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Yuanning Liang
Ivan J. Rudik
Eric Zou
Alison Johnston
Amanda D. Rodewald
Catherine L. Kling

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ABSTRACT

Massive wildlife losses over the past 50 years have brought new urgency to identifying both the drivers of population decline and potential solutions. We provide the first 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 industrial emissions during summer ozone seasons has generated substantial benefits in conserving bird populations. Our results imply that air quality improvements over the past four decades have substantially slowed the decline in bird populations, preventing a loss of 1.5 billion birds, approximately 20 percent of current totals. Our results highlight that in addition to protecting human health, air pollution regulations have previously unrecognized and unquantified conservation co-benefits.

Yuanning Liang
Cornell University
Dyson School of Applied Economics
and Management
yl2544@cornell.edu

Ivan J. Rudik
Cornell University
Dyson School of Applied Economics
and Management
irudik@cornell.edu

Eric Zou
University of Oregon and NBER
Department of Economics
ericzou@uoregon.edu

Alison Johnston
Cornell University
Cornell Lab of Ornithology
aj327@cornell.edu

Amanda D. Rodewald
Cornell University
Cornell Lab of Ornithology
Department of Natural Resources
arodewald@cornell.edu

Catherine L. Kling
Cornell University
Dyson School of Applied Economics
and Management
ckling@cornell.edu

Air pollution is widely recognized as a leading cause of human morbidity and mortality (e.g., Dockery et al., 1993; Pope et al., 2002; Chen et al., 2013; Dominici, Greenstone, and Sunstein, 2014; Schlenker and Walker, 2016; Landrigan et al., 2018; Deryugina et al., 2019). Regulation of anthropogenic emissions, especially the combustion of fossil fuels, is key to alleviating global health burdens from pollution exposure. Air pollution policies, such as the United States' Clean Air Act, have improved ambient air quality, reduced disease incidence, and increased life expectancy (e.g., Chay, Dobkin, and Greenstone, 2003; Deschênes, Greenstone, and Shapiro, 2017). Quantification of the impacts of pollution exposure and the health benefits of regulation has focused predominantly on humans, and has largely ignored the benefits to broader swaths of *fauna*. Many of these other species, especially birds, have respiratory system characteristics that make them more susceptible to air pollution than humans (Rombout et al., 1991; Brown et al., 1997; Cuesta et al., 2005; Sanderfoot and Holloway, 2017). Identifying and measuring a policy intervention's full suite of co-benefits is necessary to accurately reflect its value (Aldy et al., 2020). In the context of air pollution policy, a comprehensive ecosystem valuation of pollution reduction is needed.

We provide the first continental-scale evidence that ground-level ozone negatively affects the American avifauna, a group of animals that are well-known indicators of environmental health and one of the only groups for which detailed abundance data are available (Morrison, 1986; Gregory et al., 2003; Niemi and McDonald, 2004; Burger and Gochfeld, 2014). We then analyze how the introduction of an air quality regulation that was nominally designed for human health protection — the U.S. Environmental Protection Agency's NOx Budget Trading Program (NBP), which limits summertime emissions of ozone precursors from large industrial sources— has provided substantial conservation co-benefits 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 (Newman, 1979; Rombout et al., 1991; Llacuna et al., 1993; Gilmour et al., 2001; Loomis et al., 2013; Sanderfoot and Holloway, 2017; Isaksson et al., 2017; Salmon et al., 2018). Like thousands of other species that have experienced massive declines in abundance and increasing risk of extinction (Grooten and Almond, 2018; Díaz, S. et al., 2020), North American bird populations have declined by a staggering 2.9 billion over the last 50 years (Rosenberg et al., 2019). Our results indicate that these observed declines in bird populations would have been 50 percent larger in the absence of ground-level ozone reductions achieved since 1980. In short, the regulation of ozone has saved 1.5 billion birds, approximately 20% of current populations.

Our analysis is based on bird observations across the contiguous United States between 2002 and 2016, derived from over 11 million eBird checklists (Sullivan et al., 2009). Following Sauer and Link (2019) and Rosenberg et al. (2019), we develop a statistical model to estimate changes in bird abundance over time, based on the counts of birds reported. We adjust the count of birds in each eBird checklist to correct for birder observing effort (e.g. the number of observers per checklist or hours spent observing), and bird detectability (e.g. the trip's time of day) using a fixed effects regression approach (Fig.1). The supplementary information documents the consistency of our findings with other approaches and their robustness to our modeling choices. While these adjustments do not provide absolute levels of bird populations, they do generate data on the relative levels of population, which we refer to as abundance. By studying how the abundance of birds is affected by pollution, we can infer the impacts on total levels by combining our estimates with independent estimates on bird population totals.

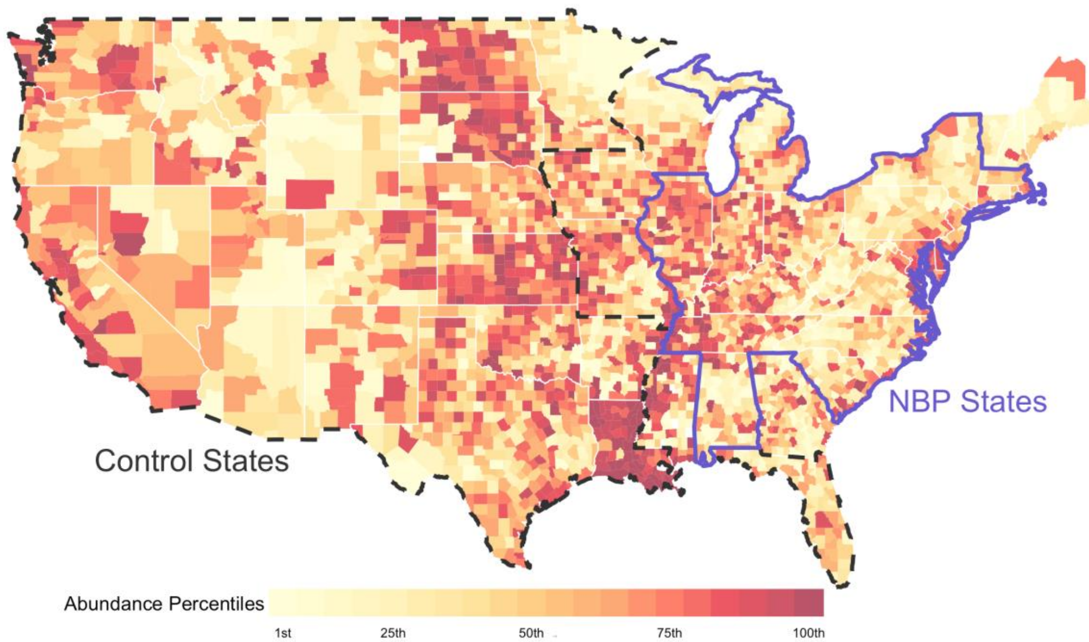
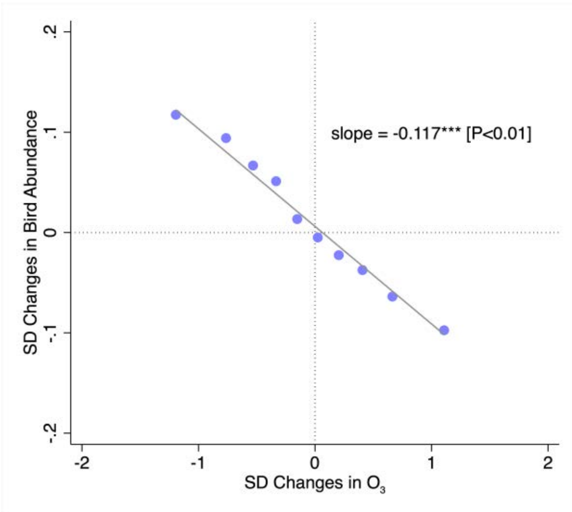


Fig. 1. The spatial distribution of bird abundance. County colors indicate ventiles of bird abundance across all years. Darker colors indicate greater abundance. The set of states outlined in solid blue are those subject to the NO_x Budget Trading Program (NBP). The set of states outlined in dashed black 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 (Deschenes, Greenstone, and Shapiro, 2017). The states omitted from the NO_x Budget Trading Program analysis are Georgia, Iowa, Maine, Mississippi, Missouri, New Hampshire, Vermont, and Wisconsin.

The abundance estimates are combined with the United States Environmental Protection Agency's (U.S. EPA) 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-year timespan. 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 years), 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, land use, impervious surfaces, and other relevant factors. 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 average breeding season bird abundance. Finally, county-season fixed effects control for all county-specific seasonal trends, such as local seasonal variation in bird 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 rich set of fixed effects and weather controls ensures that we are controlling for the multiplicity of geographically and annually varying factors that can affect abundance, leaving variation in pollution that is as good as random. Importantly, the focus on *changes* in abundance rather than *levels* allows us to estimate the abundance-pollution relationship without having to estimate the absolute level of the bird population at any point in time. We discuss estimation details and assumptions in supplementary information.



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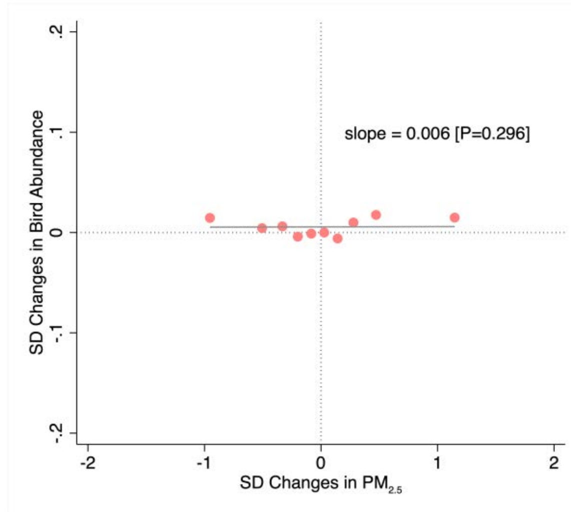


B

Fig. 2. The association between bird abundance and different pollutants. The two panels correspond to ozone (A) and fine particulate matter (B). 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. Standard errors are clustered at the state-season level. 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.

Fig. 2 presents the effects of air pollution on bird abundance. We estimate the effect of ozone (O_3) and fine particulate matter ($PM_{2.5}$) simultaneously in a single regression. We focus on these two pollutants as they are the two most commonly found to cause health and mortality risks. We plot the impact of each pollutant on bird abundance controlling for the other pollutant, fixed effects, and temperature and precipitation in Fig. 2A-B. Ozone is strongly negatively associated with bird abundance (Fig. 2A). A 1 standard deviation (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 trip = 98.4], and the relationship is linear over the range of ozone levels in our dataset. We find no evidence for an association with $PM_{2.5}$. We note that estimating the contemporaneous (i.e., "month-of") effect will pick up the direct effect of pollution on bird health but not longer-term phenomena such as habitat degradation or reduced breeding success. Our estimates are likely a lower bound on the true effect of pollution on bird abundance.

We next investigate the impact of the NO_x Budget Trading Program (NBP) on bird abundance through changes in ozone levels. Designed to improve air quality during the ozone season, the NBP imposes a summertime cap on emissions of ozone precursors from May 1st through September 30th. The NBP has affected approximately 1,000 combustion units in the Eastern and Midwestern U.S. starting in 2003. Fig. 1 shows which states are subject to the NBP and which states we treat as our set of control states. 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 (Deschenes, Greenstone, and Shapiro, 2017). In combination, these comparisons allow us to 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 (Supplementary Information).

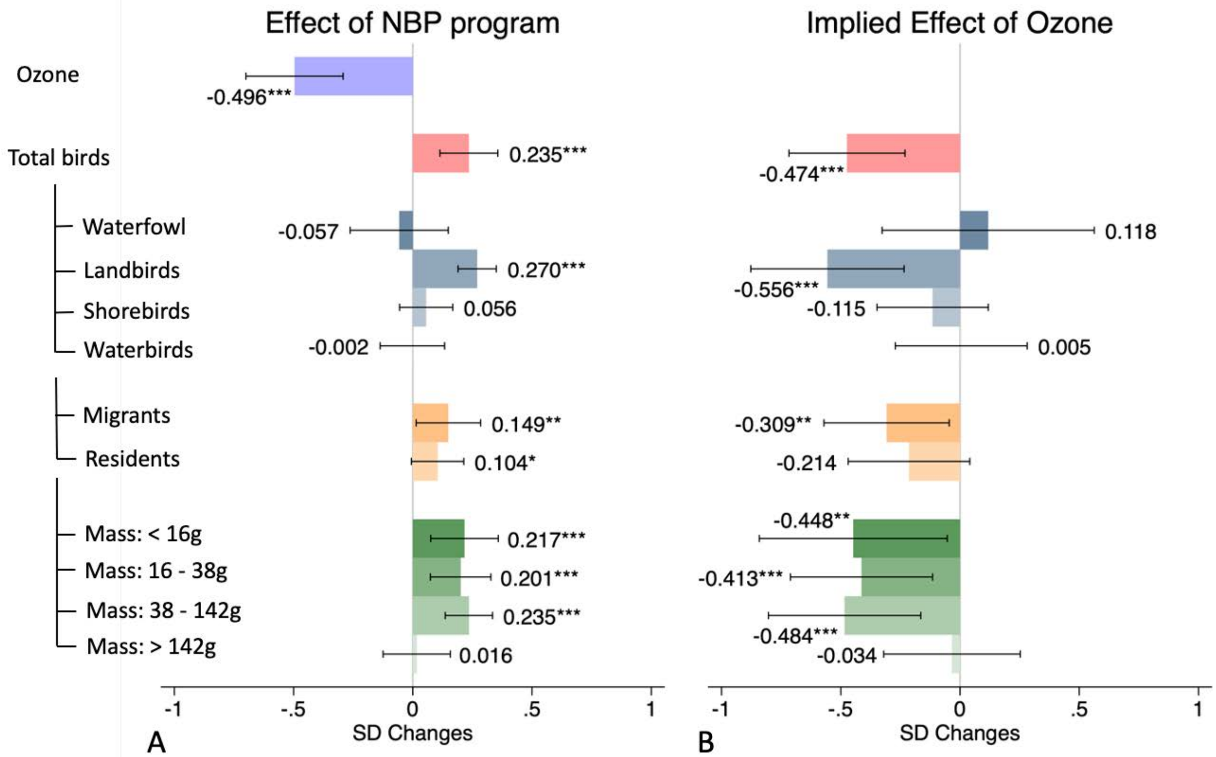
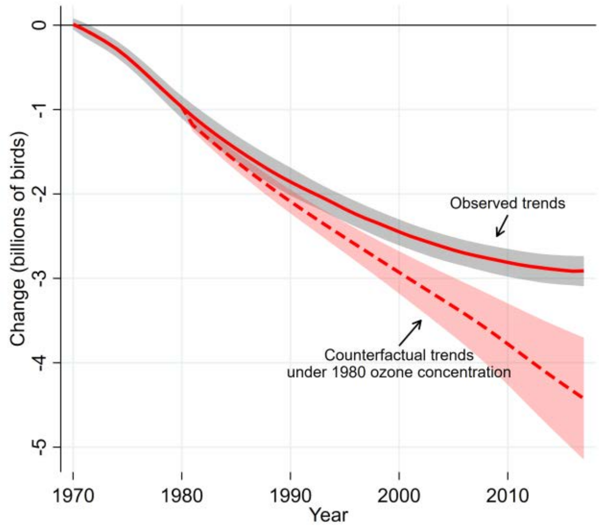


Fig. 3. (A) shows the effect of the NOx Budget Trading Program on ozone and bird abundance in standard deviation units. (B) shows the implied effect of ozone from results in (A). This is done using an instrumental variable approach that combines the effect of the NO_x Budget Program on ozone and the effect of predicted ozone on bird abundance. Birds are classified into groups following Rosenberg et al. (2019). Bird groups by mass are divided into 4 quartiles according to their mass distribution. The black bars indicate 95% confidence intervals. Standard errors are clustered at the state-season level. 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: < 16g) to 22.67 (shorebird). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Figure 3, Panel A shows that 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]. The NBP had a positive effect on landbird 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 weighing less than 142 grams, which corresponds to the first three quartiles of bird mass distribution (less than 16 grams [0.217 SD, $P < 0.01$], 16-38 grams [0.201 SD, $P < 0.01$], and 38-142 grams [0.235 SD, $P < 0.01$]). We do not find evidence that birds weighing more than 142 grams are affected by the NBP [0.016 SD, $P = 0.819$]. This is consistent with the positive effect on landbirds, which mostly fall into the smaller bird groups (85.6% of landbirds in our sample are less than 142 grams). 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 have generated substantial conservation co-benefits for other species. While our study focuses on the impact of the NBP program, it is useful to know what our estimates of the bird abundance-pollution relationship imply about the effect of air quality regulations in general. To assess the magnitude of the impacts of historical air quality regulations, we use our estimates to quantify bird conservation co-benefits from the decline in U.S. ozone concentrations since 1980. We do so in three steps. First, we convert the NBP program's effects on ozone and bird abundance into the *direct* effect of ozone on bird abundance. Our finding in Panel A of Figure 3 shows that a 0.496 SD decline in ozone is associated with a 0.235 SD increase in bird abundance, so that a 1 SD decrease in ozone is associated with a 0.235/0.496 = 0.474 SD increase in bird abundance (Figure 3, Panel B). In the supplementary information, we provide the full description of this Instrumental Variable approach. Second, we simulate a 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 by Rosenberg et al. (2019), which suggest that bird populations declined by 2.9 billion from 1970 to 2018.

Panel A of Figure 4 plots the results from this procedure. 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 (Figure 4, Panel 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. 20% of the current bird population of approximately 7 billion individuals can thus be attributed to improvements in ozone concentrations over the past 40 years. 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.



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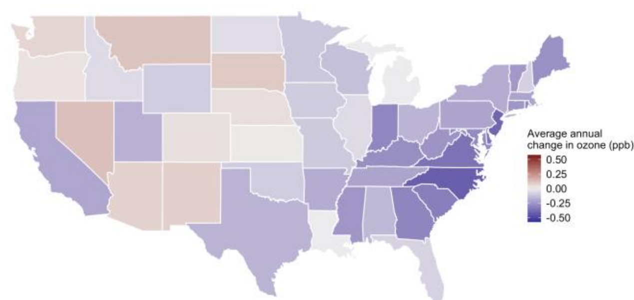

B

Fig. 4. (A) shows the observed trend in bird populations from Rosenberg et al. (2019) 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. (B) shows the state-wide average annual change in ozone concentrations at U.S. EPA monitors between 1980 and 2018. Blue indicates decreases in ozone; red indicates increases in ozone.

Devastating biodiversity and abundance losses are evident even in countries with strong records of conservation. Because birds are well-known ecological indicators, they provide us with useful and readily observable metrics of ecosystem health and biodiversity that can be used to understand the causal factors behind these losses. Our finding that population declines would have been 50% larger in the absence of air pollution improvements suggests that further pollution reductions can play a significant role in reversing widespread declines in wildlife populations, and that conservation co-benefits from air pollution regulation may be substantial.

Existing studies of avian ecosystem service values are too limited to estimate continental scale values, but localized studies suggest they could be substantial (Clucas et al., 2014; Kolstoe and Cameron, 2016; Haefele et al., 2019). These co-benefits are rarely acknowledged in cost-benefit analyses of air pollution regulation, though they are clearly required for accurate assessment of benefits. Fully estimating the economic value of species conservation is imperative to the production of well-designed air pollution policy.

Methods:

Data

Our data on bird counts come from the eBird Reference Dataset (ERD). 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.

Our data on pollution come from the U.S. Environmental Protection Agency's Air Quality System database, which documents ground monitor readings of ambient pollution levels.[1] 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' NOx Budget Trading Program (NBP) regulation status from Deschenes, Greenstone, and Shapiro (2017).

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 trip characteristics is thus important for recovering bird abundance (Boakes et al., 2010; Sullivan et al., 2014; Xue et al., 2016). 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 trip 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 (Sauer and Link, 2011):

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

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

$$\begin{aligned}\#\,\text{birds observed}_{\text{cohdmy}} \\ &= \exp\left(\beta_{\text{d}}\text{hours}_{\text{cohdmy}} + \beta_{\text{n}}\text{number of observers}_{\text{cohdmy}} + \zeta_{\text{h}} + \Gamma_{\text{cmy}} + \varepsilon_{\text{cohdmy}}\right).\end{aligned}$$

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. $\text{hours}_{\text{cohdmy}}$ is the time spent birding by the group, which controls for the length of time spent observing. $\text{number of observers}_{\text{cohdmy}}$ 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

[1] https://aqs.epa.gov/aqsweb/airdata/download_files.html

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 (Sauer and Link, 2011):

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

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 equation (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 equation (1) do not systematically correlate with month-over-month changes in air pollution. As we detail further below, 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 ordinary least squares for results reported in Fig. 2 and SM Table S2 Panel A:

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

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 zero and standard deviation one (i.e., a z-score) so that coefficient estimates are more easily interpretable. Our variables of interest are $\text{std}(\text{ozone})_{cmy}$ and $\text{std}(PM_{2.5})_{cmy}$, 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 standard deviation change in bird abundance from a 1 standard deviation 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 Deschenes, Greenstone, and Shapiro (2017), who used the exact same set of controls, combined with an Instrumental Variable approach (which we discuss below), to study on the impact of NBP program on human healthcare use and health outcomes. ϵ_{cmy} is the error term.

Several econometric assumptions are required for estimates of β_{ozone} and β_{PM} to be unbiased and consistent. The first assumption is that $E[\text{std}(\text{ozone})_{cmy} \times \epsilon_{cmy}|\text{controls, fixed effects}] = 0$ and $E[\text{std}(\text{PM}_{2.5})_{cmy} \times \epsilon_{cmy}|\text{controls, fixed effects}] = 0$. 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 equation (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 non-classical measurement error induced by the effort adjustment procedure such that it becomes correlated with pollution conditional on our 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 equation (1):

$$\hat{\Gamma}_{cmy} = \log(\#\,\widetilde{birds}_{cmy}) + \varepsilon^{\Gamma}_{cmy}. \tag{3}$$

Our second econometric assumption states that $E[\varepsilon^{\Gamma}_{cmy} \times \text{std}(\text{ozone})_{cmy}|\text{controls, fixed effects}] = 0$ and $E[\varepsilon^{\Gamma}_{cmy} \times \text{std}(\text{PM}_{2.5})_{cmy}|\text{controls, fixed effects}] = 0$. In equation (3), any systematic errors in our estimates of bird abundance that occurs at the county-year level (e.g. we systematically over 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 over 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 equation (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 SM Tables S2 and S3. First, we report β_{ozone} (both OLS estimates and Instrumental Variable estimates as detailed below) from a range of alternative fixed effects in the estimation of equation (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 equation (1) using different effort-adjustment specifications – such as using raw bird counts per birding trip *without* effort adjustments, a Poisson regression without log-linearization, models with data-driven choice (Least Absolute Shrinkage and Selection Operator, LASSO) of effort variables – and we report β_{ozone} estimates with these alternative effort-adjustment specifications.

In the next section, we describe an instrumental variable (IV) approach to estimate the impact of the U.S. EPA's NOx Budget Trading Program (NBP) on air pollution, 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 NO_x Budget Trading Program (Instrumental Variables)

In Fig. 3 and SM Table S2 Panel B we employ an instrumental variables (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 (Wooldridge, 2010).

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

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

$\text{std}(\text{ozone})_{\text{cmy}}$ is the standardized monthly average ozone concentration in county c, month-of-year m, and year y. $1(\text{NBP}_{\text{cmy}})$ 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.[2] The rest of the variables are identical to the previous equation. $\xi_{cmy}^{1^{st}stage}$ is the error term. β_{NBP} is the effect of the NBP on ozone concentrations and is the top estimate in Fig. 3A.

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

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

$\beta^{IV}{}_{ozone}$ 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. 3B. Depending on the outcome, $\mathrm{std}(\hat{\Gamma})_{cmy}$ accounts for either total bird counts, waterfowl, landbirds, shorebirds, waterbirds, migrants, residents, birds with mass under 16g, birds with mass 16-38g, birds with mass 38-142g, or birds with mass over 142g.

The rest of the estimates in Fig 3A 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:

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

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. 4A, 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:

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

The dependent variable is the average 8-hour 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

[2] This is essentially a triple difference strategy that compares counties in and out of NBP-affected states, summer season (May through September) and non-summer season, before and after year 2003. We use one year (2002) of pre-treatment 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 non-summer seasons). These additional results are available upon request. We prefer the triple difference strategy as it helps address pre-existing 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.

error term. Intuitively, the β_τ's (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:

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

where $\beta_{\text{ozone}}^{\text{IV}(\%)}$ is the percentage change in birds per 1 percentage point change in ozone, an "elasticity" version of the original $\beta_{\text{ozone}}^{\text{IV}}$ estimate on a 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 provided by Rosenberg et al. (2019). The counterfactual trends are thus

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

where $\text{Population}_\tau^{\text{observed}}$ is from Rosenberg et al. (2019). 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 $\beta_{\text{ozone}}^{\text{IV}}$ estimates as reported in Fig. 3B. 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 $\text{Population}_\tau^{\text{counterfactual}}$ on τ and plot the smoothed value in Fig. 4A.

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Supplemental Information for:
Conservation Co-Benefits from Air Pollution Regulation

Supplementary Text

Summary Statistics

Table S1 displays summary statistics for the data. Since pollution monitors are not in every county we have fewer pollution observations than bird abundance observations.

Robustness and Sensitivity Checks: OLS and IV Fixed Effects

Table S2 shows the robustness of our main results when using different sets of fixed effects to control for different kinds of unobservable variables and using alternative levels of clustering to control for arbitrary within-cluster correlation in error terms. Our results are highly robust to the choice of fixed effects except in the case of month-of-sample and county-by-month fixed effects for the OLS approach where the estimates are attenuated. Our results are also robust to whether we cluster at the summer-state level, or more conservatively at just the state level. In all cases the Kleibergen-Paap F-Statistic suggests the instrument is strong.

Robustness and Sensitivity Checks: Bird Abundance Estimation Method

Table S3 shows the robustness of our OLS and IV results when using alternative approaches to log-linearization when estimating bird abundance. Column 1 shows results from the simplest approach where we use the average number of birds per checklist for each county-year-month without any effort or detectability adjustments. Column 2 corresponds to using equation (1) to estimate bird abundance, where it is estimated using Poisson Pseudo Maximum Likelihood instead of log-linearizing the equation. Column 3 corresponds to our preferred log-linearized approach for comparison. Column 4 uses LASSO to select a set of effort and detectability variables to include. In this approach, we include all possible interactions of linear, quadratic, and cubic functions of hours, numbers of observers, distance covered, and area covered. We also include the set of 24 hour-of-day fixed effects, a dummy variable for if distance covered was 0 indicating that the checklist corresponds to backyard birding, and a dummy variable for if there was just one observer for the checklist. Estimates are strongly negative across all possible specifications for both the OLS and IV approach.

Robustness and Sensitivity Checks: Spatial Displacement

One potential threat to our approach is that we may simply be picking up on spatial displacement where birds move into neighboring counties but are not physically harmed by the pollution itself. If this is the case, we would estimate the same negative relationship as counties with more pollution would see a decline in birds while those with less pollution would see an increase in birds as the birds shifted away from pollution. To address this potential threat to identification of the effect of ozone, we aggregate up to a larger geographical level. We replace our ozone variable above in the OLS approach with the average ozone level of a county and all of its bordering counties. If spatial displacement is occurring we should expect the estimated coefficient to be significantly attenuated. We find very similar result (β_{ozone} = -0.1214, $P < 0.01$), suggesting there is no spatial displacement where birds avoid high ozone areas.

Checklist Statistics and Locations

Figures S1A-S1C show the spatial distribution of checklists and birder effort. Checklist locations and effort are concentrated near population centers, illustrating the potential need for effort-adjusted counts.

Species Maps

Figure S2A-S2F shows abundance maps for six different bird species of different sizes, ranges, and seasons. The abundance distributions match closely to the distributions obtained from alternative modeling approaches like the Spatio-Temporal Exploratory Model (STEM) developed for eBird data, which provided rich geo-spatial details in the abundance estimates. The drawback of using these alternative approaches like STEM in our study context is that they often do not provide time series variation in abundance which is key to our implementation of the “within” (i.e., fixed effects) estimation that exploits month-over-month variation in air pollution.

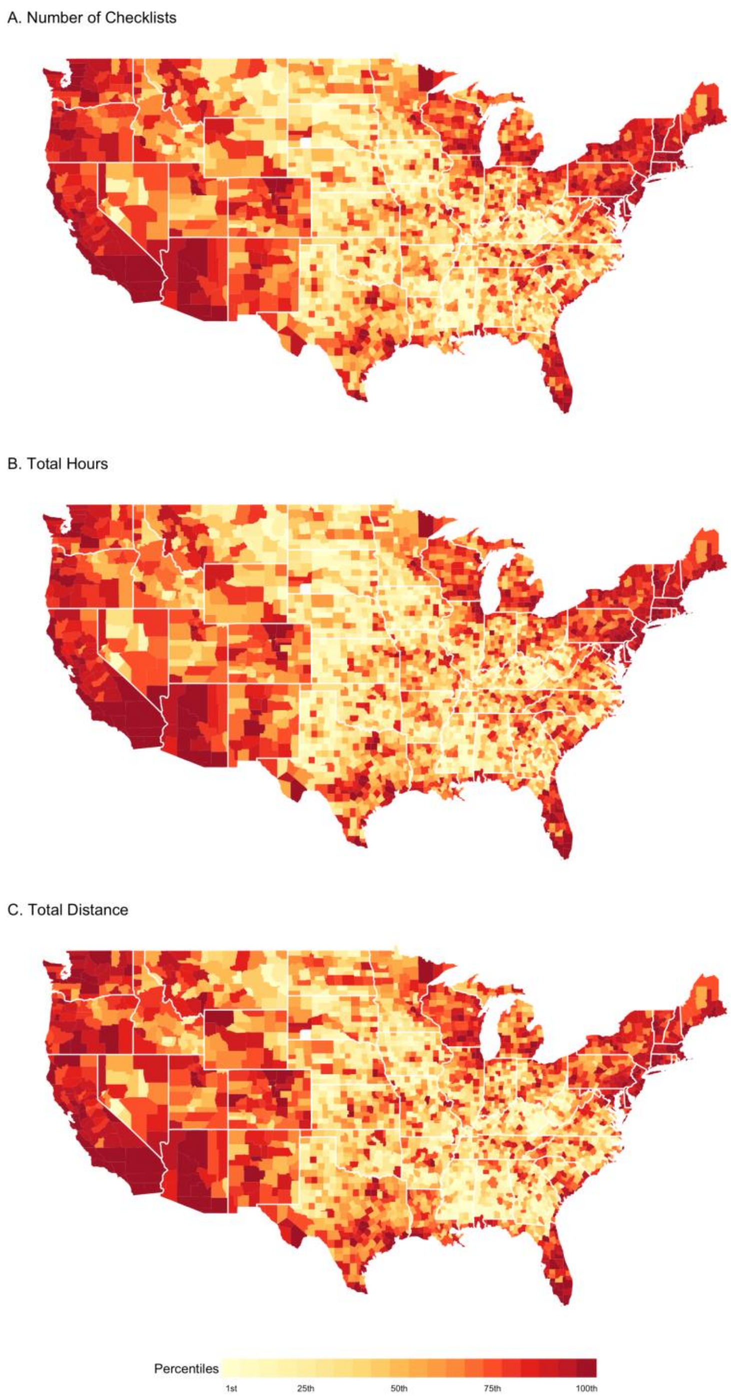

Fig. S1.
The number of eBird checklists (A), total hours spent birding (B) and total distance covered (C) per county in percentiles.

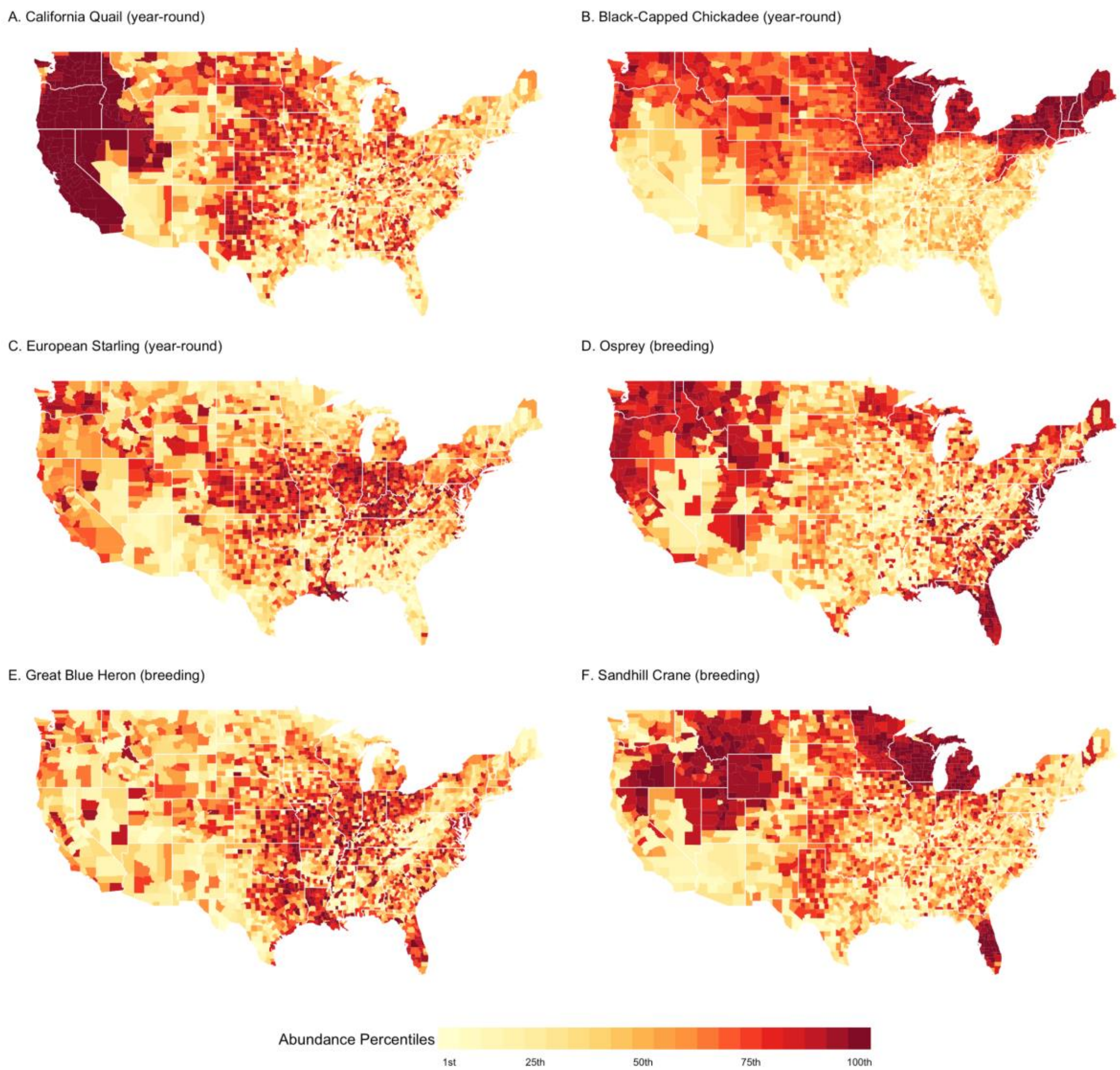

Fig. S2.

Year-round abundance map for California Quail (A), Black-Capped Chickadee (B), European Starling (C). Breeding season abundance map for Osprey (D), Great Blue Heron (E), and Sandhill Crane (F). County colors indicate ventiles of bird abundance across all years. Darker colors indicate greater abundance.

Note: Counties in the lower ventiles often all have effectively zero abundance. For example, outside the top ventile for California Quail, all counties have effectively 0 observations in the checklist and variation in color is just statistical noise.

Summary statistics.

	(1) Observations	(2) Mean	(3) S.D.
Total number of trips	276,685	41.04	113.87
Birding time per trip (hours)	276,685	1.62	1.57
Number of observers per trip	276,685	2.08	3.31
Most common birding time of day	276,685	8 AM	-
Total bird counts per trip	276,685	149.61	227.42
Migrants	279,764	120.14	191.54
Residents	279,663	9.54	10.73
Waterfowl	279,797	21.70	52.36
Landbirds	279,526	59.79	68.78
Shorebirds	280,197	4.07	12.86
Waterbirds	279,934	21.23	53.78
Mass: < 16g	279,853	8.83	11.93
Mass: 16 – 38g	279,780	18.54	23.55
Mass: 38 – 142g	279,575	30.20	43.89
Mass: > 142g	279,879	39.88	82.32
Air Quality Index (AQI)	207,210	40.19	13.27
Ozone	157,091	0.03	0.01
SO_2	105,177	1.89	2.01
CO	78,967	0.36	0.22
NO_2	82,048	9.73	6.01
$PM_{2.5}$	156,742	9.43	3.74

Table S1. The number of observations in column 1 is the number of county-by-year-by-month-level observations for each variable. The analysis drops the largest 1% bird counts within each bird group to eliminate outlier counts.

OLS (Panel A) and IV (Panel B) specifications varying the fixed effects included in the model.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: OLS							
Standardized Monthly Average Ozone	-0.1146***	-0.1166***	-0.0468***	-0.0513***	-0.0055	-0.0079	-0.1166***
	(0.0112)	(0.0121)	(0.0119)	(0.0126)	(0.0077)	(0.0073)	(0.0133)
Observations	93,408	92,072	93,282	91,924	92,498	91,068	92,072
Panel B: NBP IV							
Standardized Monthly Average Ozone	-0.2981	-0.4737***	-0.4463*	-0.4982***	-0.3527	-0.5520***	-0.4737***
	(0.3124)	(0.1240)	(0.2317)	(0.1231)	(0.3151)	(0.1772)	(0.1473)
Observations	116,667	114,810	116,525	114,626	115,557	113,511	114,810
Weather controls	Y	Y	Y	Y	Y	Y	Y
State×Year FE	Y		Y		Y		
County×Year FE		Y		Y		Y	Y
Summer×Year FE	Y	Y					Y
County×Summer FE	Y	Y					Y
Quarter-of-sample FE			Y	Y			
County×Quarter FE			Y	Y			
Month-of-sample FE					Y	Y	
County×Month FE					Y	Y	
IV First Stage F-statistics	19.53	22.65	36.23	23.61	19.20	11.66	15.63

Table S2. The entries in Panel A are the coefficient estimates of the associations between air pollution and bird abundance using ordinary least squares regressions. The entries in Panel B are the coefficient estimates from the triple difference estimator. Column 2 is the preferred specification. Additional control variables are listed at the bottom of this table. Reported standard errors are clustered at the state-season level in column 1-6. In column 7, the reported standard errors are clustered at the state level. The regressions are weighted by the number of checklists in a given county-year-month. The data used is from 2002 to 2016 for 1,900 counties. Both bird count and air pollution variables are standardized to be mean zero, SD one. All regressions use binned temperature and precipitation as weather controls. *** p < .01, ** p < .05, * p < .10.

OLS (Panel A) and IV (Panel B) specifications varying the effort adjustment method.

	(1)	(2)	(3)	(4)
Effort Adjustment Method:	No Adjustment	Poisson	Log-Linear	Post-LASSO Log-Linear
Panel A: OLS				
Standardized Monthly Average Ozone	-0.1324***	-0.1903***	-0.1166***	-0.1284***
	(0.0080)	(0.0101)	(0.0121)	(0.0124)
Observations	104,202	92,121	92,072	92,072
Panel B: NBP IV				
Standardized Monthly Average Ozone	-0.2482**	-0.4337***	-0.4737***	-0.3442***
	(0.1176)	(0.1620)	(0.1240)	(0.1227)
Observations	113,511	114,810	116,667	114,810
Abundance Estimation Model Adj. R^2	—	0.3070	0.2856	0.3491
No. of Effort Variables in Abundance Estimation	—	26	26	(275)27
IV First Stage F-statistics	24.00	22.70	22.65	22.65

Table S3. The entries in Panel A are the coefficient estimates of the associations between air pollution and bird abundance using ordinary least squares regressions. The entries in Panel B are the coefficient estimates from the triple difference estimator. Column 1 is from regressing the number of birds observed on county-month-year fixed effects to estimate bird abundance. Column 2 corresponds to estimating the multiplicative version of equation (1) with Poisson Pseudo Maximum Likelihood to estimate bird abundance. Column 3 is the preferred specification and corresponds to using equation (1) to estimate bird abundance. Column 4 corresponds to equation (1) but uses LASSO with 10-fold cross validation to select the set of control variables to address effort and detectability. All regressions use county-by-year, summer-by-year, county-by-summer fixed effects, and binned temperature and precipitation as weather controls. Reported standard errors are clustered at the state-season level. In column 4, LASSO selected 27 out of 275 possible effort variables. The regressions are weighted by the number of checklists in a given county-year-month. The data used is from 2002 to 2016 for 1,900 counties. Both bird count and air pollution variables are standardized to be mean zero, SD one. *** p < .01, ** p < .05, * p < .10.