Received: 20 January 2022 | Accepted: 3 March 2023

DOI: 10.1111/ajae.12422

ARTICLE

Estimating habit-forming and variety-seeking behavior: Valuation of recreational birdwatching

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Abstract

Past experiences influence choices, and people's preferences for more similar (habit-forming) or different (variety-seeking) experiences are reflected in these choices. We develop a structural estimation framework to capture whether people are habit forming or variety seeking and apply it to the choice of recreation site. This research contributes to the revealed preference literature by demonstrating how to account for habit or variety-seeking behavior in recreation site choice models in a two-stage framework. Using this framework, we estimate similarity weights that reflect the birders habit formation and variety seeking preferences. Predicted probabilities from the first stage model are then incorporated into the second stage, a mixed logit recreation site choice model of bird watching trips from eBird, by their members. We find that including the dynamic elements of choice, specifically variety-seeking behavior, can double the estimated willingness to pay (WTP) for individual sites relative to the static model. Although our sample of bird watching trips taken by eBird members is a sample of convenience, these results suggest that static models of recreation site choice are a lower bound on our recreation demand WTP estimates. We find variety-seeking preferences are related to land cover and the site's fixed attributes, whereas habit formation appears for seasonality in the bird watching context.

KEYWORDS

case-based reasoning, citizen science, habit formation, site choice, variety seeking

JEL CLASSIFICATION

Q51, Q57

1 | INTRODUCTION

Past experiences influence people's preferences, shape beliefs, and by extension inform the decisions they make. For example, people may repeat behaviors that are satisfactory to them based on their history, consistent with habit-forming behavior, or may explore new experiences that differ from their past, consistent with variety-seeking behavior. These types of behavior, habit formation and variety seeking, suggests there is a dynamic aspect of human behavior to choices that may be important to consider in discrete choice modeling when repeat choice panel data are available (Lupi et al., 2020). For this reason, recreation site choice models, and other applications of discrete choice modeling using panel data, have incorporated dynamic measures that vary with individual histories, ranging from using an indicator to state dependence (Adamowicz, 1994; Boto-García, 2022; Hailu et al., 2005; Hicks et al., 2020; Goldsmith et al., 2020; Kolstoe & Cameron, 2017; Smith, 2005; Swait et al., 2004; McConnell et al., 1990).

Structural estimation of a similarity function provides an alternative to existing options (e.g., indicator and state dependence) to model habit formation and variety-seeking behavior, thus capturing how similar (or not) the current site choice is to the individual's previous site choice.[1] In this paper we provide the structural estimation framework of a similarity function using individuals' histories in a discrete choice model of recreation site choice model. We test our framework empirically using diary-type data repeated choice data of bird watching trips reported to eBird, a large-scale citizen/community science project of the Cornell Lab of Ornithology, by its members.

Bird watching is a popular recreational activity in the country, as evident based on data from 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 sites to go bird watching.[3] During such travels, birdwatchers, also known as birders, spend on accommodation, food, transportation, and bird watching equipment.

Studies on birder motivations have categorized them into affiliation-oriented motivation, achievement oriented, appreciative oriented, and conservation oriented (Decker & Connelly, 1989; McFarlane, 1994). Any 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 birds, thereby prompting a similarity or dissimilarity pattern across site choice preferences over time. Understanding the site choice behavioral pattern of birdwatchers 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. Research and behavioral modeling related to birders and their choice preferences can provide useful information for decision makers, policymakers, and conservationists to understand what attracts bird watchers to bird watching recreation sites.

To estimate preferences of birding location we use a two-stage model to capture dynamic elements of location choice in a way that is consistent case-based decision theory (CBDT), which is empirically supported in other settings of human choice behavior (Gayer et al., 2007; Guilfoos & Pape, 2016; Ossadnik et al., 2013; Pape & Kurtz, 2013; Thomas & Guilfoos, 2022). In the first stage, we use a CBDT framework to model a nonlinear structural equation to estimate parameters that captures habit formation and variety-seeking behavior using the similarity function. In the second stage, we include the predictions obtained from the first stage as a generated regressor in our recreation site choice model. We use the parameters from the second stage to estimate WTP measures.

[1]Many of the studies that look at variety seeking and habit formation have focused on the context of the decision being made as important to the behavior observed rather than individual preferences. For instance, the literature on consumer buying and habit formation finds that certain types of products elicit more habitual buying than others (Adamowicz & Swait, 2013; Trijp et al., 1996). One outlier, Yoon and Kim (2018), explores how perceived economic mobility affects consumption. They find that individuals that perceive low economic mobility exhibit more variety seeking in consumption.

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

[3]These individuals traveled more than a mile from their home.

Our framework applies a similarity equation consistent with the CBDT framework from Gilboa and Schmeidler (1995) in the first stage of a two-stage model, which uses both the current trip site attributes and the individual's most recent recorded trips. We extend the work of Guilfoos and Pape (2020) and Thomas and Guilfoos (2022), who use a one stage case-based model. A one stage model is used in their work due to the relative simplicity of their data, namely having very few locations to model and the potential choice set are the same across all agents. We use a two-stage model to accommodate the large number of sites within choice sets as well as the fact that choice sets differ across eBird members. This two-stage approach allows for a more portable estimation of dynamic choice across different contexts.

The construct of CBDT is useful for dynamic choice environments for two reasons. First, the formulation of CBDT captures variety-seeking and habit-forming behavior through the concept of the similarity function (Gilboa & Schmeidler, 1995; Magnusson & Ekehammar, 1978; Nosofsky, 1992; Shepard, 1987). A similarity function assigns a non-negative value to pairs of choice occasions, the current decision being considered and one in memory. The similarity function based on CBDT provides the numerical mapping between choice occasions and preferences of the decision maker. Thus, the similarity function captures the presence of habit-forming (or variety-seeking) behavior based on the similarity between past and current consumption of a particular good or attribute (Pollak, 1970). Second, CBDT naturally captures how expectations form under new problems when rationality is bounded (Kahneman, 2003). Thus CBDT allows for the case that a decision make can be surprised by a new state of the world, unlike expected utility theory (EUT) (Harsanyi, 1978). CBDT provides a mechanism for such updates whereas in EUT, decision makers are never surprised by a new state of the world, they just update probabilities of occurrence, a potentially problematic and implausible assumption for many decision problems encountered in real life.

Case-based type models are closely related to dynamic models that incorporate expectations of future conditions explicitly into the model. For example, Englin and Moeltner's (2004) site choice of ski resorts highlights how expectations of weather conditions can influence recreation site choice, even after controlling for experience. CBDT in theory may include near-future conditions in the attributes considered, or as a reinforcement mechanism to the current choice set. In our paper, we have a measure of expectations of the current birding conditions through expected bird species richness as an attribute. The CBDT framework is useful because it is naturally extended to new state spaces (climate change, unexpected changes in birding sites). In a departure from the other case-based research, we use CBDT to understand the interpretation of the estimated parameters in similarity, whether attributes of the choice occasion reinforce repeated behavior or not, because it is able to represent variety-seeking and habit-forming behavior without modification, allowing for the estimated parameters to be interpreted as habit-forming or variety-seeking behavior. And, we explicitly measure the welfare implications of using CBDT. The framework is robust to learning effects and captures in a general sense, state dependence.

We find habit formation is exhibited through seasonality, or that birders visit similar sites during the same times of year, but that variety seeking is observed in the choice of landscapes. Presumably, birders may enjoy different environments to explore or like to observe different species of birds that exist in varying landscapes. We also find that our two-stage model has the best goodness of fit among the models considered, and that incorporating past experience plays an essential role in non-market valuation estimates. Our approach of estimating a structural similarity function based on CBDT allows for a compact and natural way to include experience in recreation site choice modeling. Our results also suggest that including the dynamic elements of choice, specifically variety-seeking behavior, can double the estimated willingness to pay (WTP) for individual sites relative to the static model, suggesting that static model WTP may be a lower bound. It is unclear how robust our findings are as this study modeled behavior for birdwatchers, and it may differ among different recreation user groups. Thus, more studies are needed to understand the empirical differences in our approach in other settings. Our proposed framework is flexible in that it can capture aspects of state-dependence, variety-seeking, and habit-forming behavior in one compact function and is easily applied to other applications.

2 | CASE-BASED DECISION THEORY

Here we describe CBDT using an illustrative example and define key terms. In CBDT, decisions are made through analogy. To provide an example, let us suppose CBDT describes a hiker's choice behavior. The hiker has memories of the past locations they have visited and their attributes (the view, day of the week, weather, congestion) and remembers the result of the trips (did they enjoy the hike). In a new choice occasion, they use a similarity function and past results (or analogy to past problems) to weigh the attributes of the current decision. A decision maker with this type of reasoning might say "This trail looks similar to the trail we like at Narrow Lake, let's try it." The hiker is using past situations that are analogous to the current situation to make choices.

The terms used to describe CBDT are formal concepts that have specific meanings and are used throughout the paper. 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 occasion, individuals refer back to their memory of cases and choose after weighing the similarity between the current problem (p) and past problems (q). The similarity function is used to map current and past problems (choice occasions). Similarity functions are typically decreasing as distance increases between attributes of current and past problems. These past problems may be from their own previous experience or experience relayed to them by others (Gilboa & Schmeidler, 1995). In addition to memory and *problems*, decision makers may reinforce decisions by the result of a past decision, similar to reinforcement learning. When decision makers obtain a good result from an action taken, they are likely to repeat the choice under similar situations. In the next section, we will provide empirical definitions of the problems (p and q), the actions (location chosen to go birding), and similarity functions used to compare past problems to current problems. We lack a result (R) of each trip and therefore do not include that in the empirical estimation.

In the following, we use "case" to refer to the choice occasion's problem, action, and result. We use the term "problem" to describe the choice occasion and its attributes (site characteristics). The choice occasion is where a birder must select a preferred location given that they have chosen to go birding that day. The birders are choosing which birding site to visit, assuming they are going on that day.

In our setting we posit that past choices affect current choices, though birders may not be following a dynamic optimal plan of birding site visits. Further assumptions need to be made regarding the rationality, incentives, and likelihood that agents are solving a dynamic optimization problem. The researcher can make different assumptions about agent's dynamic optimization using a framework similar to Provencher and Bishop (1997) or Hicks and Schnier (2006) to estimate a dynamically optimal plan of choices with site histories as a dynamic programming problem. The assumptions needed are about the agent's incentives and rationality to be following a dynamically optimal plan. In examples, like a fishery, where current period decisions change the future outcomes, the optimal dynamic planning problem may exhibit large welfare changes compared to myopic behavior. One could also characterize utility to exhibit case-based histories into the utility function of the agent into the dynamic programming problem.

3 | METHODOLOGY: TWO-STAGE MODEL

This model's first stage uses a case-based model with the functional form inspired by CBDT. The second stage includes the predicted probabilities from the first stage to account for habit-forming or variety-seeking behavior in a random parameters logit model to the choice data. One way to view this two-stage model is to separate the dynamic and static components of decision making by stage. The target for both stages is the actual location visited by the birder from among all possible locations within 60 min driving time for the birder. The first stage estimates the similarity weights given to the dynamic elements of choice behavior, using the differences in current attributes of the choice problem and past attributes of the actual choices by a birder. This is similar to state-dependence models except that we use the information about past visits to make attributions about birders' variety-seeking and habit-formation behavior. In the second stage, we estimate the mixed logit model's parameters using the predictions from the first stage.

Using a two-stage process to estimate this model makes it easier to estimate the model and makes the CBDT framework portable to other econometric models. CBDT is a nonlinear model that can be computationally difficult to estimate inside of a mixed effects model. Using a first-stage can make CBDT more portable to computationally intensive models. In simple processes where there are limited choice options for participants and shared choice options like a prisoner's dilemma experiment, it is simple to estimate a CBDT model as in Guilfoos and Pape (2020). But, in choice situations with different choice sets (different birding site options) and many choices per choice occasion, using a two-stage model allows CBDT to be more portable.

3.1 | First-stage: Case-based model

We use the framework of CBDT to construct the first-stage estimates. In this study, a birder's past trips are what populate their memory, where each past trip becomes a "case." 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 attributes in the problems. For example, if the past trip was a wetland, then a difference would appear for all current sites that were not wetlands. The site attributes include but are not limited to seasons, date of the trip, land cover, ecoregions, and whether the site is a national wildlife refuge. The difference between site attributes (i) of current problem (p) and past problem (q) are as shown in Equation (1):

$$d(p_{it}, q_{im}) = w_i (p_{it} - q_{im})^2 \tag{1}$$

The parameter w in Equation (1) is a coefficient to be estimated by the model that weighs the information in the similarity function for attribute i, indexed by times t and m, the current and past time periods. The meaning of distance is the measurement of the difference between the attribute in the past problem, q, and the one in the current problem, p. The similarity between cases aggregates all Euclidean distances across the site attributes as given in Equation (2):

$$S(p_t, q_m) = \frac{1}{\exp \sqrt{\sum_{i=1}^{I} d_i(p_{it}, q_{im})}} \tag{2}$$

In the similarity function, p_t and q_m are vectors of attributes included to define the similarity between two different sites. The number of attributes in the definition of the "problem" is given by I in Equation (2). This specification restricts weights in the similarity function such that not all of them can be negative and the sum of the differences must be positive, though this is easily resolved by removing the square root function. The distance metric transformation is dynamic because 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.

Research in psychology suggests a surprisingly specific similarity function (Pape & Kurtz, 2013; Shepard, 1987). The approximation of similarity and distance measures that Shepard (1987) suggests is the functional form we have used in Equations (1) and (2), which uses a Euclidean distance measure (Nosofsky, 1992; Shepard, 1987). The functional form of similarity, inverse exponential, is an approximation of an invariant monotonic function that can generalize responses to stimuli in learning. Any functional form of similarity that is decreasing in distance measures may work in practice, yet we choose one that is supported by psychology as a generalized learning response to stimuli. The suggested approximation also works with a "city-block" distance function (Aulet & Lourenco, 2021; Shepard, 1964, 1987).

The estimated coefficient (w_i) for each attribute is the weight given to 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 are 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 (e.g., Guilfoos and Pape, 2016), but it is unclear how to estimate mixed logit models of discrete choice using these simulations jointly. Similarly, memory may 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.

$$y_{nj\phi} = \alpha + \sum_{m=\max(\pi-M,0)}^{\phi-1} S\left(p_{\phi}, q_{m}\right) \times \frac{1}{\Phi} + \epsilon_{nj\phi} \tag{3}$$

The response variable y is a binary indicator for 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 $\phi \in 1,\ldots,\Phi$ for each individual $n \in 1,\ldots,N$. The target y is the list of possible sites with a value of 1 if the site was chosen on that choice occasion. M is the maximum length of memory considered. Further, when referencing past cases, we index memories over time ϕ. The first case considered by a birder is listed as $m = \max(\phi - M, 0)$. This has a straight-forward interpretation: either considered memory begins at period 0, which is the beginning, or, if $\phi > M$ (and therefore $\phi - M > 0$), then only the last M periods are considered in memory. For example, if $M = 4$, then every utility calculation only considers the last four periods in memory. We divide this function by a weighting variable (Φ) 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 summation of similarity between 0 and 1, providing an intuitive interpretation of similarity values. The error term ϵ is assumed to be independent and identically distributed with a normal distribution.[4]

The first-stage model is solved by finding the minimum of the residual sum of least squares, $\text{RSS} = \sum_{n=1}^{N}\left(y_{nj\phi} - \hat{y}_{nj\phi}\right)^2$, where $y_{nj\phi}$ is the indicator for is a location was chosen and $\hat{y}_{nj\phi}$ is the prediction from the estimated model.[5] We obtain the predicted probabilities ($\hat{y}$) from Equation (3) and include them in the second-stage model as the function of past experiences.

[4]Other distributional assumptions may be appropriate based on the data. We found through trial and error that convergence and robustness of estimates using nonlinear OLS to estimate the first stage worked best.

[5]The program used to minimize the residual sum of squares (RSS) is 'nl' in Stata. This method uses a Taylor series approximation and minimizes the RSS in step wise search for the best parameters. Details of this estimation process are available in the Stata Manual for the 'nl' command.

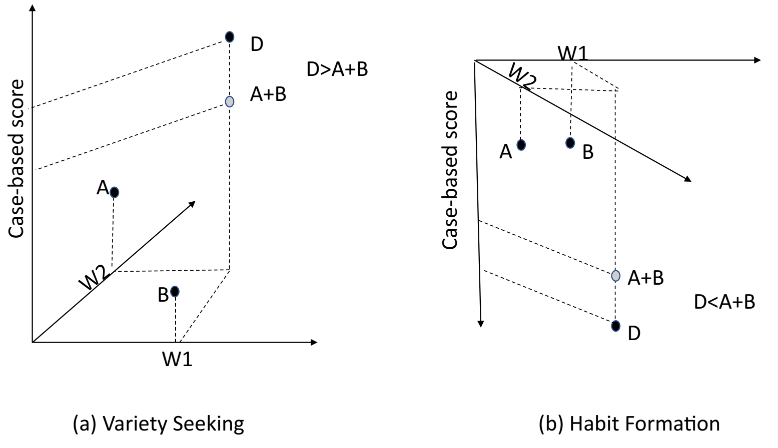

FIGURE 1 Case-based variety seeking and habit formation. The coordinates listed represent a change in case-based scores. The origin is the baseline case-based score used for comparisons. The dotted lines are only for reference to gain spatial awareness of the points. This figure assumes that case-based scores are a decreasing function of the absolute differences in attributes. The coordinates 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. This figure assumes that case-based scores are a decreasing function of the absolute differences in attributes.

The estimated weights in the similarity function from this stage have an intuitive interpretation of variety seeking or habit formation. Variety-seeking behavior (negative parameter) will increase a case-based score, whereas habit-forming behavior (positive parameter) will decrease the case-based score as the distance measure increases for an attribute. The case-based scores are the predicted probabilities coming from the first stage. As the distance metric of an attribute increases, variety seeking will increase the likelihood of choosing the site, whereas a habit formation will decrease the likelihood of choosing the site.

To conceptualize the meaning of variety-seeking in the CBDT model, we provide a visual shown in Figure 1. The nonvertical axes represent a positive difference between the current and past attribute in memory $(d(p,q) = w_i)$, which is binary[6] on case-based scores, with two attributes and weights depicted as W1 and W2. The dark dots (A, B, and D) in Figure 1 are the change in case-based scores over combinations of attributes. Given a decreasing function in absolute differences in attributes (as in Equation (2)), a negative weight shows an increase in the function for a larger difference in attributes, such as in Figure 1a, whereas a positive weight decreases such a function for larger differences in attributes, as in Figure 1b. 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 point (D) represents how case-based scores change when the attributes are different for the considered site than the attributes from memory. The origin represents the base case where we hold all other attributes constant. In Figure 1a, when the signs of the coefficients are all negative, and the individual is variety seeking along both the two attributes, then a more dramatic increase in case-based scores is realized as many attributes differ for the considered site than ones from memory. Assuming that the weights are less than zero and the similarity function is as specified in Equation (2), the figure shows a combined effect (D) that is not additive but rather multiplicative, so that $D > A + B$. This is an assertion based on the assumptions of functional form of similarity, which decreases as distance measures increase, and the signs of the individual weights being negative. For instance, a birder that has not yet visited a site with forest land cover or a

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

national wildlife refuge would be willing to pay more to experience both attributes combined as it brings two new experiences in one visit.

In Figure 1b, when the signs of the coefficients are all positive, and the individual is seeking to reinforce habits along both attributes, then a more dramatic decrease in case-based scores is realized as attributes are different for the considered site than ones from memory. As more attributes match between sites the analogy between sites is more complete. 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 preferences are both variety seeking and habit seeking, then differences in attributes will have a canceling out effect on each other. The discounting of memory with time is incorporating recency into the model of memory. We expect that the value of the weight on time to be positive, therefore discounting memory as it becomes increasingly distant. Recency will shrink the size of the dotted line box in relation to the base case (points will converge to the origin).[7]

3.2 | Second-stage: RUM model

We estimate a random utility maximization (RUM) model using a mixed logit 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):

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

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, both estimated from the variable, expected species richness (ES), capture the taste variation across individuals. Utility also depends on the expected bird species richness measure (number of bird species), which depends on season or changes over time. These are captured by interactions of ES with 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. μ varies by individual and comes from a random distribution over individuals. The variable X_{jt} represents the vector of site attributes (i) included in the model, which are the other observable characteristics of the site, and our key variable, $\widehat{y}$, is case-based scores predicted from the first stage. The error term, ε_{njt}, is assumed to be independent and identically distributed (iid) with extreme value distribution.

In the RUM model estimated via mixed logit, the choice probabilities are defined to be the integral of the probability of a standard logit model as provided in Equation (5):

$$P_{njt} = \int \frac{\exp(V_{njt})}{\sum_{k=1}^{J} \exp(V_{nkt})} f \theta d\theta \quad (5)$$

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

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 (Hensher & Greene, 2003; Train, 2002).

Provided the probability of choice jt for individual n, P_{njt}, the probability of the sequence of choices conditional on the distribution of β is given by Equation (6).

$$S_n(\beta_n,\delta) = \prod_{t=1}^{T} P_{nj(n,t)t}(\beta_n,\delta) \tag{6}$$

The log likelihood for the model is given by Equation (7).

$$LL = \sum_{n=1}^{N} ln\left[\frac{1}{R}\sum_{r=1}^{R} S_n(\beta^r,\delta)\right] \tag{7}$$

where r is the number of replications and β^r is the r^{th} draw from the distribution of β. This is a simulated log likelihood as there is not an analytical solution to solve the log likelihood. Because the CBDT estimates enter the second stage as a linear additive factor, the interpretation and log likelihood are similar to other empirical applications with mixed logit models. The inclusion of the case-based scores in the second stage is very similar to a state-dependence term, which is weighted by the attributes of each site and based on the preferences of agents.

An assumption about the dynamic relationship of history and current utility is needed here, as it needs to be in any state dependent model. We assume that both the errors in the first and second stage are iid. We assume any correlation between errors across periods, unaccounted for in the case-based history, are related to preference heterogeneity as is typically assumed in mixed logit models. If this separability does not exist then there is potential for misspecification of the dynamic and static components. The estimated covariance matrix for the second stage model may need to be adjusted to take into account the variability from the prediction in the first stage (Murphy & Topel, 2002). Therefore, using a generated regressor can be an issue in calculating the standard errors in the second stage. To address this we use a bootstrap procedure without replacement to calculate standard errors of the two-stage estimates (Politis et al., 1999). B bootstrap random samples of size b are taken and scaled by τ, to calculate standard errors, given in Equation (8). $\hat{\sigma}_i$ is the estimated variance from the i^{th} sample. We use 500 bootstrap draws without replacement and $\tau = \sqrt{\frac{b}{n}}$, where n is the original sample size, to calculate the standard errors. The subsample routine is scaled to correct for the difference in sample size from the original sample. Bootstrapping with replacement is problematic in this setting because past observations end up being replicated in memory and multiple positive choices by choice occasion occur.[8]

$$se(\beta) = \tau\frac{1}{B}\sum_{i=1}^{B}\sqrt{\hat{\sigma}_i(\beta)} \tag{8}$$

3.3 | Choice rule for two-stage estimator

To help understand the choice dynamics from this estimator, we provide a simple example of the choice rule. The choice rule between sites compares the differences in utility between sites for a birder, simplified for exposition.

[8]We use 75% of the sample to establish the size of b in each sample.

$$U_{n1t} = \alpha TC_{n1y} + \beta_i X_{n1t} + \delta \hat{y}_{1t} + \epsilon_{n1t} \quad (9)$$

$$U_{n2t} = \alpha TC_{n2y} + \beta_i X_{n2t} + \delta \hat{y}_{2t} + \epsilon_{n2t} \quad (10)$$

If $U_{n1t} > U_{n2t}$ at time t, then the individual would choose Site 1. The decision rule compares the case-based scores for both sites, comparing the similarity of the two sites with the individual's history. A higher case-based score increases the likelihood that a site would be chosen if $\delta > 0$. The meaning of δ is the weight given to past experiences in the choice rule. To expound on how the first-stage affects the choice rule, consider that Site 1 is similar to past choices, and those attributes are positively weighted in the similarity function (exhibiting habit formation, and $\hat{y}_{1t} > \hat{y}_{2t}$). Combine this fact with any differences from the cross-section generated by $\beta_i X_{njt}$, which includes all other attributes. For simplicity let us say that the βs on attributes that are different between Site 1 and Site 2 in the cross-section are equal to zero. Then Site 1 will have a higher probability of being chosen.

4 | WELFARE ESTIMATION

When the utility function is linear in parameters, the estimate of the marginal WTP 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 the weight coefficient in the first stage must incorporate the nonadditive functional form of the proposed model and depends on individual histories. This also applies to the total WTP 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 possible simplification is to assume that memory is empty, in other words, for a birder without extensive data on past experience, 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 first-stage results when included cases further back in a birder's history.

We can also assume 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 found 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 first-stage weights multiplied by the coefficient on case-based scores (δ) plus the linear coefficient of attribute i (β_i) by the negative marginal utility of price (β_c).

$$\text{Marginal WTP}_i = -\left[\left(\frac{\partial y}{\partial p_i} * \delta\right) + \beta_i\right] * \frac{1}{\beta_c} \quad (11)$$

Equation (11) 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 ($\hat{y}$) multiplied by the second-stage coefficient δ, and the vector of the mean attributes for the site ($\overline{X}_j$) multiplied by the vector of coefficients for those attributes (β), and divide by the negative marginal utility of price (β_c). This is equivalent to a value of closure for a birding site, though this may be significantly different for sites based on the amount of habit formation for specific sites and the preferences of the population of birders. We use the mean attributes in the cross-section and the individual histories for the dynamic elements of WTP. In the results section, we include the individual random parameters in the calculation of WTP for a given site, which are suppressed here for simplicity.

$$\mathrm{WTP}_j = -\left[\hat{y}^{*}\delta + \overline{X}_j\beta\right] * \frac{1}{\beta_{\mathrm{c}}} \tag{12}$$

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

The WTP estimates provided have to incorporate histories (or assume some memory of cases) to be calculated in our framework. With only cross-sectional data, birder histories are likely to be unknown and be unlikely to have the information necessary to estimate the first stage. Supplemental efforts to gather histories of visits in a recreational travel study likely provide a large benefit to work with cross-sectional data. The value in adding memory (when available) is that it gives the researcher some idea to how much experience is weighing on the value of a certain choice, allows for state dependence, and can accommodate variety seeking and habit formation behavior. For birding sites, this framework can provide a better understanding of the value of a new birding site to the community. The out-of-sample exercise to compute welfare of a new site is consistent with the theory underlying the empirics, which may not be the case in EUT.

4.1 | Static model

We will compare our model to other models to understand the differences to 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 and is equal to zero. 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.

4.2 | 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 & 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 separately as additive components. 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, 1982; McAlister & Pessemier, 1982).

5 | 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 covariates can lead to overfitting, 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 & Bierlaire, 2007).

In addition to in-sample goodness of fit we will use a roll forward hold out samples to measure out-of-sample goodness of fit. We use the mean squared errors of predictions out-of-sample. To roll forward the samples we use the percentage of past periods for each birder to keep the population of birders roughly equivalent in each of the out-of-sample tests.

6 | DATA

The data come from eBird, a large citizen/community science project run by the Cornell University Laboratory of Ornithology. They manage a database of submissions (i.e. reports referred to as checklists in eBird) by their participants about bird sightings. These participants are voluntarily logging their birding trips and details of those trips into the eBird database. Information from these trips include the destination, bird sightings, and species information. We use data on trips from 2010 to 2012 taken in Oregon and Washington for the members of eBird who reported their ZIP code to eBird when they first signed up.[9] This data set is 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 submit details regarding their bird sightings at birding sites through the project's online portal (ebird.org). Our final panel data set includes 155,382 birding sites located within a travel distance of 60 minutes from the birder's residence. Birding sites are specific to the individual and are included for each individual if the site is within 60 min of that birder's residence. To be consistent with the definition of "away-from-home" trips used by the U.S. Fish and Wildlife Service, We do not use sites that are less than 1 mile from the birder's residence. There are a total of 1104 choice occasions among birders. The repetition of choice occasions varies by birder with a mean of 10 and a median of eight repeated choice occasions by birders. Only participation days are included in the choice set and model, no other restrictions were imposed. The participation decision stage could be incorporated into a nested logit and have additional stages of estimation similar to Morey et al. (1993). Further, in the correct context additional stages could be added to model regional versus local location choices, though in the birder context most trips are local and we do not model a separate nesting structure for this decision process.

The travel cost variable is constructed based on the "best route" suggested by "mqtime," a Stata command 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

[9]Sample selection corrections were applied to correct for the propensity to provide their home ZIP code information based on the county associated with the geo-weighted centroid of their trips during the study period merged with county level sociodemographics. See Kolstoe and Cameron (2017) and their supplemental appendix for additional detail.

(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 2 (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 ecoregion of designations. All of these site attributes are obtained from the National Land Cover Database (NLCD). The definition of expected endangered species is the presence of at least one endangered species at the site the prior year in the same month the previous year. The ES measure and expected endangered species indicator are built based on the fact members of eBird have access to histogram data for hotspots for previous years and can look up what species were seen at the site during a particular time of year. This construction of these measures accommodates the fact that some species, including some endangered species, are migratory and thus may only be seen during given parts of the year at a given site.

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 & 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. Reports to eBird provide a uniform record of trips across all sites. We recognize that our measure of congestion may be incomplete as it relies on the self-reporting of birders through the eBird community.

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.[10] We also include the type of land cover and ecoregion 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 seven land cover types in our model. Our data set also uses nine ecoregions. All the variables are listed in Table 1 with their means.

Our data are an unbalanced panel. We do not use site fixed effects in our model as they would overwhelm our model. The addition of fixed effects for birding sites are so numerous in this application that it swamps the model and sites also become colinear with attributes that we wish to interpret post estimation. Individual birders have different choice sets and the number sites across all choice sets would swamp the estimation of any of the models used. The implications of this is that there may be unobserved attributes that are not accounted for in estimation of all models.

The participants of eBird are bird watchers thus represent some proportion of bird watchers. Out of an abundance of caution we are conservative in our interpretation of the results by interpreting them as representative of eBird member preferences. The WTP values may not be suitable for benefit–cost analysis or benefit-transfer given they are for a sample of convenience (see Kolstoe and Cameron, 2017, and Keeler et al., 2015, for a greater discussion of this for crowdsourced data in a recreational demand framework), but may otherwise be helpful (e.g., planning). We also contend that the comparisons between models are valid with a sample of convenience.

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

TABLE 1 Summary statistics.

Variable	Mean	Std. dev.
Travel cost (TC)	41.108	17.380
Expected species richness (ES)	75.734	10.146
Congestion/popularity	6.45×10^{-4}	0.004
Expected endangered species	8.36×10^{-5}	0.009
Urban area	0.61	0.489
National wildlife refuge	0.0044	0.066
GAP status 3 (national forest, etc.)	0.27	0.443
GAP status 1 or 2 (national park, etc.)	0.03	0.186
Ecoregion: Blue Mountains	0.002	0.054
Ecoregion: Cascades	0.035	0.186
Ecoregion: Coast Range	0.015	0.123
Ecoregion: Columbia Plateau	0.026	0.159
Ecoregion: Eastern Cascades Slopes and Foothills	0.006	0.079
Ecoregion: Klamath Mountains	0.017	0.128
Ecoregion: Northern Cascades	0.006	0.074
Ecoregion: Northern Rockies	0.002	0.041
Ecoregion: Willamette Valley	0.291	0.454
Land cover: barren	0.053	0.224
Land cover: shrubland	0.041	0.197
Land cover: forest	0.143	0.350
Land cover: planted/cultivated	0.097	0.296
Land cover: water	0.109	0.312
Land cover: wetlands	0.103	0.304
Land cover: herbaceous	0.042	0.201
Deviation from median household income	1.020	2.216
Deviation from mean propensity	0.446	0.546
Case-based score	0.008	0.005

7 | RESULTS

7.1 | Two-stage model results

The first-stage results from the nonlinear estimates following the case-based functional form (refer to Equation (3)) is provided in Table 2.[11] The estimated coefficients in the first stage 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 for a particular site attribute. A positive weight implies that a birder exhibits habit-forming behavior toward the site attribute, whereas a negative weight implies variety-seeking behavior for the site attribute. The choice of variables to include in the first and second stages are made by the researcher and their understanding of the decision-making process of the stakeholder, not for econometric identification purposes.

[11]We use the Stata nonlinear 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 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)
Ecoregion indicators		
Blue Mountains	−24.672***	(3.918)
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	

Note: $N = 155{,}382$. 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%, 5% and 10%.

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 predicted probability of choosing a site, holding everything else equal. We can compare the weights across attributes, except time (Case *T*), as they are all standardized. The type of ecoregions and land covers, seasons, areas categorized as the national wildlife refuge, andurban 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 birders exhibit a high degree of variety seeking for ecoregions and land cover types. Among the ecoregions, 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 implies that a birder who once visited the Blue Mountains would be willing to pay more for a different ecoregion 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.

Some of the region weights in our first stage may conflated variety seeking and visits to distant locations, which may be rare for some birders. We note two points about this concern. All the sites considered by a birder are within a 60 min driving radius, this excludes the rare far away trips a birder might make. Second, both the CBDT model and the other reduced form model of variety seeking and habit formation suffer from this potential problem. This issue is most likely to persist if birders largely stick to one ecoregion. When investigating our data, we find that birders regularly switch ecoregions and that more than one-third of the time birders switch ecoregions over consecutive visits. Though care needs be taken to understand weights in relation to region fixed effects in other settings.

Besides site attributes, we include other variables such as seasons and 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 (Adamowicz, 1994; Guilfoos & Pape, 2016, 2020). We find positive signs on the season indicators. Because indicators enter into the similarity function, they can capture preferences for repeat visits to similar sites by season. This is consistent with our understanding of birding behavior as site visits can follow migratory patterns. A positive weight on season increases the probability of visitation of sites that were also visited in that same season. Because these values on seasons enter the similarity function they are automatically interacted with the values of other characteristics. This is nonadditive, so some sites get a bigger bump in likelihood than others. Most notably, sites with a high similarity score get the biggest benefit of repeat visits in the same season. The previous site visited variable accounts for habit formation that is associated with unobservable characteristics of the site and is found to be insignificant here. For each choice occasion there are many potential sites, which differ by birder. The nature of this data makes for a low R-squared and a difficult modeling exercise to fit the data regardless of model.

Table 3 contains the estimates from the second-stage mixed logit model. The key variable of interest is the predicted probability from the first stage 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. It marks the weight given to histories relative to static components. The second-stage estimates are in log odds ratios, and further calculations are required for direct interpretation of WTP. 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.

The interpretation of the coefficients of variables included in both stages are different than the static model interpretation. The marginal effects of these variables include both the linear coefficient and the marginal effect of history through the case-based scores. The marginal effects are separable into historical effects and static effects.

Peer effects may inform preferences and be correlated with history in our setting, though we cannot test this formally. Social networks in birder society are also likely to inform which sites are preferred which is not measured explicitly here but may be important.

TABLE 3 Mixed logit results: second-stage model.

Variables	Site visited as dependent variable	
	Estimates	Std. Err
Travel cost	−0.036***	(0.003)
Ecoregion indicators		
Blue Mountains	−0.588	(0.888)
Cascades	0.677**	(0.325)
Coast Range	0.622*	(0.368)
Columbia Plateau	−0.492	(0.790)
Eastern Cascades Slopes and Foothills	−0.894	(0.713)
Klamath Mountains	0.137	(0.433)
Northern Cascades	−0.815	(0.759)
Northern Rockies	0.246	(0.923)
Willamette Valley	1.30***	(0.362)
Land cover indicators		
Barren	0.209	(0.153)
Shrubland	0.129	(0.140)
Forest	−0.062	(0.115)
Planted/cultivated	0.203*	(0.115)
Water	0.368***	(0.108)
Wetlands	0.377***	(0.107)
Herbaceous	−0.312*	(0.189)
Other site attributes		
National wildlife refuge	0.758***	(0.197)
GAP status 3 (national forest, etc.)	0.409***	(0.077)
GAP status 1 or 2 (national parks, etc.)	0.711***	(0.131)
Expect endangered bird species	1.210	(112.642)
Urban area	−0.562***	(0.111)
Congestion	191.881***	(14.592)
$(\text{Congestion})^2$	−3703.81***	(448.124)
Expected species richness (ES): Mean and *SD*		
ES	0.017**	(0.009)
ES (std. dev.)	0.025***	(0.009)
Other interactions with ES		
ES × dev. med H. Inc. ($10,000)	0.002	(0.003)
ES interacted with time trend	0.003	(0.005)
Sample selection correction terms		
TC × dev. mean incl. prop	0.015***	(0.004)
ES × dev. mean incl. prop	0.007	(0.019)
Predicted case-based score (δ)		
δ	14.475***	(3.628)

Note: $N = 155{,}372$. 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." ***, **, and * denotes significance at 1%, 5% and 10%.

TABLE 4 Comparison of model selection criteria.

	In-sample fit			Out-of-sample fit			
Mixed logit models	**AIC**	**BIC**	**CAIC**	**25%**	**50%**	**75%**	**90%**
Static model	9276	9575	9605	710.6	404.1	171.5	57.1
Two-stage model	9258	9567	9598	695.8	404.7	171.4	57.1
Reduced form model	9298	9865	9922	662.9	405.5	174.3	57.3

Note: AIC, BIC and CAIC denotes Akaike Information Criteria, Bayesian Information Criteria and Consistent Akaike Information Criteria respectively. In the above in-sample selection criteria, the smallest represents the preferred model. The estimates for the reduced form model is provided in Appendix C (Table 2). In the out-of-sample selection criteria are the mean squared error, the smallest mean squared error is preferred. Columns represents different percentage of decision-makers history used to predict the remaining percentage of choices.

7.2 | Model comparison

Comparing the AIC, BIC, and CAIC among all the models, we find our proposed two-stage model has 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 overfitting. The consistent-AIC (CAIC) controls for overparameterization while following the consistency properties followed by AIC (Bozdogan, 1987).

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 due to the many alternative sites for each birder. The alternatives also differ by birder, and typical state dependence models cannot be estimated under these conditions. 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.

We also compare the out-of-sample goodness of fit for all models to assess competing models. We compare the rolling out-of-sample goodness of fit based on percentage of birder's past experiences. Table 4 reports the mean squared error for all models using the hold out samples in the last four columns. The results are somewhat mixed, but the two-stage model performs well as more history is available. The reduced form model appears to be over fitting the data in general. The static model is close to the two-stage model in many measures but has a worse out-of-sample fit in three out of four tests. The more parsimonious two-stage model seems to be the best option from these results. The empirical fit of the two-stage model does not improve the out of sample fit much more than the static model in this application, though the dynamic attributes have statistical significance across models.

7.3 | 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 2). 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 (13):

$$\text{CB Score for Site 1} = 0.007 + \frac{1}{\exp\sqrt{45.021^* d_T}} \tag{13}$$

where $d_T = 1$ because the agent is referencing back one period in their memory and zero otherwise because the memory and current attributes match exactly (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 (14):

$$\text{CB Score for Site 2} = 0.007 + \frac{1}{\exp\sqrt{(45.02) + \left(-24.672^* d_{p1}\right) + \left(-11.657^* d_{p2}\right)}} \tag{14}$$

where d_p is the Euclidean distance metric, which is equal to one for each site attribute. Subsequent WTP calculations based on Equation (12) 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 ecoregion increases WTP 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 also down weights 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. Variety-seeking behavior can increase more 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 WTP. This also has the effect of having the static model very close or at the minimum of the WTP for individual sites, because variety seeking will increase WTP and habit formation can only decrease WTP a small amount in most cases.

7.4 | Value of specific sites with histories

To make inferences on specific sites, we evaluate three specific sites: Smith Rock State Park (Deschutes County, Oregon), Discovery Park (in urban Seattle, WA), and a new hypothetical conservation effort to increase endangered species at at the actual site Yakima Valley, Sunnyside Dam Area in Washington State. We use the birders' histories from our data to investigate point estimates for the 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 histories to vary by individual.

Table 5 shows the mean WTP for the sites across the birders 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 ecoregion 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 overtime, which increases the value of the site considerably. The rest of the variation within groups is due to differences in individual histories, with variety-seeking attributes driving higher WTP. In the hypothetical scenario, the variation comes only from differences in history of observing

TABLE 5 Comparison of willingness to pay (WTP) for specific sites.

Site	Static model Mean	Static model Std error	Two-stage model Mean	Two-stage model Min	2-stage model Max
Discovery Park	$46.18	17.58	$58.30	$48.96	$106.70
The Smith Rock State Park	$39.26	29.50	$42.47	$30.04	$87.66
Yakima, WA (hypothetical)	$73.02	37.65	$82.67	$73.02	$104.46

Note: 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.

a site with expected endangered species status. The WTP for a new site with endangered species is higher if the individual has not visited a site with endangered species, given the positive WTP to expect to see at least one endangered bird species. Because most site visits do not include an endangered species, the addition is valuable to the majority of potential birders in this area. Note, that it would be less valuable if other sites in the area had endangered species.

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 the model is correct, it would be accurate to say that the static model 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. The statistical significance of the differences varies by site considered. Comparing the estimates and standard errors from the static model to the individual point estimates from the two-stage model shows that Smith Rock State Park has point estimates well outside the 95% range of the mean WTP estimates from the static model. The maximum individual estimate from the two-stage model is significant at 1% using a t-statistic. Discovery Park has a maximum individual estimate that is just below 5% statistical significance using a t-statistic, and the hypothetical Yakima site is statistically insignificant. The range of estimates from these models are important and economically significant but not always statistically significant.

7.5 | Marginal willingness to pay results

Table 6 shows the marginal WTP of changes in case-based scores for each attribute and total WTP for each corresponding 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 allows for it to 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. Because this is a multisite selection model, the changes are conditional on the actual site being chosen.

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

To obtain the total WTP for an attribute, we must add the marginal WTP from the first stage to the marginal effects from the static parameter coefficients from the second stage as in Equation (11). All the attributes in Table 6 are binary, and WTP is simple to calculate given a linear additive utility, once the marginal case-based scores are recovered, and are displayed in Table 6.

TABLE 6 Marginal willingness to pay (WTP) for site attributes.

Variables	CB marginal WTP	Std. err	Marginal WTP	Std. err
Ecoregion indicators				
Blue Mountains	0.015***	(0.004)	−20.023	(23.389)
Cascades	−0.027***	(0.007)	17.828**	(8.794)
Coast Range	0.019***	(0.005)	16.456	(10.117)
Columbia Plateau	−0.030***	(0.008)	−13.752	(21.136)
Eastern Cascades Slopes and Foothills	−0.006***	(0.002)	−25.362	(19.288)
Klamath Mountains	0.027***	(0.007)	2.944	(11.648)
Northern Rockies	0.036***	(0.009)	5.656	(24.676)
Land cover indicators				
Barren	0.047***	(0.012)	5.829	(4.241)
Shrubland	0.063***	(0.016)	3.552	(3.819)
Forest	0.092***	(0.023)	−1.530	(3.149)
Planted/cultivated	0.076***	(0.019)	5.748*	(3.176)
Water	0.061***	(0.016)	10.196***	(3.076)
Wetlands	0.089***	(0.023)	10.265***	(3.058)
Herbaceous	0.027***	(0.007)	−8.635*	(5.199)
Other site attributes				
National wildlife refuge	0.032***	(0.008)	21.223***	(5.625)
GAP status 3 (National forest, etc.)	−0.030***	(0.008)	11.374***	(2.334)
GAP status 1 or 2 (National parks, etc.)	−0.001***	(0.000)	19.597***	(3.913)
Expect Endangered Bird Species	0.005***	(0.001)	35.248	(27.846)
Urban Area	−0.228***	(0.058)	−15.379***	(2.535)

Note: $N = 155{,}372$. These estimates represent the additional marginal willingness to pay in dollars that is for a marginal change in case-based scores by attribute. The first column of results reports the change in case-based scores in dollar terms whereas the third column of results reports the combined results of the first and second stages of estimation in dollar terms. ***, **, and * denotes significance at 1%, 5% and 10%.

8 | 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 CBDT. The first stage incorporates case-based reasoning where coefficients capture the habit-forming and variety-seeking behavior across site attributes and seasonality. The predicted fitted values from the first stage are included in the second-stage mixed logit model to control the dynamic aspects of site choice. We find that our approach increases the WTP estimates for sites and the static model is a lower bound on estimates. We find fixed features of the environment to drive variety seeking behavior of birders estimated in the first stage. The habit formation behavior is related to seasonality; birders seek out similar sites by season.

Birders value diversity in multiple dimensions. They exhibit a clear preference for a variety of landscapes. This is clear by the strong variety-seeking preferences for different land covers, across all land covers. In addition to the desire to see a variety of bird species, a diversity in habitats is important to the value of birding sites. It is plausible if this preference for a variety of location specific attributes exists in other recreational pursuits, such as hiking, camping, or rock climbing, something others may investigate in future studies.

We find that 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. CBDT explicitly posits that individuals can be ignorant of some potential states of the world and that they extrapolate using experience, which is consistent with how a hypothetical site is constructed in this paper. An insight of this study is that variety seeking and habit formation behavior are empirically important and can be incorporated into existing theories of decision theory, as shown here.

The conventional case-based decision theory also incorporates 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 studies, researchers may find it beneficial to design studies to gather the result of trips to be consistent with the underlying decision theory to empirically test whether including the outcome or payoff obtained from previous choices affects WTP estimates.

Our proposed framework can be applied and is suitable to examine behavior whenever agents are making repeated choices or draw from outside sources to inform their memory. This study hypothesizes that repeated choices exhibit patterns of similarity or dissimilarity. For instance, the first-stage analysis shows 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. Perhaps birders are experimenting or discovering preferences; either way, histories and the attributes of past trips are important to current location choice decisions. This work highlights what additional information and methods can be implemented when diary-like data are available on recreation trips for an activity. This additional information about the preferences of recreational visitors based on behaviors and repeat choices may provide greater insights to land managers, policymakers and conservation efforts.

ACKNOWLEDGMENTS

We thank Richard Melstrom, the participants at the 2020 AERE Summer Conference, and the participants at the 2021 ASSA AERE Conference for helpful suggestions.

CONFLICT OF INTEREST STATEMENT

We declare no conflicts of interest and have no financial disclosures to make.

DATA AVAILABILITY STATEMENT

The findings and conclusions are those of the authors, and should not be construed to represent any official USDA or U.S. Government determination or policy. All remaining errors are the responsibility of the authors. The data used for this analysis contain information that could be used identify the area in which a member lives and thus we provide a simulated dataset to allow folks to see and be able to run the code we provide. Note, eBird has not shared ZIP codes with researchers in an effort to further protect the personal identifiable information (PII) of their members, but this type of framework would also be appropriate to use in a visitation model (using only destination information) as was done by Chen et al. (2022). To apply to use the eBird data, individuals must create an eBird account (go ebird.org) and then submit a request using the "Request data" form. They will be given the option to select between the "Basic Dataset (EBD)" and the eBird API. The data here are from the Basic Dataset as are what were used in Chen et al. (2022). As part of the data request, an individual will be asked to provide the Project Title, Description of Use (4000 character limit) and Use Cases. Code and simulated data are available at https://figshare.com/account/projects/159470/articles/22069895.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Guilfoos, Todd, Priya Thomas, and Sonja Kolstoe. 2023. "Estimating Habit-Forming and Variety-Seeking Behavior: Valuation of Recreational Birdwatching." *American Journal of Agricultural Economics* 1–24. https://doi.org/10.1111/ajae.12422