right)$$

- where set  $\mathbf{S}$  is the subset of most predictive cities selected by a “zero stage” linear Lasso regression

$$\text{Pollution}_{\text{Miami},t} = \lambda_0 + \sum_{c \in \{1, \dots, 3000\}} \lambda_c \cdot \max\{0, \cos(\phi_{ct})\} \cdot \text{Pollution}_{ct} + \epsilon_t$$

# Pollution instrumental variation construction: Upwind counties

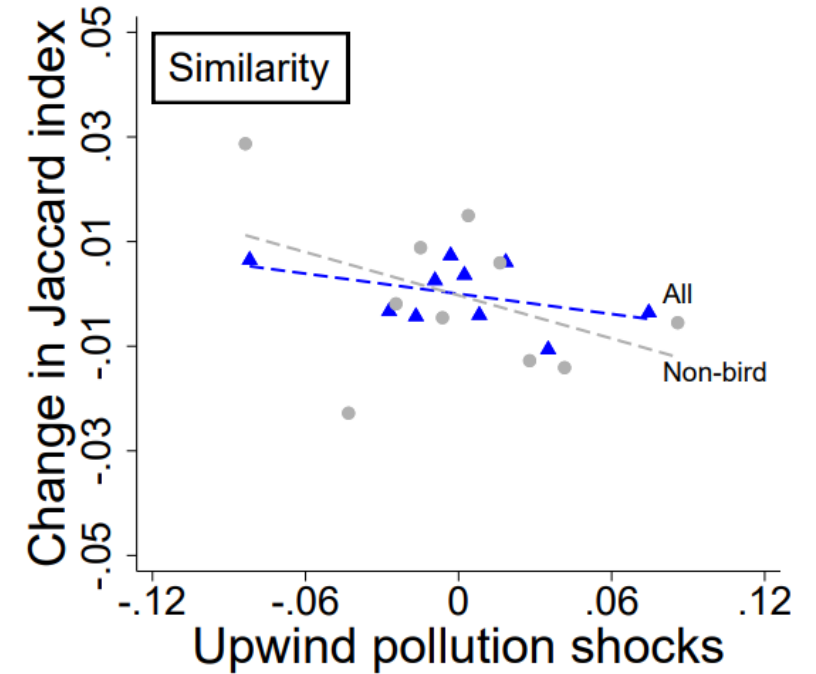
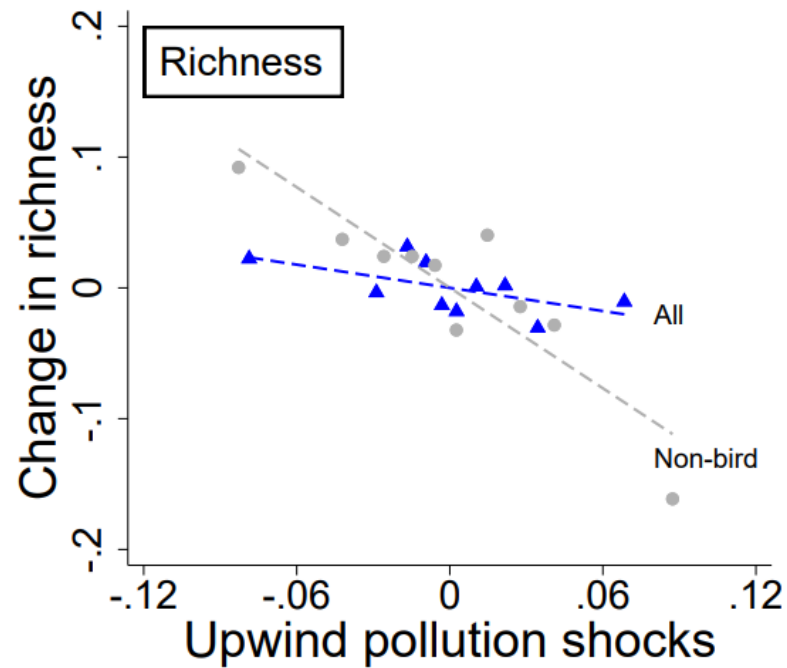
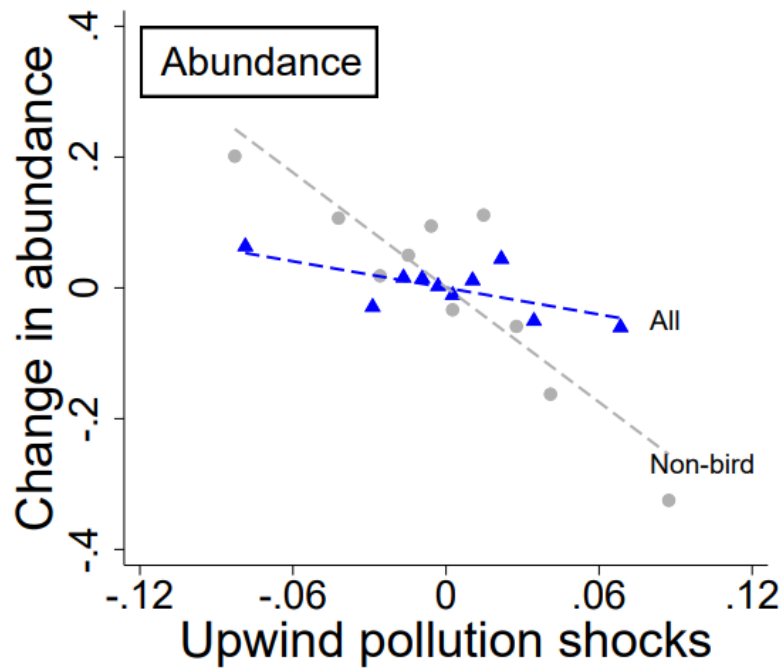
“Upwind counties” for Susquehanna, PA (L) and all counties in PA (R)



*Notes:* Left panel highlights 54 counties selected by a zero-stage LASSO regression of Susquehanna County, PA's daily aerosol pollution on all other 2,996 counties' upwind component vector pollution. The size of each circle is approximately proportional to the contributing county's post-LASSO elasticity coefficient. Red (green) circles correspond to positive (negative) correlation. In the right panel, we take all PA counties included in the BioTIME data, and highlight their LASSO-selected upwind pollution counties outside of the state of PA.

# Pollution instrumental variation construction: Upwind counties

## The impact of upwind pollution shocks on biodiversity outcomes



Notes: decile bin scatterplots of local pollution and biodiversity outcomes against the upwind pollution IV. All variables are residualized with location-by-taxa and year fixed effects. The dashed blue line displays all-species results, and the dashed gray line displays subsample results with non-bird species.

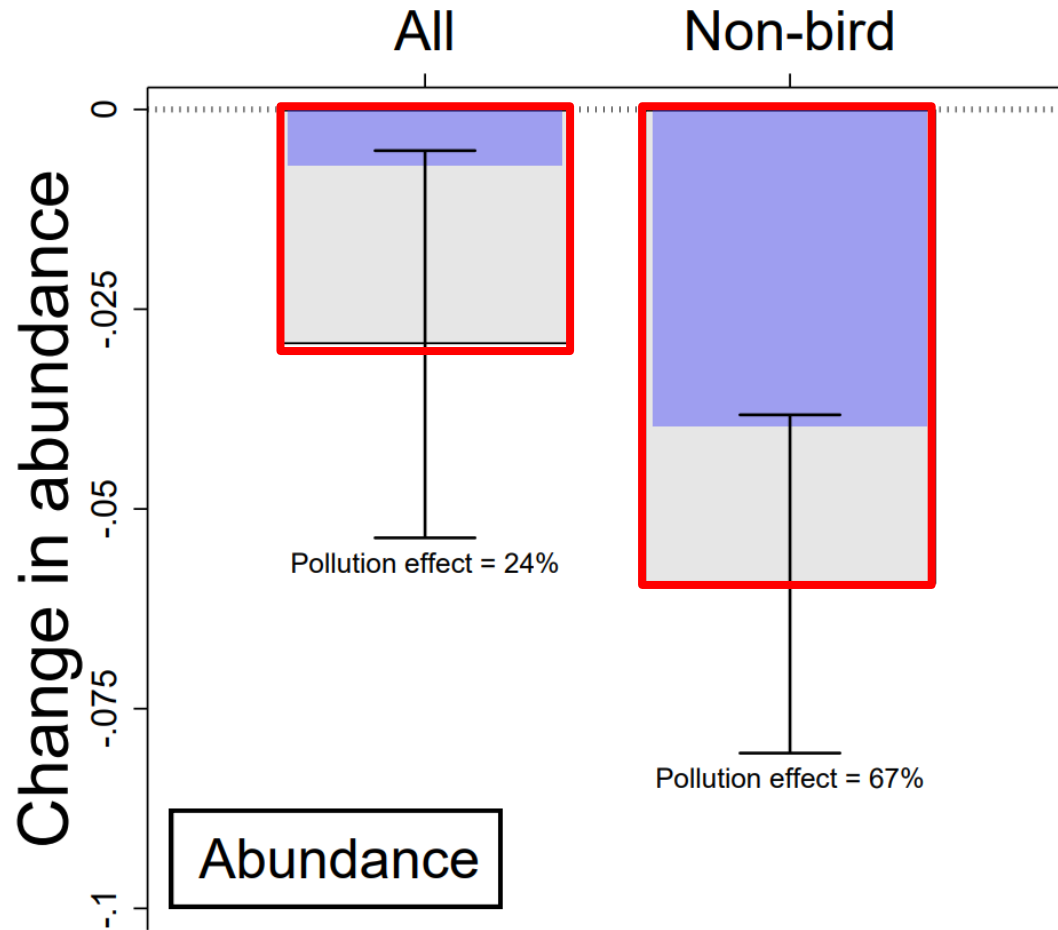
**Pollution instrumental variation construction: Upwind counties**  
 OLS and IV estimates on the effect pollution shocks on biodiversity outcomes

	(1) Abundance	(2) Richness	(3) Similarity	(4) Abundance	(5) Richness	(6) Similarity
	Panel A. All species			Panel B. Non-bird species		
Pollution (OLS)	-0.703*** (0.215)	-0.322** (0.127)	-0.074*** (0.027)	-2.072*** (0.403)	-1.020*** (0.253)	-0.070** (0.025)
$\widehat{\text{Pollution}}$ (IV)	-1.118** (0.430)	-0.565*** (0.201)	-0.084** (0.037)	-3.282*** (0.507)	-1.395*** (0.230)	-0.136 (0.098)
Kleibergen-Paap F-stat.	271.0	271.0	224.0	208.2	208.2	319.4
Observations	53,496	53,496	41,058	12,726	12,726	11,599

*Source:* 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 pollution level. The first row reports OLS regression estimates. The second row reports IV regression estimates, using county's upwind pollution shock as the instrumental variable for logged local pollution. All regressions include location-by-taxa and year fixed effects. Standard errors are clustered at the state level. \*:  $p < 0.10$ ; \*\*:  $p < 0.05$ ; \*\*\*:  $p < 0.01$ .

## The air pollution channel: Decomposition

Share of total marginal effect of policy on biodiversity through causal effect of pollution



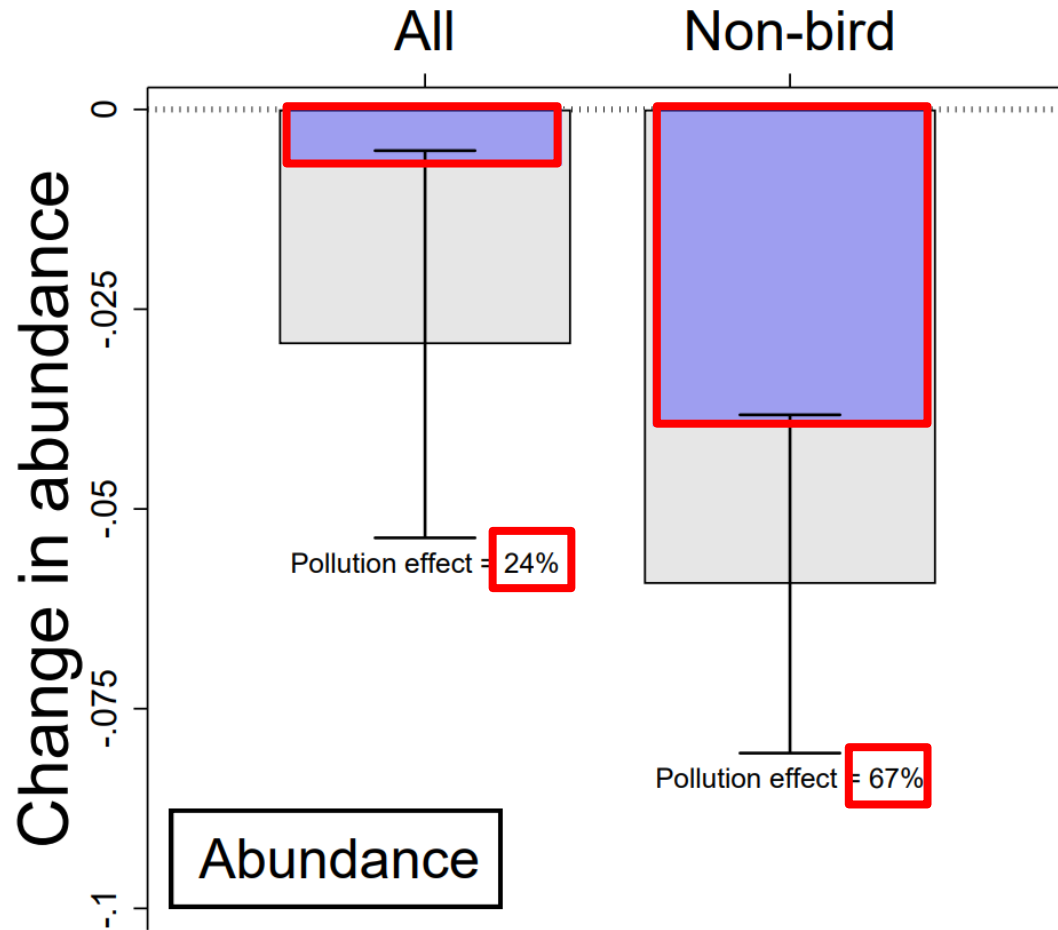
**Total effect of the policy on outcome:**

$$\frac{\partial \text{Biodiversity}}{\partial \text{Policy}}$$

*Notes:* Bars and standard error range plots show the impacts of military buildup shocks or Clean Air Act regulation shocks on biodiversity outcomes. Blue bars (“pollution effects”) indicate the predicted portion of the impacts that are explained by air pollution

## The air pollution channel: Decomposition

Share of total marginal effect of policy on biodiversity through causal effect of pollution



**Effect of the policy through pollution:**

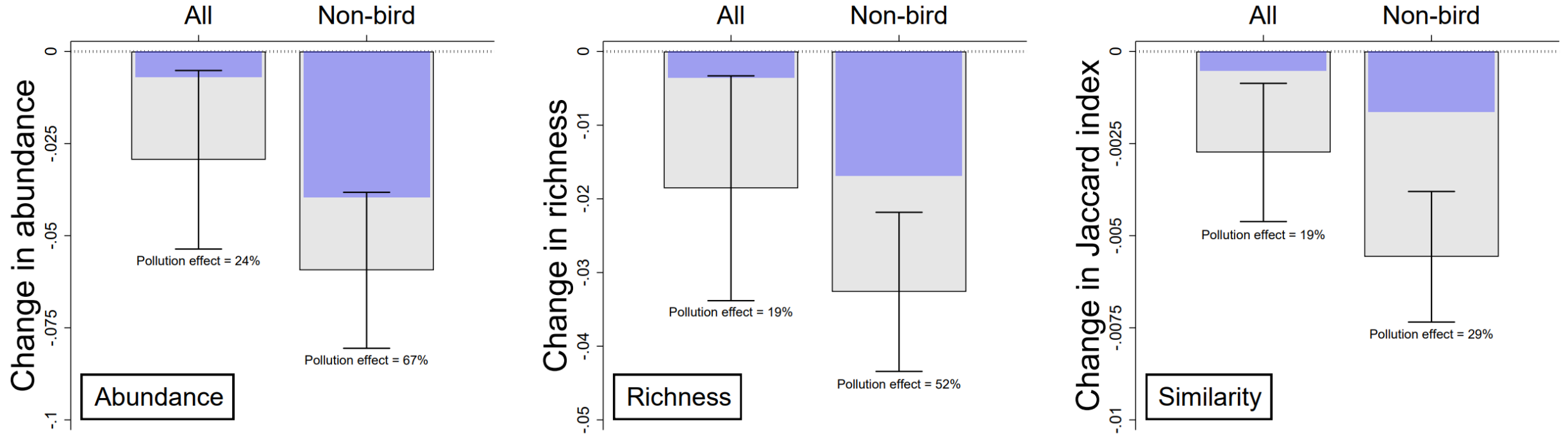
$$\frac{\partial \text{Biodiversity}}{\partial \text{Pollution}} \cdot \frac{\partial \text{Pollution}}{\partial \text{Policy}}$$

*Notes:* Bars and standard error range plots show the impacts of military buildup shocks or Clean Air Act regulation shocks on biodiversity outcomes. Blue bars (“pollution effects”) indicate the predicted portion of the impacts that are explained by air pollution



# The air pollution channel: Decomposing military spending shocks

Share of total marginal effect of policy on biodiversity through causal effect of pollution



Notes: Bars and standard error range plots show the impacts of military buildup shocks or Clean Air Act regulation shocks on biodiversity outcomes. Blue bars (“pollution effects”) indicate the predicted portion of the impacts that are explained by air pollution

# Other Channels

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- Paper also briefly examines the role of land use
  - Urbanization
  - Conservation protected areas
- Strong correlation; research design needed for future studies

## Land Use Channel: Urbanization and Biodiversity

MODIS measures of urbanization shows strong negative panel association with biodiversity

	(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*** (4.01)	-6.39** (2.38)	-2.26 (1.54)	-16.67** (6.94)	-10.53** (3.71)	-5.24*** (1.69)
Urbanization (100-km radius)	-11.59*** (2.29)	-5.15*** (1.53)	-3.94*** (1.40)	-13.79*** (2.87)	-7.48*** (2.23)	-4.47*** (0.99)
Urbanization (county)	-1.73 (1.36)	-0.69 (0.66)	-0.29 (0.38)	-16.14*** (4.18)	-8.59*** (1.56)	-4.04 (2.35)
Observations	19,611	19,611	17,188	6,830	6,830	6,752

*Source:* 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 row), 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. \*:  $p < 0.10$ ; \*\*:  $p < 0.05$ ; \*\*\*:  $p < 0.01$ .

# Outline

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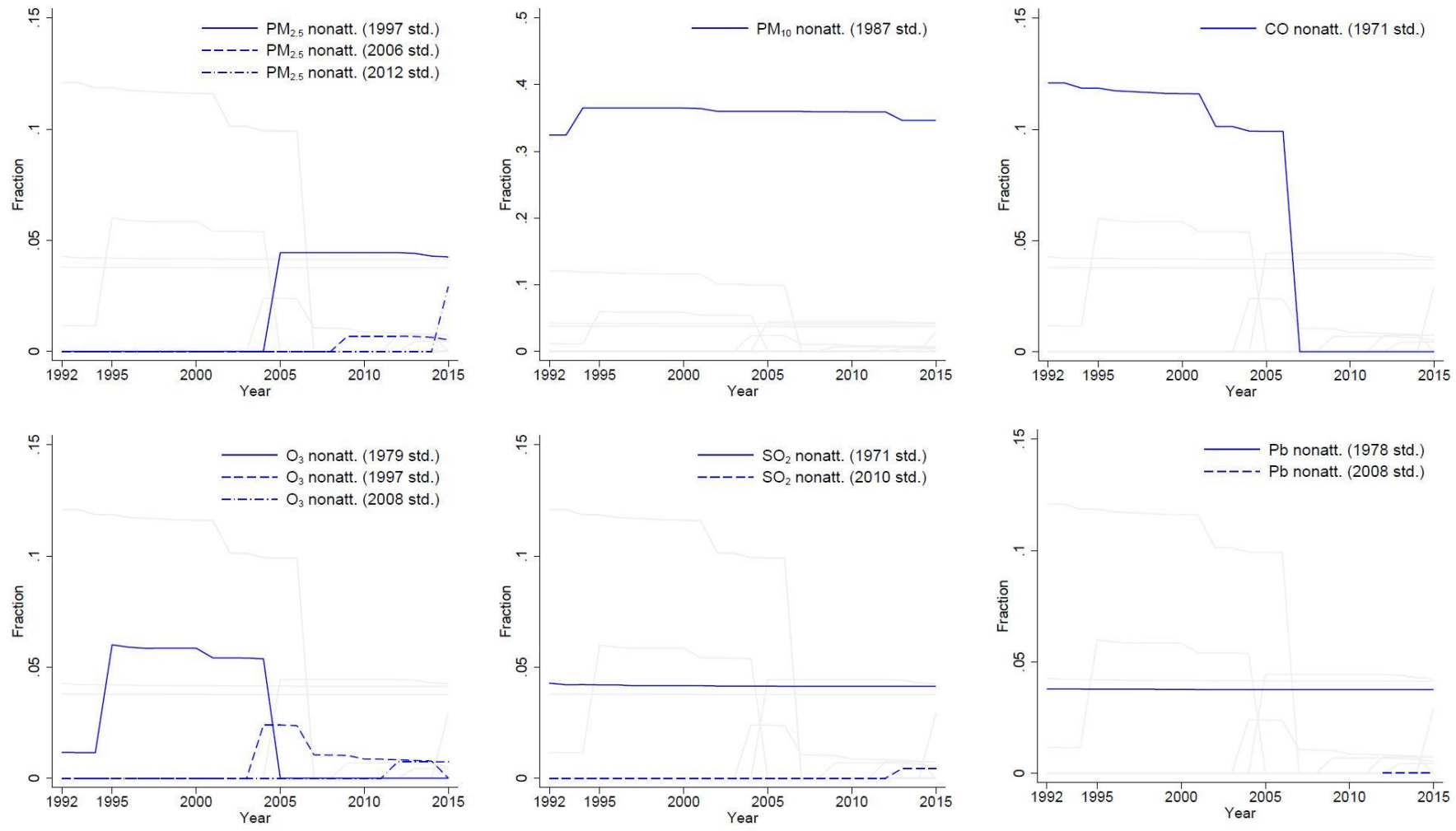
1. Measurement
2. Correlation
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5. Regulations

# Government Policy: Regulations

- Examine the effect of US EPA's **Clean Air Act nonattainment classification** policy
- Jurisdictions (mostly counties) switch in and out of nonattainment status, creating geographical and time series variations
  - Increased **compliance costs** (Blundell et al., 2020; Shapiro and Walker, 2020), reduced **productivity and output** (Becker and Henderson, 2000; Greenstone, 2002; Greenstone et al., 2012; Walker, 2013; Hollingsworth et al., 2022), and improvement in **air quality** (Chay and Greenstone, 2005)
- Data: EPA Greenbook 1992-2015
  - Six criteria pollutants (PM<sub>2.5</sub>, PM<sub>10</sub>, O<sub>3</sub>, SO<sub>2</sub>, CO, Pb)
  - Total 12 relevant standards

# Government policy: Clean Air Act nonattainment regulation

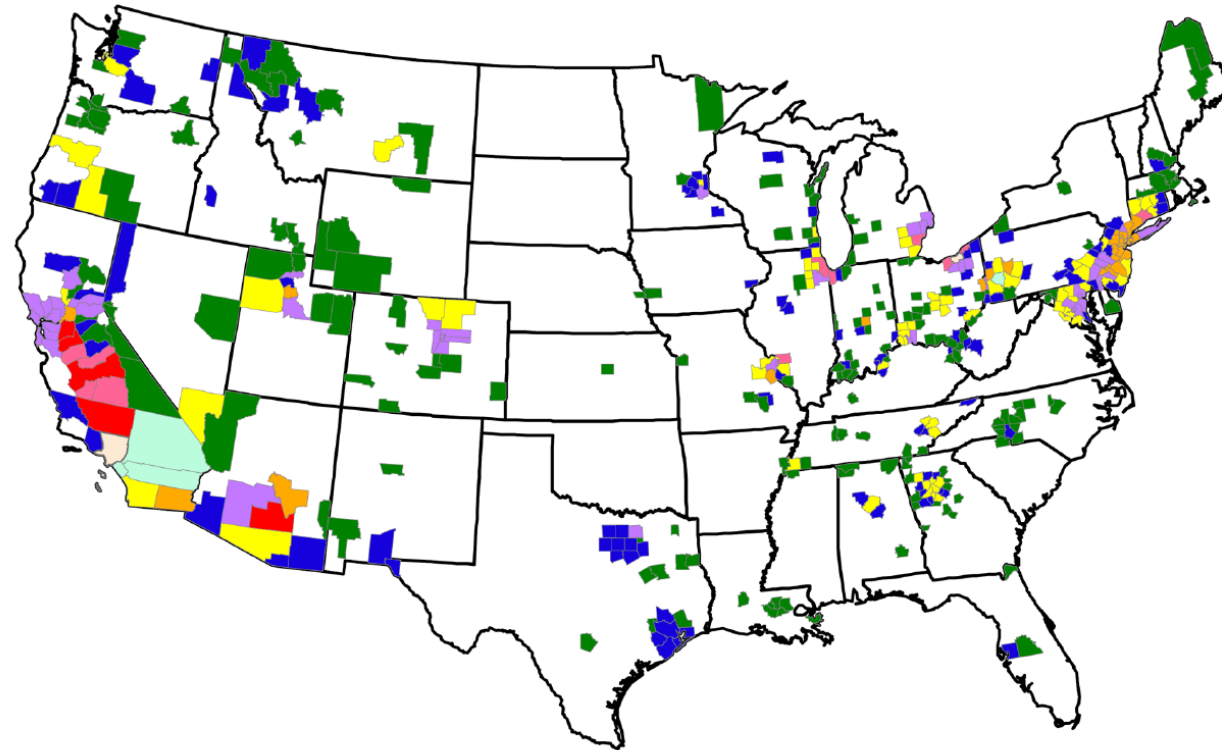
## Share of our study locations in EPA nonattainment jurisdictions



Notes: Versions of standards of the same pollutant reflect different target concentration metrics or changes in regulatory stringency over time.

# Government policy: Clean Air Act nonattainment regulation

## Geographic variation in regulatory status



Legend \*\*

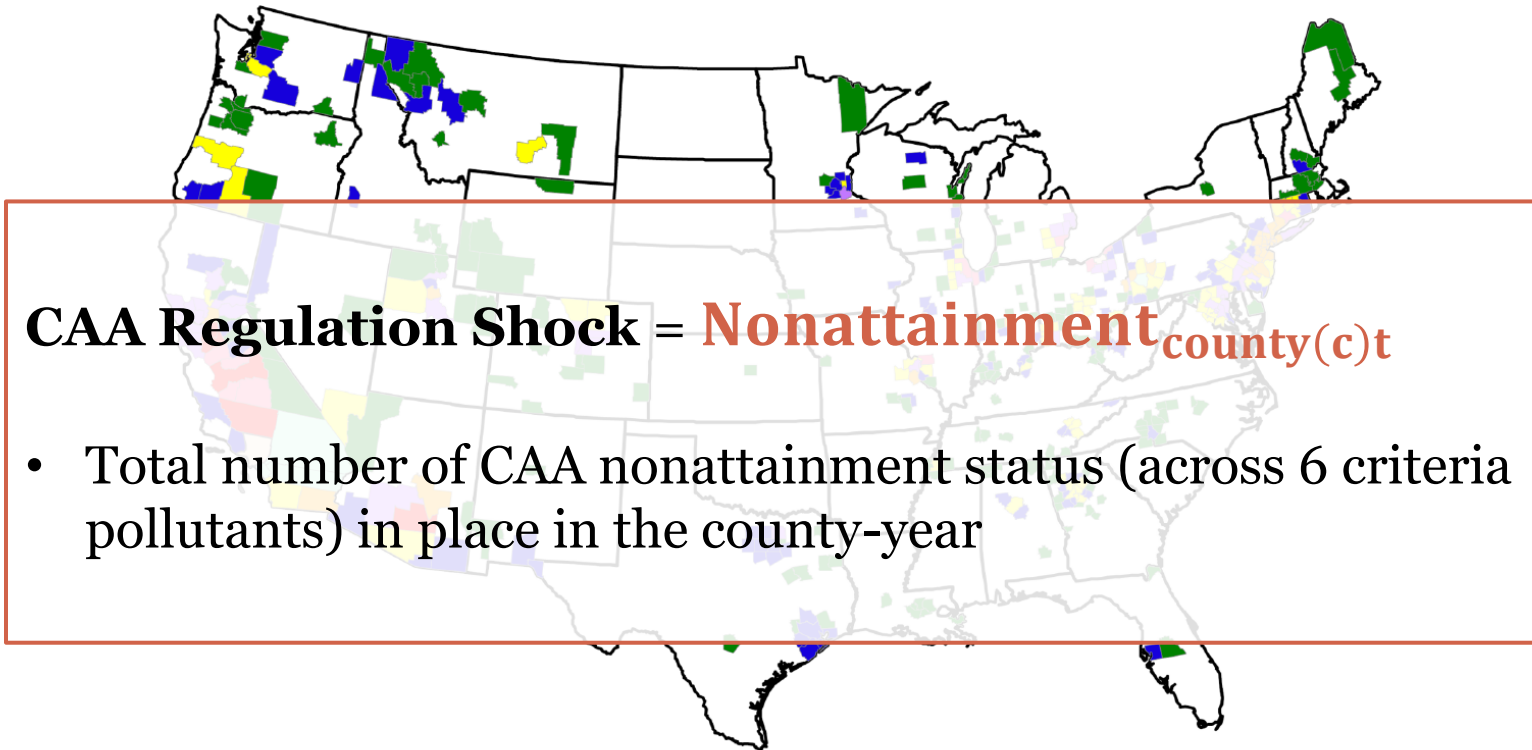
- County Designated Nonattainment or Maintenance for 9 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 8 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 7 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 6 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 5 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 4 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 3 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 2 NAAQS Pollutants
- County Designated Nonattainment or Maintenance for 1 NAAQS Pollutants

Source: EPA Greenbook



# Government policy: Clean Air Act nonattainment regulation

## Geographic variation in regulatory status

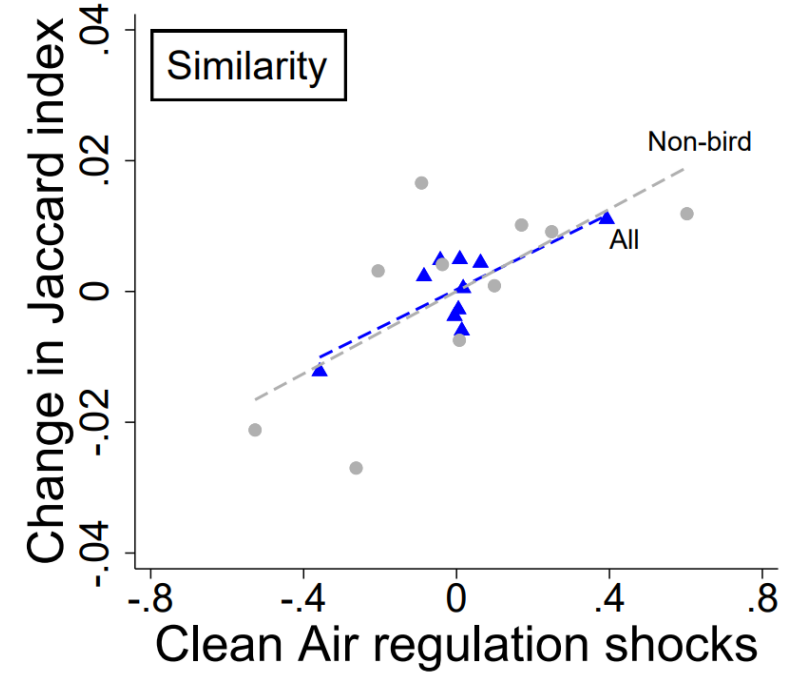
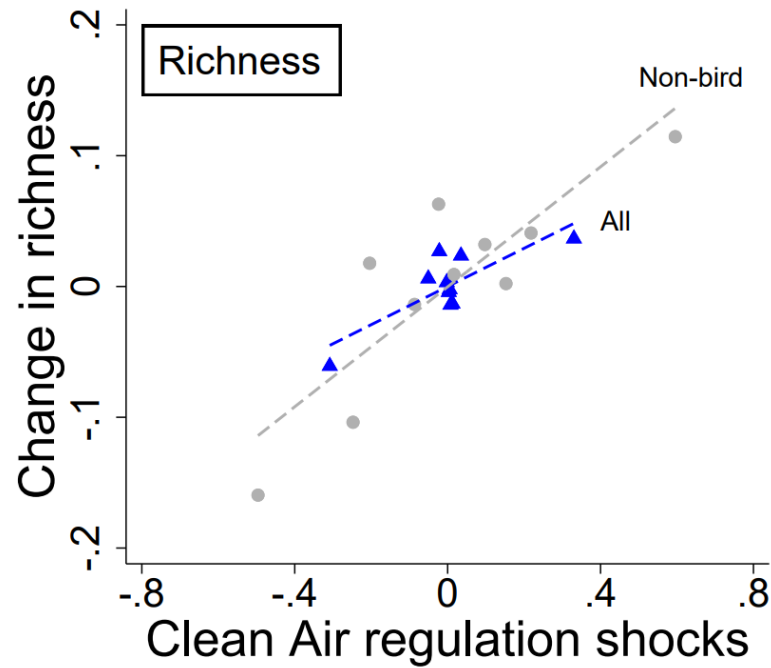
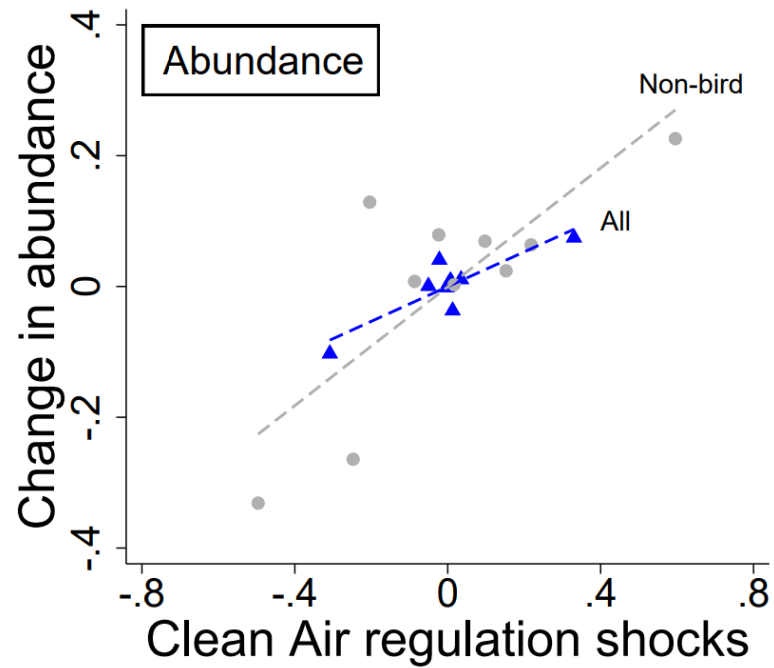


Legend \*\*

	County Designated Nonattainment or Maintenance for 9 NAAQS Pollutants
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	County Designated Nonattainment or Maintenance for 1 NAAQS Pollutants

# Government policy: Clean Air Act nonattainment regulation

## The impact of CAA regulation shocks on biodiversity outcomes



Notes: decile bin scatterplots of biodiversity and the CAA regulation shock variable, both residualized with location-by-taxa and year fixed effects. The dashed blue line displays all-species results, and the dashed gray line displays subsample results with non-bird species.

## Environmental regulation shocks and biodiversity

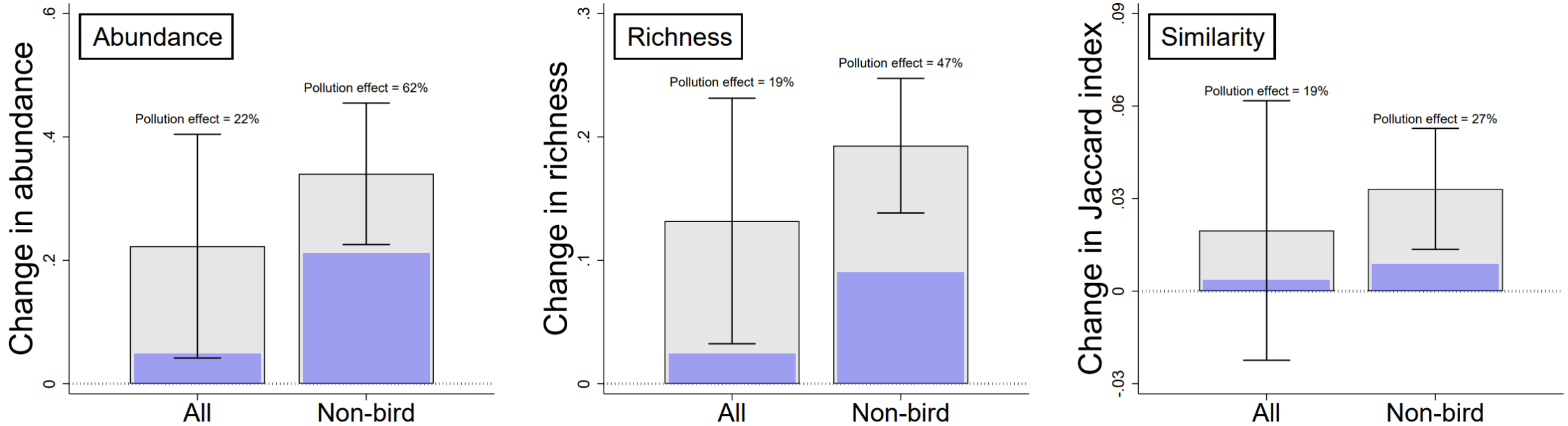
Policy shock = number of nonattainment designations in place in the county × year

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Policy Effect				Implied GDP Elasticity		
	GDP	Abundance	Richness	Similarity	Abundance	Richness	Similarity
<b>Panel A. All species</b>							
Clean Air Act Nonattainment	-0.038*** (0.014)	0.226*** (0.080)	0.121*** (0.046)	-0.020 (0.018)	-	-	-
$\widehat{\text{GDP}}$	-	-	-	-	-5.932*** (0.624)	-3.194*** (0.268)	-0.519 (0.532)
Kleibergen-Paap F-stat.	-	-	-	-	7.841	7.841	8.874
Observations	54,887	54,887	54,887	42,406	54,887	54,887	42,406
<b>Panel B. Non-bird species</b>							
Clean Air Act Nonattainment	-0.053*** (0.007)	0.373*** (0.038)	0.193*** (0.025)	0.371*** (0.007)	-	-	-
$\widehat{\text{GDP}}$	-	-	-	-	-7.005*** (0.755)	-3.631*** (0.250)	-0.704*** (0.097)
Kleibergen-Paap F-stat.	-	-	-	-	50.57	50.57	49.56
Observations	13,331	13,331	13,331	12,161	13,331	13,331	12,161

*Notes:* All first stage and reduced-from coefficients are × 100 to increase readability. All biodiversity and GDP variables in logs, except for Similarity which is already a ratio. All regressions include location-taxa and year FEs. SEs clustered at the state level.

# The air pollution channel: Decomposing Clean Air regulation shocks

Share of total marginal effect of policy on biodiversity through causal effect of pollution



Notes: Bars and standard error range plots show the impacts of military buildup shocks or Clean Air Act regulation shocks on biodiversity outcomes. Blue bars (“pollution effects”) indicate the predicted portion of the impacts that are explained by air pollution

# Protected Areas

- Destruction of habitat is one of the primary drivers of species decline (IUCN, 2021).
- Since early 1990s, adoption of conservation protected area policies has grown rapidly (Frank and Schlenker, 2016).
  - Now cover nearly 15% of the Earth's land and 10% of its water
- Empirical assessments of protected area yield mixed results (e.g., Leverington et al., 2010; Laurance et al., 2012; Watson et al., 2014; Di Marco et al., 2019; Geldmann et al., 2019)
  - Ex: Management issues; Funding; Resource exploitation; Ecological leakage to unprotected areas

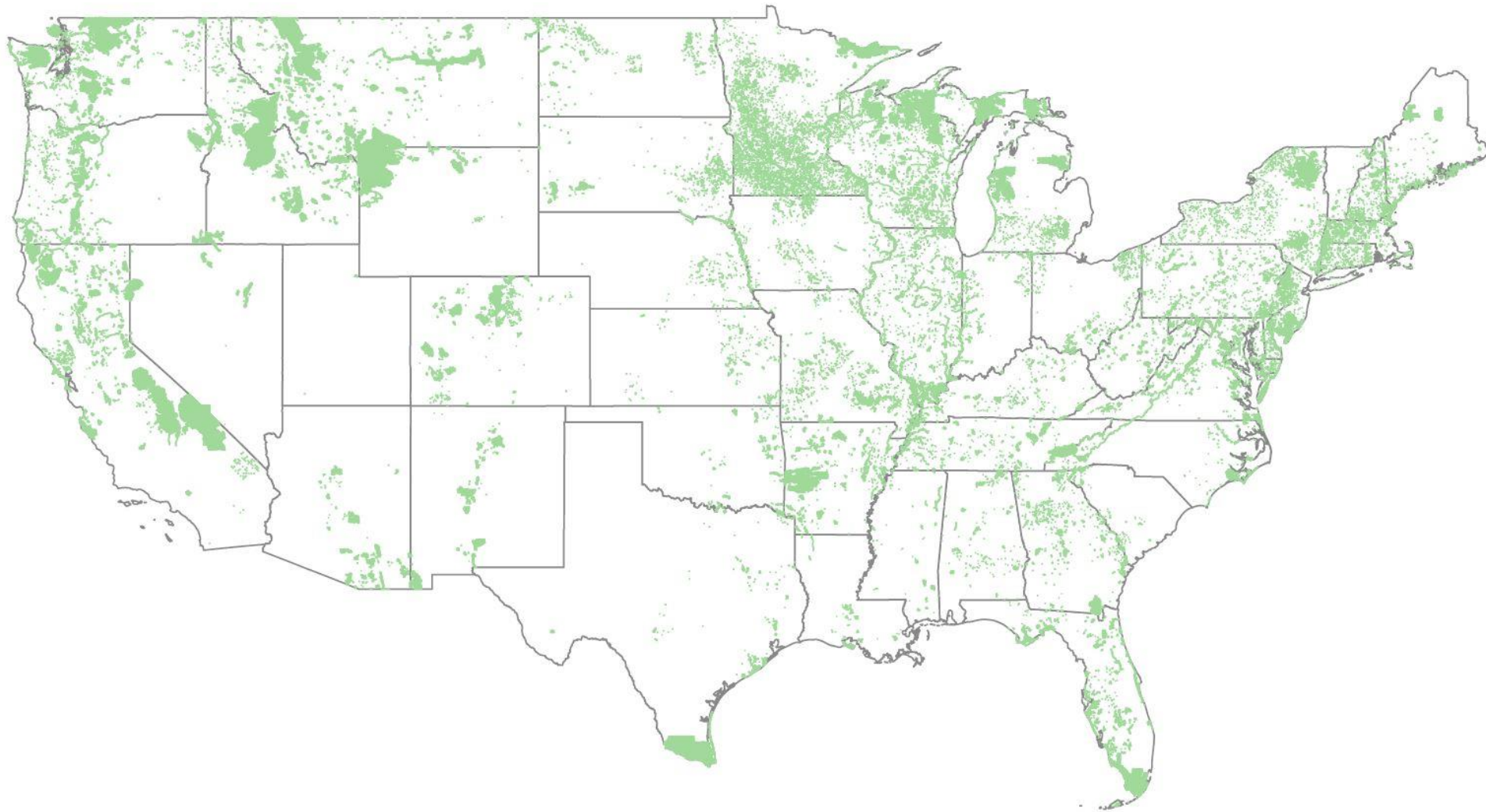
# Protected Areas

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- **Data:** World Database on Protected Areas (WDPA)
  - Geospatial database on over 250,000 marine and terrestrial protected areas
  - Outlines the location of each protected area and the year the protected area was implemented
- Measurement of protection
  - **Coverage:** Total share of land and water within 50 km of the BioTIME sampling location that is within at least one currently implemented protected area
  - **Fragmentation:** number of spatially discontinuous protected areas within 50 km radius (Haddad et al., 2015; Crooks et al., 2017; Newmark et al., 2017)

## Conservation protected areas

Data: World Database on Protected Areas



*Notes:* Map shows protected areas within 50 km any BioTIME sampling site included in our study.



## Protective policy: Conservation protected areas

Protection against GDP shocks; some evidence that area fragmentation also matters

	(1)	(2)	(3)	(4)	(5)	(6)
	Abundance		Richness		Similarity	
<hr/> Panel A. All species <hr/>						
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
<hr/> Panel B. Non-bird species <hr/>						
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:* “%Areas protected”=fraction of protected areas within 50km radius of sampling location. “#Fragmented areas”=number of discontinuous protected areas within 50km radius.

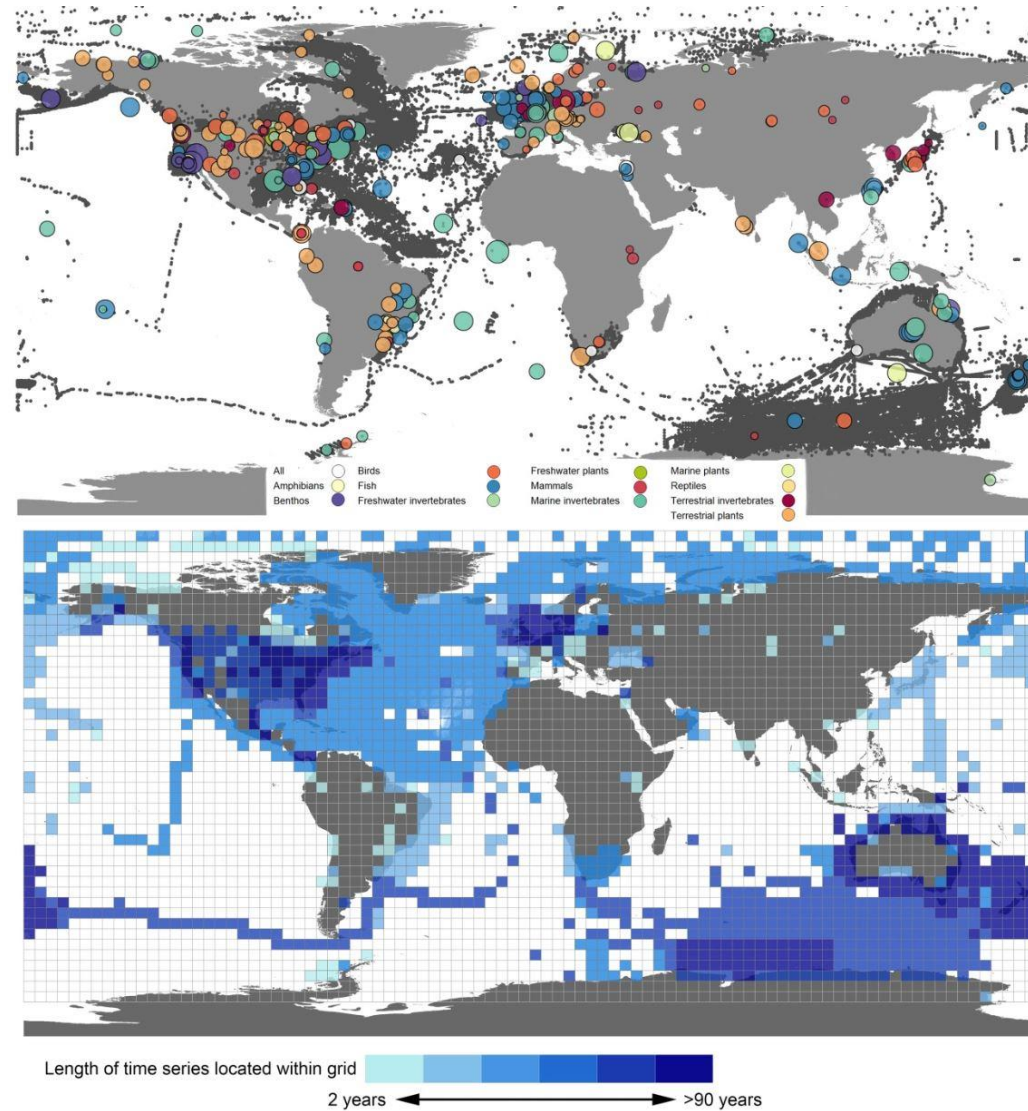


# Conclusion

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- Use a compilation of ecological data to build measures of ecosystem diversity
- Local economic production is negatively associated with biodiversity outcomes
- Policy quasi-experiments suggest this association is likely causal
- Air pollution externalities associated with production can account for 1/3<sup>rd</sup> of the observed biodiversity-production link
- Pollution regulation generates conservation co-benefits

# Potentials for more work!



Source: Dornelas et al. (2018).

# Thank you!

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## GDP growth specifications:

### Trajectory of economic growth matters in addition to year-over-year shocks

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

*Notes:* “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.

## GDP growth specifications:

Trajectory of economic growth matters in addition to year-over-year shocks

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Avg. GDP growth (last 5-y)		-11.39* (6.23)	-3.60 (6.35)		-2.93 (2.83)	3.53 (3.83)		-1.09 (0.79)	-1.56 (1.15)
Max. GDP growth (last 5-y)			-7.68*** (2.16)			-6.36** (2.46)			0.44 (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** (2.40)	-3.92*** (1.26)	-2.49** (0.90)	-5.06*** (1.39)	-3.98*** (0.92)	-3.32*** (0.79)	0.32*** (0.07)	0.67** (0.25)	0.37* (0.21)
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