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Highlights

- We develop a valuation model that can estimate cutoff levels arising from non-compensatory preferences endogenously
- We model cutoff levels as functions of demographic variables
- Our model works well with synthetic data
- When applied to real data, our model does not fit as well statistically, but avoids the potential endogeneity problems associated with stated cutoffs.

Modelling Non-compensatory Preferences in Environmental Valuation

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ABSTRACT

While the compensatory model of choice dominates the environmental valuation literature, non-compensatory models, where individuals do not tradeoff one attribute for another, are sometimes found to be better representations of choice behavior. Most non-compensatory models employ "cutoffs", the point at which utility abruptly changes. But cutoffs are usually elicited directly from respondents using a stated preference question. Such elicitation could be inaccurate and might introduce bias to the decision process. In this paper we develop a model that estimates cutoff levels endogenously. Our model has two error components, one for the utility function and one for the cutoff function. This facilitates the estimation of the cutoff as a function of individual specific variables. We estimate the model by maximizing the log-likelihood function that involves the weighted sum of the two error components. We test the model using synthetic data and find that estimated parameters are close to the true parameters. When applied to actual empirical data, our model appears to be a better fit than the compensatory preference model; however it is somewhat different than the self-reported cutoff model, highlighting the need for an approach that does not rely on stated cutoff information.

JEL classification: C51, Q28, Q40, Q51

Keywords: Environmental valuation, Stated preference, Choice model, Non-compensatory preference, Cutoff.

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1. Introduction

The compensatory preference model has been dominant in environmental valuation and more generally in choice modeling as it is straightforward to estimate and interpret. This model assumes that subjects evaluate all attributes of alternatives presented and that a change in one attribute can be compensated for by a change in another attribute. However, non-compensatory preferences may better reflect some choice behavior. There could be cases where an alternative with an attribute that has not satisfied a certain level (a "cutoff") will always be rejected regardless of the levels of other attributes. This is an example of a conjunctive decision rule originally proposed by Coombs (1964) and Dawes (1964). The presence of non-compensatory decision processes has been empirically tested by many authors, including Bettman and Park (1980), Gensch and Svetska (1984), Lussier and Olshavsky (1979), Einhorn, Kleinmuntz and Kleinmuntz (1979), Payne (1976), Grether and Wilde (1984), Klein (1983), Klein and Bither (1987), Huber and Klein (1991), Cascetta and Papola (2001), Swait (2001) and Martinez *et al*. (2009). In many cases, the non-compensatory models are found to provide better representations of choice behavior in terms of explanatory power and model prediction success (Swait 2001).

In almost all of the studies employing non-compensatory frameworks, however, a cutoff is typically elicited directly from respondents (e.g. "I would pay no more than $X."). In other words, respondents are asked to state cutoffs along with their choices of alternatives in stated preference tasks. While asking subjects for their own cutoff levels may be straightforward, such elicitation could be suspect as subjects may be unable to report their decision strategies accurately (Nisbett and Wilson, 1977), or may adapt their strategies to fit the choice context (Payne *et al*. 1988). In addition, the methods of collecting these data might introduce bias to the decision process (Elrod *et al*. 2004).

Parameters on self-reported cutoffs are also subject to endogeneity as there is possible correlation between reported cutoffs and the error term of the utility function. There is evidence that assuming cutoffs to be exogenous may be inappropriate. Ding *et al.* (2012) tested for endogeneity by comparing models with predicted cutoffs (from regressions of self-reported cutoffs on demographics) to models with self-reported cutoffs and found that endogeneity affected some of the estimated parameters. Klein and Bither (1987) found that cutoffs are affected by various factors including utility level, context and setting of the choice problem, and at times, respondents were willing to violate their stated cutoffs. Therefore, cutoffs may be correlated with the error terms of the utility function and assuming exogenous cutoffs may be incorrect.

In this paper we develop a model that can be used to estimate cutoff levels endogenously. Our model employs "soft" cutoffs, which imply that alternatives that violate the cutoff will be penalized in terms of utility rather than being eliminated from the choice set. Many of those using self-reported cutoffs also observed that subjects violated their self-reported cutoffs (e.g. see Klein and Bither 1987, Huber and Klein 1991 and Swait 2001). Thus, a soft cutoff may be a more appropriate way to model choice behavior. The model with soft cutoffs is also more flexible - if the penalty on a cutoff violation is zero, it collapses to a perfectly compensatory model; if the penalty is large enough, it effectively works as a hard cutoff model. The soft cutoff is characterized by a kinked utility function and indifference curve.

Assume an individual must choose one from a set of goods. Based on Swait (2001) the individual is assumed to maximize an objective function consisting of regular utility from a vector of attributes associated with an alternative and utility penalties in the case of cutoff violations. The lower cutoff violation is defined as the positive difference of the lower cutoff compared to the attribute level; and the upper cutoff violation is defined as the positive difference of an attribute compared to its upper cutoff level. In addition to preference parameters associated with the vector of attributes of an alternative, parameters on the cutoff violations are also estimated describing the penalty in utility terms associated with cutoff violations. If the decision maker applies a conjunctive strategy, for example, the parameters on cutoff violations are marginal penalties for violations of cutoffs and should be negative.

In our approach the error terms of the cutoff function are modeled explicitly. As a result, the model has two error components: one for the utility function which is the commonly assumed Gumbel distributed error, and one for the cutoff function. This facilitates the estimation of the cutoff directly as a function of individual specific variables (which are assumed to be exogenous). To the best of our knowledge, this approach to estimating cutoffs directly has not been employed in the literature.

We assume a Poisson distribution for cutoffs, which presumably fall into discrete categories, and estimate parameters for the utility function and the cutoff function simultaneously. We estimate the model by maximizing the log-likelihood function that involves the weighted sum of the two error components. The log-likelihood function is derived by taking convolutions of the two distribution functions.

In this paper we test the model using synthetic data to ensure that it can provide reasonable estimates of the true model parameters. We then apply the model to empirical choice data arising from a province wide survey in Alberta, Canada on conservation options for woodland caribou, a "threatened" species (COSEWIC, 2002). Respondents are asked to evaluate caribou conservation alternatives based on two attributes: the extent to which caribou is conserved (number of sustainable caribou herds) and the associated cost of conservation. In this empirical application we compare the cutoffs estimated from our models with stated cutoffs, and estimate and compare welfare measures for caribou conservation programs.

We believe the approach developed in this study provides a tractable way to estimate non-compensatory preferences without relying on stated cutoffs, and explicitly models cutoff errors. It is relevant to cases where compensatory preferences may not be appropriate, and where analysts wish to estimate cutoffs without information on stated cutoffs. Our empirical analysis illustrates that stated and estimated cutoffs yield somewhat different results, highlighting the need for an approach that does not rely on stated cutoff information.

This case study also makes an empirical contribution. Because woodland caribou is listed as "threatened", a species recovery action plan with estimated costs and benefits is required by the *Species at Risk Act* in Canada. By estimating the willingness to pay for woodland caribou conservation, this study provides a measure of the benefits generated by protecting the species. It provides information on the cutoff levels of cost and caribou herds, particularly the maximum acceptable amount each household is willing to pay and the minimum acceptable number of caribou herds, which can be useful for designing management strategies and for comparing to the costs of management options.

2. Literature Review

The "standard" model of choice as encapsulated in the random utility approach employed in applied economics assumes that individuals make tradeoffs between attributes. This assumption of compensatory preferences has been challenged in several areas of the literature. One relatively recent strand of the literature has discovered that some attributes are not relevant to consumers. This branch of the literature, referred to as attribute non-attendance, shows that models that ignore the possibility of non-attendance generate incorrect measures of preferences and welfare (e.g. Scarpa et al 2009; Hensher 2006; Hensher et al 2006). This is a form of non-compensatory preference as change in the attribute that is not attended to (effectively absent in the utility function) will not affect utility and cannot be traded off against other attributes or price to construct welfare measures. A number of factors may lead to attribute non-attendance including the range of attribute levels presented in choice tasks, the consumer's preferences for the attribute, and the tradeoff between the processing the consumer undertakes and the potential for inferior outcomes (see Cameron and DeShazo, 2011).

Another strand of literature has explored whether attribute levels can lead to an individual excluding an alternative from their choice set. This approach focuses on inclusion or exclusion of alternatives based on levels of attributes, but can also be viewed as a form of non-compensatory preference. For example, if a consumer removes high cost options from their choice set when considering choice, but the researcher includes these options when modeling the choice process, biased measures of parameters and welfare measures will result. This approach is referred to as the choice set formation literature and has its origins in the work of Swait and Ben-Akiva (1987a,b) and has been used in the environmental economics literature in travel cost applications and related literature (Haab and Hicks, 1999).

A third area of literature, initiated by Swait (2001), can be considered a hybrid of these two issues. Swait (2001) examines non-compensatory preferences in a more general fashion than attribute non-attendance. His approach includes the possibility that individuals have thresholds or minimum (e.g. quality) / maximum (e.g. cost) levels of attributes that are acceptable in an alternative. If these thresholds are considered "soft" in the sense that the individual effectively penalizes choices that go beyond the thresholds, then a non-compensatory preference structure arises. The tradeoffs between attributes will no longer be "smooth". There is a relationship between this so called "cutoff" approach and choice set formation as the basis for the cutoffs is the inclusion or removal of the alternative from the choice set. However, the use of soft cutoffs or penalties means that this approach can be implemented by examining parameters in the utility function of a random utility model, and does not require the two-step approach used in the choice set formation literature that examines both the utility function and the choice set formation process. Thus the cutoffs approach provides a mechanism to explore the possibility of a general form of non-compensatory preference that appears to arise in a number of choice problems. Below we outline the background of the cutoffs approach.

The existence of cutoffs implies that decision makers set minimum levels required for relevant attributes to satisfy in order to be further evaluated. A cutoff provides the basis for two famous decision strategies: elimination by aspects (Tversky 1972) and the conjunctive decision rule (Coombs 1964 and Dawes 1964).

Tversky (1972) demonstrated that a decision maker making a multiple alternative choice will consider the alternative a set of "aspects". At each stage of choice, she or he will select an aspect and eliminate the alternatives that do not include the aspect. The process continues until only one alternative remains.

The conjunctive decision strategy is another non-compensatory rule, which was initially discussed by Coombs (1964) and Dawes (1964). The conjunctive rule suggests that decision makers set up cutoffs for attributes, and alternatives must satisfy all cutoffs to be considered acceptable for further evaluation. The conjunctive choice rule was made popular by Einhorn (1970), who proposed nonlinear models for analyzing this non-compensatory rule, and Wright (1975) who analyzed the tradeoff between optimizing and simplifying the decision process.

Several researchers confirmed the existence of cutoffs. Bettman and Park (1980) found consistently that subjects applied a conjunctive rule. Payne (1976) examined apartment choice strategies and found that when facing two-alternative choices, compensatory rules were used; while in multiple alternative choices, subjects applied strategies with cutoffs to quickly eliminate some alternatives. Lussier and Olshavsky (1979) found that when facing more than three alternative options, decision makers appeared to eliminate alternatives using non-compensatory rules and then applied a compensatory rule to evaluate the retained alternatives. Grether and Wilde (1984) developed a theoretical framework and experimental design to test for the conjunctive choice rule and found that subjects conform to a certain conjunctive rule.

Klein (1983) found that subjects applied some non-compensatory rules and that cutoffs were specified *a priori*. Klein and Bither (1987) found that subjects choose cutoff levels at the points that maximize the utility difference between the two sets of alternatives: those that are retained and rejected. Huber and Klein (1991) also found evidence that subjects applied non-compensatory rules with cutoffs to reduce the number of alternatives, while applying compensatory rules to make the final choice.

Among research on cutoffs, Gensch and Svetska (1984), Elrod *et al*. (2005) and Martinez *et al*. (2009) were able to estimate the cutoff levels without knowing them, or having a stated measure of them, in advance. Other papers identify cutoffs by directly asking subjects whether they apply cutoffs on attributes and elicit the levels of those cutoffs. Gensch and Svetska (1984) estimated aggregate cutoff levels, which were not individual specific. As a result, they could not relate the cutoffs to individual characteristics. Elrod *et al*. (2004) provide a functional form for the utility function that allows for estimating the cutoff points. Martinez *et al*. (2009) provide a framework for estimating individual cutoffs. In almost all of the literature employing non-compensatory models, cutoff information is collected directly from respondents. However, there is relatively little literature that we are aware of that discusses the incentive properties of elicitation of cutoffs from respondents, nor is there much discussion on the methods for elicitation of cutoffs (e.g. dependent on particular quality levels or absolute in nature).

Although the use of stated cutoff levels is widely adopted, several researchers also found that subjects at times violate their self-reported cutoffs (e.g. Huber and Klein 1991, Swait 2001). In addition, the cutoffs were not always applied for a real non-compensatory decision strategy. In Lynch's (1983) experiment, subjects did not make decisions in a manner that is consistent with a true conjunctive process, but rather a "partially compensatory" rule. Subjects failed to classify alternatives into acceptable and unacceptable sets using cutoffs. Einhorn, Kleinmuntz and Kleinmuntz (1979) concluded that cutoffs may work as part of a compensatory decision process. This evidence suggests that the violation of cutoffs may not result in elimination, but rather a penalty in terms of utility. This is the basis for soft cutoffs, that is, alternatives that violate cutoffs should be penalized, not removed. We explore this approach, as implemented by Swait (2001), in more detail below.

Parameters estimated using models with self-reported cutoffs may also be subject to bias due to endogeneity. Ding (2012) tested for endogeneity by comparing models with predicted cutoffs to models with self-reported cutoffs. In the model with predicted cutoffs, instrumental variables for cutoffs were used to predict the cutoffs using individual characteristics, and then the predicted values were used for the choice model. The results show that subjects penalized alternatives with cutoff violations and that endogeneity affected some of the estimated parameters.

This paper proposes a model that estimates the cutoffs as functions of individual specific characteristics based on the theoretical model of Swait (2001). When estimating the cutoff function, we also explicitly model the error terms of the cutoff function. We present Swait's model below, and the proposed model in the following section.

3. Econometric Approach

3.1 Swait's Model

Swait (2001) developed a model in which violations of cutoffs result in utility penalties. Assuming that an individual must choose one from a set of C goods, the model could be presented as follows:

$$\max U = \sum_{j \in C} \delta_j U\left(X_j\right) + \sum_{j \in C} \sum_k \delta_j \left(w_k \chi_{jk} + v_k \kappa_{jk}\right) \tag{1}$$

s.t. $$\sum_{j \in C} \delta_j = 1 \qquad \sum_{j \in C} \delta_j c_j \leq Y$$

$$\delta_j \left(\theta_k^L - X_{jk}\right) - \chi_{jk} \leq 0 \qquad \forall j \in C, \forall k$$

$$\delta_j \left(X_{jk} - \theta_k^U \right) - \kappa_{jk} \le 0 \qquad \forall j \in C, \forall k$$

$$\delta_j = 0,1,\ \chi_{jk} \ge 0,\ \kappa_{jk} \ge 0 \qquad \forall j \in C, \forall k$$

This objective function consists of two parts. One is utility obtained from the vector of attributes X_j of good j. The second part consists of a set of utility penalties that occur in the case of cutoff violations. Note $\theta^L = [a_1,...,a_K]$ and $\theta^U = [b_1,...,b_K]$ are the sets of lower and upper cutoffs of attributes. Variable χ_{jk} is the lower cutoff violation, defined as the difference between the level of attribute k and its lower cutoff level, and κ_{jk} the upper cutoff violation, defined as the difference of attribute k and its upper cutoff level, while w_k and v_k are corresponding parameters. If the decision maker applies a conjunctive strategy, w_k and v_k are marginal penalties for violations of cutoffs and should be negative. If they are zero, the model collapses to the standard model where there is no cutoff. The first constraint indicates that only one good is chosen and c_j is the cost of alternative j in the income (Y) constraint. The second and third constraints define the lower and upper cutoff violations.

Swait's model is consistent with the elimination-by-aspect and conjunctive decision strategies because eliminating alternatives that do not satisfy the constraints and then choosing the utility-maximizing one among remaining alternatives is essentially the same as choosing the optimal one given the constraints (Swait, 2001).

3.2 The Endogenously Determined Cutoff Model

Cutoffs in Swait's model are assumed to be exogenous. The model includes cutoff violations in the utility function together with other attributes. The utility of individual i from alternative j is

$$U_{ij} = \sum_k \beta_k X_{ijk} + \sum_k w_k \chi_{ijk} + \sum_k v_k \kappa_{ijk} + \varepsilon_{ij} \tag{2}$$

and is estimated using a standard MNL model. Note that the violations are defined as

$$\chi_{ijk} = \max\left(0, \theta_{ik}^{L} - X_{ijk}\right) \text{ lower cutoff violations} \tag{3a}$$

$$\kappa_{ijk} = \max\left(0, X_{ijk} - \theta_{ik}^{U}\right) \text{ upper cutoff violations} \tag{3b}$$

To make the cutoffs endogenously determined and analyze the correlation between individual characteristics and cutoffs, the cutoffs can be made a function of individual characteristics:

$$\theta_{ik} = \theta_k\left(z_i\right) \tag{4}$$

Given an appropriate specification and functional form for (4) the model defined by (2), (3) and (4) can be estimated using a MNL approach. However, this model assumes no error in the cutoff function. The error of the cutoff function should capture the variations that are not explained by explanatory variables in z_i. If cutoff errors exist, these errors will be added to the error term of the utility function to form a total error term. In a MNL model, this total error is assumed to be Gumbel distributed. However, this may be inappropriate as the error associated with utility will include stochastic elements from the cutoff function.

In this section we model the cutoff error in a modified binary logit framework, as the data we analyze have two alternatives. We start with a single attribute X_h ($k \equiv h$) with a lower cutoff. However the model can be expanded easily to allow for lower or upper cutoffs of several attributes. For notation simplification, we suppress the subscript i in this section. Note also that the attributes we employ are quantitative and cutoffs can be viewed as maximum or minimum acceptable levels of these attributes.

The assumed distribution of the cutoff significantly affects the complexity of model as the likelihood function involves the convolution of the two error terms. A Poisson distribution makes this model tractable. In addition, it is suitable for the attribute *herd* of our data, which is an integer that counts the number of self-sustaining herds of the threatened species of Caribou. Assume a Poisson distribution for the cutoff of X_h

$$p_H = \Pr\left(\theta_h^L = H\right) = \frac{\lambda_h^H e^{-\lambda_h}}{H!},\ \lambda_h > 0, \tag{5}$$

where H takes non-negative integer values $H = H_l, H_l + 1, H_l + 2, ..., H_u$, and where H_l and H_u are lower and upper bounds of attribute X_h. The cutoff λ_h can be parameterized by setting:

$$\lambda_h = \hat{\theta}_h(z) = e^{\gamma_h z}, \tag{6}$$

where z is a vector of individual characteristics (no alternative-specific variables) and γ_h are corresponding parameters. We know that $\lambda_h = e^{\gamma_h z}$ is the expected cutoff, which is not necessarily an integer.

A cutoff violation depends on the expected cutoff and X_{jh} which is the value of attribute X_h offered by alternative j. The estimated violation is:

$$\hat{\chi}_j = \max\left(0, \lambda_h - X_{jh}\right), \tag{7}$$

and the actual violation is:

$$\chi_j = \max\left(0, \theta_h^L - X_{jh}\right). \tag{8}$$

Thus, the error term of the cutoff is the difference between the actual and estimated cutoffs:

$$u_j = \chi_j - \hat{\chi}_j = \max\left(0, \theta_h^L - X_{jh}\right) - \max\left(0, \lambda_h - X_{jh}\right). \quad (9)$$

Consider the case with two alternatives $j = 0,1$. The difference of cutoff errors between the two alternatives is:

$$u = u_1 - u_0 = \max\left(0, \theta_h^L - X_{1h}\right) - \max\left(0, \lambda_h - X_{1h}\right) - \left[\max\left(0, \theta_h^L - X_{0h}\right) - \max\left(0, \lambda_h - X_{0h}\right)\right]. \quad (10)$$

Note that u has a discrete distribution. Each value u_H has the probability of occurring p_H as defined in (5). With two alternatives $j = 0,1$, the utility function with cutoffs can be written as:

$$U_j = \beta X + w\left(\hat{\chi}_j + u_j\right) + \varepsilon_j, \quad (11)$$

where X is a vector of attributes including X_h, ε_j is the conventional Gumbel distributed error term, $\hat{\chi}_j$ is the estimated cutoff violation and u_j is the error term generated from the cutoff violation. The probability of choosing alternative 1 over 0 is:

$$\Pr\left(y=1\right) = \Pr\left(U_1 - U_0 \geq 0\right)$$

$$\Pr\left(y=1\right) = \Pr\left(\varepsilon_1 - \varepsilon_0 + wu_1 - wu_0 \leq \beta\left(X_1 - X_0\right) + w\left(\hat{\chi}_1 - \hat{\chi}_0\right)\right). \quad (12)$$

Let

$$\pi = \beta\left(X_1 - X_0\right) + w\left(\hat{\chi}_1 - \hat{\chi}_0\right) \quad (13)$$

and $\varepsilon = \varepsilon_1 - \varepsilon_0$ and $u = u_1 - u_0$. The probability of choosing alternative 1 becomes:

$$\Pr\left(y=1\right) = \Pr\left(\varepsilon + wu \leq \pi\right). \quad (14)$$

Note that if ε_0 and ε_1 are Gumbel distributed with location parameter 0 and scale parameter 1, then ε is logistically distributed with the cumulative distribution function represented by:

$$\Lambda(\varepsilon) = \frac{1}{1+e^{-\varepsilon}}. \tag{15}$$

Recall that u has a discrete distribution with each value u_h having a probability of occurrence p_h. The sum of the two error terms in (14) is the convolution of the two distribution functions where one is logistic, and one is discrete. Thus:

$$\Pr(y=1) = \sum_{H=H_l}^{H_u} \Pr(\varepsilon + wu_H \le \pi)\, p_H\ , \tag{16}$$

or

$$\Pr(y=1) = \sum_{H=H_l}^{H_u} \Pr(\varepsilon \le \pi - wu_H)\, p_H\ . \tag{17}$$

Therefore

$$\Pr(y=1) = \sum_{H=H_l}^{H_u} \Pr(\varepsilon \le \pi - wu_H) \frac{\lambda_h^H e^{-\lambda_h}}{H!}, \tag{18}$$

where $\pi = \beta(X_1 - X_0) + w(\hat{\chi}_1 - \hat{\chi}_0)$, $\lambda_h = e^{\gamma_h z}$, and u_H is defined by (10).

Note that below the smallest value and beyond the highest value of X_h used in the experiment, a change in cutoff does not change u_H because the cutoff violations of the two alternatives will change by the same amount and cancel out. As a result, the probability that the cutoff equals the highest value can be set at

$$p_{H_u} = 1 - \sum_{H=H_l}^{H_u - 1} \frac{\lambda_h^{\ H} e^{-\lambda_h}}{H!}.$$

This will ensure that the sum $\sum_{H=H_l}^{H_u} \frac{\lambda_h^{\ H} e^{-\lambda_h}}{H!} = 1$. Similar rules apply to the probabilities of H that are smaller than the smallest value used; but keep in mind that H must be non-negative.

Parameters to be estimated include: β, w, and γ. The likelihood function is:

$$L = \prod_{i=1}^{N} \left[\sum_{H=H_l}^{H_u} \Lambda\left(\pi_i - wu_{Hi}\right) \frac{\lambda_{hi}^{\ H} e^{-\lambda_{hi}}}{H!} \right]^{y_i} \left[1 - \sum_{H=H_l}^{H_u} \Lambda\left(\pi_i - wu_{Hi}\right) \frac{\lambda_{hi}^{\ H} e^{-\lambda_{hi}}}{H!} \right]^{1-y_i} \tag{19}$$

where y_i is the choice of individual i. The log-likelihood function is:

$$LL = \sum_{i=1}^{N} \left\{ \begin{array}{l} y_i \ln\left[\sum_{H=H_l}^{H_u} \Lambda\left(\pi_i - wu_{Hi}\right) \frac{\lambda_{hi}^{\ H} e^{-\lambda_{hi}}}{H!} \right] + \\ +\left(1 - y_i\right) \ln\left[1 - \sum_{H=H_l}^{H_u} \Lambda\left(\pi_i - wu_{Hi}\right) \frac{\lambda_{hi}^{\ H} e^{-\lambda_{hi}}}{H!} \right] \end{array} \right\}. \tag{20}$$

Adding upper cutoffs for attribute X_b to the above model is straightforward. Again assume a Poisson distribution and:

$$p_B = \Pr\left(\theta_b^U = B\right) = \frac{\lambda_b^{\ B} e^{-\lambda_b}}{B!},\ \lambda_b > 0,\ B = B_l, B_l + 1, B_l + 2, ..., B_u. \tag{21}$$

Similarly we can parameterize the model by setting $\lambda_b = \hat{\theta}_b\left(z\right) = e^{\gamma_b z}$. The utility function is now:

$$U_j = \beta X + w\left(\hat{\chi}_j + u_j\right) + v\left(\hat{\kappa}_j + \omega_j\right) + \varepsilon_j. \tag{22}$$

The difference of cutoff errors of the two alternatives is:

$$\omega = \omega_1 - \omega_0 = \max\left(0, X_{1b} - \theta_b^U\right) - \max\left(0, \lambda_b - X_{1b}\right) - \left[\max\left(0, X_{0b} - \theta_b^U\right) - \max\left(0, \lambda_b - X_{0b}\right)\right]. \quad (23)$$

The probability of choosing alternative 1 is now:

$$\Pr\left(y=1\right) = \sum_{H=H_l}^{H_u} \sum_{B=B_l}^{B_u} \Lambda\left(\pi - wu_H - v\omega_B\right) \frac{\lambda_h^H e^{-\lambda_h}}{H!} \frac{\lambda_b^B e^{-\lambda_b}}{B!} = P, \quad (24)$$

where $\pi = \beta\left(X_1 - X_0\right) + w\left(\hat{\chi}_1 - \hat{\chi}_0\right) + v\left(\hat{\kappa}_1 - \hat{\kappa}_0\right)$, and $\lambda_b = e^{\gamma_b z}$, and ω_B is defined by (23). The log-likelihood function becomes:

$$LL = \sum_{i=1}^{N} y_i \ln P + \left(1 - y_i\right) \ln\left[1 - P\right], \quad (25)$$

where P is defined by (24).

4. Data and Estimation

4.1 Data

Data were obtained by observing choices of woodland caribou conservation options. Respondents were asked to evaluate caribou conservation alternatives based on two attributes: the extent to which caribou are conserved (the number of self-sustaining herds) and the cost of conservation action. In each choice, respondents were asked to choose between two strategies: the current management strategy and a hypothetical proposed one. In each case the proposed management strategy provided more self-sustaining caribou herds by several measures including restrictions on resource extraction industries, predator management and growing forests, and is drawn from a set of strategies providing different numbers of self-sustaining herds at various cost levels. See Harper (2012) for detailed information about these data.

In another type of choice, respondents were also asked to choose between two proposed management strategies (not including the current management strategy). This is because it may be required by law to do something to protect woodland caribou – implying that a no cost "status quo" is not possible. In this second approach respondents were presented with pairs of management options, each defined by an annual cost and a number of caribou herds conserved.

Several focus group discussions were held to test the survey instruments before the final survey was implemented. Respondents were selected randomly from major centers in Alberta, including Edmonton, Calgary, Grande Prairie, and Lloydminster. Groups of about 30-40 subjects were invited to a central location in each city where they were introduced to the issues with an information presentation (as a PowerPoint presentation) about caribou and conservation strategies. After that they were asked to complete the questionnaire. The questionnaire also requested them to provide demographic information and solicited a number of opinions about conservation activities.

As mentioned, the attributes are *herd* and *bid*. The levels of *herd* were 2, 3, 6, 9, 13 (self-sustaining herds) and the levels of *bid* were $0, $5, $50, $75, $150, $300 and $600. We also employ *sq* as an attribute, which is a dummy variable indicating whether the alternative is the current management strategy. In addition, we also collected demographic information.

Each respondent made four choices, including two votes between the current management strategy and a proposed strategy, and two choices between two proposed strategies. A total of 259 respondents completed the survey, which provides 1,036 choice observations. Of the 258 respondents, 105 are from Edmonton, 76 from Calgary, 43 from Grande Prairie and 34 from Lloydminster. After removing missing observations, 956 choice observations remain, including 481 votes and 475 choices. We pool the votes and choices in our analyses.

The model was estimated using the authors' MATLAB code. As the model may have multiple solutions, for each run we perform a global search for an acceptable optimal solution using MATLAB's Global Optimization Toolbox.

4.2 Simulation with Synthetic Data

To test the proposed model, we estimated parameters using synthetic data. The synthetic data were generated using the empirical data, with assumed coefficients. We employed 1,000 replications of a data set of size 956 (the number of choices in the actual data set discussed below). Column 2 of Table 1 presents the assumed "true" coefficients for the utility function and cutoff functions. The utility function is assumed to be linear in parameters and includes the bid amount, the number of herds that achieve self-sustaining status, and an alternative specific constant for the current situation (status quo). The model with cutoffs includes a term for the bid and herd cutoffs. We assume a lower cutoff for caribou herd and upper cutoff for bid. Herd cutoff is assumed to be a function of *yliving* (years living in Alberta), and bid cutoff a function of *income*, both with a constant

$$\lambda_h = e^{\gamma_0 + \gamma_1 yliving} \quad \text{and} \quad \lambda_b = e^{\varphi_0 + \varphi_1 income} \tag{26}$$

The attributes, *yliving* and *income* were taken from the real data. The utility of each alternative in these data was calculated using the attributes and violations, based on the assumed coefficients, with a Gumbel distributed error added. The choice variable was then generated using the calculated utility, and used as the dependent variable in the estimation of two models. One is the binary logit model without any cutoff information (for comparison) and the other with the proposed model. We refer to the model using calculated cutoffs as "stated cutoffs" assuming that respondents know, and state, their cutoffs. In this model, we estimated a binary logit model with the choice variable on attributes and cutoff violations, where cutoff violations are calculated using equation (26) rounded to the closest integer. In this case the cutoff violations were assumed to be "exogenous".

We then estimated the "true" parameters using the proposed model by maximizing the log-likelihood function:

$$LL = \sum_{i=1}^{N} y_i \ln P + (1 - y_i)\ln[1 - P] \tag{27}$$

where

$$P = \Pr(Y = 1) = \sum_{H=0}^{15}\sum_{B=0}^{60} \Lambda(\pi - wu_H - v\omega_B)\frac{\lambda_h^H e^{-\lambda_h}}{H!}\frac{\lambda_b^B e^{-\lambda_b}}{B!} \tag{28a}$$

$$\pi = \beta(X_1 - X_0) + w(\hat{\chi}_1 - \hat{\chi}_0) + v(\hat{\kappa}_1 - \hat{\kappa}_0) \tag{28b}$$

$$\lambda_h = e^{\gamma_0 + \gamma_1 yliving} \quad \text{and} \quad \lambda_b = e^{\varphi_0 + \varphi_1 income} \tag{28c}$$

$$u_H = \max(0, H - X_{1h}) - \max(0, \lambda_h - X_{1h}) - \left[\max(0, H - X_{0h}) - \max(0, \lambda_h - X_{0h})\right] \tag{29}$$

$$\omega_B = \max(0, X_{1b} - B) - \max(0, \lambda_b - X_{1b}) - \left[\max(0, X_{0b} - B) - \max(0, \lambda_b - X_{0b})\right]. \tag{30}$$

In this model the herd cutoff is described in the following Poisson distribution:

$$p_H = \Pr\left(\theta_h^L = H\right) = \frac{\lambda_h^H e^{-\lambda_h}}{H!}, \tag{31}$$

where $H = 0,1,2,\ldots,15$. We discretize the bid cutoff by assuming it takes discrete values from \$0 to \$600 with increments of \$10, and thus $B = 0,\ 1,\ 2,\ \ldots,\ 60$ (in \$10 increments). As a result the distribution of the bid cutoff can be approximated by:

$$p_B = \Pr\left(\theta_b^U = B\right) = \frac{\lambda_b^B e^{-\lambda_b}}{B!} \tag{32}$$

where $B = 0,1,2,\ldots,60$.

[*Table 1 about here*]

Table 1 presents the assumed parameters and the estimated coefficients from the two models. In the binary logit model, the cutoff violations are calculated by using the attributes and the cutoffs defined by (26). In other words, cutoff violations enter this model as exogenous or are "accurate" statements of cutoffs that should correspond to those derived using the proposed model.

The last column of Table 1 presents the estimation results applying the proposed model. Except for the elements of the bid cutoff function the coefficients are all very well identified and not significantly different from the true parameters (the model captures the true parameter estimates). The coefficients in the bid cutoff function are not as well estimated as this element appears to be very sensitive to outliers. A few very large coefficients are produced in the simulation process – affecting the average. When these outliers are examined, the remaining coefficients provide a good representation of the true parameters. The root mean square errors are also presented. They also indicate a reasonably well fitting model. Note that the binary logit model without any cutoff information produces results that are considerably different from the models with cutoffs included illustrating the potential for significant bias if a simple model is used when cutoffs are present. Table 2 presents the percentage of rejecting the null hypothesis that each of the estimated coefficients of the models is equal to the true parameter at a 5% level of significance. The rejection rates of the binary logit model are quite high, while those of the models with cutoffs are much lower, indicating that the binary logit model might lead to bias, while the models with cutoffs fit the data well. In summary – the Monte Carlo analysis suggests that the new model for estimating cutoffs performs well.

[*Table 2 about here*]

4.3 Estimation with Real Data

As described above, the actual data include 241 individuals making 956 choices, of which 481 are votes (choices between status quo and a proposed management strategy), and 475 choices (choices between two management strategies). Table 3 presents summary statistics of individual characteristics variables used in the regressions.

[*Table 3 about here*]

Table 4 presents estimation results for two simple MNL models. Models MNL1 and MNL2 are basic MNL models; one with attributes only and one including interactions (attributes and individual characteristics). Models MNL3 and MNL4 are models with stated cutoffs; one with and one without interactions.

[*Table 4 about here*]

Model MNL1 yields the expected signs on the coefficients. The attribute *sq* has a negative sign, indicating that respondents are willing to pay to avoid the status quo (no caribou conservation program). Note that the status quo involves no costs to the respondent, but gives the minimal number of sustainable herds. The attribute *bid* has a negative coefficient, meaning respondents are less likely to choose an alternative with a higher cost. The attribute *herd* has a positive coefficient as expected, but it is not statistically significant. This may be because the attribute *sq* has partially captured the preference for sustainable herds.

When interactions of attributes and individual characteristics are added (model MNL2), the attributes' coefficients do not change, except that *herd* and interaction terms are now statistically significant. Looking at the interactions, older respondents are less likely to prefer more caribou herds. Those living longer in Alberta prefer more herds, however they are more sensitive to cost. Finally those who work full-time are less sensitive to cost. These results are stable across the various models.

Models MNL3 and MNL4 are similar to MNL1 and MNL2, but now violations of self-reported cutoffs are included as exogenous variables. Specifically, violations of lower herd cutoffs, and violations of upper bid cutoffs are included. Coefficients of the violations are negative as expected, implying that alternatives with violations are penalized in terms of utility.

When violations are included, the signs of *herd* and *bid* change and must be interpreted along with the cutoff parameters. The attribute *herd* now has a negative coefficient, implying that once the alternative reaches the minimum required number of herds (lower herd cutoff), additional herds will reduce utility. Note that below the cutoff point, an additional herd will have positive marginal utility because it reduces the herd cutoff violation. The impact of an increase in *herd* by one unit arising from the penalty (or cutoff violation) is larger than the impact from the direct effect; thus the overall effect of an increase in *herd* is positive (for high cutoff levels) even though the sign on the direct effect of *herd* is negative. Given that the average herd cutoff is 9, as presented in Table 6, the results of models MNL3 and MNL4 imply that respondents have increasing marginal utility for an additional herd up to approximately 9 herds, then have negative marginal utility for *herd*. Similarly for *bid*, models MNL3 and MNL4 indicate that respondents are willing to pay more for a given number of caribou herds, but become less willing to pay once the cost reaches the maximum acceptable cost (the upper bid cutoff).

[*Table 5 about here*]

Table 5 presents the estimation results of various specifications of the proposed model. In these models cutoffs are estimated endogenously from the choice observations. Models CEL1 and CEL2 estimate cutoffs as constants, implying aggregate cutoffs for the entire sample. Model CEL2 includes interactions. Models CEL3 and CEL4 are similar but estimate cutoffs as functions of individual characteristics. Note that in these models the cutoff violations are calculated from the estimated cutoff functions and attribute levels. The last column of Table 5 presents the direct Poisson regression of self-reported cutoffs on individual characteristics, allowing a comparison with the cutoff functions estimated from the proposed model as in models CEL2 and CEL4.

In terms of log-likelihood value, the stated cutoff models show significant improvements compared to models MNL1 and MNL2. Both likelihood ratio tests of model MNL3 against MNL1, and MNL4 against MNL2 yield p-values less than 0.001. This shows that self-reported cutoffs make a notable contribution to explaining the choice behavior. Models with endogenously determined cutoffs also improve the log-likelihood value compared to MNL1 and MNL2, but not as much as the stated cutoff models. The estimated cutoffs contribute to the log-likelihood value, but not as much as the self-reported cutoffs. This may be because the self-reported cutoffs are not well explained by individual characteristics we have and that self-reports are endogenous thereby increasing fit but potentially not explaining cutoffs.

Coefficients of cutoff violations are somewhat different from those of the stated cutoff models. Models CEL1 and CEL2 have cutoff violation coefficients that are very different, although they are negative. The bid cutoff violations are statistically insignificant. In models CEL3 and CEL4, the estimated coefficients of herd cutoff violations are very close to model MNL3 and MNL4. However, for bid cutoff violations, the estimated coefficients are only half as large as those of model MNL3 and MNL4.

Coefficients of attributes in the endogenously determined cutoff models have the expected signs; however many of them are not significant at a 10% level. In models CEL3 and CEL4, the status quo ASC has insignificant coefficients. But these attributes have to be evaluated in terms of their joint impact – including the interaction effects. Likelihood ratio tests for the inclusion / exclusion of *herd* and bid are strongly significant indicating that these attributes contribute significantly to the model Coefficients of interactions terms are close to those of models MNL3 and MNL4.

Some of the estimated cutoff functions from models CEL3 and CEL4 are very different from the Poisson regression of self-reported cutoffs on the individual characteristics (last column of Table 5).

However, in most cases they are consistent in terms of signs. In the bid cutoff function, the coefficient of income is positive, indicating that respondents with higher income have a higher cutoff. In other words, the maximum level of cost that is still acceptable is higher for higher income respondents. The variable *tvwatch*, has a positive coefficient, implying that those who frequently watch TV programs about animals have higher bid cutoff. Urban respondents have lower bid cutoffs.

Although the estimated herd cutoff functions show differences compared to the Poisson regression, their estimates are consistent in terms of signs with the Poisson regression. Full-time workers require more caribou herds in the proposed model and in the Poisson regression. In all models, urban respondents appear to have higher herd cutoffs. Those who watch TV programs about animals show no difference in herd cutoff. The variable *hunter*, indicating that the respondent went hunting in the last 12 months, is statistically significant in model CEL3 only.

[*Table 6 about here*]

In summary, some coefficients of the estimated cutoff functions are similar to the Poisson regression functions of self-reported bid cutoffs. In most cases they are consistent in terms of sign. Table 6 presents the average cutoffs, including those from self-reported data and those estimated from our proposed model. On average, a respondent requires 9 self-sustaining caribou herds and is willing to pay no more than $140 per year per household. Models CEL1 and CEL2 predict lower herd as well as bid cutoffs. Estimates from models CEL3 and CEL4 result in average bid cutoffs of $124 and $170, which are not that far from the self-reported bid cutoffs. However for herd cutoffs, the average estimate is less than 5 caribou herds, which is half of the stated herd cutoff. This is possibly because respondents set different cutoffs when making choices. (1)

4.4 Welfare Measures

This section explains the procedure of calculating welfare measures corresponding to woodland caribou conservation strategies. We calculate the willingness to pay (WTP) for three different strategies that offer 4, 8 and 12 self-sustaining herds. We start with the utility function

$$V_j = \alpha sq + \beta M + \vartheta M Z^M + \eta H_j + \mu H_j Z^H + w\hat{\chi}_j + v\hat{\kappa}_j,$$

where sq is the status quo, M is income, H is herd, Z^M and Z^H are the vectors of individual characteristics interacted with M and H, and $\hat{\chi}_j$ is the lower herd cutoff and $\hat{\kappa}_j$ upper bid cutoff defined by (3a) and (3b). The willingness to pay t that equates utilities of the two alternatives 0 (base case) and 1 (improved case or additional self-sustaining herds) is defined by:

$$\alpha + \beta M + \vartheta M Z^M + \eta H_0 + \mu H_0 Z^H + w\hat{\chi}_0 + v\hat{\kappa}_0 =$$

$$= \beta(M-t) + \vartheta(M-t)Z^M + \eta H_1 + \mu H_1 Z^H + w\hat{\chi}_1 + v\hat{\kappa}_1$$

Note that $\hat{\kappa}_0 = 0$ because there is no bid violation at the status quo. The utility difference caused by an increase in the number of herds is: $-\alpha + (H_1 - H_0)(\eta + \mu Z^H) + w(\hat{\chi}_1 - \hat{\chi}_0)$. This should be divided by the marginal utility of money to obtain WTP. However, in models with bid cutoffs, the marginal utility of money changes at the bid cutoff point. Up to the cutoff point, the marginal utility of money $\beta + \vartheta Z^M$ applies. Beyond the cutoff point, $\beta + \vartheta Z^M - v$ applies. As a result, WTP is:

$$t = \frac{-\alpha + (H_1 - H_0)(\eta + \mu Z^H) + w(\hat{\chi}_1 - \hat{\chi}_0)}{\beta + \vartheta Z^M} \qquad \text{if } t \le \theta_i^U$$

$$t = \theta_i^U + \frac{-\alpha + (H_1 - H_0)(\eta + \mu Z^H) + w(\hat{\chi}_1 - \hat{\chi}_0) - \theta_i^U(\beta + \vartheta Z^M)}{\beta + \vartheta Z^M - v} \quad \text{if } t > \theta_i^U$$

where θ_i^U is the upper bid cutoff of individual i.

Table 7 presents the welfare measures from the estimated MNL models and endogenously determined cutoff models. Columns 2, 3 and 4 present the WTP measures ($/year/household) for the three management strategies calculated for each model. Standard errors are calculated using the Krinsky-Robb method with 1,000 draws of parameters of the utility and cutoff functions.

[*Table 7about here*]

Table 7 shows that estimated WTP is approximately $200/year for the management strategy that provides 4 herds, and $250-300/year for the strategies that provide 8 and 12 herds. Model MNL1 generates WTP estimates that increase with the number of herds. Model MNL2 results in WTP estimates of about $230-240/year for all strategies.

WTPs from models with self-reported and endogenous cutoffs exhibit a common pattern. They start with WTPs for 4 herds lower than those from MNL1 and MNL2. However the WTPs from these models increase sharply when the number of herds reaches 8 and at this point the WTPs are approximately equal to those from MNL1 and MNL2. WTPs for a 12-herd management strategy are slightly lower than those for an 8-herd strategy in these models reflecting the fact that the overall marginal utility of herds is slightly negative in all models with cutoffs, except model CEL3. The main contribution to a positive WTP for a 4-herd strategy is avoiding the status quo and the reduction of the herd cutoff violation. From 4 herds to 8 herds, WTP estimates increase substantially because of the elimination of the herd cutoff violation. However, moving from 8 to 12 herds does not improve welfare because in most cases, the herd cutoffs are around 4-7 herds in the endogenously determined cutoff models or 10 in self-reported cutoff models, and thus the herd increase from 8 to 12 does not reduce, or just slightly reduces herd cutoff violations.

5. Conclusions

Several researchers have been incorporating the possibility of cutoffs, or non-compensatory preferences, into random utility models of choice. Most often the cutoff values are elicited from respondents and these stated values are incorporated directly in the econometric analysis. There is a concern that these stated cutoffs may be endogenous in the model and thus may generate bias in the resulting welfare measures. This paper developed and applied an analytical model to estimate cutoffs endogenously. In the proposed model, the cutoff function was assumed to have a Poisson distributed error term that is appropriate for our data and allowed for a tractable model. When incorporating the cutoff function in the choice model, this error term is added to the conventional Gumbel error. We estimated the model using maximum likelihood, taking into account the two error terms. Our approach provides a tractable way to estimate non-compensatory preferences without relying on stated cutoffs. It is relevant to cases where compensatory preferences may not be appropriate, and where analysts wish to estimate cutoffs without information from self-reported cutoffs. Our model depends on there being sufficient explanatory power in observed exogenous variables, such as the characteristics of those involved in making the choices, in the modeled cutoff values, and knowledge of the "true" specification.

We tested the proposed model with synthetic data and found that parameter estimates of the model were very close to the true parameters. We then applied the model to an empirical data set involving choices of caribou conservation options in Alberta. The results suggest that our model shows some improvement over basic MNL models, but is not as good in terms of in-sample prediction as the MNL models with self-reported cutoffs. Some of the estimated coefficients of cutoff functions from the proposed model are close to the Poisson regressions of self-reported cutoffs on various respondent characteristics, and most are consistent in signs with Poisson regression parameters.

Because models with cutoffs outperformed those without cutoffs, we suggest that cutoffs be considered when analyzing choice behavior. In our case study, the model with stated cutoffs was statistically better than the proposed endogenously determined cutoff model, but the latter avoids the potential endogeneity problems associated with including stated cutoffs. However, our proposed model is helpful for the case where cutoffs are important, but stated cutoff information is unavailable. Since respondents may be unable to report cutoffs accurately (e.g. Nisbett and Wilson, 1977), or may adapt their cutoff levels to the choice environment (e.g. Payne *et al*. 1988), or may be willing to adjust their cutoff when evaluating a particular alternative (Klein and Bither, 1987, Huber and Klein, 1991, Swait, 2001), a cutoff model that does not rely on stated cutoff may be more desirable than a stated cutoff model.

The bid cutoffs estimated from our proposed models are close to the self-reported cutoffs; however herd cutoffs estimated from our model are lower than the self-reported herd cutoff. This is possible because, as mentioned above, when facing the choice, respondents adjust their cutoffs to suit the choice context. In our study respondents appeared to require more caribou herds in response to the herd cutoff question, but they lowered their requirement when facing choices with information about the associated costs.

Since woodland caribou is listed as “threatened” the Canadian *Species at Risk Act* in Canada requires that an action plan for recovery must be formed together with estimated socio-economic costs and benefits. To do benefit-cost analysis, our estimated WTP for woodland caribou conservation strategies can be compared to the opportunity costs of conservation adopted from Schneider *et al*. (2010), which result from reduced activities in the forestry, oil and gas industries, reduced revenue to the government, and the direct costs of wolf control and reclamation. Harper (2012) examines costs and benefits from a relatively simple MNL models and estimates that the optimal level of conservation is between 4 to 11 herds. Our analysis of the stated cutoffs shows that additional herds do not increase utility when the number of herds is more than 9. Results from our proposed models suggest that the minimum acceptable number of herds ranges from 5 to 7 and that additional herds are not always desirable beyond these levels. While our results are within the range suggested by Harper (2012) more information is provided from our models and the cutoff estimates.

Although our proposed model works well with the synthetic data in terms of recovering the true parameters, it is more challenging to estimate using empirical choice information. The specification of the cutoff function seems to be quite important. There are two aspects that should be considered in future development of our proposed model. First, the log-likelihood function likely has multiple local optima. By the nature of the cutoff violations the utility function is kinked at the cutoff points. As a result, the model has multiple solutions. An approximation of the utility function with cutoffs developed as in Martinez *et al*. (2009) should be investigated as an alternative. Second, the Poisson distribution may not be a good approximation for the cutoffs that are continuous. Other distributions, particularly continuous probability distributions which are appropriate for continuous attributes, should be investigated. In addition the proposed model is limited to two alternative choices and thus there is a need for a model that works for choices from multiple alternatives. In addition, our approach does not incorporate unobserved heterogeneity in preferences (including cutoffs) and it does not account for the panel nature of the data. These are avenues for future research. In a broader context, there is a linkage between cutoff models of the type we investigate and models of choice set formation. The relationship between these classes of models also deserves further analysis.

NOTES

(1) We also explore the model with different specifications. The estimated coefficients and cutoff values are close to the full models presented in Table 5. These results are available from the authors upon request.

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Table 1: Simulation Results from 1000 Replications of 956 Choices Assuming "True" Parameters

		ESTIMATED COEFFICIENTS		
Variable	**True parameters**	**Binary Logit without cutoffs**	**Binary Logit with stated cutoffs**	**Proposed model**
UTILITY FUNCTION				
'ASC – status quo'	-1	-1.875 (0.911)	-1.025 (0.315)	-0.946 (0.404)
'bid'	-2	-1.859 (0.197)	-2.041 (0.189)	-2.022 (0.211)
'herd'	0.25	0.355 (0.112)	0.254 (0.046)	0.251 (0.058)
Violation of herd cutoff	-0.5		-0.496 (0.092)	-0.558 (0.149)
Violation of bid cutoff	-0.5		-0.508 (0.358)	-0.537 (0.247)
HERD CUTOFF FUNCTION				
Constant	3			2.933 (1.164)
Years living in Alberta	0.1			0.1 (0.033)
BID CUTOFF FUNCTION				
Constant	1			0.656 (1.727)
Income ($10,000)	0.25			0.301 (0.291)

Note: RMSE are in parentheses.

Table 2: Percentage of replications rejecting the null hypothesis that estimated coefficients are equal to the true values from 1,000 replications, at 5% level of significance

	PERCENT REJECTING NULL HYPOTHESIS		
Variable	**Binary Logit without cutoffs**	**Binary Logit with stated cutoffs**	**Proposed model**
UTILITY FUNCTION			
'ASC – status quo'	97.5	11.0	12.9
'bid'	31.8	11.1	8.2
'herd'	86.3	11.0	11.6
Violation of herd cutoff		11.2	14.2
Violation of bid cutoff		12.0	2.5
HERD CUTOFF FUNCTION			
Constant			49.3
Years living in Alberta			44.4
BID CUTOFF FUNCTION			
Constant			61.1
Income ($10,000)			56.4

Table 3: Descriptive Statistics for the Sample of Alberta Residents included in the Caribou Conservation Program Survey

	Mean	**Std. Dev.**	**Min**	**Max**
Age (years)	48.18	14.7	18	87
Years living in Alberta	32.6	18.72	1	80
Income ($10K/year)	8.94	4.67	1	17
Dummy variables				
Male	0.52			
College or higher	0.54			
Fulltime worker	0.49			
Often watch TV programs about animals	0.39			
Hunting in the past 12 months	0.10			

Table 4: MNL models of preferences for caribou conservation options.

MODEL	Simple MNL model (MNL1)		MNL model with interactions (MNL2)		Simple MNL model with stated cutoffs (MNL3)		MNL model with interactions with stated cutoffs (MNL4)	
ATTRIBUTES								
ASC – Status quo	-0.588 ***	(0.145)	-0.578 ***	(0.148)	-0.305 *	(0.161)	-0.318 **	(0.163)
No. of Herds	0.027	(0.018)	0.101 **	(0.042)	-0.133 ***	(0.028)	-0.068	(0.051)
Bid ($10)	-0.027 ***	(0.003)	-0.023 ***	(0.007)	0.012 **	(0.005)	0.019 **	(0.009)
INTERACTIONS								
Herd x Age			-0.004 ***	(0.001)			-0.003 ***	(0.001)
Herd x Years living in Alberta			0.003 ***	(0.001)			0.003 ***	(0.001)
Bid x Years living in Alberta			-0.0005 ***	(0.0002)			-0.0005 **	(0.0002)
Bid x full-time work			0.019 ***	(0.005)			0.012 **	(0.0054)
PENALTY ON CUTOFF VIOLATIONS								
Herd					-0.273 ***	(0.033)	-0.260 ***	(0.033)
Bid (in $10)					-0.064 ***	(0.006)	-0.062 ***	(0.007)
Log-likelihood	-601.04		-580.00		-511.44		-500.81	
Rho-square	0.093		0.125		0.228		0.244	

*Note: *** Significant at 1% level. ** Significant at 5% level. * Significant at 10%. Standard errors are in parentheses.*

Table 5: Estimation results of endogenously determined cutoff models

MODEL	CEL1	CEL2	CEL3	CEL4	Poisson[(b)]
UTILITY FUNCTION - ATTRIBUTES					
ASC – Status quo	-0.162	-0.112	0.13	0.044	
	(0.202)	(0.216)	(0.236)	(0.214)	
No. of Herds	-0.003	0.064	0.014	0.082 *	
	(0.031)	(0.049)	(0.019)	(0.045)	
Bid ($10)	-0.024 *	-0.019	-0.014 **	-0.006	
	(0.013)	(0.02)	(0.007)	(0.009)	
UTILITY FUNCTION - INTERACTIONS					
Herd x Age		-0.004 ***		-0.004 ***	
		(0.001)		(0.001)	
Herd x Years living in Alberta		0.003 ***		0.003 ***	
		(0.001)		(0.001)	
Bid x Years living in Alberta		-0.001 ***		-0.001 ***	
		(0.000)		(0.000)	
Bid x full-time work		0.02 ***		0.008	
		(0.004)		(0.006)	
UTILITY FUNCTION - PENALTY ON CUTOFF VIOLATIONS					
No. of Herds	-0.143 **	-0.159 ***	-0.356 ***	-0.289 ***	
	(0.063)	(0.058)	(0.119)	(0.081)	
Bid (in $10)	-0.006	-0.007	-0.023 ***	-0.017 ***	
	(0.013)	(0.02)	(0.007)	(0.007)	
HERD CUTOFF FUNCTION					
Constant	1.881 ***	1.908 ***	1.099 ***	1.116 ***	1.959 ***
	(0.139)	(0.117)	(0.002)	(0.19)	(0.055)
Fulltime work (=1)			0.363 ***	0.318 **	0.090 *
			(0.095)	(0.131)	(0.050)
Watch TV programs about animals (=1)			-0.044	0.021	0.046
			(0.075)	(0.088)	(0.052)
Hunter (=1)			0.217 **	0.153	0.133
			(0.099)	(0.126)	(0.082)
Urban (=1)			0.290 ***	0.337 ***	0.161 ***

			(0.091)	(0.132)	(0.055)
BID CUTOFF FUNCTION					
Constant	2.015 ***	2.015 ***	-0.762	-0.619 ***	-0.407 ***
	(0.000)	(0.001)	(0.576)	(0.007)	(0.169)
Watch TV programs about animals (=1)			2.708 ***	2.079 ***	0.954 ***
			(0.541)	(0.008)	(0.111)
Income			0.208 ***	0.277 ***	0.063 ***
			(0.005)	(0.000)	(0.012)
Urban (=1)			-1.386 ***	-2.079 ***	-0.297***
			(0.042)	(0.01)	(0.113)
Log-likelihood	-597.19	-575.70	-579.35	-567.10	
Rho-square	0.099	0.131	0.126	0.144	
Run time (a)	2	2	6	4	

*Note: *** Significant at 1% level. ** Significant at 5% level. * Significant at 10%. (a) in minutes, running on a computer with a six-core processor at 3.47GHz. (b) Direct Poisson regressions (right-censored for the case of herd cutoff) of stated cutoffs on individual characteristics. Standard errors are in parentheses.*

Table 6: Comparison of self-reported and predicted cutoffs

Mean of	Stated cutoffs	CEL1	CEL2	CEL3	CEL4
Herd cutoff (herds)	9.10	6.50	6.77	4.55	4.80
Bid cutoff ($)	140	75	75	124	170

Table 7: Willingness To Pay ($/year/household) for woodland caribou management strategies

Number of self-sustaining herds	4 herds	8 herds	12 herds
Model MNL1	237.78	277.78	317.78
	(63.78)	(75.06)	(92.99)
Model MNL2	236.69	229.79	241.74
	(307.44)	(473.98)	(651.58)
Model MNL3	222.9	278.95	277.23
	(44.02)	(64.94)	(83.94)
Model MNL4	145.4	168.02	130.63
	(58.45)	(112.99)	(173.04)
Model CEL1	161.72	279.31	274.91
	(660.82)	(411.25)	(396.35)
Model CEL2	160.37	292.81	276.62
	(123.1)	(223.51)	(371.82)
Model CEL3	201.19	286.08	302.83
	(241.21)	(223.45)	(245.96)
Model CEL4	188.77	278.4	270.57
	(123.88)	(192.75)	(271.42)

Note: Without management, the number of self-sustaining herds after 50 years is expected to be 2 herds. Measures are in $/year/household. Standard errors are in parentheses.

Appendix: Cutoff questions, and examples of vote and choice questions

Herd cutoff question: What is the **minimum number** of self-sustaining caribou herds (there are 14 caribou herds in the province of Alberta), 50 years from now, that your household would find acceptable? ________

Bid cutoff question: If caribou conservation requires additional tax funds, what is the **maximum annual increase in taxes** your household would find acceptable for the next 50 years? $________

VOTE: Suppose you were asked to consider the proposed management strategy versus maintaining the current management strategy as described below.

	Current Management Strategy	Proposed Management Strategy
Number of self-sustaining caribou herds *in 50 years*	2	10
Your household's share of the cost *per year for the next 50 years* in provincial income taxes	$0	$75

Please carefully compare the two alternatives presented in the table above. If you had to VOTE on these two options, which one would you choose?

PLEASE CHECK ONE RESPONSE ONLY

- ❑ CURRENT management strategy
- ❑ PROPOSED management strategy

CHOICE:

	Management Strategy A	Management Strategy B
Number of self-sustaining caribou herds *in 50 years*	9	6
Your household's share of the cost *per year for the next 50 years* in provincial income taxes	$92	$68

Please carefully compare the two management strategies presented in the table above. If you had to choose one of these strategies, would you choose Management Strategy A or Management Strategy B?

PLEASE CHECK ONE RESPONSE ONLY

- ❑ Management Strategy A
- ❑ Management Strategy B