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Discounting future payments in stated preference choice experiments☆

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ABSTRACT

When costs are presented as a series of recurring payments in stated preference choice experiment (CE) questions, how respondents discount future payments is important in explaining choices and in the measurement of the present value of willingness to pay. In this paper, alternative discounting approaches are compared to examine their effect on measuring preferences and values using data from a survey examining public preferences for the protection of an endangered species. Exponential and hyperbolic discounting assumptions lead to very similar results in terms of both model fit and welfare. All estimated models suggest future payments are discounted at a very high rate. Several factors likely influencing the magnitude of these estimated discount rates are discussed, and then an argument is made for using payment vehicles in stated preference studies that employ a single lump sum payment rather than a series of future payments.

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1. Introduction

Discrete choice experiments, or stated preference choice experiments (CE), have become a common tool in economics for understanding consumer preferences for a range of market and non-market goods, particularly in the environmental, transportation, marketing, and health economics fields (e.g., Johnston et al., 2017; Hanley et al., 1998; Louviere and Lancsar, 2009; Louviere, 1988). In many CE applications of non-market goods, intertemporal decision making plays a prominent role. Respondents to the CE questions are typically asked to value future benefits (e.g., environmental improvements) through payment vehicles (e.g., taxes or fees) that involve multiple payments over time. In the analysis of these decisions, accounting for time preferences through discounting future benefits and costs is critical for the proper measurement of underlying preferences and values.

In economics, it has been common to assume individuals have a constant discount rate over time implied by the discounted utility model (Frederick et al., 2002), commonly referred to as exponential discounting. Under exponential discounting, the

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present value of a cost (or benefit) in time period t, C_t, is $\mathrm{PV}(C_t) = C_t \cdot (1+r)^{-t}$, where r is the discount rate. This has been a common assumption in the stated preference (SP) literature, with several contingent valuation (CV) studies estimating implicit discount rates under the assumption of exponential discounting (e.g., Kovacs and Larson, 2008; Bond et al., 2009; Egan et al., 2015; Myers et al., 2017). However, a large literature exists that shows people's behavior is often inconsistent with exponential discounting (e.g., Soman et al., 2005; Loewenstein and Prelec, 1992). For instance, experimental research (e.g., Zauberman et al., 2009; Grijalva et al., 2014; Gintis, 2000) has revealed that people often display a "present bias"–where the discount rate decreases over time–when making intertemporal choices. This phenomenon has led some to advocate for modeling intertemporal choices using a type of discounting where the discount rate declines over time, called hyperbolic discounting. Two common (and tractable) specifications of hyperbolic discounting were introduced by Harvey (1986) and Mazur (1987).[1] In the Harvey hyperbolic model, the present value of a cost (or benefit) in time period t is $\mathrm{PV}(C_t) = C_t \cdot (1+t)^{-\mu}$, and under the Mazur model, $\mathrm{PV}(C_t) = C_t \cdot (1+\omega \cdot t)^{-1}$. Under both specifications, later time periods are valued less than more immediate ones (assuming positive discount parameters μ and ω in the respective models). To date, few empirical SP studies have allowed for hyperbolic discounting behavior, with Meyer (2013a, b) and Viscusi et al. (2008) being the exceptions in the environmental economics literature.

The focus in this paper is on assessing how respondents to CE questions discount future payments using data from a CE survey examining public preferences for the protection of an endangered species. The only other study to empirically estimate discounting behavior jointly with choices using CE data was a study by Meyer (2013a, b), which used variation in the timing of future benefits (i.e., the benefits horizon) to identify implicit discount rates with mixed logit (MXL) models (Train, 2003). Similarly here, MXL models embodying alternative assumptions about discounting behavior are estimated that allow for the joint estimation of implicit discount rates and choice behavior from variation in the payment horizon. Future payments are found to be discounted at a very high rate, regardless of whether exponential or hyperbolic discounting is assumed. In fact, the results suggest there is little difference between the discounting models in terms of welfare estimates or model fit. Furthermore, welfare estimates are shown to not just be statistically similar across exponential and hyperbolic discounting models, but also in comparison to those from a model that assumes respondents ignore future payments. Additional models show these results are robust to specifications that allow for attribute non-attendance (Scarpa et al., 2013; Hole, 2011). In light of these findings, factors likely influencing the magnitude of the estimated discount rates are discussed and an argument is made for the use of lump sum payment vehicles in stated preference surveys rather than annual future payments that have been argued for in the recent literature (Egan et al., 2015).

2. Literature review

There have been numerous empirical attempts to estimate implicit discount rates with stated preference data. There are two general approaches for measuring discount rates with SP data: exogenous and endogenous discounting approaches (Wang and Daziano, 2015). In general, exogenous, or external, discounting approaches estimate a rate used for the calculation of the present value of future costs or benefits that is determined outside of the valuation model, while endogenous, or internal, discounting approaches estimate the discount rate within the valuation model.

Among exogenous approaches, many studies employ a two-step indirect approach to estimate an implied discount rate (e.g., Crocker and Shogren, 1993; Stevens et al., 1997; Viscusi et al., 2008; Kim and Haab, 2009; Myers et al., 2017). In the first step, willingness to pay (WTP) is estimated for two different time periods or payment horizons. The second step involves solving for the discount rate parameter (r in the case of exponential discounting) in the discounting formula that equates the two values. This approach was used by Crocker and Shogren (1993) to infer discount rates from values for waiting times at ski lifts, Stevens et al. (1997) in a study of salmon restoration values, and Kim and Haab (2009) in a study of oyster reef restoration. More recently, Myers et al. (2017) calculated the implicit discount rate by comparing the present value of WTP associated with a one-time payment and the present value of WTP for a series of ongoing annual payments for a conservation program to protect a migratory species of shorebird along the east coast of the U.S. In contrast to these studies, which employed CV data and assumed exponential discounting, Viscusi et al. (2008) employed a CE approach that explicitly includes timing of future water quality benefits as an attribute and estimated discount rates under both exponential and hyperbolic discounting assumptions using the two-step approach. In an earlier CE study using a two-step approach, Layton and Brown (2000) estimated implied discount rates assuming exponential discounting behavior from WTP estimates using data from two survey versions administered to separate samples that differed in the time horizon for when forest losses would occur under mitigation programs.

Another exogenous estimation approach uses information from supplemental questions to infer individual-level discount rates, which are then applied to analyze choices. For example, Newell and Siikamäki (2014) asked a series of discount rate elicitation questions common in the experimental economics literature for exploring intertemporal decision making (e.g., Coller and Williams, 1999) in the same survey instrument as a series of CE questions. Responses to these elicitation questions were used to estimate a discount rate for each individual, which was then applied in the analysis of the CE data to reveal households' preferences for energy efficient appliances and compared against CE model results assuming commonly-used

[1] Another empirical form that is commonly employed since it captures features of hyperbolic discounting is the quasi-hyperbolic form of Laibson (1997).

discount rates in government regulatory analysis (e.g., 3 and 7%). Egan et al. (2015) use a similar approach in a CV survey of wetland restoration in Ohio, but the discount rate elicitation questions were presented as a reward lottery experiment with actual payoffs to randomly selected winners following Harrison et al. (2002). Both studies assume exponential discounting behavior when calculating discount rates.

Endogenous estimation approaches involve estimating the implied discount rate directly within the valuation model using sample-level variation in the benefits horizon (e.g., Alberini and Scasny, 2011) or payment horizon (e.g., Kovacs and Larson, 2008; Bond et al., 2009) to identify a discount rate for the sample. Two CV studies that estimated implied discount rates from differences in payment horizons are Kovacs and Larson (2008) and Bond et al. (2009). In these studies, the discount rate enters the valuation function directly as an estimable parameter. In both studies, exponential discounting is assumed, and the discount rate parameter (r) is identifiable due to variation in the payment horizon across the sample. Kovacs and Larson (2008) administered survey treatments with T = 1, 4, 7, and 10 year payment horizons and estimated an implied discount rate of around 30%, while Bond et al. (2009) used survey treatments with either T = 1, 5, or 10 year payment horizons, which resulted in implied annual discount rates between 23 and 80%.

In this paper, an endogenous estimation approach similar to Kovacs and Larson (2008) and Bond et al. (2009) is used to jointly estimate implied discount rates and preferences using CE data. The only other application of endogenous estimation using CE data is by Meyer (2013a, b), who estimates implicit discount rates from survey treatments that differ in the length of the benefits horizon for a water quality improvement program in the Minnesota River Basin. In this work, the implicit discount rate is identified from the costs of the non-market good through variations in the payment horizon in the CE questions.

3. Estimation models

The CE data are analyzed using mixed logit models that account for preference heterogeneity, as well as the ordered and panel nature of the data. Utility for the jth alternative (U_j) is assumed to consist of a deterministic (V_j) and stochastic (ε_j) component. V_j is assumed to be linear in the present value of cost (PVC$_j$) and non-cost attributes ($\boldsymbol{x}_j$) of choice alternative j. Thus, for a given individual, the deterministic component of utility of the jth choice alternative is:

$$V_j = \beta \cdot x_j + \gamma \cdot \mathrm{PVC}_j, \tag{1}$$

where $\boldsymbol{\beta}$ and γ are parameters to be estimated.

The empirical MXL models are differentiated by the assumption made about discounting behavior that is captured in the PVC term in Eq. (1), which for a series of T payments of size C beginning in time 0 and ending in time T-1 can be written as the product of C and a cumulative discount factor (ψ):[2]

$$\mathrm{PVC} = C \cdot \psi. \tag{2}$$

Under exponential (EXP) discounting, the cumulative discount factor (ψ^{EXP}) is:

$$\psi^{EXP} = \sum_{t=0}^{T-1} \left(\frac{1}{1+r}\right)^t = \left(1+\frac{1}{r}\right) \cdot \left[1 - \frac{1}{(1+r)^T}\right], \tag{3}$$

where r is the discount rate. Thus, under exponential discounting Eq. (1) becomes:

$$V_j = \beta \cdot x_j + \gamma \cdot C_j \cdot \psi^{\mathrm{EXP}}. \tag{4}$$

Under the Harvey hyperbolic (HH) discounting model, the cumulative discount factor (ψ^{HH}) is:

$$\psi^{HH} = \left[\sum_{t=0}^{T-1} \left(\frac{1}{1+t}\right)^{\mu}\right] \tag{5}$$

where μ is the discount rate parameter. In this case, the conditional indirect utility specification is

$$V_j = \beta \cdot x_j + \gamma \cdot C_j \cdot \psi^{\mathrm{HH}}. \tag{6}$$

For the Mazur hyperbolic (HM) discounting model the cumulative discount factor (ψ^{HM}) is:

$$\psi^{HM} = \left[\sum_{t=0}^{T-1} \left(\frac{1}{1+\omega \cdot t}\right)\right], \tag{7}$$

[2] Most payment vehicles in SP studies are structured with a lump sum payment (T = 1) or a series of equally sized payments (T > 1) denoted by C in Eq. (2). For simplicity, time is assumed to be measured in years, which means the discount rates in the subsequent equations are annual ones.

where ω is the discount rate parameter. The corresponding conditional indirect utility is then

$$V_j = \beta \cdot x_j + \gamma \cdot C_j \cdot \psi^{HM}. \tag{8}$$

In each choice question, an individual is asked to choose the best (most preferred) and worst (least preferred) alternative from among J alternatives; here, respondents are asked to choose between J =3 alternatives, Choices A, B, and C. As a result, a full rank ordering between the three choice alternatives can be modeled, which can be analyzed using the rank-ordered logit approach of Beggs et al. (1981) and Chapman and Staelin (1982). One can model the probability that the individual chooses the jth alternative (j = A, B, C) as best by Pr[j is best] = Pr[$V_j \geq \max\{V_A, V_B, V_C\}$]. The second best choice alternative k, given j was selected as the most preferred alternative, implies a rank ordering from most preferred to least of j, then k, and then l, where j, k, and $l \in \{A, B, C\}$ and $j \neq k \neq l$. It is common to assume that the idiosyncratic error associated with the jth alternative, ε_j, is independent and identically distributed with a type I extreme value (TEV) distribution and a scale parameter $\lambda > 0$ (such that the variance equals $\pi^2/6\lambda$). The resulting joint probability of observing the selection of j as best, k as second best, and l as worst (denoted as $j > k > l$) is:

$$\Pr[j>k>l] = \pi_{jkl} = \Pr[j \text{ is best}] \times \Pr[k \text{ is second best} | j \text{ is best}], \tag{9}$$

where
Pr[j is best] = $\exp(\lambda \cdot V_j)/\Sigma_k [\exp(\lambda \cdot V_k)]$,
and
Pr[k is second best|j is best] = $\exp(\lambda \cdot V_k)/\Sigma_{m \neq j} [\exp(\lambda \cdot V_m)]$, j,m,k,l = {A, B, C}.

This is a rank-ordered conditional logit model. Note that the scale parameter in discrete choice models is inversely proportional to the variance of the idiosyncratic error (Swait and Louviere, 1993), but is commonly normalized to be unity ($\lambda = 1$) in conditional logit models, which is the convention followed in subsequent equations.

To allow for multiple CE question responses (four in this study), the joint probability of observing the sequence of choices an individual makes is modeled as the product of individual choice probabilities (e.g., Morey et al., 1993), which assumes the TEV errors are independent across the repeated choices. Therefore, letting r_m = rank ordering in the mth choice question (e.g., A > B > C), the joint probability of observing the four rank orderings is represented as

$$Pr[r1,\ r2,\ r3,\ r4] = Pr[r1] \cdot Pr[r2] \cdot Pr[r3] \cdot Pr[r4] = \pi_{r_1} \cdot \pi_{r_2} \cdot \pi_{r_3} \cdot \pi_{r_4}, \tag{10}$$

where π_{r_m} (for m = 1, 2, 3, 4) is defined by Eq. (9).

To account for preference heterogeneity, the random parameters mixed logit (MXL) model (Train, 2003) is used. In this model, one or more utility parameters are assumed to be distributed continuously over the population instead of being fixed over the population, which allows for unobserved sources of preference heterogeneity. In the model used here, the parameters $\boldsymbol{\beta}$ in Eqs. (4), (6), and (8) are allowed to be individual-specific (i.e., the non-cost parameters).[3] More formally, assume the ith individual's conditional indirect utility (i.e., the deterministic component of the random utility) associated with the jth alternative, and under discounting assumption g (where $g \in$ {EXP, HH, HM}), is linear in utility parameters ($\boldsymbol{\beta_i}$ and γ) and takes the form:

$$V_{ij}(\beta_i) = \beta_i \cdot x_{ij} + \gamma \cdot C_j \cdot \psi^g, \tag{11}$$

where $\boldsymbol{x}_{ij}$ is a K × 1 vector of non-cost attributes describing the alternative for the ith individual and $\boldsymbol{\beta_i}$ is a K × 1 vector of individual-level utility parameters assumed to be distributed $f(\overline{\boldsymbol{\beta}}, \Omega)$. $\overline{\boldsymbol{\beta}}$ is a K × 1 mean vector and Ω is a K × K variance-covariance matrix. In the MXL model formulation, Eq. (9) becomes (dropping the individual-level index, i):

$$Pr[j > k > l] = \int \{exp(V_j(\boldsymbol{\beta}))/\Sigma_k\, exp(V_k(\boldsymbol{\beta}))\} \cdot [exp(V_k(\boldsymbol{\beta}))/\Sigma_{m \neq j}\, exp(V_m(\boldsymbol{\beta}))] f(\overline{\boldsymbol{\beta}}, \Omega) d\boldsymbol{\beta}, \tag{12}$$

for all k, l, m, and $j \in$ {A, B, C}.

The MXL model is estimated using simulated maximum likelihood. The non-cost attribute parameters are assumed to be multivariate normally-distributed such that the joint probabilities used to construct the likelihood function for the MXL model are approximated through simulation by taking R = 500 randomized Halton draws of $\boldsymbol{\eta}$ from N($\mathbf{0}$, Ω) and evaluating the conditional joint choice probabilities at each draw. The simulated joint probability is the mean over the R draws.[4]

4. Data

The models developed above are applied to CE data from a survey that collected data to measure the public's preferences and values for protecting the Cook Inlet beluga whale (CIBW), a species found only in one geographic region within Alaska and listed as endangered under the U.S. Endangered Species Act (ESA) since 2008 (National Oceanic and Atmospheric

[3] The cost parameter γ is assumed to be a fixed parameter to facilitate the calculation and interpretation of welfare estimates.

[4] The simulated maximum likelihood procedure was programmed in GAUSS and uses 500 quasi-random (randomized Halton) draws (Train, 2003; Bhat, 2003).

Q12 Here is the current program with two alternatives. Which alternative do you most prefer and which alternative do you least prefer? *Please indicate your responses below the table.*

	Alternative A Current program	Alternative B	Alternative C
Population status in 50 years…..... (endangered now)	**Endangered**	**Threatened**	**Threatened**
Risk of extinction by the year 2112…………………………….. (25% now)	**25%**	**15%**	**10%**
Added cost to your household (one-time payment)…………..	**$0**	**$40**	**$50**
	Alternative A	**Alternative B**	**Alternative C**
Which alternative do you prefer the most? *"X" only one box* →	☐	☐	☐
Which alternative do you prefer the least? *"X" only one box* →	☐	☐	☐

Fig. 1. Example of choice experiment question (Pay1 survey version).

Administration, 2016). The survey was developed with input from scientists and policy analysts involved with the CIBW and from six focus groups and 13 cognitive interviews conducted in multiple locations during 2009 and 2010.

The survey included information about threatened and endangered species in the U.S., including other threatened and endangered whale species in the U.S., and specific information about the CIBW, including a description of the population declines over time, the causes for the decline identified by scientists, and the outlook for the population if current protection and population trends continue. To set up the CE questions, respondents were informed of the possibility of additional protection measures being undertaken to help recover the CIBW,[5] where "recovery" is defined as reducing the risk of extinction to a very small level and removing the species from the ESA list.[6] Both positive and negative effects of these actions on households were noted. Included in the set-up for the CE questions were instructions on how to answer them, a budget reminder, and a cheap talk script intended to reduce hypothetical bias (Cummings and Taylor, 1999).[7] In each of the four CE questions, respondents were asked to choose their most preferred and least preferred option from among three alternatives that differ in the results of protection (in 50 years) provided to the CIBW and in their costs (see Fig. 1). The survey concluded with several questions that collect socio-demographic information about the respondent and the respondent's household.

The payment vehicle used in the CE questions was an "added cost" to the household in the form of increases in costs of goods and services and federal taxes.[8] Three different payment horizons were presented in the study. In the Pay1 survey version, the added cost for each alternative in the CE questions was presented as a lump sum payment. Respondents would not be asked to pay anything additional beyond the single payment. In the Pay5 survey version, the added cost was presented as an annual payment by the household that would occur for five years. Similarly, in the Pay10 survey treatment the added cost was presented as an annual payment made 10 years. Respondents were reminded about the number of payments in the instructions that precede the CE questions and in the questions themselves, with the "one-time payment" in the Pay1

[5] The survey discusses several protection actions that can be taken to help recover the species, including the following: further regulating commercial fishing, reducing pollution (chemical and noise) sources, minimizing impacts from coastal development on beluga whales, increasing monitoring activities to identify and rescue stranded whales, and preventing illegal hunting.

[6] Note that respondents were informed at numerous junctures that the survey's sponsor was the National Oceanic and Atmospheric Administration (NOAA), the agency in charge of managing and recovering the Cook Inlet beluga whale, which enhanced the belief that survey input would be consequential. This was reflected in focus group input about the credibility of the survey content, protection scenarios presented, and CE questions.

[7] The specific cheap talk script was the following: "For hypothetical questions like these, studies have shown that many people say they are willing to pay more for protecting threatened and endangered species than they actually would pay out of their pockets. We believe this happens because people do not really consider how big an impact an extra cost actually has to their family's budget when answering these types of questions. To avoid this, as you consider each question, please imagine your household actually paying the cost for the alternative you select from your household's budget."

[8] This combination payment vehicle potentially raises concerns over whether it was viewed by respondents as "fixed and nonmalleable" (Johnston et al., 2017) given the "increased cost" component would vary by respondent. Moreover, there may be concerns over whether respondents were able to discount the "added cost" component in the future. However, focus group and cognitive interview testing suggested people generally assumed the federal tax was certain and binding and would make up most, if not all, of the "added cost" to their household. Nevertheless, the possibility exists that some portion of the payment vehicle is viewed as avoidable by some, which could result in biased results.

Table 1
Sample Characteristics (N = 719).

Variable	Description	Value
Gender	% male	47.80
Homemakers	% homemakers	6.00
Environmental/Conservation Contribution/Membership	% who contributed time or money to, or have been a member of, an environmental or conservation organization	49.50
Education	% bachelor's degree or higher	53.96
Race/Ethnicity	% white/caucasian	87.60
Age	Mean age (years)	51.4
Household size	Mean household size (persons)	1.7
Income	Mean household income ($)	86,311

version (Fig. 1) and cost "per year" in the Pay5 and Pay10 versions underlined to highlight the payment horizon for the respondent.

Furthermore, for each survey treatment, there were 16 survey versions that differed in the attribute levels (ESA statuses, risk of extinction, and added costs) seen by respondents. The possible attribute levels for the population status under Alternatives B and C were "endangered" (the current ESA status), "threatened," or "recovered." Additionally, there were ten possible extinction risk levels that could be achieved under Alternatives B and C ranging from "less than 1%" to 22%, which is less than the 25% extinction risk associated with Alternative A, the current (status quo) program since only options that enhance the protection were assumed.[9] The experimental design also included non-zero added cost amounts for Alternatives B and C ranging from $10 to $350. The final experimental design was selected using a program developed in GAUSS that maximized the D-efficiency assuming a main effects utility specification (Louviere et al., 2000).[10] The resulting 48 survey versions (16 × 3 payment treatments) were distributed randomly and in equal numbers across the three treatment samples (Pay1, Pay5, and Pay10).

Utility is assumed to be linear in PVC and ESA status level and quadratic in extinction risk level achieved in 50 years under the jth alternative. The ESA status levels (endangered, threatened, or recovered) are represented in the model as effects-coded variables (Louviere et al., 2000). The assumed baseline level for the ESA status variables is the status quo ESA level, which is endangered for the CIBW. Thus, there are two effects-coded variables. As a result, one expects that, *a priori*, the utility parameters associated with the ESA status levels will be positive, given improvements to the species are assumed to yield positive marginal utility, all else equal. The extinction risk is modeled as a reduction in extinction risk, allowing for a non-linear (quadratic) effect of extinction risk reductions on utility. All else equal, one would expect risk reduction to have a positive marginal effect on utility.[11] Additionally, an alternative specific constant (ASC) associated with the status quo option (Alternative A) is included to identify the tendency of individuals to select or not select this alternative (Scarpa et al., 2005).

The survey was fielded in the summer and fall of 2013 to 2100 urban households in Alaska.[12] The sample was drawn from Marketing Systems Group's database, which was constructed from the U.S. Postal Services' Computerized Delivery Sequence File and therefore has nearly 100% coverage of households in Alaska. Survey implementation followed a modified Tailored Design Method mixed mode approach (Dillman et al., 2009) with five contacts: an advance letter, initial mailing with a small monetary incentive ($5), a postcard reminder, a follow-up telephone call, and a second full mailing. A total of 902 completed surveys were returned, and the overall response rate excluding undeliverables was 46.0%. The data used for the analysis consists of 719 respondents that exclude 46 individuals not answering any of the choice questions and 137 protest respondents.[13]

Table 1 presents summary statistics of several characteristics of the sample. The sample of urban Alaska household respondents is predominantly white/Caucasian (88%), has a mean age and annual household income of 51 years and $86,311, respectively, and has slightly more females than males (48% male) and over half have at least a college degree (54%). Relative to statewide estimates that include both urban and rural areas, the urban sample has a slightly higher proportion of white/Caucasian and female respondents, is older and more educated, and has a higher average household income (https://www.census.gov/quickfacts/ak). Moreover, about half of respondents (49.5%) indicated having contributed time or money to, or being a member of, an environmental or conservation organization in the past.

[9] The experimental design includes two attributes (ESA status and extinction risk levels) that are necessarily positively correlated. To minimize the correlation and allow for the identification and estimation of separate effects, the experimental design was constructed to allow multiple extinction risk levels to be associated with more than one ESA status level.

[10] A similar approach to the experimental design construction described in Lew and Wallmo (2017) was followed.

[11] Note that the linear risk reduction parameter is treated as a random parameter in the empirical utility specification while the quadratic risk reduction parameter is treated as fixed. Thus, the preference heterogeneity in risk reduction is motivated by an error components interpretation.

[12] Alaska urban households were defined as households located in a metropolitan or micropolitan statistical area as defined by the U.S. Census bureau and delineated in OMB Bulletin No. 13-1. See http://www.census.gov/population/metro/data/omb.html.

[13] Likert scale questions that directly followed the CE questions were used to identify protest respondents, who were those identified to be strongly anti-tax.

Table 2
Estimation Results for MXL Models.

	Exponential EXP Model		Hypberbolic – Harvey HH Model		Hyperbolic – Mazur HM Model		Infinite INF Model	
Parameter	Estimate	Asy. T-value	Estimate	Asy. T-value	Estimate	Asy. T-value	Estimate	Asy. T-value
Mean parameters								
SQ	−2.4995**	−7.4442	−2.4943**	−7.4612	−2.4910**	−7.4724	−2.4491**	−7.3387
Reduced risk (RR)	0.2742**	5.9984	0.2743**	6.0285	0.2747**	6.0512	0.2633**	5.9439
Reduced risk squared (RRSQ)	−0.0092**	−5.2348	−0.0092**	−5.2427	−0.0092**	−5.2490	−0.0090**	−5.1721
Threatened (THR)	0.5349**	2.6725	0.5302**	2.6602	0.5283**	2.6576	0.5015**	2.5376
Recovered (REC)	1.1313**	2.8321	1.1220**	2.8127	1.1181**	2.8075	1.0814**	2.7118
Present value cost (PVC)	−0.0105**	−6.1790	−0.0107**	−6.5999	−0.0108**	−6.5160	−0.0160**	−12.2373
Discount rate parameters								
Exponential (r)	1.2191**	2.7623						
Harvey (μ)			1.6462**	5.7147				
Mazur (ω)					2.8513**	2.4933		
Cholesky matrix parameters								
SD(SQ)	4.5319**	15.2761	4.5324**	15.2518	4.5308**	15.2723	4.5325**	15.0343
CHOL(SQ,RR)	−0.0338	−1.2660	−0.0328	−1.2325	−0.0319	−1.2022	−0.0487*	−1.9174
SD(RR)	0.4675**	15.1191	0.4661**	15.0884	0.4656**	15.0646	0.4576**	15.2462
CHOL(SQ,THR)	−0.5359*	−1.9383	−0.5318*	−1.9322	−0.5286*	−1.9310	−0.5474**	−1.9504
CHOL(RR,THR)	−0.4393	−1.3278	−0.4270	−1.2957	−0.4208	−1.2804	−0.3516	−1.0723
SD(THR)	−2.7128**	−9.5060	−2.6954**	−9.4526	−2.6860**	−9.4397	−2.6777**	−8.9538
CHOL(SQ,REC)	−0.2168	−0.4188	−0.2266	−0.4454	−0.2284	−0.4528	−0.2729	−0.5297
CHOL(RR,REC)	0.0411	0.0637	0.0521	0.0810	0.0602	0.0935	0.1301	0.2047
CHOL(THR,REC),	−2.5096**	−4.3772	−2.4624**	−4.2925	−2.4359**	−4.2463	−2.5185**	−4.2491
SD(REC)	2.7290**	6.7577	2.7297**	6.8242	2.7289**	6.8582	2.6828**	6.9874
Mean log-likelihood	−4.1853		−4.1852		−4.1854		−4.1924	
LRI	0.416		0.416		0.416		0.415	
AICc	6053.294		6053.249		6053.494		6061.431	
BIC	6130.245		6130.200		6130.445		6133.902	

Note: ** denotes statistical significance at the 5% level; * denotes statistical significance at the 10% level. SD(·) = standard deviation parameter; CHOL(·) = off-diagonal element of Choleski matrix.

5. Results

Table 2 (columns 2–7) presents the estimation results for the MXL models estimated for each of the three discounting models: the exponential discounting MXL model (EXP Model), the Harvey hyperbolic discounting MXL model (HH Model), and the Mazur hyperbolic discounting MXL model (HM Model). In general, all three models have estimated parameters that are very similar in sign and magnitude, which is unsurprising given the difference between the models lies in the cost terms alone. Across the three MXL models, the mean utility parameters are statistically significant and have the expected signs. The results suggest urban Alaska households value both reduced extinction risk and improved ESA statuses for the Cook Inlet beluga whale. The signs of the reduced risk of extinction parameter estimates (RR and RRSQ, the linear and quadratic parameters, respectively) suggest utility increases in risk reductions but at a declining rate. The marginal utility of improving the status of the species to a Threatened level (THR) is positive and generally smaller than that of improving the status to a Recovered level (REC). The parameter on the present value of cost (PVC) is negative, as expected from theory, and close in value across the three discounting models. Additionally, the ASC mean parameter (SQ) is negative and statistically significant in each model, indicating a preference for options that improve the CIBW, all else equal.[14] The variance-covariance matrix is summarized by the estimated Choleski matrix elements, at least half of which are statistically different from zero in each model. This implies preference variation over individuals in the sample, as well as correlation across some random parameters. The estimated discount rate parameters in the exponential and hyperbolic models are statistically significant at conventional levels and suggest future payments are heavily discounted. In the EXP Model, the estimated annual discount rate (r) is 1.22, or 122%. For the hyperbolic models, the estimated μ is 1.65 in the HH Model, and the estimated ω is 2.85 in the HM model. Fig. 2 displays the discount factor implied by each estimated model by year for a ten year payment horizon. The figure shows the steep drop off after year 0 with the hyperbolic specifications falling quicker than the exponential, though after year 3 the exponential discount factor becomes smaller than the hyperbolic ones. After that point, future payments are heavily discounted, with the discount factor less than 0.10 for all three discounting models.

Generally, the three MXL discounting models were statistically significant on the whole, with the likelihood ratio index (LRI), a pseudo-R^2 goodness-of-fit measure, being 0.416 across all three models, suggesting a nearly identical fit across

[14] The strong preference for non-SQ options is perhaps not surprising given the fact that about half of respondents indicated having given time, money, or been a member of an environmental or conservation organization, suggesting there is generally a pro-environmental sentiment among much of the sample.

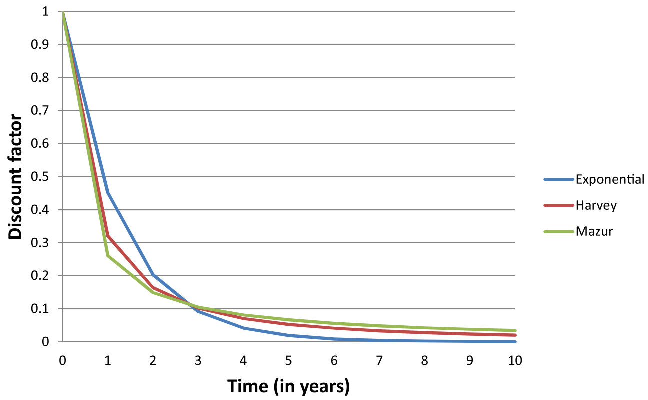

Fig. 2. Estimated discount factors by year under exponential and hypberbolic MXL models (r = 1.2191, μ = 1.6462, ω = 2.8513).

Table 3
Likelihood ratio tests for insensitivity to payment horizon for mixed logit models.

Discounting Assumption	Null hypothesis (H_0)	Test value	Critical value $X^2(.05, df = 1)$
Exponential	$r = \infty$	10.24*	3.84
Hyperbolic - Harvey	$\mu = \infty$	10.28*	3.84
Hyperbolic - Mazur	$\omega = \infty$	10.04*	3.84

* Indicates rejection of null hypothesis at 5% level of significance.

specifications (Table 2). Other model fit statistics are nearly identical across discounting specification as well; namely, the "corrected" Akaike's Information Criterion (AICc) and Bayes Information Criterion (BIC) are very similar across MXL models. Across the models, the HH Model has the lowest AICc and BIC values, suggesting it is perhaps the best fitting MXL specification, but the margin of difference from the other models is extremely small making it too close to determine a preferred model based on model fit criteria.[15]

5.1. Testing for insensitivity to payment horizon

The discounting models presented thus far assume either exponential or hyperbolic discounting by all respondents. Estimated discount rate parameters from these models suggest respondents heavily discount the future, with payments made after year 3 being discounted to less than 10% of the value in present value terms (see Discussion for how this compares to other studies). Given the very high estimated discount rate parameters, regardless of the discounting assumption, one may wish to evaluate whether respondents are insensitive to paying future costs. Those who are insensitive to the payment horizon, and hence only value the present, discount future benefits at an infinite discount rate (Stevens et al., 1997). Thus, under insensitivity to payment horizon, the PVC equals the annual payment C for all t (i.e., $PVC = C$, implying the discount factor ψ equals 1). In columns 8 and 9 of Table 2, the MXL model variant that assumes infinite discounting is presented (INF Model). Note that the infinite discounting model can be viewed as a restricted form of the exponential and hyperbolic discounting models, where the discount rate parameter for the model (r, μ, or ω) goes to infinity.

Pairwise LR tests to evaluate whether there is insensitivity to payment horizon (i.e., an infinite discount rate) are conducted by comparing the infinite discounting model (INF model) against each corresponding discounting model (i.e., EXP, HH, and HM models against INF model). The results of these tests are in Table 3, which shows that one can reject the null hypothesis of insensitivity to payment horizon (all tests suggest rejection at p-values < 0.01).

5.2. Sensitivity of willingness to pay to discounting assumptions

To determine whether different discounting assumptions lead to statistically different welfare estimates, tests for differences between welfare estimates from each discounting model are conducted. Willingness to pay is calculated for 25 scenarios representing improvements from the status quo to the Cook Inlet beluga whale in terms of reduced risk of extinction or improvement in ESA status. Expected willingness to pay, E[WTP], is calculated as $(-1/\gamma)\cdot(V^1 - V^\circ)$, where γ is the cost parameter, V° is the conditional indirect utility evaluated at the original (status quo) levels, and V^1 is the conditional indirect utility under the improved state of the world. Given V° and V^1 are functions of random parameters, E[WTP] is calculated

[15] Additionally, LR tests were done to test the null hypothesis that all parameters, as well as just the off-diagonal elements, in the variance-covariance matrix Ω are jointly zero, which would imply the conditional logit model. In all of these tests, the null hypothesis can be rejected.

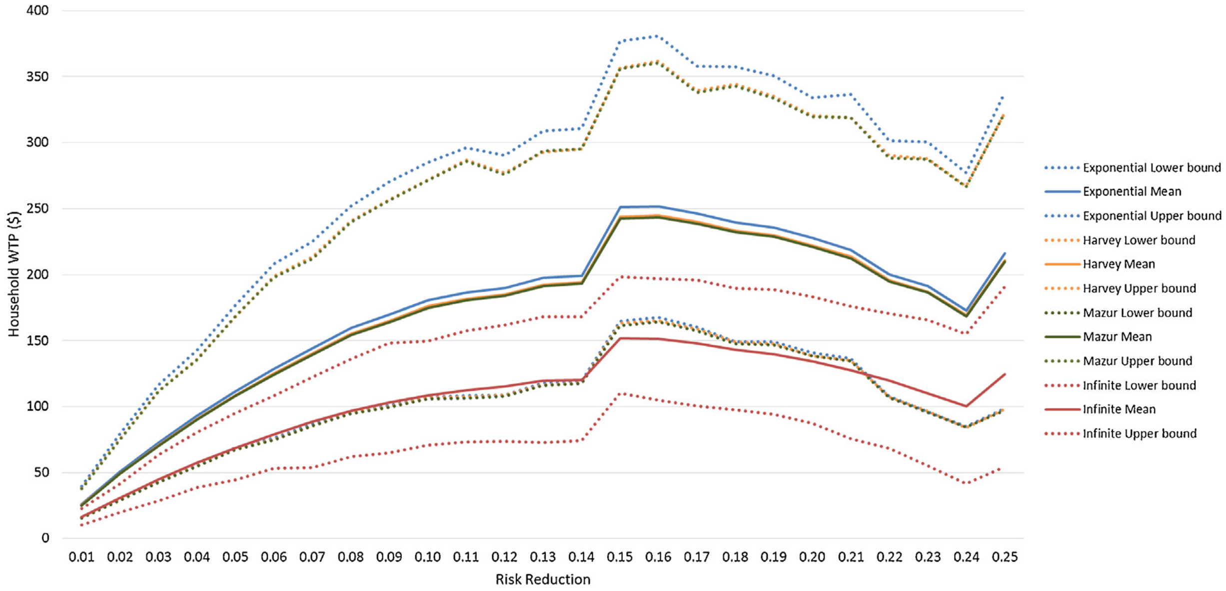

Fig. 3. Mean household willingness to pay (and 95% confidence bounds) as a function of reduced risk of extinction by discounting model (MXL models).

over the distribution of parameters in parallel fashion to the simulation-based estimation procedure. The estimated mean household WTP associated with the scenarios are presented in Fig. 3 for the MXL models.[16]

The figure shows the mean WTP as a function of risk reduction level assuming ESA status changes from endangered to threatened at a 15% risk reduction level and from threatened to recovered at 24%. There are distinct jumps in mean WTP at the risk reduction levels corresponding to moving to an improved ESA status—at 15% (endangered to threatened) and 24% (threatened to recovered). Mean WTP ranges from $26 to $252 for the EXP model, from $20 to $319 for the HH model, and $25 to $245 for the HM model, and are generally in the range seen in the endangered marine species literature for similar improvements (see Lew, 2015). For each model, mean WTP generally increases with reductions in extinction risk when the CIBW remains at an endangered ESA status. When the ESA status is improved to threatened, WTP initially increases but then decreases at the margin for risk reduction levels above the level needed for the ESA status change to threatened to occur. Mean WTP of an improvement to a recovered level is in the range of values associated with the threatened status. The figure also includes 95% confidence intervals constructed using the simulation approach of Krinsky and Robb (1986). All household mean WTP values are statistically different from zero. The 95% confidence intervals are generally wider for larger risk reduction levels than for smaller ones, and indicate that mean recovery values are statistically equivalent to values associated with the threatened status level.

In these figures, the 95% confidence intervals for WTP associated with different discounting models overlap to varying degrees. To formally evaluate whether there are differences in mean WTP between different discounting assumptions, 95% confidence intervals for the difference in mean WTP are calculated using the method of convolutions (MOC) approach (Poe et al., 2005). No statistically significant differences were found between the exponential and hyperbolic discounting models, or between the Harvey and Mazur hyperbolic discounting models. Moreover, comparisons between the exponential discounting model and the infinite discounting model indicate only three cases where the mean WTP is statistically different, in the range between 15 and 17 percent risk reduction and associated with a threatened ESA status. In that range, the MOC confidence intervals for the difference in mean WTP values between the exponential and infinite discounting models do not include zero (but only barely). For the 22 other cases, the mean WTP estimates were not statistically different. Furthermore, for all 25 mean WTP comparisons between the hyperbolic and infinite discounting models, no statistically significant differences were found. These results imply welfare estimates from exponential and hyperbolic discounting assumptions lead to statistically similar results, and one generally does not see a statistical difference in discounting models' welfare estimates from models ignoring discounting behavior.

[16] The feasible set of welfare scenarios was defined by the range of attribute levels in the experimental design, which included extinction risk reduction levels associated with multiple ESA status levels. Thus, for illustrative purposes, only 25 of the 31 possible welfare estimates are plotted graphically, assuming the switch-points for changes to the ESA status of the CIBW are at a 15% risk reduction (from Endangered to Threatened). The recovered status corresponds uniquely in the design to an extinction risk of less than 1 percent. Mean, median, and 95% confidence intervals for all 31 welfare scenarios are available upon request.

5.3. Extending the model to account for attribute non-attendance behavior

Up to this point, the analysis has proceeded using random utility maximization models that assume fully compensatory behavior—where individuals make choices in which they are fully informed and utility maximizing. However, CE researchers have increasingly come to recognize that some individuals may not utilize all the information provided to them about the choices they face and instead use simplifying decision rules or heuristics (e.g., Swait, 2001; Hensher, 2014). In particular, one type of partially compensatory behavior, attribute non-attendance (AN-A), has been the focus of a number of recent studies (e.g., Bello and Abdulai, 2016; Campbell et al., 2012; Hensher et al., 2012; Scarpa et al., 2009). AN-A occurs when an individual ignores one or more attributes in choice experiments and may arise due to several factors, including the complexity of the choices, unfamiliarity with the good being valued, and attributes being behaviorally inconsequential to the respondent (Alemu et al., 2013; Campbell et al., 2012; Sælensminde, 2002; Weller et al., 2014). Numerous studies have found that accounting for AN-A behavior has non-trivial impacts on welfare estimates (Bello and Abdulai, 2016; Campbell et al., 2012; Scarpa et al., 2009). AN-A behavior is typically identified by either directly querying respondents about which attributes, if any, are ignored when answering CE questions (e.g., Alemu et al., 2013) or by inferring the behavior through modeling approaches (e.g., Scarpa et al., 2009).

In this study, an inferred modeling approach is used to account for potential AN-A behavior because of the first-order implications ignoring the cost attribute would have on efforts to identify discounting behavior related to future payments. Specifically, the endogenous attribute attendance (EAA) model (Hole, 2011) is used to account for AN-A behavior. The EAA model assumes a two-step process. In the first step, the individual chooses which attributes will be included in the choice; that is, which attributes are paid attention to in making the choice. The second step involves choosing the alternative that yields the most utility given the underlying preferences.

The model proceeds as follows: For K attributes there are $Q = 2^K$ possible combinations of attributes, including the case with all K attributes and one where there are no attributes included. Let A_q be the set of attributes to which an individual pays attention in the choice occasion (for $q = 1, 2, \ldots, Q$). The probability of observing an attribute k ($k \in K$) being paid attention to is specified as a logit probability:

$$\Pr[k] = \exp(\theta_k)/[1 + \exp(\theta_k)]. \tag{13}$$

Note that the scalar parameter θ_k is an attribute-specific constant and could be replaced by a function of individual characteristics to allow for heterogeneity in attribute attendance behavior. Since the focus here is not on understanding factors influencing AN-A behavior, the model is specified with scalar parameters.

The probability of observing the specific set of attributes in A_q being used by the individual in the choice setting is the product of the binomial logit probabilities in Eq. (13):

$$Pr[A_q] = H_{A_q} = \prod_{k \in A_q} \left(\frac{exp(\theta_k)}{1 + exp(\theta_k)}\right) \times \prod_{k \notin A_q} \left(\frac{1}{1 + exp(\theta_k)}\right) \tag{14}$$

Note that this assumes independence of the individual attribute attendance probabilities.

Let the utility of Alternative j conditional on the individual paying attention to the A_q set of attributes be $V_j(\boldsymbol{\beta}^{Aq}) = \boldsymbol{\beta}^{Aq} \cdot \boldsymbol{x}_j^{Aq} + \gamma \cdot C_j \cdot \psi^g$, where $\boldsymbol{x}_j^{Aq}$ consists of variables associated with only the attributes included in A_q. The analog to Eq. (12), the joint probability of observing the selection of j as best, k as second best, and l as worst (denoted as $j > k > l$) conditional on A_q is then

$$Pr[j > k > l \mid A_q] = \pi_{jkl|Aq} = \int \{exp(V_j(\boldsymbol{\beta}^{Aq}))/\Sigma_k\, exp(V_k(\boldsymbol{\beta}^{Aq}))\} \cdot [exp(V_k(\boldsymbol{\beta}^{Aq}))/\Sigma_{m \neq j}\, exp(V_m(\boldsymbol{\beta}^{Aq}))]f\left(\overline{\boldsymbol{\beta}}, \Omega\right) d\boldsymbol{\beta}, \tag{15}$$

for all k, l, m, and $j \in \{A, B, C\}$. The unconditional probability is

$$Pr[j > k > l] = \sum_{q=1}^{Q} H_{A_q} \times \pi_{jkl|Aq}. \tag{16}$$

This equation is then used to construct the log-likelihood function. This mixed (random parameters) EAA model is estimated with simulated maximum likelihood estimation.

The versions of the EXP, HH, HM, and INF models accounting for attribute non-attendance are denoted the EAA-EXP, EAA–HH, EAA-HM, and EAA-INF models, respectively. Results suggest attribute non-attendance is present, statistically significant, and similar in magnitude across models regardless of the underlying discounting behavior assumed (Table 4). The attribute with the lowest probability of being ignored is the reduction in extinction risk attribute (represented in the model by RR and RRSQ), which has a probability of attendance of about 69 percent with a 95 percent confidence interval of [60%, 76%][17] for the exponential discounting (EAA-EXP) version of the model (Table 5). This suggests that on average 69% of respondents would be expected to pay attention to reduced extinction risk in answering the CE questions. In the exponential

[17] 95% confidence intervals for the probabilities of attribute attendance were calculated using the Krinsky-Robb simulation method with 1,000 draws.

Table 4
Estimation Results for Endogenous Attribute Attendance (EAA) MXL Models.

	Exponential EAA-EXP Model		Hypberbolic – Harvey EAA-HH Model		Hyperbolic – Mazur EAA-HM Model		Infinite EAA-INF Model	
Parameter	Estimate	Asy. T-value	Estimate	Asy. T-value	Estimate	Asy. T-value	Estimate	Asy. T-value
SQ	−2.3284**	−7.5211	−2.2783**	−7.6287	−2.3128**	−7.1699	−2.2295**	−7.4305
Reduced risk (RR)	0.8393**	7.2047	0.8709**	7.2103	0.8499**	6.1696	0.8661**	7.3343
Reduced risk squared (RRSQ)	−0.0236**	−6.3987	−0.0240**	−6.5422	−0.0238**	−5.7866	−0.0238**	−6.6050
Threatened (THR)	2.8552*	1.7312	3.3453**	2.8232	2.7282	1.4991	3.1584**	2.7447
Recovered (REC)	7.4412**	3.1686	7.0314**	3.9673	6.5220**	2.6157	7.3259**	4.2185
Present value cost (PVC)	−0.0453**	−3.5118	−0.0432**	−5.9661	−0.0437**	−4.8672	−0.0609**	−8.8833
Discount rate parameters								
Exponential (r)	2.2711	1.2739						
Harvey (μ)			2.0384**	4.5704				
Mazur (ω)					4.1478	1.2381		
Cholesky matrix parameters								
SD(SQ)	4.0281**	11.1294	3.9317**	11.0865	3.9784**	10.7443	3.8997**	11.1502
CHOL(SQ,RR)	−0.1705**	−3.9786	−0.1470**	−2.9081	−0.1750**	−3.4674	−0.1450**	−3.4738
SD(RR)	0.7614**	7.3373	0.7559**	9.7954	0.7751**	7.8292	0.7385**	9.4106
CHOL(SQ,THR)	−0.4123	−0.2622	0.5533	0.5143	−0.1286	−0.0611	0.5330	0.5529
CHOL(RR,THR)	−5.0968	−1.5238	−0.7455	−0.3887	−5.3617	−1.3354	−1.0379	−0.5508
SD(THR)	−4.6068**	−4.5676	−5.5128**	−5.9601	−4.3841**	−3.4940	−5.3297**	−6.0637
CHOL(SQ,REC)	3.7188**	2.4351	4.6162	2.7653	4.6522	1.8611	4.1205**	2.4308
CHOL(RR,REC)	3.1670	0.5618	12.4726	1.4908	3.5464	0.5634	6.7538	1.5405
CHOL(THR,REC),	−1.2779	−1.0546	−1.0456	−0.8676	−1.8709	−0.8597	−1.3454	−1.0161
SD(REC)	−0.1023	−0.0782	−0.3687	−0.2514	−0.7077	−0.3824	−0.2353	−0.0858
Attribute Non-Attendance Parameters								
Reduced risk (ANA-RR)	0.7953	4.1361	0.7088	3.8756	0.7688	3.6291	0.7648	4.0920
ESA Status (ANA-Status)	−1.2875	−4.9643	−1.1571	−4.4222	−1.2711	−4.5121	−1.2137	−4.5298
Cost (ANA-Cost)	−0.0176	−0.1082	0.0115	0.0815	−0.0391	−0.2113	−0.0642	−0.3988
Mean log-likelihood	−4.1227		−4.1226		−4.12226		−4.1255	
LRI	0.425		0.425		0.425		0.424	
AICc	5969.573		5969.497		5969.009		5971.604	
BIC	6059.926		6059.851		6059.363		6057.496	

Note: ** denotes statistical significance at the 5% level; * denotes statistical significance at the 10% level. SD(·) = standard deviation parameter; CHOL(·) = off-diagonal element of Choleski matrix.

Table 5
Probability of Attribute Attendance by Discounting Model (95% Confidence Bounds in Parentheses).

Attribute	Exponential	Hyperbolic-Harvey	Hyperbolic-Mazur
Reduced risk of extinction (RR)	0.687 (0.602, 0.760)	0.669 (0.583, 0.743)	0.681 (0.584, 0.765)
ESA Status - Endangered, Threatened or Recovered (END, THR, REC)	0.222 (0.142, 0.315)	0.244 (0.158, 0.345)	0.225 (0.139, 0.328)
Cost (COST)	0.498 (0.420, 0.578)	0.505 (0.434, 0.575)	0.492 (0.400, 0.584)

Note: Confidence bounds are simulated using the Krinsky-Robb approach with 1000 draws.

model, the attribute with the lowest probability of attendance is the ESA status attribute (represented by THR and REC), which is about 22 percent with a 95% confidence interval of [14%, 32%]. Note that the cost attribute attendance parameter is not statistically significant, which means in this context that the probability of attendance to the cost attribute is not different from an even chance. Specifically, the cost attribute has a probability of attendance of 50 percent with a confidence interval of [42%, 58%]. The attribute attendance probabilities for the EAA−HH and EAA-HM models are nearly identical to those of the EAA-EXP model (Table 5).

Discount rate parameters are larger in magnitude than in the corresponding MXL models. For example, the exponential EAA model has an estimated discount rate of 2.27 compared to 1.22 found in the standard model. Besides the attribute attendance parameters, other parameters are largely the same in terms of sign, but differ in magnitude, compared to the MXL models. In the EAA models, the non-SQ parameters are generally larger in magnitude, particularly the reduced extinction risk attribute parameters, while the SQ parameter in the EAA models is slightly smaller suggesting a weaker status quo effect. At the model level, accounting for AN-A behavior improves model fit, and LR tests for the null hypothesis of no AN-A are rejected at all conventional confidence levels ($p < 0.01$).

Tests of the utility specifications to identify sensitivity to payment horizon and of WTP differences between different discounting models led to similar results to those for the standard models. LR tests for insensitivity to payment horizon are

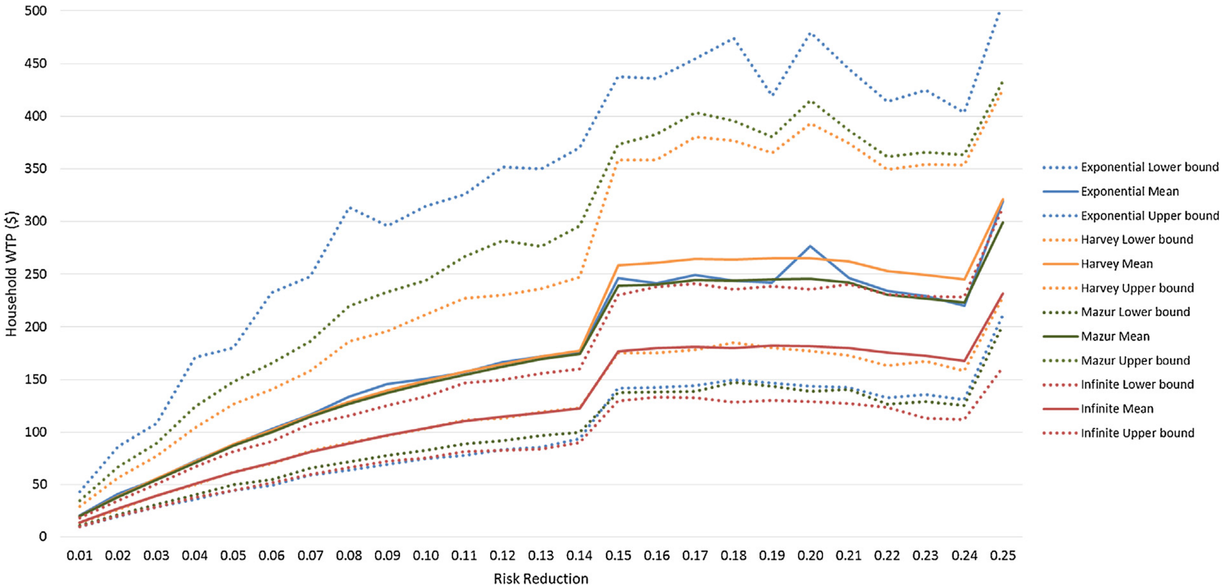

Fig. 4. Mean household willingness to pay (and 95% confidence bounds) as a function of reduced risk of extinction by endogenous attribute attendance (EAA) discounting model.

rejected at conventional levels ($p < 0.05$). Mean WTP estimates from the EAA models are not uniformly larger or smaller than the MXL model WTP estimates, though mean WTP for smaller improvements in ESA status and reductions in extinction risk tend to be smaller in the EAA models, while larger improvements are generally larger (Fig. 4). MOC tests suggest no significant differences between mean WTP calculated from the exponential and hyperbolic versions of the EAA models. Similarly to the standard MXL models, there were no cases of statistically significant WTP differences between the EAA model versions of the discount rate models and the infinite discounting model found in MOC tests. Therefore, the basic findings for the MXL models are corroborated with models accounting for AN-A behavior.

6. Discussion

In many stated preference surveys involving non-market goods, individuals are asked to trade future benefits for future costs. In these cases, how individuals make intertemporal decisions is a first order concern. In this paper, implicit rates of time preference under alternative models of discounting behavior are estimated jointly with CE data to measure preferences and values associated with the protection of an endangered species. Implied discount rates are identified through variation in the stream of future costs respondents would need to pay for future improvements in the ESA status and reduced risk of extinction for the Cook Inlet beluga whale. The CE data were estimated with a standard choice model that accounts for preference heterogeneity–the MXL model–and an extension of it that accounts for attribute non-attendance (the EAA model).

With both the MXL and EAA models, the exponential and hyperbolic discounting assumptions led to very similar results, both in terms of preferences and willingness to pay. Generally, the EAA models fit the data better and indicated the presence of attribute non-attendance. This is consistent with other recent empirical studies using inferred AN-A models (e.g., Bello and Abdulai, 2016; Campbell et al., 2012; Scarpa et al., 2009). Note that while accounting for attribute non-attendance in this application appeared to improve model fit, it only led to minor qualitative differences in the results for the discount rate parameters and welfare estimates. The general findings from the MXL discounting models – large discount rates and WTP that increases with extinction risk reductions and ESA status improvements and that are generally statistically equivalent to welfare estimates from models that ignore discounting – did not change.

In this study, a preferred discounting model could not be determined, as model fit statistics across the exponential and hyperbolic discounting models were virtually identical. This is in contrast to the only other study to employ an endogenous approach to jointly estimate discount rates and CE behavior, which found the exponential discounting model was preferred (Meyer, 2013a, b). It also runs counter to a recent experimental study by Andersen et al. (2014) that provides evidence in favor of exponential discounting. Additional empirical studies, however, are needed to see how robust this result is.

Tests for insensitivity to payment horizon were rejected in all model specifications, suggesting support for the hypothesis that people were discounting future payments, albeit at high levels. The heavy discounting of future costs found in all models had a substantial impact on present value of welfare estimates and likely drove the equivalence of the discount rate model welfare estimates with those from the infinite discounting model that ignores future costs. In the models assuming exponential discounting, the constant discount rate was estimated to be 122% in the MXL model and 227% in the EAA model. These discount rates are generally larger than (or at least on the upper end of) those found in other studies that have used endogenous approaches to jointly estimate discount rates with SP responses from variations in payment horizons for non-market goods (Bond et al., 2009; Kovacs and Larson, 2008). Annual discount rates in those studies were between 23 and 80%. The estimated discount rates for the exponential models are on the high end of those from studies using exogenous approaches.[18] For instance, using the two-step exogenous approach to identify discount rates under exponential discounting, Kim and Haab (2009) estimated discount rates between 20 and 131% from estimates of WTP for an oyster reef restoration program, and Egan et al. (2015) estimated implied discount rates of between 15 and 104% by comparing WTP estimates for a wetlands restoration program. Also, discount rates elicited from supplemental survey questions asking respondents to choose between current and future payments were on average 20% or less in both Egan et al. (2015) and Newell and Siikamäki (2014). The discount rates estimated in this study are, however, smaller than those found by Myers et al. (2017), who reported discount rates of over 300% using a two-step indirect approach.[19]

Compared to other studies that have identified discount rates through variation in the benefits horizon (e.g., Layton and Brown, 2000; Meyer, 2013a,b), the results here are also on the high end. For example, in the only other study to endogenously estimate discount rates from CE data, and for different types of discounting behavior, Meyer (2013a, b) estimated exponential discount rates between 10 and 13%. Importantly, Meyer (2013a, b) also estimated models assuming hyperbolic discounting, finding that the Harvey and Mazur models did not fit the data as well as the exponential model. As one would expect given his results for the exponential model, the estimated discount rate parameters associated with the hyperbolic discounting models were much smaller than those estimated here (μ and ω were less than 1.0 in all specifications) (Meyer, 2013a, b). On the other hand, Viscusi et al. (2008) did find evidence of hyperbolic discounting by comparing marginal WTP estimates for future water quality improvements over different time horizons, though discount rates in that study were likewise smaller than those observed here.

However, one should be careful in comparing discount rates derived from variation in benefit horizons with those derived from alternate payment horizons because there are likely time preference inconsistencies between gains (benefits) and losses (payments) (Crocker and Shogren, 1993; Abdellaoui et al., 2009). Kim and Haab (2009) suggest they can be different due to factors such as the market discount rate and uncertainty in the financial market. The relative difference in uncertainty about the provision of the future benefits relative to paying future costs itself is likely to create a wedge in the discount rates observed. In fact, in a study analyzing the difference between implied discount rates between money-risk trade-offs and money-money trade-offs, Alberini and Chiabai (2007) found that people had a higher discount rate for money-money trade-offs.

Myers et al. (2017) expressed concern that the large discount rates found in the literature that are in the range found in this study are “implausibly high” and indicative of respondents not seriously considering the future stream of payments implied by the payment vehicle. This would suggest there exists a disconnect between actual discount rates and estimated ones. In stated preference studies specifically, this disconnect could potentially occur because of poor survey design; for instance, if the survey does not clearly present the payment vehicle as a series of payments specified over a fixed time period. Here, however, feedback from multiple focus groups and cognitive interviews suggest that this feature of the payment vehicle was clear to respondents and influenced decision-making about CE questions. Thus, the survey design is not likely a biasing factor in this application. Another possible source of a disconnect between actual and measured discount rates is attribute non-attendance, particularly as it relates to the cost attribute. Although attribute non-attendance behavior was found in this study, accounting for it did not decrease the magnitude of discounting; rather, discount rates were higher. That said, one cannot rule out a potential role of inattention to the survey as a whole on choice behavior, an issue that has received some recent attention (e.g., Malone and Lusk, 2018), though the pattern of survey responses does not immediately suggest this was an issue.

Given the rejection of insensitivity to payment horizon in hypothesis testing, it is unlikely the large estimated discount rates are a reflection of respondents fully ignoring future payments in their CE responses. Instead, there may be other reasons to expect high empirical discount rates. Frederick et al. (2002) note that even in the broader economics literature there is a predominance of high empirical discount rates. They discuss several “confounding factors” that are not generally accounted for in empirical studies and that may influence this pattern. First, the role of inflation on future costs will mean money has less buying power in the future. To the extent respondents factor this into their decision making, the estimated discount rate will be biased upward. Second, respondents are expected to assume future payments (and program benefits) are certain to occur. Respondents instead may attach some level of uncertainty to the future payments they would be expected to make in the future. This would impact the magnitude of the discounting behavior if their expectation is that they would not have to continue paying in the future, either due to a programmatic change or a change in their own circumstances (e.g., if their life expectancy is short). Third, respondents may have expectations about their changing utility that would create an upward bias in observed discount rates, such as the marginal utility of money decreasing in the future due to an increase in wealth. These confounding factors do not create a full disconnect between actual and measured discount rates, but they do suggest potential sources of bias embedded in empirical discount rates that have been generally under-investigated (Frederick et al., 2002). Unfortunately, the present study was not designed to identify these confounding factors. Thus to the extent they are

[18] However, they are below several others reported in Table 1 of Frederick et al. (2002).

[19] Note, however, that the CV question used in Myers et al. (2017) did not highlight or emphasize the payment horizon information to respondents, which may have resulted in respondents not understanding how many times they were being asked to pay the cost amount presented. This could explain the large observed discount rates.

present, respondents' true discount rates are likely lower than those estimated. Research to understand how much of an influence these confounding factors have on estimated discount rates and to develop methods for minimizing these effects in studies measuring rates of time preference is clearly needed.

This discussion and the heavy discounting of future costs observed in this study raise questions about the appropriate discount rate to apply in benefit-cost analyses for non-market goods with significant non-use value, like the endangered species examined here. The discount rates suggested by the Office of Management and Budget's Circular A-94, which provides guidance on the discount rates to use in regulatory analyses in the U.S., are generally much lower than the discount rates estimated here by an order of magnitude or more (see https://obamawhitehouse.archives.gov/omb/circulars_a094/a94_appx-c). This underscores a problem that could arise when trying to apply results from a SP study in which there is a fixed payment horizon and implicit discount rates are not estimable (which describes most empirical studies in the literature!). Clearly, for non-market goods for which there is likely significant discounting of future payments (even accounting for the potential role of confounding factors), using discount rates commonly used for policy analysis (e.g., 3 or 7%) to calculate the present value of people's WTP may greatly overestimate the actual present value. At the same time, transferring a discount rate from an existing SP study valuing a similar good is itself a dubious approach, given the wide range of discount rates estimated in the literature and the potential for individual-level heterogeneity in discount rates to complicate transfers.[20] This suggests that in cases where future benefits or costs are valued, discount rates should be estimated using one of the approaches discussed herein.

Of course, it may not always be possible to include discount rate elicitation questions like those in Newell and Siikamäki (2014) and Egan et al. (2015) in the SP survey or to include alternative survey treatments that allow for estimation of implied discount rates. Thus, a natural question for SP researchers to ask is whether or not future payments should be used as part of payment vehicles in these cases. This is especially important if one is uncertain about being able to accurately measure discount rates for future costs, either because of confounding factors that may bias discount rates or because of a general concern about individuals being unable to meaningfully consider future payments in their responses to CE questions. For these reasons, an argument can be made for using a lump-sum payment as a payment vehicle in SP questions, which would eliminate the need to estimate, transfer, or otherwise choose a discount rate for determining the present value of WTP, at least in cases where the benefits horizon is fixed. While a significant pitfall of this approach is that WTP would be constrained by present-day income, which would likely lead to underestimates of the true present value of WTP, it does represent a conservative, or lower bound, approach to inclusion of economic benefits similar in spirit to some efforts to mitigate sources of hypothetical bias (Loomis, 2014) or the practice of adjusting downward the population over which welfare is aggregated done in many SP studies (Loomis, 1987).

Note that this lump-sum payment vehicle approach runs counter to the recent suggestion by Egan et al. (2015) (and the guidance provided in Recommendation 11 regarding payment vehicles in Johnston et al., 2017), who argued in favor of using a payment horizon for recurring payments that matches with the benefits horizon.[21] While their suggested approach makes comparisons of benefits and costs easier for respondents in a given year (in fact, it eliminates the need for discounting calculations), to the extent present value calculations need to be done for policy analysis, information on discount rates would still be needed. Therefore, in many cases their approach still requires selecting or estimating discount rates. As a result, researchers should carefully assess the extent to which present value calculations are needed for applying the SP information being measured when constructing surveys (generally) and payment vehicles (specifically), and either include means for understanding discounting behavior when deemed appropriate and feasible, or use a lump-sum payment vehicle to reduce the reliance on discount rates for calculating the present value.

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[20] While not explored in this application, other studies have found evidence that discounting behavior may be affected by individual characteristics (e.g., Frederick et al., 2002; Meyer, 2013b; Newell and Siikamäki, 2014).

[21] One of the arguments Egan et al. (2015) make for using annual payments instead of a lump sum payment is the convergence of WTP estimates from analysis of referendum CV data using annual payments and a travel cost model. However, Whitehead (2017) provides evidence that their finding in favor of annual payments in the analysis is sensitive to the model chosen and assumptions made about the data and discount rates to test.

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