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Analysis

The Non-market Value of Birding Sites and the Marginal Value of Additional Species: Biodiversity in a Random Utility Model of Site Choice by eBird Members

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ABSTRACT

The eBird database is the product of a huge citizen science project at the Cornell University Laboratory of Ornithology. Members report their birding excursions both their destinations and the numbers and types of birds they observe on each trip. Based on home address information, we calculate travel costs for each birder for trips to alternative birding hotspots. We focus on the Pacific Northwest U.S. (Washington and Oregon states). Many birders are "listers" who seek to maximize the cumulative number of species they have been able to see, and each hotspot is characterized by the number of bird species expected to be present. In a random utility model of destination site choice, we allow for seasonal as well as random heterogeneity in the marginal utility per bird species. For this population of birders, marginal WTP for an additional bird species is highest in June when birds are in their mating-season plumage (at more than $3 per species per trip). Total WTP for a birding outing also depends on other site attributes (including ecological management regime, the possible presence of endangered bird species, urban/rural location, ecological region and relative congestion/popularity). Evidence of variety-seeking can also be discerned in birders' destination choices.

1. Introduction

From the notion of the "canary in the coal mine", to the influential book *Silent Spring* by Carson (1962), birds have long been appreciated as an early indicator of changes in environmental quality. Experts continue to be concerned about the rates of decline for many bird species.[1] Human interest in biodiversity among wild birds remains pervasive, with bird-watching ("birding") continuing to be a popular recreational pursuit. According to the 2011 National Survey of Fishing, Hunting and Wildlife Associated Recreation (NSFHWAR) approximately 46.7 million people in the U.S. reported that they actively engaged in bird watching in the United States in 2011. This is roughly 15 percent of the US population, for people aged 16 and older. Certainly, many other individuals who do not report active participation in bird-watching are likely to derive non-zero utility from "passive" bird sightings even if these sightings are incidental to some other activity in which they are engaged.[2]

Many birders are "listers" who keep track of all the different species of birds they have seen. Some prestige is attached to having a large number of species on one's life list, and some birders aspire to have a "Big Year".[3] The non-market economic value of species richness to birders, however, remains an open question. Early research considered the value of waterfowl to hunters (e.g. Brown and Hammack (1973)), and the regional economic impacts of wildlife-watching activities have also been documented by the NSFHWAR survey since 1991. For benefit-cost analysis of policies that affect avian biodiversity, however, it would help to know something about the *net social benefits* associated with bird-watching and how these will be affected by changes in the biodiversity of bird species. Our research responds to this need by utilizing birders' diary data from the Cornell University eBird project, supplemented with data from BirdLife International.

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[1] BirdLife International is one organization that monitors the numbers and ranges of bird species (see http://www.birdlife.org/datazone/sowb/spotthreatbirds).

[2] "Non-use" values (e.g. option, existence, and bequest values) for bird populations can likewise be expected to be non-zero.

[3] Noah Stryker, followed by Audubon, tallied 6042 species in his world-wide Big Year in 2015.

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Not much non-market valuation research has been attempted with the data from eBird. The eBird project has been criticized by Lamb (2013) for assigning a universal value of $30 per wild bird, as determined by measures of economic impact as opposed to welfare analysis. We use eBird data to help construct measures of the "expected number of bird species" at different birding destinations, based on the number of species reported in the same month of the previous year. We then use this expected species richness measure as the key biodiversity attribute associated with each birding "hotspot" reported to eBird. Hotspots in eBird are publicly accessible locations that people visit regularly for birding and are suggested to eBird by eBird members. These sites undergo a review by eBird prior to being added to the list. Measuring biodiversity using species richness allows us to estimate the marginal value per trip, to this group of bird watchers, of an additional expected bird species at birding destinations, while controlling for an assortment of other site attributes.

The literature on ecotourism (and more specifically on "avitourism") is informative about the preferences of bird watchers who take grander-scale trips to visit premium birding destinations outside their local region. Ecotourism has brought to the forefront the value of biodiversity and the importance of conservation e orts because of the economic impact of tourist dollars, i.e. as addressed by Naidoo et al. (2011). Studies in ecotourism and biological conservation point out that ecotourists, in general, tend be interested primarily in distinctive and charismatic species, such as the large mammalian predators of the African Savannah, as described in Di Minin et al. (2013a), Di Minin et al. (2013b), or Grünewald et al. (2016). This literature also explores the issue of how to broaden the interests of ecotourists to include a wider array of species, as in Di Minin et al. (2013b).

In some ecotourism contexts, it is something distinctive about the destination that draws ecotourists. For example, Naidoo and Adamowicz (2005) find that bird species richness and wildlife viewing are significant predictors of which rainforest reserves tourists choose to visit in southern Uganda. For Finland, Siikamäki et al. (2015) find that national parks with the highest biodiversity values attract more visitors than those with lower levels of biodiversity. In other cases, Booth et al. (2011) determine that the rare appearance of some species, such as a "vagrant" bird species, will temporarily increase the number of bird watchers travelling to a particular destination.

Compared to the research to be described in this paper, the closest recent valuation studies of birds employ either the travel cost methodology or stated preference methods. Some recent single-site travel cost models include (1) Edwards et al. (2011), who estimate the economic value of viewing migratory shorebirds, and (2) Gürlük and Rehber (2008) who estimate the economic value of bird watching at a single park. Stated preference studies sometimes focus on the value of a specific type of bird, often an iconic, endangered or threatened species, for example Yao et al. (2014), Myers et al. (2010), Loomis and Ekstrand (1997), Edwards et al. (2011), and Stoll et al. (2006). Other stated preference studies also focus on the value of birds at one particular site, such as Naidoo and Adamowicz (2005), Hvenegaard et al. (1989) or Cooper and Loomis (1991).[4]

Revealed-preference methods (based on observed travel costs to different birding destinations and formal modeling of preferences) are desirable because they reflect actual birder behavior and permit us to infer measures of consumer surplus. We develop a random-utility recreational site-choice model, using the Cornell eBird hotspot data set for the states of Oregon and Washington in the northwest U.S. We demonstrate the feasibility of using citizen science data to estimate the value of bird biodiversity to these citizen scientists. We derive fitted values for trips to specific types of birding sites based on observed birder choices, differences in expected bird species richness across sites, as well as other (potentially correlated) differences in site attributes. Utility-preserving trade-offs between money and site attributes can then reveal the implied total willingness to pay (TWTP) for birding trips to particular types of sites, as well as marginal willingness to pay (MWTP) for incremental numbers of bird species.

2. Data

The eBird dataset contains information contributed by birdwatchers who are project members. The early data starting in 2002 were rather sparse, but the number of members has expanded greatly since 2009. Worldwide membership in early 2016 exceeded 307,000. The available information includes the trip entries of individual bird watchers, so that it is possible to connect the trip origin (the member's enrollment-date home address from their member profile) and the geocoded destination for each trip. For this paper, we focus on just those eBirders who live in northwestern U.S. states of Washington and Oregon. To make these trip data useful for valuing avian biodiversity, each birding destination must be separately characterized by its various attributes.

2.1. Consideration Sets

There are a total of 2,340 eligible "birding hotspot" destinations in our two-state area (see Appendix note 1). Hotspots are included as potential destinations if they are listed as a hotspot on the eBird website. We use a one-hour one-way travel time to define the consideration set for each birder, and conduct sensitivity analyses with respect to this somewhat arbitrary maximum travel time.

2.2. Expected Numbers of Species

Each eBird trip record includes information about which bird species, and how many of each, are observed during each outing. To fill the gaps in the eBird data, we integrate a second external data set, this one from BirdLife International, via Ridgely et al. (2011), into our calculation of ex ante expected sightings. The BirdLife dataset provides geographic references for bird ranges, their presence (likelihood of being seen), origin (e.g., native or introduced) and seasonality (e.g., resident, breeding, nonbreeding or passage). The BirdLife data are particularly important when no eBird visits were recorded in the same month of the previous year at a particular hot-spot destination. Although no eBird member may have visited a particular site in a particular month, this does not mean that zero species of birds (a.) were present at the site last year or (b.) could be expected to be seen at that site this year. Our RUM models require a conformable set of attributes for all sites that comprise an individual's potential choice set, even when no eBird member visited that site in the same month of the previous year.

2.3. Travel Costs

Distances and travel times for our study are calculated for the "best route".[5] We do not model reported bird sightings that involve a travel distance of less than one mile, so utility from backyard birds or other very local bird populations does not enter into our analysis. Thus we have no revealed-preference measures of WTP for backyard birds, even though such sightings undoubtedly contribute substantially to the aggregate net social welfare associated with avian biodiversity.

The opportunity cost of time is always an important consideration in the construction of the travel cost variable for a site-choice model. The

[4] Loomis (2005) reports on use values from outdoor recreation in National Forests and other public lands, and summarizes results from the literature for 30 different recreation activities. He reports average estimates of consumer surplus values per person per day for different types of activities. For birding, the estimates are based on the results of four studies, and suggest that average consumer surplus is about $29.60 (in 2004 dollars), with a range of $5.80 to $78.46.

[5] The best route is suggested by MapQuest, when using the Stata MQtime.ado utility by Voorheis (2015).

basic eBird data do not include individual-specific income or wage information. Thus we resort to each birder's American Community Survey (ACS) census-tract median income level as a rough approximation, converted into an hourly wage. We then count the value of travel time at one-third of this wage a common approximation in the literature (see Appendix note 2).

2.4. Other Destination Attributes

Destination attributes that vary across sites can be included as variables that shift the *level* of willingness to pay itself. These attributes include indicators for site management regimes related to biodiversity, indicators for the expected presence of an endangered bird species (state and federal listings), an indicator for whether the site lies in an urban area, and indicators for the type of ecosystem at the destination.[6]

2.5. Collective Prior Behavior

Our expected congestion site attribute is based on the share of total eBird member visits to the site in question, in the same month of the previous year. Unfortunately, this measure is observationally equivalent to a measure of the popularity of the site.[7] The intent of a congestion/popularity measure is to proxy for the number of other recreationalists the individual expects to encounter during a visit to a particular hotspot. Congestion/popularity may be undesirable from the individual's perspective if it implies crowding for a rivalrous quasi-public good. But some degree of congestion/popularity may be desirable if the environmental good in question is essentially non-rival and there are pleasant social interactions among like-minded participants at most destinations.[8]

2.6. Individual Prior Behavior

Other potentially important variables can be constructed from each eBird member's personal recent history of birding trips. These variables are intended to summarize the particular individual's away-from-home bird-watching habits.[9] To assess whether variety-seeking behavior or habit-forming behavior dominates, we construct a measure of each birder's total trips *to the site in question* in the same month of the previous year. If birders also have preferences for variety in their birding destinations, for example, we would expect that a prior trip to the same site in same season of the previous year might tend to decrease the individual's chance of a repeat visit to this site at the same time of year. In contrast, if someone derives greater utility from visiting a favorite hotspot which they visited during the same season of the previous year, this might be interpreted as habit formation.

Table 1 contains brief descriptions of the main variables. Other variables are used as incidental controls in our main specifications, but we do not report their coefficients here (see Appendix note 3).

[6] We categorize site management regimes using data from the Conservation Biology Institute and the U.S. Geological Survey namely the Protected Area Database of the U.S. Early versions of the paper included an indicator for the expected presence of a threatened bird species, but it was never statistically significant and so is omitted from the model.

[7] A measure of relative congestion, consisting of visits to a given site as a share of all visits to all sites, has been used previously in the literature (Murdock (2006); Phaneuf et al. (2009); Timmins and Murdock (2007)).

[8] While our congestion/popularity measure is not completely exogenous, it is at least predetermined. Most other studies that attempt to control for expected congestion/popularity do not enjoy our luxury of prior years of trip data for each individual.

[9] As a measure of overall birding avidity, we calculate the overall number of birding trips made by each eBird member in the previous calendar year. For seasonal avidity, we calculate each birder's overall birding trips in the same month of the previous year. However, the estimated coefficient on the total number of previous-year trips is persistently not statistically significantly different from zero. Thus, this variable is not included in the preferred model specification.

3. Empirical Strategy

3.1. Basic Specification With Seasonality and Site Attributes

Within our conditional logit random utility method (RUM) framework, we assume that birder i's utility associated with a bird-watching trip to site j on choice occasion t, namely U^i_{jt}, has a systematic component, V^i_{jt}, that depends (linearly, for convenience) on income net of the full cost of round-trip travel to that site, $(Y^i - C^i_{jt})$. The marginal utility of net income (i.e. other consumption) is given by the coefficient α. Utility also depends on the expected bird species richness measure (number of bird species), $E[S]_{jt}$, with the marginal utility of species richness perhaps depending upon the season or changing over time, as captured by a vector of variables represented as T_t. Utility is also likely to depend upon a vector of other observable site attributes, $A^i{}_{jt}$, some of which may be correlated, to some extent, with species richness. Omitting these attributes could therefore bias the estimated effects of changes in bird species richness if these other attributes remain unchanged. There is also a stochastic component, ϵ^i_{jt}, that is known to the birder but unobserved by the analyst:

$$U^i_{jt} = V^i_{jt} + \varepsilon^i_{jt} = \alpha\left(Y^i - C^i_{jt}\right) + (\beta_0 + T_t\beta_1)E[S]_{jt} + A_{jt}\gamma_1 + \epsilon^i_{jt} \tag{1}$$

The error term ϵ^i_{jt} for the conditional logit estimation is assumed to be independently and identically distributed according to a Type I Extreme Value distribution.

Birders are assumed to consider the utility to be gained from a trip to any given destination, U^i_{jt} versus the utility to be gained with no trip, U^i_{0t}, so we model the choice to visit this destination as a function of utility differences, $U^i_{jt} - U^i_{0t}$:

$$\begin{aligned}
&U^i_{jt} = \alpha\left(Y^i - C^i_{jt}\right) + (\beta_0 + T_t\beta_1)E[S]_{jt} + A_{jt}\gamma + \epsilon^i_{jt} \text{ for site } j \\
&U^i_{0t} = \alpha\left(Y^i\right) + \epsilon^i_{0t} \text{ if no site is visited} \\
&U^i_{jt} - U^i_{0t} = \alpha\left(-C^i_{jt}\right) + (\beta_0 + T_t\beta_1)E[S]_{jt} + A_{jt}\gamma_1 + \left(\varepsilon^i_{jt} - \varepsilon^i_{0t}\right)
\end{aligned} \tag{2}$$

In our data, however, the choice of a particular birding hotspot is conditioned on the decision to visit at least some hotspot. Choices among alternative destinations are likewise based on the utility differences between these destinations. On any given choice occasion, t, the choice of a trip to site j rather than site k implies $U^i_{jt} > U^i_{kt}$ for all $k \neq j$.

It is likely that preferences differ across birders, not just over time. There is little in the way of individual characteristics in the basic eBird data. Thus we follow Train (2009) and allow for unobserved preference heterogeneity across people via mixed logit models. These models allow for random variation in preference parameters. It proves computationally daunting to introduce a great variety of random coefficients into this model, given the huge number of alternative hotspots in each individual's consideration set. As is common in the literature, we specify the marginal utility of net income, α, as a fixed coefficient. We settle for random variation in tastes only for species richness, namely in the coefficient β_0 on the expected species attribute, $E[S]_{jt}$. The coefficient will have a random component, μ_i, in addition to its fixed component, β_0, and its systematically varying component, $\beta_1 T_t$. The indirect utility Eq. (1) now becomes:

$$\begin{aligned}
U^i_{jt} &= V^i_{jt} + \varepsilon^i_{jt} = \alpha\left(Y^i - C^i_{jt}\right) + \left(\left(\beta_0 + \mu^i\right) + T_t\beta_1\right)E[S]_{jt} + A_{jt}\gamma_1 + \epsilon^i_{jt} \\
&= \alpha\left(Y^i - C^i_{jt}\right) + \beta_0 E[S]_{jt} + \left(E[S]_{jt} \times T_t\right)\beta_1 + A_{jt}\gamma_1 + \left(\mu^i E[S]_{jt} + \varepsilon^i_{jt}\right)
\end{aligned} \tag{3}$$

The usual error term ϵ^i_{jt} is still assumed to be i.i.d. extreme value, both over time and across individuals and alternatives. The new random component, μ^i, of the coefficient on $E[S]_{jt}$ is assumed to be normally distributed with mean zero and variance σ^2_μ.

Table 1
Selected descriptive statistics, birding hotspot consideration sets, Oregon and Washington[a].

Variable	Brief description	Mean	Std. dev.
Travel time to hotspots	From home address to considered hotspots	37.60	12.92
One-way site distance	From home address to considered hotspots	27.31	12.22
Roundtrip travel cost	MapQuest distance[b] times AAA mileage rate	32.01	14.34
Travel cost variable: C_j^i			
Travel cost w/ time cost	Using 1/3 imputed wage for Census tract	40.24	17.05
Expected species richness plus interactions: $E[S]_{jt}$			
Expected # bird species	eBird for seasonal species, same month last year; Birdlife for resident species	75.74	10.14
Deviation from neighborhood household income ($10,000)	Deviation from sample mean of neighborhood level income (based on the 2007–2011 5 year estimates at the census tract level) per $10,000	0.93	0.902
Other site attributes: A_{jt}			
1(National Parks, etc.)	Permanent protection[c], e.g. National Parks, Wilderness Areas, National Wildlife Refuges	0.036	–
1(National Forests, etc.)	Some extractive uses[d], e.g. National Forests, State Parks, recreation management areas	0.27	–
1(Urban area)	>50.000 people, at 2010 Census	0.61	–
Share of all eBird trips	For same month of previous year (proxy for expected relative congestion/popularity)	6.45×10^{-04}	3.57×10^{-03}

[a] 60 minute maximum travel time for considered alternative hotspots, 2010–2012 trips (221 total birders with home address information; 1,094 trips; 155,495 total alternatives; average 201 alternatives per birder (std. dev. 80.8 alternatives).
[b] Calculated using mqtime.ado written by Voorheis (2015).
[c] GAP status 1 or 2.
[d] GAP status 3; see online Appendix (additional information about the data).

3.2. Models With Individual Prior Behavior Variables

The basic model outlined in the previous section assumes that every birding trip is independent, which may not be the case. Birder preferences may differ systematically with the individual's overall birding avidity. Furthermore, birders may make repeated trips over the years to a favorite hotspot, or they may prefer variety in their destinations as well as in the types of birds they see.

We discuss our specifications with trip history variables in a separate section because an individual's prior trip-taking behavior, while predetermined, is not completely exogenous. Our multiple years of data make it possible for us to consider predetermined variables that allow for systematic differences in preferences across different groups of eBird members. For example, we can control for differences in the year in which the individual joined the eBird project. This is a prior behavior (e.g. "history") variable that does not change over time, denoted H^i.

We can also consider individual-specific prior behavior variables that are constant across sites, but *do* vary over time, H_t^i. We use an evolving measure of the individual's birding avidity, captured by their total number of birding trips to any hotspot during the most-recent complete calendar year.[10]

Finally, we can construct some site-specific and time-varying prior behavior variables for each birder, H_{jt}^i. In this category, we consider an indicator for whether the individual took *any* trips to the site in question in the same month of the previous year. We also consider a count variable for the *number* of times the individual visited the same site in the previous year.

The H^i and H_t^i types of variables do not differ across alternatives for any given choice occasion (i.e. birding trip). These variables can thus enter only as interaction terms that shift the marginal utility of some destination attribute that does differ across alternatives. We can, however, include stand-alone variables that reflect the individual's history of visits to the *same* hotspot in the same month of the previous year, H_{jt}^i. The utility function can thus be expanded to:

$$U_{jt}^i = \alpha\left(Y^i - C_{jt}^i\right) + \left(\left(\beta_0 + \mu^i\right) + T_t\beta_1 + H^i\beta_2 + H_t^i\beta_3\right)E[S]_{jt} + A_{jt}\gamma_1 + H_t^i\gamma_2 + \epsilon_{jt}^i \quad (4)$$

where the systematically varying parameters can be distributed, as in Eq. (2), to reveal some of the key interaction terms in the estimating specification: $(E[S]_{jt} \times T_t)$, $(E[S]_{jt} \times H^i)$ and $(E[S]_{jt} \times H_t^i)$.

3.3. Estimation and Inference: WTP Measures

The first step in our analysis is to estimate the mixed logit preference parameters in our model (see Appendix note 4). Next, we are interested in calculating estimates of total willingness to pay (TWTP) for single trips to specific types of birding sites. Likewise, we seek to calculate marginal willingness to pay (MWTP) for increments of key site attributes, such as the richness of bird species at a destination.

Assuming that individual i maximizes their utility by the choice over the $j = 1,\dots, J$ sites, we can estimate TWTP by individual i for a trip to destination j by setting the utility difference $U_{jt}^i - U_{0t}^i$ equal to zero. We can then solve for the implied level of travel cost that would make the individual just indifferent between incurring the cost of access to that type of site and enjoying the birding opportunity it represents, or avoiding this cost but missing out on this birding opportunity. For our basic model, this formula will be:

$$TWTP = C_j^{i^*} = \frac{1}{\alpha}\left(\left(\left(\beta_0 + \mu^i\right) + T_t\beta_1\right)E[S]_{jt} + A_{jt}\gamma_1 + \left(\epsilon_{jt}^i - \epsilon_{0t}^i\right)\right) \quad (5)$$

If we are willing to assume that all of the errors ϵ_{jt}^i, including ϵ_{0t}^i, are i.i.d. and mean zero, and if we focus on the individual with the mean value for the distribution of tastes for species richness, so that $\mu^i = 0$, we can evaluate this TWTP at the zero means of all of the random terms. TWTP for access to a particular birding hotspot thus depends upon time-varying observable site attributes ($E[S]_{jt}$ and A_{jt}), the observable seasonal indicators or our three-year time trend (collectively denoted as T_t), and a vector of asymptotically joint normally distributed maximum likelihood parameter estimates.[11]

A measure of the marginal willingness to pay (MWTP) for an additional expected bird species, and time-wise variations in MWTP for an additional species namely the systematic effects of the T_t variables on

[10] We retain the option for these types of variables as we develop the model. However, they prove not to in influence destination choices to any significant extent in this application, so we ultimately exclude them from our preferred specifications.

[11] The assumption that utility is approximately linear in income allows the individual's income to drop out of the choice model, which is admittedly handy because we have no individual-specific data on household incomes for this sample.

this MWTP can be calculated as:

$$MWTP = \frac{\partial C_j^{i^*}}{\partial E[S]_{jt}^i} = \frac{\widehat{\beta_0}}{\hat{\alpha}} + T_t \frac{\widehat{\beta_1}}{\hat{\alpha}}; \quad \frac{\partial}{\partial T_t}(MWTP) = \frac{\partial}{\partial T_t} = \frac{\partial}{\partial T_t}\left(\frac{\partial C_j^{i^*}}{\partial E[S]_{jt}^i}\right) = \frac{\widehat{\beta_1}}{\hat{\alpha}} \tag{6}$$

Given the undefined mean of a ratio of jointly asymptotically normally distributed maximum likelihood parameters, we make 10,000 random draws from this joint parameter distribution to build up an approximate sampling distribution for each TWTP and MWTP estimate that we calculate. For an individual with the mean level of the model's single random parameter on $E[S]^i{}_{jt}$, simulated distributions based on the estimated covariance matrix for the model's parameters yield approximate interval estimates for these TWTP and MWTP values which allow us to discern whether zero values can be rejected.

4. Results

We simplify the discussion of our results by featuring only the key coefficient estimates in Table 2. The first three columns of results in Table 2 give selected parameter estimates for a sequence of three increasingly general mixed-logit specifications. Model 1 explains site choices using only travel costs, the expected number of bird species and an interaction term between the expected species and the deviation of median census tract income from the sample average of median census tract incomes. This interaction term allows for some heterogeneity in willingness to pay for additional bird species as a function of neighborhood income levels. Model 1 also includes indicators for different types of management regimes, an urban-area indicator, and a quadratic form in a congestion/popularity measure for each destination (see Appendix note 5). Model 2 is otherwise identical to Model 1, but includes additional controls for the different ecoregions corresponding to each alternative destination. In Models 1 through 3, controlling for ecosystem differences can be seen to make little qualitative difference in the key marginal utilities of travel cost or expected species richness.

Model 3 is our preferred specification. It is otherwise identical to Model 2, but introduces time-wise heterogeneity in preferences for species richness, captured by a set of seasonal (monthly) indicators and a three-year time trend interacted with the species richness measure. Thus a vector of β coefficients must be considered. Note that only those sources of timewise heterogeneity with coefficients statistically significantly different from zero are included in Table 2.

Table 2
Selected coefficients, mixed logit models, 60-minute consideration sets, 2010–2012 trips (complete results in online Appendix).

Variable: coefficient	(1) Basic model	(2) Add ecoregion	(3) Add trend & seasonality	(4) Visited history
Travel cost variable: C_j^i				
Roundtrip, 1/3 wage: α	−0.0372***	−0.0369***	−0.0366***	−0.0376***
	(0.00306)	(0.00310)	(0.00310)	(0.00313)
Expected species richness: $E[S]_{jt}$; interactions: $T_t \times E[S]_{jt}$				
$E[S]_{jt}$ random coef. mean: β_0	−0.0372***	−0.0368	−0.0366	−0.0099***
	(0.00306)	(0.00310)	(0.00310)	(0.0152)
$E[S]_{jt}$ random coef. variance: σ_μ^2	0.0241***	0.0235***	0.0207**	0.024*
	(0.00801)	(0.00802)	(0.00923)	(0.00917)
ES × dev. med H. Inc. (\$10,000): $\beta_{0,1}$	0.00465	0.00448	0.00850*	0.00948**
	(0.00513)	(0.00505)	(0.00505)	(0.00539)
$E[S]_{jt} \times 1(February)_t$: $\beta_{1,2}$			−0.0358**	−0.0388**
			(0.0147)	(0.0151)
$E[S]_{jt} \times 1(June)_t$: $\beta_{1,6}$			0.113***	0.108***
			(0.0316)	(0.0319)
$E[S]_{jt} \times 1(November)_t$: $\beta_{1,11}$			0.0446*	0.0475**
			(0.0233)	(0.0240)
$E[S]_{jt} \times 1(December)_t$: $\beta_{1,12}$			0.0477**	0.0474**
			(0.0236)	(0.0241)
Other site attributes: A_j, A_{jt}				
1(*National Wildlife Refuge*): $\gamma_{1,1}$	0.900***	0.880***	0.907***	1.0198***
	(0.182)	(0.184)	(0.185)	(0.186)
1(*National Parks*, etc.)$_j$: $\gamma_{1,2}$	0.759***	0.746***	0.738***	0.768***
	(0.123)	(0.125)	(0.125)	(0.125)
1(*National Forests*, etc.)$_j$: $\gamma_{1,3}$	0.383***	0.382***	0.379***	0.397***
	(0.0739)	(0.0745)	(0.0746)	(0.0747)
1(*Expect Endangered Bird*): $\gamma_{1,5}$	1.701**	1.676**	1.643*	1.548*
	(0.813)	(0.822)	(0.854)	(0.853)
1(*Urban Area*)$_j$: $\gamma_{1,6}$	−0.634***	−0.655***	−0.649***	−0.671***
	(0.0775)	(0.0788)	(0.0788)	(0.0790)
1(*Willamette V alley*)$_j$: $\gamma_{1,15}$		1.212***	1.274***	1.365***
		(0.360)	(0.360)	(0.366)
†*Congestion/Popularity*$_{jt}$: $\gamma_{1,16}$	198.2***	193.3***	190.7***	203.6***
	(13.56)	(13.56)	(13.50)	(13.67)
$(Congestion/Popularity_{jt})^2$: $\gamma_{1,17}$	−4105.8***	−3776.1***	−3719.8***	−3956.4***
	(433.0)	(441.8)	(438.8)	(445.2)
Prior behavior: H^i_{jt}				
l(trips to same site: same month last year) $^i{}_{jt}$: $\gamma_{2,1}$				−1.990***
				(0.553)
Sample selection adjustment?	Yes	Yes	Yes	Yes
Ecoregion indicators?	No	Yes	Yes	Yes
ES × time trend?	No	No	Yes	Yes
Total alternatives	155,495	155,495	155,495	155,495
Log likelihood	−4643.50	−4628.79	−4606.10	−4557.21
AIC	9313.00	9301.57	9280.19	9186.43

Standard errors in parentheses.
Estimated using STATA *mixlogit.ado* with 500 Halton draws.
* $p < 0.1$.
** $p < 0.05$.
*** $p < 0.01$.
† Share of all eBird trips, same month, last year, to site j; maximum of function occurs at share of about 0.025, beyond the range of all except a few sites in the sample. Implies positive but diminishing marginal utility from other birders at a given hotspot.

4.1. Travel Costs C^i_{jt}

For our willingness-to-pay calculations, the marginal utility of other consumption (i.e. the negative of the α coefficient on the travel cost variable in a linear specification) serves as the denominator, so this travel-cost coefficient is very important. The results in Table 2 demonstrate that the coefficient on the travel cost variable is strongly significantly different from zero, with the expected negative sign. Its estimated value is also very robust across all of our specifications.

4.2. Expected Species Richness $E[S]_{jt}$

We are particularly interested in the marginal utility of our species richness (biodiversity) measure, represented by the expected number of different bird species at each destination based on the previous year's data for the same site in the same month. In our preferred Model 3, with time-wise heterogeneity, the sample mean of the random coefficient on $E[S]_{jt}$, namely β_0, gives the baseline January 2010 estimated marginal utility of the expected number of species for an eBird member living in a census tract having the sample average of tract-level median household income. This baseline marginal utility turns out to be negative and statistically significantly different from zero. With the limited number of variables available in the eBird data, we can only speculate on the reasons for this seemingly counter-intuitive finding. One possibility is that, in January, eBird members may be seeking specific species (e.g. swans, snow geese and raptors), rather than a greater variety of songbirds or wading birds. In particular, the hunting season for migratory waterfowl has concluded, creating safer opportunities to view game birds. In mid-winter, with inclement weather and less daylight, birders may be less likely to travel to distant sites with higher levels of biodiversity. Instead, they make take advantage of nearby opportunities to see large (but homogeneous) flocks of waterfowl. If birders seek to view raptors during mid-winter (e.g. hawks, eagles, osprey), they may find that relatively few other bird species are present at locations where raptors can be spotted. These possible explanations could be explored in future research.

4.3. Deviation From Average of Census Tract Median Income

In Model 3, the statistically significant estimated coefficient on the interaction term with the deviation of the eBirder's census tract median household income from the average of median household incomes across the sample (i.e. $\beta_{0,1}$) suggests that January 2010 marginal utility from an additional expected species becomes positive only for eBirders in census tracts with median household incomes about $43,000 higher than average. This median income deviation is well beyond the range of deviations in the sample. While this deviation has a marginally statistically significant effect on preferences for species richness, it does not overcome the baseline mid-winter effect.

4.4. Seasonal Effects

For February, the estimated marginal utility from an additional bird species is even more negative than the baseline in January of 2010. In these two most-severe winter months (falling after the surge in birding trips related to the nationwide annual Audubon Christmas Bird Count), eBird members seem to prefer sites with less biodiversity, perhaps for the reasons suggested above. For peak birding months, however, the average 2010 marginal utility from an additional bird species is positive and significant. This marginal utility is highest in June, probably the best month for birding in the Pacific Northwest. At that time of year, many songbirds display their most striking breeding-season plumage. Marginal utilities are also positive and significant in November, the time of the fall migration, and in December, the month of the Christmas Bird Count.[12]

The maximized value of the log-likelihood for the mixed logit model is markedly higher than for the corresponding conditional logit model by more than 800 points for the single additional parameter in the mixed logit specification. Thus we feature the mixed logit models in this paper.

4.5. Adding Prior Behavior Variables

Finally, Model 4 in Table 2 controls for a number of potentially endogenous variables related to each individual's prior birding trip behavior. The new variables (not all of which have their estimated coefficients reported in Table 2) include an indicator for earlier enrollment in eBird in 2009 or 2010 (an H^i variable). This shifter allows preferences to be different for earlier enrollees who may perhaps have been more technologically savvy and thus perhaps younger and with lower household incomes. We also introduce some H^i_{jt} variables that differ across sites and over time for each individual. These include a key indicator for whether the member visited the specific site in question in the same calendar month of the previous year. This gives us an opportunity to discern habit formation versus variety-seeking behavior in birders' choices of destinations. The $\gamma_{2,1}$ coefficient on this indicator is negative and significant, suggesting that variety-seeking behavior dominates habit-formation, on average.

4.6. Marginal Utilities of Other Site Attributes (A_j and A_{jt})

A number of other site attributes bear statistically significant marginal-utility coefficients in Table 2. These include indicators for the expected presence of an endangered bird species, for different ecological management regimes at each hotspot, for urban hotspots, and for different ecoregions, along with our continuous congestion/popularity measure for each hotspot.

The potential for seeing an endangered bird species adds to the utility derived from a visit to a birding hotspot. The potential to see birds designated only as threatened bird species does not have a statistically significant effect and this indicator has thus been dropped from the model.

The estimated marginal utility from visits to more heavily managed sites is highest for National Wildlife Refuges, as might be expected since these sites are explicitly managed (in part) for their roles as bird habitats. The marginal utility for National Parks, etc., is statistically larger in magnitude than the marginal utility from visits to less-managed sites (National Forests, etc.). Both are larger than the utility derived from visits to sites which are not managed for their ecological integrity. It seems reasonable that trips to more-pristine areas should confer greater utility for birders than trips to less-pristine areas, regardless of the number of bird species present.

We find a persistently negative coefficient on the indicator for an urban destination (activated for hotspots which lie within an Urban Area as defined by the 2010 Census). This suggests that some set of latent attributes shared by birding hotspots in urban areas confers disutility relative to non-urban sites, regardless of species richness.

We include controls for destination ecoregions automatically, to preempt any omitted variable bias from this source in the estimated coefficients on expected number of species. An individual may derive utility directly from the type of ecosystem at the destination, separate from the incremental utility associated with the expected number of bird species at that destination. There is some risk, of course, that ecoregion indicators will be correlated with expected numbers (and types) of species present. Birders may choose their destinations because these hotspots have other unmeasured attractive features, besides just the number of bird species they expect to see there.[13]

The congestion/popularity variable is proxied using all eBird members' reported visits to *this* hotspot in the same month last year, as a proportion of all eBird members' visits to *any* hotspot during that same time frame. The fitted coefficients suggest that greater congestion/popularity is initially a good thing. However, there is a threshold beyond which greater previous-year congestion/popularity begins to diminish people's anticipated utility from a visit this year. If birding is a social activity, and if there are not *too* many other birders at a destination (perhaps scaring the birds away), then additional expected visitors increase the utility anticipated from the outing. The parameters of the quadratic form in congestion/popularity suggest that utility is maximized when the share of visits to a site reaches about 0.025. Only a few sites in our sample receive this share of eBird visits in the previous year, suggesting that the marginal utility from the presence of other birders is positive but decreasing within most of the range of the data. Linearity in this variable is strongly rejected by the data, however. There is a point where a birding hotspot becomes “too crowded”.

5. Welfare Calculations: Simulations of TWTP and MWTP

Our sample of eBird members is not necessarily representative of all birders, or even of all birders in the states of Washington and Oregon. Thus it would be inappropriate to emphasize the mean fitted total willingness to pay across the birding trips taken by just these birders, or to

[12] Another possibility is that the random component, μ^i, of the baseline coefficient on expected species, $E[S]^i_{jt}$, in these specifications is merely absorbing much of the underlying heterogeneity in preferences among those eBird members who report birding trips in different months.

[13] Models 2 through 4 in Table 2 include a full set of ecosystem indicators for each destination, with the base category being the Puget Lowlands area in Washington state. This region accounts for 56% of all the hotspots actually visited by eBird members in our sample, and the Willamette ecosystem accounts for 29%. None of the other eight regional ecosystems accounts for >2% of visits, and none of these ecosystems bears a statistically significant coefficient.

attempt to extrapolate these values to the general population. Instead, we wish to illustrate the scale of the implied welfare effects of different statistically significant determinants of utility for these birders. In Tables 3 and 4, for Model 3 (our preferred specification), we rotate through the classes of explanatory variables in our choice models, one group at a time, permuting the values of these variables and observing the effects on our welfare measures relative to a benchmark case where we focus on a rural unmanaged hotspot in the Puget Lowlands in June of 2012 with congestion/popularity set to the mean value in the sample. (Baseline settings for the other variables in the model are reviewed in the subheading for each section in these tables.) This strategy allows us to illustrate the extent of the influence of each of these different types of variables on the implied total willingness to pay (TWTP) for a birding outing. We also calculate effects on implied marginal willingness to pay (MWTP) for an additional bird species.

Our TWTP and MWTP estimates are artifacts of our estimated marginal utility parameters for site characteristics, normalized on the marginal utility of net income (the negative of the coefficient on the travel cost variable in models where utility is linear and additively separable in travel costs). We focus on the differences in simulated TWTP and MWTP across cases where the estimated marginal utility parameters are individually statistically significant different from zero or where they differ significantly between some baseline category and other categories.

Table 3
Selected simulations concerning expected species richness, based on the parameter estimates in Model 3 from Table 2.

Simulation	$ Total WTP for trip	$ Marg WTP (per species)
A. By number of species ($E[S]_{jt}$)		
(At mean congestion, June 2012, not managed, rural, Puget Lowlands)		
5 species (minimum)	31.90[a]	3.38[a]
	(24.09, 40.62)	(1.97, 4.88)
69 species (10th percentile)	248.01[a]	"
	(151.34, 351.61)	
72 species (25th percentile)	258.14[a]	"
	(157.34, 366.33)	
78 species (50th percentile)	278.40[a]	"
	(169.28, 395.47)	
81 species (75th percentile)	288.53[a]	"
	(175.16, 410.02)	
84 species (90th percentile)	298.66[a]	"
	(181.02, 424.72)	
98 species (maximum)	345.93[a]	"
	(208.42, 492.90)	
B. By month (T_t variable)		
(At mean $E[S]$, mean congestion, 2012, not managed, rural, Puget Lowlands)		
January	36.97	0.27
	(0, 80.27)	(−0.32, 0.85)
February	0.52	-0.72[b]
	(0, 0.55)	(−1.26, −0.19)
March	54.90	0.51
	(0, 109.94)	(−0.21, 1.24)
April	61.96[c]	0.61
	(3.42, 121.50)	(−0.15, 1.40)
May	50.52	0.46
	(0, 100.99)	(−0.22, 1.12)
June	271.75[a]	3.38[a]
	(165.34, 385.93)	(1.97, 4.88)
July	23.17	0.03
	(0, 70.18)	(−0.65, 0.72)
August	89.82[b]	0.98[c]
	(21.98, 159.81)	(0.09, 1.90)
September	102.09[b]	1.14[c]
	(17.61, 186.19)	(0.03, 2.25)
October	66.54[c]	0.67
	(7.22, 124.71)	(−0.11, 1.44)
November	128.59[a]	1.49[b]
	(48.71, 211.08)	(0.44, 2.57)
December	136.08[a]	1.59[a]
	(59.05, 217.39)	(0.58, 2.66)
C. By year (T_t variable)		
(At mean $E[S]$, mean congestion, June, not managed, rural, Puget Lowlands)		
2010	239.28[a]	2.95[a]
	(128.69, 354.98)	(1.50, 4.46)
2011	255.52[a]	3.16[a]
	(149.25, 368.35)	(1.77, 4.63)
2012	271.75[a]	3.38[a]
	(165.34, 385.93)	(1.97, 4.88)

Simulated 90% bounds in parentheses. Negative values of TWTP set to zero.
[a] 99% simulated confidence interval excludes zero.
[b] 95% simulated confidence interval excludes zero.
[c] 90% simulated confidence interval excludes zero.

Table 4
Selected simulations concerning site attributes, based on the parameter estimates in Model 3 from Table 2.

Simulation	$ Total WTP for trip	$ Marg WTP (per species)
D. By presence of endangered species in previous calendar year		
(At means of cont. variables, June 2012, not managed, rural, Puget Lowlands)		
No endangered species present	271.75***	3.38***
	(165.34, 385.93)	(1.97, 4.88)
Endangered species present	317.28***	"
	(202.52, 443.28)	
E. By management regime (A_{jt} variables)		
(At mean $E[S]$, mean congestion, June 2012, rural, Puget Lowlands)		
National Wildlife Refuges	317.00***	3.38***
	(207.91, 434.26)	(1.97, 4.88)
National Parks, etc.	292.05***	"
	(184.12, 407.69)	
National Forests, etc.	282.19***	"
	(175.37, 397.73)	
Not managed (repeat)	271.75***	"
	(165.34, 385.93)	
F. By urban/rural (a A_{jt} variable)		
(At mean $E[S]$, mean congestion, June 2012, not managed, Puget Lowlands)		
Urban	253.91***	3.38***
	(147.60, 367.77)	(1.97, 4.88)
Rural	271.75***	"
	(165.34, 385.93)	
G. By congestion/popularity measure (A_{jt} variables)		
(At mean $E[S]$, June 2012, not managed, rural, Puget Lowlands)		
Mean eBird congestion = 0	256.74***	3.38***
	(150.00, 370.67)	(1.97, 4.88)
Mean eBird congestion = 0.000645	260.08***	"
	(153.29, 374.15)	
Mean eBird congestion = 0.010481	300.52***	"
	(192.78, 416.48)	
H. By Ecoregion (A_{jt} variables)		
(At mean $E[S]$, mean congestion, June 2012, not managed, rural)		
Blue Mountains	252.86***	3.38***
	(140.22, 374.69)	(1.97, 4.88)
Cascades	286.11***	"
	(177.83, 402.21)	
Coast Range	285.00***	"
	(176.15, 402.06)	
Columbia Plateau	262.66***	"
	(149.69, 384.42)	
Eastern Cascades Slopes and Foothills	245.06***	"
	(135.22, 362.79)	
Klamath Mtns and CA High N. Coast Range	269.54***	"
	(162.44, 383.79)	
North Cascades	246.17***	"
	(137.39, 363.26)	
Northern Basin and Range	271.75***	"
	(165.34, 385.93)	
Northern Rockies	279.91***	"
	(164.76, 404.34)	
Puget Lowlands	271.75***	"
	(165.34, 385.93)	
Willamette Valley	306.96***	"
	(198.20, 425.37)	

See footnotes to Table 3.

5.1. By Number of Expected Species

In our welfare simulations based on these mixed logit models, note that we calculate our TWTP and MWTP measures using only the estimated mean of the random coefficient on expected species.[14]

Simulation A in Table 3 explores how the implied total willingness to pay for a birding trip changes as the expected number of species changes across a selection of percentiles of this variable in the data. The mean number of expected species across all birding hotspots in our estimating sample is approximately 77. The marginal utility of an expected species is constant at about $3.38 because the $E[S]$ variable enters linearly for any given setting of the other variables in the model (see Appendix note 6).[15]

5.2. Time Patterns

Simulation B in Table 3 shows how implied total willingness to pay for a benchmark birding trip appears to vary across the seasons. The differential coefficients on the indicators for February, June, November and December are significant in our Model 3. Simulated TWTP for a birding trip is insignificantly different from zero in some months (January through March, plus May and July) but reaches a high of about $272 in June. The highest MWTP values for an additional species are $3.38 in June, $1.49 in November and $1.59 in December. In these months, species richness may be more what birders seek. June is the peak of the breeding season, so bird plumage is its most colorful. Winter waterfowl first arrive in Oregon and Washington at the end of the year, and the annual Christmas Bird Count turns out large numbers of birders every December.

The coefficient on the three-year annual time-trend interaction with expected species richness is not individually statistically significantly different from zero in the specifications in Table 2. For completeness, however, we include Simulation C, which shows increasing point estimates for TWTP and MWTP over the three years of our sample. This may reflect the diffusion of the eBird reporting technology to older (and higher-income) birders who may not have joined eBird as quickly.[16]

5.3. Endangered Species

Simulation D in Table 4 reveals that trips to sites at which an endangered bird was present in the previous year have a TWTP almost $46 higher than other sites.

5.4. Ecological Management Regimes

Simulation E in Table 4 suggests that bird-watching trips to destinations that are managed specifically for their ecological integrity have greater value, regardless of the expected number of bird species. For an otherwise benchmark case, trips to National Wildlife Refuges are valued most highly at about $317 per trip. Destinations such as National Parks (about $292 per trip) are more valuable to birders than are destinations such as National Forests (about $282 per trip).[17] Trips to unmanaged destinations (the baseline category in our models) have the lowest values, but the TWTP for the benchmark case is still about $272 per trip.

5.5. Urban/rural

Simulation F in Table 4 suggests that urban bird-watching destinations are valued much less than rural destinations, controlling for any differences in the expected numbers of bird species. The Urban indicator captures all manner of relative disamenities at urban destinations.

5.6. Congestion/popularity

The effects of congestion/popularity on WTP are reported in Simulation G in Table 4. Our expected congestion/popularity measure is the proportion of all eBird trips in the prior year that were taken to the destination in question. We use the average value of this variable in our sample as the baseline in our other simulations. Here, however, we simulate the effects of changing this measure from zero to the 50th percentile among cases where this number is nonzero, and then to the 90th percentile of these values. The effect of congestion/popularity on WTP is positive, up to a threshold at about 0.025, namely for a hotspot that receives 2.5% of all reported eBird visits in the prior year. After that point, the estimated effect becomes negative. However, this threshold lies beyond the vast majority of the values of this variable in our estimating sample (see Appendix note 8).

5.7. Ecoregions

Simulation H in Table 4 reports the differences in total WTP for a birding trip to destinations in different ecoregions in the Pacific Northwest. The most-valued ecosystem for birders appears to be the Willamette Valley (about $307 per June trip in 2012 at the benchmark levels of other variables). This is qualitatively greater than the TWTP for a baseline trip to the Puget Lowlands (the omitted category in our models), for which the baseline TWTP is roughly $272. The least-valued ecosystems appears to be the Eastern Cascades Slopes and Foothills and the North Cascades (at about $245 $246 per June trip in 2012), although the marginal utility parameters upon which these two lowest estimates are based are not statistically different from that for the omitted ecoregion of the Puget Lowlands.

5.8. Individual Past Behavior

Unlike Simulations A-H discussed in the preceding sections (based on Model 3 in Table 2), Simulation I in Table 5 is based on Model 4 in Table 2, which includes the potentially endogenous prior behavior variables for each birder. This simulation indicates the variety-seeking nature of preferences for different birding hotspots. Model 4 suggests that TWTP for a birding trip to the baseline destination adjusts to about $256 if the person has made *no* trips to that destination in the previous calendar year. If they have made one such prior trip to that destination, their total WTP drops to about $191. It then drops to only about $179 if the individual made two prior visits to that destination in the same month of the previous calendar year. These eBirders thus demonstrate a taste for variety in birding destinations, not just for variety in bird species at any given site. *Prior* birding behavior, however, is likely

[14] The estimated variance of the random parameter, σ_u^2, is strongly statistically significantly different from zero, suggesting there is substantial unexplained heterogeneity in this marginal-utility coefficient across the sample, beyond the systematic variation captured by the interaction terms in our model. To focus on sample mean preferences, we simulate a variance of zero. It is likely that the amount of noise in this random coefficient could be reduced considerably with richer data on individual eBird member characteristics, which are unfortunately not available for this sample. We leave this inquiry for future work. If we include the noise in the baseline coefficient on $E[S]$ in our calculations of TWTP and MWTP, the simulated 90% interval estimates *all* include zero, pointing to the importance of converting more of this random heterogeneity into systematic heterogeneity.

[15] Additional specifications/calculations run as sensitivity analyses are available in the online appendix (see Appendix note 7).

[16] The data do not contain systematic updates of home addresses since the time of enrollment in eBird. To be conservative, we limit our sample to members who have enrolled in 2009 or later, but if an eBird member has moved to a new area since their time of enrollment, it could appear (after their move) that they are driving to more-distant hotspots, whereas they are actually just visiting hotspots near their new residential location. This could contribute to an upward bias in imputed travel costs that could exaggerate WTP measures for some earlier enrollees by the later years of our sample.

[17] This estimate contrasts sharply with the roughly $6 to $78 consumer surplus estimates for National Forests reported by Loomis (2005), cited in the introduction to this paper. Netting out average overall travel costs of about $40 in our sample, the implied consumer surplus for these trips is still well over $200 per trip for these eBird members.

Table 5
Selected simulations concerning past birding behavior, based on the parameter estimates in Model 5 from Table 2.

Simulation	$ Total WTP for trip	$ Marg WTP (per species)
I. By prior year same-month visits to this site ($H_j^i t$) variable		
(At mean $E[S]$, mean congestion, June 2012, not managed, rural, Puget Lowlands)		
No trips to this site last year	256.36***	3.17***
	(153.11, 367.43)	(1.81, 4.62)
One trip to this site last year	191.29***	"
	(87.39, 300.99)	
Two trips to this site last year	179.10***	"
	(74.71, 287.73)	

See footnotes to Table 3.

to depend upon some of the same unobserved individual characteristics as *current* birding behavior, so we do not rely upon Model 4 for the rest of our WTP calculations.

5.9. Trips to Specific Sites in the Region

Finally, we revert back to Model 3 in Table 2 to consider eBirders' fitted TWTP for trips to selected *specific* hotspots in this two-state region. The set of estimates for Simulation J in Table 6 emphasize the versatility of our fitted models. We illustrate the implications of our random utility model for the TWTP in this sample for June and December birding trips to the Nisqually National Wildlife Refuge (in rural Washington State), Discovery Park (in urban Seattle, WA), William Finley National Wildlife Refuge (in rural Oregon) and Waterfront Park & Eastbank Esplanade (in urban Portland, OR). Recall that MWTP differs by month, but not by site, so Table 6 shows only two different values for MWTP.

5.10. Counterfactual Simulations

Revealed preference travel-based data such as the eBird trip-logs cannot quantify the value of back-yard bird watching or other incidental bird-sighting opportunities. However, we can make some rough calculations of the effects of some counterfactual scenarios on the welfare of birders who actually travel to see birds.

Table 6
Selected simulations of WTP for trips to selected actual hotspots, based on the parameter estimates in Model 3 from Table 2.

Simulation	$ Total WTP for trip	$ Marg WTP (per species)
J. By Specific site examples		
(At means of cont. variables) Nisqually NWR[a] - June	297.84***	3.38***
	(187.48, 415.98)	(1.97, 4.88)
Nisqually NWR - Dec	172.44***	1.59***
	(84.71, 266.43)	(0.58, 2.66)
Discovery Park[b] - June	280.84***	3.38***
	(170.49, 398.30)	(1.97, 4.88)
Discovery Park - Dec	127.79**	1.59***
	(45.02, 214.95)	(0.58, 2.66)
William L. Finley NWR[c] - June	313.37***	3.38***
	(201.93, 435.03)	(1.97, 4.88)
William L Finley NWR - Dec	171.10***	1.59***
	(90.84, 255.72)	(0.58, 2.66)
Waterfront Park & Eastbank Esplanade[d] - June	309.57***	3.38***
	(196.43, 432.11)	(1.97, 4.88)
Waterfront Park & Eastbank Esplanade - Dec	168.58***	1.59***
	(85.91, 255.78)	(0.58, 2.66)

See footnotes to Table 3.
[a] In Washington, between Tacoma and Olympia, on Puget Sound.
[b] An urban park about six miles northwest of downtown Seattle, Washington, on Puget Sound.
[c] In Oregon, between Corvallis and Eugene along the 99W highway.
[d] An urban hotspot in Portland, Oregon, along the Willamette River.

5.10.1. Hypothetical Species Loss

Suppose one species of bird, on average (perhaps not the same species everywhere), disappears from all birding destinations in the Pacific Northwest. In Oregon in 2011, there were about 4.0 million birding trips to destinations more than one mile from home, according to the Survey of Fishing, Hunting, and Wildlife-Associated Recreation. In Washington State, there were about 5.2 million such trips. Simulation B in Table 3 suggests that the marginal WTP for an additional species varies by month for the benchmark case at the means of the continuous data. Suppose we could assume that this sample of eBird members is representative of the entire population of birders, and that their trips are proportional to the general population. Then, we use the percentage of trips taken within a given month (see Appendix note 9) to scale the total trips taken in a given year by these marginal values for the corresponding trip month. This yields an estimated aggregate welfare loss of about $2.5 million per year in Oregon and $3.3 million per year in Washington State. Given that the average number of expected bird species at the hotspots in our study is about 77, larger species losses could produce some very substantial lost use value among birders in these two states.[18]

5.10.2. Losses in Bird Biodiversity Due to Climate Change

The Audubon Society has conducted a continent-level analysis of North America to see how the distribution and abundance of bird species may adjust in response to climate change, as reported in Langham et al. (2014). Their analysis forecasts the impact of climate change on bird biodiversity and identifies geographic areas which are expected to be important to the preservation of bird species.[19]

We can explore some of the implications of our preferred model for the potential welfare effects of forecasted climate-change impacts on bird species richness by 2020, using Audubon's A2 climate scenario. We acknowledge that urbanization and land-cover are also likely to change over time, as climate changes, but for now we focus solely on the effects of changes in bird species richness implied by these Audubon scenarios. Our main model suggests, for example, that the TWTP for a trip to Nisqually NWR would increase by about $2.48, to a total of about $300, based on Audubon's predicted *increase* in bird species richness (+0.94%) at that location. For the William L. Finley NWR, however, there is a predicted *decrease* in bird species (−5.33%) and our results suggests the TWTP for a trip to the William F. Finley NWR would thus fall by about $14, to a total of about $299.

6. Caveats and Directions for Future Research

The members of eBird may not be entirely representative of the population of people who enjoy opportunities to see birds. For citizen science data such as that collected by eBird to be most useful for economic analyses such as this, it would be extremely helpful to know more about self-selection into participation in citizen science projects. For example, it might be possible to add a question about the respondent's participation in different citizen science projects to the screening version of the National Survey of Fishing, Hunting and Wildlife Associated Recreation (for 2021, since it is too late to modify the 2016 survey). Such information would make it possible to use sample selection correction methods with economic analyses that use citizen science data such as that provided by the eBird project.

Congestion is a potentially endogenous site attribute in many recreational site choice applications, although in our study it reflects the aggregate of individual site preferences in the previous year and is not a

[18] We recognize that eBird members may be more avid than the average in the general population of less technologically savvy birders. If so, these estimates may be upper bounds. But recall that we are not able to measure the values of backyard birds in this study.
[19] The complete report can be found online at http://www.climate.audubon.org/sites/default/files/Audubon-Birds-Climate-Report-v1.2.pdf.

consequence exclusively of the individual birder's decision in the current year. McConnell (1988) explores a theoretical treatment of the congestion issue, while Jakus and Shaw (1997) suggest empirical use of ex ante measures of congestion because destination choices are likely to be based on anticipated or expected congestion at each site. Schuhmann and Schwabe (2004) point out that the appropriate empirical measure of congestion varies with the nature of the recreational activity, confirmed by Boxall and Adamowicz (2001) in a stated-preference study.

Any *contemporaneous* measure of congestion, of course, is potentially endogenous and estimation would certainly require an e ort to instrument for congestion. For an alternative specific logit model, Murdock (2006) uses a variation on the contraction mapping method proposed by Berry et al. (1995) to estimate the first stage.[20] Given that there are so many potential destinations in our study, and the consideration sets for our eBird members overlap so little, it is rather difficult to adapt conventional contraction mapping algorithms to this application. Thus we do not use this approach in the present paper, but acknowledge these concerns. We reiterate that, fortunately, our specific congestion measure is based on observed congestion evidence *one year previously*. These visitation data are available online to all eBird members, whereas for many previous studies which have attempted to address expected congestion, the relevant information about last year's congestion is not as fully accessible, ex ante, to all participants.

RUM site choice models must also address the question of the value of travel time (VTT). Efforts to incorporate the VTT into travel-cost-based models reflects the fact that the full price of a trip involves both the opportunity costs associated with out-of-pocket expenditures and the opportunity costs of the time required to make the trip. Ignoring the time cost of access to a site can bias downward the resulting estimate of access value, as pointed out by Knetsch (1963). We include an allowance for the VTT in our models, but do not pursue the measurement of the VTT to its frontiers of the literature.[21] The eBird data unfortunately do not provide enough information to warrant the use of more-innovative methods (see Appendix note 10).

Finally, recreational demand models increasingly seek to take prior choices into account when this information is available. Models of habit-formation or variety-seeking behavior stem from early work by Pollak (1970), Pollak (1976) and Spinnewyn (1981). An early paper by Adamowicz (1994) looks at three different ways to incorporate these types of considerations. Train (2009) suggests including the individual's prior choice as an indicator variable for having previously visited site *j*. However, Smith (2005) points out that we need to model individual preference heterogeneity to avoid concluding simply that past choices cause future choices. Smith uses a mixed logit model to consider whether preference heterogeneity or state-dependence (or both) can be detected statistically across repeated choices by the same individuals. However, we do not, in this paper, attempt a fully dynamic multiple choice specification.

7. Conclusions

The main contribution of this research is to demonstrate the use of diary data from the eBird citizen science project to estimate a detailed random utility model of destination site-choice for these birders. The richness of the diary data from eBird provides us with an unbalanced panel data set for individual trips taken to a wide variety of destinations over a large spatial extent. This model allows us to infer the trade-o s made by a group of recreational birders based upon their revealed preferences. When birders are willing to travel farther to reach more-desirable birding hotspots, they reveal their total willingness to pay for different types of trips as well as their marginal willingness to pay for additional expected bird species at each destination.

We address an open question about the value of species richness to recreational birders who travel (but not its value to backyard birdwatchers or to others who may harbor only option, bequest, or existence values for sites with biodiversity in their bird populations). We thus produce value estimates for a type of "non-consumptive" use that appears not to have been comprehensively addressed in previous research. For our baseline case, consisting of a birding trip to a rural site in the Puget Lowlands, in June of 2012, with the mean expected number of species and mean level of congestion/popularity, our preferred specification suggests that the MWTP for an additional species is about \$3.38. June is the month with the highest marginal value of extra species, likely because this is a peak time for mating plumage and birds are easier to spot. The TWTP for such a trip in 2012 was about \$272.

The TWTP for a birding trip is also found to vary systematically with destination attributes such as the type of ecological management regime, the possible presence of endangered bird species, the degree of urbanization, the type of ecoregion where the site is located and the degree of congestion/popularity of the site in the same month of the previous year. In our auxiliary model that controls for (potentially endogenous) prior behavior, we find evidence of a preference for variety in birding *destinations*, in addition to the preference for greater species richness at individual destinations.

Our random-parameter specification shows a strongly statistically significant *variance* in the key marginal utility for an additional expected species. This evidence of extensive preference heterogeneity suggests that additional research is warranted, for example involving additional data collected from eBirders, to explore the sources of this currently unobserved preference heterogeneity in greater detail.

We caution, again, that our findings based on solely our eBird sample are not necessarily generalizable to the entire population of recreational birders. The value of backyard birding (with no travel costs) cannot be discerned from our current data.

Our research complements the existing literature, which provides a number of examples of values for specific birding sites and iconic bird species (e.g. related to the Endangered Species Act). This emphasis on endangered species overlooks how recreational bird-watching has grown in popularity since the 1970s. In the Pacific Northwest U.S., many local economies have seen a dramatic decline in extractive industries such as logging. Several areas have now found that their locations on migration flyways for numerous species of wild birds allow them to draw large in fluxes of birding-related tourism for events such as birding festivals. The economic impact of such events can be calculated from increased revenues for local businesses. Our endeavor in this work, however, is to provide a better picture of the social surplus enjoyed by birders, derived from greater species richness among wild bird populations. At least for this set of birders, this social surplus seems large. The median number of expected species at these birding hotspots is about 78; at roughly \$3.38 per species, species richness contributes about \$264 to the roughly \$278 total willingness to pay for a trip to a benchmark site. Other site characteristics produce positive and negative differentials in total willingness to pay, to be sure, but biodiversity in expected bird populations is unambiguously important in prime birding seasons.

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[20] Alternatives to contraction mapping include a Bayesian technique demonstrated by Phaneuf et al. (2009). Another possibility is the data augmentation technique proposed by Albert and Chib (1993) to handle latent variables by simulating these missing components of the data in a first-stage estimation to obtain the causal effect to use in the second stage.

[21] Lew and Larson (2011) find that the VTT is heterogeneous, because individuals differ in how they value travel time to recreational sites, echoing earlier results of Lew and Larson (2005). Fezzi et al. (2014) find that VTT increases with income, but decreases for individuals over age 60, when more people are likely to be retired. Larson and Lew (2014) consider the value of using a "wage fraction with noise" for the value of travel time, to avoid potential downward biases in the standard error estimates for the resulting welfare measures.

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Appendix A

Note 1. Detailed maps of the study area and birding hotspots are provided in Fig. A2 of our extensive online Appendix to accompany this paper [insert URL when assigned].

Note 2. If one uses a higher wage-fraction as an estimate of the opportunity cost of time, a higher estimate of total willingness to pay for a trip will result (see Larson and Lew (2014) and Fezzi et al. (2014)). Given that we must rely on neighborhood income levels, rather than individual household income measures, we use a simple one-third wage fraction which may tend to yield conservative monetized estimates of willingness to pay. Larson and Lew (2014) estimate the appropriate wage-fraction in their application and find it to be close to one-third. Fezzi et al. (2014), however, argue that it is more appropriate to use a fixed three-quarter wage fraction. We explore our assumptions about the wage fraction in auxiliary sensitivity analyses.

Note 3. See online Appendix Table A1 for the complete list of variables used in any model in this paper.

Note 4. In online Appendix Table A7, we compare a more-restrictive conventional fixed parameter conditional logit specification with the mixed logit models emphasized in the body of this paper.

Note 5. These models also include other incidental control variables detailed in the full set of parameter estimate in online Appendix Tables A2 and A3.

Note 6. In a model where choice sets are limited to only those sites visited by at least one eBird member, this baseline MWTP estimate drops to around \$3.15, as detailed in online Appendix Tables A9 and A10.

Note 7. Online Appendix Tables A14 to A17 show the results of all of the TWTP and MWTP simulations when we include the estimated noise in the mixed logit random coefficient on $E[S]$.

Note 8. Online Appendix Fig. A6 gives a histogram for the distribution of the shares of all eBird trips across all hotspots in our estimating sample.

Note 9. Online Appendix Fig. A7 gives a histogram for the distribution of birding trips across the seasons, as reported to eBird in 2012.

Note 10. Online Appendix Table A11 shows the robustness of our results to the use of alternative wage fractions in the calculation of travel costs.

Appendix B. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ecolecon.2017.02.013.

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