Lumpy Heterogeneity in Groundwater Service Values and Time Preferences

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ABSTRACT *From a choice experiment about groundwater management, we consider time preferences and groundwater service values through sociodemographic characteristics using a model called the discounted latent class model. A policy-motivated latent class has a higher income, greater familiarity with an aquifer, and more concern for the risks that groundwater decline poses to people and the environment. A business-as-usual latent class has a conservative ideology. Exponential discounting is preferred, and the discount rate is larger for the policy group than the business-as-usual group. Other models we use include the discounted mixed logit model and the discounted logit-mixed logit model.* (JEL Q25, Q51)

1. Introduction

Economists who study the environment and natural resources contemplate projects that separate those who benefit from those who incur the costs by many years or even generations. Discounting determines whether the interests of future generations will be at all significant. The appropriate discount rate is controversial, and some economists advocate that policy makers use a declining discount rate given the uncertainty about future discount rates (Arrow et al. 2013). Uncertainty about the discount rate exists because of unknowns about the opportunity cost of money (i.e., strength of economic activity, inflation, and risk) and ethical debates about the pure rate of time preference (Brennan 1999). Empirical evidence about the rate of time preference is therefore useful to help narrow the range and distribution of the uncertain discount rates. Studies to elicit discount rates use several methodologies, including laboratory and field experiments (Ubfal 2016; Andreoni et al. 2019) and stated preference surveys (Howard, Whitehead, and Hochard 2021).

Regardless of the methodology, a wide range of discount rates emerge, and the discount rates correlate with individual characteristics (Andreoni et al. 2019) and the type of good (Ubfal 2016; Vásquez-Lavín et al. 2019). Joint preferences for time and nonmarket goods may coexist in a lumpy rather than a smooth way across the population, and a finite number of preference groups, with strong homogeneity in each group, might coalesce within the population. We explore this possibility and contribute to the literature by developing a generalization of the latent class model (LCM) to estimate the attribute and time preference parameters from a choice experiment (CE).

The simultaneous classification of decision-making individuals into segments and the estimation of utility parameters conditional on segment membership is possible with the LCM (Beharry-Borg and Scarpa 2010). Observable variables to the analyst enter a membership likelihood function to predict an individual's membership in a segment. Provencher, Baerenklau, and Bishop (2002), Milon and Scrogin (2006), and Ruto, Garrod, and Scarpa (2008), among other studies, use

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socioeconomic variables to specify LCMs and capture observed taste heterogeneity. This study is the first to use LCM to jointly determine implicit discount rates and the marginal willingness to pay (WTP) for the attributes of a nonmarket good with CE data. The extension, which we call the discounted latent class model (D-LCM), is a way to explore the existence of lumpy preferences for time and the attributes of nonmarket goods through observable characteristics. Heterogeneity in discounting behavior (i.e., exponential vs. hyperbolic) is also possible to examine with the D-LCM because experimental (Andersen et al. 2014) and stated preference studies (Lew 2018; Kovacs and Snell 2021) have not definitively determined discounting behavior.

CE is useful for understanding the preferences of a nonmarket good when actual behavioral data related to the nonmarket resource are unavailable. CEs do not typically ask respondents to consider the intertemporal stream of the benefits and costs in the choice situation. However, a small body of literature uses stated preference surveys to estimate discount rates. Howard, Whitehead, and Hochard (2021) review the existing literature using stated preference surveys to estimate discount rates and categorize them by model estimation (e.g., conditional logit, probit, mixed logit) and estimation procedure (e.g., ex post vs. endogenous). The endogenous method estimates the parameter(s) of the discounting function in the optimization process of the model (Lew 2018; Vásquez-Lavín et al. 2019; Kovacs and Snell 2021). Conversely, the ex post approach uses the parameters estimated from the choice model to subsequently determine the discount rate (Kim and Haab 2009; Egan, Corrigan, and Dwyer 2015). Howard, Whitehead, and Hochard (2021) evaluate whether methodological differences are the reason for the significant variation in the discount rates in the stated preference literature and find that the estimated discount rates are not heavily influenced by the estimation procedure or the model. However, Vásquez-Lavín et al. (2021) argue that the ex post approach can misrepresent the underlying discount rate. The differences in the observed discount rates may be due to natural preference heterogeneity in the population.

The use of flexible taste distributions through a logit-mixed logit (LML) model that includes discounting (D-LML) is a recent innovation in choice modeling with discounting behavior (West et al. 2021). One finding from that study is that quasi-hyperbolic (QH) discounting behavior fits the data best because some individuals can express exponential discounting while others can express hyperbolic discounting. Three modes for the discount rate are present, one between 80% and 100%, another close to 60%, and the third around 30%. However, the rich heterogeneity observed in the discount rates in the D-LML is not distinguishable by the socioeconomic characteristics of the individuals. Without knowing who has a low or high discount rate or WTP, efficient fundraising for public good provision is less effective.

A few studies using stated preference data examine how socioeconomic characteristics affect the discount rate, though not through an LCM (Kovacs and Larson 2008; Bond, Cullen, and Larson 2009; Meyer 2013a; Vásquez-Lavín et al. 2019; Carrasco-Garcés et al. 2021). Although the good being valued varies, individual characteristics, such as education, income, and participation in an environmental organization, tend to increase patience (Bond, Cullen, and Larson 2009; Wang and He 2018; Kovacs and Snell 2021). The D-LCM, on the other hand, does not determine whether a specific socioeconomic characteristic (e.g., income) increases or decreases patience but only indicates the probability of being in a latent class with a particular discount rate based on the socioeconomic characteristic. The D-LCM indicates how preferences for the attributes of a public good bundle with the preference for patience in a way explicable through socioeconomic characteristics. The D-LCM is a way to sort out the effect of numerous socioeconomic characteristics to identify a group with similar preferences. Policy makers can use information about the groups to tailor strategies to raise funds for public goods. Howard, Whitehead, and Hochard (2021) advocate continued research using innovative models to estimate implicit discount rates through models with stated preference data, and our article falls within that vein.

Investigating heterogeneity in one or more of the latent classes is not in this study. In a particular latent class, there may be further differences in the preferences for groundwater attributes or for discounting that can be explained through socioeconomic characteristics. We felt that an exploration of heterogeneity in a latent class could potentially muddle the insights of this initial contribution. There is a comparison of the D-LCM model to the D-LML and the discounted mixed logit (D-MXL) models. The D-LML and D-MXL allow for a greater expression of individual heterogeneity in the sample. The D-LCM allows the flexibility to consider heterogeneity across WTP values and discount rates in the valuation model through the observable characteristics in a class membership function.

It is difficult for policy makers to increase the welfare of the population at the lowest cost if group preferences are unknown. Suppose a policy maker observes that group A has higher income and lower education but cannot observe that it has a high discount rate and low WTP for a nonmarket good. Conversely, the policy maker observes that group B has lower income and higher education but does not know it has a low discount rate and high WTP for a nonmarket good. Group B should theoretically pay more for the nonmarket good than group A, but a policy maker who only has data about socioeconomic characteristics would request each group pay an equal amount for the nonmarket good. The reason socioeconomic characteristics would lead the policy maker to request an equal payment is that income and education, according to available information, would lower the discount rate and increase WTP, and both groups have a balance of lower income and higher education or a balance of higher income and lower education.

2. Survey Design and Data

Our application is to the protection of an aquifer, the Mississippi River valley alluvial aquifer (MRVA), underneath agricultural cropland in eastern Arkansas. The MRVA supports substantial irrigated agriculture, including rice, and Arkansas is the leading producer of rice in the nation (USDA-NASS 2014; ANRC 2017). Depletion of the aquifer continues and, in some years, accelerates under the current farming practices (Konikow 2015). The survey begins with questions for respondents about their perceptions of the environment and issues related to the MRVA. Regarding the risk that respondents believe MRVA groundwater decline will have on people and the environment in Arkansas, about 26% see "little to no risk," 39% believe in a "medium risk," and 35% see a high to extreme risk. We asked how people think groundwater resources should be managed in the MRVA. The study describes what aquifers are, shows a map of the depth to MRVA groundwater levels, and provides details about groundwater availability and current conservation policies. Respondents then received instructions for the CE and answered several "warm-up" choice questions.

Three alternatives for MRVA management are available: surface water infrastructure (SWI), cap and trade (C/T), and a status quo involving no change to current management. Five groundwater services, or attributes, that contribute to the value of the MRVA were presented: water quality for irrigated agriculture, provision of jobs in the agricultural economy, provision of wildlife for local tourism, avoidance of subsidence and infrastructure costs, and the certainty of an adequate supply of water in case of drought. We supposed that for the attribute about the provision of jobs, respondents have an altruistic concern for employment in agriculture. Although Arkansas is among the states with the highest share of employment in agriculture, the percentage is still only 3.5% of all employment in the state (BEA 2024), and we therefore assumed that few (if any) of the respondents directly received income from the agricultural sector.

Appendix Figure B1 is a sample choice set. Levels for the attributes are for year 2050 and appear in terms of a percentage of current levels, such that 100% is no change from current levels. The numerical values for the levels come from the experimental design approach described later. There are five attribute levels, with the status quo in italics, for water quality, wildlife, and infrastructure (*75%*, 80%, 85%, 90%), certainty of groundwater supply (*25%*, 40%, 55%, 70%), and jobs (*80%*, 90%, 100%, 110%). A reminder above each choice set indicates that the social and environmental attributes decline steadily to 2050 and remain constant thereafter. A cognitive burden on the respondents to imagine a steady decline in attributes to 2050 is a concern, but reasonable estimates for the marginal WTP of the attributes in West et al. (2021) offer assurance that the burden was manageable.

The payment attribute is an increase in state income taxes either only once (*$0*, $30, $90, $150, $210, $270) or permanently (*$0*, $12, $24, $36, $48, $60). The levels for the payment attribute allow for the estimation of a wide range of values for the time parameters (e.g., an implicit discount rate from the exponential discounting between −123% and 310%). Four payment schedules exist: a lump sum paid either this year or next year and a perpetual payment that goes on indefinitely (to infinity) that begins either this year or next year. The delay by a year at the start of a payment schedule is to estimate both time parameters in the QH discounting model described in the next section. The variation in the payment schedules to estimate the time parameters is between respondents rather than each individual responding to different payment schedules.

The experimental design uses a sequential Bayesian approach with the software Ngene to achieve attribute balance, and the selected design had 30 choice sets that were organized into six blocks with five choice sets in each block (Bliemer, Rose, and Hess 2008; Scarpa and Rose 2008). We used recommended best practices to reduce hypothetical bias through a "cheap talk" script (Cummings and Taylor 1999) and reduced low perceived consequentiality through text on the importance of respondent feedback for policy outcomes to encourage more effort on truthful responses (Zawojska et al. 2015; Vossler, Doyon, and Rondeau 2012). The scripts for cheap talk and consequentiality are found in Appendix A. The assignment of choice question blocks and the order in which the choice sets appear in a block are randomized.

The survey occurred in fall 2018 using an online panel made available by Qualtrics, and our design for the survey was compatible with traditional and mobile Internet platforms. The screen for the panel is voting-aged Arkansan residents, and it imposed a quota on respondents' gender of 50/50 male-female. The gender quota was later relaxed to increase the responses to allow more females. The sample size is 777 respondents (or 3,885 choices because each person completes five choice sets). Appendix Table B1 compares the descriptive statistics of the sample with the corresponding statistics of the Arkansas population (U.S. Census Bureau 2022). A *t*-test for the null hypothesis of equality of means cannot be rejected at the 5% level for nearly all demographics, except for the percentage female and the percentage with a bachelor's degree. The characteristics related to the MRVA suggest that respondents were largely unaware of MRVA groundwater decline pressures and had no strong feelings about the risk that aquifer decline poses to people or the environment. Details on the treatment-specific (i.e., payment schedule) demographics of the sample and tests for balance across the treatments are shown in Appendix Table B2.

Appendix Table B3 indicates a summary of CE responses. The data mostly conform to the law of demand; the only exception is at the highest cost to the household. For the lump sum (with and without the delay) and the perpetual treatments (with and without the delay) as the cost of the policy alternative to the household increases, the proportion of the status quo responses increases. A shift toward smaller payments in the payment schedules might have revealed more about preferences because at the smallest lump-sum payment of $30, only 44% of the sample chose one of the policy alternatives; at the smallest perpetual payment of $12, only 42% of sample chose an alternative. The percentage of votes that favor the SWI policy is consistently higher than the percentage of votes in favor of the cap-and-trade policy.

3. Methods

The D-LCM assumes as a starting point that there is exponential discounting, but we also consider hyperbolic discounting. We suppose there is additive separability of time periods. Variation in the time frame over which the households make payments for a policy is how we estimate the discount rate.

Discounting Behavior

The exponential discounting model, with one discount rate parameter, is the standard for the modeling of intertemporal utility (Frederick, Loewenstein, and O'Donoghue 2002). The form of the exponential discounting function in equation [1] is

$$U\left(c_0,\ c_1,\ \ldots,c_T\right) = \sum\nolimits_{t=0}^{T} \psi_t u(c_t), \qquad [1]$$

where the discount factor is $\psi_t = \left[1/(1+\rho)\right]^t$ for year t and the discount rate is ρ.

A discounting behavior where discount rates decline over time is commonly called hyperbolic discounting (Cairns and van der Pol 2000). The general form of hyperbolic discounting in equation [2] is

$$\psi_t = (1+\alpha t)^{-\beta/\alpha}, \text{ where } \alpha,\ \beta > 0 \qquad [2]$$

(Loewenstein and Prelec 1992). Constraining α to equal one (Harvey 1986), only a single parameter is necessary for estimation, and this hyperbolic form in equation [3] is

$$\psi_t^{Harvey} = (1+t)^{-\mu}. \qquad [3]$$

The Harvey discounting form approximates the exponential form as μ approaches infinity. By constraining the term β/α to equal to one, the Hernstein (1981) and Mazur (1987) (HM) hyperbolic form in equation [4] is

$$\psi_t^{HM} = (1+\omega t)^{-1}. \qquad [4]$$

The QH model (Laibson 1997) is like the exponential model except that all future time periods are multiplied by an additional β time parameter between zero and one. Equation [5] has the functional form for QH discounting:

$$\psi_t = \left\{ \begin{array}{c} 1 \text{ if } t=0 \text{ and} \\ \beta\left[\dfrac{1}{1+\rho}\right]^t \text{ if } t>0 \end{array} \right\},$$

$$\text{where } 0 \le \beta \le 1, \text{ and } \left[\frac{1}{1+\rho}\right]^t < 1. \qquad [5]$$

From the present to the first period, individuals with QH discounting behavior exhibit great impatience, but there is a constant level of patience for all periods afterward.

Latent classes for discount rates allow for the expression of heterogeneity in discounting tastes in the population through distinct groups. Each type of discounting behavior is considered separately in the D-LCM. Every latent class in a particular D-LCM has the same discounting behavior. We compare the Bayesian information criterion (BIC) of the D-LCM with one type of discounting to the BIC of the D-LCM with a different type of discounting to decide which discounting behavior best explains the data.

4. Empirical Models

Through endogenous discount rates, the model provides estimates for the marginal WTP for five different groundwater services and two groundwater policy alternatives. Through a WTP-space specification (Train and Weeks 2005), D-LCM allows for latent classes of WTP for groundwater services and policy alternatives.

D-LCM

For the analysis of the data from a CE about a good providing intertemporal services, suppose that utility is additively separable over the periods from the present to period T for an individual i in latent class m for alternative j in choice situation k be given by equation [6]:

$$U_{(i|m)jk} = \sum\nolimits_{t=0}^{T} \psi_{mt}\left((\lambda_m \omega_m)' x_{ijkt} - \lambda_m Cost_{ijkt}\right) + \varepsilon_{ijk}, \qquad [6]$$

where the discount factor of an individual in latent class m for year t is ψ_{mt}; the weighted sum for all instantaneous error draws is $\varepsilon_{ijk} = \sum\nolimits_{t=0}^{T} \psi_t \xi_{ijkt}$ with an iid extreme value distribution; x_{ijkt} is a vector of service attributes from groundwater in year t for the alternative j; ω_m is a vector of estimated marginal WTPs for an individual in latent class m;

$Cost_{ijkt}$ denotes the cost of the policy alternative to the individual in year t; and λ_m is a scalar representing the cost/scale parameter. Consistent decision-making requires the application of the same discount factor to costs and benefits that occur in the same year (Arrow et al. 2013). The period T is 65 years, chosen for the empirical analysis to be an adequate time frame for the representation of future-minded respondents. Beyond 65 years, the present value of a benefit or cost is assumed negligible, even at a low discount rate.

To calculate the choice probability for a given choice occasion k, we use the D-LCM and assume that individuals are utility maximizers. Conditional on the vector $< \lambda_m, \omega_m >$, and ψ_m , the probability that an individual in latent class m makes a sequence of choices over K choice situations is the logit formula in equation [7]:

$$P_m\left(\langle\lambda_m,\omega_m\rangle,\psi_m\right)= \prod_{k=1}^{K}\frac{e^{U_{(i|m)jk}}}{\sum_{j=1}^{J}e^{U_{(i|m)jk}}}. \quad [7]$$

By summing over the discrete mixing distribution for ω_m of latent classes m = 1,…, M (see Train 2009), the unconditional choice probability of the sequence of choices of individual i in equation [8] is then

$$P(\mathrm{ijk})=\sum_{m=1}^{M}s_m\cdot\left(\prod_{k=1}^{K}\frac{e^{U_{(i|m)jk}}}{\sum_{j=1}^{J}e^{U_{(i|m)jk}}}\right), \quad [8]$$

where s_m is thus the probability of membership in segment m and may be written in equation [9] as

$$s_m=\frac{e^{\theta_m Z_i}}{\sum_{S=1}^{S}e^{\theta_m Z_i}}, \quad [9]$$

where Z_i is a vector of socioeconomic characteristics, and θ_m is a vector of parameters (Boxall and Adamowicz 2002). LCMs are a mixture of the segmentation choice based on the socioeconomic characteristics of the individual and the behavior observed from the choice sets. The model is not sensitive to the assumption of the independence of irrelevant alternatives [IIA]) because the choice probability depends on the utility of other alternatives through the probabilistic membership of s_m. By placing structure on intertemporal utility through the formulas described in the section on discounting behavior, the estimation of D-LCM models can consider four discounting forms.

Comparison of the D-LCM with Other Discounted Random Utility Models

We can compare the D-LCM to conditional logit, mixed logit, and LML models that incorporate discounting behavior. The random utility models vary in their level of sophistication for explaining preference heterogeneity. The discounted conditional logit (D-CL) supposes that the utility that individual i receives from alternative j in choice situation k in equation [10] is

$$U_{ijk}^{CL}=\sum_{t=0}^{T}\psi_{it}\left((\lambda\omega)'x_{ijkt}-\lambda Cost_{ijkt}\right)+\varepsilon_{ijk}, \quad [10]$$

where the definition of the terms is the same as in equation [6], except that λ and ω no longer have subscripts for each latent class m. The D-LCM with one latent class is equivalent to D-CL. A limitation of the conditional logit is the assumption of IIA. A model wherein the parameters associated with observed variables are allowed to vary randomly across individuals is known as mixed logit (also referred to as random parameters logit). In this case, the utility that a person i obtains from alternative j in choice situation k in equation [11] is

$$U_{ijk}^{MXL}=\sum_{t=0}^{T}\psi_{it}\left((\lambda_i\omega_i)'x_{ijkt}-\lambda_i Cost_{ijkt}\right)+\varepsilon_{ijk}, \quad [11]$$

where the coefficient vector $\mu_i = < \lambda_i,\ \omega_i,\ \psi_i >$ is not observed for each i and varies in the population with density $f\ (\mu_i|\ \theta^*)$ where θ^* are the true parameters of the distribution. The unconditional probability is the integral over the possible values of μ_i in equation [12], which depends on

$$P^{MXL}(\text{ijk}) = \int f(\mu_i|\theta^*)\left(\prod_{k=1}^{K}\frac{e^{U_{ijk}^{MXL}}}{\sum_{j=1}^{J}e^{U_{ijk}^{MXL}}}\right)d\mu_i. \quad [12]$$

The D-MXL was first estimated with discounting functions other than exponential in Meyer (2013b). West et al. (2021) estimated the D-MXL with normally distributed random parameters using our application of groundwater in the MRVA. Added flexibility in the distribution of the random parameters is possible with the LML model. A researcher describes the shape of the distribution of a random parameter by defining the terms for the probability of each parameter value in finite parameter space from a logit function. In LML, the person can choose a spline, polynomial, or other step function to direct the search for the shape of the parameter's distribution in estimation (Caputo et al. 2018).

The D-LML model supposes that the cumulative distribution function F ($<\lambda_i,\ \omega_i,\ \psi_i>$), known as the mixing distribution, is discrete and has a finite support set S (Train 2016). Defining a probability mass for $\mu_r \in S$ through an additional logit term in equation [13] gives us

$$P(\theta_r) = \frac{e^{\alpha'\text{z}(\mu_r)}}{\sum_{s\in S}e^{\alpha'\text{z}(\mu_r)}}, \quad [13]$$

with the $z(\mu_r)$ defining the shape of F and the corresponding probability mass coefficients vector is α, and the denominator summation of [13] ensures the probabilities sum to one (Train 2016). The utility of the D-LML, U_{ijk}^{LML}, is the same as the utility of the D-MXL (i.e., U_{ijk}^{MXL}). Equation [14] shows the unconditional probability that individual i makes the observed sequence of choices:

$$P^{LML}(\alpha) = \sum_{r\in S}\left(\frac{e^{\alpha'\text{z}(\mu_r)}}{\sum_{s\in S}e^{\alpha'\text{z}(\mu_r)}}\right)\left(\prod_{k=1}^{K}\frac{e^{U_{ijk}^{LML}}}{\sum_{j=1}^{J}e^{U_{ijk}^{LML}}}\right), \quad [14]$$

where there is a logit term for the probability of a sequence of choices and another logit term for the probability that the individual has coefficients $\mu_r = <\lambda_r,\ \omega_r,\ \psi_r>$. West et al. (2021) developed the D-LML, and they flexibly mix parameter distributions with splines through visual inspection using the application of groundwater in the MRVA. All model estimates come from MATLAB (version 2019a), and the D-MXL and D-LML use 1,000 Halton draws.

The D-LCM falls in the spectrum of approaches to address preference heterogeneity in random utility models. One end of the range is the D-CL that supposes preferences are homogeneous (i.e., a single segment or class), and the other end is the D-MXL and D-LML that allows everyone to be their own segment. The D-LCM has the advantage that socioeconomic characteristics can explain heterogeneity that is present in a lumpy form. The D-LCM is not able to determine how socioeconomic characteristics directly influence a single preference parameter or time parameter. Instead, the D-LCM considers all the preference and time parameters together as a bundle in the process of using socioeconomic characteristics to assign a latent class. There may be heterogeneity in the time parameter in each class that can be explained with the same or a different set of socioeconomic characteristics than those that distinguish the latent classes.

5. Results

The optimal number of classes for each discounting behavior is determined through the BIC, Akaike information criterion (AIC), and log-likelihood statistics of models with one to five classes (Table 1). The log-likelihood statistic for the exponential and QH forms shows improvement in model fit until the fourth class and then a poorer model fit for the fifth class. The AIC and BIC statistics for the exponential form indicate a bumpy trend that shows improvement until the second class, a worsening in the third class, an improvement in the fourth class, and a dramatic worsening in the fifth class. For the QH form, the AIC and BIC statistics show a steady improvement until

Table 1
Criteria for Selecting the Optimal Number of Classes by Discounting Model

Discounting Model	No. of Classes	Log-Likelihood	AIC	BIC	Parameter
Exponential	1	–4,185.30	8,388.61	8,445.00	9
	2	–3,571.86	7,195.73	7,358.61	18
	3	–3,557.42	7,200.84	7,470.23	27
	4	–3,482.19	7,084.39	7,460.29	36
	5	–3,654.94	7,463.88	7,946.28	45
Hyperbolic (HM)					
	1	–4,199.30	8,416.61	8,472.99	9
	2	–3,579.80	7,211.60	7,374.48	18
	3	–3,939.42	7,964.85	8,234.24	27
	4	–4,011.48	8,142.96	8,518.86	36
	5	–4,022.11	8,198.23	8,680.63	45
Hyperbolic (Harvey)					
	1	–4,197.39	8,412.78	8,469.17	9
	2	–3,623.60	7,299.21	7,462.09	18
	3	–4,115.93	8,317.87	8,587.26	27
	4	–4,038.28	8,196.57	8,572.46	36
	5	–3,639.52	7,433.04	7,915.44	45
Quasi-hyperbolic					
	1	–4,185.31	8,390.62	8,453.27	10
	2	–3,571.87	7,199.73	7,375.15	20
	3	–3,489.97	7,071.94	7,360.12	30
	4	–3,479.66	7,087.33	7,488.28	40
	5	–3,762.20	7,688.41	8,202.13	50

Note: N = 777 in total (3 alternatives per question) × (5 questions per person) = 11,655 observations. Bootstrap standard errors using 250 bootstrap samples for the exponential form: l (log-likelihoods are 10.31 for one class and 9.22 for two classes); Akaike information criteria (AIC) are 21.35 for one class and 19.45 for two classes; Bayesian information criteria (BIC) are 20.87 for one class and 19.70 for two classes.

the third class and a worsening thereafter. All the goodness-of-fit statistics for the HM and Harvey hyperbolic forms improve until the second class and worsen thereafter. The minimum value of the BIC statistic for the exponential and QH forms are the second and third classes, respectively. Two latent classes provide a significant improvement in all statistics over one latent class (i.e., the D-CL). Formal testing through bootstrapped standard errors confirms the superiority of the two-class choice model over the one-class model for the exponential form (see the note below Table 1 for the standard errors).

We follow the BIC statistics to select the best model for each discounting form (Chakrabarti and Ghosh 2011). The optimal number of classes for the exponential, HM, and Harvey discounting forms is two, and the optimal number of classes for the QH form is three (Table 2). The exponential provides the best fit according to the BIC criterion, while the QH provides the best fit by the log-likelihood and AIC statistics. There is no statistical difference in the goodness of fit, according to the BIC criterion, between the exponential and QH forms. The estimate for the additional β time parameter in the QH is close to one for all latent classes, further indicating the similarity in fit between the exponential and QH forms. The HM hyperbolic form has a better fit than the Harvey hyperbolic form. The overlap of the confidence intervals using the bootstrap standard errors of the BIC for the exponential, HM hyperbolic, and the QH forms in the note below Table 2 shows that those discounting approaches are not statistically different.

The D-LCM model with two classes for the exponential form indicates preference heterogeneity surrounding the implementation of a groundwater conservation policy (Table 3). The positive ASCs in class A indicate a desire of that group to choose a policy, with a slight preference for the SWI option. However, we fail to reject the null hypothesis that

Table 2
Time Parameter Results by Discounting Model for the Optimal Number of Latent Classes

	Exponential	Hyperbolic (HM)	Hyperbolic (Harvey)	Quasi-hyperbolic (QH)
No. of classes	2	2	2	3
Log-likelihood	–3,571.86	–3,579.80	–3,623.60	–3,489.97
AIC	7,195.73	7,211.60	7,299.21	7071.94
BIC	7,358.61	7,374.48	7,462.09	7360.12
Time parameter				
r	0.430*** (0.095)			0.159 (0.158)
	0.188*** (0.044)			0.656*** (0.095)
				0.186*** (0.044)
w		1.4585*** (0.338)		
		0.5364*** (0.174)		
u			2.5978*** (0.2952)	
			0.0989 (0.0725)	
β				0.97 (0.961)
				0.96*** (0.194)
				0.98*** (0.168)

Note: Standard errors are in parentheses. Bootstrap standard errors of the BIC using 250 bootstrap samples are 19.70 for the exponential form, 22.45 for the HM form, and 19.85 for the QH form. AIC = Akaike information criterion; BIC = Bayesian information criterion.
*, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

the ASC1 and ASC2 estimates are the same ($p > 0.1$) through the *t*-test. In contrast, class B prefers continuing with business as usual, seen through a dislike of both policies but a greater dislike of the cap-and-trade option. Those who prefer a policy, namely class A, have significant attributes for buffer, water quality, and jobs in agriculture. The MWTP for water quality is the highest, followed by buffer and then jobs. The participants in class B, who care for business as usual, have significant attributes for water quality and infrastructure, and the MWTP for water quality is again the largest. Both classes A and B believe groundwater has value, though for somewhat different reasons, and the difference between the classes is due to conflicting beliefs about whether a policy is worthwhile or effective in preserving groundwater value. For class A, the discount rate is higher, 0.430, for those who want a policy. The discount rate for class B, who prefer business as usual, is 0.188.

The class membership model (the lower part of Table 3) uses socioeconomic variables to explain class assignment to the business-as-usual class B, and class A is the reference. There is a 71% probability of belonging to class A and a 29% probability of belonging to class B. More education and more conservative ideology increase the probability of assignment to class B, and because there are only two classes, this decreases the probability of belonging to class A. Conversely, awareness of pressure on the MRVA and concern for the risk of aquifer decline to people and environment decreases the probability of belonging to class B, but this increases the probability of membership to class A.

Another perspective on preference segmentation comes from the D-LCM model with three classes and the QH form. The new class, the one not seen in Table 3, is called "No preferences" because no MWTP or time parameter estimate is significant. The policy-motivated latent class now has larger MWTP estimates for both policies and for the significant groundwater services. The magnitude of MWTPs for the groundwater services has the same order in the "policy-motivated" group, but one difference is the lack of significance in the MWTP for water quality. The discount rate in the group that wants a policy is higher at 0.656 rather than 0.430. As in Table 3, the business-as-usual group in Table 4 has significant MWTPs for water quality and infrastructure groundwater services, and the discount

Table 3
Results for Exponential Discounting Latent Class Model in Willingness-to-Pay Space

	A (Reference)	B
Variable/Class	Policy Motivated	Business as Usual
Utility function		
ASC1 (C/T)	8.490*** (2.2717)	–6.811*** (1.8702)
ASC2 (SWI)	10.461*** (2.4728)	–6.423*** (1.8339)
Buffer	9.926*** (3.8444)	0.622 (0.9661)
Quality	13.103*** (7.6828)	9.094** (4.1318)
Jobs	8.770*** (5.0589)	2.441 (1.6997)
Infrastructure	1.735 (5.8754)	6.561*** (3.4596)
Wildlife	4.769 (5.9324)	1.959 (2.8899)
Scale (λ)	0.358*** (0.044)	0.774*** (0.18)
r	0.430*** (0.0952)	0.188*** (0.044)
Class membership function		
Constant	—	–0.525 (0.518)
INC	—	–0.004 (0.029)
EDU	—	0.158*** (0.059)
AQU	—	–0.104 (0.121)
PRESS	—	–0.591** (0.263)
EMP	—	–0.281 (0.208)
IDEO	—	0.200*** (0.064)
GRISK	—	–0.222*** (0.045)
Latent class probability	0.71	0.29
Log-likelihood	–3,571.8	
AIC	7,195.7	
BIC	7,358.6	
Observations	11,655	

Note: Standard errors are in parentheses. An average respondent has a yearly income of $49,991, a vocational/technical degree, knew what an aquifer was but did not know about the MRVA and its uses, and are mostly unaware of the pressure on the MRVA. Half are employed full- or part-time, have a middle-of-the-road ideology, and believe that the decline of the MRVA holds a medium risk to people. AIC = Akaike information criterion; BIC = Bayesian information criterion; C/T = cap and trade; SWI = surface water infrastructure.
*, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

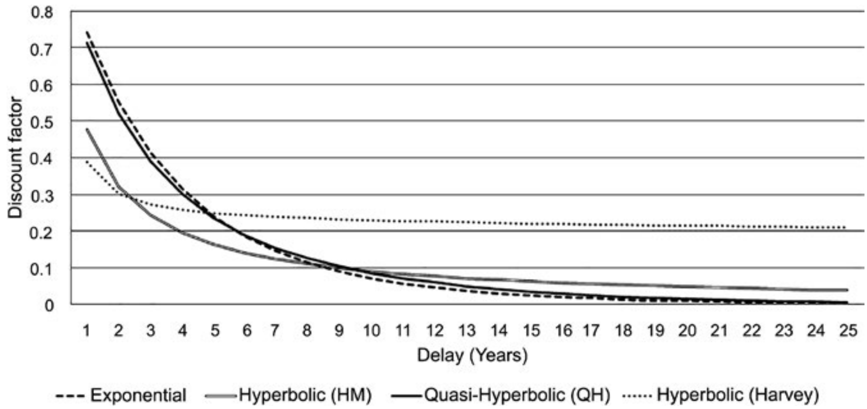
rate is nearly the same at 0.185. Figure 1 plots the best-fitting estimates of the exponential and hyperbolic discounting behavior.

The coefficient estimates on the socioeconomic variables in the class membership model in the lower part of Table 4 provide insight into the new reference class “No preferences.” The policy and business-as-usual groups have positive and significant coefficients for education, and there are negative and significant coefficients on the variables for the awareness of pressure on the MRVA and for employment full-/part-time. The “No preferences” group appears to have less education, claims awareness of pressure on the aquifer, and is full-/part-time employed. This group may represent a subset of the Qualtrics panel who respond randomly to survey questions to receive the monetary incentive, and this is why none of the MWTP or time parameter estimates are significant. The distinguishing characteristics of the policy group are higher income, familiarity with an aquifer, and greater concern for the risks that aquifer overdraft poses to people and the environment. The distinctive feature of the business-as-usual group is a conservative ideology. The probability of belonging to the “No preferences” group is 22%, the probability of belonging to the policy group is 44%, and the probability of belonging to the business-as-usual group is 34%. The D-LCM results for the best-fitting HM and Harvey discounting forms are in Appendix Tables C1 and C2.

Comparing the MWTP of the attributes and time parameter in the D-LCM to the discounted CL, MXL, and LML models (Table 5) further illustrates the usefulness of latent class modeling. The exponential form has the best fit for the D-CL and the D-MXL, and the QH form has the best fit for the D-LML. The D-CL, D-MXL, and D-LML in the WTP space for the other discounting forms are shown in Appendix Tables D1–D3, respectively. The D-CL and D-MXL estimates for the ASC1 (C/T) parameter are negative and significant, but the D-LML estimate for the ASC1 parameter is positive and significant. The D-CL estimate for ASC2 (SWI) is negative and not significant, whereas the D-MXL and D-LML estimates for the ASC2 parameter are positive and significant. The standard deviations for the ASC1 and ASC2 are large and significant. This leaves an analyst wondering whether the ASC1 and ASC2 parameters are positive or negative. The D-LCM model shows that the ASC1 and ASC2 estimates are positive and significant for class A but negative and significant for class B. The histograms from West et al. (2021) for the D-LML in Appendix Figure E1 show probability masses for the ASC1 and ASC2 estimates in both negative and positive ranges, but the reason for those separate probability masses is unknown without a model like the D-LCM.

The MWTP for the buffer and jobs attribute is positive and significant in the D-CL,

Figure 1
Discount Factors for Best-Fitting Estimates of Class Membership Weighted Exponential and Hyperbolic Discounting Behaviors



Note: The exponential, HM, Harvey discounting forms have two classes, and the QH discounting form has three classes.

Table 4
Results for Quasi-hyperbolic Discounted Latent Class Model in Willingness-to-Pay Space

	A (Reference)	B	C
Variable/Class	No Preferences	Policy Motivated	Business as Usual
Utility function			
ASC1 (C/T)	3.20 (4.51)	19.21*** (5.84)	–4.49*** (1.68)
ASC2 (SWI)	5.16 (4.77)	21.02*** (5.82)	–4.11*** (1.61)
Buffer	1.46 (2.74)	18.89*** (7.66)	0.547 (0.879)
Quality	7.62 (10.11)	18.96 (12.74)	5.83* (3.39)
Jobs	2.62 (4.39)	15.26* (8.09)	1.68 (1.58)
Infrastructure	–3.53 (6.64)	13.50 (12.13)	6.80* (3.51)
Wildlife	0.033 (5.15)	14.14 (11.66)	–1.15 (2.36)
Scale (λ)	0.111 (0.077)	0.659 (0.093)	1.25 (0.27)
r	0.159 (0.157)	0.656*** (0.195)	0.185*** (0.05)
β	0.97 (0.961)	0.96*** (0.194)	0.98*** (0.168)
Class membership function			
Constant	—	–4.96*** (1.04)	–2.49*** (0.683)
INC	—	0.114*** (0.044)	0.049 (0.041)
EDU	—	0.243*** (0.089)	0.329*** (0.081)
AQU	—	0.316* (0.161)	–0.030 (0.160)
PRESS	—	–0.663* (0.368)	–0.828** (0.349)
EMP	—	–0.656** (0.265)	–0.543** (0.262)
IDEO	—	0.014 (0.087)	0.248*** (0.088)
GRISK	—	0.442*** (0.086)	–0.029 (0.062)
Latent class probability	0.22	0.44	0.34
Log-likelihood	–3,489.96		
AIC	7,071.93		
BIC	7,360.12		
Observations	11,655		

Note: Standard errors are in parentheses. An average respondent has a yearly income of $49,991, a vocational/technical degree, knew what an aquifer was but did not know about the MRVA and its uses, and are mostly unaware of the pressure on the MRVA. Half are employed full- or part-time, have a middle-of-the-road ideology, and believe that the decline of the MRVA holds a medium risk to people. AIC = Akaike information criterion; BIC = Bayesian information criterion; C/T = cap and trade; SWI = surface water infrastructure.

*, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

Table 5
Results of Discounted Conditional Logit (D-CL), Discounted Mixed Logit (D-MXL), and Discounted Logit-Mixed Logit (D-LML) Models in a Willingness-to-Pay Space

Parameter	D-CL (Exponential)	D-MXL (Exponential)	D-LML (Quasi-hyperbolic)
ASC1 (C/T)	–2.44** (1.16)	–0.451*** (0.737)	13.12* (8.51)
ASC2 (SWI)	–0.789 (1.16)	16.471*** (0.801)	29.56*** (7.43)
Buffer	7.05*** (2.05)	6.327*** (0.192)	5.22* (3.85)
Quality	12.58** (4.91)	9.968*** (0.383)	9.32* (6.59)
Jobs	7.63*** (2.87)	4.315*** (0.220)	6.64*** (0.07)
Infrastructure	4.133 (3.99)	–8.254*** (0.187)	6.05 (11.19)
Wildlife	3.661 (3.95)	–1.556*** (0.198)	8.92* (4.20)
Scale (λ)	0.371*** (0.04)	1.639*** (0.241)	0.700* (0.124)
R	0.362*** (0.05)	0.491*** (0.0054)	0.626*** (0.047)
B			0.613* (0.42)
SD (ASC1, C/T)		51.952*** (0.186)	74.40*** (4.88)
SD (ASC2, SWI)	—	44.645*** (0.151)	88.64*** (6.68)
SD (buffer)	—	16.237*** (0.180)	23.96*** (2.65)
SD (quality)	—	64.774*** (0.726)	34.83*** (3.72)
SD (jobs)	—	0.073 (0.058)	0.36*** (0.03)
SD (infrastructure)	—	53.070*** (0.706)	44.44*** (6.16)
SD (wildlife)	—	83.207*** (1.005)	22.06*** (2.04)
SD (scale (λ))	—	4.882*** (0.850)	0.458* (0.08)
SD (*r*)	—	0.005 (0.014)	2.65*** (0.24)
SD (β)	—		1.76*** (0.22)
Log-likelihood	–4,185.3	–3,531.7	–3,377.9
AIC			
B	8,388.6	7,099.4	7,005.9
BIC			
BIC	8,445.0	7,212.2	7,789.0
Obs	11,655	11,655	11,655

Note: D-MIXL and D-LML have bootstrap standard errors given in parentheses obtained using 250 bootstrap samples. Results for all the discounting models for each estimation method are in Appendix Tables A1 and A2 (tests for β are against 1; all others are against 0). AIC = Akaike information criterion; BIC = Bayesian information criterion; C/T = cap and trade; SD = standard deviation; SWI = surface water infrastructure.
*, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

D-MXL, and the D-LML models but only significant and positive in the policy-motivated class of the D-LCM. Only individuals who want to have a policy have significant and positive MWTP for the buffer value of groundwater and the jobs from agriculture. The MWTP for infrastructure is positive and significant for class B in the D-LCM but not positive and significant in the D-CL, D-MXL, or D-LML models. The MWTP for wildlife is negative and significant in the D-MXL, positive and significant in the D-LML, and positive and insignificant in both classes of the D-LCM. There are large and significant standard deviations for the MWTPs for buffer, infrastructure, and wildlife. Evidence of the wide variation in the MWTP for the attributes is in the histograms for the D-LML in WTP space from Appendix Figure E1 depicting the probability mass distributions. The D-LCM sheds light on why there are large and significant standard deviations and sometimes contradictory signs and significance for MWTP across the other models.

The discount rate for the D-CL of 0.362 is very close to the weighted average of the discount rates for the classes in the D-LCM in Table 3, where the weights are the latent class probabilities. The discount rate for the D-MXL is 0.491, and the D-LML discount rate is larger still at 0.626, with a significant standard deviation of 2.65. The discount rate for the policy group in Table 4 is 0.656. The average discount rates for the D-MXL and D-LML may be larger because each person is their own segment (or class), rather than being lumped together in the D-LCM, and those with very high discount rates pull up the average. The histogram for the discount rate in Appendix Figure E1 shows a sizable probability mass for discount rates in the range of 0.8

to 1. Howard, Whitehead, and Hochard (2021) find that the endogenous D-CL (i.e., the D-CL in this study) and ex post D-MXL with a fixed price (which differs from the endogenous D-MXL in this study) have similar discount rates. A high outlier discount rate from the ex post D-MXL with log-normal price leads Howard, Whitehead, and Hochard (2021) to conclude that the use of a random parameter model improves model fit but lowers predictive accuracy due to model misspecification.

WTP by Estimation Method and Discount Rate

Parameter estimates from the discounted random utility models can generate WTPs for groundwater conservation scenarios. Appendix F has a short derivation of the formula to calculate the WTP. Equation [15] indicates the WTP for a groundwater conservation scenario:

$$\mathrm{WTP} = CV = \sum_{t=0}^{T} \psi_t CV_t = \sum_{t=0}^{T} \psi_t \left(\omega' \Delta x_t\right), \qquad [15]$$

where CV is the present value of the Hicksian compensating variations over all periods t, CV_t represents the compensating variation in period t, and Δx_t is the change in the attributes for period t of the scenario.

We consider the WTP for three scenarios of groundwater conservation in the MRVA. The first scenario supposes there will be 100% of current levels of groundwater attributes from the present to 2050 and no policy for groundwater conservation. The second and third suppose the implementation of the C/T and the surface water SWI policies, respectively, and 100% of current levels of groundwater attributes from the present to 2050. Survey respondents are told the CE attributes decline steadily to 2050 and remain constant thereafter, and this means each period has a different change in attributes from the present to 2050. There is no change in the attributes for the present period because the present has 100% of current levels. The period just after the present experiences a small change in the attributes from the current levels because the attributes decline steadily to 2050. The largest difference in attributes from the present occurs in 2050 and thereafter. Equation [15] indicates that we calculate the present value of the compensating variations for each period to achieve the WTP, and 65 years is chosen as the time frame for the present value calculation as in the rest of the empirical analysis.

Table 6 shows the WTPs for three potential future conditions of the MRVA from the estimates of the D-MXL, D-LML, and the D-LCM models. It displays the mean, the bottom 33rd percentile (low), and the upper 33rd percentile (high) from 1,000 random draws of WTP from the D-MXL and D-LML. The mean WTP from the D-LCM in Table 3 is shown for the entire sample and for the classes A and B. We use the delta method to calculate the standard errors for the WTP estimates. The WTP changes only slightly from scenario 1 to scenario 2 for the D-MXL and D-LCM approaches because the implementation of a C/T policy on its own does not have much influence on value, although there is a noticeable increase for the D-LML. Scenario 1 to scenario 3 increases the WTP more than from scenario 1 to scenario 2 because the SWI policy is more desirable than the C/T policy.

The low-end WTP from the D-MXL is negative, suggesting that a segment of the population finds groundwater to be undesirable. However, the high-end WTP of the D-MXL indicates that another portion of the population finds groundwater very valuable. The variation in the WTP across low and high WTPs of the D-LML is less extreme, but the low-end WTP from the D-LML is close to zero. The mean WTPs from the D-LML and the D-MXL are somewhat similar, and we fail to reject the hypothesis that they are the same ($p < 0.001$), based on a t-test. The mean WTP from the D-LCM is significantly higher than the mean WTP from the D-LML and D-MXL. Class B has a higher WTP than class A because the discount rate for class B is lower, even though the MWTPs for the groundwater buffer services, water quality, and jobs are all higher in class A. The WTP for class B is more than the high-end WTP for D-MXL, and the class A WTP is greater than the high-end WTP for D-LML. The mean WTP from the D-LML is most preferred because the D-LML methodology captures the full scope of the

Table 6

Heterogeneity in Willingness to Pay (WTP) through Estimation Methods in Discounted Mixed Logit (D-MXL), Discounted Logit-Mixed Logit (D-LML), and Discounted Latent Class (D-LCM) Models in a WTP Space

Estimation Method	Scenario 1 (Status Quo Levels in 2050 and No Policy)	Scenario 2 (Current Levels in 2050 and C/T Policy)	Scenario 3 (Current Levels in 2050 and SWI Policy)
D-MXL ($r = 0.491$)			
Mean	116.4***	115.5***	149.9***
	(1.38)	(1.73)	(1.79)
Low	–233.3***	–210.1***	–186.0***
	(2.72)	(2.82)	(2.83)
High	400.6***	396.0***	392.53 ***
	(4.02)	(4.09)	(4.10)
D-LML ($r = 0.626$; $\beta = 0.613$)			
Mean	133.3***	160.0***	193.5***
	(26.07)	(28.76)	(28.14)
Low	18.58	–3.12	12.37
	(28.21)	(29.86)	(29.73)
High	236.37***	238.89***	286.07***
	(30.08)	(31.63)	(31.64)
D-LCM ($r = 0.430$ [class A]; $r = 0.188$ [class B])			
Mean	426.43***	430.00***	433.8***
	(34.92)	(35.12)	(35.10)
Class A	363.4***	383.16***	387.7***
	(35.32)	(35.48)	(35.50)
Class B	580.7***	544.67***	546.7 ***
	(33.93)	(34.21)	(34.20)

Note: Standard errors are in parentheses. Scenario 1 supposes no change from current levels by 2050 without a policy; scenarios 2 and 3 suppose no change from current levels by 2050 with the cap-and-trade (C/T) policy and surface water infrastructure (SWI) policy, respectively. Low = bottom 33rd percentile of WTP from 1,000 random draws of WTP; high = upper 33rd percentile of WTP from 1,000 random draws of WTP.

*, **, *** Significance at the 10%, 5%, and 1% levels, respectively.

heterogeneity in the sample. However, the D-LCM reveals that surprising differences in WTP across classes, identifiable through socioeconomic characteristics, can occur due to different discount rates.

The findings suggest that a worthwhile strategy to generate public revenue for groundwater conservation through a referendum is to appeal to the business-as-usual group latent class, which has the largest WTP. Appealing to this group means emphasizing the benefits of the better quality of groundwater and the avoidance of subsidence that can damage infrastructure. The policy group has a higher discount rate, and a delay in implementing the extra income tax with a small delay is advisable. The U.S. Office of Management and Budget (OMB) suggests a low-end 3% rate to represent social time preferences and a high-end rate of 7% to represent market time preferences (OMB 2003). The endogenous discount rate from the estimation methods is larger (although not by much for the D-LCM class B) than the high-end rate of 7% from the OMB. If the elicitation of WTP does not use lump-sum payments, overestimation can occur in the present value calculation of the stream of benefits with OMB rates. Where possible, stated preference studies should estimate implicit discount rates and use those in present value calculations for policy discussion.

6. Discussion and Conclusion

Preferences for nonmarket goods and services and the patience for those goods have been shown to depend on the type of good or service and the characteristics of the person (Ubfal 2016; Andreoni et al. 2019; Vásquez-Lavín et al. 2019). There might then be distinct segments in the population, where one group has preferences for specific attributes of a good and a corresponding discount rate, while another group has preferences for different attributes of the good and a different discount rate. By allowing for segmented preferences through a class membership function, valuable details emerge about heterogeneity for policy discussion and decision-making. Our results indicate that the best-fitting D-LCM models are either exponential discounting with two latent classes or QH discounting with three latent classes. One group prefers business as usual, values infrastructure and water quality for crops, and has an implicit discount rate of 19%. The second group wants to see policy implemented for groundwater conservation, values attributes for the buffer against drought and agricultural jobs, and has a higher discount rate of 43%–65%. The group that prefers business as usual has a more conservative outlook, whereas the policy-motivated group has higher income and more concern for the risks of groundwater decline.

The goodness of fit for the exponential and hyperbolic forms in the D-LCM are not statistically different in this study. West et al. (2021) find QH discounting has the best fit in the D-LML. Lew (2018) and Meyer (2013a) find that exponential discounting is the most appropriate given their models and data. Vásquez-Lavín et al. (2019) find exponential discounting is the best fit for some conservation goals, and hyperbolic discounting is the best fit for other conservation goals. Viscusi, Huber, and Bell (2008) find that hyperbolic discounting is the best fit for stated preferences related to water quality improvements. The D-LCM provides insight into the marginal WTPs for groundwater policies and services by comparing the marginal WTP estimates in the D-CL, D-MXL, and D-LML models. For instance, the D-LML has positive and significant signs for ASC1 (C/T) and ASC2 (SWI), while the D-CL has negative signs for ASC1 and ASC2. The D-LCM estimates reveal that this is because there are two groups in the sample: one that does not want any groundwater policy and the other that wants a policy implemented. The D-CL, D-MXL, and D-LML all have positive and significant coefficients for the attributes for buffer and jobs, but the LCM shows that this is due to the value for those attributes from people who want a policy. The marginal WTP for infrastructure is not positive and significant in the D-CL, D-MXL, and D-LML, but the D-LCM shows that the business-as-usual group has a positive and significant WTP for infrastructure.

Our study extends the small literature using stated preference surveys to estimate implicit discount rates. Howard, Whitehead, and Hochard (2021) call for further work that uses additional models, allows discount rates to be random parameters or vary by demographics, and allows for discounting behavior other than exponential. Most of those features are in one or more of the models in this article. Random time parameters can show substantial unobserved heterogeneity, as the standard deviation on the discount rate in the D-LML indicates, but the reason for that heterogeneity remains a mystery without the D-LCM. Both hyperbolic and exponential discounting behaviors appear possible in our data. Among these contributions, the main finding of this study is that time preferences and the preferences for groundwater attributes can be lumpy and connected.

Efficient policy involves tailoring rules or incentives to different segments of the affected population. Uniform payment for a public good often leads to inefficiency—either the payment exceeds marginal benefit or vice versa. The D-LCM can alleviate this problem by identifying different group benefits and associated discount rates. Information on the reasons for different preferences about public goods is useful for designing referenda to fund public goods. Future extensions to the D-LCM could include allowing discounting behavior to differ from one class to another. For instance, one latent class might follow hyperbolic discounting, while another latent class could follow exponential discounting. Second, a random parameters D-LCM could indicate if there are differences in the unobserved heterogeneity (i.e., the standard deviations) of time and attribute preferences across the classes. West et al. (2021) find that QH discounting is preferred in a LML model because this allows for the expression of multiple discounting behaviors. The incorporation of the LML technique into an LCM would also allow that flexibility. Although these models might have a better goodness of fit, the researcher should exercise vigilance so that predictive accuracy is not lost (Klaiber and von Haefen 2019).

Implicit discount rates with D-LCM and the other discounted random utility models are heterogeneous and higher than the OMB rates. Future stated preference studies should then consider estimating a discount rate along with attribute preferences to aid in policy making because the rates appear to vary significantly across groups in the population. Tailored policies can improve efficiency and help generate confidence in the funding of public services, and the class membership function in the D-LCM can suggest how to tailor those funding strategies. The practice of assuming homogeneous WTPs and discount rates has the potential to miss meaningful heterogeneity in a population.

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