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RESEARCH ARTICLE

# The recreational value of birding and crane abundance

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**Abstract**
We estimate the economic value of birding, which is an important ecosystem service produced by bird populations in recreation areas. Our research identifies the link between values and species richness as well as the abundance of the sandhill crane (*Grus canadensis*), which migrates each year through our study area. Sandhill crane stopovers at state and federal wildlife areas can attract many birders. We estimate this nonmarket value using the zonal travel cost method and data from the eBird project on wildlife areas in Indiana. We compare crane counts based on eBird with those from the Indiana Department of Natural Resources (DNR). We find important differences depending on whether we use eBird or DNR counts. On average, birders are willing to pay $28 per trip to sites in the study area and less than $1 per trip to see an additional species, while the value of 1000 more cranes is either about $1 or $10 per trip depending on how abundance is measured.

**Keywords:** Nonmarket valuation; ecosystem services; zonal travel cost method; eBird

## Introduction

This paper measures the economic value of bird watching in Indiana using the travel cost method. We propose that the demand for birding at recreation areas is a function of species richness and bird abundance. We estimate a demand model of birding visits using data from eBird, a citizen science database that tracks species distributions, habitat use and population abundance using checklists submitted by birdwatchers (Sullivan et al. 2014). We use eBird's sampling event and bird sighting databases to generate panel data on trips and site attributes. We also measure population abundance of the sandhill crane (*Grus canadensis*), a charismatic migratory species in the study area. Focusing on crane abundance helps shed light on different abundance measures in valuation studies, because the Indiana Department of Natural Resources (DNR) has a unique weekly crane count program, which allows us to compare eBird-based estimates with those generated by the DNR.

Few valuation topics have been studied as extensively as wildlife, with hundreds of published estimates on the value of hunting, fishing, and wildlife watching (Rosenberger 2016). One common approach applies the travel cost method to a recreation demand model describing site visits (Haab and McConnell 2002; Lupi et al. 2020). Ideally, this model includes species abundance or related measures, such as harvest rates, as site attributes, which allows a researcher to measure the effect of wildlife on demand (e.g. Adamowicz et al. 1997). In practice, though, collecting this data is challenging. Wildlife populations, if they are even measured, may vary little between sites or suffer from collinearity with other site attributes (von Haefen and Phaneuf 2008). Except for applications to recreational fishing, which benefit from the availability of harvest statistics and creel surveys (Melstrom et al. 2015; Hunt et al. 2019), few valuation studies measurably account for the effect of wildlife populations per se on demand (Fenichel et al. 2018). This is a crucial knowledge gap because natural capital and income accounting relies on marginal population values (Fenichel and Abbott 2014). This has pushed researchers toward stated preference methods (e.g. Naidoo and Adamowicz 2005; Grilli et al. 2018), which can identify the effect of wildlife populations on demand but obviously not in situ values for wildlife in settings where such data are missing.

One promising solution to this missing data problem is citizen science in which volunteers enter descriptions of their wildlife experiences to a database. Several of the earliest citizen science efforts focused on documenting bird populations, such as the Audobon Society's Christmas Bird Count, which continues to this day. One increasingly popular project is eBird. Recent research has used eBird to estimate the economic value of birdwatching (Kolstoe and Cameron 2017; Chen et al. 2022; Jayalath et al. 2023). These studies show that researchers can use citizen science data to link economic values to wildlife populations, although the reliability of estimates based on voluntary data remains unclear.

Our research contributes to this literature in three ways. First, it provides information about the value of birdwatching in an area not previously studied. Prior research on the value of birdwatching may not be suitable for policy evaluations or benefit transfer in all contexts, including Indiana or the US Midwest (Newbold and Johnson 2020). Our research could support future recreational policy and benefit transfer applications in this region. Second, we explore differences using eBird and DNR abundance data, which helps shed light on the reliability of voluntary reporting to value wildlife populations. Third, our research provides evidence that demand for wildlife viewing depends on population abundance because we find that birding trips generally increase in locations with more cranes. This addresses a key research gap in the recreation demand and valuation literatures (Fenichel et al. 2018).

## Methods

### *Model*

This section describes the zonal travel cost method, which begins with a demand model of the form:

$$trips_{ijt}/N_i = e^{\rho tc_{ij} + \delta_{jt} + \alpha_j + \tau_t} \tag{1}$$

where $trips_{ijt}$ is the number of trips to site $j$ from residential zone $i$ at time $t$, $N_i$ is the population of birders living in $i$, and $tc_{ij}$ is the travel cost between $i$ and $j$ (Willis and Garrod 1991). In our application, $\delta_{jt}$ describes the effect of time-varying site quality, $\alpha_j$ is a site fixed effect, and $\tau_t$ is a time fixed effect. These fixed effects will control for site

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attributes or time-varying shocks not explicitly included in the model, such as the presence of a lake, parking, or weather. Our application pools trips across several sites and characterizes time-varying site quality using measures of species richness and crane abundance.[1]

We modify eq. (1) so that quantity demanded is trips per zone rather than trips per zonal resident:

$$trips_{ijt} = e^{ln(N_i)+\rho tc_{ij}+\delta_{jt}+\alpha_j+\tau_t} \tag{2}$$

which we estimate using Poisson regression. This means that we can interpret the parameters in terms of changes in trips rather than trips per resident. Note that eq. (2) takes the form of a count data model, which is similar to traditional single-site recreation demand models (Parsons 2003). We briefly discuss this similarity further below. Although it is common in the recreation demand literature to estimate count data models using negative binomial regression to avoid problems with "overdispersion" (Holmes and Englin 2010), this is not necessary. Trips do not need to be Poisson distributed for the regression to produce consistent parameters, which are robust to distributional misspecification. Overdispersion can, however, severely bias Poisson standard errors. We correct this bias by reporting "robust" standard errors using the sandwich estimator recommended by Wooldridge (1999).[2]

Our approach identifies the effect of site attributes in $\delta_{jt}$ because we estimate eq. (2) using data pooled across months and sites. The zonal method also implicitly pools trip data across individuals coming from the same residential location. In contrast, traditional single-site demand models use data on individuals' seasonal trips. This allows researchers to identify the effect of travel cost and individual characteristics on demand but not site attributes. So, it is not possible to value quality changes with traditional single-site demand models. However, researchers can value attributes by pooling trips over time, when quality changes, or by stacking visitation and attribute data from multiple sites (Parsons 2003). Our approach does both.

We estimate several specifications for $\delta_{jt}$. The first is

$$\delta_{jt} = \beta_1 richness_{jt} + \beta_2 anycranes_{jt} \tag{3}$$

where $richness_{jt}$ is the count of species present and $anycranes_{jt}$ is an indicator that equals one if sandhill cranes are among those present and zero otherwise. We follow Kolstoe and

[1]As pointed out by a reviewer, there are other methods to estimate values related to birding. Contemporary valuation research prefers discrete choice models based on random utility maximization (RUM) theory, which typically identifies the effects of site attributes using variation in a large number of substitute sites. Recent studies on the value of birding apply RUM models to revealed preference data (Kolstoe and Cameron 2017; Jayalath et al. 2023). Other research uses count data models of individual trips (Edwards et al. 2011). Both RUM and count data models use the travel cost method to value trips. In addition, many researchers have used contingent valuation (Bowker and Stoll 1988; Hvenegaard et al. 1989; Heberlein et al. 2005; Stoll et al. 2006; Lee et al. 2009). There is also a literature on the expenditure value of birding (Eubanks and Stoll 1999; Eubanks et al. 2004; Callaghan et al. 2018). We use a count data model and the zonal travel cost method because we can summarize individual trips as a zonal count and the study area is limited to a narrow list of sites. Although we do not estimate a RUM model, there is a link between our approach and utility theory (Guimaraes et al. 2003; Schmidheiny and Brülhart 2011).

[2]Note that fixed effects negative binomial regression applied to panel data can fail to control for individual effects (Guimarães 2008). We avoid the negative binomial for this reason, although we do note that in trial regressions it produced similar parameters to the Poisson.

Cameron (2017) and Jayalath et al. (2023) by including the number of species as a site attribute.[3] The parameter $\beta_1$ measures the average effect of an additional species on trips per zone, while the parameter $\beta_2$ measures the contribution of cranes relative to other species. A positive $\beta_1$ would indicate that trips increase with the number of species, and a positive $\beta_2$ would indicate an even larger increase occurs if cranes are present. Put differently, $\beta_2 > 0$ implies that cranes have a larger positive effect than the presence of another species, on average, while $\beta_2 < 0$ means that cranes have a smaller effect than another species.[4]

The next specification replaces the $anycranes_{jt}$ indicator with a measure of abundance,

$$\delta_{jt} = \beta_1 richness_{jt} + \beta_2 cranes_{jt}. \tag{4}$$

where $cranes_{jt}$ is the population of cranes at $j$ at time $t$. Crane abundance could affect trips if birders prefer sites with more rather than fewer cranes, in which case $\beta_2 > 0$. Of course, by modeling this preference linearly, eq. (4) implicitly assumes that abundance has a constant marginal effect. The third specification allows for nonlinear effects by separating abundance into four bins,

$$\delta_{jt} = \beta_1 richness_{jt} + \beta_2 \Phi_{25jt} + \beta_3 \Phi_{50jt} + \beta_4 \Phi_{75jt} + \beta_5 \Phi_{100jt}. \tag{5}$$

where $\Phi_{pjt}$ is an indicator for population in quartile $p$, conditional on the presence of cranes. Parameters $\beta_2$ through $\beta_5$ can shed light on the effect of cranes at different population levels. For example, $\beta_5 = \beta_4 = \beta_3 > \beta_2 > 0$ implies that the effect of abundance saturates when the population surpasses the median population at sites.

In the application that follows, we estimate equations (2)–(5) twice. First, we use measures of richness and crane abundance generated from eBird. Second, we replace the abundance variable with data from the Indiana DNR. The goal of eBird is to measure populations that organizations do not have the resources to track professionally, but using volunteers could lead to bias. Comparing DNR and eBird crane counts can shed light on the accuracy of transferring models and welfare estimates based on one type of data to another.

We can use the parameters to calculate consumer surplus for site access and quality changes. The formula for access value, expressed in terms of willingness to pay (WTP), is

$$WTP = -\frac{1}{\rho} \tag{6}$$

which is denominated in dollars per trip (Parsons 2003). In our application below, we also estimate the value of a one-unit increase in species, $WTP_{ijt} = -\frac{1}{\rho}\left[e^{\beta_1} - 1\right]trips_{ijt}$, and a 10% increase in the number of species, $WTP_{ijt} = -\frac{1}{\rho}\left[e^{\beta_1 richness_{ijt} \times 0.1} - 1\right]trips_{ijt}$, where the terms in brackets measure the proportional change in trips in the location and time period that experienced the change. Denominated per trip, the value of a one-unit increase is

$$WTP = -\frac{1}{\rho}\left[e^{\beta_1} - 1\right], \tag{7}$$

[3]In addition, Kolstoe and Cameron (2017) and Jayalath et al. (2023) allow for individual-specific and seasonal heterogeneity in the effect of species richness. Similar to Jayalath et al. (2023), we found in trial regressions some evidence of seasonal heterogeneity, with the smallest richness parameters in winter and the largest parameters in summer. These results are available upon request. We also note that Jayalath et al. (2023) find that there can be discrete effects associated with the presence of endangered birds.

[4]This interpretation also depends on whether $|\beta_2| < \beta_1$ or not. In particular, $\beta_2 < 0$ and $|\beta_2| > \beta_1$ means that trips decrease when cranes are present and hence birders have a distaste for cranes.

and for a 10% increase,

$$WTP = \sum\nolimits_i \sum\nolimits_j \sum\nolimits_t \frac{1}{\rho}\left[e^{\beta_1 richness_{ijt} \times 0.1} - 1\right]/\Psi, \tag{8}$$

where $\Psi$ is the number of observations. Additionally, we use the form of eq. (7) and eq. (8) to value unit and percentage changes in cranes when the effect of abundance is measured as in eq. (4).

*Study area*

We apply the demand model to three areas in Indiana that experience large increases in migratory species in the fall and spring. One of these species, the sandhill crane, is popular with birders because it travels in large flocks and has a loud, distinct call. Like the endangered whooping crane (*Grus americana*), sandhill cranes are large, standing about three feet tall with a wingspan of six feet, although unlike their biological cousin, they are not at risk of extinction. Public locations in Indiana with ideal habitat for cranes include the Jasper-Pulaski, Goose Pond, and Muscatatuck wildlife areas (A. Phelps, DNR, personal communication). These are also the properties where the Indiana DNR operates crane counts, and thus where we apply the demand model. The remainder of this section briefly describes these areas.

Jasper-Pulaski is a state fish and wildlife area that protects about 8200 acres of habitat in northwest Indiana. Developed in the 1930s as a hunting and fishing preserve, large parts of the wildlife area are now managed by the Indiana DNR as waterfowl habitat. The site includes a crane observation platform and viewing scopes. DNR biologists have recorded migration events that can bring as many as 30,000 cranes to the area on some days. The media attention this generates makes this one of the best-known birdwatching locations in the state, particularly during the fall (Greene 2020; Zorn 2021).

Goose Pond is a state fish and wildlife area that includes about 9000 acres of prairie and marshland in southwest Indiana. After purchasing the property in 2005, the DNR restored a wetland complex that had originally been drained for farming. In 2016, the DNR opened a visitor center with an observation deck. The area provides habitat for a variety of wildlife, with over 260 different types of birds documented. This makes it popular with birdwatchers year-round (A. Phelps, DNR, personal communication).

Muscatatuck National Wildlife Refuge covers 7700 acres in south central Indiana. Unlike the other two sites, Muscatatuck is a federally protected area. The US Fish & Wildlife Service manages the site primarily as migratory waterfowl habitat and for wildlife viewing. Visitors have access to hiking trails and a driving loop. Similar to Goose Pond, the area provides ideal habitat for a large number of species that attracts birdwatchers throughout the year, while the number of sandhill cranes during the migration season is comparable to Jasper-Pulaski (Freedman 2023).

Although located in different areas, Jasper-Pulaski, Goose Pond and Muscatatuck are similar in terms of size and habitat, which consists of a mix of wetland, prairie, and bottomland forest. This similarity makes them potential substitutes for birdwatchers and good candidates for a pooled site demand model. To be clear, there are many other wildlife viewing areas in Indiana popular with birders. One concern is that excluding potential substitutes from the model could lead to bias. However, in Appendix A, we show that expanding the group of sites does not qualitatively affect the estimates. This suggests that our conclusions are robust to a larger number of choice alternatives. In fact, as we discuss below, WTP for site access and species richness from the model compare favorably with estimates from existing, more complex RUM models of birdwatching in the literature.

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## Data

The primary data set comes from eBird, which tracks bird observations recorded through a mobile application. After an observation or "sampling event," volunteers submit a checklist that indicates whether birding was the primary purpose and the birds they identified by sight or sound. We downloaded the 2022 eBird database in two files: eBird data (EBD) and sampling event data (SED). The EBD records the species data from sampling events, including common and scientific name, number observed, location details, travel protocol, date, an observed identifier, a group identifier, and a sampling event ID code. The location data specifies state, county, and an eBird locality. Localities are geocoded and classified as either personal or hotspot. Personal localities, which are observer-specific, can range from an apartment balcony to the side of a county road. Hotspot localities are public areas frequently used by birders. Travel protocol records whether a volunteer made an observation while traveling, stationary, or incidentally. We used this data to drop incidental trips.[5] The SED contains the same variables as the EBD except that it is organized by checklist rather than species, which we used to zero-fill crane counts, as described below.

We used hotspots, the three wildlife areas and county boundaries to define sites in the model. We identified five hotspots in Jasper-Pulaski, eight in Goose Pond, and sixteen in Muscatatuck. We followed eBird's recommendation to group hotspots in the same vicinity by aggregating those in the same wildlife area and county. This is because wildlife areas can have several hotspots with similar coordinates (e.g. different trails). Our approach ensures that localities in the same vicinity are grouped to a common site. This produced two sites for Jasper-Pulaski, one for Goose Pond, and three for Muscatatuck.

Next, we measured trips by counting the number of sampling events in the SED. To separate trips by residential zone, we assigned each event to a ZIP code tabulation area in three steps nesting an iterative procedure. The first step linked a sampling event to the ID code assigned to each eBirder. In the second step, we searched through sampling events for personal localities the eBirder named "Home" or included "home," "residence," etc. in the name. We used the latitude-longitude for this locality as the eBirder's residential location. For the remainder, though, we had to interpolate home locations, using either the coordinate of an eBirder's modal personal locality or, for anyone who never submitted a personal locality, the average latitude-longitude of visited hotspots.[6] This is necessary to avoid skewing the sample toward birders willing to identify their home, which could exacerbate bias. Of course, the interpolation itself could lead to bias, and in Appendix B we present estimates after applying a more conservative interpolation procedure. Third, we assigned each sampling event to the corresponding observer's home location and hence ZIP code. ZIP codes not assigned as a residential location for any Indiana eBirder were dropped from the model. Finally, we summed trips by ZIP code and site in each biweekly period.

An important concern, as noted by Kolstoe et al. (2018), is that eBird volunteers self-report and may not be representative of the population overall. Recent research appears to

[5]Dropping incidental trips is consistent with Lupi et al.'s (2020) recommendation to focus on trips whose primary purpose is recreation. Note that eBird defines traveling and stationary trips as primarily for the purpose of birdwatching. Traveling refers to an event in which, at the destination, the observer walks, drives, or boats more than 100 feet and generally less than five miles. In our data, 30% of trips are stationary, 50% are traveling, and 20% are incidental.

[6]The idea here is that an eBirder's residential location should lie near the center of their birding activity. We dropped eBirders who submitted fewer than three sampling events without naming their home, to limit bias from this imputation.

validate this concern. Cameron and Kolstoe (2022) find that a representative sample were less willing to consider traveling to more distant sites compared with eBird volunteers. Similarly, Rosenblatt et al. (2022) conclude that eBird volunteers are more avid than the average birder. Volunteers also have a higher average income relative to the general population (Grade et al. 2022), although birders on the whole tend to have above-average incomes (Carver 2019). We address this concern using weights. First, we correct for differences in representation by geography by weighting the data by the number of households relative to the number of eBirders in a ZIP code. This stratifies the sample so that it matches the population in each zone. Second, we use the income distribution from a nationally representative sample of birders (Carver 2019) to construct sample selection weights that account for response differences by income. Finally, we use statistics on the eBird volunteering rate as a function of birdwatching distance (Cameron and Kolstoe 2022) to construct zonal-site weights that limit the share of individuals in a zone who would travel to more distant locations.[7]

Next, we calculated species richness and crane abundance. After pooling the hotspot data by site, we counted the number of unique species observed in the EBD in each biweekly period, which includes the days up to the 15$^{th}$ or after the 15$^{th}$ of each month. We then calculated the abundance of sandhill cranes by merging the EBD and SED data sets. Most volunteers who reported seeing cranes counted the number observed. We assume an observer saw no cranes if their checklist appeared in the SED but they reported no cranes in the EBD. Thus, if a sampling event occurred at one of the hotspots (in the SED) in our study area but did not count any sandhill cranes (in the EBD), we assigned it a count of zero.[8] In hotspots where volunteers reported different numbers at the same time, we used the median. We then measured the eBird crane population by summing the (median observed) number of cranes across hotspots at a site. We explore alternative methods of measuring abundance in the discussion section below.

We filled in missing species richness and crane abundance data using imputation. While the study area includes hundreds of sampling events, occasionally a site had no sampling events in a biweek. We imputed these data by applying Poisson regression to the model $s_{jt} = \exp(\lambda_j + \mu_t)$, where $s_{jt}$ is either $richness_{jt}$ or $cranes_{jt}$, $\lambda_j$ is a county effect, and $\mu_t$ is a time effect. To leverage observations from other hotspots in the same counties as our study sites, which could correlate with species richness and crane abundance, we estimated the model using data on all $j$ in Indiana, rather than just the sites in the model.

We aggregated the DNR crane counts to the same biweekly periods as the eBird data. Property staff perform these counts weekly during the migration season, which runs from the last week of August to the last week of January. The counts are made when cranes leave their roost in the morning. After estimating the number remaining in the roost, the counts are aggregated across staff. We did not impute the DNR's missing values as we did for eBird because the DNR counts appeared complete during the migration season. To address any concerns that the timing of this season could skew the comparison between eBird and DNR data, one of our robustness checks restricts all of the eBird observations to the migration season.

We calculated travel cost using latitude-longitudes, fuel and mileage-related depreciation costs, and an estimate of the value of travel time. We calculated travel

[7]Cameron and Kolstoe (2022) show that eBird volunteers but not birders in general are willing to travel more than 100 miles on a typical trip. They also show 11% of birders use eBird. We use these statistics to reweight the data so that the number of households in a zone willing to take a trip declines 89% if the distance is more than 100 miles.

[8]We set the count to missing if the sampling event reported seeing but did not count sandhill cranes.

**Table 1.** Summary statistics of variables used in the pooled site demand model

| Variable | Description | Mean | St. dev. | Min | Max |
|---|---|---|---|---|---|
| Trips | Count of trips between ZIP code and site. | 0.017 | 0.187 | 0 | 11 |
| Birders | Count of eBirders in ZIP code. | 3.965 | 6.844 | 1 | 122 |
| Distance | Travel distances in miles; used in the travel cost calculation | 118.711 | 59.011 | 2.2 | 276.1 |
| Time | Travel time in minutes; used in the travel cost calculation | 148.919 | 66.785 | 4.5 | 382.5 |
| Income | Median ZIP code income; used in the travel cost calculation | 64245.759 | 19161.709 | 20755 | 250001 |
| Travel cost | Travel cost | 117.382 | 57.577 | 3 | 540 |
| Richness | Species richness measured as number of unique species. | 42.823 | 35.276 | 1 | 170 |
| Cranes | Crane abundance based on eBird; summed across hotspots at site, measured in thousands of birds. | 0.206 | 0.707 | 0 | 5.5 |
| Cranesany | =1 if one or more cranes present and 0 otherwise, based on eBird. | 0.528 | 0.499 | 0 | 1 |
| Cranes | Crane abundance based on Indiana DNR; summed across hotspots at site, measured in thousands of birds. | 6.570 | 9.955 | 0 | 31.5 |
| Cranesany | =1 if one or more cranes present and 0 otherwise, based on Indiana DNR. | 0.769 | 0.421 | 0 | 1 |

The number of observations is 77,760 except that the DNR cranes data has 35,100 observations.

distances $dist_{ij}$ and travel times $time_{ij}$ between the centroid of each ZIP code $i$ and the average latitude-longitude of site $j$'s hotspots. We used AAA's 2022 *Your Driving Cost* report to calculate the cost per mile of driving, by subtracting the average cost of driving 10,000 miles from the cost of driving 15,000 miles, and then dividing by 5,000. We then estimated the value of travel time by dividing the median household income $income_i$ in a ZIP code by 2000 multiplied by one-third, which assumes working 2000 hours in a year and that travel time is valued at one-third the wage rate (Parsons 2003). Finally, we calculated travel cost using the formula:

$$tc_{ij} = 2\left[dist_{ij} \times 0.2718 + \frac{1}{3} \times time_{ij} \times \left(\frac{income_i}{2000}\right)\right]$$

In Appendix C, we present results after setting the value of travel time equal to one-half the wage rate.

Table 1 summarizes the data. Between six sites, 24 biweekly periods, and 540 ZIP codes, there are 77,760 observations. The average number of trips is 0.017; this is less than one because there are zero trips in most ZIP code-site-biweek combinations. The average travel cost is $117 across all observations, or $75 after weighting on trips. Using eBird, the average number of species is 43 and the average crane count is 206. The average eBird crane count is substantially less than the maximum, which exceeds 5,000. The average DNR count is 6,570 cranes and the maximum is 31,536.

Before turning to the results, we should clarify that a trip in our data is taken primarily for the purpose of birding but could include multi-destination trips. Lupi et al. (2020) recommend excluding multi-destination trips. Unfortunately, eBird checklists do not indicate whether a single trip covered multiple sites. However, we can infer multi-destination trips by identifying eBirders who submitted more than one checklist on the same day. Twenty-three percent of trips could be multi-destination following this approach. Appendix D presents estimates after dropping these trips, which we find does not qualitatively affect the results.[9]

## Results

Table 2 shows the parameters from each of the three specifications applied to the eBird data. We refer to these as the benchmark results. Note that in each case we estimated the coefficient on ln(birders) – that is, $ln(N_i)$ in eq. (2) – rather than fixing it to one, although the estimate indicates that we cannot reject the hypothesis that it is one. Turning to the other estimates in column (1), the travel cost parameter indicates that for a \$1 increase there is a 100% × (exp(−0.036) − 1) = −4% change in trips per zone. The species richness parameter implies that an additional species is associated with 2% more trips per zone. The crane indicator is not significantly different from zero, so we cannot reject the possibility that cranes have the same effect on trips as other species on average.

Now consider the estimates in column (2). When we replace the dummy variable for crane presence with the variable for cranes, the parameters on the other variables are largely unchanged. In particular, the species richness parameter continues to imply that an additional species is associated with about 2% more trips. The parameter on cranes is positive and statistically significant, implying that an additional 1000 cranes is associated with 39% more trips per zone.

Column (3) replaces the cranes variable with four indicators. In contrast to the linear effect in column (2), which implies that visitation scales with abundance, this regression provides little evidence that visitation is greater at sites with more cranes. None of the indicators are individually significantly different from zero, and a test of joint significance fails to reject the null hypothesis that all are zero ($p = 0.978$).

Table 3 presents the results when we use the DNR data. In column (1), the parameter on ln(birders) is not significantly different from 1, the travel cost parameter implies that a \$1 increase is associated with 3% fewer trips per zone, and the richness parameter indicates that an additional species is associated with 2% more trips per zone; all of which are similar to the benchmark estimates in Table 2. Furthermore, the crane indicator remains insignificantly different from zero. Turning to the estimates in column (2), the positive and significant parameter on cranes implies that an additional 1000 cranes is associated with about 1% more trips per zone. This effect is an order of magnitude smaller than its counterpart in Table 2. We also see a notable change in column (3), where the first indicator is now significantly negative while the fourth indicator is significantly positive, which implies that birders visit sites more (less) frequently when the crane population there is toward the upper (lower) end of the distribution.

Let us take the estimates for the second specification, which appear in column (2) of Tables 2 and 3, as the baseline. The travel cost parameter in Table 2 indicates that average birder WTP for a trip is −1/(−0.036), or \$27.67. This implies that birders are willing to pay

[9]A slight drawback with defining multi-destination trips based on same-day checklists is that a birder could have visited one site, returned home, and then visited another site that day, for two separate, single-destination trips.

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**Table 2.** Results of the demand model using eBird for species richness and crane abundance

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(birders) | 1.110*** | 1.110*** | 1.110*** |
| | (0.062) | (0.066) | (0.062) |
| Travel cost | −0.036*** | −0.036*** | −0.036*** |
| | (0.003) | (0.003) | (0.003) |
| Richness | 0.016*** | 0.021*** | 0.016*** |
| | (0.005) | (0.005) | (0.005) |
| Cranesany | −0.012 | | |
| | (0.203) | | |
| Cranes | | 0.331*** | |
| | | (0.074) | |
| Cranes (<p25) | | | −0.0921 |
| | | | (0.368) |
| Cranes (p25-p50) | | | 0.077 |
| | | | (0.250) |
| Cranes (p50-p75) | | | −0.082 |
| | | | (0.238) |
| Cranes (>p75) | | | 0.048 |
| | | | (0.339) |
| Constant | −3.852*** | −3.783*** | −3.297*** |
| | (0.488) | (0.500) | (0.520) |
| Site fixed effects | Yes | Yes | Yes |
| Biweek fixed effects | Yes | Yes | Yes |
| Log likelihood | −696412.8 | −690331.5 | −696251.2 |
| R-squared | 0.316 | 0.322 | 0.317 |
| Observations | 77,760 | 77,760 | 77,760 |

Robust standard errors in parentheses below parameters. *, **, and *** indicate significance at 10, 5 and 1% levels. R-squared calculated as the squared correlation coefficient between the actual and predicted number of trips.

$27.67 more than they spend in travel costs to visit one of the sites in the study area. The mean number of trips by an eBirder to these sites is 1.435, which implies an annual consumer surplus of $39.76 per birder. In Table 3, the travel cost parameter implies WTP of –1/(–0.033), or $30.30, which is just slightly larger than the benchmark WTP per trip. Next, we calculate consumer surplus for four hypothetical changes in birding quality. Applying eq. (7) to the benchmark estimates, we find birder WTP is $0.58 per trip for one additional species and $10.84 per trip for an additional 1000 cranes. Using eq. (8), the same results imply that on average birder WTP is $2.64 per trip for 10% more species and $0.20

**Table 3.** Results using Indiana DNR crane abundance during migration season

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(birders) | 1.083*** | 1.083*** | 1.083*** |
| | (0.098) | (0.098) | (0.097) |
| Travel cost | −0.033*** | −0.033*** | −0.033*** |
| | (0.004) | (0.004) | (0.004) |
| Richness | 0.018** | 0.015* | 0.022** |
| | (0.008) | (0.008) | (0.008) |
| Cranesany | −0.055 | | |
| | (0.399) | | |
| Cranes | | 0.036** | |
| | | (0.016) | |
| Cranes (<p25) | | | −1.159** |
| | | | (0.537) |
| Cranes (p25-p50) | | | 0.213 |
| | | | (0.603) |
| Cranes (p50-p75) | | | 0.045 |
| | | | (0.530) |
| Cranes (>p75) | | | 1.219*** |
| | | | (0.491) |
| Constant | −3.373*** | −3.423*** | −4.253*** |
| | (0.671) | (0.646) | (0.749) |
| Site fixed effects | Yes | Yes | Yes |
| Biweek fixed effects | Yes | Yes | Yes |
| Log likelihood | −319833.3 | −318252.6 | −312127.7 |
| R-squared | 0.279 | 0.283 | 0.296 |
| Observations | 35,100 | 35,100 | 35,100 |

Robust standard errors in parentheses below parameters. *, **, and *** indicate significance at 10, 5 and 1% levels. R-squared calculated as the squared correlation coefficient between the actual and predicted number of trips.

per trip for 10% more cranes. Applying the same welfare calculations to Table 3, WTP is \$0.45 per trip for an additional species, \$1.09 per trip for an additional 1000 cranes, \$2.04 per trip for 10% more species and \$0.73 per trip for 10% more cranes. Keep in mind that these are experience values and not nonuse or existence values. The total value from additional species or cranes could be much larger after accounting for the values held by those who do not visit the study area.

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## Discussion

The results confirm the important role that species presence plays in the demand for recreation. The positive and significant effect of species richness provides evidence that birdwatchers are significantly more likely to visit sites with more birds. As the number of species increase at a site, so does the frequency and value of birding trips. When we allowed the effect of crane presence to vary systematically from species richness, the estimate was statistically indistinguishable from zero. This insignificance held regardless of whether we used crane data from eBird or the Indiana DNR. Note that this does not mean the effect or value of cranes is zero. Taken as a whole, these results indicate that birders like additional species, including cranes, but that the presence of cranes is not more influential than any other species, on average.

The results also provide evidence that populations matter. The positive and significant relationship between the number of sandhill cranes and trips turned up using both eBird and Indiana DNR counts. The effect lost significance when we modeled trips as a function of four abundance ranks using the eBird counts, which suggests the relationship in this case could be spurious or driven by outliers. However, using the DNR counts, the rank effects moved sequentially from significantly negative, to insignificant, to significantly positive. This sign pattern implies that, conditional on an additional species, the expected change in trips is smaller when the addition is a small population of cranes – in such a case, birders prefer a different species on the margin – about the same as other species when the addition is a modest population of cranes, and greater than other species when the addition is a large population of cranes. Put another way, birders prefer cranes to other species if it means seeing a particularly large number of cranes.

The eBird and DNR crane counts imply substantially different demand effects and welfare estimates. For a unit change, the DNR count produced a WTP 90% smaller than the eBird count ($1.09 versus $10.84 per trip for 1000 more cranes), while for a proportional change it was larger ($0.73 versus $0.20 per trip for 10% more cranes). One explanation for this difference is that eBird volunteers underreport the number of cranes. Summary statistics suggest that the eBird count is about one-tenth smaller than the DNR count on average. It should not by too surprising, therefore, that WTP for a unit change also differs by a factor of ten.

We ran several additional regressions to assess the robustness of the differences implied by the eBird and DNR counts. Table 4 presents coefficients and Table 5 presents WTP estimates from these regressions. The first robustness check uses eBird counts again, but this time restricting the study period to the immigration season, matching the period covered by the DNR data. The estimates in Table 4, column (1), are largely unchanged from those in Table 2, column (2). Table 5 shows that the implied WTP is little changed, too. Second, we measured crane abundance with the eBird data differently, using the maximum observed count rather than the median across sampling events.[10] The coefficient on cranes is much smaller and in fact approaches the magnitude of the coefficient based on the DNR data. WTP per trip is $1.71 for an additional 1000 cranes, which is 84% smaller than the baseline estimate of $10.84 and much closer to the estimate

[10]Recall that the baseline estimates are based on the median number of cranes reported by eBirders at hotspots, which we then summed across the hotspots at a site. This approach should work well if the crane count is measured with random error and normally distributed. However, some eBirders may be more accurate at counting and exhibit less error. If these eBirders tend to find more cranes, then the correct statistic will be in the upper half of the distribution. We designed the second sensitivity analysis to measure these greater counts. We also examined using the maximum observed number of species rather than the median, but found the species richness parameter to be little changed.

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**Table 4.** Results using alternative measures of crane abundance from eBird

| Variable | (1) Restrict data to migration season | (2) Use maximum hotspot counts | (3) No imputation for missing counts |
|---|---|---|---|
| Ln(birders) | 1.083*** | 1.110*** | 1.110*** |
| | (0.098) | (0.062) | (0.066) |
| Travel cost | −0.033*** | −0.036*** | −0.036*** |
| | (0.004) | (0.003) | (0.003) |
| Richness | 0.024*** | 0.016*** | 0.019*** |
| | (0.008) | (0.005) | (0.005) |
| Cranes | 0.289*** | 0.060*** | 0.294*** |
| | (0.073) | (0.011) | (0.072) |
| Constant | −4.068*** | −3.349*** | −3.618*** |
| | (0.715) | (0.486) | (0.497) |
| Site fixed effects | Yes | Yes | Yes |
| Biweek fixed effects | Yes | Yes | Yes |
| Log likelihood | −315523.5 | −688385.1 | −685297.2 |
| R-squared | 0.289 | 0.324 | 0.292 |
| Observations | 35,100 | 77,760 | 59,400 |
| Mean of Cranes (in thousands) | 0.366 | 0.915 | 0.246 |

Robust standard errors in parentheses below parameters. *, **, and *** indicate significance at 10, 5, and 1% levels. R-squared calculated as the squared correlation coefficient between the actual and predicted number of trips.

of $1.09 based the DNR data. Third, we narrowed the pool of sites and time periods to those with reported cranes in the eBird data rather than imputing missing counts. Parameters and WTP estimates are little changed with this adjustment, though, which suggests that imputation is not contributing bias.

This sensitivity analysis shows that the eBird data produces an abundance effect comparable to professional and presumably accurate DNR counts when abundance is based on the maximums reported by eBird volunteers. Otherwise, additional changes to the data or study design do little to align the estimates between these two potential data sources. Of course, measuring the effect of wildlife on recreation demand is a complicated exercise, and there may be factors the baseline estimates do not account for. In particular, abundance could be correlated across species and thus omitting the populations of other birds could produce omitted variables bias. Appendix E shows that the results are little changed when we include the abundance of great egrets – another large water bird – which should reduce concern about the abundance of other species. Nevertheless, this bias cannot be ruled out entirely, which in practice could depend on the strength of many cross-species correlations as well as with species richness. This should be addressed in future research. Other potential criticisms could focus on how we identified home locations, the value of travel time and accounting for multi-destination trips. Note that the appendix to this paper

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**Table 5.** Welfare estimates under alternative assumptions

| | | WTP per trip for 1000 more cranes in study area | Percent change from baseline |
|---|---|---|---|
| Baseline estimate based on self-reported crane counts from eBird (Table 2, Column 2) | | $10.84 | |
| Benchmark assumption | Alternative assumption | | |
| Use self-reported eBird crane counts | Uses DNR crane counts | $1.09 | −90% |
| Use one year of data | Use data from crane migration season | $10.15 | −6% |
| Use median crane counts at hotspots | Use maximum crane counts at hotspots | $1.72 | −84% |
| Impute missing crane counts | Drops missing crane counts | $9.49 | −12% |
| Include three wildlife areas | Include six wildlife areas | $10.23 | −6% |
| Impute missing home locations using modal personal locations or centroid of all trips | Drop birders who do not volunteer home location or do not have common centroid and personal locations | $21.87 | 102% |
| Value of travel time is 33% of wage | Value of travel time is 50% of wage | $14.01 | 29% |
| Include multi-destination trips | Drops probable multi-destination trips | $8.91 | −18% |
| Include self-reported species richness and crane counts | Include self-reported species richness, crane counts and egret counts | $11.54 | 6% |

explores several potential alternative designs, which for the most part affect the results in intuitive ways. Table 5 shows WTP estimates from these alternatives.

Finally, as pointed out by a reviewer, the demand for trips could be more closely related to sightings than population size or the number of species per se. By presenting estimates based on professional and citizen science counts, our results show that this distinction is an important one. Professional counts may accurately describe ecological characteristics but not how they are experienced by users. This could lend greater credibility to using the median or mean numbers submitted by eBirders. Our research aims to measure use values, so the number of birds actually seen by people could be interpreted as the more relevant measure.

How do our results compare with prior research? Kolstoe and Cameron (2017) find median birder WTP per trip is $278.40 ($340.26 in 2022 dollars) to access rural sites in the Puget Lowland region of Washington state, and that WTP for an additional species is $3.38 ($4.13). Myers et al. (2010) use contingent behavior data to estimate that birder WTP per trip is $96 ($134.98 in 2022 dollars) for Delaware beaches. Our estimates are smaller, as they indicate WTP per trip of $27.67 to access sites in Indiana, with an additional species worth $0.58. These differences could be due to differences in study setting.[11] Our estimates align more closely with Jayalath et al. (2023), who use eBird data, too, and find WTP per trip for an additional species to be CAN$0.68 on average (US$0.64 in 2022 dollars) or CAN $0.92 (US$0.86 in 2022 dollars) at the 25$^{th}$ percentile (39 species, which is near the average in our sample). Furthermore, Jayalath et al.'s model implies that birder WTP per trip is CAN$36.30 (US$34.10 in 2022 dollars) to access sites in Alberta. Our estimate of access value also lies near the center of the range in the valuation literature. One set of estimates, the Recreational Use Values Database, reports an average WTP of $51.96 ($65.09 in 2022$) for wildlife viewing trips in the Midwest (Rosenberger 2016).

Stoll et al. (2006) use contingent valuation to measure the value of preserving riparian habitat in the Platte River region, using scenarios with different levels of species diversity and sandhill crane abundance. They find birders are willing to pay $14.82 ($27.22 in 2022 dollars) for 10% more sandhill cranes relative to the status quo. This is much larger than the values implied in our study for a similar percentage increase. However, Stoll et al.'s baseline is much greater – around 500,000 birds – and includes nonuse values, whereas ours reflects the value of recreation only. Nevertheless, both Stoll et al. (2006) and this study provide evidence that willingness to pay for cranes scales with abundance.

We can use the pooled site demand model to measure the aggregate value of areas in the study region. For example, the annual number of visitors to Muscatatuck is about 180,000, of whom 62,000 went to see wildlife (Muscatatuck National Wildlife Refuge 2020).[12] Using the WTP per trip from the baseline specification ($27.67), the aggregate annual value of Muscatatuck for birding is $1,715,540. If we apply the average WTP per trip for recreation in the Midwest ($65.41) from the Recreational Use Values Database (Rosenberger 2016) to the other trips, then the value for Muscatatuck as a whole is $9,433,920.

[11]They could also be due to underlying differences in the eBird samples. The number of sampling events has increased nearly exponentially since the project's launch in 2002 (Zhang 2020), so population coverage could be much better now than just a few years ago. It is also possible that earlier eBird samples were of more avid birders.

[12]Although Muscatatuck does not distinguish birders from other wildlife viewers, it is safe to assume that wildlife viewing in this context is nearly synonymous with bird watching because the refuge is managed primarily for waterfowl.

## Conclusion

This study measured the economic value of birdwatching using a recreation demand model and the zonal travel cost method. In our application to wildlife areas in Indiana, we estimated that a birding trip is worth about $28, that visitors are willing to pay higher amounts to access sites with more species, and that visitors value larger populations of sandhill cranes. Of course, this relationship may not hold in other contexts. The sandhill crane is a large, migratory waterfowl, and the abundance of other, less-charismatic birds may not factor as strongly in recreation demand. Nevertheless, the results provide evidence that wildlife factor into recreation decisions and that protecting species diversity and abundance is valuable. This study does not account for nonuse and existence values, which would be additional to the welfare measures described here.

We measured birdwatching trips and site characteristics using eBird, which provides a rich source of citizen science data. Birder WTP per trip was about $0.50 for an additional species, which is lower than other published estimates for birds. We also leveraged professional counts from the Indiana DNR to examine the reliability of counts recorded by eBird volunteers. Using the median counts from eBird, WTP was $11 for an additional 1000 cranes, whereas using the DNR counts WTP was just $1 for the same increase. This large difference shows that wildlife populations reported in citizen science data should be handled with caution. When we used maximum counts from eBird, though, WTP per trip was a little under $2 for an additional 1000 cranes, which aligned better with the estimates based on the DNR counts. However, using eBird comes with other caveats, including representativeness, whether trips may be targeting specific species, the portion of total recreational value captured among all birders, and the role of other ecosystem services. These will be important topics for future research.

The differences between citizen science and professionally generated data have important implications for informing decision makers. Using citizen science for wildlife data or transferring values from studies relying on such data should be done cautiously. Our research showed that the effect of abundance on birding trips was not robustly estimated when based on observations from eBird volunteers. Our research also suggests that naively transferring values from citizen science to professionally generated data could lead to bias, although calibrating for differences in population levels between contexts could help mitigate this issue. Applications of benefit transfer that must rely on citizen science should therefore consider adjusting for different population scales. Otherwise, research could significantly over or underestimate the value of changes in wildlife populations.

**Data availability statement.** Data and code available from the corresponding author upon request.

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**Competing interests.** Melstrom, Nielsen, and Reeling declare none.

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## Appendix A. Expanding the pool of sites.

This section presents the results after expanding the study area. The original analysis includes three wildlife areas divided into six sites that compose the destinations in the demand model. We focus on these areas because they are where the Indiana DNR measures crane populations. However, we are not restricted to these sites if we use cranes counts from eBird. We therefore examine the sensitivity of the estimates to changes in the study area. Table A1 presents the results using the baseline specification after adding Atterbury Fish & Wildlife Area (one site), Big Oaks National Wildlife Refuge (two sites), and Glendale Fish & Wildlife area (one site). In all three regressions, the implied willingness to pay for 1 more species and 1000 more cranes is only about 5% different from the baseline estimate.

**Table A1.** Results of expanded demand model using eBird species and crane counts

| Variable | (1) Adding Atterbury hot-spots | (2) Adding Atterbury and Big Oaks hotspots | (3) Adding Atterbury, Big Oaks and Glendale hotspots |
|---|---|---|---|
| Ln(birders) | 1.138*** | 1.134*** | 1.131*** |
| | (0.062) | (0.062) | (0.061) |
| Travel cost | −0.039*** | −0.040*** | −0.040*** |
| | (0.003) | (0.003) | (0.003) |
| Richness | 0.023*** | 0.024*** | 0.024*** |
| | (0.005) | (0.005) | (0.005) |
| Cranes | 0.337*** | 0.341*** | 0.343*** |
| | (0.071) | (0.070) | (0.070) |
| Constant | −3.944*** | −3.998*** | −4.031*** |
| | (0.458) | (0.453) | (0.449) |
| Site fixed effects | Yes | Yes | Yes |
| Biweek fixed effects | Yes | Yes | Yes |
| Log likelihood | −7765566.3 | −780456.0 | −790383.3 |
| R-squared | 0.330 | 0.352 | 0.355 |
| Observations | 90,720 | 116,640 | 129,600 |

Robust standard errors in parentheses below parameters. *, **, and *** indicate significance at 10, 5, and 1% levels. R-squared calculated as the squared correlation coefficient between the actual and predicted number of trips.

## Appendix B. Narrowing the sample to those with more credible home locations.

This section presents estimates after dropping a large portion of the sample. The original analysis identified an eBirder's residential location using either the location of their home locality – if one was named – or else their modal personal locality – if any were present – or finally the average latitude-longitude of visited hotspots. This imputation could lead to biased travel costs if the modal personal localities or the centroid of visited hotspots do not align with actual residential locations. To address this concern, we restricted the sample to eBirders who self-identified their homes or whose modal personal locality was in the same ZIP code as the centroid of visited hotspots. Intuitively, this should produce a sample with less biased residential locations. Unfortunately, it reduces the number of trips to the study area by 75%.

The results appear in Table B1. The parameters are qualitatively similar to those in Table 2, although most of the estimates are less precise and insignificant. The loss of precision is not surprising given the reduction in the sample size. The exception is travel cost, which is much closer to zero and more precisely measured. This could be because most of the sample is now composed of eBird volunteers who intentionally use personal localities and tend to be more active than other birders (Rosenblatt et al. 2022). More activity could reflect a lower marginal disutility from travel cost and therefore, among this sample, a smaller travel cost parameter.

**Table B1.** Results after filtering the sample to eBirders with more credible home locations

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(birders) | 1.258*** | 1.258*** | 1.258*** |
| | (0.180) | (0.180) | (0.180) |
| Travel cost | −0.012*** | −0.012*** | −0.012*** |
| | (0.003) | (0.003) | (0.003) |
| Richness | 0.006 | 0.014 | 0.014 |
| | (0.013) | (0.014) | (0.012) |
| Cranesany | 0.244 | | |
| | (0.516) | | |
| Cranes | | 0.233 | |
| | | (0.184) | |
| Cranes (<p25) | | | 0.575 |
| | | | (1.167) |
| Cranes (p25-p50) | | | 0.279 |
| | | | (0.550) |
| Cranes (p50-p75) | | | −0.304 |
| | | | (0.501) |
| Cranes (>p75) | | | −0.231 |
| | | | (0.690) |
| Constant | −5.396 *** | −6.103 *** | −4.854*** |

(*Continued*)

https://doi.org/10.1017/age.2024.10

**Table B1.** (*Continued*)

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| | (1.361) | (1.319) | (1.177) |
| Site fixed effects | Yes | Yes | Yes |
| Biweek fixed effects | Yes | Yes | Yes |
| Log likelihood | −217420.7 | −216944.8 | −216819.5 |
| R-squared | 0.275 | 0.277 | 0.277 |
| Observations | 77,760 | 77,760 | 77,760 |

Robust standard errors in parentheses below parameters. *, **, and *** indicate significance at 10, 5, and 1% levels. R-squared calculated as the squared correlation coefficient between the actual and predicted number of trips.

## Appendix C. Increase the value of travel time.

This section presents the estimates after increasing the value of travel time from one-third to one-half of the wage rate, following English et al. (2018). Table C1 presents the results. The travel cost parameter indicates that WTP for a trip is −1/(−0.028), or approximately $36, which is 29% more than in the benchmark analysis.

**Table C1.** Results assuming a larger value of travel time

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(birders) | 1.127*** | 1.127*** | 1.127*** |
| | (0.067) | (0.067) | (0.067) |
| Travel cost | −0.028*** | −0.028*** | −0.028*** |
| | (0.003) | (0.003) | (0.003) |
| Richness | 0.016*** | 0.021*** | 0.016*** |
| | (0.005) | (0.005) | (0.005) |
| Cranesany | −0.012 | | −0.092 |
| | (0.203) | | (0.368) |
| Cranes | | 0.331*** | |
| | | (0.075) | |
| Cranes (<p25) | | | −0.0921 |
| | | | (0.368) |
| Cranes (p25-p50) | | | 0.077 |
| | | | (0.250) |
| Cranes (p50-p75) | | | −0.082 |
| | | | (0.238) |
| Cranes (>p75) | | | 0.048 |

(*Continued*)

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**Table C1.** (*Continued*)

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| | | | (0.339) |
| Constant | −3.399*** | −3.899*** | −3.413*** |
| | (0.512) | (0.500) | (0.520) |
| Site fixed effects | Yes | Yes | Yes |
| Biweek fixed effects | Yes | Yes | Yes |
| Log likelihood | −702148.4 | −696067.1 | −701986.8 |
| R-squared | 0.311 | 0.317 | 0.311 |
| Observations | 77,760 | 77,760 | 77,760 |

Robust standard errors in parentheses below parameters. *, **, and *** indicate significance at 10, 5, and 1% levels. R-squared calculated as the squared correlation coefficient between the actual and predicted number of trips.

## Appendix D. Excluding probable multi-destination trips.

This section presents the estimates after dropping a portion of the sample that may have multi-destination trips. In the original analysis, we defined trips as all sampling events that occurred at one of the study sites, which could include eBird volunteers who visited other sites on the same trip. To examine the sensitivity of the results to excluding multi-destination trips, we ran the analysis again after dropping a volunteer's sampling events on the days they submitted multiple checklists. These results appear in Table D1. The resulting willingness to pay for an additional species is $0.62, which is only 8% larger than in the baseline analysis; and willingness to pay for 1000 more cranes is $9, which is 18% less than the baseline.

**Table D1.** Results after excluding probable multi-destination trips

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(birders) | 1.134*** | 1.134*** | 1.134*** |
| | (0.072) | (0.072) | (0.072) |
| Travel cost | −0.037*** | −0.037*** | −0.037*** |
| | (0.003) | (0.003) | (0.003) |
| Richness | 0.019*** | 0.023*** | 0.019*** |
| | (0.006) | (0.006) | (0.006) |
| Cranesany | −0.010 | | |
| | (0.253) | | |
| Cranes | | 0.285*** | |
| | | (0.078) | |
| Cranes (<p25) | | | −0.195 |

(*Continued*)

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**Table D1.** (*Continued*)

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| | | | (0.427) |
| Cranes (p25-p50) | | | 0.087 |
| | | | (0.304) |
| Cranes (p50-p75) | | | −0.067 |
| | | | (0.325) |
| Cranes (>p75) | | | −0.061 |
| | | | (0.414) |
| Constant | −3.748*** | −4.193*** | −3.720*** |
| | (0.618) | (0.594) | (0.606) |
| Site fixed effects | Yes | Yes | Yes |
| Biweek fixed effects | Yes | Yes | Yes |
| Log likelihood | −554325.7 | −551036.1 | −554110.0 |
| R-squared | 0.316 | 0.322 | 0.318 |
| Observations | 77,760 | 77,760 | 77,760 |

Robust standard errors in parentheses below parameters. *, **, and *** indicate significance at 10, 5, and 1% levels. R-squared calculated as the squared correlation coefficient between the actual and predicted number of trips.

## Appendix E. Including variables for other bird populations.

This section presents the results after adding great egret (*Ardea alba*) counts. We assembled these counts following the same procedure for sandhill cranes described in the main text. We use egrets because they are similar to cranes in a number of ways, so excluding their population from the model could lead to omitted variables bias. Like cranes, egrets are large, migratory water birds with seasonal habitat in Indiana. These results appear in Table E1. The resulting willingness to pay for one additional species is $0.59, which is very similar to the baseline estimate; and willingness to pay for 1000 more cranes is $11.54 and therefore 6% more than in the baseline analysis. The effect of egret counts is not statistically significant.

**Table E1.** Results of the demand model that includes egret abundance

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Ln(birders) | 1.110*** | 1.110*** | 1.110*** |
| | (0.062) | (0.066) | (0.066) |
| Travel cost | −0.036*** | −0.036*** | −0.036*** |
| | (0.003) | (0.003) | (0.003) |
| Richness | 0.017*** | 0.021*** | 0.017*** |
| | (0.005) | (0.005) | (0.005) |

(*Continued*)

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**Table E1.** (*Continued*)

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| Egrets | 2.164 | 3.763 | 2.469 |
| | (2.405) | (2.363) | (2.496) |
| Cranesany | −0.040 | | |
| | (0.202) | | |
| Cranes | | 0.348*** | |
| | | (0.073) | |
| Cranes (<p25) | | | −0.146 |
| | | | (0.379) |
| Cranes (p25-p50) | | | 0.051 |
| | | | (0.252) |
| Cranes (p50-p75) | | | −0.076 |
| | | | (0.232) |
| Cranes (>p75) | | | 0.102 |
| | | | (0.324) |
| Constant | −3.313*** | −3.868*** | −3.376*** |
| | (0.510) | (0.492) | (0.510) |
| Site fixed effects | Yes | Yes | Yes |
| Biweek fixed effects | Yes | Yes | Yes |
| Log likelihood | −696116.5 | −689441.7 | −695898.5 |
| R-squared | 0.317 | 0.323 | 0.317 |
| Observations | 77,760 | 77,760 | 77,760 |

Robust standard errors in parentheses below parameters. *, **, and *** indicate significance at 10, 5, and 1% levels. R-squared calculated as the squared correlation coefficient between the actual and predicted number of trips.

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