Blending Supplementary Surveys with Citizen Science Data to Estimate Representative Use Values for Non-market Environmental Goods: An eBird example

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Abstract

Citizen science projects provide unique opportunities to assemble large quantities of data concerning human observations (or utilization) of environmental goods, for example wild birds. Volunteer monitoring of birds by amateur citizen scientists dates back to the first annual Christmas Bird Count in 1900. The monitoring of bird populations by citizen scientists has now been modernized to involve online reporting and year-round observations via the eBird project run by the Cornell Ornithology Lab. The long-running nature of bird-related citizen science projects provides unique insights about how bird species diversity is changing as ecological conditions and climate change, thus impacting bird watcher welfare.

The eBird data has proven valuable for estimating the non-market use value of this resource to eBird members who report to eBird their trips to different birding sites. However, these values are not representative of the distribution of values in the general population. In this paper, we address how to render the benefits estimates from citizen science data scalable to the general population. This process is necessary to make citizen science data useful for policy makers who need population-level benefits for comprehensive benefit-cost analyses, including research relating to the biodiversity effects of climate change.

We use a special-purpose supplementary survey of eBird members to collect data specifically to overcome the sample of convenience problem in citizen science data. This additional information allows us to develop population weights to correct for the systematic sampling problem when these citizen science data are used by themselves. We also relax an assumption made in previous work that the marginal benefit of an additional bird species is the same across all species. In our current analysis, we allow the marginal utility of species richness (a biodiversity measure) to be different across four different categories of bird species: water birds, birds of prey, perching birds and game birds.

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1 Introduction

Economists have been eagerly taking advantage of new opportunities to exploit "big data," and state-of-the-art methods for working with these data have been evolving quickly. For environmental economists, the wealth of ecological information provided by so-called "citizen science" projects is of great interest. A recent *Web of Science* search on the topic of "citizen science" yielded over 5000 results—confirmation of the widespread attention to citizen science data in the broader published literature. Furthermore, about ten percent of these papers focus on climate change. Citizen science projects have proliferated because of the growing ability of participants to contribute real-time field observations using convenient smart-phone applications. There are now more than 1,000 active citizen science projects, according to the *Citizen Science Association* (see `CitizenScience.Org`). The volumes of information contributed by ordinary people participating in these projects gives scientists data on a broader spatial and temporal scale than could be collected by teams consisting only of experts. In recognition of the vast potential of citizen science data to inform policy-making, the U.S. Environmental Protection Agency (EPA), via its National Advisory Council for Environmental Policy and Technology (NACEPT), issued a report on 13 December 2016 stating that the EPA needs to "embrace citizen science as a core tenet of environmental protection."

One way in which economists and other social scientists can help policy-makers take advantage of the power of citizen science data is to demonstrate the ways in which these data can be brought to bear on questions concerning the non-market valuation of environmental goods—especially for use in benefit-cost analysis of environmental policy. Only a few published papers have used citizen science data, or geocoded information from social-media platforms, to estimate willingness-to-pay use values for the represented populations. A paper by Kolstoe and Cameron (2017) uses off-the-shelf citizen science data from eBird, a large year-round citizen science project run by the Cornell Lab of Ornithology to estimate eBirders' willingness-to-pay (WTP) for bird biodiversity as evidenced by the destination choices in their reported birding trips. A paper by Keeler et al. (2015) uses geo-coded photography data from the social-media platform, Flickr, to estimate members' WTP for lake water clarity. Both of these papers demonstrate the potential to use a sample of convenience to infer non-market values of an environmental good, but these values are not necessarily scalable to the general population because the estimating samples are not representative. Both of these papers include caveats that the estimated benefits apply only to the sample, and not to the general population, but population-level benefits are necessary for comprehensive benefit-cost analyses for policy purposes.

In this paper, we endeavor to answer two specific research questions. The first question concerns how the value of bird biodiversity (to eBirders) varies across different categories of bird species (e.g. water birds, birds of prey, perching birds and game birds), as well as by birder type (e.g. for casual birders versus "listers"). The second question concerns what additional information is necessary to render benefits estimates from citizen science data scalable to the general population.

We use a different and newer sample from the eBird project, supplemented with additional information about each eBirder from a supplementary survey of these same people, to build on the research reported in Kolstoe and Cameron (2017). We specifically address how to employ supplementary survey data to help overcome the "sample of convenience" problem. Our auxiliary survey data was gathered specifically to permit the construction of population weights to correct for the systematic samples to be expected in data contributed by volunteers, who (in this case) are more likely than average to be avid birders (Green, 2007).

A further innovation over our earlier work is that we disaggregate bird species into four sub-groups, and allow birders' marginal utilities from additional species richness to differ across these groups (water birds, perching birds, birds of prey and game birds). This relaxes the restrictive assumption made in the Kolstoe and Cameron (2017) that the marginal value of an additional species is equal across all bird species.

Section 2 provides a brief overview of the relevant literature. Section 3 outlines the data sets used in this analysis. Section 4 outlines our empirical approach, including the sample selection correction model for participation, the random utility model and its estimation. We also describe how to construct and use population weights based on the U.S. Fish & Wildlife quinquennial survey of Fishing, Hunting, and Wildlife-Associated Recreation, as well as a special-purpose question posed to 2,000 nationwide general-population respondents as part of the Qualtrics Omnibus survey. Section 5 discusses our estimation results. Section 6 discusses the willingness-to-pay (benefits) estimates inferred from the parameter estimates for our preferred specification employing our auxiliary data, and Section 7 concludes.

2 Relevant Literature

Recreational demand models originated with the single-site travel cost method (TCM), first proposed by Hotelling in 1947 as a response to the National Park Service's appeal to researchers for new methods that could be used to value National Parks.[1]

2.1 RUM Model

McFadden (1974) first proposed the random utility maximization (RUM) model as an approach that would make it possible to infer utility-theoretic population demands for a new public transportation system from consumer choices among a variety of existing transportation modes. McFadden's model is now the basis for the predominant approach to valuation of environmental attributes, at least in a context where "use" demand can be observed and

[1]Since then, the TCM has evolved to be able to handle choices among multiple sites, based on site attributes, using the random utility maximization (RUM) model framework.

demand is expressed through a willingness to incur travel costs to gain access to an environmental good. The RUM framework can produce welfare measures on a per-trip basis for marginal changes in environmental quality, as in (Phaneuf and Requate, 2017, Chapter 16). Research since the initial development of RUM applications has explored a variety of ways whereby the implicit restrictive assumptions in the original specification can be relaxed. The RUM framework has been used widely in the non-market environmental valuation literature because it can exploit travel costs and destination attributes, along with the socioeconomic characteristics of recreators, to explain destination choices. This framework also makes it possible for the researcher to infer the trade-offs that different types of recreators are willing to make between access costs and site attributes, from which we can infer an implicit willingness to pay for these non-market environmental goods when they can be quantified as examples of site attributes.

The conditional logit estimator used with RUM models has long been a workhorse in the literature; advances in computer processing power and econometrics have led to the development of logit models which relax the restrictive property known as the independence of irrelevant alternatives (IIA) of the conditional logit (Phaneuf and Requate, 2017, Chapter 17). The IIA assumption assumes that the unobserved components of utility (for a given choice occasion) are uncorrelated across alternatives, which may not be true. Train (2009, Chapter 6) points to this assumption as being unrealistic, given the strong possibility that unobserved site attributes are correlated within subsets of alternatives. Concern about the problem of unobserved heterogeneity, and a desire for a more-flexible RUM model, led to the development of the mixed logit, which allows for random parameters, known up to some parametric distribution. This approach allows for unobserved heterogeneity, for a more-flexible pattern of substitution between alternatives, and for correlations across across choices, by estimating a joint distribution for a subset of random parameters in the model (Train, 2009, Chapter 6). All these characteristics of the more-general mixed logit specification are desirable for estimating a repeated RUM model where individuals in the sample are observed to make choices on multiple occasions (Freeman III et al., 2014, p.285).

2.2 Heterogeneity in Preferences

The possibility of *systematic* heterogeneity in preferences is an important consideration whenever a non-representative sample must be used to estimate preferences for use in non-market valuation problems. Socioeconomic characteristics for each person, as proxies for broad differences in preferences based on observables, are typically incorporated via their interactions with site attributes that differ across alternatives. This approach allows the marginal utility of a given attribute to vary systematically across individuals with differing characteristics.[2]

Allowing for heterogeneous preferences is a key step towards making a model scalable to the general population, because people have different tastes and/or past experiences that are likely to influence their observed choices. Systematic selection is unavoidable when one works with citizen science data, because no one can be compelled to participate, and volunteers are inevitably more interested in the topic than the average person in the population would be. Phaneuf (2013) argues that "heterogeneity in micro-level data sets is a shorthand way of saying that the behavior observed across individuals is determined by countless numbers of factors that reflect the complexity of human decision making." For example, models in the "horizontal sorting" literature take advantage of observable heterogeneity to explain people's choices (Murdock, 2006; Timmins and Murdock, 2007). Failure to allow for preference heterogeneity thus has been recognized, as in Hynes et al. (2008), as an issue that will potentially introduce bias into a model's coefficient estimates.

How one chooses to allow for heterogeneity in a RUM specification can yield different results. This has been noted by both Hynes et al. (2008) and Haab et al. (2012), who explore

[2] As a practical matter, continuous sociodemographic variables such as age are sometimes expressed in terms of their deviations from the sample (or population) mean level of age, so that baseline coefficients can be interpreted as applying to an individual of mean age (Phaneuf and Requate, 2017, Chapter 16).

heterogeneous preferences and compare WTP estimates from conditional logit, mixed logit (continuous distribution) or latent class logit (finite mixture) models. Hynes et al. (2008) find that skill levels appear to affect welfare estimates for the white-water river kayakers in their mixed logit model, although not in their latent class model.[3] Haab et al. (2012) motivate their choice to contrast different ways of modeling heterogeneity among recreational anglers (using the Marine Recreational Fishery Statistics Survey (MRFSS)) with an explanation that the mixed logit approach will allow them to estimate a distribution for the willingness-to-pay estimates, whereas a latent class model allows for finite mixtures of preferences across a small number of inferred "types". They argue that the latent class approach permits them to identify the different motivations or objectives of different subsets of anglers. These distinctions may be important to government agencies for understanding broad differences between different classes of anglers.[4] Haab et al. (2012) find significant preference heterogeneity in preferences within the MRFSS data. As a result, their WTP estimates tend to vary, depending on which model specification is used. They suggest that, in cases where the population has such heterogeneous preferences, it may be appropriate to report ranges for the possible welfare estimates, as estimated across a suite of alternative specifications (conditional logit, nested logit, mixed logit and latent class logit).

To accommodate preference heterogeneity, we follow the first two recommendations of Moeltner and Von Haefen (2011), who point out that there are basically three ways to do this: (1) including observable socio-demographic variables; (2) the use of so-called "mixed" logit models with one or more random parameters; and (3) the use of latent class models.[5] The first method is perhaps the most straightforward when the mix of sociodemographic

[3]Hynes et al. (2008) uses site attributes as perceived by recreators, in this case white-water kayakers, where each kayaker's reported skill level is treated as one draw from the distribution of a random parameter (for the mixed logit). They acknowledge that their results are limited by their sample size and also reflect the preferences only of those kayakers who self-selected into the sample by completing their questionnaire.

[4]Haab et al. (2012) also look at the nested logit model which we do not explore at in this paper.

[5]Due to convergence problems with a large number of parameters we choose to not use latent class models for this analysis.

characteristics in the sample can be mapped to the corresponding (joint) distribution of these characteristics in the population. This information permits the researcher to generate exogenous weights based on the relative frequencies of these observable characteristics in the population as opposed to the sample. The first two methods are the most commonly seen in the literature, and in particular the second option because the mixed logit model also allows for implicit but very flexible substitution patterns between sites. This is particularly advantageous in the "repeated RUM" model with panel data when there is information for multiple choice occasions for each individual. As well as heterogeneity across consumers in the sizes of the marginal utilities derived from specific attributes, the mixed logit can allow for correlations across consumers in the marginal utility derived from different attributes. It may be expected that consumers' preferences for one attribute at a site can be related to their preferences for another attribute at the site (as well as over time, in the case of the repeated RUM). For example, see Revelt and Train (1998); Train (1998). Finally, McFadden and Train (2000) show that any choice model can be approximated by a mixed logit.

Moeltner and Von Haefen's third approach, that of using destination-specific fixed effects, is commonly used to control for unobserved site characteristics due to data limitations on site-attribute variables across many sites. In our data, we have a huge number of birding hotspots, which would necessitate a huge number of alternative-specific dummy variables in our model. We could accommodate *individual*-specific fixed effects through the repeated choices of each eBird member. However, the huge number of alternative-specific constants that would be required with our data, combined with the fact that these would sweep out a number of important non-time-varying characteristics of our destinations (such as the ecoregion indicators, the management regime at each site, and the urban/rural status of a site) may recommend against the use of site-specific fixed effects.[6]

[6]Our key explanatory variable, expected species richness at each destination, does vary over time, mostly because of the migratory habits of birds, so it would still be possible, in principle to measure our key marginal utility parameter in a context with enough observed trips by a population of birders with a small enough

2.3 Willingness To Pay Space

The standard approach to estimating discrete choice models to obtain willingness to pay (WTP) measures for welfare or benefit-cost analysis can be somewhat problematic when the model is estimated in preference space and then solved to obtain the corresponding WTP function. Calculation of the WTP function involves ratios of asymptotically normally distributed preference parameters estimated by maximum likelihood. Using the Delta, Fieller or Krinsky-Robb approaches may lead to large positive WTP measures if the price coefficient is small (and large negative values if the price coefficient is unconstrained and passes slightly into the negative domain). WTP estimates by these methods can have large variances, whereas more-reasonable WTP estimates tend to be found when models are estimated directly in WTP space. Both Train and Weeks (2005) and Scarpa et al. (2008) note that the marginal utility of net income, as captured by the price coefficient in these models, is unlikely to be constant across people. To ensure that a random price parameter is negative, researchers may parameterize the coefficient on price as $\beta = -exp(\beta^*)$ so that the estimated parameter, $beta^*$, has an unbounded normal distribution but the effective coefficient $-\beta$, while random, remains strictly negative. However, the model can be re-parameterized and estimated directly in WTP space. In that case, the ratios of the marginal utility of each attribute to the marginal utility of net income can be estimated directly as redefined single parameters, rather than estimating the two components of the ratio separately and having to calculate corresponding values for these ratios. In WTP space, the price coefficient as well as other key parameters can be random (and, if appropriate, correlated). This specification allows for scale-heterogeneity in addition to the other desirable features of the mixed logit, which include its ability to relax the independence of irrelevant alternatives (IIA) assumption, to capture unobserved heterogeneity, and to allow for more-flexible substitution patterns across alternatives. (See Train (1998); Scarpa et al. (2008); Thiene and Scarpa

set of alternative birding destinations.

(2009); Hess and Train (2017).)

2.4 Quality of Data from Volunteered Geographic Information Projects

Citizen science data (e.g. eBird), as well as the voluminous quantities of data that can be harvested from geotagged sources (e.g. Flickr, Instagram and Twitter) can provide researchers with more and different information than they have ever enjoyed before. A key question, however, concerns the quality of this "big data." Lewandowski and Specht (2015) conduct a review of the literature looking at the quality of data collected by volunteers and find that while data gathered by professionals tends to be more accurate, this is not true in all cases. They find no study that shows conclusively that professionally gathered data is strictly better (i.e. in the sense of having less variation). Goodchild and Li (2012) propose three approaches to quality-control for data submitted/collected by volunteered geographical information (VGI) projects: (1) crowd-sourcing approaches; (2) social approaches; and (3) geographic approaches. Of these available solutions, none is perfect. To address these types of data-quality concerns, the eBird project (for example) has taken care to verify submitted observations which appear questionable according to an algorithm used to check individual submissions. The eBird project thus takes a "social" approach by using moderators to evaluate questionable bird sighting submissions (Wiersma, 2010).[7]

[7] To deal with data-quality concerns and guard the data against identification errors by its members, eBird has implemented an automated data filter to verify the validity of submitted observations by comparing the new data entry with prior data entries within close proximity, to filter out improbable sightings (Wiersma, 2010).

2.5 Use of Citizen Science/ Social Media Data in Sciences & Social Sciences

Citizen science projects provide researchers with data that may not otherwise have been collected, or would otherwise have been collected on a smaller spatial or temporal scale, according to Wood et al. (2011). For example, these authors point to the Christmas Bird Count (CBC) as the original citizen science project, and thus one that provides researchers with a richer times series of data than would have otherwise have been generated by scientists alone. The CBC also stands out as a model for how to design citizen science projects, due to its longevity as project and its geographic extent.[8] Dunn et al. (2005) note that the CBC has demonstrated substantial evidence of citizen scientists' abilities and their commitment to such projects as well as the value of the project to the research community and the insights that this research has generated. More recently, CBC data are being used to test hypotheses about the causes and patterns of species-specific changes in bird populations. One notable research project is by Langham et al. (2015). These authors integrate data from the U.S. Geological Survey's Breeding Bird Survey (BBS) to forecast how species ranges are expected to change based on the IPCC (2007) climate scenarios. Their work is just one example among many that use citizen science data. Citizen science data are valuable specifically because of the widespread availability of the data, making it possible to produce forecasts on a continent-wide basis, as is necessary to assess questions concerning climate change.

The literature using data from social-media platforms—namely Flickr or Instagram (using geo-tagged photos), as well as Twitter (with geo-tagged tweets)—to gather data on recreational behavior is relatively more developed than the literature using citizen science data concerning ecological variables. Most of the research using social-media platforms, to date, has used Flickr data. For nature-based tourism and recreation, Wood et al. (2013) first

[8]The CBC started in 1900 by Frank M. Chapman as an alternative to the tradition of the the Christmas hunt (see `http://www.audubon.org/conservation/history-christmas-bird-count`).

pointed to online social media applications as a possible source of "big data" information for economic analysis.

A major concern with using geo-tagged data, in the literature, is to compare the number of posts with the number of actual visits, to get a sense of whether the citizen science reports or activity on social-media platforms can act as an adequate proxy for the number of visits to a site. For example, Wood et al. (2013) focus on estimating visitation rates to specific destinations, based on their Flickr data, and find that the data are sufficiently rich to be used as a proxy for visitation rates for the 836 sites (worldwide) that they observe in their sample. A later study by Keeler et al. (2015) used the geotagged Flickr photos posted by recreationists visiting lakes in the Midwest. These authors analyze the relationship between lake visits and lake attributes to determine which lake attributes can predict lake visitation. Keeler et al. (2015) also estimate a recreational site-choice model and find lake users in the states of Iowa and Minnesota are willing to incur an additional $22.26 per trip in travel costs (their marginal WTP) for an additional meter of water clarity. An additional study by Sonter et al. (2016) also uses Flickr data, along with trip expenditure data, to quantify the effects of conservation on tourism in Vermont by considering in-state and out-of-state visits to conserved lands.

How well do citizen-science projects or social-media data proxy for visitation data? In the case of popular citizen science "apps" for recreational anglers, data on fishing effort has been shown to be comparable to creel and mail survey data, according to Martin et al. (2014), Stunz et al. (2014), and Papenfuss et al. (2015). However, this is not the case for less-popular citizen science "apps" for fishing (Venturelli et al., 2017). Tenkanen et al. (2017) conduct a broader study using 2014 data from Instagram, Twitter and Flickr and compare it to high-resolution visitor statistics data for 56 national parks in Finland and South Africa. Their results show that social-media platforms perform best in more-visited parks, with Instagram outperforming Twitter and Flickr. The results from Tenkanen et al. (2017) thus show that caution is necessary when dealing with data from social-media platforms as these sources still constitute samples of convenience.

The eBird citizen science dataset contains information contributed by bird-watchers who are project "members." The early data were sparse, but improved as eBird transformed from being a citizen science project focused on collecting data for just scientists to use, into a collaborative effort with the exchange of information between citizen scientists and researchers (Sullivan et al., 2014). The success of eBird is attributed to its role as a project that engages the data-gathers (the citizen scientists) with the researchers and the research products being generated from the data. The different eBird participants, be they data-gathers or data-users, are all stakeholders in the success of the eBird project. This level of two-way engagement appears to be an important factor contributing to the sustained success of this particular citizen science project (Sullivan et al., 2014; Venturelli et al., 2017).

3 Empirical Strategy

3.1 The Mixed Logit Model & WTP Space

The destination choice models in this paper use a mixed logit RUM framework in WTP space, following Scarpa et al. (2008). In the context of this model of birders' choices among publicly accessible birding "hot spots," birder i derives utility U^i_{jt} from a birdwatching trip to site j (among J alternatives) on choice occasion t within the sample time period.[9] We are using diary data which yields an unbalanced panel dataset, so the total number of trips, T^i, varies across individuals. The birder's utility function has a systematic component, V^i_{jt}, that depends (linearly, for convenience) on income net of the cost of travel to that site: $(Y^i - C^i_{jt})$. The marginal utility of net income (i.e. the marginal utility of other consumption) is given

[9]Per eBird, a "hotspot" is a good public birding location that has been identified by eBird members and by which aggregate results about birds is available through eBird. See `http://help.ebird.org/customer/portal/articles/1900690-all-about-hotspots?b_id=1928` for additional information

by the coefficient α. Utility depends on expected bird biodiversity at the destination, by species categories, denoted as the vector X^i_{jt}. Utility also depends on other observable site attributes (included in vector A_{jt}). We allow for preferences for bird biodiversity to vary systematically with the seasons and to trend across calendar years, with these time indicators included as the vector T_t. Preferences for bird biodiversity are also allowed to vary systematically with observable sociodemographic characteristics (gender, age, income) and reported birding avidity measures (i.e. whether the birder identifies as a "lister" and if so, how many bird species are on their "life list"). These birder-specific characteristics are included in vector Z^i.

The utility function is thus specified as:

$$U^i_{jt} = \alpha^i(Y^i - C^i_{jt}) + (\theta^i_0 + \theta_1 T_t + \theta_2 Z^i)' X^i_{jt} + \theta'_3 A_{jt} + \epsilon^i_{jt} \tag{1}$$

where the marginal utility of net income, α^i, and the vector of marginal utilities of species richness by category of species, θ^i_0, are allowed to vary randomly over eBirders, but we assume that the vectors of parameters θ_1, θ_2 and θ_3 are fixed. The error term ϵ^i_{jt} is assumed to be approximated by a Gumbel distribution. By allowing for random parameters, the variance of the error term is rendered as $\mu^i\epsilon^i_{jt}$, which is individual-specific, so $var(\mu^i\epsilon^i_{jt}) = (\mu^i)^2(\pi^2/6)$. To accommodate scale heterogeneity in the model, in addition to allowing for unobserved preference heterogeneity, we divide each individual's preference function in equation (1) by μ^i. This transformation is allowable as utility is merely an ordinal measure, and marginal rates of substitution remain unaffected by a simple change of scale. The advantage, however, is that this change of scale allows us to work with an error term that has the identical variance for all birders (see Scarpa et al. (2008) and Hess and Train (2017).) When we divide the entire utility function by μ^i, every effective marginal utility coefficient is divided by μ^i, so that there is a distribution of such parameters across individuals, as noted by Scarpa et al.

(2008). Without the additional randomness in the α^i and θ_0^i parameters, the full set of utility parameters would be perfectly correlated across individuals.

$$U_{jt}^i = \left(\frac{\alpha^i}{\mu^i}\right)(Y^i - C_{jt}^i) + \left[\left(\frac{\theta_0^i}{\mu^i}\right) + \left(\frac{\theta_1}{\mu^i}\right)T_t + \left(\frac{\theta_2}{\mu^i}\right)Z^i\right]' X_{jt}^i + \left(\frac{\theta_3}{\mu^i}\right)' A_{jt} + \varepsilon_{jt}^i \tag{2}$$

where ε_{jt}^i is again independently and identically distributed (i.i.d), with constant variance $\pi^2/6$.

We can rewrite equation (2) by redefining the coefficients to account for this transformation: $\lambda^i = (\alpha^i/\mu^i)$, $\tilde{\theta}_0^i = \theta_0^i/\mu^i$, $\tilde{\theta}_1^i = \theta_1/\mu^i$, $\tilde{\theta}_2^i = \theta_2/\mu^i$ and $\tilde{\theta}_3^i = \theta_3/\mu^i$.

$$U_{jt}^i = \lambda^i(Y^i - C_{jt}^i) + (\tilde{\theta}_0^i + \tilde{\theta}_1^i T_t + \tilde{\theta}_2^i Z^i)' X_{jt}^i + \tilde{\theta}_3^{i\prime} A_{jt} + \varepsilon_{jt}^i \tag{3}$$

To transform the equation (3) from preference space into WTP space, one first divides each parameter by λ^i. Define $\beta_0^i = \tilde{\theta}_0^i/\lambda^i$, $\beta_1^i = \tilde{\theta}_1^i/\lambda^i$, $\beta_2^i = \tilde{\theta}_2^i/\lambda^i$ and $\beta_3^i = \tilde{\theta}_3^i/\lambda^i$. Then multiply these new parameters by λ^i to offset this scaling and leave the constant-variance error term unchanged:

$$U_{jt}^i = \lambda^i(Y^i - C_{jt}^i) + ((\lambda^i\beta_0^i) + (\lambda^i\beta_1^i)T_t + (\lambda^i\beta_2^i)Z^i)' X_{jt}^i + (\lambda^i\beta_3^i)' A_{jt} + \varepsilon_{jt}^i \tag{4}$$

Note this conversion into "utility in WTP space" only works when assuming that net income (income minus travel costs) enter linearly and additively separably into the utility function. We assume the negative of the "price" coefficient, α_i (the marginal utility of net income) has a log-normal distribution to force the random travel cost coefficient to be bounded away from zero.

The choice probabilities for a mixed logit are based on birder i choosing alternative j on choice occasion t. To simplify the representation of equation (4), in fashion similar to Thiene and Scarpa (2009), let utility be written as $U^i_{jt} = V^i_{jt}(\omega^i, \kappa)$ where $\omega^i = (\alpha^i, \beta^i_0)$, the scaled by μ^i random parameters within the model and $\kappa = (\beta^i_1, \beta^i_2, \beta^i_3)$, the scaled by μ^i fixed parameters in the model. Then following the usual intuition behind discrete choice models that birder i chooses destination j in period t because $U^i_{jt} > U^i_{kt}$, $\forall\ j \neq k$. Let y_{it} denote the birder's selection on choice occasion t over their Y^i choice occasions and $y^i = (y^i_1, y^i_2, \ldots, y^i_{Y^i})$ be their sequence of choices. The conventional logit probabilities evaluated at parameters (ω^i, κ) for birder i is:

$$L^i_{jt} = \sum_{t=1}^{t=T^i} \frac{e^{V^i_{jt}(\omega^i,\kappa)}}{\sum_j e^{V^i_{jt}(\omega^i,\kappa)}} \tag{5}$$

On any given choice occasion, then, the mixed logit choice probabilities are given by the integral of $L(y^i|\omega^i)$ over the distribution of the random parameters ω^i:

$$P^i_{jt}(y^i) = \int L^i_{jt}(y^i|\omega^i, \kappa) f(\omega^i|\kappa) d\omega^i \tag{6}$$

where $f(\omega^i|\kappa)$ in equation (6) is the density function for the random parameters ω^i, given the fixed parameters κ.

3.2 Estimating TWTP

Estimating the model "in WTP space" yields direct estimates of the mean marginal WTP (MWTP) associated with each destination attribute, which can then be used to calculate the mean total willingness to pay (TWTP) for a single trip to a birding destination with specified attributes, in a specific season and year, for a birder with specific characteristics. If we want further to incorporate the distributions of the coefficients which were allowed to be random across the population of birders, a subsequent step is necessary. Assume that $\gamma \sim N(b, \Omega)$ represents the vector of coefficients on the expected species richness variables by category. These coefficients are specifed as being random and correlated across the population of birders. Then we can use the vector of means for these parameters and the symmetric matrix of parameter covariances and make draws from this distribution, based on a vector of independent standard normal deviates, z, using $\gamma = b + Lz$ where L is the lower-triangular Cholesky factorization of Ω (such that $LL' = \Omega$). Including the seasonal and individual-characteristic systematic shifters, the MWTP for species richness for each category of bird species, c, now becomes:

$$MWTP_c = \gamma_c + \beta_{1c}T_t + \beta_{2c}Z^i \tag{7}$$

Thus the TWTP for one trip to a given site is:

$$TWTP = \left[\sum_{c=1}^{C} \left(\gamma_c + \beta_{1c}T_t + \beta_{2c}Z^i\right)\right]' X_{jt} + \beta_3' A_{jt} \tag{8}$$

4 Data

Our recreational site-choice data for birdwatchers are drawn from eBird, an extensive citizen science project managed by the Cornell Ornithology Lab and the National Audubon Society and funded since 2002 through several grants from the National Science Foundation.[10] The eBird dataset contains information contributed by birdwatchers who are project "members." Early membership was relatively low, expanded greatly since 2009, especially

[10]The eBird project is online at `www.ebird.org`.

with the availability of the smart-phone app, and quality controls for the contributed data on bird sightings have been implemented. The available information from eBird includes the trip entries of individual birdwatchers, where it is possible to connect the trip origin (i.e. the member's home address from their member profile) and the recorded destination for each trip. We use trips taken by Oregon and Washington eBirders to destinations in Oregon and Washington states to build on the work in Kolstoe and Cameron (2017).[11] Summary statistics concerning site and trip attributes, and the characteristics of eBird members taking these trips, are provided in Tables 3 and 4.

4.1 eBird Individual Data and the Auxiliary Supplementary Survey Data

The individual characteristics in the analysis reported in Kolstoe and Cameron (2017) were limited to the profile information eBird collected from its members when they registered for the project. To collect additional information deemed valuable for demand modeling, we conducted an auxiliary survey of eBirders in the states of Oregon and Washington during the winter of 2015-2016. This auxiliary survey included standard demographic questions (to permit matching to the relative population frequencies from the American Community Survey of the U.S. Census). Also included were questions about eBirders' recreational behavior (similar to those asked by the U.S. Fish and Wildlife as part of their quinquennial survey), and questions about their personal birding and trip preferences (the survey instrument is available upon request from the authors).[12] This analysis takes advantage of about nine

[11]Boundary-related problems are also minimized for this pair of states, because the Canadian border serves to limit trips to the north, while the Pacific Ocean constrains trips to the west. The relatively low populations along the eastern boundaries of these states, or along the Oregon-California border, likewise minimize the truncation of trips. This is one reason we combine the two states. The Portland, Oregon and Vancouver, Washington metropolitan area spans the border between Washington and Oregon, which would complicate any analysis of either of these two states considered separately.

[12]The survey had 1,277 respondents, of which 974 completed income questions and 531 of which reported bird sightings from a birding trip more than one mile away from home during the sample period of 2013-2015.

times as much trip data as our earlier study, and augments the simple eBirder membership profile data with additional information (see Kolstoe and Cameron (2017)).[13] Summary statistics about the respondents are provided in Table 5.

Travel costs. Distances and travel times for our study are calculated for the "best route" based on the algorithm coded as ORSMtime.ado in STATA and ggmap in R.[14] 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.[15] 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 basic eBird data do not include individual-specific income or wage information. However, we collected data on household income brackets in our auxiliary survey. We use the midpoint of each income bracket as an approximation for household income. We convert this annual income into an approximate hourly wage. We then count the value of travel time at one-third of this wage—a common approximation in the literature.[16]

Not all of these trips satisfy the necessary inclusion criteria for the estimating sample. These criteria pare down the sample to 321.

[13]The eBird data collects limited information from its members when they first sign-up for the project (e.g. home address, age-range, education, gender) and as this data is sparse).

[14]The OSRMtime.ado relies on OpenStreet map to query "best route" data. As a small handful of routes where not found using OSRMtime, ggmap in R which uses Google Maps API as a back end was used to fill-in the missing routes.

[15]This metric conforms with how the U.S. Fish and Wildlife define a trip away from home Carver (2013). We do have a stated preference survey underway that will allow us to get at the value of backyard birding in future work.

[16]Larson and Lew (2014) and Fezzi et al. (2014) test this assumption allowing for a noisy-wage fraction and find that this assumption is reasonable.

4.2 Expected Number of Bird Species

The eBird data is rich with reports of actual bird sightings on each trip. However, one must be careful to build a measure of ex ante expected bird sighting to avoid endogeneity problems associated with trip-specific observations. Destinations for each trip are chosen in advance of knowing which species will actually be seen. Each eBird trip record includes information about which bird species, and how many of each, are observed during each outing. Not all sites are equally visited, or visited in every year, so to fill in the gaps in the eBird data, we take advantage of a second external data set, this one from BirdLife International, via Ridgely et al. (2011). This dataset allows us to incorporate seasonal variations in species richness into our calculations of ex ante "expected sightings." The BirdLife dataset provides geographic references for bird ranges, their presence (i.e. their likelihood of being seen), their origin (e.g., native or introduced) and seasonality (e.g., resident, breeding, non-breeding or passage). The BirdLife data are particularly important when no eBird visits are recorded in the same month of the prior year for a particular birding hot-spot destination.[17] 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 during the time period before which forms the basis of the construction of the expected species measure. We also break out our "expected sighting" attribute into "expected sighting by type" for four categories of bird species—water birds, birds of prey, perching birds and game birds.[18]

[17]In the future, we plan to alter the expected species variable to be constructed as a moving average of sightings in the area, to better reflect how quickly eBirders can access the data submitted by other members (once it has been verified).

[18]We distinguish these four types based on the way that birds are grouped for the Pocket Naturalist Guide. Species not featured in *Oregon Birds: An Introduction to Familiar Species* are grouped using class and genus according to the Clements Checklist, version 6.8.

4.3 Other destination attributes.

Destination attributes that vary across sites can be included as variables that shift the overall *level* of total willingness to pay for a trip to a specific destination, independent of the specific levels of biodiversity in categories of bird species at that destination. These attributes include indicators for site management regimes that may be related to the overall level of 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, land cover at a destination and indicators for the type of ecosystem at the destination. We use data from the U.S. Geological Survey—namely the Protected Area Database of the U.S.[19] These data categorize the ecological management regime for each hotspot location, such as who owns the land, who manages the land, whether and how it is managed for biodiversity, and the spatial extent of the protected area. These datasets were created to facilitate landscape analyses. Our omitted GAP category is "no known ecological management of the site."[20] We use data from the U.S. Census to indicate whether a site is within an urban area (based on the 2010 U.S. Census). We include data from the USGSs 2011 National Land Cover Data which gives us land cover information on a 30-meter by 30-meter resolution level. We also use the U.S. Environmental Protection Agency (EPA) ecoregion dataset (level III) to capture broader abiotic and biotic differences across the various hotspots (for twelve regions within the two-state area for this study).

4.4 Collective prior behavior

Our current "expected congestion/popularity" 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. In the

[19] Specifically we use the USGS Gap Analysis Program (GAP) Version 1.4).

[20] GAP Status Code Definitions can be found in the USGS GAP-PAD-US Standards and Methods for State Data Stewards, 5 May 2016)

future, we plan to comparing the results from this version of the variable to results that we obtain when we measure congestion as the spatial densities of visits per unit area per month, rather than as shares of total eBird visits, thus exploring an approach used by Bujosa et al. (2015). Regardless of whether the variable is constructed as a share of total visits, or as an average monthly density of visitors per unit of site area, this congestion measure is observationally equivalent to a measure of the popularity of the site.[21] The intent of a congestion/popularity measure is to proxy for the number of other visitors the individual might expect to encounter during a visit to a particular birding 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.[22]

4.5 Sample Selection

This prototype analysis employs a sample of convenience and thus we need to control for selection into the sample: responding to the survey and taking a trip they reported to eBird. For this analysis, travel costs are calculated only for eBird members who responded to the auxiliary survey so we can geocode their home address (their trip origin). This restriction limits us to approximately 10 percent of total eBird membership, so some effort to assess and correct for any systematic sample selection is required.[23]

In the future we will build on the sample selection method employed in Kolstoe and

[21] 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)).

[22] 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.

[23] There are 7,469 user who submitted reports to eBird for the 2013-2015 time frame in the states of Oregon and Washington.

Cameron (2017), as well as look at the sample selection stemming from the choice to report a trip to eBird.[24]

4.6 Exogenous Weights

We are currently awaiting a final installment of survey data from two questions which we placed in the Qualtrics Omnibus survey during April and May of 2018. Our two questions, as shown to the respondents are reproduced in Figures 4a and 4b . Once the data from these two waves of the survey are available, we will use these data to construct weights that reflect the relative frequency and scope, in the general population, of engagement with major citizen science projects related to wild birds, and people's corresponding levels of participation in bird watching.

In the interim, we show what can be accomplished by using weights based on the 2016 U.S. Fish & Wildlife Service's (FWS) quinquennial National Survey of Fishing, Hunting and Wildlife-Associated Recreation, specifically for wildlife watching.[25] Our weights are based on the FWS's sampling weights, age, gender, living in the Pacific Census Division, and having taken a trip for wildlife-watching more than a mile from home during 2016.

5 Results

The main results are featured in Tables 6, 7, 8 and 9. The results shown are based on 9,287 trips taken by 321 birders who responded to the auxiliary survey. Our preferred model is featured in column 6 of each of these tables which incorporates the exogenous weights from

[24]In the presence of limited data, the best recourse was to model who selected to report home address information versus who did not. This method is based on an ad hoc method proposed by Cameron and DeShazo (2013) that employs sociodemographic data at the county level for the "likely" home address of each birder, based on the spatial center of gravity of their trips

[25]We have attempted to estimate our models using weights generated from the 2011 survey. However, for the more-complex random-parameters specifications, the models employing these weights failed to achieve convergence.

the 2016 U.S. FWS data.

Consideration Sets We limit eBirders choice set to all possible sites within 60-miles of their home address. Due to computational limits, we are currently only using 10 percent of the non-chosen alternatives from the full set of alternatives; the number of sites in a consideration set ranges from 2 to 89, with the average being 44. Note the results presented here are preliminary and the results featured in the paper include only the population weights constructed with the 2016 U.S. FWS data. In the appendix (available upon request from the authors) we also show results using the 2011 U.S. FWS data.

5.1 Mixed Logit in WTP Space

Marginal Utilities: Net Income Across all models in Tables 6, 7, 8 and 9, the marginal WTP of other consumption (the negative α coefficient on the travel cost variable, linear in this specification) is statistically significant and negative, the expected sign. The parameter is robust across all of our specifications.

Marginal WTP of Expected Number by Type and Correlations In Table 6, the main variable of interest in the model is β_1^i and X_{jt} which contain a vector of expected species by type (water birds, birds of prey, perching birds and game birds). In our preferred specification, shown in column 6 in Tables 6 and 7 , we find that the marginal WTP of expected species by type is heterogeneous. Part of the heterogeneity is captured through interaction terms with observable characteristics and temporal fixed effects. Considerable unobservable heterogeneity remains as evidence by the statistical significance of the random parameters and the covariance-variance matrix for these parameters. The baseline parameters for the expected number of water birds and birds of prey are each respectively positive and significant, game birds is positive, but statistically insignificant, whereas the parameter for the expected number of perching birds is negative. The variance parameters for each type is statistically significant and only the covariance term that is not statistically significant is between the expected number of perching birds and travel cost.

The negative and statistically significant covariance terms between the expected number of water birds and birds of prey, game birds and travel cost as well as between the expected number of game birds and perching birds suggesting lower levels of utility along the distribution on one of the attributes whereas all the other statistically significant covariance terms are positive.

Systematic Variation in the Marginal WTP of Expected Number by Type: Water Birds The sources of observable heterogeneity in the marginal WTP of an additional water bird species comes from observable differences in birder characteristics and time. The results suggest birders have a higher marginal WTP of seeing an additional water bird species if they are both female and a lister. The temporal differences in marginal WTP for an additional water bird species is higher for March, August and the fall months of September, October and November, but negative for the months of April, May, June and the linear time trend.

Systematic Variation in the Marginal WTP of Expected Number by Type: Birds of Prey

The sources of observable heterogeneity in the marginal WTP of an additional birds of prey species comes from observable differences in birder characteristics and time. The results suggest that birders have a lower marginal WTP of seeing an additional bird of prey if they are from a higher income bracket (than the sample average), and/or are older (than the sample average), and/or are female or a lister. However, female listers marginal WTP is higher for an additional bird of prey species than a male lister. The temporal differences in marginal WTP for an additional birds of prey bird species is higher in March, and the linear time trend parameter is positive and statistically significant.

Systematic Variation in the Marginal WTP of Expected Number by Type: Perching Birds The sources of observable heterogeneity in the marginal WTP of an additional perching bird species comes from observable differences in birder characteristics and time. The results suggest birders have a higher marginal WTP of seeing an additional perching bird if they are from a higher income bracket (than the sample average), and/or are a lister. The temporal differences in marginal WTP for an additional birds of prey bird species is lower in September.

Systematic Variation in the Marginal WTP of Expected Number by Type: Game Birds The sources of observable heterogeneity in the marginal WTP of an additional game bird species comes from observable differences in birder characteristics and time. The results suggest birders have a higher marginal WTP of seeing an additional game bird species if they are older, and/or female, and/or are a lister, and lower a lower marginal WTP if they are from a higher income bracket (than the sample average). The marginal WTP of a female lister is lower for an additional game bird species than a male lister. The temporal differences in marginal WTP for an additional game bird species is lower in July, November, December, and for the linear time trend.

Other Site Attributes A number of other site attributes bear statistically significant marginal-utility coefficients in Table 8 and 9. These include indicators for different management regimes for biodiversity, ecoregions, land cover classes, urban hotspots, along with our continuous "congestion/popularity" measure for each hotspot.[26] As in Kolstoe and Cameron (2017), the estimated marginal WTP from visits to National Wildlife Refuges which are specifically managed for bird biodiversity yields the highest to eBirders. The marginal WTP for a visit to a National Wildlife Refuge is statistically significant, implying there is a higher value (utility) for a birder for specifically visiting a site managed for bird biodiversity, above and beyond managing a site managed for biodiversity (this parameter is additive to the parameter for National Parks, etc.). This may not be surprising in light of when individuals

[26]We originally did include a variable to capture the expected presence of an endangered bird species, however, it was not statistically significant in any of the models, nor was the expected presence of threatened bird species so we have since omitted them from the model.

are traveling to see birds, they are primarily traveling to see waterfowl which can be found at National Wildlife Refuges (Wilson, 2010). The marginal WTP of a visit to a site such as National Parks (e.g. a site with GAP 1 or 2 status) or National Forests (e.g. a site with GAP 3 status) sites are positive, but are not statistically significant.

We also 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), as was the case in Kolstoe and Cameron (2017). This suggests there are latent attributes of sites in urban areas that confers disutility to non-urban sites, independent of species richness.

To control destination ecoregions and land cover, to pre-empt any omitted variable bias from these two sources in the estimated coefficients on the expected number of bird species. These two sets of controls account for any utility that is accounted for directly from either the type of ecoregion or land cover at a site. The baseline ecoregion for the trips is the Puget Lowland. The indicators for the Coast Range, Columbia Plateau, North Rockies, Willamette Valley, North Cascades, Klamath Mountains, and the Northern Basin Rage are positive and statistically significant, indicating a higher value (utility) than to a site in the Puget Lowland. However the indicators for the Blue Mountains is negative and statistically significant, whereas the indicator for the Cascades is negative and statistically insignificant. The land cover class indicators for barren land, forest, planted and wetlands are positive and statistically significant whereas the indicators for water, shrub/scrub and herbaceous land cover are not statistically significant. As in Kolstoe and Cameron (2017) 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 parameters suggest that the marginal WTP of anticipated congestion/popularity is a good thing, and only is in the range where it diminishes for one-percent of the site alternatives. Only a few sites in our sample receive this share of eBird visits in the previous year, thus over most of the range of the data, this variable is positive.[27]

6 Discussion

The results suggest there is significant preference heterogeneity for birds, and most notably by bird species type by eBirders, and more generally based on the results with the results using the exogenous weights from the U.S. FWS. While we would have like to explore the heterogeneity across groups further with the latent class models for the models by species by type, it is evident that controlling for differences in gender, age, lister status and income are critical.

The results suggest the highest marginal WTP are for water birds and birds of prey. Based on the results of the 2016 U.S. FWS this is congruent with the fact most birders who travel away from home, do so to see water fowl and birds of prey. The other bird species rank lower with perching birds being third on this list, with herons, shore birds and other water birds in second to last place and game birds as the bird type people the fewest number of people travel to see. We suspect that negative marginal WTP for perching birds in our results captures the fact most see perching birds around their home. The positive, but statistically insignificant marginal WTP for game birds may be capturing the fact the sites with this type of species attracts fewer species, and in particular during hunting season (November and December).

7 Still To Do

- Constructing expected species measures (for water birds, birds of prey, perching birds & game birds) as moving-averages (2-weeks and 4-weeks before trip date) to reflect eBird's is continually updating its histograms for its members.

[27] Linearity in this variable is strongly rejected by a likelihood ratio test.

- Include a rare species indicator

- Explore non-linearity in the by types model for the baseline parameters (note the models where we assume the random parameters have a log-normal do not converge)

- Explore different sample selection models using the 2015 auxiliary survey data and Qualtrics Ominbus survey (once the data is available)

- Incorporate population weights generated from the Qualtrics Ominbus survey (once the data is available)

8 Caveats and Directions for Future Research

Citizen science data offers researchers the possibility of working with rich data sets, however, the caveat remains that these are samples of conveniences. Our work here is to provide a flexible model to estimate the value of bird biodiversity and best approximate the general population of birders' value of different bird species types. To date this work has focused solely on birders who travel away from home (more than a mile) to see birds. This does not address the question of the value of bird biodiversity to birders who see them around their home. Per the U.S. FWS, most birders see birds around their homes, and the vast majority of these individuals, feed the wild birds around their home (U.S. FWS Report, 2018). In our other work, we are seeking to address this issue.

9 Tables

Table 1: Descriptive Statistics across All Alternatives, Featured Variables, Oregon and Washington States[a]

Variable	Mean	Std. Dev	Min	Max
Roundtrip, 1/3 wage	27.74	27.92764	1.555612	166.8201
Bird species type				
Water Birds (WT)	12.10	2.10	1	20.84
Birds of Prey (PR)	13.52	2.16	1	20.5
Perching Birds (PH)	24.43	3.64	1	35.06
Game Birds (GM)	12.37	4.85	0	20.63
Destination type				
1(National Wildlife Refuge)	0.100			
1(National Parks, etc.)	0.198			
1(National Forests, etc.)	0.408			
1(Urban Area)	0.728			
†$Congestion/Popularity_{jt}$	.0017	.003	0	.0227142
Seasonal and trend variables				
$1(January)$	.102			
$1(February)$	.092			
$1(March)$	.091			
$1(April)$	.106			
$1(May)$	.101			
$1(June)$	.072			
$1(July)$	.069			
$1(August)$	.068			
$1(September)$	.072			
$1(October)$	.0813			
$1(November)$	.085			
$1(December)$	.062			
$t13$ ($t13 = year - 2013$)	1.05			
Ecoregion indicators				
$1(Coast\ Range)_j$	0.069			
$1(Columbia\ Plateau)_j$	0.056			
$1(Blue\ Mountains)_j$	0.041			
$1(North\ Rockies)_j$	0.033			
$1(PugetLowlands)_j$	0.465			
$1(Willamette\ Valley)_j$	0.218			
$1(Cascades)_j$	0.0058			
$1(North\ Cascades)_j$	0.010			
$1(Klamath\ Mtns,\ Coast\ Range)_j$	0.043			
$1(North\ Basin)_j$	0.0005			
Land cover indicators				
$1(LC\ Developed)$	0.37			
$1(LC\ Water/Perennial\ Snow\ \&\ Ice)$	0.051			
$1(LC\ Barren\ Land)$	0.080			
$1(LC\ Forest)$	0.210			
$1(LC\ Shrub/Scrub)$	0.061			
$1(LC\ Herbaceous)$	0.011			
$1(LC\ Planted)$	0.084			
$1(LC\ Wetlands)$	0.120			

NOTES: [a]60-miles maximum travel distance for considered alternative hotspots, 2013-2015 trips; statistics for other control variables used in our models have been relegated to the Appendix.
† Share of all eBird trips, same month, last year, to site j

Table 2: Descriptive Statistics across All Alternatives,
Featured Birder Characteristics, Oregon and Washington States

eBirders in Sample: Sociodemographics	Mean	Min	Max
Females	.517	-	-
Listers	.561	-	-
Avg. Age	57.26	14	78
Diff. from Sample Avg. Age	-0.55	-44.38	19.62
Working	.433	-	-
Avg. Income (in $10,000)	9.484	1.8	22.5
Diff. from Sample Avg. Income (in $10,000)	1.80	-6.81	13.89

10 Tables

Table 3: Descriptive Statistics across All Alternatives, Featured Variables, Oregon and Washington States[a]

Variable	Mean	Std. Dev	Min	Max
Roundtrip, 1/3 wage	27.74	27.92764	1.555612	166.8201
Bird species type				
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Perching Birds (PH)	24.43	3.64	1	35.06
Game Birds (GM)	12.37	4.85	0	20.63
Destination type				
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$1(North\ Cascades)_j$	0.010			
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$1(LC\ Planted)$	0.084			
$1(LC\ Wetlands)$	0.120			

NOTES: [a]60-miles maximum travel distance for considered alternative hotspots, 2013-2015 trips; statistics for other control variables used in our models have been relegated to the Appendix.
† Share of all eBird trips, same month, last year, to site j

Table 4: Descriptive Statistics across All Alternatives,
Featured Birder Characteristics, Oregon and Washington States

eBirders in Sample: Sociodemographics	Mean	Min	Max
Females	.517	-	-
Listers	.561	-	-
Avg. Age	57.26	14	78
Diff. from Sample Avg. Age	-0.55	-44.38	19.62
Working	.433	-	-
Avg. Income (in $10,000)	9.484	1.8	22.5
Diff. from Sample Avg. Income (in $10,000)	1.80	-6.81	13.89

Table 5: Selected Summary Statistics from the 2015 eBird Auxiliary Survey Relative to the 2016 USFWS Survey for Birders Who Took Trip(s) Away from Home

Survey Sample Statistics	% New Survey	% USFW 2016
Gender		
Male	43	55
Female	57	45
Age		
16 to 24	1	5
25 to 34	6	13.9
35 to 44	9	16.8
45 to 54	15	17.8
55 to 64	31	17.8
65 to 74	31	20.8
75 +	2.8	7.9
Income		
Less than $20,000	3.34	0
$20,000 to $24,999	3.02	4
$25,000 to $29,999	3.18	0
$30,000 to $49,999	12.71	5
$50,000 to $74,999	18.34	6.9
$75,000 to $99,999	13.53	28.7
$100,000 to $149,999	15.15	45.6
$150,000 or more	9.86	11.9

Table 6: Progression of Models, Pooled Oregon and Washington Sample; Select Key Coefficients Results – 60-Mile Choice Set

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
Expected # water bird species (WT)	0.878***	1.630***	3.241**	3.173***	2.980***	3.403***
	(0.202)	(0.449)	(1.267)	(0.996)	(0.771)	(0.749)
Expected # bird of prey species (PR)	-0.565***	2.990***	3.342**	2.380**	-1.356*	4.351***
	(0.216)	(0.654)	(1.395)	(1.036)	(0.741)	(0.747)
Expected # perching bird species (PH)	0.0398	-0.802***	-0.312	-1.223*	-1.868***	-2.347***
	(0.137)	(0.242)	(0.509)	(0.726)	(0.402)	(0.436)
Expected # game bird species (GM)	0.930***	-0.786**	-0.711**	0.914**	2.228***	0.621
	(0.132)	(0.340)	(0.310)	(0.451)	(0.330)	(0.384)
Var(WT)	5.930***	0.655	1.260	6.456***	5.686***	6.591***
	(0.260)	(1.446)	(1.158)	(1.561)	(0.267)	(0.302)
Cov(PR,WT)	-3.722***	-6.883***	-7.252***	-2.343***	-3.786***	-2.687***
	(0.274)	(1.709)	(1.195)	(0.862)	(0.357)	(0.354)
Cov(PH,WT)	-0.205	2.539***	2.281***	2.203**	0.0286	1.884***
	(0.141)	(0.741)	(0.838)	(1.007)	(0.163)	(0.183)
Cov(GM,WT)	1.636***	6.455***	7.950***	-0.530*	2.289***	-0.806***
	(0.184)	(1.990)	(1.425)	(0.319)	(0.140)	(0.175)
Cov(TC3, WT)	0.422***	0.806***	0.835***	-0.168***	0.391***	-0.0828***
	(0.0206)	(0.122)	(0.199)	(0.0406)	(0.0158)	(0.0184)
Var(PR)	3.913***	3.026**	2.385**	5.150***	5.350***	7.013***
	(0.321)	(1.354)	(1.184)	(0.707)	(0.260)	(0.340)
Cov(PH,PR)	-1.376***	-3.632***	-3.943***	2.068***	-1.777***	2.640***
	(0.132)	(0.628)	(0.594)	(0.364)	(0.133)	(0.209)
Cov(GM,PR)	2.211***	2.901***	3.560***	0.867**	1.708***	1.114***
	(0.149)	(0.465)	(0.421)	(0.405)	(0.138)	(0.233)
Cov(TC3,PR)	0.239***	0.402***	0.411***	0.397***	0.0968***	0.493***

Table 6 Continued

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
	(0.0200)	(0.0728)	(0.0712)	(0.0486)	(0.0184)	(0.0219)
Var(PH)	0.385**	1.566***	1.665***	1.969***	0.745***	1.688***
	(0.166)	(0.321)	(0.291)	(0.373)	(0.166)	(0.233)
Cov(GM,PH)	3.894***	0.651**	0.637***	-4.049***	4.398***	-6.133***
	(0.230)	(0.299)	(0.202)	(0.735)	(0.199)	(0.286)
Cov(TC3,PH)	-0.498***	-0.408***	-0.433***	0.118**	-0.700***	-0.0252
	(0.0355)	(0.0502)	(0.0393)	(0.0536)	(0.0240)	(0.0208)
Var(GM)	2.921***	2.168***	2.724***	0.572***	3.793***	0.958***
	(0.255)	(0.430)	(0.407)	(0.163)	(0.164)	(0.108)
Cov(TC3, GM)	0.564***	0.135***	0.147**	0.293***	0.396***	0.258***
	(0.0541)	(0.0487)	(0.0710)	(0.0423)	(0.0238)	(0.0155)
Var(TC3)	0.116***	0.420***	0.409***	0.728***	0.0867***	0.667***
	(0.0246)	(0.0375)	(0.0680)	(0.0978)	(0.0163)	(0.0210)
Sample Selection?	No	No	No	No	No	No
Time fixed effects?	No	No	Yes	Yes	Yes	Yes
Ecoregion?	Yes	Yes	Yes	Yes	Yes	Yes
Total Alternatives	308,922	308,387	308,387	308,387	308,620	308,620
Log Likelihood	-17421.11	-352125.71	-347230.04	-311840.57	-17240.16	-17228.46
AIC	34926.21	704335.41	694648.07	623869.14	34700.32	34676.92
BIC	35373.13	704782.25	695648.15	624869.22	35870.70	35847.30

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

† Share of all eBird trips, same month, last year, to site j

NOTES: Estimates estimated via STATA *mixlogitwtp.ado*. These results use 500 Halton draws for the mixed logit in WTP model simulations. Baseline coefficient represents the marginal utility for an eBirder who is visiting a rural site that is not managed for biodiversity in the Puget Lowland in January of 2013. Models are the results for choice sets within a 60-mile drive from a member's home.

Table 7: Progression of Models, Pooled Oregon and Washington Sample; By Interaction Terms Results – 60-Mile Choice Set

Select Coefficients

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
WT × diff. mean ($10,000)			0.0214	-0.0121	-0.0425	0.0257
			(0.0809)	(0.0878)	(0.0376)	(0.0375)
WT× diff. mean age					-0.0207*	-0.00757
					(0.0126)	(0.0139)
WT× 1($female$)					0.129	0.573
					(0.855)	(0.810)
WT× 1($lister$)					-1.357**	-0.845
					(0.588)	(0.567)
WT× 1($female$)× 1($lister$)					-0.603	2.952***
					(0.953)	(0.936)
PR × diff. mean income ($10,000)			-0.0666	-0.359***	-0.179***	-0.400***
			(0.112)	(0.127)	(0.0516)	(0.0573)
PR× diff. mean age					0.0278**	-0.0370**
					(0.0138)	(0.0151)
PR× 1($female$)					-1.109	-2.801***
					(0.828)	(0.764)
PR× 1($lister$)					1.878***	-1.483**
					(0.668)	(0.610)
PR× 1($female$)× 1($lister$)					-0.209	2.617***
					(0.999)	(0.954)
PH × diff. mean income ($10,000)			-0.109***	0.248**	0.00855	0.206***
			(0.0304)	(0.107)	(0.0245)	(0.0301)
PH× diff. mean age					0.00944	0.00408
					(0.00752)	(0.00823)
PH× 1($female$)					-0.979**	-0.497

Table 7 Continued

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
					(0.486)	(0.475)
PH× 1($lister$)					1.603***	1.867***
					(0.309)	(0.344)
PH× 1($female$)× 1($lister$)					0.882	-0.885
					(0.562)	(0.564)
GM× diff. mean income ($10,000)			0.129***	-0.0646	0.00663	-0.116***
			(0.0231)	(0.0505)	(0.0153)	(0.0226)
GM× diff. mean age					-0.0222***	0.00975*
					(0.00488)	(0.00534)
GM× 1($female$)					1.081**	2.860***
					(0.450)	(0.457)
GM× 1($lister$)					-0.369	0.856***
					(0.248)	(0.303)
GM× 1($female$)× 1($lister$)					0.168	-3.131***
					(0.472)	(0.533)
WT× 1($February$)			-0.641	0.904	0.658	1.174
			(2.177)	(0.876)	(0.696)	(0.726)
WT× 1($March$)			0.744	1.400	0.684	1.478*
			(1.728)	(1.188)	(0.787)	(0.777)
WT× 1($April$)			-2.836***	-2.513**	-1.803**	-1.664**
			(1.085)	(1.038)	(0.717)	(0.735)
WT× 1(May)			-1.483	-2.243***	-1.622**	-1.430*
			(1.307)	(0.857)	(0.730)	(0.736)
WT× 1($June$)			-2.101**	-1.645**	-1.451*	-1.561*
			(1.010)	(0.812)	(0.767)	(0.821)
WT× 1($July$)			2.587	1.043	0.446	0.471
			(2.105)	(0.829)	(0.847)	(0.827)

Table 7 Continued

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
WT$\times$ 1($August$)			0.517	2.038*	2.507***	2.061**
			(2.572)	(1.129)	(0.898)	(0.980)
WT$\times$ 1($September$)			-0.210	1.101	2.228***	1.957**
			(2.651)	(1.283)	(0.848)	(0.864)
WT$\times$ 1($October$)			1.960	1.599	1.725**	2.194***
			(1.293)	(1.081)	(0.785)	(0.822)
WT$\times$ 1($November$)			2.886***	1.731*	2.156***	2.107***
			(0.918)	(0.979)	(0.808)	(0.775)
WT$\times$ 1($December$)			-0.922	-0.966	-1.554**	-0.979
			(1.719)	(1.004)	(0.744)	(0.818)
WT$\times$ $t13$			-1.044	-1.041**	-1.245***	-1.327***
			(0.755)	(0.447)	(0.246)	(0.252)
PR$\times$ 1($February$)			0.242	-0.989	-0.716	-0.809
			(1.816)	(0.663)	(0.766)	(0.795)
PR$\times$ 1($March$)			0.572	0.974	1.140	1.494*
			(1.004)	(0.696)	(0.929)	(0.904)
PR$\times$ 1($April$)			1.012	0.494	0.301	0.313
			(1.300)	(0.890)	(0.788)	(0.789)
PR$\times$ 1(May)			-2.032*	0.818	0.329	0.722
			(1.045)	(0.886)	(0.796)	(0.780)
PR$\times$ 1($June$)			-0.419	-0.748	-1.026	-0.541
			(0.956)	(0.666)	(0.800)	(0.839)
PR$\times$ 1($July$)			-0.440	-1.104	-1.023	-0.728
			(1.215)	(0.739)	(0.843)	(0.845)
PR$\times$ 1($August$)			-1.387	-1.648	-2.107***	-1.328
			(1.755)	(1.006)	(0.807)	(0.853)
PR$\times$ 1($September$)			-0.154	-0.521	-0.804	-0.365

Table 7 Continued

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
			(1.875)	(0.960)	(0.775)	(0.786)
PR× 1(*October*)			-0.0727	-0.485	-0.250	-0.150
			(1.552)	(0.826)	(0.802)	(0.833)
PR× 1(*November*)			-0.703	-0.247	-0.581	0.303
			(1.219)	(0.798)	(0.840)	(0.809)
PR× 1(*December*)			-0.102	0.544	0.109	0.595
			(1.315)	(0.852)	(0.827)	(0.863)
PR× $t13$			0.124	0.575	0.162	0.415*
			(0.833)	(0.408)	(0.242)	(0.241)
PH× 1(*February*)			-0.0234	-0.127	-0.491	-0.563
			(0.497)	(0.411)	(0.435)	(0.443)
PH× 1(*March*)			0.590	0.965	0.420	0.400
			(0.510)	(0.673)	(0.553)	(0.564)
PH× 1(*April*)			-0.193	0.266	0.408	0.206
			(0.595)	(0.469)	(0.417)	(0.442)
PH× 1(*May*)			0.736	0.559	0.708*	0.475
			(0.784)	(0.527)	(0.420)	(0.446)
PH× 1(*June*)			0.615	0.734*	0.850*	0.502
			(0.430)	(0.427)	(0.441)	(0.491)
PH× 1(*July*)			-0.863	0.430	0.824*	0.494
			(0.786)	(0.627)	(0.476)	(0.491)
PH× 1(*August*)			0.0340	0.344	1.104**	0.117
			(0.933)	(0.778)	(0.503)	(0.547)
PH× 1(*September*)			-1.002	-0.543	-0.694*	-0.955**
			(0.826)	(0.668)	(0.418)	(0.459)
PH× 1(*Octber*)			-1.558**	-0.204	0.0250	-0.247
			(0.710)	(0.624)	(0.435)	(0.479)

Table 7 Continued

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
PH$\times$ 1($November$)			-1.256***	-0.357	-0.392	-0.546
			(0.486)	(0.589)	(0.449)	(0.447)
PH$\times$ 1($December$)			-0.656	-0.424	0.372	-0.138
			(0.498)	(0.551)	(0.427)	(0.486)
PH$\times$ $t13$			-0.0831	-0.155	0.181	0.0493
			(0.245)	(0.304)	(0.135)	(0.142)
GM$\times$ 1($February$)			0.132	0.0783	0.146	0.117
			(0.314)	(0.228)	(0.302)	(0.324)
GM$\times$ 1($March$)			-0.693**	-0.551*	-0.217	-0.270
			(0.287)	(0.282)	(0.288)	(0.312)
GM$\times$ 1($April$)			-0.125	0.0537	-0.0919	0.178
			(0.290)	(0.244)	(0.296)	(0.325)
GM$\times$ 1(May)			-0.0837	0.0624	0.373	0.504
			(0.365)	(0.422)	(0.303)	(0.330)
GM$\times$ 1($June$)			-0.169	0.0582	0.0144	0.0442
			(0.418)	(0.309)	(0.361)	(0.384)
GM$\times$ 1($July$)			-0.279	-0.632**	-0.413	-0.624*
			(0.178)	(0.289)	(0.323)	(0.360)
GM$\times$ 1($August$)			0.165	-0.300	-0.153	-0.197
			(0.450)	(0.433)	(0.310)	(0.346)
GM$\times$ 1($September$)			0.222	-0.156	-0.197	-0.254
			(0.362)	(0.295)	(0.329)	(0.372)
GM$\times$ 1($Octber$)			-0.0325	-0.346	-0.305	-0.368
			(0.298)	(0.363)	(0.281)	(0.328)
GM$\times$ 1($November$)			0.244	-0.504	-0.599**	-0.785**
			(0.409)	(0.527)	(0.274)	(0.316)
GM$\times$ 1($December$)			-0.459**	-0.743***	-0.715**	-0.926***

Table 7 Continued

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
			(0.207)	(0.247)	(0.309)	(0.348)
GM× $t13$			0.149*	-0.0986	-0.0421	-0.177*
			(0.0884)	(0.131)	(0.0922)	(0.104)
Sample Selection?	No	No	No	No	No	No
Time fixed effects?	No	No	Yes	Yes	Yes	Yes
Ecoregion indicators?	Yes	Yes	Yes	Yes	Yes	Yes
Total Alternatives	308,922	308,387	308,387	308,387	308,620	308,620
Log Likelihood	-17421.11	-352125.71	-347230.04	-311840.57	-17240.16	-17228.46
AIC	34926.21	704335.41	694648.07	623869.14	34700.32	34676.92
BIC	35373.13	704782.25	695648.15	624869.22	35870.70	35847.30

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
† Share of all eBird trips, same month, last year, to site j

NOTES: Estimates estimated via STATA *mixlogitwtp.ado*. These results use 500 Halton draws for the mixed logit in WTP model simulations. Baseline coefficient represents the marginal utility for an eBirder who is visiting a rural site that is not managed for biodiversity in the Puget Lowland in January of 2013. Models are the results for choice sets within a 60-mile drive from a member's home.

Table 8: Progression of Models, Pooled Oregon and Washington Sample; Select Key Site Attribute Coefficients Results – 60-Mile Choice Set

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
	(1)	(2)	(3)	(4)	(5)	(6)
1(National Wildlife Refuge)	10.48***	1.487	1.918	6.191*	9.954***	10.72***
	(1.042)	(7.128)	(7.059)	(3.411)	(1.019)	(1.068)
1(National Parks, etc.)	-0.0768	1.644	1.707	1.207	0.918	0.605
	(0.738)	(2.500)	(2.749)	(2.347)	(0.753)	(0.779)
1(National Forests, etc.)	0.0519	-0.923	-0.929	0.755	0.531	0.551
	(0.499)	(1.584)	(1.528)	(1.608)	(0.518)	(0.531)
1(Urban Area)	-7.913***	-5.243***	-5.032***	-5.380**	-6.971***	-5.865***
	(0.769)	(1.581)	(1.579)	(2.531)	(0.782)	(0.792)
†$Congestion/Popularity_{jt}$	7936.6***	7479.5***	7459.8***	7865.1***	7962.5***	8042.5***
	(253.1)	(1032.1)	(923.8)	(941.6)	(252.1)	(256.1)
$(Congestion/Popularity_{jt})^2$	-312837.3***	-303912.9***	-305342.5***	-336081.2***	-316396.7***	-330533.7***
	(16051.4)	(60670.3)	(52251.1)	(46911.0)	(16616.4)	(16625.7)
Sample Selection?	No	No	No	No	No	No
Time fixed effects?	No	No	Yes	Yes	Yes	Yes
Ecoregion indicators?	Yes	Yes	Yes	Yes	Yes	Yes
Total Alternatives	308,922	308,387	308,387	308,387	308,620	308,620
Log Likelihood	-17421.11	-352125.71	-347230.04	-311840.57	-17240.16	-17228.46
AIC	34926.21	704335.41	694648.07	623869.14	34700.32	34676.92
BIC	35373.13	704782.25	695648.15	624869.22	35870.70	35847.30

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

† Share of all eBird trips, same month, last year, to site j

NOTES: Estimates estimated via STATA *mixlogitwtp.ado*. These results use 500 Halton draws for the mixed logit in WTP model simulations. Baseline coefficient represents the marginal utility for an eBirder who is visiting a rural site that is not managed for biodiversity in the Puget Lowland in January of 2013. Models are the results for choice sets within a 60-mile drive from a member's home.

Table 9: Progression of Models, Pooled Oregon and Washington Sample; Select Coefficients By Interaction Terms Results – 60-Mile Choice Set

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
$1(Coast\ Range)_j$	9.201***	26.82***	27.84***	14.50**	10.63***	14.18***
	(2.515)	(3.406)	(4.517)	(5.829)	(2.440)	(2.490)
$1(Columbia\ Plateau)_j$	5.021	16.03	16.98	23.03	8.336*	14.69***
	(4.134)	(12.39)	(11.68)	(102.9)	(4.408)	(4.992)
$1(Blue\ Mountains)_j$	-2.744	-0.355	-0.421	-4.492	-6.212***	-3.562*
	(2.085)	(4.373)	(3.891)	(3.408)	(2.088)	(2.119)
$1(North\ Rockies)_j$	6.414	14.40	15.16	23.53	11.73**	15.60**
	(6.049)	(13.83)	(13.20)	(101.7)	(5.290)	(6.310)
$1(Willamette\ Valley)_j$	17.70***	41.35***	41.49***	19.70***	21.73***	27.52***
	(2.823)	(8.012)	(7.172)	(7.496)	(2.951)	(3.236)
$1(Cascades)_j$	1.255	-0.104	-0.0132	-0.834	2.030	-2.454
	(3.401)	(6.575)	(7.153)	(6.907)	(3.120)	(3.676)
$1(North\ Cascades)_j$	8.796***	12.03**	13.51**	12.67	11.92***	16.64***
	(2.966)	(6.012)	(5.381)	(9.384)	(3.009)	(3.538)
$1(Klamath\ Mtns,\ Coast\ Range)_j$	32.94***	52.62***	58.42***	39.38***	32.73***	43.14***
	(4.688)	(6.184)	(7.108)	(9.770)	(4.183)	(5.118)
$1(N.\ Basin\ Range)$	20.26**	15.46*	15.98*	17.40	16.52**	15.42**
	(7.966)	(8.880)	(8.960)	(12.51)	(7.105)	(7.102)
$1(LC\ Water/Perennial\ Snow\ \&\ Ice)$	0.762	1.450	1.213	-0.165	0.642	0.488
	(0.818)	(2.336)	(2.278)	(2.992)	(0.842)	(0.910)
$1(LC\ Barren\ Land)$	10.88***	6.159	5.766	4.579	10.60***	9.800***
	(0.833)	(4.349)	(4.766)	(3.436)	(0.839)	(0.886)
$1(LC\ Forest)$	7.806***	11.24***	11.00***	6.542***	7.032***	7.058***
	(0.677)	(2.333)	(2.118)	(2.428)	(0.644)	(0.661)
$1(LC\ Shrub/Scrub)$	-0.283	-0.149	0.143	-1.239	-1.328	0.844
	(1.001)	(3.975)	(3.985)	(3.607)	(0.993)	(1.092)

Table 9 Continued

	No Interactions		Ecological Economics Specification		+ Gender, Age, Lister Status	
	No Weights	2016 Weights	No Weights	2016 Weights	No Weights	2016 Weights
Mean Coefficients	(1)	(2)	(3)	(4)	(5)	(6)
1(*LC Herbaceous*)	-0.0118	-1.170	-0.932	-1.342	0.105	-0.462
	(1.694)	(3.343)	(3.349)	(3.642)	(1.602)	(1.669)
1(*LC Planted*)	4.917***	6.869***	6.923**	6.559***	4.981***	5.734***
	(0.750)	(2.498)	(2.699)	(2.258)	(0.796)	(0.800)
1(*LC Wetlands*)	9.156***	7.838***	7.119**	9.420***	8.960***	10.49***
	(0.702)	(2.989)	(3.069)	(3.432)	(0.718)	(0.737)
Sample Selection?	No	No	No	No	No	No
Time fixed effects?	No	No	Yes	Yes	Yes	Yes
Ecoregion?	Yes	Yes	Yes	Yes	Yes	Yes
Total Alternatives	308,922	308,387	308,387	308,387	308,620	308,620
Log Likelihood	-17421.11	-352125.71	-347230.04	-311840.57	-17240.16	-17228.46
AIC	34926.21	704335.41	694648.07	623869.14	34700.32	34676.92
BIC	35373.13	704782.25	695648.15	624869.22	35870.70	35847.30

Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
† Share of all eBird trips, same month, last year, to site j

NOTES: Estimates estimated via STATA *mixlogitwtp.ado*. These results use 500 Halton draws for the mixed logit in WTP model simulations. Baseline coefficient represents the marginal utility for an eBirder who is visiting a rural site that is not managed for biodiversity in the Puget Lowland in January of 2013. Models are the results for choice sets within a 60-mile drive from a member's home.

Table 10: Variations in the value of a birding trip based on the expected number of bird species by type (mean of continuous variables, for January 2013, unmanaged site, non-urban developed destination in the Puget Lowlands). Estimates incorporate the 2016 FWS weights.

Simulation		$ Total WTP for trip
Minimum	(1 water bird, 1 bird of prey, 1 perching bird, 0 game birds)	$1.78 (.75, 2.81)
10th percentile	(10 water birds, 12 birds of prey, 22 perching birds, 0.14 game birds)	$111.66 (105.33, 117.99)
25th percentile	(11 water birds, 12.84 birds of prey, 24 perching birds, 12 game birds)	$111.37 (104.4, 118.34)
50th percentile	(12.03 water birds, 13.07 birds of prey, 25 perching birds, 14 game birds)	$118.87 (111.42, 126.32)
75th percentile	(13.36 water birds, 15 birds of prey, 26 perching birds, 14 game birds)	$105.49 (97.38, 113.59)
90th percentile	(14.29 water birds, 15.11 birds of prey, 27.39 perching birds, 16.02 game birds)	$126.19 (117.63, 134.76)
Maximum	(20.84 water birds, 20.5 birds of prey, 35 perching birds, 20.63 game birds)	$170.07 (158.27, 181.87)

NOTE: The values in parenthesis represent the values within one standard deviation and include the correlations between the random variables

Table 11: Systematic seasonal variations in the value of a birding trip (calculated at mean species richness and mean congestion level, for January 2013, unmanaged site, non-urban developed destination in the Puget Lowlands). Estimates incorporate the 2016 FWS weights.

Simulation	Total WTP for a trip	MWTP per WT	MWTP per PR	MWTP per PH	MWTP per GM
B. By month (T_t variable)					
(At mean $E[S]$, means of cont. variables, January, 2013, not managed, rural, Puget Lowlands)					
January	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
February	$-165.44	$4.62	$2.82	$-2.54	$.53
	(-172.73, -158.15)	(4.25, 4.99)	(2.78, 2.87)	(-2.61, -2.47)	(.52, .54)
March	$771.67	$4.93	$5.13	$-1.58	$.14
	(764.38, 778.96)	(4.56, 5.3)	(5.08, 5.17)	(-1.65, -1.51)	(.13, .15)
April	$86.01	$1.79	$3.94	$-1.77	$.59
	(78.72, 93.3)	(1.41, 2.16)	(3.9, 3.99)	(-1.84, -1.7)	(.58, .6)
May	$390.36	$2.02	$4.35	$-1.5	$.92
	(383.07, 397.65)	(1.65, 2.39)	(4.31, 4.4)	(-1.57, -1.43)	(.91, .92)
June	$115.62	$1.89	$3.09	$-1.47	$.46
	(108.32, 122.91)	(1.52, 2.26)	(3.05, 3.13)	(-1.54, -1.4)	(.45, .46)
July	$270.89	$3.92	$2.9	$-1.48	$-.21
	(263.6, 278.18)	(3.55, 4.29)	(2.86, 2.95)	(-1.55, -1.41)	(-.22, -.2)
August	$230	$5.51	$2.3	$-1.86	$.22
	(222.7, 237.29)	(5.14, 5.88)	(2.26, 2.35)	(-1.93, -1.79)	(.21, .22)
September	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
October	$204.99	$5.64	$3.48	$-2.22	$.04
	(197.7, 212.29)	(5.27, 6.02)	(3.44, 3.53)	(-2.29, -2.15)	(.04, .05)
November	$33.41	$5.56	$3.93	$-2.52	$-.37
	(26.12, 40.7)	(5.18, 5.93)	(3.89, 3.98)	(-2.59, -2.45)	(-.38, -.37)
December	$-128.09	$2.47	$4.23	$-2.12	$-.51
	(-135.38, -120.79)	(2.1, 2.84)	(4.18, 4.27)	(-2.19, -2.04)	(-.52, -.51)
C. By year (T_t variable)					
(At mean $E[S]$, mean continuous variables, mean congestion, January, not managed, rural, developed, Puget Lowlands)					
2013	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
2014	$8.27	$2.12	$4.05	$-1.93	$.23
	(.98, 15.56)	(1.75, 2.49)	(4, 4.09)	(-2, -1.86)	(.23, .24)
2015	$-103.76	$.79	$4.46	$-1.88	$.06
	(-111.05, -96.47)	(.42, 1.17)	(4.42, 4.51)	(-1.95, -1.81)	(.05, .07)

NOTE: The values in parenthesis represent the values within one standard deviation and include the correlations between the random variables

Table 12: Systematic variation by sociodemographics in the value of a birding trip (calculated at mean species richness and mean congestion level, for January 2013, unmanaged site, non-urban developed destination in the Puget Lowlands). Estimates incorporate the 2016 FWS weights.

Simulation	Total WTP for a trip	MWTP per WT	MWTP per PR	MWTP per PH	MWTP per GM
D. By gender					
(At means of cont. variables, January, 2013, not managed, rural, Puget Lowlands)					
Male, not a Lister(baseline)	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
Female	$120.79	$3.45	$3.63	$-1.98	$.41
	(113.5, 128.08)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
E. By lister status					
(At means of cont. variables, January, 2013, not managed, rural, Puget Lowlands)					
Lister	$130.1	$3.45	$3.63	$-1.98	$.41
	(122.81, 137.39)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
Female Lister	$127.36	$3.45	$3.63	$-1.98	$.41
	(120.07, 134.65)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
F. By difference in income (Z^i variables)					
(At mean $E[S]$, mean of other continuous variables, mean congestion, January, 2013, rural, developed, Puget Lowlands)					
Min of difference from sample mean income ($0000)=-6.812	$-249.21	$3.23	$7.07	$-3.75	$1.41
	(-256.5, -241.92)	(2.86, 3.6)	(7.03, 7.12)	(-3.82, -3.68)	(1.4, 1.42)
10th %ile of difference from sample mean income ($0000)=-4.6121	$-154.82	$3.28	$6.2	$-3.3	$1.16
	(-162.11, -147.53)	(2.91, 3.66)	(6.15, 6.24)	(-3.37, -3.23)	(1.15, 1.16)
25th %ile of difference from sample mean income ($0000)=-2.3621	$-58.27	$3.34	$5.3	$-2.83	$.89
	(-65.57, -50.98)	(2.97, 3.71)	(5.25, 5.34)	(-2.9, -2.76)	(.89, .9)
50th %ile of difference from sample mean income ($0000)=-2.3621	$-58.27	$3.34	$5.3	$-2.83	$.89
	(-65.57, -50.98)	(2.97, 3.71)	(5.25, 5.34)	(-2.9, -2.76)	(.89, .9)
Mean difference from sample mean income ($0000)=.985421	$85.36	$3.43	$3.96	$-2.14	$.51
	(78.07, 92.65)	(3.06, 3.8)	(3.91, 4)	(-2.21, -2.07)	(.5, .51)
90th %ile of difference from sample mean income ($0000)=5.1379	$263.53	$3.54	$2.3	$-1.29	$.02
	(256.24, 270.82)	(3.16, 3.91)	(2.25, 2.34)	(-1.36, -1.22)	(.02, .03)
Max difference from sample mean income ($0000)=10.1379	$478.07	$3.66	$.3	$-.26	$-.56
	(470.78, 485.36)	(3.29, 4.04)	(.25, .34)	(-.33, -.19)	(-.56, -.55)
G. By difference in age (Z^i variables)					
(At mean $E[S]$, mean of other continuous variables, mean congestion, January, 2013, rural, developed, Puget Lowlands)					
-44 year difference from sample mean age=-44.378689	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
-38 year difference from sample mean age=-38.378689	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
-28 year difference from sample mean age=-28.378689	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
-18 year difference from sample mean age=-18.378689	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
-8 year difference from sample mean age=-8.378689	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
1.6 year difference from sample mean age=1.6213112	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
11.6 year difference from sample mean age=11.6213112	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)
19.6 year difference from sample mean age=19.6213112	$120.3	$3.45	$3.63	$-1.98	$.41
	(113.01, 127.59)	(3.08, 3.82)	(3.59, 3.68)	(-2.05, -1.91)	(.4, .42)

NOTE: The values in parenthesis represent the values within one standard deviation and include the correlations between the random variables

Table 13: Variations in the value of a birding trip based on observable site attributes (mean of continuous variables, for January 2013, unmanaged site, non-urban developed destination in the Puget Lowlands). Estimates incorporate the 2016 FWS weights.

Simulation	\$ Total WTP for trip
H. By management regime (A_{jt} variables)	
(At mean $E[S]$, mean continuous variables, mean congestion, January, 2013, rural, developed, Puget Lowlands)	
National Wildlife Refuges	\$131.62 (124.33, 138.91)
National Parks, etc.	\$120.9 (113.61, 128.19)
National Forests, etc.	\$120.85 (113.56, 128.14)
Not managed (repeat)	\$120.3 (113.01, 127.59)
I. By urban/rural (a A_{jt} variable)	
(At mean $E[S]$, mean continuous variables, mean congestion, January, 2013, rural, developed, Puget Lowlands)	
Urban	\$120.3 (113.01, 127.59)
Rural	\$126.16 (118.87, 133.45)
J. By congestion/popularity measure (A_{jt} variables)	
(At mean $E[S]$, mean continuous variables, mean congestion, January, 2013, rural, developed, Puget Lowlands)	
10th %ile of eBird congestion=0	\$117.76 (110.47, 125.05)
Mean eBird congestion=.00032	\$120.3 (113.01, 127.59)
75th %ile of eBird congestion=.000221	\$119.52 (112.23, 126.81)
90th %ile of eBird congestion=.000768	\$123.74 (116.45, 131.03)
Max eBird congestion=.02441176	\$117.11 (109.82, 124.41)

NOTE: The values in parenthesis represent the values within one standard deviation and include the correlations between the random variables

Table 14: Variations in the value of a birding trip based on ecoregion (mean of continuous variables, for January 2013, unmanaged site, non-urban developed destination in the Puget Lowlands). Estimates incorporate the 2016 FWS weights.

Simulation	$ Total WTP for trip
K. By Ecoregion (A_{jt} variables)	
(At mean $E[S]$, mean continuous variables, mean congestion, January, 2013, rural, developed, Puget Lowlands)	
Blue Mountains	$116.74 (109.45, 124.03)
Cascades	$117.84 (110.55, 125.14)
Coast Range	$134.48 (127.18, 141.77)
Columbia Plateau	$134.99 (127.7, 142.28)
Eastern Cascades Slopes and Foothills	$120.3 (113.01, 127.59)
Klamath Mtns and CA High N. Coast Range	$163.44 (156.15, 170.73)
North Cascades	$136.94 (129.65, 144.23)
Northern Basin and Range	$135.72 (128.42, 143.01)
Northern Rockies	$135.9 (128.61, 143.19)
Puget Lowlands	$120.3 (113.01, 127.59)
Willamette Valley	$147.81 (140.52, 155.11)

NOTE: The values in parenthesis represent the values within one standard deviation and include the correlations between the random variables

Table 15: Variations in the value of a birding trip based on ecoregion (mean of continuous variables, for January 2013, unmanaged site, non-urban developed destination in the Puget Lowlands). Estimates incorporate the 2016 FWS weights.

Simulation	$ Total WTP for trip
L. By land cover type	
(At means of cont. variables, January, 2013, not managed, rural, Puget Lowlands)	
Developed (baseline)	$120.3 (113.01, 127.59)
Water	$120.79 (113.5, 128.08)
Barren land	$130.1 (122.81, 137.39)
Forest	$127.36 (120.07, 134.65)
Shrubland	$120.3 (113.01, 127.59)
Herbaceous	$119.84 (112.55, 127.13)
Planted/cultivated	$126.03 (118.74, 133.32)
Wetlands	$130.78 (123.49, 138.08)

NOTE: The values in parenthesis represent the values within one standard deviation and include the correlations between the random variables

11 Figures

Figure 1: Map of the home addresses of the survey respondents [dots represent home address location]

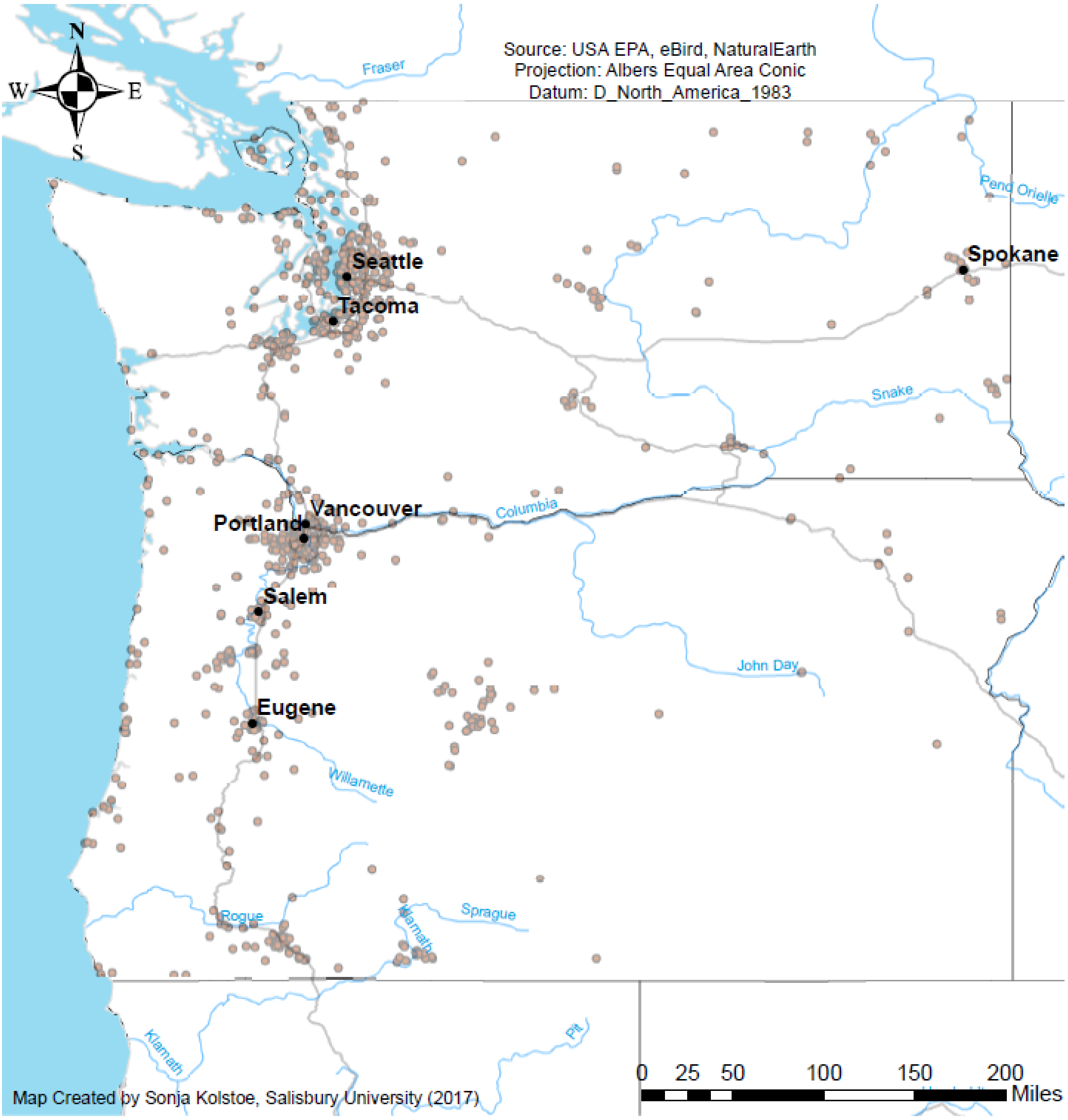

Figure 2: Map of the eBird Hotspots

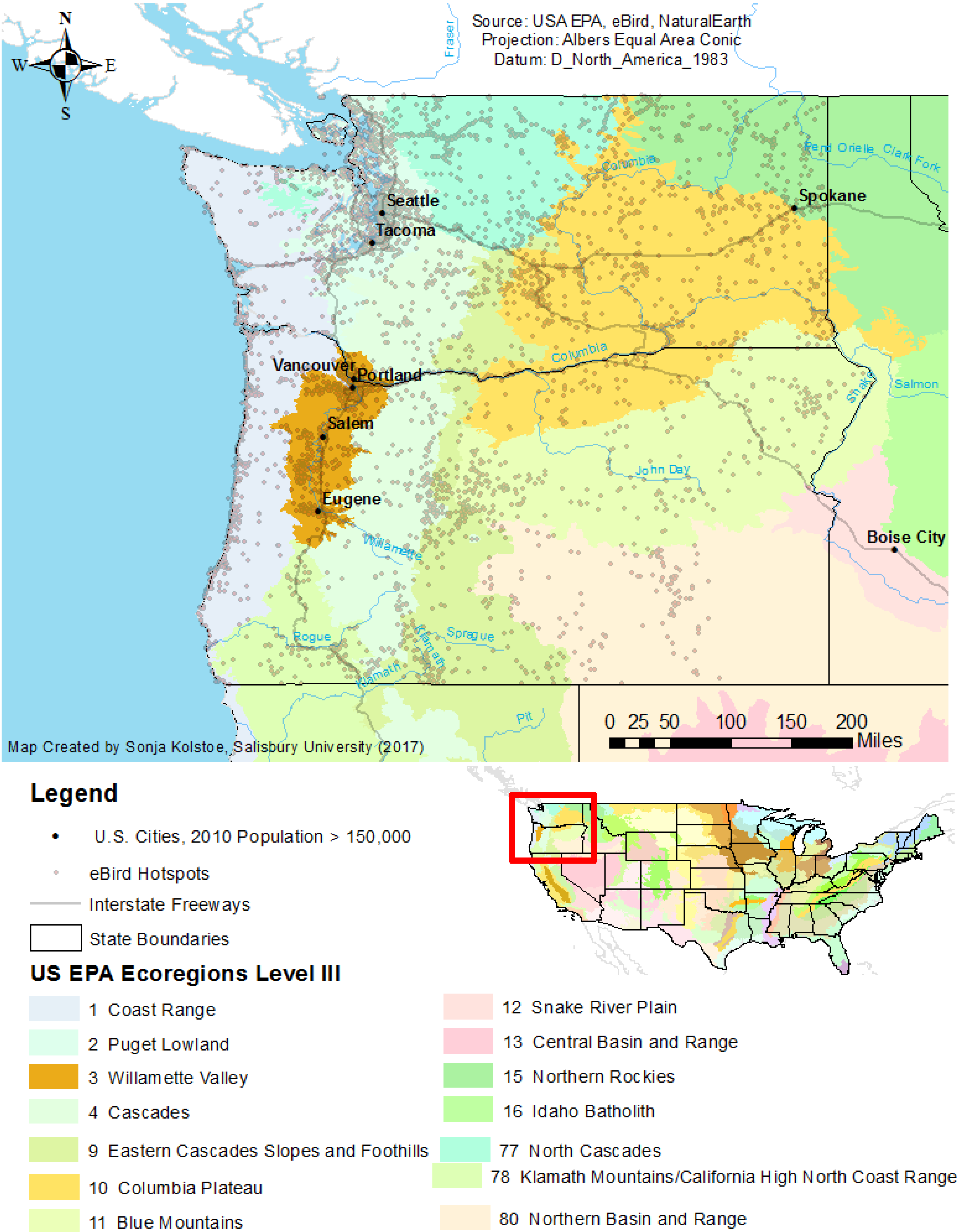

Figure 3: Histogram of Trips

(a) By Month

(b) By Year

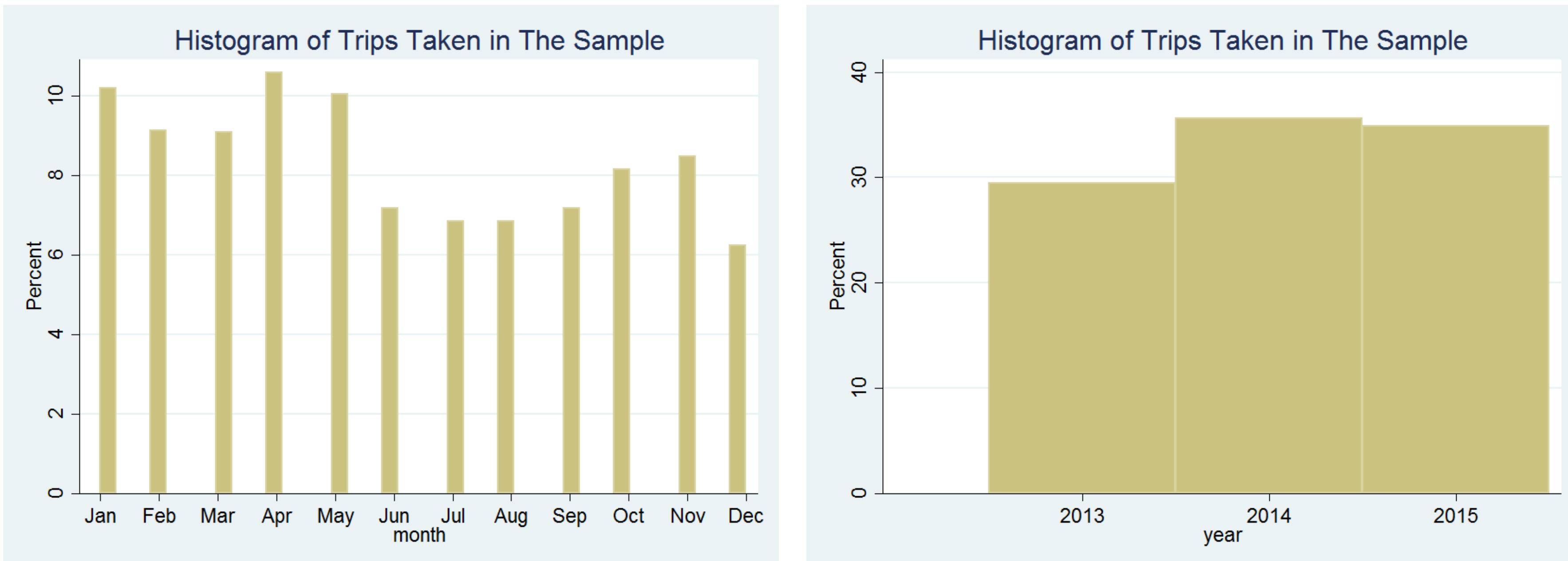

Figure 4: Qualtric Questions

(a) Bird Citizen Science Project

So-called "Citizen Science" projects recruit ordinary people to help gather data for scientific research. For each of the following projects related to wild bird populations, please indicate your level of familiarity or participation. [Please choose one answer per project]

	I am unfamiliar with this project	I have heard of this project, but have not signed up	I participate, but report observations only rarely, if at all	I participate, but report less than half of my observations	I participate, and report more than half of my observations	I participate, and report virtually all of my observations
Audubon Christmas Bird Count	○	○	○	○	○	○
BirdSleuth K-12	○	○	○	○	○	○
Breeding Bird Survey	○	○	○	○	○	○
Celebrate Urban Birds	○	○	○	○	○	○
eBird	○	○	○	○	○	○
Great Backyard Bird Count	○	○	○	○	○	○
Habitat Network	○	○	○	○	○	○
Hummingbirds at Home	○	○	○	○	○	○
Hummingbird Migration Tracker	○	○	○	○	○	○
iNaturalist	○	○	○	○	○	○
Nestwatch	○	○	○	○	○	○
North American Bird Phenology Program	○	○	○	○	○	○
Project FeederWatch	○	○	○	○	○	○
Other (please describe)	○	○	○	○	○	○

(b) Level of Engagement in Birding

Over the last year, on how many different days did you interact with wild birds in each of the following ways? Use the slider to pick an approximate number between 0 and 365. (For reference, *if you participated all year long*: once a month = 12 days, once a week =52 days, twice a week = 104 days, three times a week = 156 days.)

0 61 122 183 243 304 365

Pause what you are doing to observe wild birds

Put out food for wild birds

Seek opportunities to learn more about wild birds

Photograph wild birds

Visit public parks/areas less than one mile from home to see, photograph or feed wild birds

Travel more than one mile from home to see, photograph or feed wild birds

Employ measures to keep wild birds from harming your garden or property

Hunt wild birds for sport or for food

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