Journal of Choice Modelling 46 (2023) 100398

Contents lists available at ScienceDirect

Journal of Choice Modelling

journal homepage: www.elsevier.com/locate/jocm

Heterogeneity in choice experiment data: A Bayesian investigation

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ARTICLE INFO

Keywords:
Bayesian discrete mixture
Contextual concavity
Random regret
Discrete choice experiment

ABSTRACT

Discrete mixture (DM) models recognize the presence of heterogeneity across individuals in a given population. In the context of a public land use discrete choice experiment, we use DM models to allow for respondent behavior to probabilistically mix over multiple competing process heuristics. We pairwise combine the Random Utility Model (RUM), Contextual Concavity Model (CCM), and Random Regret Minimization (RRM) heuristic into three DM models, in which the probability of an individual adhering to a particular heuristic is modeled as a function of sociodemographic characteristics. We present a comprehensive Bayesian analysis for which we explicitly describe prior selection, inferential procedures, and model comparison metrics. We use a fully Bayesian information criterion to rank the models. We find evidence that responses are best modeled using random regret. After accounting for preference heterogeneity, the DM models estimate two latent groups of decision makers. For the DM models, we develop a novel algorithm to calculate posterior-weighted willingness to pay estimates for improvements in different public park amenities in Polk County, Iowa.

1. Introduction

The discrete choice experiment is an important nonmarket valuation tool. When analyzing data from a discrete choice experiment (DCE), researchers usually assume respondents are utility maximizing, and use the random utility framework to model the data. Respondents' indirect utility is typically specified as a linear function of predictor variables explaining a choice from an array of options. Within the random utility maximization (RUM) framework, there are a number of studies modeling preference heterogeneity in novel ways (Mueller et al., 2017; Scarpa et al., 2021; Admasu et al., 2021). Recently, however, a variety of studies have explored modeling DCE data using process heuristics other than RUM (Hensher, 2014; Leong and Hensher, 2015).

A complicating matter is that of imposing, *ex ante*, a single process heuristic on a sample of respondents. Several studies, especially in the value of travel time saved (VTTS) literature, have analyzed DCE data through the lens of multiple process heuristics. The studies can be grouped into two basic categories. The first set of studies simply compares two process heuristics to see if one outperforms the other (Chorus and Bierlaire, 2013; Hensher et al., 2013; Leong and Hensher, 2014, 2015; Hensher et al., 2016; Masiero et al., 2019). A second category of studies deal with this issue by nesting multiple process heuristics in a single model. In joint heuristic models, respondents are allowed to weight multiple types of heuristics simultaneously to make a decision (Leong and Hensher, 2012b; Hensher et al., 2018). Latent class models, on the other hand, place an individual into a single latent heuristic group up to an estimated probability (Boeri et al., 2014; Hess et al., 2012; Schaak and Musshoff, 2020). A confounding factor in identifying multiple process heuristics is accounting for preference heterogeneity, and several studies have addressed this issue. Balbontin et al. (2017a,b, 2019) all tackle this using joint heuristics or latent class-based models, in addition to developing a combined

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https://doi.org/10.1016/j.jocm.2022.100398
Received 15 April 2022; Received in revised form 2 December 2022; Accepted 6 December 2022
Available online 4 January 2023

WTP or elasticity measures for the nested model results. van Cranenburgh and Alwosheel (2019), on the other hand, address the confounding issue by developing a non-latent class based model called an Artificial Neural Network to identify multiple process heuristics within the data. Chorus (2014) suggests the issue is knotty enough that DCE data might not contain enough information to identify heterogeneity in process heuristics, though Gonzalez-Valdes et al. (2022) recently developed a set of necessary conditions to do just that in the presence of preference heterogeneity.

Within the literature examining different process heuristics, there is evidence that respondents may not treat all changes in attribute levels equally when making decisions in a DCE. Extremeness aversion (EA) is a phenomenon in which respondents are observed to be averse to choosing the more "extreme" levels of a particular attribute or set of attributes. Two different models have been employed to account for the EA effect in the data. The first, Random Regret Minimization (RRM), assumes that instead of utility maximizing, respondents seek to minimize future regret. RRM is the most prevalent in the alternative heuristic literature because it is econometrically as parsimonious as the RUM (Chorus et al., 2014; Dekker, 2014; Masiero et al., 2019; Thiene et al., 2012). The second, called the Contextual Concavity Model (CCM), assumes respondents are utility maximizing and uses a nonlinear utility functional form to estimate an additional set of parameters that identifies the extent to which extremeness aversion occurs for each attribute in the data. Since the initial effort of Kivetz et al. (2004) examining choice behavior around desktop computers, additional researchers in the marketing literature (Geyskens et al., 2010), operations research (Bechler et al., 2021), and the transportation choice literature (Chorus and Bierlaire, 2013; Hensher et al., 2018; Leong and Hensher, 2012a) have also estimated the CCM in an effort to identify extremeness aversion. Despite evidence uncovered in other fields, there remains a paucity of studies estimating the CCM and the RRM in the environmental and natural resource nonmarket valuation literature, with the notable exceptions of Thiene et al. (2012) and Boeri and Longo (2017).

We contribute to this latter small body of literature that incorporates multiple decision heuristics into one model. We develop what is, to the best of our knowledge, the first Bayesian discrete mixture model (DM) embedding multiple process heuristics with random parameters. Indeed, aside from Gonzalez-Valdes and Raveau (2018), this represents only the second study to model a DM analyzing multiple process heuristics with DCE data using Bayesian methods. While others have incorporated both preference and process heterogeneity within a latent class framework, Bayesian methods allow us to do so without relying on asymptotic methods, which in turn produces exact inference. With these estimates, we develop a single, posterior-weighted WTP (PWWTP) estimate. Because WTP is a highly nonlinear function, the use of Bayesian methods means we are better able to quantify uncertainty around our posterior-weighted willingness to pay estimates. Finally, this study is the first to exploit our proposed methodology using data from an environmental nonmarket valuation DCE.

The rest of the paper proceeds as follows. In Section 2 we review three decision making heuristics, develop a discrete mixture model incorporating two heuristics simultaneously, and also describe the Bayesian methods and model selection techniques. Section 3 describes the survey and resulting data for the empirical application. Section 4 discusses the results of the analysis, and Section 5 concludes.

2. Methods

To set notation, we lay out the simplest models as building blocks to the more complicated models that capture the two sources of heterogeneity. In the random utility formulation of McFadden (1974), the researcher is able to elicit indirect utility as a function of varying attribute levels. We represent indirect utility using the formulation below, as a weighted linear combination of an action indicator and attribute levels. Let i index individual, j index alternative, and s index choice scenario:

$$\eta_{ijs}^{RUM} = \alpha action_{ijs} + \sum_a \beta_a x_{aijs} + \beta_{price} price_{ijs} \tag{1}$$

where $action_{ijs}$ is a dummy variable that takes on the value 1 if alternative j is action (as opposed to status quo) and is 0 otherwise. Therefore, α controls for status quo bias, and picks up the tendency of individuals to go with the status quo. β_a and β_{price} are the coefficients corresponding to the ath attribute and price level, respectively.

Let Y_{ijs} represent the random variable associated with the ith individual's binary choice when presented with the jth alternative in the sth choice scenario. Then, the probability of a particular choice is represented as:

$$P^{RUM}(Y_{ijs} = 1 \mid \theta^{RUM}) = \frac{exp(\eta_{ijs}^{RUM})}{\sum_j exp(\eta_{ijs}^{RUM})}.$$

The contextual concavity model of Kivetz et al. (2004) is built upon the principle of diminishing marginal returns, which can be modeled mathematically by allowing indirect utility to be a concave function of the attributes. Context is incorporated by focusing on the difference between the attribute level and the least desirable attribute level of the choice set. In our specification of indirect utility below, note that β_a and β_{price} enter linearly while the attribute and price levels are taken to a power:

$$\eta_{ijs}^{CCM} = \alpha action_{ijs} + \sum_a \beta_a (x_{aijs})^{\phi_a} + \beta_{price} \left(\widetilde{price}_{is} - price_{ijs}\right)^{\phi_{price}}$$

$$P^{CCM}(Y_{ijs} = 1 \mid \theta^{CCM}) = \frac{exp(\eta_{ijs}^{CCM})}{\sum_j exp(\eta_{ijs}^{CCM})} \tag{2}$$

where $\tilde{price}_{is}$ is the maximum price seen in scenario s seen by person i.[1] As $(\tilde{price}_{is} - price_{ijs})$ increases, we might expect a person's utility to increase as well, and therefore expect β_{price} to be positive to reflect this. Similarly, we would expect each β_a to be positive. ϕ_a represents the extremeness aversion parameter associated with attribute a. Values of $\phi < 1$ indicate extremeness aversion, while $\phi > 1$ is an indication of extremeness seeking. $\phi > 0$ by necessity, and in fact is constrained to be positive by the prior we impose.

The two process heuristics presented thus far represent mathematical models for maximizing utility, but there are many reasons why an individual might instead choose to minimize their regret. Boeri et al. (2014) lists several of these drivers which include pessimism, already being content, and the fear of choices being judged by someone with different values. Recently, van Cranenburgh et al. (2015) found the μRRM model improves model fit over the traditional RRM. In it, an additional μ parameter is estimated to describe profundity of regret. We use this more flexible model in our estimation.

Like utility, regret is modeled as a function of an action indicator and the levels of the attributes. More specifically, regret corresponding to choice j is determined by the deviation of attribute levels j from the remaining $J-1$ levels:

$$\eta_{ijs}^{RRM} = \alpha action_{ijs} + \sum_a \sum_{j'} \mu ln\left(1 + exp\left(\frac{\beta_a}{\mu}(x_{aij's} - x_{aijs})\right)\right)$$
$$+ \sum_{j'} \mu ln\left(1 + exp\left(\frac{\beta_{price}}{\mu}(price_{ij's} - price_{ijs})\right)\right)$$

Minimizing regret is mathematically equivalent to maximizing the negative of regret, resulting in choice probabilities:

$$P^{RRM}(Y_{ijs} = 1 \mid \theta^{RRM}) = \frac{exp(-\eta_{ijs}^{RRM})}{\sum_j exp(-\eta_{ijs}^{RRM})} \tag{3}$$

In the context of DCEs, our discrete mixture models specify that individuals can identify with multiple decision heuristics according to given probabilities. We limit the scope of our investigation to the possibility of two heuristics (denoted $m, m' \in \{RUM, CCM, RRM\}$) being present in the population. The membership of an individual in a particular heuristic group while viewing choice set s is controlled by a latent categorical variable, z_{is}. We start by writing the distribution of the response conditional on this variable.

$$P(Y_{ijs} = 1 \mid \theta^m, \theta^{m'}, z_{is}) = \begin{cases} P^m(Y_{ijs} = 1 \mid \theta^m) & \text{if } z_{is} = 1 \\ P^{m'}(Y_{ijs} = 1 \mid \theta^{m'}) & \text{if } z_{is} = 0 \end{cases}$$

where the $P^m(Y_{ijs} = 1 \mid \theta^m)$ formulations are as described in (1), (2), and (3).

We then let $z_{is} \sim Bernoulli(\rho_i)$. z_{is} is traditionally summed out of the model for computational purposes, resulting in the marginal likelihood typically presented in the literature. That is,

$$P(Y_{ijs} \mid \theta^m, \theta^{m'}, \rho_i) = \rho_i P^m(Y_{ijs} \mid \theta^m) + (1 - \rho_i) P^{m'}(Y_{ijs} \mid \theta^{m'})$$

where ρ_i is further modeled as the logit of a linear combination of sociodemographic characteristics in order to meaningfully explain membership probabilities.[2]

We let $logit(\rho_i) = \boldsymbol{d}_i^T \boldsymbol{\gamma}$ where $\boldsymbol{d}_i$ is a vector of the aforementioned sociodemographic characteristics. We estimate a discrete mixture model for the three potential heuristic pairs.

Model heterogeneity can come in the form of heuristic heterogeneity, as described above, or in the form of preference heterogeneity. In any of the aforementioned models, individuals may display varying preferences that manifest in the form of varying coefficients. Therefore, it makes sense to test whether the data support use of a model with heuristic heterogeneity, preference heterogeneity, or a combination of both. Thus, we additionally incorporate random effects (RE) coefficients into each of the six models, resulting in twelve competing models.

2.1. Bayesian estimation

We use Bayesian methods to estimate the models largely because they allow for exact (non-asymptotic) inference, and also allow us to more effectively answer our research questions. Let θ represent the collection of unknown parameters we wish to learn about and y represent the set of data. Bayesian methods focus on estimating $p(\theta \mid y)$ using Bayes' rule, which states $p(\theta \mid y) \propto p(y \mid \theta)p(\theta)$. Intuitively, $p(\theta \mid y)$ represents our beliefs about the unknowns θ *after* seeing the data. We obtain it by specifying the data model, $p(y \mid \theta)$, and priors, $p(\theta)$, which describe our beliefs about the unknowns *before* seeing the data.

In the six model frameworks that do not account for preference heterogeneity, the elements of $\boldsymbol{\beta}$ and α are assigned independent truncated $Normal(0, .25)$ priors. The truncation is either on the positive or negative side of the density to constrain resulting WTP estimates to a reasonable domain. *A priori* we expect no association but consider it not unlikely that the absolute magnitudes of the effects are anywhere between 0 and 3. For the random effects models that account for preference heterogeneity, we assume $\beta \sim N(\mu_\beta, \sigma_\beta^2)$ where μ_β and σ_β^2 are further given priors of $N(0, .25)$ and $N^+(0, .1)$, respectively. In the CCM formulation, each

[1] The least desirable level of each of the attributes is 0.

[2] Other factors could be included in the membership function, of course. For example, Hensher et al. (2021) note that experience can systematically explain differences in preferences.

element of $\boldsymbol{\phi}$ is given independent $N^{+}(0.5, 1)$ priors. This represents the prior belief that it is most likely individuals are extremeness averse but accommodates non-negligible probabilities that the extremeness aversion parameter is larger than 1. To complete the specification of the DM model, we assign the elements of $\boldsymbol{\gamma}$ independent $N(0, 1)$.

Follett and Vander Naald (2020) demonstrated the importance of carefully assigning prior distributions and avoiding distributions that unduly influence the posterior or even contradict the information supplied by the likelihood. We thus use weakly informative priors on all of the unknowns. This should be contrasted with extremely diffuse, or even uniform (the limit of an increasingly diffuse probability distribution), priors. These are often used in an attempt to let the data speak for itself. These strategies are misguided, however, as they can result in the overstatement of attribute effects by placing an irrational amount of prior mass in the extremes (Gelman et al., 2017). The Uniform(a, b) prior with arbitrarily chosen bounds a, b has the potential to be extremely influential, since the posterior mean and variability can be highly sensitive to the choice of those bounds, especially if the truth lies anywhere near them. Instead, following the advice in Gelman et al. (2008), we choose our priors from the t-distribution family in order to stabilize the model estimation and to reflect our genuine beliefs about the parameters.

2.2. Inferential procedures

Any theoretical quantity can be estimated using the posterior samples. For example, we estimate the posterior means of the β_a parameters using samples $r = 1, \dots, R$ by

$$E(\beta_a \mid \boldsymbol{y}) = \int p(\beta_a \mid \boldsymbol{y})\beta_a d\beta_a \approx \frac{1}{R}\sum_{r=1}^{R}\beta_a^{(r)} \tag{4}$$

where $\beta_a^{(r)}$ represents the rth draw of β_a from the posterior distribution. For any parameter, posterior means will serve as point estimates, analogous to the frequentist maximum likelihood estimates.

In the Bayesian framework, we use posterior probabilities to answer our research questions in lieu of the traditional frequentist p-value used in hypothesis testing. For example, in the CCM heuristic, we quantify evidence of extremeness aversion for a certain attribute by using an estimate of $P(\phi_a > 1 \mid \boldsymbol{y})$, the posterior probability the extremeness aversion parameter is greater than 1. We estimate this from the posterior as:

$$P(\phi_a > 1 \mid \boldsymbol{y}) = E(I(\phi_a^{(r)} > 1) \mid \boldsymbol{y}) \approx \frac{1}{R}\sum_{r=1}^{R} I(\phi_a^{(r)} > 1) \tag{5}$$

where $I()$ is the indicator function taking on a value of 1 if the logical statement is true and a value of 0 otherwise. Intuitively, we are calculating the proportion of times out of R posterior samples that ϕ_a exceeds 1 to measure the extent to which the posterior favors a concave shape on the utility function. $P(\phi_a > 1 \mid \boldsymbol{y})$ approaching 0 is evidence that attribute a is subject to extremeness aversion. $P(\phi_a > 1 \mid \boldsymbol{y})$ approaching 1 is evidence of extremeness seeking behavior for attribute a. Probabilities that are close to 0.5 suggest that ϕ_a is not meaningfully different from 1 and, thus, the indirect utilities are close to being linear in the attribute levels. In the second case mentioned, the posterior distribution of ϕ_a is likely mounded around 1.

In this paper, we aim to estimate the amount individuals are willing to pay for a one unit increase (improvement) in the ath attribute. Of particular interest is whether these amounts vary according to the type of heterogeneity modeled. WTP is estimated as the ratio of marginal utilities for the attribute and price. Regardless of heuristic, for the ath attribute,

$$WTP_a = -\frac{\frac{\partial \eta_{js}}{\partial x_{ajs}}}{\frac{\partial \eta_{js}}{\partial price_{js}}} \tag{6}$$

approximates the instantaneous rate of change of price relative to the ath attribute at the value x_{aijs}. This is the amount a person is willing to pay for a one unit increase in the ath attribute, all else held constant.

WTP is a fairly simple calculation for the RUM since both parameters and attribute covariates enter η_{js} linearly:

$$WTP_a^{RUM} = -\frac{\beta_a}{\beta_{price}} \tag{7}$$

For the contextual concavity model we have

$$\frac{\partial \eta_{ijs}}{\partial x_{aijs}} = \phi_a \beta_a x_{aijs}^{\phi_a - 1} \tag{8}$$

$$\frac{\partial \eta_{js}}{\partial price_{jis}} = -\phi_{price}\beta_{price}\left(\tilde{price}_{is} - price_{ijs}\right)^{\phi_{price}-1} \tag{9}$$

which leads to an estimand of

$$WTP_a^{CCM} = \frac{\phi_a \beta_a x_{aijs}^{\phi_a - 1}}{\phi_{price}\beta_{price}\left(\tilde{price}_{is} - price_{ijs}\right)^{\phi_{price}-1}}. \tag{10}$$

The interpretation of WTP_a^{CCM} is dependent on the highest price seen ($\tilde{price}_{is}$), as well as the level of the attribute and price currently assumed, $(x_{aijs}, price_{ijs})$. Conditioning on a maximum price, we calculate the posterior mean of the above quantity for varying values of price and attribute levels, resulting in WTP curves for each unique level of price.

We obtain an analogous quantity for the RRM heuristic, though it lacks the microeconomic underpinnings that support WTP^{CCM} and WTP^{RUM} (Chorus, 2012):

$$WTP_a^{RRM} = \frac{\sum_{j'} \beta_a (1 + exp\left(-\frac{\beta_a}{\mu}(x_{aij's} - x_{aijs})\right))^{-1}}{\sum_{j'} \beta_{price} (1 + exp\left(-\frac{\beta_{price}}{\mu}(price_{ij's} - price_{ijs})\right))^{-1}}. \tag{11}$$

WTP_a^{RRM} is dependent upon the alternate $x_{aij's}$ levels seen in a choice set, the alternate $price_{ij's}$ levels seen in a choice set, and the set $(x_{aijs}, price_{ijs})$ at which the WTP is being calculated. We calculate the posterior means of WTP_a^{RRM} for each combination seen in the DCE and display the variability in posterior means corresponding to the varying alternate levels.

We use the posterior draws from the full posterior to obtain posterior draws of WTP_a^m for model m, which effectively quantifies our posterior beliefs about the true state of WTP_a^m. For $m = CCM$ we would calculate

$$\begin{aligned} &E(WTP_a^{CCM} \mid \boldsymbol{y}, x, price, \tilde{price}) \\ &= \int p(\phi, \beta \mid \boldsymbol{y}) \left(\frac{\phi_a \beta_a x^{\phi_a - 1}}{\phi_{price}\beta_{price} \left(\tilde{price} - price\right)^{\phi_{price}-1}} \right) d(\phi, \beta) \\ &\approx \frac{1}{R} \sum_{r=1}^{R} \frac{\phi_a^{(r)} \beta_a^{(r)} x^{\phi_a^{(r)}-1}}{\phi_{price}^{(r)}\beta_{price}^{(r)} \left(\tilde{price} - price\right)^{\phi_{price}^{(r)}-1}}. \end{aligned}$$

The above formulas are valid for estimating WTP based on samples that are homogeneous in terms of heuristic. The DM models, however, assume the presence of at least two distinct groups of individuals. Thus, the WTP surface can change depending on which heuristic an individual with demographics characteristics $\tilde{\boldsymbol{d}}$ belongs to. We propose a method to calculate WTP that appropriately considers the probability with which individuals fall into the two latent groups. Let $\tilde{z}$ represent the latent membership variable which takes on the value 1 if the individual falls into group m and 0 otherwise. Then, the hypothetical individual's WTP for attribute a is $\tilde{z}WTP_a^m + (1-\tilde{z})WTP_a^{m'}$. Just as there is uncertainty associated with WTP_a^m, $\tilde{z}$ is not known with certainty. We incorporate posterior beliefs about $\tilde{z}$ by averaging over the posterior samples to estimate

$$\tilde{z}WTP_a^m + (1-\tilde{z})WTP_a^{m'} \tag{12}$$

using the Algorithm 1.

Algorithm 1 Estimating WTP based on posterior samples $\{\boldsymbol{\theta} : r = 1, \dots, R\}$.

1. Sample parameters $\boldsymbol{\theta}^{(r)}$ from their joint conditional posterior distribution, $f(\boldsymbol{\theta}|\cdot)$.
2. Compute $\rho^{(r)} = logit^{-1}(\tilde{\boldsymbol{d}}^T \boldsymbol{\gamma}^{(r)})$.
3. Sample $\tilde{z}^{(r)}$ from Bernoulli($\rho^{(r)}$).
4. Compute $WTP_a^{m(r)}$ and $WTP_a^{m'(r)}$.
5. Compute $\tilde{z}^{(r)}WTP_a^{m(r)} + (1-\tilde{z}^{(r)})WTP_a^{m'(r)}$.

The above procedure effectively integrates over posterior uncertainty in the unknown parameters and latent decision heuristic states. The result is an estimate that reflects our posterior beliefs about how much an individual with demographics $\tilde{\boldsymbol{d}}$ is WTP for an attribute. We note that, while our estimate is a weighted average, it is weighted over the appropriate posterior, not the survey sample. The quantity (12) is for a fixed demographic $\tilde{\boldsymbol{d}}$ that can be chosen based on relevant population characteristics.

We do not expect Bayesian and frequentist point estimates to differ substantially and so do not claim this estimation method is better in that sense. However, one advantage of using Bayesian estimation relative to frequentist estimation is that the distribution of WTP_a – or that of any nonlinear function of parameters – does not have to be calculated analytically or approximated using asymptotic theory. Importantly, Algorithm 1 produces exact estimates of the distribution using samples drawn from the posterior distribution. That means we are not required to use asymptotic methods such as the Delta method, which make strong assumptions that are often questionable under practical sample sizes, especially for heavily parameterized models. We obtain exact inference about the variability and, more generally, the distribution of WTP_a, simply by examining the distribution of the posterior samples. This is because MCMC samples naturally incorporate the variability of, and correlations between, each involved component.

To compare the twelve models and gather evidence for (or against) incorporating varying levels of heterogeneity, we use a Bayesian model comparison measure. The deviance information criterion (DIC, Van Der Linde, 2005) is the Bayesian analog to the frequentist AIC and BIC and has traditionally been used to compare multiple competing models in Bayesian DCEs (Gonzalez-Valdes and Raveau, 2018; Thomas et al., 2006). However, this measure is not fully Bayesian because it uses a point estimate plug-in method to compute. As Vehtari et al. (2017) points out, this can lead to further issues including the potential for negative estimates of the number of effective parameters. A second information criterion, called the WAIC, is asymptotically equivalent to cross validation techniques that estimate out-of-sample prediction accuracy and it improves on the DIC method by using the entire posterior distribution. The expected log posterior density (ELPD), a third information criterion, is even more robust than WAIC in many situations. It arises from the leave-one-out cross validation (LOO) method proposed by Vehtari et al. (2017). We compare each of the twelve competing models using the ELPD.

Table 1
Attributes and levels.

Attribute	Survey group	Attribute levels	N
Water clarity	1	[0, 50, 100]	502
Game fish	1	[0, 50, 100]	502
Bird diversity	1	[0, 10, 20]	502
Park land	1	[10, 20, 30]	502
Trails	1	[10, 20, 30]	502
Cost	1	[5, 25, 50, 75, 100, 150]	502

3. Data

3.1. Experimental design

In November 2012, residents of Polk County, Iowa passed the ten-year, $50 million Polk County Water and Legacy Bond. The overarching goal of the bond was to protect water quality around the watersheds of the two largest rivers converging in Des Moines. One projected outcome of the bond was an improvement to recreational opportunities at watershed dependent public parks in Polk County. Using a discrete choice experiment, we estimate willingness to pay for improvements in different park amenities.

In developing the DCE, we used best practices outlined in Johnston et al. (2017). Like managers of other public lands, Polk County Conservation must decide how to allocate scarce dollars across the functions of maintaining and improving their parks. Therefore, the attributes and levels used in the DCE were determined in consultation with experts from Polk County Conservation. In the final survey, six attributes were considered. The attribute most commonly affecting visitor experience across all Polk County parks is water quality. The visible representation of water quality improvements is increased water clarity, which is the first attribute. High water clarity was described as the visible outcome of good water quality. Scientists typically measure water clarity using a Secchi disk. When water is turbid or polluted, one will not be able to see the Secchi disk very far below the surface. Conversely, when water is clear, Secchi disk depth is greater. The levels of improved water clarity were 0%, 50%, and 100%. A co-benefit of improved water quality is an improved ability for desirable, or good, game fish to thrive in water bodies. Levels of improvement were 0%, 50%, or 100%. Another co-benefit of healthy water is more desirable habitat for birds. Increases in bird diversity levels were 0%, 10%, and 20%. From the built environment perspective, many users are interested in the amount of park land available (10%, 20%, 30%), as well as the network of nature and multi-use trails (10%, 20%, 30%). Finally, the cost attribute had potential values of $5, $25, $50, $75, $100, and $150. The payment vehicle was described as a one-time increase in annual property taxes. To avoid dominated strategies within choice tasks between alternatives, larger improvements in attributes were always more expensive than smaller improvements. A summary of the attributes and levels is shown in Table 1.

We used a D-optimal fractional factorial design to create 24 different choice tasks, which were then split into 12 blocks of two tasks. Each respondent was randomly allocated to one of the twelve blocks of two tasks. Each task contained three alternatives: two "action" alternatives containing a combination of attributes and levels different from the status quo, and one status quo alternative, containing attribute levels that remained constant across choice tasks. Within choice tasks, each alternative was described according to the six attributes previously discussed.

The survey was broken into three sections. The first section asked questions about respondents' travel to the park: from where they traveled, the number of people in their party, primary activities while visiting the park, substitute activities, frequency of visits, expenditures, and substitute locations. The second section presented respondents with two choice scenarios in which they were asked to make tradeoffs between different park attributes at an annual cost to their household. Each choice scenario included three distinct choices. Each choice contained different levels of the six attributes, and a picture depicting what water clarity would be given the option they choose. Each choice scenario contained one status quo option, for which the respondent paid nothing and resulted in the worst water clarity. A sample choice scenario is shown in Fig. 1. The final section collected sociodemographic information.

The choice experiment was administered by pen and paper in summer 2017 by pen and paper using random intercept sampling at three different parks managed by Polk County Conservation: Easter Lake Park, Fort Des Moines Park, and Jester Park. The three parks vary in their available activities. For example, Easter Lake Park offers a multi-use trail circumventing the lake, which itself is available for swimming, fishing, and boating. Fort Des Moines park offers boating, fishing, and hiking. Jester Park, the largest of the parks, offers the full range of activities previously listed, as well as a natural playscape, a bison herd, and overnight camping. Between the three parks, the nearly full suite of activities available at all of the 20 parks managed by Polk County Conservation.

Visitors to these parks are users, so the survey has salience to them. The majority of the users come from the Des Moines metro area, but vary in their origin. To ensure the survey effort was spread across different types of visitors, both the time of day and day of the week during which surveying occurred was systematically varied. Surveying occurred in two blocks: from 7 a.m. to 1 p.m., and 1 p.m. to 7 p.m. During those times, systematic sampling of potential respondents occurred. The roll of a six-sided die determined which subjects to survey on a given day (e.g., every *n*th person, where n is determined by the die roll). While not a true random sample, this method provided a sample with reasonable heterogeneity of sociodemographic characteristics (Landry et al., 2016).

Choice Scenarios

Sometimes when people are asked to evaluate a choice menu like this one, it is easy for them to say they support a policy either because they are not being asked to pay at the same time, or they don't think they will have to pay based on their response. Please make your choices below *as if you had to pay* and considering your household budget. There is no right or wrong answer, but results from this study will be shared with Polk County policy makers.

Scenario 1

	Option A	**Option B**	**No Action**
Increased Water Clarity	100% increase in water clarity	0% increase in water clarity	No increase in water clarity
Water Clarity visual	Picture 3	Picture 1	Picture 1
Increased quantity of good game fish	50% increase in the number of good game fish	50% increase in the number of good game fish	No increase in abundance of good game fish
Increase in bird diversity	20% increase in number of bird species	0% increase in number of bird species	No increase in number of bird species
Increase in nature/multiuse trails	10% in the number of nature/multiuse trails	30% in the number of nature/multiuse trails	No increase in the number of nature/multiuse trails
Increase in parkland	20% increase in acres of parkland	20%increase in acres of parkland	No increase in acres of parkland
Cost to HH/year (increase in annual property taxes)	\$150	\$50	\$0
Preferred program:	☐	☐	☐

Fig. 1. Example choice scenario.

3.2. The sample

After dropping respondents for incomplete, protest, and nonsensical responses, 502 complete surveys remained. Since each respondent completed two choice tasks with three alternatives, the result was 3012 observations available for estimation. Descriptive statistics are presented in Table 2. The sample is compared to average statistics for Polk County in parentheses. The average age of the sample is 45.2 (median = 35.8), 48% of the sample is female (mean = 50.7%), 36% obtained an education of at least a bachelor's degree (36.1%), the average household income is \$86,060 (median = \$68,291). Moreover, 38% reported that they either belong, or have donated, to an environmental organization. 18% of respondents owned property near the park, with the average value of that property being about \$160,000.

4. Results and discussion

To estimate each of the 12 models, we used Stan (Stan Development Team, 2018), an open-source probabilistic programming language which employs the No-U-Turn sampler (NUTS).[3] We ran four chains of length 10,000, discarding the first 5000 of each as burn-in, resulting in $R = 20{,}000$ samples from $p(\theta \mid y)$. We assessed convergence by monitoring effective sample size and $\hat{R}$. Plots of resulting convergence diagnostics are shown in Fig. 2. The Stan code from which we obtained the results is publicly available on Github.[4]

4.1. Model selection

To determine our preferred model, we estimate the expected log predictive density (ELPD) using Bayesian leave-one-out (LOO) methods, as described in Section 2. Larger model-based probabilities of unseen data imply a better description of the underlying

[3] NUTS is considered to be an improvement over standard Gibbs sampling as it uses first-order derivatives to inform jumping behavior and, thus, improve convergence especially in high-dimensional models with correlated parameters (Hoffman et al., 2014).

[4] https://github.com/LendieFollett/Heterogeneous-Decision-Paradigms

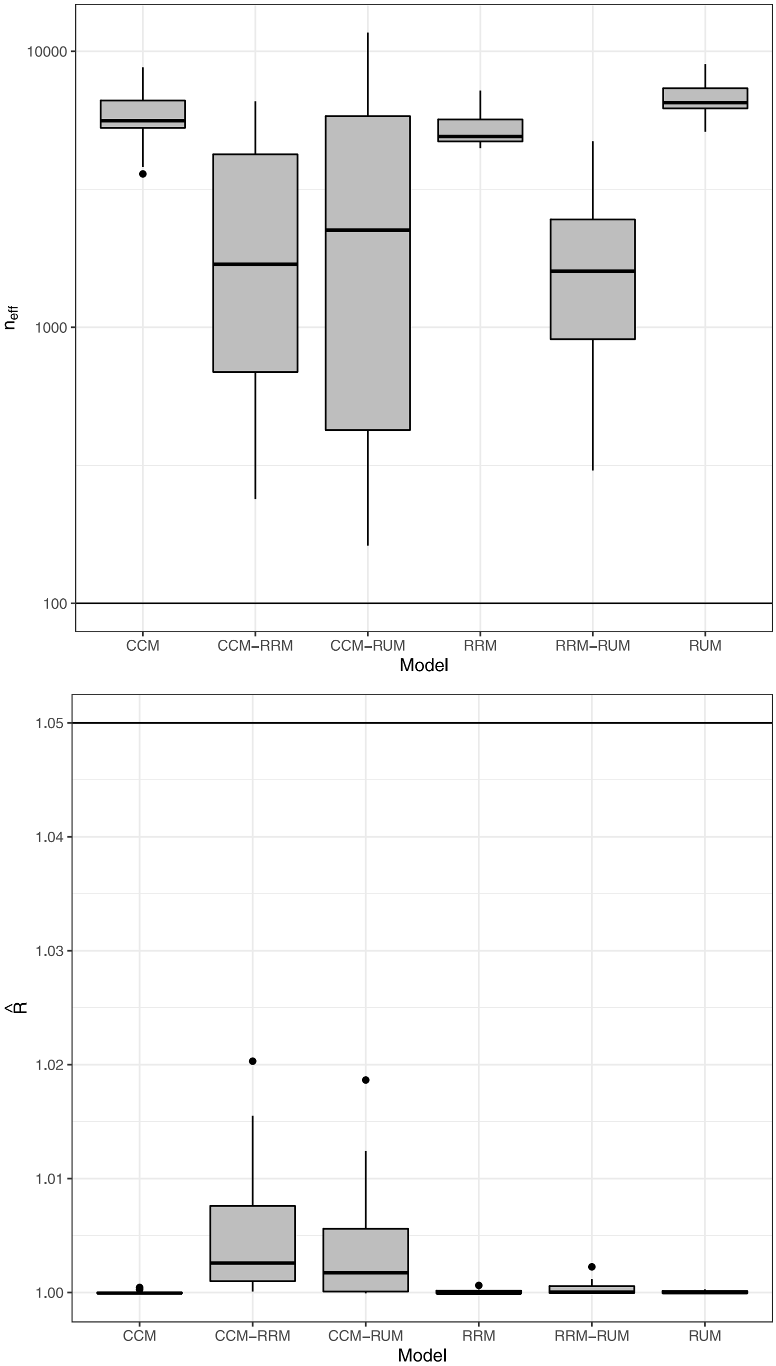

Fig. 2. Convergence diagnostics.
Convergence diagnostics for all model parameters of each of the six models. Effective sample size (top panel) and $\hat{R}$ (bottom panel). Lowest n_{eff} is 162 (100 used as rule-of-thumb minimum) and largest $\hat{R}$ is 1.0203 (1.05 used as rule-of-thumb maximum).

data generating process (DGP), which increases our confidence in the WTP estimates. Table 3 presents these ELPD estimates. A larger ELPD (smaller magnitude in absolute value when negative) means the model has better predictive ability on unseen data than a model with a smaller ELPD. Strong evidence in favor of one model over another is gathered when the difference in ELPD is several times the standard error. The ELPD, in this case, appears to strongly favor models incorporating regret minimization and preference heterogeneity.

Model preference matters for land use policy more broadly. Since there are typically several nonmarket benefits associated with public land use, it is important that WTP estimates be based on a realistic sense of the underlying DGP. If respondents in this sample are erroneously constrained to use a single process heuristic, that will not be the case. LOO estimates consistently suggest

Table 2
Sample statistics.

Variable	N	mean	sd	min	max
Age	2976.00	45.21	15.97	15.00	87.00
Is female	2988.00	0.48	0.50	0.00	1.00
Income	2694.00	86.06	54.82	7.50	220.00
Political preference	2916.00	4.14	1.64	1.00	7.00
At least Bachelor's degree	2988.00	0.36	0.48	0.00	1.00
Environmental group	2670.00	0.38	0.49	0.00	1.00
Owns property near park	2988.00	0.18	0.38	0.00	1.00
Value of property near park	486.00	160.19	62.89	25.00	250.00

Table 3
LOO estimates.

	ELPD		Difference in ELPD	
	(1)	(2)	(3)	(4)
	estimate	se	estimate	se
DM RRM-RUM	−674.86	17.24	−249.40	15.86
CCM	−672.74	16.36	−247.29	16.53
RUM	−670.89	16.41	−245.44	16.05
RRM	−670.86	16.46	−245.41	16.15
DM CCM-RUM	−669.76	16.56	−244.30	15.96
DM CCM-RRM	−669.68	16.57	−244.23	15.97
RP CCM-RUM	−580.97	15.31	−155.51	9.04
RP RUM	−544.12	17.11	−118.67	6.50
RP CCM	−532.64	16.16	−107.19	6.52
RP CCM-RRM	−502.30	13.12	−76.84	6.66
RP RRM-RUM	−462.44	11.04	−36.98	7.88
RP RRM	−425.45	15.66	0.00	0.00

*Difference in ELPD based on baseline of RP RRM model.

that the data is best represented by a DM model incorporating multiple process heuristics with random parameters, which suggests willingness to pay estimates derived from these models are more likely to reflect the truth. In what follows, we focus on the six models incorporating preference heterogeneity as they are highly favored over fixed parameter models.

4.2. Parameter estimates

Table 4 displays the results of six random parameter models. Here, β coefficient estimates represent estimates of the shared mean of the random parameters. The first three columns show, respectively, results from the RUM, CCM, and μRRM models. In each, every respondent has a single process heuristic imposed upon them. Results of Model 1, the RUM, are displayed in the top panel of the table. For all $\hat{\beta}_a^{RUM}$ except $\hat{\beta}_{price}^{RUM}$, the interpretation is the marginal utility of a one percentage point increase in the attribute from its current level. $\hat{\beta}_{price}^{RUM}$ represents the marginal utility of a one dollar increase in the cost of an option. Model 2 shows the results of imposing the CCM on all respondents. The quantity $\hat{\beta}_a^{CCM}\phi_a(x_a^{\phi_a-1})$ is interpreted as the marginal utility of a one percentage point increase in the attribute from its current level. A positive coefficient indicates more of attribute a being desirable, although the extent to which this is true depends on the reference value of x_a. Model 3 shows the results of imposing the μRRM on all respondents. The coefficients for the μRRM results, $\hat{\beta}_a^{RR}$, are interpreted differently than those of the utility-based models. Each $\hat{\beta}_a^{RR}$ is a coefficient corresponding to a difference. A positive $\hat{\beta}_a^{RR}$ means that regret increases as the unchosen level increases (performs better) relative to the chosen level of attribute a.[5] The $\hat{\mu}$ indicates the degree to which the μRRM model is likely to be different in fit and profundity of regret when compared to the simple linear RRM model. In model 3, $\hat{\mu} = 0.848$, suggesting the results from our μRRM model are not different from the linear RRM model in both fit and profundity of regret. Columns 4–6 display results from three discrete mixture models: the RUM-RRM DM model, the CCM-RRM DM model, and the CCM-RUM DM model, respectively.

We compare the parameter estimates across all relevant models to gauge whether splitting by latent group changes interpretations and, ultimately, WTP calculations. For each of RUM, CCM, and RRM process heuristics, there is at least one case of a parameter differing in magnitude across representations. This suggests that WTP may be highly dependent on model choice.

As described in Section 2, class membership probabilities were specified as an inverse logit function of an intercept term (γ_0), gender, environmental organization membership, political preferences, and income. Table 5 displays posterior summaries for the membership class parameters, $\boldsymbol{\gamma}$, estimated for each of the six DM models. In each column, the model that appears first in the name

[5] When the alternative level j' is less than level j, regret is approximately 0.

Table 4
Main results.

	RUM (1)	CCM (2)	RRM (3)	RUM-RRM (4)	CCM-RRM (5)	CCM-RUM (6)
α^{RUM}	0.612			0.362		0.008
	(0.203)			(0.992)		(0.098)
β^{RUM}_{bd}	0.006			0.289		0.065
	(0.014)			(0.22)		(0.055)
β^{RUM}_{gf}	0.013			0.263		0.066
	(0.004)			(0.142)		(0.067)
β^{RUM}_{pl}	0.027			0.169		0.074
	(0.014)			(0.228)		(0.061)
β^{RUM}_{price}	−0.007			−0.083		−0.022
	(0.004)			(0.042)		(0.02)
β^{RUM}_{tr}	0.055			0.026		0.15
	(0.016)			(0.24)		(0.094)
β^{RUM}_{wq}	0.029			0.14		0.137
	(0.006)			(0.106)		(0.054)
α^{CC}		1.323			0.039	0.045
		(0.55)			(0.249)	(0.098)
β^{CC}_{bd}		0.064			0.151	0.082
		(0.057)			(0.108)	(0.08)
β^{CC}_{gf}		0.095			0.259	0.117
		(0.07)			(0.138)	(0.098)
β^{CC}_{pl}		0.178			0.174	0.331
		(0.173)			(0.126)	(0.192)
β^{CC}_{price}		0.036			0.157	0.175
		(0.028)			(0.118)	(0.13)
β^{CC}_{tr}		0.1			0.147	0.342
		(0.08)			(0.123)	(0.179)
β^{CC}_{wq}		0.118			0.225	0.221
		(0.05)			(0.148)	(0.15)
ϕ_{bd}		0.461			0.916	0.48
		(0.305)			(0.55)	(0.352)
ϕ_{gf}		0.587			1.046	0.459
		(0.159)			(0.597)	(0.281)
ϕ_{pl}		0.438			0.599	0.52
		(0.277)			(0.446)	(0.365)
ϕ_{price}		0.679			0.408	0.621
		(0.095)			(0.247)	(0.239)
ϕ_{tr}		0.739			0.472	1.134
		(0.166)			(0.363)	(0.287)
ϕ_{wq}		0.699			0.458	0.95
		(0.103)			(0.294)	(0.211)
α^{RR}			−0.104	−0.778	−0.06	
			(0.242)	(0.863)	(0.251)	
β^{RR}_{bd}			0.022	0.031	0.032	
			(0.017)	(0.027)	(0.029)	
β^{RR}_{gf}			0.027	0.016	0.016	
			(0.009)	(0.016)	(0.016)	
β^{RR}_{pl}			0.047	0.061	0.061	
			(0.024)	(0.043)	(0.038)	
β^{RR}_{price}			−0.005	−0.012	−0.014	
			(0.004)	(0.01)	(0.01)	
β^{RR}_{tr}			0.096	0.132	0.141	
			(0.032)	(0.06)	(0.051)	
β^{RR}_{wq}			0.061	0.101	0.117	
			(0.018)	(0.038)	(0.035)	
RRmu			0.848	0.613	0.561	
RRmu			(0.413)	(0.388)	(0.397)	

*Posterior means of all parameters in models involving random parameters. Standard deviations in parentheses.

represents a “positive” event. A positive membership probability coefficient for a sociodemographic characteristic in a particular DM model indicates that individuals with the sociodemographic characteristic are more likely to be modeled by the first process heuristic relative to individuals without it. Alternatively, a negative membership probability coefficient indicates that individuals with the sociodemographic characteristic are less likely to be modeled by the first process heuristic. Notably, including random parameters significantly influences the inferences we get from these estimates as sign changes are common. Comparisons across traits is possible since we standardize income as in Gelman (2008) by subtracting the mean and dividing by two times the standard deviation. We interpret the coefficient as a shift of two standard deviations, from the low end of the income spectrum to the high

Table 5
Gamma estimates.

	RUM-RRM	CCM-RRM	CCM-RUM
γ_0	−0.943	−0.87	−0.207
	(0.188)	(0.198)	(0.512)
γ_{cons}	−0.12	−0.145	−0.031
	(0.199)	(0.203)	(0.233)
γ_{donate}	−0.143	−0.109	−0.099
	(0.228)	(0.213)	(0.24)
γ_{female}	−0.008	−0.036	−0.091
	(0.218)	(0.214)	(0.231)
γ_{income}	0.354	0.402	0.146
	(0.225)	(0.226)	(0.328)

*Standard deviations in parentheses. Positive events (m) are: *RUM-RRM(RUM), CCM-RRM(CCM), CCM-RUM(CCM).

end. If $\gamma_{income} > 0$, then the odds that an individual on the high end of the income spectrum identifies with heuristic m are larger than those of an individual on the lower end of the income spectrum. In the random parameter RUM-RRM DM model, the odds of an individual on the high end of the income spectrum having their decisions more appropriately modeled by the RUM are about $e^{0.354} = 1.42$ times (42% greater than) those of an individual on the lower end of the income spectrum. Similar patterns are observed in the CCM-RRM model where we again see lower income individuals being more likely to be modeled by RRM. Further, there is moderately strong evidence of a relationship between income and membership probability as the posterior means are large relative to the posterior standard deviations, suggesting high posterior probabilities of the form $P(|\gamma| > 0 \mid \boldsymbol{y})$. Indeed, most of the posterior mean estimates of ϕ_a in Table 6 are well below one, even relative to their corresponding standard errors. The estimated posterior probability of exceeding 1, $P(\phi_a > 1 \mid \boldsymbol{y})$, is usually less than 0.1, indicating strong evidence of extremeness aversion for all five attributes. The exceptions to this are ϕ_{bd} and ϕ_{gf} in the CCM-RRM model which are largely centered around 1 and have estimates .412 and .418, respectively, for $P(\phi_a > 1 \mid \boldsymbol{y})$.

4.3. Willingness to pay

Ultimately, we are interested in how well our models can inform policy. The ELPD measure of model fit favors random parameter models over fixed parameter models. Moreover, models incorporating regret-minimization also fare better than models without regret in them, meaning WTP estimates from these models should be more appropriate than WTP estimates from models with the other process heuristics. To calculate WTP, we use what, intuitively, is a weighted average of the heuristic-implied WTP values over MCMC posterior samples.

Fig. 3 displays posterior means and 95% credible intervals of WTP estimates based on each of the six random parameter DM models. A unique and important feature of this algorithm is that the overall WTP estimates can be calculated for any collection of sociodemographic traits $\tilde{\boldsymbol{d}}$, influencing the membership probability ρ. We set $\tilde{\boldsymbol{d}}$ at the means observed in the sample, and thus the WTP estimates reflect the posterior probability that an 'average' sampled individual will adhere to either of the particular heuristics. The DM model often, but not always, suggests a WTP estimate that is in between the WTP estimates derived from the appropriate two single-heuristic models. That not all DM model WTP estimates fall within the range of the individual model WTP estimates is consistent with Hensher et al. (2018), and could occur because of model misspecification. Importantly, Fig. 3 incorporates variability due to parameter uncertainty, heuristic heterogeneity, and preference heterogeneity. We note the asymmetry, and in particular right-skewedness, indicated by the means and 95% credible intervals in Fig. 3. This suggests that some conventional methods, such as the Delta method, may be unreliable for quantifying WTP uncertainty as it would tend to underestimate the upper and lower bounds of the distribution.

Inasmuch as nonmarket values play a role in benefit-cost analysis, the policy implications of these results are potentially quite large. Suppose, for example, that we were interested in using the WTP for a one percentage point increase in the number of nature/multiuse trails in a public park for policy purposes. If we imposed the usual process heuristic of RUM instead of allowing the flexibility of the RRM-RUM DM model preferred by the ELPD, we would underestimate WTP by 31.87-11.47 = $20.40, a three-fold difference.[6]

5. Conclusion

It is frequently assumed that respondent decisions in DCE studies can be modeled using a linear RUM model. Implicitly, this also means that decisions are assumed to conform to a single process heuristic. In the context of public park land use decisions, those assumptions may not hold. This paper developed a Bayesian discrete mixture model that allows for multiple process heuristics to describe respondent choices in DCE data while also controlling for preference heterogeneity. For the first time in

[6] See Table 8 in Appendix A for exact figures.

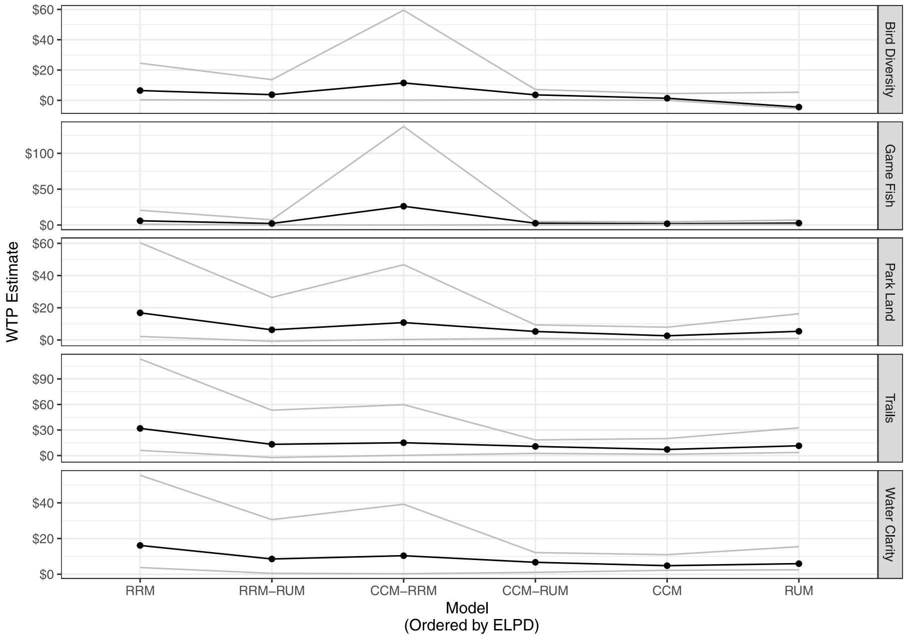

Fig. 3. Posterior means.
Posterior means (black line) and 95% posterior credible intervals (gray line) for a one unit increase in each attribute, as estimated by each random parameter model. Posterior means for DM models are based on Algorithm 1. Attribute levels and price levels are set at lowest non-baseline in survey and $50.00, respectively. In the case of RRM, we average posterior quantities over all survey scenarios.

the environmental nonmarket valuation literature, we estimated a Bayesian DM model and developed a transparent algorithm to calculate a posterior-weighted WTP estimate for each DM model.

In the empirical application, the ELPD goodness of fit measure indicated that models including preference heterogeneity dominated models without preference heterogeneity. Moreover, the models including the RRM process heuristic outperformed models with other process heuristics. Contrary to our expectations, the model with the best fit was the single heuristic version of the RRM. This data-dependent result is supported by the fact that the two DM models containing RRM ranked below the single heuristic version of the model and above the models containing the other heuristics, in terms of goodness of fit. Finally, we illustrate how the implications of failing to allow for flexible process heuristics when estimating WTP are potentially large.

There are several limitations to this work, in which we reveal a number of different opportunities for future research. We were interested in developing a WTP estimator using a DM incorporating alternative process heuristics specifically related to extremeness aversion in decision-making. However, there are other process heuristics (e.g., attribute-nonattendance, relative advantage maximization) to consider in the context of DCE data, and they could all be incorporated into the DM model developed in this paper. Moreover, preference and process heterogeneity could still be confounded in our data, and there are other methods available to identify heterogeneous process heuristics in the data, such as the Artificial Neural Network (ANN) method. Further, our sample is limited to public park users. Specific inference concerning behavioral characteristics and, in particular, WTP, is limited to the population of park users. Finally, we considered only cases of one or two underlying behavioral groups. Future research might focus on a modeling scheme that is more flexible, and should carefully consider the implications of imposing a particular process heuristic on DCE data.

Acknowledgments

Data collection for the empirical application was funding in part by Polk County Conservation. We thank David Hensher and an anonymous reviewer for their helpful comments and insight. Finally, we are grateful to participants of the W-4133 Meeting in Athens, Georgia.

Appendix A

See Tables 6–8.

Table 6
Posterior means of all parameters for models not involving random parameters. Standard deviations in parentheses.

	RUM (1)	CCM (2)	RRM (3)	RUM-RRM (4)	CCM-RRM (5)	CCM-RUM (6)
α^{RUM}	0.509			0.577		0.009
	(0.206)			(0.225)		(1.012)
β_{bd}^{RUM}	0.011			0.008		0.775
	(0.006)			(0.006)		(0.512)
β_{gf}^{RUM}	0.005			0.001		0.622
	(0.001)			(0.001)		(0.354)
β_{pl}^{RUM}	0.003			0.006		0.315
	(0.006)			(0.005)		(0.387)
β_{price}^{RUM}	−0.003			−0.004		−0.158
	(0.001)			(0.002)		(0.151)
β_{tr}^{RUM}	0.02			0.014		0.934
	(0.006)			(0.007)		(0.605)
β_{wq}^{RUM}	0.011			0.011		1.653
	(0.002)			(0.003)		(0.745)
α^{CC}		−0.545			−0.416	−0.44
		(0.562)			(0.597)	(0.603)
β_{bd}^{CC}		0.083			0.106	0.107
		(0.071)			(0.097)	(0.097)
β_{gf}^{CC}		0.129			0.106	0.108
		(0.108)			(0.108)	(0.11)
β_{pl}^{CC}		0.328			0.366	0.368
		(0.331)			(0.354)	(0.353)
β_{price}^{CC}		0.062			0.395	0.391
		(0.064)			(0.265)	(0.262)
β_{tr}^{CC}		0.383			0.378	0.39
		(0.343)			(0.358)	(0.365)
β_{wq}^{CC}		0.15			0.247	0.246
		(0.144)			(0.19)	(0.192)
ϕ_{bd}		0.39			0.378	0.385
		(0.323)			(0.326)	(0.333)
ϕ_{gf}		0.336			0.308	0.316
		(0.269)			(0.26)	(0.273)
ϕ_{pl}		0.235			0.26	0.259
		(0.219)			(0.225)	(0.227)
ϕ_{price}		0.295			0.2	0.2
		(0.256)			(0.155)	(0.157)
ϕ_{tr}		0.417			0.334	0.328
		(0.264)			(0.256)	(0.249)
ϕ_{wq}		0.505			0.313	0.31
		(0.229)			(0.238)	(0.235)
α^{RR}			−0.347	0.015	0.017	
			(0.237)	(0.994)	(1.001)	
β_{bd}^{RR}			0.007	1.036	0.757	
			(0.004)	(0.774)	(0.528)	
β_{gf}^{RR}			0.003	1.013	0.591	
			(0.001)	(0.527)	(0.312)	
β_{pl}^{RR}			0.005	0.555	0.303	
			(0.003)	(0.534)	(0.356)	
β_{price}^{RR}			−0.002	−0.137	−0.078	
			(0.001)	(0.094)	(0.075)	
β_{tr}^{RR}			0.014	1.022	0.954	
			(0.005)	(0.8)	(0.628)	
β_{wq}^{RR}			0.008	0.582	1.591	
			(0.001)	(0.466)	(0.735)	
μ^{RR}			0.901	0.938	0.993	
			(0.575)	(0.596)	(0.581)	

Table 7
Posterior means and standard deviations (in parentheses) of shared parameters in non-random parameters DM models. Positive events (m) are: RUM-RRM(RUM), CCM-RRM(CCM), CCM-RUM(CCM).

	RUM-RRM	CCM-RRM	CCM-RUM
γ_0	1.306	0.767	0.78
	(0.24)	(0.349)	(0.35)
γ_{cons}	0.3	0.198	0.201
	(0.318)	(0.26)	(0.27)
γ_{donate}	0.09	−0.157	−0.154
	(0.335)	(0.282)	(0.289)
γ_{female}	0.013	−0.283	−0.286
	(0.329)	(0.29)	(0.297)
γ_{income}	−0.963	−0.689	−0.685
	(0.314)	(0.292)	(0.283)

Table 8
Posterior means and 95% credible intervals of WTP for random parameter models only.

	Model	Mean	Lower	Upper
Bird diversity	CCM	1.38	0.03	4.47
Bird diversity	RUM	−4.44	−5.52	5.34
Bird diversity	RRM	6.46	0.35	24.51
Bird diversity	CCM-RRM	11.49	0.19	59.49
Bird diversity	CCM-RUM	3.63	0.38	7.13
Bird diversity	RRM-RUM	3.75	0.13	13.65
Game fish	CCM	1.83	0.66	4.45
Game fish	RUM	2.67	0.93	6.89
Game fish	RRM	5.88	1.11	20.56
Game fish	CCM-RRM	26.16	0.06	137.49
Game fish	CCM-RUM	2.52	0.23	4.85
Game fish	RRM-RUM	2.13	0.11	7.26
Park land	CCM	2.62	0.11	7.94
Park land	RUM	5.38	1.03	16.29
Park land	RRM	16.85	2.18	60.40
Park land	CCM-RRM	10.82	0.32	46.76
Park land	CCM-RUM	5.28	1.04	9.38
Park land	RRM-RUM	6.31	−0.77	26.43
Trails	CCM	7.16	1.52	19.94
Trails	RUM	11.47	3.65	32.62
Trails	RRM	31.87	6.09	113.40
Trails	CCM-RRM	15.09	0.26	59.80
Trails	CCM-RUM	10.71	2.58	18.38
Trails	RRM-RUM	13.21	−2.25	53.24
Water clarity	CCM	4.78	2.18	10.94
Water clarity	RUM	5.90	2.45	15.43
Water clarity	RRM	16.12	3.74	55.49
Water clarity	CCM-RRM	10.36	0.26	39.25
Water clarity	CCM-RUM	6.66	1.02	12.12
Water clarity	RRM-RUM	8.54	0.48	30.57

Appendix B. Survey instrument

Water Quality at Polk County Parks

The Polk County Water and Land Legacy Bond (PCWLL) was passed in 2012 to fund improvements in water quality and land acquisition at and surrounding Polk County Parks. Many improvements have already been made, and many more improvements are coming. Your answers will help inform Polk County Conservation of your preferences.

Preliminary Questions

P1 Please enter your 5-digit home zip code ___________

P2 How many people are in your party? ________

P3 What is your primary reason for coming to the park?

- ☐ Fishing
- ☐ Boating
- ☐ Kayaking/Canoeing
- ☐ Swimming/Beach
- ☐ Hiking/Biking/Running
- ☐ Picnicking
- ☐ Bird Watching/Nature/Wildlife
- ☐ Camping
- ☐ Shelter Use
- ☐ CCB Event/Clinic
- ☐ Other ___________

P4 Are you participating in any other activities while you're here? Please check all that apply.

- ☐ Fishing
- ☐ Boating
- ☐ Kayaking/Canoeing
- ☐ Swimming/Beach
- ☐ Hiking/Biking/Running
- ☐ Picnicking
- ☐ Bird Watching/Nature/Wildlife
- ☐ Camping
- ☐ Shelter Use
- ☐ CCB Event/Clinic
- ☐ Other ___________

P5 Have you previously been surveyed for this study? ☐Yes ☐No

P6 How many times per month do you visit this park? _________________

P7 On this particular trip to the park, approximately how much will your household spend in each of the following categories?

Food and Beverages (restaurants, grocery/convenience store): $_________
Gas and Other Travel Expenses: $_________
Fishing Supplies (bait, license): $_________
Is fishing license annual? ☐Yes ☐No
Camping/Picnicking (bug spray, charcoal, paper plates): $_________
Lodging Costs (camping fees, hotels, cabin rentals): $_________
Other (Indicate _____________): $_________

P8 See the attached map of Polk County Parks. Please review the map and then answer the question below based on the map.

How many trips did you make to the following Polk County Parks in the past 12 months, whether a day-visit or overnight? (Select all that apply; leave blank if zero)

		Number of Day Trips	Number of Overnight Trips	Number of Nights on Overnight Trips
1)	Beaver Creek Greenbelt	[___]	[___]	[___]
2)	Brown's Woods	[___]	[___]	[___]
3)	Carney Marsh	[___]	[___]	[___]
4)	Chichaqua Bottoms Greenbelt	[___]	[___]	[___]
5)	Chichaqua Valley Trail	[___]	[___]	[___]
6)	Easter Lake Park	[___]	[___]	[___]
7)	Eagle Roost Wildlife Area	[___]	[___]	[___]
8)	Engeldinger Marsh	[___]	[___]	[___]
9)	Fort Des Moines Park	[___]	[___]	[___]
10)	Four Mile Creek Greenbelt	[___]	[___]	[___]
11)	Gay Lea Wilson Trail	[___]	[___]	[___]
12)	Great Western Trail	[___]	[___]	[___]
13)	High Trestle Trail	[___]	[___]	[___]
14)	Jester Park	[___]	[___]	[___]
15)	Mally's Weh-Weh-Neh-Kee Park	[___]	[___]	[___]
16)	Oralabor Gateway Trail	[___]	[___]	[___]
17)	Sycamore Trail	[___]	[___]	[___]
18)	Thomas Mitchell Park	[___]	[___]	[___]
19)	Trestle to Trestle Trail	[___]	[___]	[___]
20)	Yellow Banks Park	[___]	[___]	[___]

Choice Scenarios

Sometimes when people are asked to evaluate a choice menu like this one, it is easy for them to say they support a policy either because they are not being asked to pay at the same time, or they don't think they will have to pay based on their response. Please make your choices below *as if you had to pay* and considering your household budget. There is no right or wrong answer, but results from this study will be shared with Polk County policy makers.

Scenario 1

	Option A	**Option B**	**No Action**
Increased Water Clarity	50% increase in water clarity	50% increase in water clarity	No increase in water clarity
Water Clarity visual	Picture 2	Picture 2	Picture 1
Increased quantity of good game fish	0% increase in the number of good game fish	50% increase in the number of good game fish	No increase in abundance of good game fish
Increase in bird diversity	20% increase in number of bird species	10% increase in number of bird species	No increase in number of bird species
Increase in nature/multiuse trails	20% in the number of nature/multiuse trails	20% in the number of nature/multiuse trails	No increase in the number of nature/multiuse trails
Increase in parkland	20% increase in acres of parkland	20%increase in acres of parkland	No increase in acres of parkland
Cost to HH/year	$75	$75	$0
Preferred program:	☐	☐	☐

C1 How confident are you in your choice above?

☐Not at all confident ☐Pretty confident ☐Very confident

Once again, please make your choices below *as if you had to pay* and considering your household budget. There is no right or wrong answer, but results from this study will be shared with Polk County policy makers.

Scenario 2

	Option A	**Option B**	**No Action**
Increased Water Clarity	100% increase in water clarity	0% increase in water clarity	No increase in water clarity
Water Clarity visual	Picture 3	Picture 1	Picture 1
Increased quantity of good game fish	50% increase in the number of good game fish	50% increase in the number of good game fish	No increase in abundance of good game fish
Increase in bird diversity	0% increase in number of bird species	20% increase in number of bird species	No increase in number of bird species
Increase in nature/multiuse trails	30% in the number of nature/multiuse trails	10% in the number of nature/multiuse trails	No increase in the number of nature/multiuse trails
Increase in parkland	10% increase in acres of parkland	30%increase in acres of parkland	No increase in acres of parkland
Cost to HH/year	\$150	\$50	\$0
Preferred program:	☐	☐	☐

C2 How confident are you in your choice above?

☐Not at all confident ☐Pretty confident ☐Very confident

Sociodemographic Questions

S1 In what year were you born? _______

S2 What is your gender?

☐Male ☐Female

S3 Including yourself, how many members in your household are in each age group? (If none in an age group, write "0")

___ Under 18 years of age
___ 18-64
___ 65 and over

S4 Think about the way the information in this survey was presented. How important do you think it is *to this research team* for people to value water quality at Polk County Parks highly?

☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7
Not at all important			Neutral			Extremely important

S5 What is your employment status?

☐ Employed Full Time
☐ Employed Part Time
☐ Full-time Homemaker
☐ Unemployed
☐ Retired
☐ Student
☐ Other (Please Specify)_____________

S6 In terms of politics, how do you consider yourself?

☐	☐	☐	☐	☐	☐	☐
1	2	3	4	5	6	7
Very liberal			Moderate			Very conservative

S7 What is your highest level of education?

☐ Less than high school
☐ High school graduate
☐ Some college, no degree
☐ Degree (occupational)
☐ Associate degree (academic)
☐ Bachelor's degree
☐ Master's degree
☐ Professional degree
☐ Doctorate degree

S8 In the past year, have you held membership or donated time or money to any environmental organizations or groups? (Check the best answer)

☐ Yes ☐ No

S9 Do you own property within ¼ mile of this park?

☐ Yes ☐ No

S9a If yes, what is the approximate tax value of your property?

☐ Less than $50,000
☐ $50,000 – $99,999
☐ $100,000– $249,999
☐ $250,000 or more

S10 What is your total household income before taxes and other deductions? (Check the best answer)

☐ Less than $15,000
☐ $15,000 – $24,999
☐ $25,000 – $34,999
☐ $35,000 – $49,999
☐ $50,000 – $74,999
☐ $75,000 – $99,999
☐ $100,000 – $149,999
☐ $150,000 – $199,999
☐ $200,000 or more

S11 Please tell us how you would identify yourself using the standard U.S. Census categories for:

a. Race

☐ American Indian or Alaska Native
☐ Asian
☐ Black or African American
☐ Native Hawaiian or Other Pacific Islander
☐ White

b. Ethnicity

☐ Hispanic or Latino
☐ Not Hispanic or Latino

S12 Anything else you would like to add?

____

____

____

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