Conservation cobenefits from air pollution regulation: Evidence from birds

Yuanning Liang[a,1], Ivan Rudik[a,1,2], Eric Yongchen Zou[b,c,1], Alison Johnston[d], Amanda D. Rodewald[d,e], and Catherine L. Kling[a,2]

[a]Charles H. Dyson School of Applied Economics and Management, Cornell University, Ithaca, NY 14850; [b]Department of Economics, University of Oregon, Eugene, OR 97403; [c]National Bureau of Economic Research, Cambridge, MA 02138; [d]Cornell Lab of Ornithology, Cornell University, Ithaca, NY 14850; and [e]Department of Natural Resources, Cornell University, Ithaca, NY 14850

This contribution is part of the special series of Inaugural Articles by members of the National Academy of Sciences elected in 2015.

Contributed by Catherine L. Kling, September 25, 2020 (sent for review July 1, 2020; reviewed by Christopher Costello and David Evers)

Massive wildlife losses over the past 50 y have brought new urgency to identifying both the drivers of population decline and potential solutions. We provide large-scale evidence that air pollution, specifically ozone, is associated with declines in bird abundance in the United States. We show that an air pollution regulation limiting ozone precursors emissions has delivered substantial benefits to bird conservation. Our estimates imply that air quality improvements over the past 4 decades have stemmed the decline in bird populations, averting the loss of 1.5 billion birds, ~20% of current totals. Our results highlight that in addition to protecting human health, air pollution regulations have previously unrecognized and unquantified conservation cobenefits.

birds | cobenefits | citizen science | air pollution | conservation

Air pollution is widely recognized as a leading cause of human morbidity and mortality (1–7). Regulation of anthropogenic emissions, especially the combustion of fossil fuels, is key to alleviating global health burdens from pollution exposure. Indeed, air pollution policies, such as the US Clean Air Act, have improved ambient air quality, reduced disease incidence, and increased life expectancy (8, 9). Quantifying the impacts of both pollution exposure and regulation has been largely restricted to humans, and our understanding of benefits to nonhuman species—many of which are sensitive to pollution—remains poor. The physiology and unique respiratory systems of birds, in particular, should make them especially susceptible to air pollution (10–14). For this reason, birds are a useful focal taxon to examine how policy interventions for air pollution may deliver broader benefits to ecosystems.

We provide continental-scale evidence that ground-level ozone negatively affects the North American avifauna, a group of animals that are well-known indicators of environmental health and one of the only groups for which abundance data are available at fine resolution across broad spatial and temporal scales (15–18). We then analyze how the US Environmental Protection Agency (EPA) NO_x Budget Trading Program (NBP), an air quality regulation that was designed to protect human health by limiting summertime emissions of ozone precursors from large industrial sources, has provided substantial conservation cobenefits for avifauna.

Current understanding of the impact of air pollution on birds is limited to case- or laboratory-based studies on the toxicology of pollution exposure, whereas species- or continental-scale impacts are largely unknown (10, 11, 14, 19–23). We expand the spatial and temporal lens of previous studies to better understand the extent to which pollution contributed to population declines in North American birds, which have lost a staggering 2.9 billion breeding individuals over the last 50 y (24). A rough calculation based on our estimated ozone response suggests that observed declines in bird populations would have been 50% greater in the absence of reductions in ground-level ozone since 1980. In short, the regulation of ozone has led to an additional 1.5 billion birds, ~20% of current populations.

There are several ways in which ozone is expected to harm individual birds in ways that can scale up to affect population size and trends. High levels of ozone can directly impact birds via physical harm, such as damage to respiratory systems, or indirectly via changes to habitat conditions, food supplies, and/or species interactions. There exists strong evidence that elevated ozone reduces primary productivity, inhibits growth rate and biomass of plants (especially deciduous trees), reduces plant species richness and community composition, chemically impedes plant–pollinator interactions, changes foliar quality and content of nitrogen, increases plant susceptibility to damage and disease, impacts soil microbial communities, and increases secondary (defensive) plant compounds to reduce herbivory by insects, which in turn have lower biomass and higher rates of mortality (25). For example, the literature shows that ozone damages plants in ways that affect growth, architecture, and chemical composition, including the secondary compounds used to defend against herbivory from insects. Likewise, research has found 17% lower arthropod abundance when ozone levels were elevated compared to normal ambient levels which may harm insectivorous birds (26). When access to high-quality habitat or

Significance

Understanding the drivers of abundance and biodiversity decline across numerous taxa is imperative for designing conservation policy. We use highly detailed citizen science data to show that there is a strong, robust negative association between bird abundance and ambient ozone concentrations in the United States. In particular, we find that a regulation aimed at reducing ozone precursors has significantly bolstered populations in the eastern United States. Our estimated effects suggest that the large decline in average US ozone concentrations over the past several decades has averted the loss of potentially billions of birds. Environmental policies nominally aimed at humans can also provide substantial benefits to other species.

Author contributions: Y.L., I.R., E.Y.Z., A.J., A.D.R., and C.L.K. designed research; Y.L., I.R., and E.Y.Z. performed research; Y.L., I.R., and E.Y.Z. analyzed data; and Y.L., I.R., E.Y.Z., A.J., A.D.R., and C.L.K. wrote the paper.

Reviewers: C.C., University of California, Santa Barbara; and D.E., Biodiversity Research Institute.

The authors declare no competing interest.

See QnAs on page 30868.

[1]Y.L., I.R., and E.Y.Z. contributed equally to this work.

[2]To whom correspondence may be addressed. Email: irudik@cornell.edu or ckling@cornell.edu.

This article contains supporting information online at https://www.pnas.org/lookup/suppl/doi:10.1073/pnas.2013568117/-/DCSupplemental.

First published November 24, 2020.

food resources is reduced, mortality of individuals (adults, juveniles, and nestlings) may increase due to immediate health consequences or longer-term impacts that carry over across seasons. For example, a bird that has insufficient energetic reserves is more likely to die during migration, which reduces the population by way of the loss of that individual and its future reproductive productivity. Even in less severe cases, that individual may produce fewer young than it would have otherwise.

Our analysis is based on bird observations across the contiguous United States between 2002 and 2016, derived from over 11 million eBird checklists (27). Following the literature (24, 28), we develop a statistical model to estimate changes in bird abundance over time, based on the counts of birds reported. We model the count of birds in each eBird checklist, while accounting for effects of observer effort (e.g., hours spent amassing observations) and bird detectability (e.g., time of day) (Fig. 1). *SI Appendix* documents the consistency of our findings with other approaches and their robustness to our modeling choices. While these adjustments do not estimate actual population sizes, they do generate data on the relative abundance of bird populations. By studying how the relative abundance of birds is affected by pollution, we can infer the impacts on absolute abundance by combining our estimates with independent estimates on bird population sizes.

The abundance estimates are combined with the US EPA's ground-level pollution monitor readings and states' pollution regulation information. These data allow us to construct a longitudinal database that tracks month-over-month changes in bird abundance, air quality, and regulation status for 3,214 counties over a 15-y time span. The longitudinal nature of our data allows us to identify the effect of air pollution using a "within" estimator that links a county's changes in bird abundance to changes in air pollution. We use a research design that flexibly accounts for spatial (3,214 counties), temporal (15 y), and seasonal (12 calendar months) patterns in the data, constructing a three-way interactive fixed effects estimator that controls for all observable and unobservable confounding factors within a county–year, season–year, and county–season. Specifically, county–year fixed effects control for differences in attributes across counties within each year, such as conservation policies or land use (e.g., impervious surfaces, forest, and cropland). Season–year fixed effects control for changes in a season from one year to the next that are common across all counties, such as changes in average summer ozone or mean abundance of breeding birds. Finally, county–season fixed effects control for all county-specific seasonal trends, such as local seasonal variation in observer activity and seasonal trends in bird abundance due to migration. We also control for contemporaneous changes in weather elements including temperature and precipitation. The weather controls and the rich set of fixed effects control for a large set of (potentially unobservable) ecologically relevant factors that affect abundance, leaving variation in pollution that is as good as random. Importantly, the focus on changes or trends in relative abundance rather than absolute number of birds allows us to track the abundance–pollution relationship without having to estimate population sizes. We discuss estimation details assumptions in *SI Appendix*.

We estimate the effect of ozone (O_3) and fine particulate matter ($PM_{2.5}$) on relative bird abundance in a single regression, controlling for the other pollutants, fixed effects, and temperature and precipitation (Fig. 2). We focus on these two pollutants as they are the two most commonly found to cause health and mortality risks in humans. Ozone is strongly negatively associated with bird abundance (Fig. 2*A*). One SD increase in ozone concentrations (8.4 parts per billion) is associated with a 0.117 SD decrease in bird abundance ($P < 0.01$, 1 SD bird counts per checklist = 98.4), and the relationship is linear over the range of ozone levels in our dataset. We find no evidence for an association with $PM_{2.5}$. Importantly, this initial analysis of contemporaneous (i.e., month-of) effects of pollution on relative abundance of birds does not capture longer-term damage caused by pollution.

We next investigate avian responses to changing ozone levels in response to the NBP, which imposes a cap on emissions of ozone precursors from 1 May through 30 September. The NBP has affected ∼1,000 combustion units in the eastern and midwestern United States starting in 2003 (Fig. 1). To estimate the impact of the NBP, we use a triple difference approach that explores treatment versus control comparisons along three dimensions: 1) states that participated in the NBP versus states that did not, 2) summer months when the NBP restrictions are in place versus winter months when they are not, and 3) years after 2003 when the NBP came into effect versus years before it went into effect (9). In combination, these comparisons allow us to

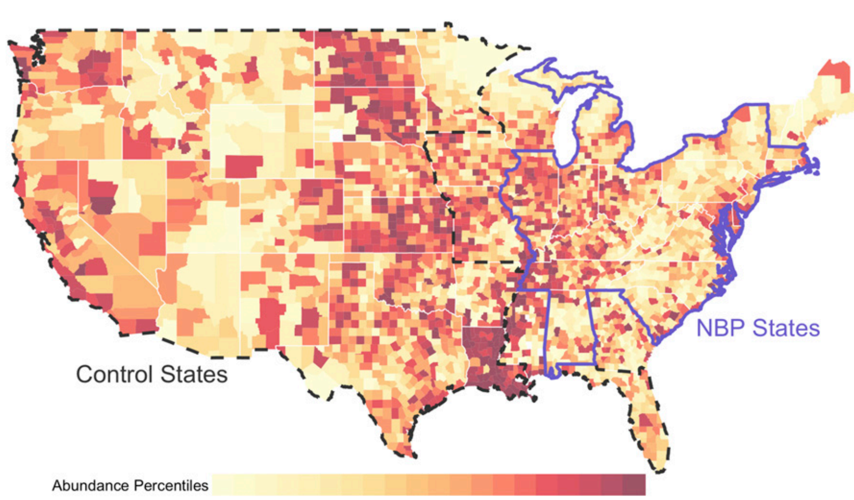

Fig. 1. The spatial distribution of bird abundance. County colors indicate ventiles of bird abundance across all years. Darker colors indicate greater abundance. The set of states outlined in solid blue are those subject to the NBP. The set of states outlined in dashed black are the control states. The states not within the blue or black areas are omitted from the analysis due to potential atmospheric transport of pollution (9). The states omitted from the NBP analysis are Georgia, Iowa, Maine, Mississippi, Missouri, New Hampshire, Vermont, and Wisconsin.

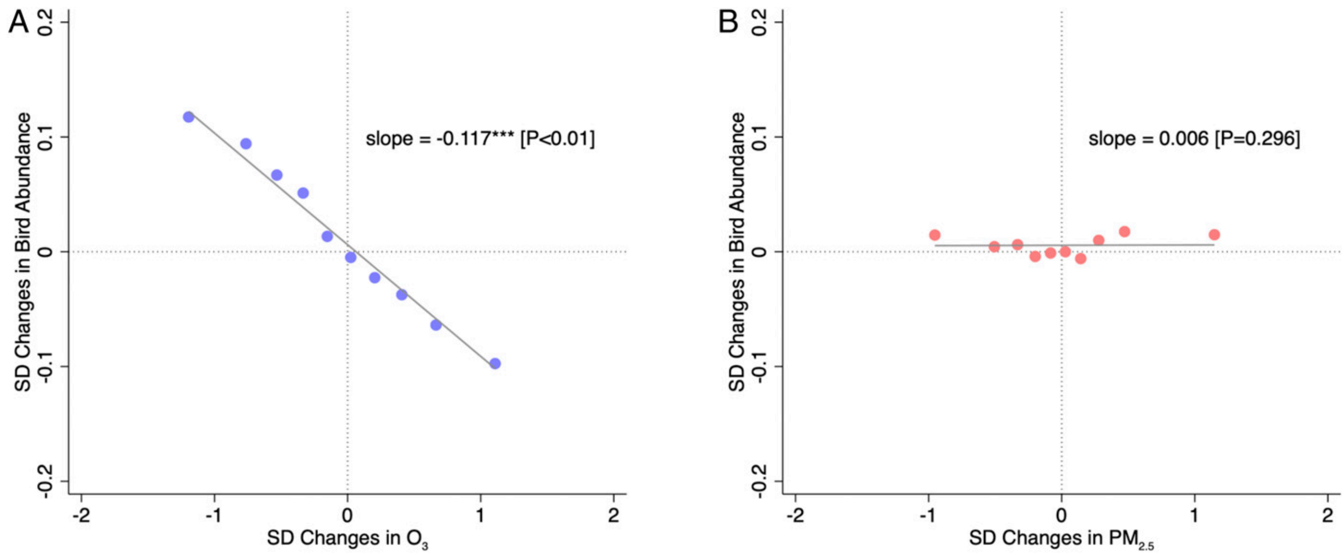

Fig. 2. The association between bird abundance and different pollutants. (*A*) Ozone and (*B*) fine particulate matter. The line is the estimated best fit line from a linear regression of bird abundance on both pollutants, weather variables, and fixed effects. The points correspond to the mean values of the pollutant and bird abundance within each pollutant decile after removing the effect of the other pollutant, weather variables, and fixed effects. SEs are clustered at the state–season level and robust to heteroskedasticity. The regressions are weighted by the number of checklists in a given county–year–month. $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.10$. The number of observations is 92,072.

isolate the changes in pollution and bird abundance that are specific to NBP-affected states and specific to months when the NBP market is operating. The triple difference approach is robust to differential trends in bird abundance due to differences in species composition in NBP states versus control states. For example, the triple difference approach allows us to still estimate the causal effect of the NBP despite the observed differential declines in western versus eastern birds (24). The critical assumption is that in the absence of the NBP program, the difference in summer bird abundance trends between NBP and control states would have evolved similarly to the difference in winter trends.

The NBP decreased ambient ozone concentrations in the average county by 0.496 SD (4.2 parts per billion) ($P < 0.01$) and increased bird abundance by 0.235 SD ($P < 0.01$) (Fig. 3*A*). The NBP had a positive effect on land bird abundance (0.270 SD, $P <$ 0.01), while the estimated impacts on waterfowl (−0.057 SD, $P =$ 0.585), shorebirds (0.056 SD, $P = 0.327$), and waterbirds (−0.002 SD, $P = 0.972$) are small and not statistically significant. In addition, we find statistically significant positive effects of the NBP on birds with a mass less than 142 g, which is approximately the mass of a northern flicker *Colaptes auratus cafer* or a ring-necked dove *Streptopelia capicola*. Birds with mass less than 142 g correspond to the first three quartiles of bird mass distribution (less than 16 g [0.217 SD, $P < 0.01$], 16 to 38 g [0.201 SD, $P < 0.01$], and 38 to 142 g [0.235 SD, $P < 0.01$]). We do not find evidence that birds weighing more than 142 g are affected by the NBP (0.016 SD, $P = 0.819$). This is consistent with the positive effect on land birds, which mostly fall into the smaller bird groups (85.6% of land birds in our sample are less than 142 g). One potential mechanism consistent with previous research is that ozone reduces insect abundance (26) and would thus reduce abundance of land birds which tend to be the most insectivorous group. We further find that the effect on migratory birds (0.149 SD, $P = 0.030$) is greater than on resident birds (0.104 SD, $P = 0.064$), although the estimates are not statistically distinguishable from each other.

Our results suggest that environmental regulations primarily designed to protect human health can generate substantial conservation cobenefits for other species. To further explore the generality of bird–ozone relationships at national scales since 1980, we use a three-pronged approach. See *SI Appendix* for a full description of the instrumental variable (IV) approach used. First, by converting the NBP program's effects on ozone and bird abundance into the direct effect of ozone on bird abundance, we show that each 0.496 SD increase in ozone is associated with a 0.235 SD decrease in bird abundance (Fig. 3*A*), translating to a 0.235/0.496 = 0.474 SD decrease in bird abundance for every 1 SD increase in ozone (Fig. 3*B*). Second, we simulate a back-of-the-envelope counterfactual scenario in which ambient ozone pollution is held constant at its 1980 level, the year when ozone was first measured and regulated by EPA, instead of following the actual pollution trajectories driven by air quality regulations like the NBP and Clean Air Act. Third, we then compare this counterfactual with recent estimates which reported the loss of 2.9 billion birds from 1970 to 2018 (24).

Ozone has, on average, declined by 0.13 parts per billion per year between 1980 and 2018, with the largest declines seen in the eastern states that were regulated by the NBP (Fig. 4*B*). In the absence of regulation-driven ozone reductions between 1980 and 2018, bird populations would have declined by an additional 1.5 billion: 50% more than if ozone concentrations had remained the same (Fig. 4*A*). As such, 20% of the current bird population of ∼7 billion individuals can thus be attributed to improvements in ozone concentrations over the past 40 y. The observed and counterfactual bird trends begin diverging more rapidly in the 2000s when pollution regulation policies, such as the NBP, accelerated ambient ozone concentration improvements.

Several points on the interpretation of our abundance–decline results bear mentioning. Birds' responses to air pollution are likely to occur through a number of mechanisms and at a number of different timescales. We expect some mechanisms may result in rapid effects, for example, reduced ability to forage, movement to a less optimal local habitat, or the death of birds in poorer health. However, some mechanisms may take time, such as increased mortality of healthier birds due to long-term accumulation of pollution throughout a year or reduced reproductive productivity due to poorer body condition. The measures of relative bird abundance will reflect a combination of these short-term and long-term processes.

Although we are unable to pin down the exact mechanisms in this study, we can rule out several alternative explanations. First,

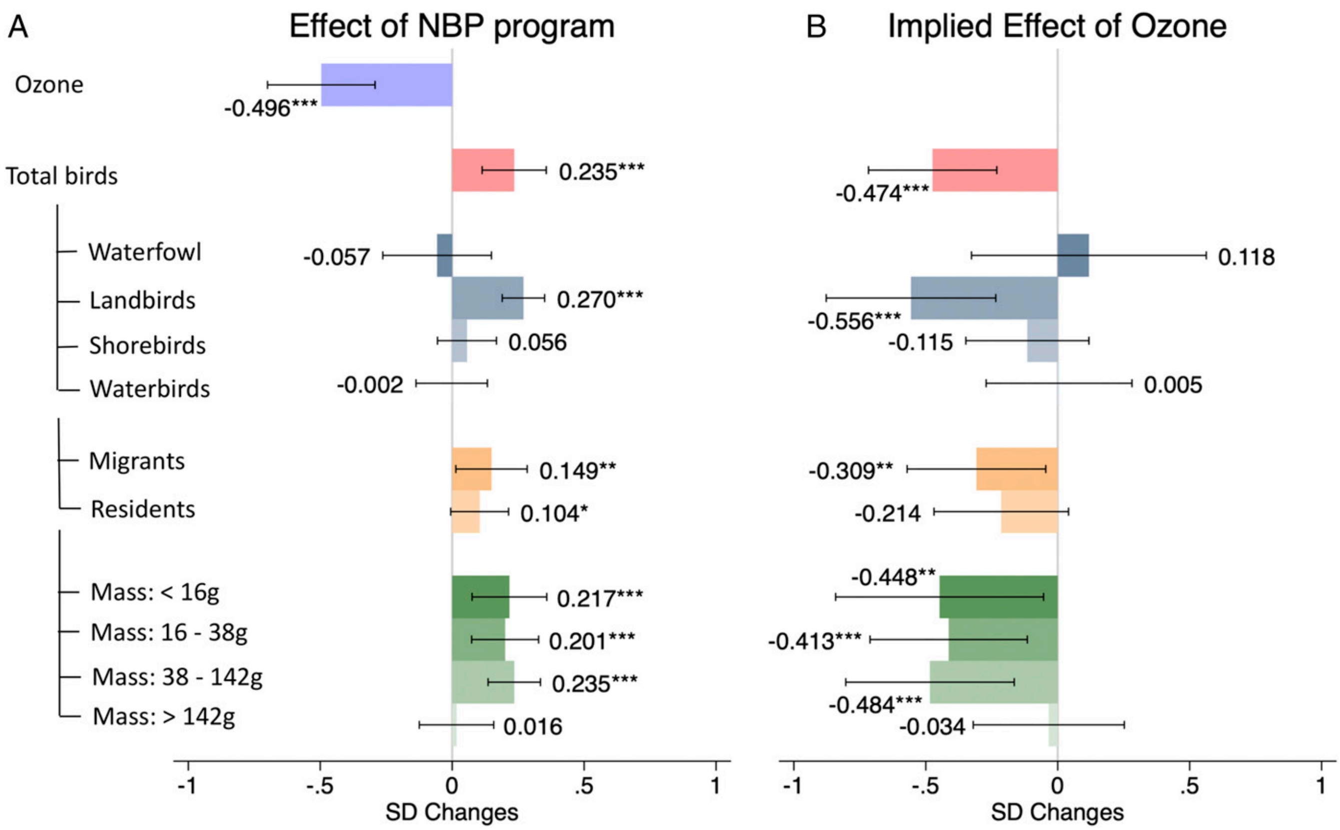

Fig. 3. (*A*) Effects of the NBP on ozone and bird abundance in SD units. (*B*) Implied effects of ozone from results in *A*, as calculated using an IV approach that combines the effect of the NBP on ozone and the effect of predicted ozone on bird abundance. Birds are classified into groups following previous work (24). Bird groups by mass are divided into four quartiles according to their mass distribution. The black bars indicate 95% confidence intervals. SEs are clustered at the state–season level and robust to heteroskedasticity. The regressions are weighted by the number of checklists in a given county–year–month. The IV first stage F statistics in estimating the effect of NBP on bird groups from the second to the last row range from 22.39 (mass < 16 g) to 22.67 (shorebird). $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.10$.

our results are unlikely to be explained by reduced visibility or detectability of birds during high-ozone events. Ozone is a part of smog but is effectively invisible. The visibility effects of smog come from particulates like $PM_{2.5}$ (e.g., black carbon), which we have controlled for in our regressions (Fig. 2 and *SI Appendix*, Table S4). Also, most bird detections during surveys are based on auditory, not visual, cues (e.g., songs and calls) making visibility less of an issue for detection. Second, it is possible that high levels of ozone may cause birds to hide or reduce their propensity to sing and thus reduces the likelihood that they are spotted. However, these hiding behaviors are most likely to be transient as it is not feasible for birds to change their behavior at a monthly scale—they need to forage, defend territories, and feed their young. Therefore, even if an extreme ozone event did affect behavior briefly, effects would not be consistent over the month, which is the time frame of our analysis. Finally, we note our findings are not explained by a change in human birding effort, such as time spent birding, or distance traveled, which we controlled for in constructing the abundance measure (Fig. 1).

As individual countries and the global community writ large struggle to address a multitude of complex social and environmental problems with limited resources, we are challenged to identify interventions that can deliver benefits on multiple fronts. We have shown that air quality improvements in the United States have significantly stemmed the decline in bird populations. This suggests that further improvements in air quality could meaningfully contribute to efforts to halt or reverse widespread declines in wildlife populations. We contend that these conservation cobenefits from air pollution regulation may be substantial.

Although our study investigated the impact of pollution regulations on bird populations, we did not examine the ultimate value of the associated changes in ecosystem services provided by more robust bird populations. These bird-provisioned ecosystem services, which include pollination, seed dispersal, insect control, and nutrient transfer, can be substantial at local and regional scales (29–31). Yet these cobenefits are rarely acknowledged in cost–benefit analyses of air pollution regulation, although they are clearly required for accurate assessment of the full suite of benefits. Fully estimating the economic value of species conservation is imperative to the design and implementation of well-designed air pollution policy. This work provides a first step toward quantifying these values.

Methods

Data. Our data on bird counts come from the eBird Reference Dataset (ERD) (32). The ERD is a citizen science dataset consisting of reports from eBird users detailing information on characteristics of their birding trips as well as the species and quantity of birds seen. We call each separate report of birds in the dataset a "checklist."

Our data on pollution come from the US EPA's Air Quality System database, which documents ground monitor readings of ambient pollution levels.* We measure pollution concentrations for each county by spatially averaging readings from all monitors within 20 miles of the county's centroid, with the inverse of distance as weights. We use data on states' NBP regulation status from ref. 9. Our data are available at https://www.openicpsr.org/openicpsr/project/125422/version/V2/view.

*https://aqs.epa.gov/aqsweb/airdata/download_files.html.

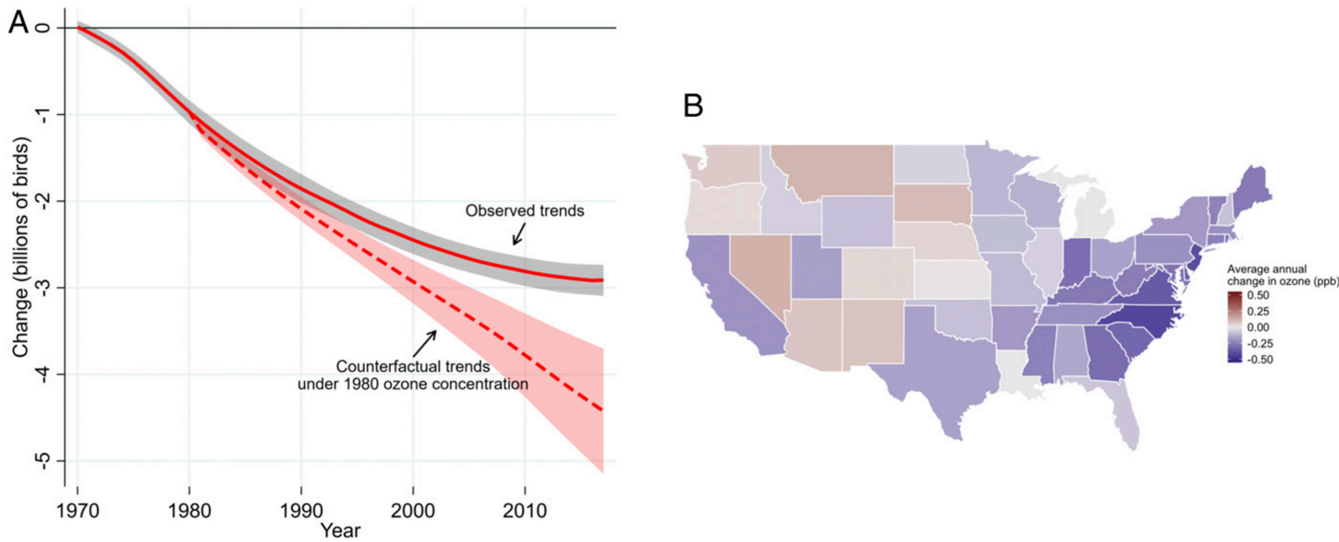

Fig. 4. (*A*) The observed trend in bird populations from ref. 24 as a solid line and the counterfactual trend if ozone concentrations held at their 1980 levels as a dashed line. The shaded areas correspond to the 95% confidence interval for each where the 95% confidence intervals are derived from the cluster-robust SEs associated with the top estimate in Fig. 3*B*. (*B*) The statewide average annual change in ozone concentrations at US EPA monitors between 1980 and 2018. Blue indicates decreases in ozone; red indicates increases in ozone.

Methods: Bird Abundance Estimation. Our basis for estimating bird abundance is a database of 11 million eBird checklists across the United States. These data reflect birding effort and preferences in addition to objective bird counts. Controlling for birding checklist characteristics is thus important for recovering bird abundance (33–35). We estimate the relationship between bird abundance and air pollution by first adjusting for birder effort in the eBird dataset.

We begin by using complete checklists in the eBird data to predict the average count of birds in a county–month–year (e.g., May 2015 in Orange County, CA) conditional on reported characteristics of the checklist and effort by the birder group. We model bird counts in the eBird data as a Poisson process that is jointly determined by a function f of birder effort, detectability of birds, true bird abundance, and a random component ε (28):

$$\#\ \text{birds observed} = \exp\{f(\text{effort}, \text{detectibility}, \text{abundance}, \varepsilon)\}.$$

To take this model to the data, we proxy for effort and detectability using data reported in the eBird checklists:

$$\#\text{birds observed}_{cohdmy} = \exp\big(\beta_d \text{hours}_{cohdmy} + \beta_n \text{number of observers}_{cohdmy} + \zeta_h + \Gamma_{cmy} + \varepsilon_{cohdmy}\big).$$

The left-hand side is the number of birds reported in an eBird checklist by birder group o in county c, at hour of day h, on day of month d, in month of year m, and in year y. The control variables in the Poisson model address different margins for how observers can affect the number of birds they see per trip. hours_{cohdmy} is the time spent birding by the group, which controls for the length of time spent observing. $\text{number of observers}_{cohdmy}$ is the number of people in the group, which addresses the group's intensity at any given time. ζ_h is an hour-of-day fixed effect that controls for all variables common across days within an hour of day, such as average bird detectability or ability to observe birds in day versus night; these controls address differential bird activity or observer ability to detect birds depending on the time of day. ε_{cohdmy} is the random error term.

We are interested in the Γ_{cmy} estimates, i.e., the county-by-month-by-year fixed effects, which captures bird abundance at the county–month–year level after conditioning on the effort variables and hour-of-day fixed effect.

To operationalize the estimation, we log-linearize the Poisson equation and estimate the model with ordinary least squares (28):

$$\log(\#\text{birds observed}_{cohdmy}) = \beta_d \text{hours}_{cohdmy} + \beta_n \text{number of observers}_{cohdmy} + \zeta_h + \Gamma_{cmy} + \varepsilon_{cohdmy}. \quad \textbf{[1]}$$

We then recover the estimated fixed effects $\hat{\Gamma}_{cmy}$, which are our measures of bird abundance in each county–month–year.

The choice of model specification in Eq. **1** is meant to be simple and transparent, and it does not capture all effort margins. Importantly, because our goal is to estimate how bird abundance changes with air quality rather than bird abundance per se, the effort adjustment variables included in the estimation need not be comprehensive as long as the omitted determinants of eBird counts from Eq. **1** do not systematically correlate with month-over-month changes in air pollution. *SI Appendix*, Table S3 reports that our estimation results are robust to alternative model specifications, such as models using raw bird counts per checklist without any effort or detectability adjustments, or models with data-driven variable choice (Least Absolute Shrinkage and Selection Operator [LASSO]) using a large set of potential effort variables.

Methods: The Association between Air Pollution and Bird Abundance (Ordinary Least Squares). After we have recovered an estimate of $\hat{\Gamma}_{cmy}$, we estimate the following model with (weighted) ordinary least squares for results reported in Fig. 2 and *SI Appendix*, Table S2*A*:

$$\text{std}(\hat{\Gamma})_{cmy} = \beta_{ozone}\text{std}(\text{ozone})_{cmy} + \beta_{PM}\text{std}(\text{PM}_{2.5})_{cmy} + g(\text{weather}_{cmy}, \omega) + \theta_{sy} + \nu_{cy} + \sigma_{sc} + \epsilon_{cmy}. \quad \textbf{[2]}$$

The left-hand-side variable $\text{std}(\hat{\Gamma})_{cmy}$ is the estimated adjusted bird count at the county–month–year level, standardized to mean 0 and SD 1 (i.e., a z score) so that coefficient estimates are more easily interpretable. Our variables of interest are $\text{std}(\text{ozone})_{cmy}$ and $\text{std}(\text{PM}_{2.5})_{cmy}$, standardized monthly average concentrations of ozone and fine particulate matter. We use the standardized values so that we can compare the relative magnitudes of β_{ozone} and β_{PM} since the different pollutants have different units of measurement. The coefficients can be interpreted as the SD change in bird abundance from a 1 SD increase in ozone or particulate matter. $g(\text{weather}_{cmy}, \omega)$ is a set of weather variables—average daily temperature and precipitation in a county–year–month—that flexibly control for how weather may affect pollutant concentrations and bird abundance. For temperature, we include 10 bins corresponding to each decile of the temperature distribution; for precipitation, we include 5 bins corresponding to each quintile of the precipitation distribution. θ_{sy} is a set of season-by-year fixed effects that control for common characteristics of seasons in all counties in a year, such as weather or pollution seasonality. ν_{cy} is a set of county-by-year fixed effects that control for unobserved factors common within a county in a given year, such as county-level conservation policies, county average annual trends in pollution, or county-level year-to-year changes in habitat. σ_{sc} is a set of season-by-county fixed effects that control for county-specific seasonal fluctuations in pollution and other factors that may affect bird abundance. This model specification is adapted from ref. 9, which used the exact same set of controls, combined with an IV approach [which we discuss in *Methods*: *The Effect of the NBP (IVs)*], to study the impact of the NBP program on human healthcare use and health outcomes. ϵ_{cmy} is the error term. In all specifications, the estimated SEs are robust to heteroskedasticity and clustered at the state–season level, which allows for arbitrary correlation in the error term within a state–season. We weight observations by the number of checklists in a county–year–month.

Several econometric assumptions are required for estimates of β_{ozone} and β_{PM} to be unbiased and consistent. The first assumption is that $E[\text{std(ozone)}_{cmy} \times \epsilon_{cmy} | \text{controls, fixed effects}] = 0$ and $E[\text{std}(PM_{2.5})_{cmy} \times \epsilon_{cmy} | \text{controls, fixed effects}] = 0$. In words, variation in air pollution is orthogonal to omitted determinants of bird abundance after conditioning on the weather controls and the set of fixed effects we included in Eq. **2**. If an omitted variable is time-invariant (e.g., location) or varying within a county annually (e.g., year-over-year changes in annual migration patterns), it is controlled for by the county-by-year fixed effects. If an omitted variable is a recurring seasonal trend within a county (e.g., breeding behavior in the summer), it is controlled for by the county-by-season fixed effects. If an omitted variable is varying over time in a way that is common across all counties (e.g., federal conservation policy), it is controlled for by the season-by-year fixed effects. For our first econometric assumption to be violated, there must be a variable omitted from the regression that is correlated with both pollution and our estimates of bird abundance $\hat{\Gamma}_{cmy}$ while also varying within a county, within each year, and within each season.

The second econometric assumption is that there is no nonclassical measurement error induced by the effort adjustment procedure such that it becomes correlated with pollution conditional on our ordinary least squares (OLS) controls and fixed effects. We can write the $\hat{\Gamma}_{cmy}$ estimate as a combination of the true log average bird abundance in a county–month–year $\log(\widetilde{\#birds}_{cmy})$ and measurement error $\varepsilon^{\Gamma}_{cmy}$, which may be a function of other variables that we do not control for in estimating Eq. **1**:

$$\hat{\Gamma}_{cmy} = \log(\pi \widetilde{\#birds}_{cmy}) + \varepsilon^{\Gamma}_{cmy}. \qquad [3]$$

Our second econometric assumption states that $E[\varepsilon^{\Gamma}_{cmy} \times \text{std(ozone)}_{cmy} | \text{controls, fixed effects}] = 0$ and $E[\varepsilon^{\Gamma}_{cmy} \times \text{std}(PM_{2.5})_{cmy} | \text{controls, fixed effects}] = 0$. In Eq. **3**, any systematic errors in our estimates of bird abundance that occurs at the county–year level (e.g., we systematically overestimate or underestimate actual bird abundance in Los Angeles County in 2006) will be controlled for by county-by-year fixed effects. If the error systematically occurs at the county–season level (e.g., we systematically overestimate or underestimate actual bird abundance in Los Angeles County every summer), it will be controlled for by the county-by-season fixed effects. If the error systematically occurs across all counties in a given season (e.g., we systematically over or underestimate bird abundance in all counties in summer 2009), it will be controlled for by season-by-year fixed effects. The econometric assumption is thus similar to the previous one: that any omitted variable correlated with actual bird abundance (which will be captured by $\varepsilon^{\Gamma}_{cmy}$ in Eq. **3**) is not varying within a county, within each year, and within each season, after controlling for the weather variables.

Under these econometric assumptions, β_{ozone} and β_{PM} reflect changes in bird abundance given changes in ozone and $PM_{2.5}$. Importantly, these assumptions do not require estimation of the true level of abundance, only that any variation in estimated bird abundance that is correlated with pollution, after conditioning on the weather controls and fixed effects, is not caused by other factors.

While the validity of these assumptions cannot be directly tested, we report two sets of robustness checks in *SI Appendix*, Tables S2 and S3. First, we report β_{ozone} [both OLS estimates and IV estimates as detailed in *Methods: The Effect of the NBP (IVs)*] from a range of alternative fixed effects in the estimation of Eq. **3**, such as state-by-year fixed effects, quarter-of-sample fixed effects, and/or month-of-sample fixed effects. Second, we estimate alternative versions of Eq. **1** using different effort adjustment specifications—such as using raw bird counts per birding checklist without effort adjustments, a Poisson regression without log-linearization, and models with data-driven choice (LASSO) of effort variables—and we report β_{ozone} estimates with these alternative effort adjustment specifications.

In the next section, we describe an IV approach to estimate the impact of the US EPA's NBP on air pollution and bird abundance, as well as the implied effect of air pollution on bird abundance. Unlike the OLS approach, which uses all variation in ozone after parsing out fixed effects and weather controls, the IV approach further restricts to policy-induced pollution variation. Under the assumption that the NBP is a valid instrument for air pollution (i.e., the NBP strongly affects air pollution, and it influences bird abundance only through changes in air pollution), the IV provides consistent estimates of β_{ozone} that are free from omitted variable and classical measurement error concerns.

Methods: The Effect of the NBP (IVs). In Fig. 3 and *SI Appendix*, Table S2*B*, we employ an IV approach. The IV serves two general purposes. First, it tells us the impact of the NBP on air pollution and bird abundance. Second, under the exclusion restriction assumption that NBP affects bird abundance only through its impact on air pollution, the IV approach overcomes potential omitted variable bias and classical measurement error problems we mentioned in the previous section, and it yields consistent estimates, i.e., that the estimator converges in probability to the true parameter value, of the impact of air pollution on bird abundance (36).

In the first stage of the IV we estimate the effect of the NBP on monthly average ozone:

$$\text{std(ozone)}_{cmy} = \beta_{NBP} 1(\text{NBP}_{cmy}) + g(\text{weather}_{cmy}, \omega) + \theta_{sy} + \nu_{cy} + \sigma_{sc} + \xi^{1^{st}\text{stage}}_{cmy}.$$

std(ozone)_{cmy} is the standardized monthly average ozone concentration in county c, month of year m, and year y. $1(\text{NBP}_{cmy})$ is an indicator variable equal to 1 if county c is in a state under NBP regulation and if the current month–year is one where the NBP is in effect.[†] The rest of the variables are identical to the previous equation. $\xi^{1^{st}\text{stage}}_{cmy}$ is the error term. β_{NBP} is the effect of the NBP on ozone concentrations and is the top estimate in Fig. 3*A*.

In the second stage of the IV we estimate the effect of predicted ozone from the previous equation on adjusted bird counts:

$$\text{std}(\hat{\Gamma})_{cmy} = \beta^{IV}_{ozone} \text{std}(\widehat{\text{ozone}})_{cmy} + g(\text{weather}_{cmy}, \omega) + \theta_{sy} + \nu_{cy} + \sigma_{sc} + \xi^{2^{nd}\text{stage}}_{cmy}.$$

$\beta^{IV}{}_{ozone}$ recovers the effect of ozone on bird abundance using variation in ozone concentrations generated by the NBP. Results from this specification are plotted in Fig. 3*B*. Depending on the outcome, $\text{std}(\hat{\Gamma})_{cmy}$ accounts for either total bird counts, waterfowl, land birds, shorebirds, waterbirds, migrants, residents, birds with mass under 16 g, birds with mass 16 to 38 g, birds with mass 38 to 142 g, or birds with mass over 142 g.

The rest of the estimates in Fig. 3*A* come from the reduced form version of the IV, where we regress adjusted bird counts directly on the NBP indicator variable and our set of controls and fixed effects:

$$\text{std}(\hat{\Gamma})_{cmy} = \beta_{NBP} 1(\text{NBP}_{cmy}) + g(\text{weather}_{cmy}, \omega) + \theta_{sy} + \nu_{cy} + \sigma_{sc} + \xi^{\text{reduced form}}_{cmy}.$$

This estimates the effect of the NBP directly on the abundance of different bird groups.

Methods: Trends in the Bird Population under Counterfactual Pollution Levels. In Fig. 4*A*, we compute trends in the total bird population under the counterfactual scenario in which the ground-level ozone concentration is held constant at its 1980 level. The trends are computed using the following steps.

First, we estimate annual trends in ozone concentrations between 1980 and 2018. We begin with monitor-year level ozone concentrations, and we use the following equation to estimate year-to-year changes:

$$\text{Ozone}_{iy} = \sum_{\tau=1980}^{2018} \beta_\tau 1(y = \tau) + \alpha_i + \eta_{iy}.$$

The dependent variable is the average 8-h concentration of ozone at monitor i in year y. Because monitors differ by their initiation date, we include monitor fixed effects (α_i) to account for cross-sectional differences in average pollution levels across monitors in the unbalanced panel. η_{iy} is the error term.

[†]This is essentially a triple difference strategy that compares counties in and out of NBP-affected states, summer season (May through September) and nonsummer season, before and after year 2003. We use 1 y (2002) of pretreatment data, which is the first year when eBird data became available. In unreported analysis, we have confirmed that both our OLS and IV findings are qualitatively unchanged if we drop 2002 data and instead use a double difference strategy (NBP and non-NBP counties, summer and nonsummer seasons). These additional results are available upon request. We prefer the triple difference strategy as it helps address preexisting differences in pollution and bird abundance across the treatment and comparison groups prior to the introduction of the NBP program. Any year-to-year changes in data quality from 2002 are accounted for by county-by-year fixed effects.

Intuitively, the β_τ values (with the regression constant added back) tell us the average annual level of ozone across all monitors by exploiting variation within a monitor and over time.

Next, for each year since 1980, we calculate the percentage difference between the estimated ozone level and the 1980 level: $\left(\frac{\beta_{1980}-\beta_\tau}{\beta_{1980}}\right)\times 100$. The predicted percentage change in bird population—that is, the difference between the observed and counterfactual populations if ozone is held at its 1980 level—is given by

$$\Delta\%(\text{Population}_\tau) = \beta^{IV(\%)}_{ozone} \times \left(\frac{\beta_{1980}-\beta_\tau}{\beta_{1980}}\right)\times 100,$$

where $\beta^{IV(\%)}_{ozone}$ is the percentage change in birds per 1 percentage point change in ozone, an elasticity version of the original β^{IV}_{ozone} estimate on an SD bird – SD ozone scale. We then convert percentage population change $\Delta\%(\text{Population}_\tau)$ to population change $\Delta(\text{Population}_\tau)$ using historical population estimates (24). The counterfactual trends are thus

$$\text{Population}^{counterfactual}_\tau = \text{Population}^{observed}_\tau + \Delta(\text{Population}_\tau),$$

where $\text{Population}^{observed}_\tau$ is the observed population (24). To derive the 95% confidence interval of the counterfactual trends, we repeat the steps above while using the upper/lower 95% confidence interval of the β^{IV}_{ozone} estimates as reported in Fig. 3*B*. Finally, to smooth out noise in the trends estimates due to year-to-year fluctuations in ozone levels, we estimate a locally weighted regression (LOWESS) of $\text{Population}^{counterfactual}_\tau$ on τ and plot the smoothed value in Fig. 4*A*.

Data Availability. Data on states' NBP regulation status have been deposited in https://www.openicpsr.org/openicpsr/project/125422/version/V2/view/ (37).

ACKNOWLEDGMENTS. We thank Trudy Cameron, Chris Costello, David Evers, Andrew Farnsworth, Sonja Kolstoe, Kenneth Rosenberg, and seminar participants at the Cornell Lab of Ornithology for comments and suggestions. We thank Marley Bonacquist-Currin and Angela Zeng for research assistance.

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