Estimating Habit-forming and Variety-seeking Behavior: Valuation of Recreational Birdwatching

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Abstract

This research introduces a two-stage model to account for habit-forming and variety-seeking behavior when examining location choice preferences among recreational birdwatchers. The first stage employs a Case-Based Decision Theory (CBDT) framework to estimate the weights for each site attribute that measure the similarity between cases, called case-based scores. In the second stage, we apply predicted case-based scores from the first stage into a mixed logit estimation of birding location choice. We find that dynamic elements of choice, specifically variety seeking behavior, can more than double the willingness to pay for individual sites. In this particular setting the static model of choice underestimates WTP and generally acts as a lower bound on estimates.

JEL Codes:

Keywords: Discrete Choice Models, Variety-seeking, Habit Formation, Recreational Bird Watching, Case-based Reasoning

1 Introduction

Past experiences can influence people's preferences for site attributes and affect the choice of where to go on a given trip for outdoor recreation, suggesting there is a dynamic aspect to incorporate into recreation site choice. For this reason, recreation site choice models and other applications of discrete choice modeling have incorporated aspects of habit formation and variety-seeking (Adamowicz, 1994; Hailu et al., 2005; Smith, 2005; Swait et al., 2004) to capture these dynamic aspects of choice. In this paper, we hypothesize that habit forming and variety-seeking behavior can be represented by particular functional form consistent with the assumptions followed by a decision theory called case-based decision theory (CBDT). We provide a simple framework to include this theory into the Random Utility Maximization (RUM) model used to model discrete choices such as recreation site choice. Our study applies the framework from CBDT to estimate weights for habit formation and variety-seeking behavior among recreational bird watchers in a two-stage model. We find the two-stage model has the best goodness of fit between the models considered. Our case-based approach generally increases the willingness to pay estimates for birding sites, and the static model is typically biased downwards. We find that incorporating past experience plays an essential role in non-market valuation estimates, and this approach allows for a compact and natural way to include experience in recreation site choice modeling.

A recreationist's previous experience with a site can be incorporated to account for variety-seeking and habit forming behavior (Adamowicz, 1994; Hailu et al., 2005; Smith, 2005; Adamowicz and Swait, 2013). Adamowicz (1994) examines the effect of habit formation and variety-seeking in recreation sites by transforming previous visits to each site to a depreciated stock of visits. Hailu et al. (2005) estimate recreation demand after incorporating frequency of previous trips to each site and other place attachment variables in a travel cost model. Other studies such as Smith (2005); Hunt (2005); Keane (1997); Guadagni and Little (1983) and Smith and Wilen (2002) uses state dependence, a variable which is a function of past choices, to account for any influence from previous experiences to a site. All the above studies conclude that decision-makers past choices have a significant effect when modeling recreational site choice preferences. Nevertheless, the question remains of what is the best way to account for individual histories in choice models.

In this work, we incorporate CBDT (Gilboa and Schmeidler, 1995) to recreation site choice modeling, which is similar to the existing models of variety-seeking and habit formation. We also build on the previous case-based estimation framework (Guilfoos and Pape, 2020), which focused on learning in a game theory setting. CBDT is a decision theory that under certain axioms can be described by specific mathematical representations of utility. In CBDT, when a person faces a new choice problem, they ask themselves: how similar is this case (i.e., choice situation, action, and results of choice) to past cases and then use those similarities to construct an expectation over choice sets. The construct of CBDT is useful for dynamic choice environments like recreational choice behavior for two reasons. First, the formulation of CBDT captures variety-seeking and habit forming behavior through the concept of the similarity function (Gilboa and Schmeidler, 1995; Shepard, 1987; Magnusson and Ekehammar, 1978; Nosofsky, 1992). Second, CBDT naturally captures how expectations form under new problems, whereas expected utility theory (EUT) relies on a decision-maker with complete information about states of the world. With CBDT, rationality is bounded (Kahneman, 2003). In EUT, agents are not surprised by new states of the world; rather, they update the probability that they give to a state of the world, perhaps with a Bayesian process (Harsanyi, 1978).

We choose CBDT as a choice framework because it suggests itself from other empirical applications in other domains (Guilfoos and Pape, 2020; Pape and Kurtz, 2013; Guilfoos and Pape, 2016; Ossadnik et al., 2013; Kinjo and Sugawara, 2016; Bleichrodt et al., 2017) and also suggest specific functions for estimation [1]. We propose a two-stage model that incorporates CBDT into the standard random utility model to model location choice. We use similarity functions to measure variety-seeking and habit formation behavior (Shepard, 1987; Magnusson and Ekehammar, 1978; Nosofsky, 1992). The presence of habit-forming behavior depends on the similarity between past and current consumption of a particular good or attribute (Pollak, 1970). Distance metrics are used in similarity indices to measure the similarity or dissimilarities between past and current problems.

We apply our model to the dynamic choice setting of recreational bird watching. Bird watching is one of the most popular recreational activities in the country. The 2016 National Survey of Fishing, Hunting, and Wildlife-Associated Recreation Report[2] estimates that 45.1 million US residents participate in bird watching. Among them, 16.3 million US residents travel to locations popular for bird watching, also called birding sites. During such travels, birdwatchers, also known as birders, spend on accommodation, food, transportation, and bird watching equipment. Understanding the site choice behavioral pattern of bird watchers can be beneficial in terms of economic returns for the host state and the conservation and preservation of bird species. Analyzing birder behavior helps in realizing the common interest among various stakeholders. Preserving and maintaining locations rich in bird species are among the main objectives for bird

[1]Other decision theories are more ambiguous as to how to operationalize the specific functions of choice to distinguish themselves.

[2]Source link: https://wsfrprograms.fws.gov/Subpages/NationalSurvey/nat_survey2016.pdf

watchers, researchers, social planners, conservationists, and other bird enthusiasts. Birding sites serve as revenue generators by attracting birders and tourists for the state. Therefore, research and behavioral modeling related to bird watchers and their choice preferences can provide useful information for policymakers and conservation efforts.

Studies on birder motivations have categorized them into affiliation-oriented motivation, achievement-oriented, appreciative-oriented and conservation-oriented (Decker and Connelly, 1989; McFarlane, 1994). Either one of these motivations can prompt habit formation or variety-seeking behavior. For instance, achievement-oriented birders tend to follow specific birds found in sites with common attributes or target a specific genre of birders, thereby prompting a similarity or dissimilarity pattern across site choice preferences over time.

We make multiple contributions with this work. We propose a two-stage model to capture dynamic elements of location choice in a way that is consistent with a particular decision theory, and empirically supported in other settings of human choice behavior. In the first stage, we use a CBDT framework to model a non-linear structural equation that captures dynamic aspects of habit formation and variety-seeking behavior. In the second stage, we apply the predicted probabilities from the first stage using a linear functional form and mixed logit estimation to obtain welfare estimates of site attributes. To evaluate this two-stage model's performance, we also run an additional benchmark model called the reduced form model. The reduced form model transforms the site attributes to form dynamic cumulative differences between current choice and past choices based on the Euclidean squared distance metric. Another contribution is to demonstrate the potential bias in willingness to pay estimates of birding sites by ignoring dynamic choice, static models tend to underestimate willingness to pay estimates for birding sites. It is unclear how robust this second contribution as more studies are needed to understand the empirical differences in our approach in other settings.

2 Methodology: Two-Stage Model

This model's first stage uses a case-based model (CBM) with the functional form inspired by CBDT to create case-based scores. The second stage includes the predicted probabilities from the first stage (as case-based scores) to account for habit-forming or variety-seeking behavior in a random parameters logit model to the choice data.

2.1 First Stage: Case-based Model

We use the framework of CBDT to construct the first stage estimates. In the CBDT framework, each individual has a memory (M), which contains cases. A case (C) is a triplet of problems (P), the actions (A) taken to address each problem, and the results (R) obtained from applying the actions to the problems. When faced with a choice situation, individuals refer back to their memory of cases and make choices after weighing the similarity between the current problem (p) and past problems (q). These past problems may be from their own previous experience or experience relayed to them by others (Gilboa and Schmeidler, 1995; Kinjo and Sugawara, 2016). In this study, a birder's past trips are what populate their memory, where each past trip becomes a case. The problem definition would constitute the site attributes associated with each birding site. Choosing a birding site is the action, and the result is the pay-off or outcome from each trip. Agents using a case-based framework use similarity between problems to form expectations. We use a Euclidean distance metric in this study to capture the distance between problems. The site and environmental attributes define the 'problem' for an individual and include but are not limited to seasons, date of the trip, land cover, eco-regions, and whether the site's a national wildlife refuge. The difference between site attributes (i) of current (p) and past (q) choices are as shown in equation 1:

$$d(p,q) = w_i(p_i - q_i)^2 \tag{1}$$

The parameter w in equation 1 is a coefficient to be estimated by the model that weighs the information in the similarity function. The similarity between cases aggregates all Euclidean distances across current and past site attributes as given in equation 2:

$$S(p,q) = \frac{1}{\exp\sqrt{\sum_{i=1}^{\#Dims} d(p,q)}} \tag{2}$$

Further, when referencing past cases, we index memories over time T. The distance metric transformation is dynamic since it is a function of past attributes, similar to Adamowicz (1994); McAlister and Pessemier (1982) and Smith (2005). Our framework supposes how memory maps from past experiences to current choices and expectations.

We use an inverse exponential functional form for the similarity function and Euclidean distance to measure the distance between current and past site attributes; both of which are commonly used in the CBDT literature (Pape and Kurtz, 2013; Guilfoos and Pape, 2016, 2020) and have roots in psychology (Shepard, 1987). The estimated coefficient (w_i) for each attribute is the weight for each attribute. The magnitude of the estimated weight represents the degree of importance in defining the similarity between past and current choices. The sign of the estimated weight represents whether or not birdwatchers follow a habit-forming or variety-seeking pattern (Guerdjikova, 2007, 2008). A positive sign implies habit-forming, whereas a negative sign implies variety-seeking behavior for that site attribute.

An important assumption about this model is that memory is a construct of the information available to the researcher. There may be a reason to believe that some data is omitted from memory or ignored by an agent. This issue plagues all dynamic models with dependence on past attributes or past utility. Simulations can model forgetfulness (Guilfoos and Pape, 2016), but it is unclear how to estimate mixed-logit models of discrete choice using these simulations jointly. Similarly, memory could include observations of birding trips shared by other birders and do not have to be experienced by the agent. For simplicity, we assume memory to be limited to the birder's past trips.

Equation 3 is estimated using the dynamic aspect of the CBDT framework in the first stage.

$$y_{njt} = \alpha + \sum_{t=1}^{T} \left\{ \frac{1}{S(p,q)} \right\} \times \frac{1}{T} \tag{3}$$

The response variable y is a binary indicator for chosen site $j \in 1, \ldots, J$ with α as the estimated constant and $S(p, q)$ representing the similarity function, as provided in equation 2, aggregated across cases $t \in 1, \ldots, T$ for each individual $n \in 1, \ldots, N$. We divide this function by a weighing variable (T) equal to the number of cases in memory. By dividing the similarity function by the number of cases, we get an average similarity between the current case and all cases in memory. This parameter binds the value of the similarity function between 0 and 1. We obtain the predicted probabilities ($\hat{y}$) from equation 3, which we call case-based scores, and include them in the second stage model as the function of past experiences.

The estimated weights from this stage have an intuitive interpretation of variety-seeking or habit formation. Variety-seeking behavior will increase a case-based score (negative weight parameter), while habit-forming behavior will decrease the case-based score (positive weight parameter). As the distance metric of an attribute increases, variety seeking will increase the likelihood of choosing the site, while a habit formation will decrease the likelihood of choosing the site.

To conceptualize the meaning of variety seeking in the CBDT model we can use figure1. In figure 1 the axes represent a positive difference between the current and past attribute in memory ($d(p, q) = w_i$) which is is binary[3] on case-based scores, with two attributes weights depicted (W1

[3]This is the case with all categorical variables in the first stage.

and W2). The dark dots in the figure are the change in case-based scores over combinations of attributes. The intercepts of the graph depict the change in case-based score when there is a difference in that one attribute. The coordinates of the points (D) represents how case-based scores change when multiple attributes change. The origin represents the base-case where we hold all other attributes constant. In figure 2a, when the signs of the coefficient weights are all negative, and the individual is variety seeking along all the two attributes, then a more dramatic increase in case-based scores is realized as attributes across many dimensions are different for the considered site than ones from memory. The combined effect is not additive. Think of a person that hasn't visit a site with forest or a national wildlife refuge, the birder would be willing to pay more to experience both attributes combined as it brings two new experiences in one visit. In figure 2b, when the signs of the coefficient weights are all positive, and the individual is seeking to reinforce habits along all three attributes, then a more dramatic decrease in case-based scores is realized as attributes across many dimensions are different for the considered site than ones from memory. So the reference case has the highest case-based score and sites with different attributes than ones in memory will be penalized with lower case-based scores. Of course, if the mix of attributes are both variety seeking and habit seeking, then differences will have a canceling out effect on each other. As memory becomes increasingly distant, the effect will shrink the size of the dotted line box in relation to the base-case (points will converge to the origin)[4].

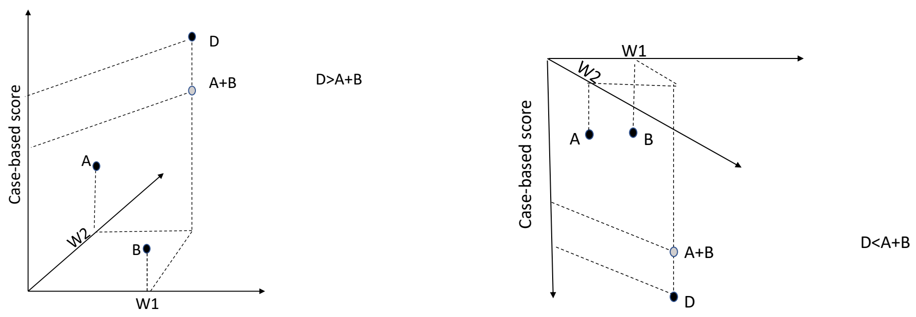
2.2 Second Stage: Mixed Logit Model

We apply a mixed logit random utility maximization (RUM) model to our data set in the second stage. The utility function, U_{njt}, for individual n, when visiting site j at time t has two components; a deterministic and a stochastic component. The deterministic component in this utility function is assumed to be a linear additive combination of explanatory variables. The stochastic component, ε_{njt}, accounts for other variables that are unobservable but affect utility. We adapt the general framework followed in Kolstoe et al. (2018) and estimate a linear additive utility function as shown in equation 4:

$$U_{njt} = \beta_c TC_{njt} + ((\beta_0 + \mu) + \beta_1 Y_{dev} + \beta_2 T_t) ES_{jt} + \beta_i X_{jt} + \delta\hat{y} + \varepsilon_{njt}. \tag{4}$$

Equation 4 represents the indirect utility function where the travel cost coefficient, β_c, is the marginal utility of net income and is used for further welfare calculations. The mixed logit model allows for taste variation across individuals. The coefficient, β_0, and random component, μ,

[4]The size and shape of this shift depends on the similarity function. In the case of an inverse exponential function there is a non-homogeneous shift in points toward the origin.



(a) Variety Seeking

(b) Habit Formation

Figure 1: Case-based Variety Seeking and Habit Formation.

Notes: The coordinates are listed represent a change in case-based scores. The origin is the baseline case-based score used for comparisons. The dotted lines are only for reference to gain spatial awareness of the points.

both estimated from the variable, expected species richness (ES), capture the taste variation across individuals. The interactions of ES include T_t, which is a vector of time-related variables such as binary indicators for each month and year, and Y_{dev}, which denotes the mean deviation from median household income. The variable X_{jt} represents the vector of site attributes (i) included in the model, and our key variable, $\hat{y}$, is case-based scores from the first-stage. The error term, ε_{njt}, is assumed to be independent and identically distributed (iid) with extreme value distribution.

In the mixed logit model, the choice probabilities are defined to be the integral of the probability of a standard logit model as provided in equation 5:

$$P_{njt} = \int \frac{\exp(\mathrm{V}_{njt})}{\sum_{k=1}^{J} \exp(\mathrm{V}_{nkt})} f\theta d\theta \tag{5}$$

where $j, k \in 1, \ldots, J$ are alternatives and $j \neq k$. V_{njt} represents the deterministic component of the utility function and θ is the mixing distribution containing the random parameter (Train, 2002; Hensher and Greene, 2003).

3 Welfare Estimation

When the utility function is linear in parameters, the estimate of the marginal willingness to pay for an attribute is the negative ratio between the attribute coefficient and the cost coefficient (Hanemann, 1983). However, estimating the change in utility for a unit change in weight coefficient in the first-stage is more complicated due to the non-additive functional form of the proposed model and depends on individual histories. This complexity also applies to the total willingness to pay for a birding site.

The aspects of variety-seeking and habit formation depend on past experience explicitly. In the context of a CBDT agent, we must assume the population of memory. One simplification we could make is that memory is empty, in other words, for a birder without extensive data on past experience for which we would assume that our case-based score is equal to zero when constructing measures of welfare for a trip. This assumption would simplify our utility specification to resemble the static model. Another assumption we can make is to take an average memory experience from our sample. For instance, let us assume the average Euclidean distance for each site attribute represents the sample's history. Our study constructs the history (memory of cases) for each birder by looking back four cases ($T = 4$), which assumes that birders 'forget' or highly discount memories further in the past. We choose to use the previous four cases to constitute memory through trial and error and assessing the goodness of fit of the first-stage results. We notice a negligible difference in estimated weights when included cases further back in a birder's history.

We also presume memory to be a combination of select attributes based on specific scenarios. For instance, we can compare the difference in birder preferences between those who visited a specific site during their last visit and those who did not. In the CBDT framework, the combination of attributes is not additive or linear; therefore, the combinations of attributes may be important to welfare. We derive equation 3 from the first-stage with respect to site attributes to estimate its marginal effect on case-based scores ($\partial y/\partial p_i$). Derivations involved in the marginal welfare calculations are in Appendix B.

The marginal WTP for an attribute is the change in cost per trip by dividing the marginal utility of the site attribute by the negative marginal utility of price (travel cost per trip). We obtain the welfare effect of variety seeking and habit formation, for an attribute, by dividing the change of predicted estimate of the case-based score (δ) by the negative marginal utility of price.

$$\text{MarginalWTP}_i = \left[\left(\frac{\partial y}{\partial p_i} * \delta \right) + \beta_i \right] * \frac{1}{\beta_c} \tag{6}$$

Equation 6 represents the marginal WTP for site attribute i after combining the marginal effect of a change on the case-based scores ($\partial y/\partial p_i$) along with the mixed logit estimates. p_i is the change in site attribute, δ is the second stage coefficient for case-based scores, β_i and β_c are the coefficient estimates for the site attribute and travel cost, respectively.

To obtain the total WTP for site j, we take the predicted case-based scores for that site () multiplied by the second stage coefficient δ, and the vector of attributes for the site (X_j) multiplied by the vector of coefficients for those attributes (β).

$$\text{WTP}_j = \left[\hat{y} * \delta + \beta * X_j\right] * \frac{1}{\beta_c} \tag{7}$$

As before, we need to make assumptions about memory to extract the predicts case-based scores. One possibility is to sample the memory of subjects that have site j as a possible choice, which is what we will do in the results.

Static Model

We will compare our model to other models to understand the differences created by our proposed framework. The static model is a linear additive mixed logit random utility estimation of the general model, as shown in Equation 4 without including the case-based scores from the first-stage. In other words, δ is not estimated. We call it the static model because it does not have any dynamic choice aspects and depends only on the cross-sectional variation in the data to identify behavior.

Reduced Form Model

We also estimate a reduced form model using the methodology adapted from previous studies on habit formation and variety-seeking (Adamowicz, 1994; McAlister and Pessemier, 1982). We first transform the site attributes to form dynamic cumulative differences between current choice and past choices. This transformation of site attributes are based on the Euclidean distance metric (for comparability) and follows the same framework as provided in equation 1. The distance measures for each site attribute are then directly included in the mixed-logit model estimation. The parameter estimates for the transformed site attributes indicate variety-seeking if they are positive and habit forming if they are negative (Adamowicz, 1994; McAlister and Pessemier, 1982; McAlister, 1982).

4 Model Goodness of Fit Comparison

To evaluate the goodness of fit, we compare the in-sample goodness of fit using the Akaike Information Criteria (AIC) and the Bayesian Information Criterion (BIC). The inclusion of more co-variates can lead to over-fitting, especially in the AICs. We include the Consistent-Akaike Information Criteria (CAIC) for each of the models to counter this problem. The model with the smaller AIC, CAIC, and BIC has a better in-sample goodness of fit (Atkinson, 1981; Bozdogan, 1987). We use the Likelihood Ratio (LR) test of the nested models to ascertain statistical differences between the static and variety-seeking and habit formation models (Fosgerau and Bierlaire, 2007).

5 Data

We use data from the eBird database obtained from a citizen science project. This data set, contributed by members of the eBird community, contains information about sites visited by 221 eBird members in Washington and Oregon for the years 2010 to 2012. This data set is previously used in Kolstoe and Cameron (2017) and Kolstoe et al. (2018). We extend this analysis to evaluate the methodologies of how to estimate dynamic choice. Members from the eBird community provide details regarding bird sightings and birding sites and volunteer residential information. Our final data set includes 155,382 birding sites located within a travel distance of 60 minutes from the birder's residence. We do not use sites that are less than one mile from the birder's residence to exclude backyard birdwatchers.

The travel cost variable is constructed based on the 'best route' suggested by 'mqtime', a Stata software tool that uses MapQuest to map the travel time and distance from the birder's residence to the birding site (Voorheis, 2015). Following the framework used in Fezzi et al. (2014) to calculate the value of travel time (VTT) in recreational models using revealed preference, our study assumes one-third of the wage rate as the opportunity cost of time. VTT, together with the distance traveled (multiplied with mileage rate from AAA), is used to obtain the round trip travel cost (TC). Site attributes include expected species richness (ES); indicators for whether the site is a national wildlife refuge, categorized as GAP status 1 or 3 (National Park, etc.) and GAP status 3 (National Forest, etc.), urban areas and areas that expects relatively more birds that are endangered; land cover types; and eco-region of designations. All of these site attributes are obtained from the National Land Cover Database (NLCD).

The number of people encountered during a recreational visit to a site can impact the utility of the trip itself. The level of congestion, to an extent, speaks to the popularity of the site. However, a high degree of congestion can adversely affect individual utility (McConnell, 1977; Timmins and Murdock, 2007). Kolstoe and Cameron (2017) has found that birders attach a positive and significant marginal value to congestion/popularity in a birding site. Once the threshold of popularity is met, there is a notable fall in marginal utility. The total number of trips taken to a site by birders, within the eBird community, in the same month of the previous year is taken as a proxy to measure the expected congestion per month at each site.

The average number of bird species reported by birders in the same month of the previous year is used to calculate each birding site's expected species richness. The bird species count comes from two data sets; Birdlife International for resident bird species and eBird data for nonresident or seasonal bird species. Sites with a high measure of expected species richness are 'hotspots' for birders. We expect this measure to vary over time and individual preferences. To account for this individual heterogeneity, expected species richness (ES) varies across birders in the mixed logit model specification. We also include sample selection correction terms in our models to account for possible sample selection bias due to the volunteered information on the birder's home address. The propensity for an individual to be in the estimated sample is calculated using a separate probit model. The deviations from the mean propensity interact with expected species and travel cost in the model[5]. A description of these variables are provided in Table 1.

We also include the type of land cover and eco-region of the birding site as each birding site's attributes. Sites are categorized into land cover types based on the classification system used in National Land Cover Database (NLCD) of 2011. We use 7 land cover types in our model. Our data set also uses 9 eco-regions. Further description and mean estimates for each of these land cover and eco-region types are in Appendix A.

[5]Refer to the online appendix http://dx.doi.org/10.1016/j.ecolecon.2017.02.013 for details on sample selection bias

Table 1: Description of Variables.

Variable	Description	Mean
Travel Cost (TC)	Round trip travel cost based on distance times mileage rate (AAA) and 1/3 of wage rate from census tract.	41.1
Expected Species Richness (ES)	Reported count of bird species taken per month in the previous year.	75.73
Congestion/Popularity	Share of eBird trips to each site for the same month, last year.	6.45 x 10^{-4}
Expected Endangered Species	Binary indicator equal to one if there is an expectation of presence of endangered bird species.	8.36 x 10^{-5}
Urban Area	Binary indicator equal to one for areas with population greater than 50,000 (2010 US Census).	0.61
National Wildlife Refuge	Binary indicator equal to one for areas under permanent protection as a National Wildlife Refugee. These areas are also rich in bird biodiversity.	0.0044
GAP status 3 (National Forest, etc.)	Binary indicator equal to one for areas protected with some extractive use and categorized under GAP status 3 (e.g., National Forests, State Parks, Recreation Management Areas, Areas of Critical Environmental Concern).	0.27
GAP status 1 or 2 (National Park, etc.)	Binary indicator equal to one for areas under permanent protection and categorized as GAP status 1 or 2 (e.g., National Parks, Wilderness Areas, National Wildlife Refuges).	0.03

6 Results

6.1 Two-Stage Model Results

The first-stage results from the non-linear estimates following the case-based functional form (refer to equation 3) is provided in Table 2[6]. The estimated coefficients in the CBM are weights assigned to each site attribute. As mentioned before, we use the sign of the estimated weights to identify habit-forming or variety-seeking behavior. A positive weight implies that a birder exhibits habit-forming behavior towards the site attribute, whereas a negative weight implies variety seeking behavior for the site attribute.

We find significance in most of the estimated weights of the site attributes. The magnitude of the weight coefficient is the degree of similarity (or dissimilarity). The larger the estimated weight coefficient, the more it changes case-based scores, holding everything else equal. We can only compare the weights across attributes, except time (Case T), as they are all standardized. The type of eco-regions and land covers, seasons, areas categorized as the national wildlife refuge, urban and areas protected under GAP status 3 (e.g., National Forest, etc.) and GAP status 1 or 2 (e.g., National Park, etc.) are all binary dependent variables. We notice that an average birder exhibits a high degree of variety-seeking for majority eco-regions and land cover types. Among them, the eco-regions, the Blue Mountains (-24.67), the Coast Range (-7.82), and the Klamath Mountains (-20.19) are statistically significant. Likewise, the majority of land cover types also exhibit negative and statistically significant weight coefficients. This estimated dissimilarity implies that a birder who once visited the Blue Mountains would be willing to pay more for a different eco-region in a future trip, or that a birder that has not visited the Blue Mountains would pay more to visit there on their next trip.

Table 2: First Stage Results: Case-based Model

Variables	Site Visited as Dependent Variable	
	Estimates	Std. Err.
Constant	0.006***	(0.000)
Case T	45.021***	(6.007)
Eco-region Indicators		
Blue Mountains	-24.672***	(3.918)

Continued on next page

[6]We use the STATA non-linear least squares command to estimate the first-stage coefficients. Errors are assumed to be normally independent and identically distributed. Code is published and publicly available on the author's website.

Table 2 – *Continued from previous page*

Variables	Estimates	Std. Err.
Cascades	6.655**	(2.977)
Coast Range	-7.826***	(1.258)
Columbia Plateau	26.022	(25.833)
Eastern Cascades Slopes and Foothills	6.577**	(3.164)
Klamath Mountains	-20.192***	(3.020)
Northern Rockies	-40.625	(26.146)
Land Cover Indicators		
Barren	-8.665**	(3.372)
Shrubland	-13.947***	(3.003)
Forest	-11.657***	(3.019)
Planted/Cultivated	-10.772***	(3.053)
Water	-8.143***	(3.125)
Wetlands	-11.179***	(3.013)
Herbaceous	-6.458*	(3.471)
Other Site Attributes		
National Wildlife Refuge	-10.012***	(1.627)
GAP status 3 (National Forest, etc.)	2.965***	(0.840)
GAP status 1 or 2 (National Parks, etc.)	0.170	(0.189)
Expect Endangered Bird Species	-29.895***	(3.465)
Urban Area	21.023*	(12.187)
Seasonality Controls		
Spring	-1.042	(0.706)
Summer	1.910**	(0.776)
Fall	4.974***	(1.815)
Previous Site Visited	0.481	(11.809)
R-squared	0.003	

Notes: $N = 155,382$. Parameter estimates from the case-based model and the respective standard errors are presented in this table. All the independent variables used in this model are binary indicators. ***, ** and * denotes significance at 1 percent, 5 percent and 10 percent.

Besides site attributes, we include other variables such as 'seasons' and 'case' used as an index in the birders' memory. 'Case' captures the measure of recency in the case-based model. The positive weight coefficient for 'case' indicates that agents discount past cases in memories. This finding of recency is consistent with the other work in CBDT and dynamic choice literature

(Guilfoos and Pape, 2016; Adamowicz, 1994; Guilfoos and Pape, 2020).

Table 3 contains the estimates from the second-stage mixed logit model. The key variable of interest is the case-based predicted probability or case-based score (δ). This estimate's positive and significant value marks the importance of accounting for variety-seeking or habit formation in recreational site choice literature, controlling for the static components. The second-stage estimates are in log odds ratios, and further calculations are required for direct interpretation of willingness to pay. The travel cost (TC) estimate is negative and significant as expected. The statistically significant standard deviation for expected species richness (ES (SD)) implies the presence of unobserved heterogeneity. We also include interactions of ES to control for time trends as well as sample selection correction terms.

We find a positive and statistically significant preference for sites categorized under GAP status 1 or 2 (such as National Parks) and GAP status 3 (such as National Forests). We find that urban areas are not preferred sites for bird watching. We find a preference for sites with a certain amount of congestion as it speaks to the popularity of the site; however, beyond a certain degree, congestion is undesirable.

One potential issue in assessing the stastistical significance of parameters using the two-stage model with a estimated regressor in the second stage is the construction of the standard errors. Similar to a two stage least squares we could bootstrap standard errors, but this is computationally challenging based on the mixed logit framework and size of our data. Therefore, we provide estimates of bootstrapped standard errors in appendix D using a conditional logit model in the second stage and find consistent results to our main mixed logit model.

Table 3: Mixed Logit Results: Second Stage Model

Variables	Site Visited as Dependent Variable	
		Std. Err
Travel Cost	-0.036***	(0.003)
Eco region Indicators		
Blue Mountains	-0.588	(0.852)
Cascades	0.677**	(0.317)
Coast Range	0.622*	(0.366)
Columbia Plateau	-0.492	(0.758)
Eastern Cascades Slopes and Foothills	-0.894	(0.691)
Klamath Mountains	0.137	(0.422)

Continued on next page

Table 3 – *Continued from previous page*

Variables	Estimates	Std. Err
Northern Cascades	-0.815	(0.729)
Northern Rockies	0.246	(0.889)
Willamette Valley	1.30***	(0.357)
Land Cover Indicators		
Barren	0.209	(0.153)
Shrubland	0.129	(0.139)
Forest	-0.062	(0.114)
Planted/Cultivated	0.203*	(0.114)
Water	0.368***	(0.108)
Wetlands	0.377***	(0.106)
Herbaceous	-0.312*	(0.187)
Other Site Attributes		
National Wildlife Refuge	0.758***	(0.192)
GAP status 3 (National Forest, etc.)	0.409***	(0.076)
GAP status 1 or 2 (National Parks, etc.)	0.711***	(0.128)
Expect Endangered Bird Species	1.210	(0.989)
Urban Area	-0.562***	(0.085)
Congestion	191.881***	(13.550)
(Congestion)^2	-3,703.81***	(441.610)
Expected Species Richness (ES): Mean and Standard Deviation.		
ES	0.017**	(0.009)
ES (Std. Dev.)	0.025***	(0.009)
Other Interactions with ES		
ES x dev. med H. Inc. ($10,000)	0.002	(0.003)
ES interacted with time trend	0.003	(0.005)
Sample Selection Correction Terms		
TC x dev. mean incl. prop	0.015***	(0.004)
ES x dev. mean incl. prop	0.007	(0.011)
Predicted Case-based Score (δ)		
δ	14.475***	(3.476)

Notes: $N = 155,372$. The controls variables for time trends and sample selection corrections are included in this model. The deviation from median household income is denoted as 'dev. med H. Inc. ($10,000)' in the table and the deviation from mean propensity to be included in the estimated sample is denoted as 'dev. mean incl. prop'.

6.2 Model Comparison

Comparing the AIC, BIC, and CAIC among all the models, we find our proposed two-stage model to have a better goodness of fit to the data. We expected the model with relatively more parameters, the reduced form model, to have a closer fit with AIC due to over-fitting. The Consistent-AIC (CAIC) controls for overparameterization while following the consistency properties followed by AIC (Bozdogan, 1987).

Table 4: Comparison of Model Selection Criteria

Mixed Logit Models	AIC	BIC	CAIC
Static Model	9276	9575	9605
2-Stage Model	9258	9567	9598
Reduced Form Model	9298	9865	9922

Notes: AIC, BIC and CAIC denotes Akaike Information Criteria, Bayesian Information Criteria and Consistent Akaike Information Criteria respectively. In the above model selection criteria, the smallest represents the preferred model. The estimates for the reduced form model is provided in Appendix C (Table 9).

Based on the model selection criteria in Table 4, we conclude that the two-stage model has a better goodness of fit. This specific domain of choice modeling is a challenge for model fitting, mostly due to the uncertainty involving picking a site choice in each period with, sometimes, many alternative sites. Although this complication does not benefit any model over the others, it does explain the small margins among all models. The Likelihood Ratio (LR) test results reveal the two-stage model is selected over the static model with a test statistic of 18.72 which is highly significant (p-value <0.000). As expected, in this setting the dynamic aspect of choice is found to be important.

6.3 Willingness to Pay Results

In this application of dynamic choice, we notice how stable the estimates of the static model is to the inclusion of dynamic elements (refer to Table 9). That is a good sign that any correlation and dependence across time did not bias the coefficients using only cross-sectional variation in the data. Still, the interpretation of welfare may be biased if dynamic choice dependence is omitted, as shown by the coefficient estimate of the case-based score in Table 3.

Suppose a birder has visited one site located in the Blue Mountains with forest land cover. This birder then compares two sites, one with the above attributes and one without those attributes.

Referencing back one period in memory would imply the distance between the current and past choice of an attribute to be one ($T = 1^2$). The case-based score for a site with these attributes based on equation 3 and using the estimates from Table 2 is as provided below in equation 8:

$$\text{CB Score for Site 1} = 0.007 + \frac{1}{\exp\sqrt{45.021 * d_T}} \tag{8}$$

where $d_T = 1$ since the agent is referencing back one period in their memory, and zero otherwise because the memory and current attributes match across (The euclidean distance is zero). Similarly, for the site in question, the case-based score for the site outside of the Blue Mountains and without forested land cover is provided in equation 9:

$$\text{CB Score for Site 2} = 0.007 + \frac{1}{\exp\sqrt{(45.02) + (-24.672 * d_{p1}) + (-11.657 * d_{p2})}} \tag{9}$$

where d_p is the Euclidean distance metric, which is equal to one for each site attribute. Subsequent WTP calculations based on equation 7, results in an increase in WTP by approximately \$20.95 per trip for the difference between these two sites. In this example, the variety-seeking preferences to explore a site with different land cover in a new eco-region drives willingness to pay up significantly. This difference in WTP between two sites varies according to the combination of site attributes chosen. The gap between the case-based scores depends upon the combination of attributes and can have large effects for certain combinations.

It is important to note that habit formation does not have the same magnitude of effect on case-based scores as variety-seeking. We find a relatively high discount rate on past experiences, which down weights past history. As euclidean distances increase in habit-forming attributes of the choice set, the case-based score varies by getting closer to zero compared to the baseline case-based score, which is already close to zero. And case-based scores are bounded between zero and one. While variety-seeking behavior can increase more as the case-based score increases from the baseline scores close to zero. In settings where choices are more often reinforced, we would expect that habit formation would exhibit larger impacts on willingness to pay. This also has the effect of having the static model very close or at the minimum of the WTP for individual sites, since variety seeking will increase WTP and habit formation can only decrease WTP a small amount in most cases.

6.4 Value of Specific Sites with Histories

To make inferences on specific sites, we evaluate three specific birding sites: The Smith Rock State Park (Deschuetes County, Oregon), Discovery Park (in urban Seattle, WA), and a new hypothetical conservation effort to increase endangered species at a site in Yakima, WA. We use the birders' histories in our data set to investigate point estimates for WTP for each of these sites and compare the estimates to the static model estimates. We use the means of expected species, the time trend, congestion, and sample selection terms in constructing the mean WTP but allow the case-based score and histories to vary by individual.

Table 5 shows the mean willingness to pay for the sites across the birders in our sample that have these sites in their choice sets. At the Smith Rock site, all the variation comes from differences in the histories of the birders. Specifically, the birders that have not experienced the land cover and eco-region of Smith Rock State Park have much higher WTP to visit this site than birders that have experienced similar sites in the region. Discovery Park's main source of variation is a change in expected endangered species at the site, which leads to two clusters of WTP. The rest of the variation within groups is due to differences in individual histories. In the hypothetical scenario, the variation comes only from differences in history of observing a site with expected endangered species status. The willingness to pay for a new site with endangered species is higher if the individual has not visited a site with endangered species.

Table 5: Comparison of WTP for Specific Sites

Site	Static Model (Mean)	2-Stage Model (Mean)	2-Stage Model (Min)	2-Stage Model (Max)
The Smith Rock State Park	\$46.18	\$58.30	\$48.96	\$106.70
Discovery Park	\$39.26	\$42.47	\$30.04	\$87.66
Yakima, WA (Hypothetical)	\$73.02	\$82.67	\$73.02	\$104.46

Notes: The mean WTP of individuals taking into consideration their individual site histories under different models. We use the means of expected species, the time trend, congestion, and sample selection terms in constructing the mean WTP but allow the case-based score and histories to vary by individual.

In the examples above, including the dynamic estimates with the two-step model leads to higher estimates than the static model based on variety seeking behavior. If our model is correct, it would be accurate to say that the static model generally provides lower bounds on WTP estimates. The magnitude of bias in WTP estimates depends on the history of the individual birder. Habit-forming can also cause WTP bias but is not significant across our estimates.

For one birder in our data set, figure 3 shows the distribution of mean WTP over all sites in their choice set over time. The memory index indicates how many time periods have elapsed

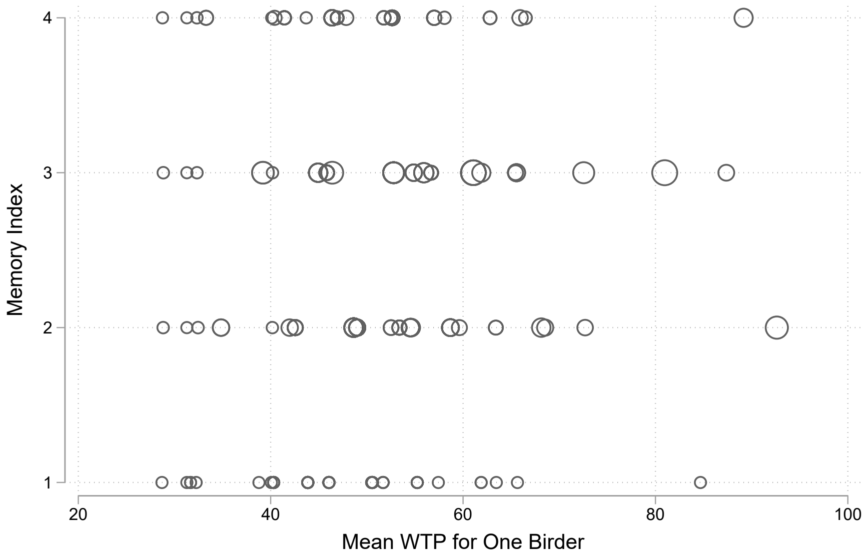


Figure 3: Individual WTP for Birding Sites

Note: This figure shows the mean WTP for sites over time for one eBirder; circle size is weighted by the case-based scores. A larger circles indicates case-based scores relative effect on WTP and are shifted right on the graph accordingly.

and the size of the circles is weighted by case-based scores. A larger circle size indicates that case-based scores play a larger role for that particular site. A larger case-based score will increase the mean WTP and shift the circle rightwards on the bubble figure. In the first period memory is empty, which leads to the smallest size circle for all sites, and all case-based scores are zero. As this birder visits a site they increase the weight from case-based scores accordingly and some sites start shifting right. But, as more varied sites are visited the size and shifts change. This indicates that this birder was variety seeking in a particular attribute, but then satisfied that 'itch' to visit a particular kind of site which has a moderating effect of the case-based scores. This type of shifts indicates the importance of memory and how individual histories can be important to site values.

6.5 Marginal Willingness to Pay Results

Table 6 shows the marginal WTP of changes in case-based scores for each attribute. The derivative of the case-based scores adds additional value in terms of the average cost per trip. Although we see positive and negative differences, the direction of change could go in either direction and depends on individuals' history (are we moving closer or further away to a similar case from memory)—the signs of coefficients in Table 6 represents moving away from past experiences.

The attributes display a small effect on marginal willingness to pay. The small magnitude is mostly a function of the baseline case-based score, driven by a considerable discount rate of memories. When marginal changes are evaluated at different levels, the margins may be considerably larger. This explains why the combination of attribute changes, or WTP for a particular site, can be significant, but the marginal effects reported in Table 6 can be economically small.

Table 6: Case-based Marginal WTP on Site Attributes

Variables	Marginal WTP	Std. Err
Eco region Indicators		
Blue Mountains	0.015***	(0.004)
Cascades	-0.027***	(0.007)
Coast Range	0.019***	(0.005)
Columbia Plateau	-0.030***	(0.008)
Eastern Cascades Slopes and Foothills	-0.006***	(0.002)
Klamath Mountains	0.027***	(0.007)
Northern Rockies	0.036***	(0.009)
Land Cover Indicators		
Barren	0.047***	(0.012)
Shrubland	0.063***	(0.016)
Forest	0.092***	(0.023)
Planted/Cultivated	0.076***	(0.019)
Water	0.061***	(0.016)
Wetlands	0.089***	(0.023)
Herbaceous	0.027***	(0.007)
Other Site Attributes		
National Wildlife Refuge	0.032***	(0.008)
GAP status 3 (National Forest, etc.)	-0.030***	(0.008)
GAP status 1 or 2 (National Parks, etc.)	-0.001***	(0.000)
Expect Endangered Bird Species	0.005***	(0.001)
Urban Area	-0.228***	(0.058)

Notes: $N = 155,372$. These estimates represent the additional marginal willingness to pay in dollars that is for a marginal change in case-based scores by attribute.

7 Conclusion

This research finds that accounting for habit-forming and variety-seeking behavior in recreational choice literature is important to welfare calculations. We propose a two-stage model to account for these behavioral responses that leverage case-based decision theory. The first-stage incorporates case-based reasoning where weights capture the habit-forming and variety-seeking behavior across site attributes. The predicted fitted values from the first-stage are included in the second-stage mixed logit model to control the dynamic aspects of location choice. We find that in general, our approach increases the willingness to pay estimates for sites and the static model is typically biased downwards and is a lower bound on estimates. The static model being a lower bound will only be the case for when variety seeking is the dominant behavior.

The impact on valuation for a birding site depends on the combination of attributes contained at the chosen site and the birder's memory of experiences. This approach to calculating the total value of sites and potential conservation efforts has policy relevance. Primarily it allows researchers to evaluate new hypothetical scenarios that are internally consistent with the decision theory underlying the model.

Our proposed framework can be applied and is suitable to examine behavior whenever agents are making repeated choices. This study hypothesizes that repeated choices exhibit patterns of similarity or dissimilarity. For instance, the first-stage analysis concludes that birders heavily discount memories in the past. Birders exhibit variety-seeking tendencies for land covers, they typically do not habitually return to the same specific land cover type when choosing birding sites. We find that birders exhibit habit-forming behavior by season, which indicates a pattern of the seasonality of bird watching for similar sites.

The conventional case-based decision theory and repeated choices also incorporate the outcome or pay-off obtained from their previous choices. Whether or not the action taken in response to a problem by an individual decision-maker is a success is an important component in CBDT. This study incorporates the case-based framework without including a variable that can proxy outcome, as it is not available. This is a limitation to the study, and most studies using the travel cost approach. In future work, it would be beneficial to gather the outcome of trips and incorporate that into the dynamic choice model to be consistent with the underlying decision theory.

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Appendix A Types of Eco-region and Land Cover

The number of eco-region classifications and its mean statistics are provided in Table 7. There are a total of nine eco-region categories in the data set used in this study. These variables are binary indicators equal to one if the birding site belongs to the respective eco-region. Further details on these eco-region types can be found in Kolstoe and Cameron (2017).

Table 7: Types of Eco-region

Variables	Mean
Blue Mountains (Yes=1)	0.0029
Cascades (Yes=1)	0.036
Coast Range (Yes=1)	0.015
Columbia Plateau (Yes=1)	0.026
Eastern Cascades Slopes and Foothills (Yes=1)	0.006
Klamath Mountains (Yes=1)	0.017
Northern Cascades (Yes=1)	0.0055
Northern Rockies (Yes=1)	0.0018
Willamette Valley (Yes=1)	0.29

The mean and description of the type of land cover are provided in Table 8. All site attributes in this table are binary indicators equal to one if the birding site destination is categorized as the respective type of land cover. The land cover types are obtained from the 2011 National Land Cover Database (NLDC).

Table 8: Types of Land Cover

Variables	Description	Mean
Barren (Yes=1)	Areas which have less than 15% vegetation.	0.053
Shrubland (Yes=1)	Areas with shrubs less than 5 meters tall.	0.041
Forest (Yes=1)	Areas which have deciduous, evergreen and mixed forests.	0.143
Planted/Cultivated (Yes=1)	Areas which have pastures, hay and cultivated crops.	0.097
Water/Perennial Ice/Snow (Yes=1)	Areas of open water with less than 25% vegetation or soil.	0.109
Wetlands (Yes=1)	Areas which have woody and emergent herbaceous wetland	0.103
Herbaceous (Yes=1)	Areas which have more than 80% herbaceous vegetation.	0.042
Developed (Yes=1)	Low, medium and high intensity developed areas and open spaces.	0.412

Appendix B Estimation of Marginal Change in CB score

In this section we will be describing in detail how to estimate the marginal change in case-based score when a particular site attribute changes in the first stage.

The first stage equation is based on CBDT, where the utility is a non-linear combination of the inverse exponential of the Euclidean squared difference ($d(p,q)$) between the current choice (p) and past choice (q) for each individual across site attributes (i) summed over T periods in the individuals memory. This equation with y as the binary indicator for site chosen is provided in 10:

$$y = \alpha + \left(\sum_{t=1}^{T} \left\{ \frac{1}{\exp\left(\sqrt{\sum_{i=1}^{Dim} w_i d(p,q)} \right)} \right\} \right) \times \frac{1}{T} \tag{10}$$

The squared difference ($d(p,q)$) between the current choice (p) and past choice (q) across site attributes is shown in 11.

$$d(p,q) = (p_i - q_i)^2 \tag{11}$$

The first step to estimate the marginal effect of a change in case-based score of a site attribute is by making assumptions about the history of cases a representative birder draws from his memory when making a site choice decision.

For instance, consider an individual (or birder in this study) who refers back to only one case in his memory when making a choice. The case-based utility function would simplify to include only one distance measure for each site attribute as provided in equation 12:

$$y = \alpha + \frac{1}{\exp\left(\sqrt{\sum_{i=1}^{\#Dim} w_i(p_i - q_i)^2}\right)} \times \frac{1}{T} \tag{12}$$

where $q = p_{t-1}$ since we are only looking back one period. Further expanding equation 12 we obtain the following equation in 13

$$y = \alpha + \frac{1}{\exp\left(\sqrt{w_1(p_1 - q_1)^2 + w_2(p_2 - q_2)^2 + \ldots + w_i(p_i - q_i))^2}\right)} \times \frac{1}{T} \tag{13}$$

To estimated the marginal effect due to change in one site attribute say $i = 1$, we further simplify the equation to 14, where α is a constant representing the expansion of other dimensions in the problem

$$y = \alpha + \frac{1}{\exp\left(\sqrt{w_1(p - q_1)^2 + \alpha}\right)} \times \frac{1}{T}. \tag{14}$$

Following the chain rule for we derive equation 14 with respect to the site attribute 1 at current choice p to obtain 15

$$\frac{\partial y}{\partial p_1} = -\frac{1}{T} \times \frac{w_1(p - q_1) * \exp\left(-\sqrt{w_1(p - q_1)^2 + \alpha}\right)}{\sqrt{w_1(p - q_1)^2 + \alpha}} \tag{15}$$

The weighing variable, T, which is used to evenly distribute the function across all cases in the memory. $T = 1$ since we are estimating the marginal effect for a change in the site attribute in the current case (p is for when t = 1), and only have the memory of one period in the past.

Now, let us consider when the birder refers back to four cases ($T = 4$) in his memory when making a choice. Since cases are included additively, the case looking back one period is separate from the case from two periods ago. The total derivative is the sum of each individual derivative of the history of cases, as is displayed in equation 16.

$$\frac{\partial y}{\partial p_1} = \sum_{t=1}^{T} -\frac{1}{T} \times \frac{w_1(p - q_t) * \exp\left(-\sqrt{w_1(p - q_t)^2 + \alpha}\right)}{\sqrt{w_1(p - q_t)^2 + \alpha}} \tag{16}$$

Appendix C Mixed Logit Models

Table 9: Mixed Logit Results: All Models

VARIABLES	(1)	(2)	(3)
Models	Static	Two Stage	Reduced Form
Travel Cost	-0.036***	-0.036***	-0.036***
	(0.003)	(0.003)	(0.003)
Eco region Indicators (Yes = 1)			
Blue Mountains	-0.897	-0.588	-1.036
	(0.839)	(0.852)	(0.921)
Cascades	0.601*	0.677**	0.718
	(0.320)	(0.317)	(0.474)
Coast Range	0.515	0.622*	-0.071
	(0.367)	(0.366)	(0.417)
Columbia Plateau	-0.584	-0.492	-0.655
	(0.762)	(0.758)	(1.146)
Eastern Cascades Slopes and Foothills	-0.966	-0.894	-0.878
	(0.695)	(0.691)	(0.719)
Klamath Mountains	0.025	0.137	0.028
	(0.425)	(0.422)	(0.539)
Northern Cascades	-0.879	-0.815	-1.226
	(0.738)	(0.729)	(1.173)
Northern Rockies	0.178	0.246	-0.052
	(0.884)	(0.889)	(1.252)
Willamette Valley	1.209***	1.300***	0.873*
	(0.356)	(0.357)	(0.467)
Land Cover Indicators (Yes = 1)			
Barren	0.222	0.209	-0.026
	(0.152)	(0.153)	(0.235)
Shrubland	0.166	0.129	-0.036
	(0.138)	(0.139)	(0.178)

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Table 9 – *Continued from previous page*

	Static	Two Stage	Reduced Form
Forest	-0.048	-0.062	-0.249
	(0.114)	(0.114)	(0.163)
Planted/Cultivated	0.219*	0.203*	-0.031
	(0.114)	(0.114)	(0.160)
Water	0.376***	0.368***	0.336**
	(0.107)	(0.108)	(0.150)
Wetlands	0.387***	0.377***	0.254*
	(0.106)	(0.106)	(0.144)
Herbaceous	-0.294	-0.312*	-0.743**
	(0.186)	(0.187)	(0.309)
Other Site Attributes			
National Wildlife Refuge	0.775***	0.758***	0.893***
	(0.191)	(0.192)	(0.252)
GAP status 3 (National Forest, etc.)	0.413***	0.409***	0.387***
	(0.076)	(0.076)	(0.082)
GAP status 1 or 2 (National Parks, etc.)	0.734***	0.711***	0.753***
	(0.128)	(0.128)	(0.169)
Expect Endangered Bird Species	1.848**	1.210	1.765
	(0.825)	(0.989)	(1.080)
Urban Area	-0.568***	-0.562***	-0.552***
	(0.084)	(0.085)	(0.086)
Congestion	191.819***	191.881***	192.343***
	(13.550)	(13.550)	(13.686)
$(\text{Congestion})^2$	-3,688.644***	-3,703.810***	-3,756.235***
	(441.844)	(441.610)	(447.256)
Expected Species Richness (ES): Mean and Standard Deviation.			
ES	0.015*	0.017**	0.015*
	(0.008)	(0.009)	(0.008)
ES (Std. Dev.)	0.021**	0.025***	0.020**
	(0.008)	(0.009)	(0.008)
Other Interactions with ES			
ES x dev. med H. Inc. ($10,000)	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)
ES interacted with time trend	0.004	0.003	0.004

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Table 9 – *Continued from previous page*

	Static	Two Stage	Reduced Form
	(0.005)	(0.005)	(0.005)
Sample Selection Correction Terms			
C x dev. mean incl. prop	0.015***	0.015***	0.015***
	(0.004)	(0.004)	(0.004)
ES x dev. mean incl. prop	0.009	0.007	0.008
	(0.012)	(0.011)	(0.012)
Variable differences across models			
Case-based Score (δ)		14.475***	
		(3.476)	
Euclidean distance weights	No	No	Yes

Notes: All estimates from the three models used for model fit comparison (in Table 4) are presented in this table. The 'Reduced Form' model presented in column (3) includes the euclidean distance weights for all variables used in the first stage (i.e., CBM) for comparability. Standard errors are given in parentheses. ***, ** and * denotes significance at 1 percent, 5 percent and 10 percent.

Appendix D Bootstrapping with Conditional Logit Model

Table 10: Conditional Logit Results: All Models

VARIABLES	(1)	(2)	(3)
Models	Static	Two Stage	Bootstrap
Travel Cost	-0.036***	-0.036***	-0.036***
	(0.004)	(0.004)	(0.004)
Eco region Indicators (Yes = 1)			
Blue Mountains	-0.993	-0.696	-0.696
	(0.647)	(0.683)	(2.223)
Cascades	0.520*	0.580**	0.580*
	(0.285)	(0.277)	(0.310)
Coast Range	0.411	0.501	0.501
	(0.413)	(0.401)	(0.431)
Columbia Plateau	-0.806	-0.732	-0.732
	(0.660)	(0.659)	(1.478)
Eastern Cascades Slopes and Foothills	-0.995*	-0.958*	-0.958
	(0.583)	(0.575)	(0.720)
Klamath Mountains	-0.023	0.060	0.060

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Table 10 – *Continued from previous page*

	Static	Two Stage	Bootsrap
	(0.474)	(0.476)	(0.535)
Northern Cascades	-0.999	-0.948	-0.948
	(0.645)	(0.630)	(1.829)
Northern Rockies	0.043	0.098	0.098
	(0.815)	(0.823)	(1.553)
Willamette Valley	1.148***	1.222***	1.222***
	(0.354)	(0.349)	(0.374)
Land Cover Indicators (Yes = 1)			
Barren	0.247*	0.243*	0.243*
	(0.132)	(0.133)	(0.136)
Shrubland	0.155	0.119	0.119
	(0.126)	(0.128)	(0.130)
Forest	-0.046	-0.062	-0.062
	(0.094)	(0.095)	(0.094)
Planted/Cultivated	0.231**	0.219**	0.219**
	(0.099)	(0.100)	(0.100)
Water	0.382***	0.374***	0.374***
	(0.106)	(0.107)	(0.114)
Wetlands	0.395***	0.388***	0.388***
	(0.096)	(0.096)	(0.098)
Herbaceous	-0.291*	-0.311**	-0.311**
	(0.154)	(0.155)	(0.156)
Other Site Attributes			
National Wildlife Refuge	0.772***	0.752***	0.752***
	(0.179)	(0.180)	(0.189)
GAP status 3 (National Forest, etc.)	0.417***	0.412***	0.412***
	(0.073)	(0.073)	(0.070)
GAP status 1 or 2 (National Parks, etc.)	0.731***	0.710***	0.710***
	(0.115)	(0.117)	(0.121)
Expect Endangered Bird Species	1.769***	1.089	1.089
	(0.628)	(1.007)	(3,338.131)
Urban Area	-0.570***	-0.564***	-0.564***
	(0.088)	(0.088)	(0.086)
Congestion	198.406***	199.668***	199.668***

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Table 10 – *Continued from previous page*

	Static	Two Stage	Bootsrap
	(14.405)	(14.521)	(14.717)
$(\text{Congestion})^2$	-3,831.705***	-3,877.631***	-3,877.631***
	(515.271)	(522.839)	(538.307)
Expected Species Richness (ES) and its Interactions.			
ES	0.010	0.010	0.010
	(0.007)	(0.007)	(0.008)
ES x dev. med H. Inc. ($$10,000$)	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)
ES interacted with time trend	0.003	0.003	0.003
	(0.005)	(0.005)	(0.005)
Sample Selection Correction Terms			
C x dev. mean incl. prop	0.015***	0.015***	0.015***
	(0.005)	(0.005)	(0.005)
ES x dev. mean incl. prop	-0.005	-0.005	-0.005
	(0.010)	(0.010)	(0.013)
Case-based Score (δ)		13.681***	13.681***
		(2.711)	(3.133)

Notes: Conditional logit estimates for the static mode, two-stage model and two-stage with bootstrapped standard error re-sampled 1000 times are presented in this table in column (1), (2) and (3) respectively. Standard errors are given in parentheses. ***, ** and * denotes significance at 1 percent, 5 percent and 10 percent.