Place of Residence and Cost Attribute Non-Attendance in a Stated Preference Choice Experiment Involving a Marine Endangered Species

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ABSTRACT

Spatial variation of economic benefits associated with endangered species based on place of residence may be important to understand given conservation actions often place an unequal burden on rural and non-rural areas. In this article, place of residence differences are examined using split-sample stated preference choice experiment survey data from a study involving public preferences for protecting an endangered species, the Cook Inlet beluga whale. Standard mixed logit models provide evidence of a difference in estimated preference functions and willingness to pay (WTP) between households from rural and non-rural areas. However, when cost attribute non-attendance is accounted for, both rural and non-rural WTP estimates are scaled downward and differences in WTP dissipate.

Key words: Attribute non-attendance, choice experiments, endangered species, mixed logit, stated preferences, rural, willingness to pay.
JEL Codes: Q5, Q57.

INTRODUCTION

Over the past several decades, studies to measure economic benefits of protecting threatened, endangered, and at-risk (TER) species have been conducted for a wide range of species across a handful of countries (Richardson and Loomis 2009; Lindhjem and Tuan 2012; Lew 2015). The total economic value associated with TER species is comprised largely, if not exclusively, of non-consumptive value, which can be measured with stated preference (SP) methods. Among studies valuing the total economic value of TER species protection, SP choice experiments (CE) are increasingly being used (e.g., Bartczak et al. 2016; Lew, Layton, and Rowe 2010; Lew and Wallmo 2011, 2017; Rudd, Andres, and Kilfoil 2016; Wallmo and Lew 2012, 2016; Wakamatsu et al. 2018).

Heterogeneity of public preferences is important to understand in modeling CE data in TER species applications. Generally, allowing for heterogeneity in models of choice behavior is a

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desirable way to relax restrictive assumptions about people's preferences and potentially improve model fit and predictions. One common model that accounts for preference heterogeneity by allowing utility parameters to vary over people is the mixed, or random parameters, logit (MXL) model (Train 2003; Greene and Hensher 2003). In a CE study by Lew, Layton, and Rowe (2010), MXL models are used to estimate the value of increasing the population size and improving the conservation status of the endangered Steller sea lion. MXL models are also used by Wallmo and Lew (2012, 2016) and Lew and Wallmo (2017) to estimate the value of improving the conservation status of multiple TER species in the U.S. and by Wakamatsu et al. (2018) to examine differences in preferences for conserving whales between samples in Australia and Japan. An alternative approach to allow for preference heterogeneity is the latent class logit model (Boxall and Adamowicz 2002; Greene and Hensher 2003), which assumes there is a finite number of groups composed of individuals with identical preferences. Rudd, Andres, and Kilfoil (2016) use this model to analyze CE data to value three lesser-known, at-risk aquatic species in Canada. Further, Bartczak et al. (2016) follow this approach in a model that combines responses to questions identifying their risk preferences with CE data to value threatened lynx species in Poland, and Wakamatsu et al. (2018) employ a two-class latent class logit model to estimate preferences toward whale conservation in Japan.

One potentially important dimension over which preferences may vary is geography. Understanding spatial variation in preferences for TER species can be important given the benefits and costs of policies to protect these species may differentially affect people in different areas. Two recent CE-based species valuation studies investigate spatial heterogeneity of preferences for TER species (Wallmo and Lew 2016; Johnston et al. 2015). Using samples of households in different regions of the U.S., Wallmo and Lew (2016) evaluate whether the willingness to pay (WTP) to recover eight TER species varies across nine regions of the country. They find evidence of regional variation in WTP values for several species. On a more micro level, Johnston et al. (2015) use spatial interpolation and local indicators of spatial association approaches to show that individual WTP estimates for protecting TER species are clustered in hot (high WTP) and cold (low WTP) spots in the U.S.

A spatially related characteristic that can be a particularly important source of heterogeneity is place of residence—particularly residency in rural areas (regions of low population density with most employment in primary production activities) as opposed to non-rural areas (regions with higher concentrations of people and economic activity not as dependent on primary production activities) (Irwin et al. 2009). There is evidence that people living in rural and non-rural—particularly urban—areas[1] have different attitudes toward environmental goods and services generally (Freudenburg 1991; Berenguer, Corraliza, and Martin 2005), which are likely to manifest in differences in behavior (Ajzen 1991). Understanding these differences may be important for policy evaluations, particularly for understanding distributional issues and assessing impacts on different stakeholder groups. In many cases, conservation and environmental protection actions place an unequal burden on rural and non-rural areas. For some threatened or endangered species, for instance, conservation actions may more directly impact households in rural areas that are near species habitat. These households may be less likely to support conservation actions that could potentially impact them negatively (e.g., limits on recreational or

1. Non-rural areas can include urban and suburban areas (towns and cities), as well as exurban areas (low-density areas in proximity to urban and suburban areas with high economic and social dependence on them).

commercial activities) due to their proximity to habitat areas. For example, Bandara and Tisdell (2003) examine attitudes and preferences related to conserving the endangered Asian elephant in Sri Lanka, where the species is viewed as a nuisance by those who live in the rural areas within its habitat. They find that while both rural and urban Sri Lankan households generally support conservation of the Asian elephant, there is considerably more variation in support among rural households. Similarly, Ericsson, Bostedt, and Kindberg (2008) find evidence among households in Sweden of an urban-rural divide in preferences for protecting large carnivores, like wolves and bears. In the valuation literature, urban-rural differences have been found for a range of environmental goods and services (e.g., Bergmann, Colombo, and Hanley 2008; Yoo and Ready 2014; Tiller, Jakus, and Park 1997). In this literature, only a contingent valuation study by Veisten, Hoen, and Strand (2004) examines the effects of place of residence on species values, finding that WTP for preserving forest habitat in Norway for several endangered species is higher for households that are less rural.

In this article, the extent to which there is a difference in rural and non-rural preferences and economic values for the conservation of an endangered species, the Cook Inlet beluga whale (CIBW), is explored. The CIBW is one of a handful of distinct populations of beluga whales found throughout the northern hemisphere and is listed as endangered under the U.S. Endangered Species Act (ESA) (Hobbs et al. 2015). CE data from a survey administered to separate rural and non-rural samples are analyzed with several MXL models. With conventional MXL models, there is evidence of a difference in both estimated preference functions and WTP. However, when allowing for payment vehicle, or cost, attribute non-attendance (ANA) in the model, which accounts for cases in which CE respondents ignore the cost attribute (Koetse 2017), both rural and non-rural WTP estimates are scaled downward and welfare differences dissipate.

In addition to investigating whether there is a divide between rural and non-rural households in both preferences and welfare estimates for an endangered species, this article makes two additional contributions. First, the cost ANA model of Koetse (2017), originally applied to a conditional logit (CL)-based latent class model, is extended to a mixed logit (MXL) specification to capture preference heterogeneity (similar to Thiene, Scarpa, and Louviere [2015]). As argued by Hess et al. (2013), this is necessary to disentangle preference heterogeneity from ANA (i.e., to distinguish true zero marginal utilities from those that are probabilistically zero). Second, it is the first study to value reductions in extinction risks for an endangered species using a CE approach.[2] Recent TER species valuation studies using CE surveys have largely focused on valuing conservation status improvements that consequently provide limited information about the economic benefits of more marginal improvements to species. This limits the utility of these studies to be used for evaluating alternative conservation actions that do not result in status changes. The CE questions in this study include an attribute that matches up with a typical output of population viability analyses (PVAs), extinction risk, which have the potential to be used to evaluate the economic benefits of alternative conservation actions' effects on TER species (Beissinger and Westphal 1998; Boyes 1992; Gerber and Gonzalez-Suarez 2010).

2. Few contingent valuation studies have estimated WTP for discrete reductions in extinction risk for endangered species. See, for example, Whitehead (1992) and Reaves, Kramer, and Holmes (1999).

EMPIRICAL SETTING

The Cook Inlet beluga whale (*Delphinapterus leucas*) was listed as endangered under the ESA in 2008. The population of CIBWs resides exclusively in the waters of the Cook Inlet in Alaska (figure 1). It was listed as endangered due to persistent population declines since the 1970s from both anthropogenic and natural sources. A recent population assessment estimates there are only 340 individuals left, down from about 1,300 in the 1970s (Hobbs et al. 2015).

To understand the public's preferences and values for protecting the CIBW, a SP survey was developed by the National Marine Fisheries Service (NMFS). It was developed with input from marine mammal scientists in the Alaska Fisheries Science Center's Marine Mammal Laboratory, as well as others involved in CIBW management. In addition, six focus groups were held in three cities to evaluate early survey designs, and 13 cognitive interview sessions in two cities were used to refine wording and presentation to ensure comprehension of the information and questions presented in the survey.

The survey was developed to be administered by mail and is divided into several sections. It begins with a question that asks about general opinions towards government spending on several broad issues facing society (including the environment as one issue). This question is followed by a section that provides basic information about threatened and endangered species in the U.S. It describes the ESA and how and what it protects, provides definitions of threatened and endangered species, and lists reasons why people may be interested in protecting threatened and endangered species (i.e., benefits of protection) or not protecting them (i.e., costs of protection). Also included is an infographic displaying other threatened and endangered whale species

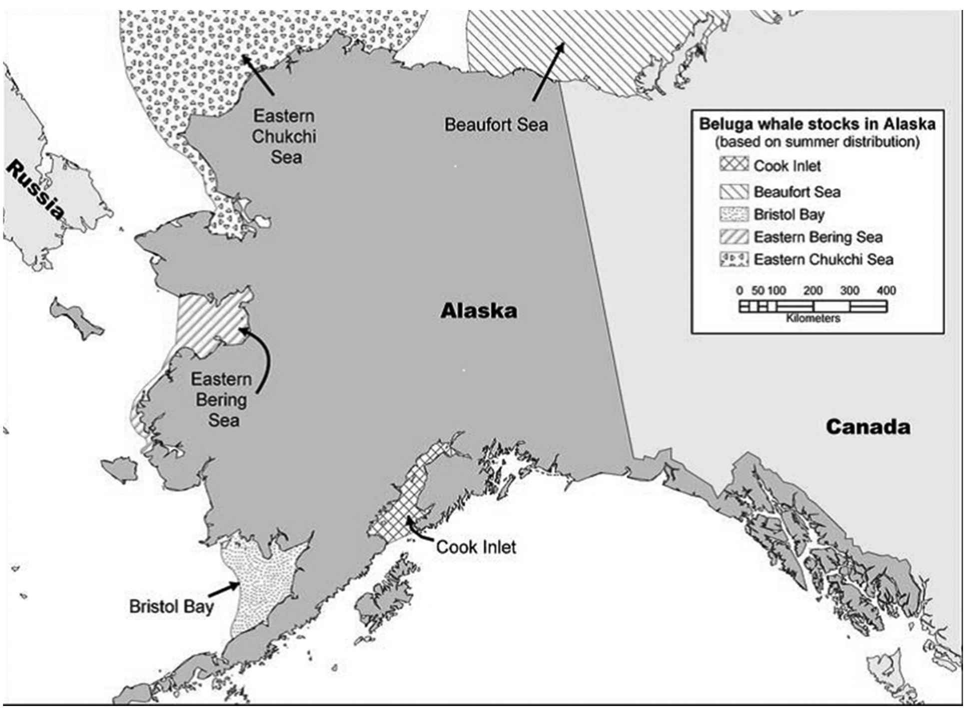

Figure 1. Distribution of the Cook Inlet Beluga Whale and Other Beluga Whales in U.S. Waters
Source: National Marine Fisheries Service.

in the U.S. and some basic information on the number of other threatened and endangered species protected under the ESA. Presentation of this information is critical to respondents who may view other whale species, or other threatened and endangered species, as substitutes (or even complements) in their preferences for protecting the CIBW. The information also serves as a reminder to all respondents that other species may need protection while answering questions about paying for CIBW protection in the SP questions, and thus acts as another budget constraint reminder (as does the question on government spending).

The next two sections of the survey present information on other beluga whale populations in the U.S. that are not endangered, as well as specific information about the CIBW. Basic information on the CIBW is presented, such as their size and appearance, what they eat, where the species is found, and a description of the population declines over time as well as causes for the decline identified by scientists. This section also presents current threats to the CIBW and the outlook for the population if current protection and population trends continue. These sections are followed by one that discusses the possibility of additional protection measures being undertaken to help recover the CIBW, where "recovery" is defined as reducing the risk of extinction to a very small level and removing the species from the ESA list. Both positive and negative effects of these actions on households are noted.

This sets up the CE questions, which are preceded by instructions on how to answer them, a budget reminder, and a cheap talk script intended to reduce hypothetical bias (Cummings and Taylor 1999).[3] In each of the four SP CE questions, respondents are asked to choose their most preferred and least preferred option from among three alternatives that differ in the level of protection provided to CIBW and in their costs (figure 2). The survey concludes with several questions that collect socio-demographic information about the respondent and the respondent's household.

The payment vehicle used in the CE questions is an "added cost" to the household in the form of increases in costs of goods and services and federal taxes.[4] The added cost for each alternative in the CE questions is presented as a one-time payment. There were 16 survey versions that differed in the attribute levels (ESA status, risk of extinction, and added cost) seen by respondents. The possible attribute levels for the ESA population status under Alternatives B and C are "threatened" or "recovered," since only options that enhance the protection are assumed. Along the same lines, there were 10 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. The experimental design also included non-zero added cost amounts for Alternatives B and C ranging from $5 to $350.[5] The final experimental design was selected using a program developed in GAUSS that

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3. 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."

4. The combination payment vehicle potentially raises concerns over whether it can be viewed as "fixed and nonmalleable" to respondents given the "increased cost" component would vary by respondent (Johnston et al. 2017). 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.

5. To ensure sufficient cost variation across the extinction risk-status level combinations, 15 cost amounts were used: $5, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 125, 150, 250, and 350.

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 →*	☐	☐	☐

Figure 2. Example of a Choice Experiment Question

maximized the D-efficiency assuming a main effects utility specification (Louviere, Hensher, and Swait 2000).[6] The resulting 16 survey versions were distributed randomly and in equal numbers to each of the two samples (rural and non-rural samples).

The survey was fielded in the summer and fall of 2013 to 1,392 rural and non-rural households in Alaska. In Alaska, the existence of rural and non-rural differences in politics, resource access, governance, and infrastructure are fairly well-known within the state (e.g., Rossi 2017; Commonwealth North 2000). Concerns about the different values held by those living in "rural" areas from those in more "urban" (non-rural) areas of the state are also present and have led to organized efforts to bridge the divide in understanding between "rural" and "urban" Alaskans (e.g., Commonwealth North 2000). In this study, non-rural Alaska 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. In short, all households in areas with populations of at least 10,000 persons were included in our definition of a non-rural area.[7] For Alaska, which does not have a dense population distribution and consists of less than 1% of the U.S. population, there were only five qualifying non-rural areas by this definition: the Anchorage metropolitan statistical area, Fairbanks North Star borough, the City and Borough of Juneau, the City and Borough of Ketchikan, and the Kodiak Island Borough. All other areas were classified

6. A similar approach to the experimental design construction described in Lew and Wallmo (2017) was followed. 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. The experimental design was also constructed to preclude fully dominant alternatives within each choice set and across choice sets in each survey version.

7. Note that the non-rural definition employed here uses a larger population threshold than the U.S. Census Bureau, which defines rural areas as areas with 2,500 or fewer people. See https://www.census.gov/geo/reference/ua/urban-rural-2010.html.

Table 1. Descriptive Statistics of Rural and Non-rural Samples

Variable	Description	Rural	Non-rural
Gender*	% male	60.00	44.31
Retired*	% retired	28.21	16.67
Full-time workers*	% of sample working full-time	40.00	54.47
Homemakers	% homemakers	3.08	6.50
Environmental contribution/ membership	% who contributed to or were members of environmental or conservation organization	46.67	50.41
Education – HS or less*	% with high school diploma or equivalent or less	27.18	11.79
Education – grad school+*	% with at least some graduate or professional school	20.00	28.05
Ethnicity – white*	% white/caucasian	72.31	87.80
Ethnicity – Alaska Native/ Am. Indian*	% Alaska Native or American Indian	26.67	10.57
Not hunting*	% not hunting in last 3 years	44.62	65.45
Not fishing	% not fishing in last 3 years	23.59	28.46
Home ownership	% owning own home/residence	80.00	76.83
Age*	Mean age (years)	55.91	51.50
Household size	Mean household size (persons)	7.17	5.59
Income*	Mean household income ($)	59,333	81,413
Sample size		195	246

* Statistically different between the rural and non-rural samples at the 5% level.

as rural. Two random samples for Alaska households, one of non-rural households (694) and the other of rural households (698), were drawn from Marketing Systems Group's database, which was constructed from the U.S. Postal Services' Computerized Delivery Sequence File that has nearly 100% coverage of households in Alaska (and the U.S. generally).

The survey implementation followed a mixed mode approach 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 560 completed surveys were returned (291 non-rural and 269 rural), and the overall response rate (excluding non-deliverables) was 40.2% (41.9 and 38.5%, respectively). The data used for the analysis consists of 246 respondents from non-rural households and 195 respondents from rural households. These samples exclude individuals not answering any of the choice questions and protest respondents.[8]

Table 1 presents summary statistics of several characteristics of each sample. Not surprisingly, there are numerous differences between the rural and non-rural sample respondents. Compared to the non-rural sample, the rural sample had a larger proportion of males, retirees, Alaska Natives, and hunters; were less educated, on average; and had a lower average household income and higher average respondent age.

METHODS

The general approach for evaluating preference and value differences in the protection of the CIBW along rural/non-rural lines involves estimating separate conditional indirect utility (preference) functions for the two samples using the CE responses from the survey. Likelihood ratio (LR) tests based on Swait and Louviere (1993) are then conducted to determine whether the

8. Several Likert scale questions were asked to identify protest respondents. Individuals indicating they strongly rejected the payment vehicle were classified as protesters and dropped.

preference functions are statistically equivalent, in effect to assess the equality of preferences between rural and non-rural households. WTP estimates for 31 different combinations of possible improvements in the ESA listing status and reduction in extinction risk for the species (i.e., policy scenarios) are also compared between the rural and non-rural models. Specifically, for each policy scenario i, the null hypothesis that $\text{WTP}_i^{\text{non-rural}} = \text{WTP}_i^{\text{rural}}$ ($i = 1, \ldots, 31$) is tested. To compare the mean WTP estimates for the rural and non-rural samples, a method of convolutions (MOC) approach is employed (Poe, Giraud, and Loomis 2005). This involves developing precise confidence intervals for the difference between the mean WTP estimates using a complete combinatorial convolutions approach.[9] If the MOC-based confidence interval for a particular difference in mean WTP estimates contains zero, then one cannot reject the null hypothesis that the mean WTP between the two samples is the same.

MODELING APPROACH

The CE data are analyzed using random utility maximization (RUM) discrete choice models that account for utility heterogeneity as well as the ordered and panel nature of the data. In RUM models, utility for the jth alternative (U_j) consists of a deterministic (V_j) and stochastic (ε_j) component. Here V_j is assumed to be linear in the cost to the household and ESA status level and quadratic in extinction risk level. The ESA status levels (endangered, threatened, or recovered) are represented in the model as effects-coded variables (Louviere, Hensher, and Swait 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 being equal. 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. 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, Ferrini, and Willis 2005).

In each choice question, an individual is asked to choose the best (most preferred) and worst (least preferred) alternative from among J alternatives. Individuals will choose as best the alternative that yields the highest utility from among the J alternatives in the choice set as their most preferred alternative. Here, $J = 3$ with corresponding choice alternatives A, B, and C, so one can model the probability that the individual chooses the jth alternative as best by $\Pr[j \text{ is best}] = \Pr[U_j \geq \max\{U_A, U_B, U_C\}]$. 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 $\pi^2/6\lambda$), which leads to the CL model and probabilities of the form:

$$\Pr[j \text{ is best}] = \exp(\lambda \cdot V_j) / \textstyle\sum_k [\exp(\lambda \cdot V_k)] \quad j, k = A, B, C. \tag{1}$$

9. To construct the method of convolutions confidence interval, the iterations of the Krinsky-Robb simulation used to empirically simulate the confidence bounds of welfare (Krinsky and Robb 1986) are used. In this case, every possible difference between the WTP values of the rural and non-rural samples is calculated and collectively used to form an empirical distribution of the mean WTP difference from which confidence intervals can be determined.

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 CL models, which is the convention followed here, except when noted.

In addition to selecting the best choice alternative, respondents are asked to select the worst choice alternative out of the three in the choice set. As a result, a full rank ordering between the three choice alternatives (A, B, and C) can be modeled following the rank-ordered logit approach of Beggs, Cardell, and Hausman (1981) and Chapman and Staelin (1982). To this end, note that 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 $j \neq k \neq l$. The choice of best remaining alternative after j is selected as the best out of the full choice set represented by:

$$\Pr[k \text{ is second best} | j \text{ is best}] = \exp(V_k) / \textstyle\sum_{m \neq j}[\exp(V_m)], \qquad j, m, k = A, B, C. \tag{2}$$

The joint probability of observing the selection of j as best, k as second best, and l as worst (denoted as $j > k > l$) is:

$$\Pr[j > k > l] = \pi_{jkl} = \Pr[j \text{ is best}] \times \Pr[k \text{ is second best} | j \text{ is best}] \qquad j, k, l \in \{A, B, C\}. \tag{3}$$

This is a rank-ordered conditional logit model.

To account for the fact that each respondent faced four choice questions in the survey, the joint probability of observing the sequence of choices an individual makes is modeled as the product of individual choice probabilities, 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:

$$\begin{aligned} \Pr[r_1, r_2, r_3, r_4] &= \Pr[r_1] \cdot \Pr[r_2] \cdot \Pr[r_3] \cdot \Pr[r_4] \\ &= \pi_{r_1} \cdot \pi_{r_2} \cdot \pi_{r_3} \cdot \pi_{r_4}, \end{aligned} \tag{4}$$

where π_{r_m} (for $m = 1, 2, 3, 4$) is defined by equations 1–3.

To account for preference (i.e., taste) heterogeneity, the random parameters MXL model is used (Train 2003). Assume the ith individual's conditional indirect utility (i.e., the deterministic component of the random utility) associated with the jth alternative is linear in utility parameters ($\boldsymbol{\beta}_i$) and takes the form:

$$V_{ij}(\boldsymbol{\beta}_i) = \boldsymbol{\beta}_i \times \boldsymbol{x}_{ij}, \tag{5}$$

where $\boldsymbol{x}_{ij}$ is a K × 1 vector of 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 $(f(\bar{\boldsymbol{\beta}}, \Omega)$. $\bar{\boldsymbol{\beta}}$ is a K × 1 mean vector and Ω is a K × K variance-covariance matrix. In the MXL model formulation, equation 1 becomes (dropping the individual-level index, i):

$$\Pr[j \text{ is best}] = \int \left[\left(\frac{\exp[V_j(\boldsymbol{\beta})]}{\sum_k \exp[V_k(\boldsymbol{\beta})]} \right) \right] f(\bar{\boldsymbol{\beta}}, \Omega) \mathrm{d}\boldsymbol{\beta}, \tag{6}$$

for all k and $j \in \{A, B, C\}$. An analog for equation 2 in the MXL model is similarly structured and then used in equation 4 to construct the likelihood function in the model accounting for the panel and rank-ordered nature of the CE data. In this study, we assume all non-cost attributes and the ASC representing the status quo alternative are normally distributed random parameters; hence $f(\cdot)$ in equation 6 is a normal distribution. The MXL models are estimated by maximum simulated likelihood estimation using 500 randomized Halton draws (Bhat 2003).

The MXL model described above assumes respondents fully consider (or attend to) all attributes in the CE question when making choices. This assumption has been challenged in recent years, as researchers have found evidence in support of individuals ignoring one or more attributes when answering CE questions (Scarpa et al. 2009), generally referred to as ANA behavior. Koetse (2017) proposed using a simplified ANA model that focuses on payment vehicle, or cost, ANA as a way of mitigating hypothetical bias.[10] Using CE data from three applications, he found that accounting for cost attribute ANA reduced WTP by over 50% in some cases when compared to CL models and argued this represents a reduction in hypothetical bias and a lower bound estimate of WTP.

Like most other inferred ANA models (e.g., Scarpa et al. 2009; Thiene, Scarpa, and Louviere 2015), the Koetse model is a type of latent class logit model where each latent class represents a different type of ANA behavior. A single parameter vector, $\boldsymbol{\beta}$, is estimated in the model, and each latent class is differentiated by which parameters in $\boldsymbol{\beta}$, if any, are ignored and thus assumed to be zero. Since the parameters that are attended to are assumed to be the same across classes, these models are generally referred to as equality-constrained latent class logit (EC-LCL) ANA models. In the Koetse EC-LCL model, there are only two latent classes of individuals—those who fully attend to all attributes (no parameters are assumed zero; class 1) and those who ignore the cost attribute (the cost parameter is assumed equal to zero; class 2).

In this study, the Koetse (2017) EC-LCL model is extended to allow for preference heterogeneity.[11] Let $\boldsymbol{\beta_c}$ be the $K \times 1$ parameter vector associated with class c ($c = 1, 2$), then the unconditional probability of observing the individual choosing Alternative j as the best is:

$$\Pr[j \text{ is best}] = \int \sum_{c=1}^{2} \left[\left(\frac{\exp(\theta_c)}{\sum_{l=1}^{2} \exp(\theta_l)} \right) \times \left(\frac{\exp\left(V_j(\boldsymbol{\beta_c})\right)}{\sum_k exp\left(V_k(\boldsymbol{\beta_c})\right)} \right) \right] f(\bar{\boldsymbol{\beta}}, \Omega) d\boldsymbol{\beta}, \tag{7}$$

for all c and for all k and $j \in \{A, B, C\}$. The left-most term in the right-hand side equation is the probability of membership in latent class c, where θ_c ($c = 1,2$) is a class-specific constant parameter to be estimated. The middle term is the probability of observing alternative j being selected conditional on being in class c, which is associated with the random parameter vector, $\boldsymbol{\beta_c}$. The parameter vector, $\boldsymbol{\beta_1}$, is associated with full attendance to the attributes (class 1); therefore, no parameters are set equal to zero. Cost ANA is imposed on the parameter vector for class 2 respondents by setting the cost parameter equal to zero in $\boldsymbol{\beta_2}$. Analogs to equation 2 in the MXL model are similarly constructed for the cost ANA model and then used in equation 4 to construct the likelihood function for the model.[12] For identification purposes in estimation, θ_1 is set to zero and θ_2 is freely estimated. As a result, the probability of being in latent class 1 (full attribute attendance) is $1/[1+\exp(\theta_2)]$, while the probability of being a member of latent class 2 (cost ANA) is $\exp(\theta_2)/[1+\exp(\theta_2)]$. Note that when $\theta_2 = 0$, the probability of cost ANA is 0.5, so

10. Note that in focus group testing for this study there were some respondents who indicated they did not consider or pay attention to the cost attribute when answering the CE questions, which is suggestive of cost ANA behavior.

11. Fixed parameter model results are not reported here since all model fit statistics (BIC, AIC, LRI) suggest the mixed logit versions (MXL-CANA) reported in the article performed much better overall.

12. The simulated maximum likelihood procedure was programmed in GAUSS version 18.

$\theta_2 > 0$ implies a greater than 50% probability of cost ANA, and $\theta_2 < 0$ implies less than 50% probability of cost ANA. Thus, a statistically significant θ_2 suggests the probability of cost ANA is not even odds.

Separate panel rank-ordered MXL models without (MXL) and with (MXL-CANA) cost ANA are estimated for the rural and non-rural survey treatments. Pooled models that combine rural and non-rural data are estimated as well, with one set ("equal-scale" pooled models) that assumes no utility scale differences (at a group level) between the rural and non-rural treatments and another set that allows for a systematic scale difference between them ("free-scale" pooled models).[13] In the latter set of models, a relative scale parameter, λ, which is the ratio of scale parameters of the two data sets, is estimated. To ensure it is positive, let $\lambda = \exp(\lambda^*)$, such that equal scale implies $\lambda = 1$, or equivalently, $\lambda^* = 0$.

RESULTS

Table 2 presents the estimation results for the MXL models estimated for the separate rural and non-rural samples, as well as for the pooled data when restricting scale to be equal across the samples (equal-scale pooled model, which assumes $\lambda = 1$) and when allowing it to be free (free-scale pooled model, which allows λ^* to be estimated). For the non-rural (and pooled) MXL models, the mean parameters are statistically significant and have the expected signs. In the rural MXL model, all mean parameters have the expected signs, but some (reduced risk and threatened status parameters) are not statistically different from zero. The results suggest non-rural households value both reduced extinction risk and improved ESA status for the CIBW, while rural households valued improving the CIBW to a recovered level (REC), but not incremental improvements in its ESA status (to a threatened level) or reductions in extinction risk, at least on average. For the non-rural model, the signs and magnitudes 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 corresponding parameters in the rural model have the same signs, but are not statistically significant at conventional levels. The marginal utility of improving the status of the species to a threatened level (THR) is positive in both models, but only statistically significant in the non-rural model. In both models, the THR parameters are smaller than those for improving status to REC. REC is statistically different from zero in all models. The cost parameter is negative, as expected from theory. Additionally, the ASC parameter is negative and statistically significant in each model, indicating a tendency to prefer improvements to the CIBW by both rural and non-rural households, all else equal. In the table, the variance-covariance matrix is summarized by the estimated Choleski matrix elements, with several being statistically different from zero in each model. This suggests statistically significant preference variation over the samples, as well as correlation across some random parameters. The estimated relative scale parameter in the free-scale pooled model (λ^*) is positive and statistically different from zero. Its magnitude suggests that the non-rural sample has a smaller error variance relative to the rural sample. Comparisons between model fit statistics (Bayes Information Criterion [BIC], corrected Akaike Information Criterion [AICc], and likelihood ratio index [LRI]) of the MXL models with corresponding CL models

13. There are a number of studies that have obtained group or sample-level measures of scale differences, typically in studies that combine multiple data sources in estimation (e.g., Whitehead, Haab, and Huang 2011). In these studies, relative scale parameters have been identified and estimated.

Table 2. Panel Ordered Mixed Logit (MXL) Model Estimation Results

	Rural		Non-rural		Pooled Equal-scale		Pooled Free-scale	
Variable	Estimate	Asy. T-value	Estimate	Asy. T-value	Estimate	Asy. T-value	Estimate	Asy. T-value
Status quo ASC	–2.1471**	–4.8883	–2.2843**	–4.4238	–2.2629**	–6.5106	–1.9780**	–6.1562
Reduced risk (RR)	0.0805	1.2731	0.2654**	3.5462	0.1894**	4.0503	0.1400**	3.2864
RR squared	–0.0017	–0.6742	–0.0106**	–3.6763	–0.0062**	–3.2474	–0.0056**	–3.3179
Threatened (THR)	0.1934	0.6117	1.0282**	3.1356	0.5213**	2.5234	0.4585**	2.3163
Recovered (REC)	1.3972**	2.3650	1.4609**	1.9710	1.3652**	3.0838	1.1266**	2.7971
COST	–0.0164**	–7.4228	–0.0082**	–4.2917	–0.0129**	–9.2582	–0.0104**	–7.7554
SD(ASC)	3.1467**	7.3498	3.1782**	8.0800	3.4195**	11.6845	2.9362**	9.9057
CHOL(RR,ASC)	–0.0408	–0.8962	–0.0096	–0.1578	–0.0438	–1.3691	–0.0548*	–1.8034
SD(RR)	0.3104**	6.6485	0.3865**	8.2581	0.3553**	11.1517	0.3026**	8.9627
CHOL(ASC,THR)	0.3308	0.8129	–0.2022	–0.4322	–0.0168	–0.0578	–0.0572	–0.2054
CHOL(RR,THR)	0.7023	1.2317	0.4983	0.9994	0.3779	1.0398	–0.5243	–1.5151
SD(THR)	1.9175**	4.8262	2.4081**	5.3163	2.0057**	6.7139	1.9589**	6.8064
CHOL(ASC,REC)	0.7834	1.4354	0.0967	0.0902	0.2205	0.3954	0.2829	0.5774
CHOL(RR,REC)	0.5103	0.5489	–0.4946	–0.4132	0.1526	0.2098	–0.0629	–0.0935
CHOL(THR,REC),	–1.3438*	–1.6781	–3.2335**	–3.5606	–1.7118**	–2.6710	1.7888**	3.3145
SD(REC)	0.0842	0.0438	3.2600**	4.8012	2.2477**	5.1957	1.4992**	3.9571
Scale (λ*)							0.1910**	2.0752
Mean log-likelihood	–4.7849		–4.3531		–4.5732		–4.5799	
Sample size	195		246		441		441	
Likelihood ratio index	0.332		0.393		0.362		0.361	
AICc	1901.174		2176.118		4066.823		4074.943	
BIC	1950.486		2229.828		4130.964		4143.010	

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. The panel model analyzes responses to the four choice experiment questions in each survey.

suggest the MXL models are considerably better at fitting the data (results available upon request). LR tests for the null hypothesis of fixed, rather than randomly distributed, parameters are strongly rejected ($p<0.001$).[14]

In the MXL-CANA models, the signs and statistical significance across all models are very similar to the MXL model results (table 3). Notably, however, the linear reduced risk parameter is statistically significant (and positive as expected) in the rural model and the cost parameter is larger in magnitude (more negative) in each model, which is consistent with the results in Koetse (2017) and with the presence of cost ANA. The cost ANA parameter, θ_2, is statistically different from zero in the rural and non-rural models, which suggests the probability of cost ANA—the probability of being in class 2— is below (for rural) or above (for non-rural) even odds. It is estimated to be 36.06% in the rural MXL-CANA model and 64.22% in the non-rural MXL-CANA model.[15] Both probabilities are statistically significant with Krinsky-Robb 95% confidence

14. 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. Additional specifications that control for demographic differences were also estimated, but led to qualitatively similar results. See the online-only Appendix for details.

15. For parallel models that analyze the best choice responses only (i.e., ignoring the full rank ordering information), similar cost ANA levels are obtained—25% for the rural sample and 48% for the non-rural sample. Moreover, the best choice model results are qualitatively the same as those presented here (available on request).

Table 3. Panel Ordered Mixed Logit Cost Attribute Non-Attendance (MXL-CANA) Model Estimation Results

	Rural		Non-rural		Pooled Equal-scale		Pooled Free-scale	
Variable	Estimate	Asy. T-value	Estimate	Asy. T-value	Estimate	Asy. T-value	Estimate	Asy. T-value
Status quo ASC	–2.3104**	–4.8876	–2.3410**	–4.2182	–2.2548**	–6.7073	–1.8950**	–6.2654
Reduced risk (RR)	0.1164*	1.7978	0.3239**	4.2876	0.2243**	4.7184	0.2033**	4.7478
RR squared	–0.0028	–1.0503	–0.0109**	–3.7059	–0.0071**	–3.7266	–0.0063**	–3.7779
Threatened (THR)	0.2124	0.7622	1.0384**	2.8500	0.5518**	2.6049	0.4703**	2.5231
Recovered (REC)	1.3359**	1.9839	1.9114**	2.6054	1.4330**	3.1757	1.2191**	3.0482
COST	–0.0278**	–7.4344	–0.0466**	–5.2505	–0.0345**	–8.7208	–0.0308**	–8.0814
SD(ASC)	3.5075**	7.1945	3.0899**	7.5640	3.1726**	10.3692	2.6576**	8.9019
CHOL(RR,ASC)	–0.1051**	–2.1960	–0.0493	–0.7480	–0.0686**	–2.1460	–0.0472	–1.6438
SD(RR)	0.2512**	4.1784	0.3619**	6.3098	0.3416**	8.9183	0.3066**	8.2853
CHOL(ASC,THR)	0.5414	1.4492	–0.2316	–0.4192	0.1791	0.6097	0.1263	0.4899
CHOL(RR,THR)	–0.6411	–0.9141	0.4807	0.8016	0.0086	0.0200	0.1090	0.2976
SD(THR)	0.7927	0.9366	2.6444**	4.6228	1.7882**	4.9235	1.5296**	4.8243
CHOL(ASC,REC)	0.6394	0.9028	0.3653	0.3240	0.6382	1.1752	0.4270	0.8402
CHOL(RR,REC)	–0.1315	–0.1069	0.2016	0.1731	–0.0412	–0.0519	0.2456	0.3543
CHOL(THR,REC),	–0.1641	–0.0835	–2.8505**	–2.5672	–0.9746	–1.3629	–0.9323	–1.5581
SD(REC)	0.3811	0.1657	1.6783*	1.8915	0.5623	0.4540	0.7915	1.1215
ANA-Cost (θ_2)	–0.6090*	–1.7106	0.6016*	1.9209	0.1319	0.5510	0.1698	0.7224
Scale (λ*)							0.2916**	2.7988
Pr(class 2)	0.361		0.642		0.536		0.573	
(95% Conf. Int.)	(0.236, 0.505)		(0.496, 0.770)		(0.421, 0.651)		(0.521, 0.622)	
Mean log-likelihood	–4.7560		–4.3099		–4.5392		–4.5333	
Sample size	195		246		441		441	
Likelihood ratio index	0.332		0.393		0.362		0.361	
AICc	1892.30		2157.18		4039.03		4036.00	
BIC	1944.48		2214.08		4107.10		4107.98	

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. The panel model analyzes responses to the four choice experiment questions in each survey.

bounds of [21.39%, 53.71%] and [49.62%, 77.01%], respectively.[16] Mean log-likelihood values and model fit statistics suggest the MXL-CANA models are statistically better than the MXL models, and LR tests reject the null hypothesis of no cost ANA behavior ($p < 0.01$).

TESTS FOR PLACE OF RESIDENCE DIFFERENCES

To determine whether there is a difference in preference functions between the rural and non-rural samples in the MXL and MXL-CANA models, the null hypothesis that the parameters of the non-rural model were equal to those in the rural model for each econometric specification was tested. To this end, the two-step procedure of Swait and Louviere (1993) is followed. The first step involves evaluating whether the parameters of the rural and non-rural models are equal while allowing scale to differ (free-scale pooled model). If the null hypothesis of equal parameters, while allowing scale to differ, is not rejected, the second step is to evaluate the differences in scale. For the MXL model, the first step test statistic is 31.63 with a critical value of $X^2(0.05, \text{df}=17) = 27.59$, suggesting the null hypothesis of equality of rural and non-rural MXL preference functions can be

16. Based on 1,000 draws.

rejected at the 5% level of significance. For the MXL-CANA model, the first step test statistic is 23.05 with a critical value of $X^2(0.05, \mathrm{df}=18) = 28.87$, suggesting one cannot reject the equality of the rural and non-rural MXL-CANA preference functions at the 5% level. However, the second step statistic associated with the test for equal scale is 5.20 in the case of the MXL-CANA model, which exceeds the critical value of $X^2(0.05, \mathrm{df}=1) = 3.84$. Thus, there is evidence that when allowing for cost ANA, there are scale differences between the rural and non-rural MXL-CANA preference functions.

Next, tests for differences between welfare estimates from the rural and non-rural MXL models are conducted. WTP is calculated for 31 scenarios representing improvements from the status quo to the CIBW in terms of reduced risk of extinction or improvement in ESA status. $\mathrm{E[WTP]} = (-1/\gamma)\cdot(V^1 - V^0)$, where γ is the cost parameter, V^0 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.[17] Given V^0 and V^1 are functions of random parameters, E[WTP] is calculated over the distribution of parameters in parallel fashion to the simulation-based estimation procedure. The estimated mean annual household WTP associated with the scenarios associated with the MXL and MXL-CANA models are presented graphically in figure 3.[18] The 95% confidence intervals are constructed using the simulation approach of Krinsky and Robb (1986).

Figure 3 shows the mean WTP calculated from the MXL model (panel A) and the MXL-CANA model (panel B) as a function of risk reduction level assuming ESA status changes from endangered to threatened at a 15% risk reduction level (10% risk of extinction) and from threatened to recovered at a 24% risk reduction level (consistent with the experimental design, which defines recovery as <1% risk of extinction). For the non-rural mean WTP functions, there are distinct jumps up in WTP at the risk reduction levels corresponding to moving to an improved ESA status—at 15% (endangered to threatened) and 24% (threatened to recovered). For the rural mean WTP functions, mean WTP is smoother around both changes in ESA status. For both models, the mean WTP for the non-rural model is larger than for the rural model.

For the MXL models, rural household mean WTP ranges from about $5 for the smallest risk reduction to about $86 for the largest. Note, however, that many of these mean WTP values are not statistically significant. For non-rural households, on the other hand, all but two household mean WTP values are statistically different from zero at the 5% level. The non-rural household mean WTP values range from $33 for the smallest risk reduction to upwards of $300 for larger risk reduction levels. The household mean WTP associated with recovering the CIBW is $190, but this is one of two estimates that are not statistically significant.

For the cost ANA models, the mean household WTP estimates are much smaller than those for the MXL models across welfare scenarios, with mean WTP estimates from the MXL-CANA models being 22 and 76% lower, on average, than the corresponding estimates from the rural

17. In welfare estimation, the non-zero alternative specific effect represented by the ASC parameter is removed from V^0, which would otherwise bias welfare estimates (e.g., Adamowicz et al. 1998). Recall that the ASC parameter measures non-modeled factors influencing respondents to choose or not choose the status quo. Inclusion of the ASC parameter in welfare calculations leads to estimates that are outside the range of cost levels in our experimental design and must therefore be viewed skeptically.

18. 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 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%. The full set of welfare estimates for each of the 31 welfare scenarios are contained in the online-only Appendix.

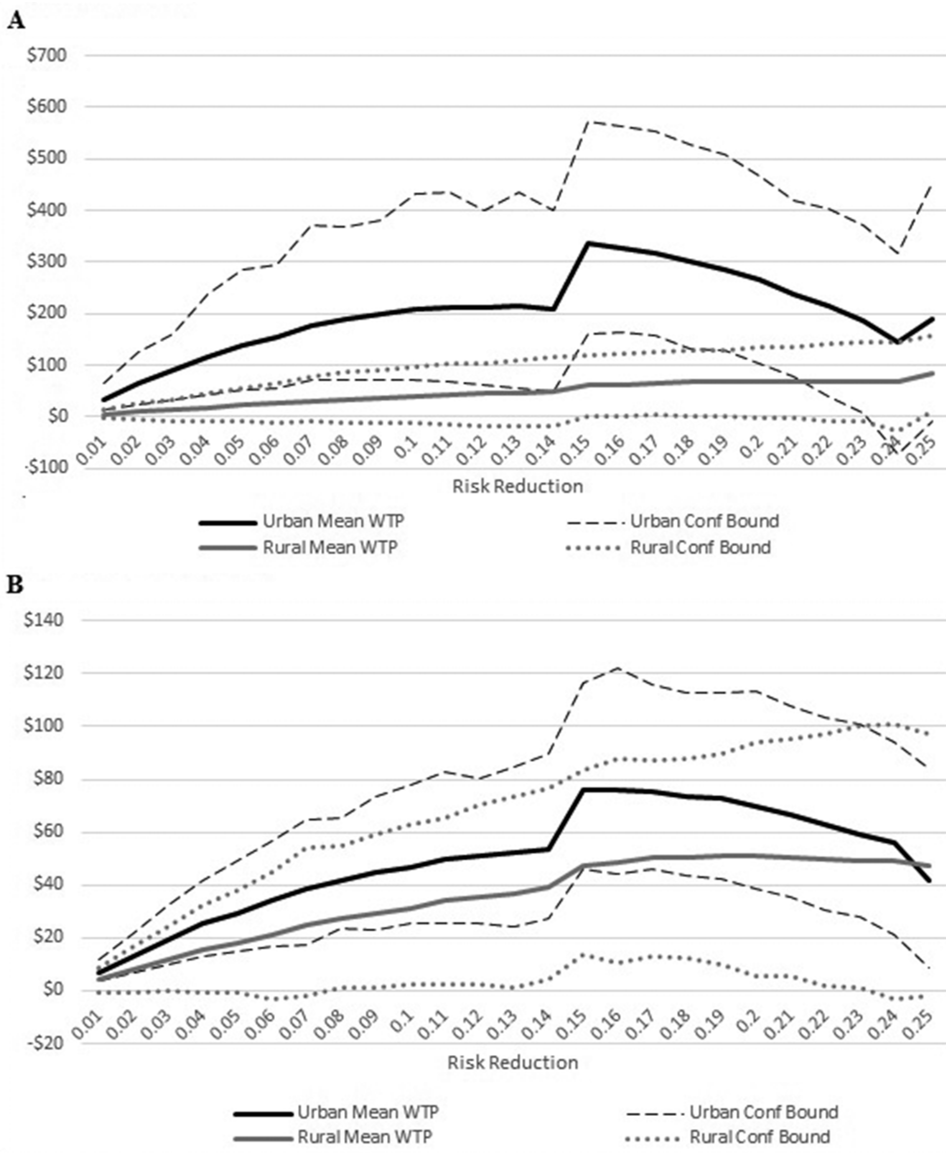

Figure 3. Mean WTP as a Function of Risk Reduction with Upper and Lower Bounds of 95% Confidence Intervals for the MXL and MXL-CANA Models

and non-rural MXL models, respectively. Mean WTP estimates for non-rural households in this model ranged from about $7 to $76, and from $4 to $51 for rural households. The much larger decrease in mean WTP in the non-rural model likely reflects the higher estimated probability of cost ANA behavior in the model.

In figure 3, the 95% confidence intervals for the rural and non-rural mean WTP for the MXL and MXL-CANA models overlap to varying degrees. However, overlapping confidence intervals are not sufficient for evaluating differences in the empirical distributions of mean WTP (Poe, Giraud, and Loomis 2005). To formally evaluate whether rural and non-rural WTP differ,

Table 4. Marginal Willingness to Pay (95% Krinsky-Robb confidence intervals in parentheses)

Attribute	Rural MXL	Non-rural MXL	Rural MXL-CANA	Non-rural MXL-CANA
Reduced risk (0 to 1%)	4.81	31.20	4.09	6.72*
	(–2.48, 13.45)	(13.25, 69.06)	(–0.34, 8.59)	(3.67, 11.42)
Threatened status	11.81	125.95*	7.64	22.29*
	(–29.81, 53.29)	(38.06, 267.14)	(–11.89, 28.34)	(7.90, 46.16)
Recovered status	85.35*	178.96	48.07	41.02*
	(17.14, 161.99)	(–2.62, 485.07)	(–1.66, 98.67)	(9.45, 84.22)

* Indicates welfare estimate is statistically different from zero at the 5% level.

90% confidence intervals for the difference in mean WTP are calculated using the MOC approach described earlier. MOC confidence intervals that do not include zero indicate cases where rural and non-rural mean WTP are statistically different. For the MXL models, at the 10% level, the mean WTP between the rural and non-rural models is statistically different in 27 of the 31 cases—specifically for all welfare scenarios except the four associated with the greatest improvement in extinction risk reduction (>21%) and when the CIBW is recovered. This suggests that the mean WTP for the non-rural sample is statistically different from the mean WTP for the rural sample over at least part of the range. However, there are no statistically significant differences between the rural and non-rural mean WTP estimates calculated from the MXL-CANA model estimates.

In addition to the welfare estimates displayed in figure 3, the marginal values of each attribute are calculated for each model (table 4). For the kth attribute, the expected marginal value is $E[MV_k] = (\partial V_j/\partial x_k)/\gamma$. For extinction risk reduction (RR), $E[MV_{RR}] = -(2 \cdot RR \cdot \beta_{RRsquared} + \beta_{RR})/\gamma$ and is calculated at a reduced risk level of 1%. For the other attributes, $E[MV_k] = -\beta_k/\gamma$, which is calculated over the distribution of the attribute parameter β_k, noting that the cost parameter is assumed fixed. Similar to the WTP estimates discussed above, a similar pattern between rural and non-rural models and between the MXL and MXL-CANA models emerges with marginal attribute values. The marginal WTP for a one unit change in extinction risk reduction is \$4.81 for the rural MXL model and \$31.20 for the non-rural MXL model, but estimates from the MXL-CANA models are lower for both the rural and non-rural models and not statistically different according to a MOC test, again suggesting that cost ANA dissipates the welfare differences between rural and non-rural households. The same conclusions can be drawn by an examination of the marginal values for the ESA status levels (THR status and REC status).

DISCUSSION

In this article, tests for identifying whether or not there is a rural/non-rural difference in preferences and WTP estimates for an endangered species were conducted. Differences were found in both the preference functions and WTP values when preferences were modeled with standard logit models that allow for continuous preference heterogeneity over the population. However, in models that allow for cost ANA in addition to preference heterogeneity, the equality of rural and non-rural preference parameters, while allowing scale to be different across the models, could not be rejected. Instead, scale differences were found between rural and non-rural preference functions, suggesting larger variance in the utility for rural households. Moreover, mean WTP estimates were considerably smaller than those for the standard models, and rural/non-rural WTP differences were no longer statistically significant.

Based on model fit statistics, the cost ANA models were preferred to the standard MXL models. The estimated probabilities of cost ANA were statistically significant for both rural and non-rural models, with non-rural households (64%) having a higher probability of cost ANA than rural households (36%). The difference in cost ANA probabilities may be due to the higher incomes among the non-rural sample, which may lead to a larger percentage of non-rural respondents viewing the cost levels in the surveys as being too low to matter in their choices, even if cost levels exist that would have mattered to them (Hensher, Rose, and Greene 2012). Nevertheless, these estimated probabilities are within the range found by others in the literature. For example, across the three CE datasets examined in Koetse (2017), the probability of cost ANA ranged from 8 to 45%. In another study by Campbell, Hensher, and Scarpa (2011), the probability of cost ANA was about 60%. Here, accounting for this ANA behavior deflated WTP estimates compared to the standard MXL models for both the rural and non-rural household samples, with non-rural household mean WTP reduced proportionately more, likely reflecting the higher probability of non-rural households exhibiting cost ANA behavior.

The cost ANA model estimated here extends the simple EC-LCL ANA model to allow for preference heterogeneity within the model. This is important, not only because accounting for heterogeneity of preferences through random parameters was found to be statistically important, but because of the potential for ANA to be misidentified in the simple EC-LCL ANA model specification. Hess et al. (2013) point out that the EC-LCL model does not distinguish individuals with true zero preferences for an attribute from those who ignore the attribute. Thus, without explicit accounting for preference heterogeneity, the EC-LCL model may overestimate the true probability of ANA.

Some limitations of this work should be noted. First, the model presented here focused solely on ANA behavior related to one attribute, program cost. As pointed out by Koetse (2017), the fact that people are unlikely to ignore cost when making real-world choices, but are believed to do so in SP choice settings, suggests that controlling for this type of ANA will mitigate an important form of hypothetical bias. Additionally, one could argue that other forms of ANA are included in the MXL-CANA model, albeit in a way that confound them with true zero preferences as discussed in Hess et al. (2013). Of course, non-cost ANA cannot be dismissed as a possibility given the prevalence of evidence in the ANA literature that non-cost attributes are often ignored (e.g., Scarpa et al. 2009; Thiene, Scarpa, and Louviere 2015; Petrolia, Interis, and Hwang 2018). Thus, a natural extension of this work is to investigate other types of ANA and attribute processing behaviors. Secondly, the sample sizes in this study were not very large, which likely limits the precision of the model estimates and welfare estimates and could contribute to the lack of finding statistically significant welfare differences between samples.

Moreover, it deserves mentioning that the welfare estimates generated from the cost ANA models are interpreted differently from those of conventional MXL models. The MXL WTP estimates represent the average over the entire sample, but by construction, the MXL-CANA model assumes a class of individuals that ignores cost for whom welfare estimates cannot be calculated. Thus, the mean WTP calculated in the MXL-CANA model only apply to the proportion that attend to cost under assumptions of the model (Hensher, Rose, and Greene 2012). It is likely that some proportion of those included in the cost ANA class have a non-zero WTP that is precluded from measurement. This has led some to advocate applying the ANA-adjusted WTP estimate to the full sample (e.g., Scarpa et al. 2009).

Nevertheless, the WTP estimates from the cost ANA models are generally lower than other recent estimates for similar TER whale species, though this is perhaps unsurprising given the strong downward effect on WTP from accounting for cost ANA behavior. For example, the mean household WTP for recovery was about $47 for rural households and $41 for non-rural households. This is a lump sum amount. In the only other study to value beluga whales, which was for a threatened stock of beluga whales located in the St. Lawrence estuary in Canada, Boxall et al. (2012) estimate Canadian households are willing to pay an average of $114 per year (over an unspecified time period) for an improvement to a status in which it is no longer threatened.[19] Annual mean WTP for recovery of two U.S. endangered whale species, the North Pacific right whale and North Atlantic right whale, are estimated in Wallmo and Lew (2012), and WTP estimates for the Southern resident killer whale are presented in Wallmo and Lew (2016). The mean annual WTP estimates for recovery in these U.S. studies range from $75 to $84 per year for 10 years.

Furthermore, the results indicate WTP varies over reductions in extinction risk, information that can be used to provide economic benefit information to outputs from PVAs for the CIBW. Hobbs, Wade, and Shelden (2015) recently conducted a PVA to evaluate the risk of extinction for the CIBW under 15 scenarios. The scenarios represent different hypotheses about factors that may inhibit CIBW recovery, with each varying in the assumed biological parameters (survival, fecundity, predation, and carrying capacity) and other factors (mortality events). Results from this study can potentially provide information about the public benefits accruing to Alaska households from each scenario, but that is left for future work.

A recovery plan was finalized for the CIBW that outlines actions that can be taken to aid in the recovery of the species (NOAA 2016). Understanding public preferences for these actions and the extent to which heterogeneity of preferences across different segments of the public should be considered can help decision-makers better evaluate options for recovering the species. The findings of this study suggest public preferences in Alaska for protecting the CIBW between rural and non-rural households may not be that different. Admittedly, the finding of an absence of a difference for Alaska households based on place of residence in this context may be due to a weaker distinction between rural and non-rural households in Alaska relative to other parts of the U.S. In Alaska, even the more populous, higher density non-rural areas are contiguous to natural areas abundant with outdoor recreation opportunities. Thus, the public's awareness and engagement with nature is likely higher than in many other areas of the country. Further investigation is needed to assess whether this is unique to the CIBW and does not extend to other endangered species as well as to determine if preferences based on place of residence in other regions display similar patterns.

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