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Estimation of the preferences for the intertemporal services from groundwater

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Abstract

We estimate random parameters for time preferences and groundwater service values with flexible taste distributions that allow for multimodal preferences. Our data come from a choice experiment examining public preferences for long-term groundwater management in the Mississippi River Valley Alluvial aquifer. Flexible mixing distributions for time preferences enable hyperbolic and quasi-hyperbolic discounting models to represent heterogeneity in the time parameter such that some individuals can take on values that approximate exponential discounting. Discounting most closely exhibits a quasi-hyperbolic form. Both time preferences and groundwater service values are not normally distributed, but instead multimodal. One group of individuals takes on discount rates that approach zero, a second group takes on rates around 40%, and a third group has discount rates larger than 80%.

Introduction

The objective of this paper is to evaluate complex heterogeneity in the way that people value and discount groundwater services using data from a CE survey about the protection of groundwater in the Mississippi River Valley Alluvial Aquifer (MRVA). The MRVA is the third most used aquifer in the United States (US) and supports extensive irrigated agriculture, especially water-intensive rice production (USDA-NASS, 2014). We conduct our CE in the state of Arkansas, which is the largest consumer of water from the MRVA and produces half of all rice grown in the US (USDA-ERS, 2018). Policy makers would benefit from greater knowledge about the value of groundwater services to help with informing optimal management among competing uses (NRC, 1997; Tentes and Damigos, 2015). In aquifer regions such as the MRVA that support substantial irrigated agriculture and suffer from overdraft, voluntary incentive programs have targeted extractive agricultural users because they hold long-term financial interests linked to groundwater availability. Aquifer depletion, however, continues and even accelerates in many cases despite current programs (Konikow, 2015; Schaible and Aillery, 2012). Evidence about the way that people value non-extractive or future groundwater services could help to bolster expanded incentive programs. Since meaningful aquifer change occurs over decades, present value calculations are useful for valuation and policy deliberation related to groundwater. An understanding of time preferences for the flow of groundwater services is necessary for those present value calculations. The commonly held assumption that people apply the same time preferences to utility from different sources of consumption may not be true (Ubfal, 2016). For example, an average person might be more impatient about the consumption of environmental goods such as groundwater services or foods than about money or other goods.

This makes the joint estimation of time preferences with the choice of a particular good valuable for policy makers managing the intertemporal flow of services from that good.

Notable deficiencies exist among previous CE studies that examine groundwater preferences. Typically, groundwater CEs oversimplify environmental scenarios either by limiting the range of services considered (e.g., Tempesta and Vecchiato, 2013), ignoring time discounting (e.g., Birol et al., 2010; Tempesta and Vecchiato, 2013; Koundouri et al., 2014a, b; Tentes and Damigos, 2015), or ignoring realistic temporal and environmental dynamics (e.g., Meyer, 2013a, b). Consideration for temporal and environmental dynamics is especially important when jointly estimating time preferences. Meyer (2013a, b) estimated discount rates through variation in the timing of river basin cleanup. However, their CE considered only water quality and used unrealistic hypothetical scenarios that asked study participants to abstract from the reality of time lags and imagine that the river basin cleans inexplicably and then becomes unclean again with no delays. We fill a need in the literature by jointly estimating time preferences and marginal WTP values for a range of groundwater services using a CE employing realistic temporal dynamics of the environmental benefits under consideration.

We use choice models and an experimental design intended to address the deficiencies with groundwater preference studies, while providing new evidence about the nature and form of people's groundwater service and time preferences using flexibly mixed random parameters. We estimate and compare model specifications for the D-LML that assume exponential discounting, different forms of hyperbolic discounting, and a quasi-hyperbolic form to the time parameter. We randomly assign respondents to CE treatments that vary the timing of the payment period to identify implicit discount rates. Treatments include perpetual payments beginning this year, perpetual payments beginning after a one-year delay, a lump-sum payment this year, or a lump-sum payment after a one-year delay. Discounting most closely exhibits the quasi-hyperbolic form with large importance given to immediate utility, and Frederick et al. (2002) indicate that quasi-hyperbolic discounting explains procrastination behavior. Policy makers might then design more effective programs to manage groundwater over the long term by thinking about ways to overcome procrastination such as the use of externally imposed or self-directed deadlines for conservation actions.

Methods

Intertemporal utility and time preference functions

Individuals typically discount the utility they receive from future outcomes relative to the utility of current outcomes. Samuelson (1937) developed the first discounted utility model for intertemporal choice commonly known as the exponential discounting model, estimating a single discount rate parameter. This is the standard model for intertemporal utility, largely because of its simplicity (Meyer, 2013a; Frederick, 2002). The exponential discounting function takes the form of

$$U(c_0, c_1, \dots, c_T) = \sum_{t=0}^{T} \psi_t u(c_t), \tag{1}$$

where the discount factor for year *t* is $\psi_t = \left[\frac{1}{1+\rho}\right]^t$ and ρ is the discount rate.

Alternative functional forms of discounted utility have been developed in order to reconcile the many situations in which the exponential model does not fit behavior. For example, inferred discount rates have been found to decline over time (Cairns and van der Pol, 2000), fitting a functional form termed hyperbolic discounting. Hyperbolic discounting in its most popular form is described by

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

(Loewenstein and Prelec, 1992). As α approaches zero, this function becomes the exponential discounting function. Harvey (1986) imposes a single-parameter structure on Equation 2 to facilitate estimation of the function by constraining α to be equal to one. The hyperbolic form described by Harvey is then (3)

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

Note that as μ approaches infinity, discounting approximates the exponential form. Herrnstein (1981) and Mazur (1987) (HM) constrain the term, β/α, to be equal to one:

$$\psi_t^{HM} = (1+\omega t)^{-1}, \tag{4}$$

and note here that it becomes the exponential form as ω approaches zero. More recently, a quasi-hyperbolic discounting model has received attention in which especially large importance is placed on immediate utility as compared to deferred utility (Meyer, 2013a; Frederick, 2002). The functional form, developed by Laibson (1997), is given by

$$\psi_t = \left\{ \begin{matrix} 1\ if\ t = 0\ and \\ \beta \left[\frac{1}{1+\rho}\right]^t\ if\ t > 0 \end{matrix} \right\}, where\ 0 < \beta < 1, and\ \left[\frac{1}{1+\rho}\right]^t < 1. \tag{5}$$

The quasi-hyperbolic model deviates from the exponential model only in that all future time periods are discounted by an additional β factor.

We integrate the time preference functions from Equation 1 (exponential), Equation 3 (Harvey), Equation 4 (HM), and Equation 5 (quasi-hyperbolic) into a D-LML model and compare estimated models for best fit similar to Meyer (2013a; 2013b) and Lew (2018). Meyer (2013a; 2013b) assumes that discount rates are normally distributed in the population. The purpose of this study is to use flexible distributional assumptions about discount rates to retrieve time preferences with more realistic distributions because the flexible distributions allow for multimodality and asymmetry.

Empirical model

The Discounted Logit-mixed Logit (D-LML) model

To analyze the discrete choice data involving intertemporal goods, let the additively separable utility through time period T for an individual i for alternative j in choice situation k be given by

$$U_{ijk} = \sum_{t=0}^{T} \psi_{it}\big(-\lambda_i Cost_{ijkt} + (\lambda_i \omega_i)' x_{ijkt}\big) + \varepsilon_{ijk}, \tag{6}$$

where ψ_{it} is the individual discount factor for year t; $\varepsilon_{ijk} = \sum_{t=0}^{T} \psi_t \xi_{ijkt}$ is the weighted sum of all instantaneous error draws weighted each period by the discount factor, ψ_t, and is assumed to be distributed iid extreme value; λ_i is a random scalar representing the cost/scale parameter; $Cost_{ijkt}$ denotes the individual cost of the policy alternative in year t; ω_i is a vector of estimated marginal WTPs; and x_{ijkt} is a vector of observed groundwater service attributes for the alternative in year t. Conditional on ψ_i and the vector $<\lambda_i, \omega_i>$, the probability that person i makes a sequence of choices over K choice situations is the logit formula:

$$P_i(\psi_i, < \lambda_i, \omega_i >) = \prod_{k=1}^{K} \frac{e^{U_{in_{ik}k}}}{\sum_{j=1}^{J} e^{U_{ijk}}}. \tag{7}$$

The researcher does not observe the utility coefficients of each individual and knows that they vary over individuals. The cumulative distribution function of $(\psi_i, < \lambda_i, \omega_i >)$ in the population is $F(\psi, < \lambda, \omega >)$, which Train (2016) calls the mixing distribution. We let F be discrete with finite support set *S*. The discretization is not a constraint because the support grid can approximate a continuous distribution to any degree of accuracy with a sufficiently broad and dense *S* (Train, 2016; Caputo et al., 2018b). Let us denote the vector containing <λ_i, ω_i> and ψ_i for individual *i* as θ_i. The probability mass at any $\theta_r \in S$ is expressed as an additional logit term,

$$Prob(\theta_i = \theta_r) \equiv \mathrm{W}(\theta_r|\alpha) = \frac{e^{\alpha' z(\theta_r)}}{\sum_{s \in S} e^{\alpha' z(\theta_s)}}, \tag{8}$$

where $z(\theta_r)$ is a vector-valued function of θ_r defining the shape of the mixing distribution and α is a corresponding vector of probability mass coefficients.[1] The summation in the denominator of the additional logit terms assures that the probabilities sum to one (Train, 2016).

The unconditional choice probability of the sequence of choices of individual *i* is then:

$$P_i(\alpha) = \sum\nolimits_{r \in S} \mathrm{W}(\theta_r|\alpha) \cdot P_i(\theta_r) = \sum\nolimits_{r \in S} \left(\frac{e^{\alpha' z(\theta_r)}}{\sum_{s \in S} e^{\alpha' z(\theta_s)}} \right) \cdot \left(\prod_{k=1}^{K} \frac{e^{U_{in_{ik}k}}}{\sum_{j=1}^{J} e^{U_{ijk}}} \right), \tag{9}$$

containing one logit term for the probability that the decision-maker chooses a sequence of choices and a logit term for the probability that the decision-maker has coefficients θ_r, a vector of marginal WTPs and a discount factor.

Structure can be placed on the type of discounting using the formulas described in the section above about modeling intertemporal utility. This allows us to avoid imposing the unrealistic data requirements necessary for estimating ψ_t at any time *t*. This specification also facilitates hypothesis testing between the functional forms for discounting (Meyer, 2013a). We

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[1] Refer to Train (2016) and Caputo et al. (2017) for a thorough discussion of the options for specifying *z* variables.

estimate D-LML models, including random discount rate parameters that are flexibly mixed, for each of the four discounting structures: exponential, Harvey, HM, and quasi-hyperbolic.

Model estimation strategy

To estimate the model, the log-likelihood function for α is given by

$$LL = \sum_{i=1}^{I} ln\left(\sum_{r\in S} \mathrm{W}(\theta_r|\alpha) \cdot P_i(\theta_r)\right). \tag{10}$$

In order to evaluate a sufficiently large and dense S, we simulate the log-likelihood function by using random draws of θ_r for each individual. Letting $S_i \subset S$ be a subset of R randomly selected values of θ, the simulated log-likelihood function is then,

$$SLL = \sum_{i=1}^{I} ln\left(\sum_{r\in S_i} W_i(\theta_r|\alpha) \cdot P_i(\theta_r)\right), \tag{11}$$

where W_i is the logit formula based on subset S_i:

$$W_i(\theta_r|\alpha) = \frac{e^{\alpha' z(\theta_r)}}{\sum_{s\in S_i} e^{\alpha' z(\theta_s)}}. \tag{12}$$

The estimator selects the value of α that maximizes the SLL function.

We use splines in the form $\alpha' z(\theta)$ to flexibly define the mixing distributions. Caputo et al. (2018b) compared LML models using splines, polynomials, and step functions and observed that polynomials and splines outperformed step functions in most cases in terms of overall model fit.[2] In our own modeling analysis, the polynomials required substantially longer estimation

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[2] Splines, polynomials, and step functions all outperformed a MXL model using normally distributed random parameters (Caputo et al., 2017).

times than splines while offering no clear advantage in terms of model fit or distributional smoothness. We use a spline specification of z with 8 knots because it produced the smoothest distributions.[3]

The support range, S, needs to be defined a-priori, and the extremes of the support range define the highest and lowest marginal WTP values or time parameter values in the parameter space. Train (2016) recommended using a range that spans two standard deviations (2SD) on either side of the mean estimated from a MXL model with normally distributed random parameters. Caputo et al. (2018b) investigated the sensitivity of LML results to variations in the support range and suggested that the researcher can obtain guidance about the optimal range by visual inspection of the histograms showing the flexible mixing distributions. In particular, the researcher can extend the upper or lower range limits whenever there is a high probability mass in the highest and/or lowest bin of the histogram (Caputo et al., 2018b). High probability mass in the tails of the distribution suggests that some individuals predicted to have parameter values at the upper (lower) end of the range in fact have larger (smaller) values outside of the investigated support range (Caputo et al., 2018b). We followed an estimation approach similar to Caputo et al. (2018b), beginning first by estimating D-MXL models with normally distributed random parameters. The price/scale parameter, λ_i, for the D-MXL models was distributed lognormal. The lower range of the price/scale parameter we set equal to zero. Then, using visual inspection we extended the upper (lower) range limit any time we observed a high probability mass in the highest (lowest) bin of the histogram. The lower range of the price/scale parameter remained set to zero.

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[3] See Caputo et al. (2017) and especially the seminal paper by Train (2016) for a detailed discussion of specifying z variables for the mixing distribution.

We include alternative-specific constants (ASCs) in our models that represent labeled choice alternatives different from the reference status quo. We estimate models with covariance in the marginal WTPs due to the probability of correlated WTPs. The D-LML model accounts for scale heterogeneity, since each utility coefficient includes λ_i (Hess and Train, 2017).[4] The results we believe are the best come from the D-LML models obtained using visual inspection to guide the choice of supports. All model estimates come from MATLAB (version 2019a) using 1000 Halton draws.

Experimental design and questionnaire

For eliciting groundwater and time preferences, we chose to conduct a CE involving MRVA outcomes. Respondents choose among three groundwater management policy alternatives, including a surface water infrastructure (SWI) alternative, a cap and trade (C/T) alternative, and a status quo (SQ) alternative involving no change to current MRVA groundwater management. There is little information available about people's preferences for a C/T groundwater permits marketplace because it is not an alternative currently receiving widespread consideration. However, stated preference methods are a valuable way to elicit preferences for new goods and services, so we chose to include it here to provide some evidence for consideration in the MRVA context. Initiatives to expand surface water infrastructure are currently promoted within several critical areas of the MRVA along with other best management practices (BMPs). We include the alternative focused on additional infrastructure to offer another alternative different from the SQ alternative that is grounded within current policy

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[4] When utility parameters are uncorrelated in a model, variation in λ_i can reflect whatever sources of correlation may be present beyond scale heterogeneity (Hess and Train, 2017). Although our model estimates covariance between the marginal WTPs, we do assume the time parameter to be uncorrelated with WTPs in the model, and variation in λ_i may reflect sources of correlation between the WTPs and the discount rate.

frameworks operating in the MRVA. Information about each alternative is clearly provided to survey respondents, and they must successfully answer comprehension questions about each alternative before advancing in the survey.

We conducted a focus group to determine the most appropriate attributes for the CE design, collecting information about the socio-environmental services people value from MRVA groundwater. Participants also reviewed survey questionnaire sections related to the MRVA and potential policy alternatives, discussing clarity, comprehension, and difficulty. Feedback and conceptual frameworks for groundwater valuation (NRC, 1997) guided the selection of the CE attributes. There are five main groundwater services, or attributes, that we identify contributing to the MRVA's TEV: water quality for irrigated agriculture, the provision of jobs in the agricultural economy, the provision of habitat for maintaining wildlife, especially fish and waterfowl for local tourism, the avoidance of subsidence and its associated infrastructure costs, and the certainty of adequate water supply in case of drought (buffer). We rely on existing hydrologic (Clark et al., 2013) and economic (Kovacs et al., 2015) simulation models to help in setting realistic attribute levels for the SQ alternative. The attributes and levels in our CE are shown in Table 1.

We express all attribute levels as percentage values in order to lessen the difficulty of comparing alternatives across multiple attributes.[5] Levels indicate outcomes for the year 2050 and appear in terms of a percentage of current levels, so that 100% indicates no change from current levels. We include a cost attribute using an increase to state income taxes for the household as the payment mechanism.

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[5] Johnston et al. (2016) use this practice in a CE with three alternatives and six environmental attributes.

To identify time preferences, we employ a split-sample design and vary the timing of the expenses associated with the cost attribute. Respondents are randomly assigned to specific treatments for the cost attribute that include perpetual annual payments beginning in the current tax year, perpetual annual payments beginning in the following tax year, a single lump payment for the current tax year, and a single lump payment for the following tax year. By varying the onset and duration of the payment mechanism in the choice sets, endogenous estimation of the time preference parameters within the discount factor for the exponential, hyperbolic, and quasi-hyperbolic functional forms is possible (Meyer, 2013a; 2013b; Lew, 2018). The range of the lump payment cost attribute levels is similar to Meyer (2013a; 2013b) and Viscusi et al. (2008). Following Egan et al. (2015), we convert lump payment levels to perpetual payment levels using a 25% discount rate and rounding to equal-interval dollar amounts in order to present similarly scaled cost levels across treatments in the absence of known discount rates.

We used a sequential Bayesian approach to construct the experimental design (Bliemer et al., 2008; Scarpa et al., 2007; Scarpa and Rose, 2008). Using the software Ngene and uninformative priors, we constructed an efficient design for use in a pilot survey (Bliemer et al., 2008). Parameter priors from the pilot study (n=203) then updated a Bayesian efficient design (Scarpa and Rose, 2008). We selected a design with 30 choice sets to achieve attribute level balance and grouped these into six blocks to reduce the number of choice sets each respondent must complete. With six block groups, respondents answer five choice sets each. The levels for the SQ alternative, including no additional household cost, are constant throughout the experimental design.

The survey questionnaire begins with a brief overview where we also collect information about topic familiarity and perception of water resources, environment, and society. Using language to augment the perceived consequentiality of the study (Vossler et al., 2012), respondents read that their groundwater management preferences from the survey will be shared with the Arkansas Natural Resources Commission and other stakeholders and might affect how Arkansas actually manages its groundwater resources. Specifically, respondents read that their responses could be used as advice on whether to implement new groundwater management policies, and that the likelihood that a particular alternative occurs could increase with the number of “yes” votes for that alternative. Respondents also read a bulleted list of information about groundwater and the MRVA. This section includes a map depicting the current depth to MRVA groundwater across eastern Arkansas.

Before completing the choice sets for the CE, respondents read that they will make a series of hypothetical voting decisions between two policy alternatives for managing groundwater resources and a SQ option representing no change to groundwater management policy. The respondents also see detailed descriptions about the SQ, SWI, and C/T alternatives.[6] Instructions that follow describe the attributes and the payment mechanism in the choice sets. To construct a groundwater scenario with realistic long-term dynamics, attribute levels presented for each alternative represent projections for the year 2050, and levels for the SQ alternative capture the evolving state of groundwater resources if no policy change occurs. Respondents read that the rate of decline (or change) from the current (100%) levels to the 2050 levels is steady over the approximately 30-year time horizon, and the levels in 2050 then remain constant into the future. This language is to minimize confounding factors by establishing a common reference point for all respondents. Each must confirm that they understand the timing of the payment mechanism, read the consequentiality language again, and view an example choice set. In addition, as previously mentioned, just prior to beginning the actual choice sets, we employ a

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[6] For reminder, these abbreviate the status quo, surface water infrastructure, and cap and trade alternatives, respectively.

"cheap talk" script to reduce hypothetical bias (Cummings and Taylor, 1999; Silva et al., 2011), and respondents have the option to review the detailed descriptions about the groundwater management alternatives again.

Survey and data

This study elicits preferences for long-term groundwater management policies implemented at the state level. We concentrate on sampling voting-aged residents of Arkansas, where the dominant portion of the MRVA is located and the most groundwater use occurs. Between August 27th and October 17th of 2018, we administered a stated preference survey regarding long-term MRVA groundwater management and outcomes using the survey research firm, Qualtrics. Our sample includes approximately 800 randomly selected adult residents of Arkansas. The survey is designed to be compatible with both traditional and mobile internet platforms. Individuals receive financial incentive for participating in Qualtrics surveys. Qualtrics filters responses for quality to remove duplicates from a single individual or any observation with a total response time less than one-third the median total response time. Incomplete responses are dropped from the analysis, leaving 777 usable survey responses and data for 11,655 choice occasions (each person sees five choice sets, and each choice set includes three choice occasions because there are three alternatives for each choice set). Table 2 summarizes the choice selections by alternative and treatment.

Overall, the sample is a close representation of the target population. Relative to the general population of Arkansas residents, our sample shares characteristics for median income and unemployment rate while being slightly older (median age 42 compared to 38), more female (66% to 51.5%), and more educated (30.1% with bachelor's degree to 23.4%) (US Census Bureau, 2018). Statistics on voters and registered voters in the US suggest that the voting electorate shares these same biases relative to the general population (File, 2018), supplying added confidence in the validity of the stated preferences for groundwater policies.

The spatial distribution of the sample (based on self-reported Zip Codes) also closely represents Arkansas's actual population density. Comparing sample proportions across Arkansas's 75 counties to the Census population proportions via the Mann-Whitney test shows no significant difference (p-value=0.259). Most respondents (89%) indicated some degree of belief that their responses would be given consideration by Arkansas policy makers. The perceived feasibility of the policy alternatives has a five-point scale where one represents "very unrealistic and infeasible" and five represents "very realistic and feasible." The mean feasibility score of the SWI alternative is 3.43 with just 6.3% who find it very unrealistic and infeasible. On the other hand, 17.1% find it very realistic and feasible. For the C/T alternative, the mean feasibility score is 3.29. A slightly larger percentage (7.9%) find it very unrealistic and infeasible when compared to the SWI alternative. Similarly, a smaller percentage (14.9%) find the C/T alternative to be very realistic and feasible.

Respondents were randomly assigned to treatments which varied the timing of the cost attribute. We find balance in observable demographic characteristics across the treatments using one-way ANOVA (means) and the Chi-square goodness-of-fit test (proportions) (see Table 3). The treatments also exhibit no significant differences in terms of perceived consequentiality, question difficulty, answer certainty, or perceived feasibility of alternatives.[7]

Results

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[7] Each was measured on a 5-point scale where 1 equals not at all difficult (certain, feasible, or taken into account by policy makers) and 5 equals very difficult (certain, feasible, or definitely taken into account by policy makers).

Table 4 presents the results of the D-LML models estimated for each of the four discounting assumptions: exponential discounting (Model I.a), Harvey hyperbolic discounting (Model I.b), HM hyperbolic discounting (Model I.c), and QH discounting (Model I.d). The time parameter estimated depends on the type of discounting assumed. Utility estimates show mean marginal WTP in net present value (NPV) along with standard deviations for a 1% increase in marginal groundwater services and for the implementation of alternative groundwater management policies. We scaled the cost of each alternative to improve estimation, so the marginal groundwater service valuations in Table 4 reflect tens of dollars. We report bootstrap standard errors based on bootstrap 95% confidence intervals (CIs) (Table B1, Table B2, Table B3, and Table B4) and use these to guide our interpretation of model results. Specifically, we interpret the β time parameter in the QH model to be significant when the bootstrap 95% CIs do not overlap with one, and we interpret all other estimates to be significant when CIs do not overlap with zero. In the absence of a proper test for selecting the best performing LML or D-LML models, we follow Caputo et al. (2018b) and use standard information criteria. A lower Akaike Information Criteria (AIC) value indicates the better fit.

All time parameters are significant in the models. Each of the alternative discounting models provides a better fit than the standard exponential discounting model (AIC = 7129.6). Among the two hyperbolic discounting models, HM discounting (AIC = 7012.2) provides a better fit than Harvey discounting (AIC = 7039.9). However, the QH discounting model (AIC = 7005.9) offers the best overall fit, and β is significant at an estimated value of 0.613. A β parameter value of one in the QH discounting model represents no departure from exponential discounting, and as the value of β deviates from one and becomes smaller, present-bias becomes larger. With QH discounting providing the best overall model fit and β significant, we find strong evidence for present-bias. Hyperbolic discounting models also support a rejection of the exponential discounting assumption. For example, the HM discounting case approximates the exponential form as the time parameter, w, approaches zero. We estimate w to be much greater than zero (1.728) and observe an overall model fit nearly as good as with QH discounting. We estimate the Harvey time parameter is $u = 1.352$, which is in line with the value of 1.646 estimated by Lew (2018). Unlike Lew (2018) however, here Harvey discounting improves model fit relative to exponential discounting. These results using flexible mixing distributions are counter to the findings of Meyer (2013a) and Lew (2018) who found no evidence to reject the exponential discounting assumption when using normally distributed and fixed time parameters, respectively. Though it is not our preferred model, we estimate a mean annual exponential discount rate of 73.7%, larger than the 12.8% in Meyer (2013a) but smaller than the 122% in Lew (2018). Both previous studies used random parameters fit to a normal distribution.[8] Comparing to studies using CV without random parameters, the exponential discount rate in our study is larger than the estimates from payment schedules in Kovacs and Larson (2008) and Bond et al. (2009). Our use of a D-MXL model that imposes a parametric normal distribution indicates a smaller mean exponential discount rate (49.1%) and a much smaller standard deviation (0.001).

Marginal groundwater service valuations vary across the different discounting types as with model fit, but there are similarities. Each of the D-LML models shows significant and positive WTP for water quality, groundwater buffer, jobs from agriculture, and wildlife. In both the exponential and the QH discounting models the WTP for the provision of infrastructure

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[8] Only Meyer estimated a random parameter for the time parameter.

integrity is not significantly different from zero. Water quality provision has the largest WTP in each of the three best fitting models (Harvey, HM, and QH) and is third-largest in the exponential discounting model. A preference for water quality is consistent with previous groundwater CEs that consider multiple groundwater services. Birol et al. (2010) used a CE to estimate WTP for promoting aquifer recharge in Cyprus. They estimated marginal WTP values for water quality, water quantity, agricultural employment, and habitat, and respondents displayed positive and significant WTP for each. About a third of the sample was farmers and the other two-thirds was the general public. Water quality was valued most by the general public, while farmers placed greater value on water quantity. Studies by Koundouri et al. (2014) and Tempesta and Vecchiato (2013) also observed the largest values for water quality services.

Looking only at groundwater services for the preferred QH discounting model, people on average will pay \$9.32 for a 1% increase in water quality. Respondents value wildlife services (\$8.92) second to water quality followed by jobs from agriculture (\$6.64) and groundwater buffer (\$5.22). Standard deviations of the marginal WTPs are all significant, and most are large relative to the mean estimate, meaning some individuals have negative WTPs. The exception is jobs from agriculture, where the WTP appears to be less variable in the population and restricted to positive values.

Marginal WTP for the C/T groundwater policy alternative is not significant for any of the models and therefore not preferred over current management, groundwater services being equal. The WTP for the SWI alternative is significant and positive in the exponential and HM hyperbolic discounting models but is not significant in the preferred QH discounting model or the Harvey hyperbolic discounting model.

In the preferred QH discounting model, WTPs for groundwater buffer and infrastructure integrity correlate positively with WTP for the C/T policy alternative (Table 5), while the SWI alternative correlates positively with wildlife habitat provision. People who like the C/T policy alternative also tend to like having the groundwater services that buffer agriculture against drought and prevent harm to infrastructure, and people who like the SWI policy want the groundwater services that provide wildlife, namely the duck hunting in the Mississippi flyway. The SWI alternative and the C/T alternative correlate positively with one another, meaning that people who like one policy alternative also tend to like the other policy alternative. Among marginal groundwater services, WTP for infrastructure integrity correlates negatively with WTP for jobs from agriculture. People who dislike the infrastructure integrity service that groundwater provides tend to like the support groundwater has for jobs in agriculture.

A consistent difference between the magnitudes of the significant WTPs is apparent across the different discounting types (Table 4). The values in the hyperbolic discounting models are smaller than either the QH discounting estimates or the exponential discounting estimates, sometimes by an order of magnitude. Marginal WTPs in the QH discounting model are also consistently smaller than with exponential discounting. Beyond the consistent differences in the magnitudes of the WTPs across discounting types, we also observe some small differences in the relative importance of the groundwater service attributes. These observable differences across the different discounting types also run counter to the findings in Meyer (2013a) and Lew (2018). Lew (2018) observed almost no differences in the magnitudes or rankings of marginal utilities across discounting types likely because the lone difference between models was discounting applied only to the cost term of the utility model. Meyer (2013a) used a model that discounted costs and benefits but observed only very small differences in the magnitude of the lone utility estimate across discounting types, potentially due to the absence of variability in the flow of beneficial services over time. Our models discount costs and benefits, and we assume a dynamic flow of benefits over a multi-decadal time scale consistent with aquifer change, potentially explaining some of the differences we observe in the WTPs and model fit across discounting types. Since hyperbolic discounting weigh benefits less strongly in the present than exponential discounting, the lower WTP for hyperbolic discounting suggests the values for groundwater services change over time with values higher in the present and lower in the future.

Another potential driver of the differences we observe between discounting types is the flexible mixing distributions. Flexible mixing allows for individual parameter mass distributions that capture the clustering of individual WTP and time preferences and reveal modes of preference 'types' in the population. Since the hyperbolic and QH discounting models can approximate the exponential discounting[9], these discounting models can improve overall fit relative to the exponential discounting form with flexible mixing because they can flexibly allow some individuals to take on the preferences of an exponential discounter and leave other individuals to follow hyperbolic discounting. This is an advantage when comparing D-LML models for evidence of heterogeneity in time preferences.

Discussion and Conclusion

To learn more about how individuals make intertemporal decisions in non-market valuation questions, we estimate random time preference and groundwater preference parameters

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[9] A β value of 1 approximates exponential discounting for the QH discounting model. A w value of 0 approximates exponential discounting for the HM hyperbolic discounting model. Harvey hyperbolic discounting approximates exponential discounting as u approaches infinity.

with flexible mixing distributions using a D-LML model. By allowing multimodality and asymmetry in the estimated parameter distributions, flexible mixing reveals valuable detail about preference heterogeneity and discounting behavior. We find three modes for the annual exponential discount rate, *r*, in our baseline QH discounting model: two groups with smaller discount rates near 0% and 40%, and a third group with larger discount rates above 80%. The β time parameter also reveals three groups of discounting types who exhibit increasing levels of present-bias. By estimating models to evaluate complex heterogeneity in groundwater service preferences and time preferences, we contribute new policy insights. For example, time preferences are multimodal, and a significant number of people have discount rates approaching zero. This is valuable because governments operate under tight budget constraints and want to know the lowest-cost incentive likely to achieve desired policy outcomes.

The D-LML enables hyperbolic and QH discounting models to improve fit relative to the exponential discounting model by representing heterogeneity in the time parameter such that some individuals can take on values that approximate exponential discounting. Meyer (2013a) and Lew (2018) failed to reject the assumption of exponential discounting using normally distributed and fixed time parameters. Like Lew (2018), we estimate time preferences by varying the payment schedule, and like Meyer (2013a), we model and discount the flows of both costs and benefits over time. The only other empirical study to find evidence of hyperbolic discounting in stated preferences is Viscusi et al. (2008), who estimated time preferences from WTP for water quality improvements realized over varying time horizons.

Estimated WTPs for marginal groundwater services and alternative groundwater management show that people value the provision of water quality, buffer protection against long-term drought, provision of habitat that promotes fishing and duck hunting, and jobs from irrigated agriculture; and they are willing to pay the most to ensure good water quality. This finding and similar findings in previous groundwater CEs (e.g., Birol et al., 2009; Tempesta and Vecchiato, 2013; Koundouri et al., 2014) could suggest that people associate groundwater quality for irrigation with food safety, as other research finds that attributes related to food safety are consistently deemed the most important in stated preference studies (e.g., Lusk and Briggeman, 2009; Bazzani et al., 2018). On average, respondents do not prefer new investments for surface water infrastructure or a groundwater permits marketplace over the SQ management alternative. However, flexible distributions reveal groups of individuals who possess high values for both new alternatives. Mean WTP is consistently smaller under hyperbolic discounting assumptions. This suggests that respondents' values for groundwater services change over time such that the values are higher in the present, when hyperbolic discounters weigh benefits less strongly than exponential discounters, and lower in the future.

Our findings and those from other stated preference studies estimating time preferences contribute to discussion about the appropriate application of discounting in benefit-cost analyses for non-market goods. Like most empirical studies (Frederick et al. 2002), we estimate discount rates much larger than commonly used in policy analysis (OMB, 2016). Compared to Meyer (2013a), who estimated an annual exponential discount rate of 12.8% using variation in the benefits horizon, we estimate much higher rates of discounting, including a mean discount rate of 73.7% under exponential discounting. However, our flexible time parameter shows groups of individuals with smaller discount rates that compare to the exponential discount rates under varying payment horizons in CV studies that range from about 20% to as much as 70% (Bond et al. 2009; Kovacs and Larson 2008). Lew (2018) estimated a fixed exponential discount rate of 122%, larger even than the upper extreme of the finite D-LML support space that fit our data best. Our discount rate with the D-MXL model is close to 49% suggesting that bias can occur by imposing a normal distribution.

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Table 1: Attribute Definitions and Levels

Attribute	**Definition**	**Levels**^{a,b}
Buffer Quantity	The percentage of current acres with adequate groundwater for 5 consecutive drought years	**25%**, 40%, 55%, 70%
Water Quality	The percentage of current acres with adequate groundwater quality for irrigation	**75%**, 80%, 85%, 90%
Jobs from Irrigated Agriculture	The percentage of current (120,000) jobs	**80%**, 90%, 100%, 110%
Wildlife Diversity & Abundance	The percentage of current wildlife diversity and abundance	**75%**, 80%, 85%, 90%
Infrastructure Integrity	The percentage of current infrastructure integrity	**75%**, 80%, 85%, 90%
Cost to Household (lump)	The one-time dollar increase in state income taxes	**$0**, $30, $90, $150, $210, $270
Cost to Household (perpetual)	The permanent dollar increase in state income taxes	**$0**, $12, $24, $36, $48, $60

Note.—The status quo levels are indicated in bold. Levels indicate outcomes for the year 2050 and 100% indicates no change from current levels.

Table 2: Summary of Choice Selections by Treatment

Alternative	**Perpetual**	**Perpetual delayed**	**Lump**	**Lump delayed**
SWI	373	358	381	343
C/T	266	319	290	286
SQ	296	313	304	356

Table 3: Demographic Summary and Sample Balance

Characteristic	**Perpetual**	**Perpetual delayed**	**Lump**	**Lump delayed**	***F*, χ^2**	**p-value**
N	187	198	195	197		
Age, mean	45.2	44.3	44.0	43.7	0.74	0.389
Household size, mean	2.89	2.92	2.74	2.89	0.22	0.643
Household income					4.80	0.851
$0 - $39,999	46.5%	50.5%	45.6%	41.1%		
$40,000 - $69,999	18.7%	19.7%	22.6%	22.8%		
$70,000 - $99,999	17.1%	15.2%	15.9%	16.8%		
$100,000+	17.6%	14.6%	15.9%	19.3%		
Female	65.8%	65.2%	67.2%	66.0%	0.19	0.979
Education					5.81	0.445
High school or less	26.2%	31.8%	24.6%	29.9%		
Some college	44.4%	41.4%	44.6%	36.5%		
College graduate	29.4%	26.8%	30.8%	33.5%		
Married	58.8%	60.1%	54.9%	57.4%	1.21	0.750
Unemployed	4.8%	3.5%	3.6%	5.6%	1.39	0.707

Table 4: Simulated Maximum Likelihood Results of the D-LML Models in WTP-space (Best Supports)

Parameter	**I.a (Exp.)**	**I.b (Harvey)**	**I.c (HM)**	**I.d (QH)**
ASC1 (C/T)	1.157 (0.883)	0.794 (0.795)	2.050 (0.914)	1.312 (0.851)
St. deviation (SD)	6.823* (0.424)	5.316* (0.378)	5.760* (0.443)	7.440* (0.488)
ASC2 (SWI)	3.845* (0.686)	2.185 (0.815)	2.748* (0.864)	2.956 (0.743)
SD	5.601* (0.334)	5.092* (0.333)	5.371* (0.412)	8.864* (0.668)
Buffer	1.291* (0.365)	0.262* (0.095)	0.120* (0.056)	0.522* (0.385)
SD	1.954* (0.171)	0.400* (0.045)	0.253* (0.029)	2.396* (0.265)
Quality	1.056* (1.099)	0.314* (0.081)	0.493* (0.078)	0.932* (0.659)
SD	5.923* (0.610)	0.393* (0.038)	0.428* (0.038)	3.483* (0.372)
Jobs	0.331* (0.034)	0.197* (0.002)	0.164* (0.119)	0.664* (0.007)
SD	0.189* (0.017)	0.009* (0.001)	0.025* (0.002)	0.036* (0.003)
Infrastructure	-0.768 (1.040)	0.295* (0.134)	0.164* (0.119)	0.605 (1.119)
SD	5.651* (0.523)	0.663* (0.091)	0.746* (0.080)	4.444* (0.616)
Wildlife	1.545* (1.191)	0.086* (0.020)	0.088* (0.120)	0.892* (0.420)
SD	6.643* (0.675)	0.081* (0.009)	0.679* (0.080)	2.206* (0.204)
λ (scale)	0.700* (0.124)	1.963* (0.226)	1.375* (0.205)	0.120* (0.009)
SD	0.458* (0.079)	1.265* (0.141)	1.145* (0.102)	0.078* (0.006)
r	0.737* (0.049)			0.626* (0.047)
SD	0.249* (0.025)			0.265* (0.024)
u		1.352* (0.085)		
SD		0.439* (0.053)		
w			1.728* (0.044)	
SD			0.210* (0.023)	
β				0.613* (0.042)
SD				0.176* (0.022)
Log L	-3448.8	-3403.9	-3390.1	-3377.9
AIC	7129.6	7039.9	7012.2	7005.9
N	11655	11655	11655	11655

Note.—WTP values are tens of dollars. Multiply by 10 to obtain dollar amounts.
Bootstrap Standard Errors given in parentheses were obtained using 250 Bootstrap samples.
*Significant based on 95% CI (tests for β are against 1, all others are against 0)

Table 5: Correlations Between Marginal WTPs in the D-LML Models (Best Supports)

	SWI	**Buffer**	**Quality**	**Jobs**	**Infra.**	**Wildlife**
C/T	0.7148*** (6.6297)	0.5663*** (3.2833)	0.1994 (0.9949)	0.0246 (0.1335)	0.3324* (1.9098)	0.1333 (0.6509)
SWI		0.4212** (2.1897)	0.3080 (1.6354)	-0.0901 (-0.4779)	0.4188** (2.3620)	0.3744* (1.8120)
Buffer			0.1039 (0.4604)	0.0359 (0.1897)	0.0254 (0.1220)	0.1826 (0.8817)
Quality				0.0159 (0.0786)	-0.1681 (-0.7689)	-0.0083 (-0.0364)
Jobs					-0.4152** (-2.1679)	0.0074 (0.0403)
Infra.						0.0904 (0.3925)

Note.—T-statistics are given in parentheses.
* $p < .10$
** $p < .05$
*** $p < .01$