**Modelling the Effect of Risk Perception on Preferences and Choice Set Formation over Time:**

**Recreational Hunting Site Choice and Chronic Wasting Disease**

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**Abstract** Chronic wasting disease (CWD) is a prion disease that affects deer, elk and other cervid wildlife species. Although there is no known link between the consumption of CWD affected meat and human health, hunters are advised to have animals from CWD affected areas tested and are advised against consuming meat from CWD infected animals (Government of Alberta, 2010). We model hunter response to the knowledge that deer in a wildlife management unit have been found to have CWD in Alberta, Canada. We examine hunter site choice over two hunting seasons using revealed and stated preference data in models that incorporate preferences, choice set formation, and scale. We compare a fully endogenous choice set model using the Independent Availability Logit model (Swait, 1984) with the availability function approach (Cascetta and Papola, 2001) that approximates choice set formation. We find that CWD incidence affects choice set formation and preferences and that ignoring choice set formation would result in biased estimates of impact and welfare measures. This study contributes to the broader recreation demand literature by incorporating choice set formation, scale and temporal impacts into a random utility model of recreation demand.

**Keywords:** Recreation demand, random utility models, Combined revealed-stated preferences, Choice set formation, risk perception.

**JEL classification:** Q260, Q280

**Abbreviations:** BSE - Bovine Spongiform Encephalopathy; CMNL - Constrained multinomial logit model; CPA - Cascetta and Papola Availability; CWD - Chronic wasting disease; IAL - Independent Availability Logit; MNL - multinomial logit; RP - Revealed preference; RUM - Random utility model; SP - Stated preference; WMU - Wildlife management unit.

**1. Introduction**

The economics of recreation demand began with the travel cost model (Hotelling 1949; Clawson 1959) in which the demand for trips to a specific site was shown to decrease with travel costs, a proxy for price. More recent developments involved Hanemann's (1978) random utility model in which every trip was considered a choice where an individual was assumed to choose the site that maximized their utility given income and time constraints. Other researchers applied random utility models (RUMs) to examine choices of specific recreation sites as a function of various attributes of the sites in addition to travel costs and to more fully incorporate substitution patterns between options.

The application of RUMs to recreation site choice allows analysis of responses to potential health risks by considering this risk as an attribute of the sites. This was first developed in the recreational fishing literature where posted advisories to anglers about consuming fish pointed out various health risks inherent in the fish. Early literature examined anglers' compliance with consumption advisories and found that most anglers ignored the advisories (Diana et al. 1993; May and Burger 1996), suggesting that advisories are not effective. However, Jakus et al. (1997) using a RUM, found that anglers were less likely to visit a reservoir with an advisory. More recently Zimmer et al. (2012a) analyzed the effect of Chronic Wasting Disease[1] (CWD), a degenerative wasting disease that affects deer, moose and elk, on hunting site choice in Alberta using a RUM and found that the prevalence of the disease, as well as wildlife management disease mitigation efforts, affected site choice.

In recreation research efforts using RUMs one of the key components is the definition of the choice set - the set from which the recreationist chooses their preferred site. The choice set is often defined exogenously by the researcher based on certain distance rules or data availability. It is increasingly

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[1] CWD is a prion disease that affects elk, deer and moose and is essentially the cervid species form of "mad cow disease" or Bovine Spongiform Encephalopathy (BSE). However, unlike BSE there is no known link between the consumption of CWD affected meat and human health. Nevertheless, hunters are advised to have animals from CWD affected areas tested and are advised against consuming meat from CWD infected animals (Government of Alberta 2010).

recognized, however, that choice set formation is an important component of choice behavior (Swait 1984, 2001a) and could be determined endogenously. This applies in recreation demand as well as in transportation mode choice, food product choice, housing choice, and other areas where random utility models are employed. In the context of CWD and hunting, choice set formation may play a very significant role as hunters may reject sites that are affected by CWD or they may simply view CWD as a site attribute and incorporate it into the tradeoffs made in choosing among sites. Furthermore, these relationships between attributes, utility and choice set formation may change over time as information is released.

This paper focuses on the issue of choice set formation and health risk perceptions over two time periods. We examine various ways of incorporating choice set formation and risk perceptions in the RUM. To the best of our knowledge none of the previous research examining health risks and recreation site choice analyzed responses in a two-stage decision process that accounted for choice set formation. If there are a large number of possible sites, recreationists could narrow their choice set using some specific criteria and make their choice from within the narrowed choice set. Mis-specification of individual choice sets might result in biased estimates of the utility function and incorrect prediction of individuals' choices (e.g. Hicks and Strand 2000). Furthermore, choice set formation may change over time, or temporal effects may be reflected in differences in scale between time periods. We examine all these elements in our assessment of the impact of CWD on hunter site choice.

In this paper we build on the work by Zimmer et al (2012a) and further examine consumer (hunter) response to the potential health risks that arise from further expansion in the prevalence and spread of CWD in Alberta. The Government of Alberta implemented several wildlife management activities to prevent the spread of CWD which could confound examination of the economic impacts of the disease on site choice behavior (Zimmer et al. 2012a). In this study we examine several approaches that attempt to untangle various choice behavior elements because hunters may initially ignore the potential risk of CWD

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and (dis)like CWD prevention activities, but may change their preferences and behaviors at a later time through learning as the disease spreads and prevalence levels change spatially.

This present study uses a unique dataset that includes two years of stated and revealed preference information on site choices from a sample of Albertan hunters. This offers a chance to examine changing behavior over a time frame in which the spread and prevalence of the disease was expanding. In our empirical study, the learning process may affect hunting site choice in two stages: choice set formation and site evaluation. On choice set formation, learning about the potential risk of CWD may make hunting sites with high occurrences of CWD less likely to be included in the choice set. In the utility function, the learning process may also make sites with high CWD occurrence less desirable over time.

While the sample size in these data do not permit the results to be robust enough for formal policy analysis, the information is sufficient to conveniently assess and compare modeling approaches that examine the effect of learning about health risks on choice set formation and preferences over the two time periods. The study analyzes whether and how CWD affects site evaluation and choice set formation over time using two choice model frameworks and compares the preferences and welfare measures associated with several hypothetical policy scenarios.

Our empirical analysis of choice set formation employs the independent availability logit model (IAL) formulated by Manski (1977) and further developed by Swait (1984), and also the approach reported by Cascetta and Papola's (2001) who developed an implicit availability function to weight the various elements in choice sets. Including CWD and time period variables into the availability models allows examination of the effects of changing levels of CWD on choice set formation, which is assumed to result from a learning process. Changes in hunting site preferences are investigated by examining the utility function. The marginal (dis)utility of the attribute CWD could change over time as the disease spreads, and management efforts to arrest its spread and prevalence are implemented. In addition, scale parameters are also estimated for the stated and revealed components of the data set each year to account

for differences in error variances over time and between preference data sources. Our contribution includes the incorporation of choice set formation, scale and temporal impacts into a random utility model of recreation demand and a comparison of various modeling approaches.

## 2. Review of Literature

### 2.1 RECREATION SITE CHOICE AND HEALTH RISK

Several attempts have been made to deal with choice set formation in RUMs. Peters et al. (1995), for example, asked respondents to specify alternatives that would be considered before making final trip decisions. Choice set formation has also been modeled endogenously. Haab and Hicks (1997), Swait (1984), Swait and Ben-Akiva (1986, 1987a,b), Roberts and Lattin (1991), Andrews and Srinivasan (1995), Ben-Akiva and Boccara (1995), Chiang et al. (1999) and von Haefen (2008) explicitly modeled choice set formation based on the two-stage choice decision process formulated by Manski (1977). Swait (2001a) developed a model that does not consider choice set generation as a separate construct, but as another expression of utility.

The explicit modeling of choice set formation is particularly challenging when there are large choice sets. Cascetta and Papola (2001) introduced the implicit availability perception function as an extension of the standard multinomial logit  model (MNL) to permit decision makers to have different weights on alternatives to be considered for final decision (see also Kuriyama et al. 2003).  While this approach is an approximation to choice set formation, it provides a tractable method for incorporating choice set formation issues into RUMs that have many alternatives.

As mentioned above, there are several studies that examine recreation site choices in response to health risks. Jakus et al. (1997) analyzed the effects of sportfish consumption advisories on fishing site choice in Tennessee and found that anglers considered advisories in making fishing site choice, and that advisories posted to a reservoir tended to drive anglers away from that reservoir. Jakus and Shaw (2003)

introduced a perceived hazard function into the site choice model which estimated the probability of keeping fish from a site. Because keeping angled fish was assumed to be for consumption, it could be considered a risk perception function. The perceived hazard function was then introduced to the site choice model as an attribute. Jakus and Shaw did not find statistically significant effects of advisory awareness on the probability of keeping fish, but found that higher risk perceptions for a site drove anglers away from the site.

Zimmer et al. (2012a) analyzed the hunting site choices of Albertan deer hunters, focusing on responses to CWD risk and prevention activities. They found that hunters were less likely to visit a site with higher CWD prevalence. In addition, one CWD management activity (deer culling) was found to have a negative effect on site demand, while another one (extra tags – the provision of additional licenses allowing higher deer harvest levels) was found to have a positive effect. Data from Zimmer et al. are part of the data used in this paper.

Some alternatives may not be in an individual's choice set for several reasons. For example, the individual may not know about some recreational sites, or rule out some sites using individual-specific criteria. Although ignoring the choice set formation process might result in biases (see Haab and Hicks 1999), choice set formation was not explicitly modeled in the risk perception research mentioned above. In Jakus et al. (1997) distance was the main factor used to identify choice sets. A reservoir located far away from an angler's origin was eliminated from the choice set of anglers from that county, unless at least one angler in the county visited it. Jakus and Shaw (2003) did not discuss choice set formation, and all anglers in their study faced a choice set of 12 major reservoirs. Zimmer et al. (2012a) developed their choice model with a two-level nested random parameter logit model, but their model did not capture the choice set generation processes.

## 2.2 Survey Approaches to Choice set definition

Researchers have used survey responses or exogenous information to define choice sets. Peters et al. (1995) estimated two models, one with all sites known to researchers as the choice set and another with choice sets that only included sites actually visited or known to each individual in their study. Their results showed that using all available sites as a choice set might result in biased estimates of preferences and welfare. Parsons and Hauber (1998), analyzing day-trip fishing demand in Maine, defined choice sets using spatial boundaries. Choice sets available to an individual included 12 randomly drawn sites within the range of 0.8 hours travel from their residence. They also varied the boundary from 0.8 up to 4 hours by 0.2 hour increments, and found that choice model parameters changes when the boundaries changed. This implies that mis-specification of choice sets may result in biased estimates of the utility function parameters. Hicks and Strand (2000) analyzed the effect of water quality on recreational beach use in Maryland with choice models. Models with three different choice sets were estimated: all sites, those within a specified distance and those familiar to the respondents (identified using survey techniques). They found that parameters and welfare measures were sensitive to choice set definition. Jones and Lupi (1999) examined the demand for recreational fishing activities in the Great Lakes using a nested logit model and found that omitting relevant alternatives resulted in biased utility functions and incorrect welfare measures.

## 2.3 Explicit Models of Choice Set Generation and choice

While choice sets can be approximated using survey responses or by imposing rules such as distance or familiarity, other researchers have attempted to explicitly model choice sets along with choices of alternatives. Swait (1984), Swait and Ben-Akiva (1987a) and Ben-Akiva and Boccara (1995) developed a formal two-stage model where the first stage consists of a choice set generation process which considers all possible subsets from a given set of all alternatives. Haab and Hicks (1997) developed a similar model presented in the next section. Cascetta and Papola (2001) proposed a RUM with an

implicit availability perception function, which permits estimation of the degree to which an alternative is available for consideration of an individual.

Models with explicit choice set generation processes are based on the two-stage decision process of Manski (1977), in which the probability of choosing alternative $j$ is:

$$p_j = \sum_{C_k \subseteq C_m} P(j \mid C_k) Q(C_k), \tag{1}$$

where $Q(C_k)$ is the probability that $C_k$ is the true choice set, $P(j \mid C_k)$ is the probability of choosing alternative $j$ conditional on the given choice set $C_k$, and $C_k$ is the choice set within $C_m$ which represents the set of subsets of the universal set $M$. Note that $k$ is an index for a choice set being in $C_m$ and $m$ is an index for all possible subsets of the universal set $M$. Choice models based on Manski's approach include the Independent Availability Logit (IAL) Model (Swait 1984, Swait and Ben-Akiva 1987a, Ben-Akiva and Boccara 1995), the GenL model (Swait 2001a), and the endogenous choice set model of Haab and Hicks (1997).[2]

In the IAL model the probability that $C_k$ is the true choice set is given by:

$$Q(C_k) = \frac{\prod_{j \in C_k} A_j \prod_{l \notin C_k} (1 - A_l)}{1 - \prod_{h \in C_m} (1 - A_h)}, \tag{2}$$

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[2] We note that von Haefen (2008) applied a Kuhn-Tucker demand system to model latent consideration sets. This model is attractive because it is tractable for large choice sets and can be estimated using standard econometric techniques. However the von Haefen approach employs a theoretical and empirical framework that is quite different from the RUM approach used in much of the literature. Therefore, we focus on the Haab and Hicks and IAL approach and do not examine the von Haefen model.

where $A_j$ is the probability of alternative $j$ being an element in choice set $C_k$. This probability can be

modeled using a binary logit model $A_j = \dfrac{1}{1+e^{-\gamma Z_{ij}}}$. In this model $P(j\,|\,C_k)$, which is the probability of

choosing alternative $j$ conditional on the choice set $C_k$, is defined using the standard MNL model. The

IAL model assumes that for each alternative the probability of being considered is independent of that of

other alternatives.

Swait (2001a) proposed the GenL approach which models choice set generation as another

expression of preferences, not a separate behavioral construct. In this case the probability of choice set

$C_k$ being considered was defined as a monotonic transformation of the expected utility of all alternatives

in the choice set shown by:

$$Q(C_k) = \frac{e^{\mu I_k}}{\displaystyle\sum_{r=1}^{K} e^{\mu I_r}} \quad \text{where} \quad I_k = \frac{1}{\mu_k} \ln\left(\sum_{j\in C_k} e^{\mu_k V_j}\right) \quad k = 1,\ldots,K\,, \qquad (3)$$

where $\mu$ is the scale parameter for the choice set formation stage, $I_k$ is the inclusive value of choice set

$C_k$, and $\mu_k$ is the scale parameter. In Swait's model $P(j\,|\,C_k)$ is defined using a standard MNL model

which is similar to the IAL approach.

Haab and Hicks' (1997) applied a variation of Manski's framework to construct an endogenous

choice set model with the probability of choosing alternative $j$ defined as:

$$p_j = \sum_{C_k \subseteq C_m} P(j\,|\,j\in C_k)P(j\in C_k)\,, \qquad (4)$$

where $P\left(j\mid j\in C_k\right)$ is the probability of choosing alternative $j$ conditional on the fact that $j$ is in the

choice set, and $P\left(j\in C_k\right)$ is the probability of alternative $j$ being in the choice set $C_k$. Considering all

possible subsets from the universal set of $J$ alternatives, the probability of choice is:

$$p_j = \sum_{k=1}^{2^J-1}\left[P\left(j\mid j\in C_k\right)\prod_{j\in C_k}P_j\prod_{j\notin C_k}\left(1-P_j\right)\right]. \qquad (5)$$

In this model, $P\left(j\mid j\in C_k\right)$ is defined as in a standard MNL model, while the probability of alternative

$j$ being in the choice set $C_k$ is defined as a function of individual specific or alternative specific

variables.

In the three models presented above, the likelihood function takes the common form

$L = \prod_{i=1}^{N}\left(p_{ij}\right)^{y_i}\left(1-p_{ij}\right)^{1-y_i}$ with $p_{ij}$, the probability of individual $i$ choosing alternative $j$, defined by

(1) for the IAL and GenL models with $Q\left(C_k\right)$ from (2) for the IAL model and from (3) for the case of

GenL model. For the Haab and Hicks model $p_{ij}$ is defined using (5).

Note that both the Haab and Hicks' and IAL models need to account for all possible choice sets

$C_m$ of the universal set $M$. The number of possible choice sets is $K = 2^J - 1$ which is large for choice

problems with large numbers of alternatives. Haab and Hicks applied their model to two cases – one with

5 alternatives and the second with 12 alternatives. In their second case the number of choice sets was

large, but they eliminated 6 of the 12 alternatives using logical rules which helped computational

complexity. Swait (1984) estimated an IAL model in a transportation context with four alternatives. The

GenL model, while not requiring enumeration of all choice sets, does not provide a logical rule to limit

the number of choice sets to be considered. This is important in the empirical case examined in this

present study which as explained below will assess 11 alternatives. In addition, the GenL model requires the estimation of an inclusive value for each choice set making the GenL model intractable for choice problems with 11 alternatives, as in our case. Given these issues we chose to estimate the IAL model to illustrate the two-stage decision process in our empirical study.

2.4 CASCETTA AND PAPOLA'S IMPLICIT AVAILABILITY AND PERCEPTION MODEL

The models discussed above were based on Manski's (1977) two-stage choice process and the number of possible choice sets would be very large for large scale choice problems. If the number of alternatives is 11 (as in our empirical case), the number of possible choice sets is 2,047 making the two-stage models challenging to estimate. An alternative model that approximates the choice set generation process is the implicit availability and perception model by Cascetta and Papola (2001) (we henceforth refer to this as the CPA model). The CPA model does not consider all possible choice sets, but rather estimates the degree to which an alternative is considered by decision makers. The availability of alternative $j$ to individual $i$ is modeled by a continuous variable in the domain of [0, 1]. The probability of choosing alternative $j$ becomes:

$$p_{ij} = \frac{A_{ij} e^{\mu V_{ij}}}{\sum_{k=1}^{J} A_{ik} e^{\mu V_{ik}}} \qquad \text{or} \qquad p_{ij} = \frac{e^{\mu V_{ij} + \ln A_{ij}}}{\sum_{k=1}^{J} e^{\mu V_{ik} + \ln A_{ik}}} \ . \qquad (6)$$

If the availability factor $A_{ij}$ is equal to 1, the utility model reduces to the standard MNL model. If $A_{ij}$ is less than 1, then alternative $j$ is less likely to be considered. To satisfy $0 \le A_{ij} \le 1$, the availability function can be defined as:

$$A_{ij} = \frac{1}{1 + e^{-\alpha Z}} \ , \qquad (7)$$

where $Z$ is a set of variables that affect choice set formation and $\alpha$ a vector of corresponding parameters. Note that the formulation in (7) is slightly different than that in Cascetta and Papola (2001) since the availability factor $\ln A_{ij}$ is not multiplied by the scale parameter. Also note that the availability term, $A_{ij}$, can be explained as a penalty to the utility function. The model in (6) is equivalent to a MNL model with the utility function:

$$U_{ij} = V_{ij} + \frac{1}{\mu} \ln A_{ij} + \varepsilon_{ij} ,$$ (8)

and $\frac{1}{\mu} \ln A_{ij}$ can be considered a penalty since it is negative.

The CPA model does not properly model the two-stage decision process because it does not explicitly model choice set formation by analyzing the probability of each possible choice set being considered. Rather, it directly models the probability of each alternative being considered. Nonetheless this model is attractive because of its ease of estimation. We chose this model to compare with the IAL model because if the CPA model is a good approximation of the IAL model, then the CPA model may more desirable due to the ease with which model parameters can be estimated.

### 3. DATA AND METHODS

3.1 TRIP INFORMATION

Data for this study come from the survey of recreational deer hunters described by Zimmer et al. (2012a; 2012b) which collected site choice information over two different years. Hunters were recruited by telephone to complete an on-line survey instrument where this trip information was solicited. The first hunting season trip information, was collected from trips taken in 2007 and is used in the study by Zimmer *et al*. (2012a). The second year of trip data (2009) were solicited from all respondents, but only a

subset of the respondents provided information for this second year. Thus, the trip information from the two periods arose from the same sample of individuals - which is relatively rare in the recreation demand literature. The dataset consists of hunting site choices based on wildlife management units (WMU) which are used by biologists to manage deer populations in Alberta. The survey focused specifically on trips to a region of the province consisting of 10 WMUs which were being examined by government biologists for the prevalence and spread of CWD among deer populations. These WMUs were subjected to specific management actions to combat the spread of CWD which consisted of culling deer herds in areas where infected animals were found, and the provision of extra licenses to hunters to increase deer harvests. These management actions represent attributes associated with the 10 WMUs in addition to estimates of the prevalence of CWD in the resident deer populations. These actions and prevalence estimates change over the two periods of study as the disease progressed and the government responded by expanding management actions. Surveyed hunters also took deer hunting trips to WMUs outside of the CWD surveillance zone, and these trips were lumped into one pseudo-WMU which we labeled as WMU 999. Zimmer et al. (2012a, b) describe CWD management actions and the hunter survey in more detail.

[*Table 1 about here*]

The hunting trip information consisted of actual trips taken to WMUs over the two years (revealed preference (RP) information) and additional stated preference (SP) trip information. The latter arose from a contingent behavior component of the survey in which hunters were invited to provide estimates of the number of trips to the 10 WMUs in response to hypothetical changes in the prevalence of disease as well as changes in disease management. The choice alternatives were "branded" in that the alternatives were labeled using the same WMU provided in the RP information. Three attributes were modified among the WMUs in each hypothetical scenario: CWD levels (*Cwd*), tags (*Tags*), and culling (*Cull*). *Cwd* had four levels: none, low, medium, and high. The respondents were given the information that those four levels corresponded to number of infected deer per 100 in the herd numerically equating to

0, 1–5, 6–10, and greater than 10 animals per 100, respectively. *Tags* was represented as either the presence or absence of an extra tags program. *Cull* was represented as either the presence or absence of culling in that area. Only these three attributes were included in the stated preference task as the WMU labels were assumed to capture all other attributes of the sites. Zimmer et al. (2012a) provide an example of the contingent behavior instrument employed in the survey.

Combining the revealed and stated site choices over the two hunting seasons provided 4,362 observations of site choices. Table 1 describes the structure of these data. A total of 84 hunter surveys were usable in 2007 and 37of the 84 provided additional information for 2009. The small number of surveys in the second year suggests caution in interpreting findings as representative of the larger sample of hunters, but the information is sufficient to permit us to consider the data as a convenience sample to examine modeling efforts[3]. Each survey first asked hunters how many hunting trips they made in 2007 to the WMUs in the surveillance zone for the RP data. Then for the SP part, the survey asked again where and how many trips they would take in new (hypothetical) situations where CWD occurrence and the presence of extra tags and culling program were randomly drawn and chosen such that they are not correlated as they were in RP data. For a complete experimental design, see Zimmer (2009).

3.2 ECONOMETRIC MODELING APPROACH

Our empirical analysis examines choices from 11 alternative hunting sites over two time periods. We model site choice, availability (choice set formation) and scale using the combined RP-SP data. The effects of time on preferences, availability and scale were examined using dummy variable interactions. For the problem under consideration, the CWD attribute and its interaction with a time dummy variable was included in both the utility function and the availability function. In this case, if learning over time heightened the perception of risk, the interaction term would be expected to have a negative impact on the

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[3] We note that the sample sizes employed are small, hence we make no claims about the ability of our study to predict the behavior of all Albertan deer hunters who may be affected by CWD. Rather we employ this data as a convenience sample to examine the usefulness of our empirical approaches.

availability of the alternative, implying that in the second year, hunters were less likely to include sites with higher occurrence of CWD in their choice sets.

*The Utility Function*

Table 2 summarizes the attributes included in the utility function and the various levels each attribute could hold. The attribute *Cwd* indicates the prevalence of CWD in affected deer populations in terms of the percentage of animals infected in the population of deer in a WMU and had four levels: none (0), low (1 to 5), medium (6 to 10), and high (>10). Midpoints were used, so the levels are 0, 2.5, 7.5 and 12.5 percent.

The travel cost *Tcost* was calculated using travel time, distance and hunters' income (see Zimmer *et al*. 2012a) as shown below:

$$\text{tcost} = \text{distance} \times 2 \times 0.3 + \left( 0.25 \times \frac{\text{total income}}{2080} \right) \times \frac{\text{distance} \times 2}{95}.$$

The first component is the driving expense for the round trip ($\text{distance} \times 2$) at a cost of \$0.3/km. The second component is the opportunity cost of time, calculated by multiplying the hourly opportunity cost of time $\left( 0.25 \times \frac{\text{total income}}{2080} \right)$, or 25% of total income divided by the average yearly working hours) and travel time of the round trip at a speed of 95 km/h.

The attribute *Tags* indicates the presence of an extra hunting tag program, so is a dummy variable. Similarly the attribute *Cull* is a dummy indicating the presence of a culling program. Several individual specific characteristics were also used by interacting them with attributes: *Yr2*, a dummy indicating the choice is in hunting season 1 (=0) or 2 (=1); Urban, a dummy indicating whether the hunter is living in an urban area (=1) or not (=0); *Yrshunt*, the number of years of experience the hunter has; and *Age*, the hunter of the time of survey in years.

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The utility function representing site choice  also included alternative specific constants (ASCs), attributes and selected interactions. ASCs included WMUs in the CWD surveillance zones $j = 148, 150, 151, 162, 163, 200, 234, 236, 256, 500$, and all those outside of the zones were coded as 999. Interactions included: *Cwd* x *Yr2* to test for the change in the effect of CWD risk perception on preferences; *Tcost* x *Urban*, to allow for the difference in sensitivity to travel cost between rural and urban hunters; *Tags* x *Urban*, to allow for a difference in response to the extra tags program between urban and rural hunters; *Cwd* x *Urban*, to test whether urban hunters are more sensitive to CWD than rural hunters; and *Cull* x *Yrshunt* to test whether more experienced hunters are more sensitive to culling program. Thus, the utility function was defined as: $V_{ij} = ASC_j + \beta X_{ij}$ for $j \neq 999$ and $V_{ij} = ASC_j$ for $j = 999$, where $X_{ij}$ includes all attributes and interactions listed above and $ASC_{500}$ was fixed at 0. WMU 999 included all sites outside of the CWD surveillance zones does not have any management program nor any CWD prevalence. This region includes many zones such that modeling each as a site is not feasible. As a result, we treat them as a single identical site. In addition, because WMU 999 includes many sites at difference distances, travel costs to this WMU are quite variable and including travel cost in the utility function of this site is not desirable as the cost data would be pooled with other unobserved information. Therefore, the utility of WMU 999 is modeled only as an ASC. This is a limitation, but the information required to model alternatives outside the region in a more complete fashion was unavailable.

*The Availability Function*

The availability function was $A_{ij} = \dfrac{1}{1 + e^{-\alpha Z_{ij}}}$ where $Z$ included a constant, *Cwd*, *Cwd* x *Yr2* (to test for the difference in effect of  CWD prevalence between the two years), and *Cwd* x *Urban*. We apply this specification for the CPA models as well as the Independent Availability Logit model.  It is challenging to identify whether CWD affects availability or utility, or both, hence CWD variables were included in both the availability and utility functions. We compared different model specifications to

isolate the effect of CWD - we estimated both the CPA and IAL models with two specifications, one with CWD related variables in availability only, one with those variables in both the availability and utility functions.

*The Scale Function*

The scale parameter for a single set of choice data cannot be identified, but the ratio of the scale parameter of one data set relative to another can be (Swait and Louviere 1993). This can be implemented by fixing the scale parameter of one set or group to unity and estimating the others. Because the data include SP and RP data for two years, it can be considered to have four sets or groups. Because $yr2$ and $sp$ (1 if stated preference data, 0 otherwise) are both dummies, there will be four possible scale parameters. So the scale parameter is estimated for four groups: Group 1 ( $yr2 = 0$ and $sp = 0$) has scale parameter $\mu_1$, Group 2 ( $yr2 = 1$ and $sp = 0$) $\mu_2$, Group 3 ( $yr2 = 0$ and $sp = 1$) $\mu_3$ and Group 4 ( $yr2$ =1 and $sp$ =1) $\mu_4$. Fixing the scale parameter of Group 1 at 1, the scale function is

$$\mu_g = e^{\gamma_1 yr2 + \gamma_2 sp + \gamma_3 sp \times yr2}.$$

Incorporating the scale function together with a utility and availability function make the model highly nonlinear. Thus, the model parameters were estimated using BIOGEME (Bierlaire 2003) and MATLAB. Likelihood ratio tests were applied to test for statistical significance of coefficients of utility and the availability function as well as the scale function.

## 4. RESULTS

Parameter estimates for six models are presented in Table 3. The first two models are basic MNL models. Model MNL1 is the basic model with a utility function only. Model MNL2 adds the scale function. The next two models are Cascetta and Papola Availability (CPA) models, one with CWD-related variables in availability function only, and one with those variables in both availability and utility

function. The last two models are the IAL models, again one with CWD-related variables in availability function only, one with those in both functions. Note that all the models utilize pooled SP and RP data for the two years, and in the CPA and IAL models, scale functions are always included. We first discuss the MNL and CPA models and compare these to the IAL model later in this section. We then analyze and compare the effects of CWD of models among models. Finally we compare the welfare measures of MNL, CPA and IAL models.

[*Table 3 about here*]

In all cases, the scale function significantly improves log-likelihood value. The likelihood ratio tests reject the null hypothesis that all coefficients of the scale functions are equal to zero (the scale factors are identical for all data sets) for all models. Therefore, we include the scale function in all CPA and IAL models For the case of model MNL2 against model MNL1, we observe a p-value less than 0.001.

In the scale function in the MNL and IAL models, all variables are statistically significant. The scale factor is smaller in year 2 data and in SP data, indicating that the variance is higher in these two data types. In model CPA2, only $sp$ is significant, implying that the scale factor is smaller for SP data, but not for the second year data. This means that the SP data exhibit a higher variance. However the interaction term $sp \times yr2$ is statistically significant, implying that the variance of SP data is even higher in year 2.

*MNL and CPA models*

Log-likelihood values further improve when accounting for choice set formation. From model MNL2 to CPA1, CWD-related variables are moved from the utility function to the availability function and the log-likelihood value shows small  improvement. Testing model CPA2 against model MNL2, a likelihood ratio test again rejects the null hypothesis that the availability factor is unity with p-value less

than 0.001. As a result, the full model with scale and availability functions appears to be a better fit than the basic MNL model.

Most variables in the utility functions of the MNL models have expected signs. Coefficients on travel costs are negative as expected. The coefficient $tc \times urban$ is positive, indicating that urban hunters are less sensitive to travel costs. The coefficient on travel cost is larger (in absolute value) in models with scale and availability function, implying that the effects of travel costs are underestimated if the scale factor and choice set formation are ignored.

In the MNL models, $tags$ has a positive coefficient while $tags \times urban$ have negative coefficients. This means hunters are motivated by the extra tags program, but urban hunters are less motivated. The culling program drives hunters away from the sites. The parameters of $cull \times yrshunt$ are positive, indicating that more experienced hunters are less likely to dislike culling programs.

CWD prevalence has different effects on site choice formation and site choice evaluation. In the utility function, its effect varies across models. The MNL models indicate that hunters prefer sites with CWD in year 1, but dislike them in year 2. In addition, urban hunters appear to dislike sites with CWD. The coefficient on $cwd \times urban$ is high enough to offset the positive coefficient of CWD such that urban hunters dislike CWD in both years. Model CPA2, however, shows that hunters dislike CWD in both years, but urban hunters appear to like sites with CWD. This is because the negative effect of $cwd \times urban$ on choice is captured by the availability function.

The effects of CWD variables in the availability function show a similar pattern with those in model MNL1. Hunters are more likely to consider sites with higher CWD prevalence in year 1, less likely to consider them in year 2, and urban hunters are less likely to consider sites with higher CWD. However, the coefficient of $cwd \times yr2$ is not significant. The coefficient of $cwd \times urban$ is (negatively) large enough to offset that of CWD in both model CPA1 and CPA2, therefore urban hunters are less likely to

consider sites with CWD in both years. CPA models also indicate that sites with higher CWD prevalence are more available to rural hunters. This may be based on habits and attachments to place, relative to urban hunters. It may also be that some hunters view CWD as a positive attribute as it may reduce congestion. Congestion is an endogenous component of recreation demand models and challenging to model (e.g. Timmins and Murdock, 2007) – nevertheless this may be an issue confounding the results in our case.

*IAL models*

The last two columns of Table 3 present the results of the IAL models that include scale effects. In terms of log-likelihood values, the IAL models are much better than corresponding CPA models as expected. In Table 4 we also present the implied probabilities of choice set sizes for the sample. If the CPA and  IAL models are similar, this would  provide some confidence in the use of the CPA model as a practical method of incorporating consideration sets.

Examining the scale function parameters, we see that the two IAL models provide qualitatively similar results to models MNL2 and CPA1. The signs of parameters are the same, but their magnitudes are larger. Error variance is higher in year 2 relative to year 1 (scale is lower), and variance is higher in the SP data than in the RP data, but the SP effects are lower in the second year of data collection. Turning to the utility function, some differences emerge. Although most parameters are qualitatively similar, they are scaled up disproportionately compared to those of the CPA models. As a result, the welfare measures are affected.

Finally, the parameters affecting availability are very similar to those of CPA models. Sites with higher CWD prevalence are more available to rural hunters, but not to urban hunters. The coefficient on $cwd \times yr2$ is not statistically significant, again indicating that the effect of CWD on availability does not change in year 2.

Despite different models and specifications, there are some consistent results. The availability factor decreases with CWD for urban hunters. The overall effect of CWD for urban hunters is negative, but not statistically significant. For rural hunters, the availability factor increases with CWD. The effect of CWD in year 2 is not different from that of year 1. The effect of CWD on availability is different between rural and urban hunters, but not between years 1 and 2. However, CWD in year 2 in the utility function has negative coefficients across models and thus the CWD effect in the utility function appears to be different between year 1 and year 2 and could generate a strong welfare impact. The effect of CWD on availability doesn't change over time, but utility does. Finally, other coefficients in the utility function are also consistent in signs.

[*Table 4 about here*]

Table 4 shows that most hunters have a choice set size of 4-8 sites. Only a small fraction of the sample is likely to have choice sets of size 10 or 11. This implies that the MNL model parameters, which assume hunters have a full choice set, may be biased. However the results show that the CPA models appear to be a reasonable approximation of the IAL models.

[*Figure 1 about here*]

As mentioned above, CWD has different effects on choice set formation and evaluation, so it may be helpful to examine how it affects the probability of choosing a site. We illustrate this with WMU 148, a currently uninfected site, to see how the probability changes when its CWD prevalence varies from 0 to 12%, holding that of other sites unchanged. We use the sample average of hunting years (as it appears in the utility function).

Figure 1 presents the probabilities of choosing WMU 148 calculated from the CPA and IAL models using RP data. Each panel presents the change in probability of choice by urban and rural hunters in the two years as the level of CWD increases. The probabilities from the CPA and IAL models for each

specification show similar patterns although the magnitudes of probabilities are different. For model CPA1 and IAL1 (CWD variables in availability only), urban hunters appear to be less likely to choose the site if CWD increases and the effect of CWD on probabilities is higher in year 2. For rural hunters, probability of choosing WMU 148 initially increase with CWD prevalence up to 1-2% and is stabilized beyond the point, in both years.

For models CPA2 and IAL2 (CWD variables in both availability and utility functions), the probabilities of choosing WMU 148 also show similar pattern between the two models. Urban hunters tend to be more likely choose the site in year 1 when CWD prevalence increases. However in year 2, this probability decreases with CWD prevalence. The probability of rural hunters choosing the site initially increases when CWD increase, but then decreases.

*Welfare Measures*

We examine the welfare measures for the change from the current CWD prevalence situation and management actions to one in which CWD prevalence levels spread to what is expected in a "worst case scenario". The "worst case" scenario is characterized by a 12.5% CWD prevalence in WMUs 150, 151 and 234 (currently infected WMUs), 7.5% in WMUs 148, 162, 200, 236 and 500, and 2.5% in WMUs 163, 256 and 999, and no management activity (no culling, no additional tags) (see Zimmer *et al*. 2012a for more details). We examine the welfare impact on rural hunters, urban hunters, and the aggregate. For the models that include availability we also examine the proportion of the impact that arises from the utility function and the proportion from the choice set formation component.

For the CPA model, the welfare change of hunter $i$ is calculated using the formula:

$$E\left(CV_i\right) = \frac{1}{\beta_i}\left[ \ln\left[\sum_{j=1}^{11}\exp\left(\frac{V_{ji}^1}{\mu_i}\right)\right]^{\mu_i} - \ln\left[\sum_{j=1}^{11}\exp\left(\frac{V_{ji}^0}{\mu_i}\right)\right]^{\mu_i}\right],$$

where $\beta_i$ is the marginal utility of money of hunter $i$, $V_{ji}^0$ is the utility of site $j$ to hunter $i$ at the

current management condition and $V_{ji}^1$ is the corresponding utility at the worst case scenario and $\mu_i$ is

the scale factor. Note that the utility function is defined as in equation (8).

The case is more complicated in the IAL models - given a choice set $C_k$, the compensating

variation of changing from $V^0$ to $V^1$ is:

$$E\left(CV_i \mid C_k\right) = \frac{1}{\beta_i}\left[\ln\left[\sum_{j \in C_k} \exp\left(\frac{V_{ji}^1}{\mu_i}\right)\right]^{\mu_i} - \ln\left[\sum_{j \in C_k} \exp\left(\frac{V_{ji}^0}{\mu_i}\right)\right]^{\mu_i}\right].$$

Thus the change from $V^0$ to $V^1$ results from changes in attributes, which may also modify the

probabilities of all choice sets $C_k$. Thus, the total welfare change is:

$$E\left(CV_i \mid C_k\right) = \frac{1}{\beta_i}\left[\begin{array}{l} \sum_{C_k \subseteq C_m} Q^1\left(C_k\right)\ln\left[\sum_{j \in C_k} \exp\left(\frac{V_{ji}^1}{\mu_i}\right)\right]^{\mu_i} \\ - \sum_{C_k \subseteq C_m} Q^0\left(C_k\right)\ln\left[\sum_{j \in C_k} \exp\left(\frac{V_{ji}^0}{\mu_i}\right)\right]^{\mu_i} \end{array}\right].$$

Table 5 presents the welfare impacts of the "worst case" scenario calculated for the MNL, CPA

and IAL models. The two columns for both MNL models outline the impact when availability is not

included in the analysis. The welfare impact is negative for hunters from urban areas, and for all hunters

in year 2. The negative impact increases in absolute value in year two indicating a worsening of the

perception of the effects of the disease.

For the models that include availability (CPA and IAL) changing from the current situation to the

worst case also reduces welfare of urban hunters in year 2. For rural hunters, the welfare reduces in cases

of CPA2 and IAL2 models, but increases in cases of using CPA1 and IAL1. Looking at model CPA2, the

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reduction is higher for rural hunters ($61.66/trip) than urban hunters ($25.98/trip). The welfare reduction in year 2 is higher than that in year 1. The welfare increases for urban hunters in year 1, largely because of the positive coefficient of $cwd \times urban$ in the utility function. The welfare changes are similar for model CPA2 and IAL2, and for model CPA1 and IAL1.

[*Table 5 about here*]

In Table 5 we also decompose the welfare change into components contributed by the utility function and the availability function. The utility component is calculated by allowing the change in the utility function, while holding the availability factor fixed at the current management level. Similarly, the availability component is calculated by allowing the availability factor to change, holding the utility fixed at the current management. The contribution of the availability function to welfare change is considerable in many cases; in some cases larger than the contribution from the utility function.


**Discussion and Conclusions**

This paper compares a fully endogenous choice set model using the Independent Availability Logit model with the availability function approach that approximates choice set formation. It analyzes the response of Albertan hunters to CWD risk, in both stages of site choice evaluation and choice set formation and over two time periods. We employ a sample of hunters that might not be representative, but useful to illustrate the empirical approach. The analyses found mixed evidence that CWD affects utility parameters in site choice evaluation as well as on choice set formation.

However, there are some consistent results across models. First, the availability factor decreases with CWD for urban hunters, but increases with CWD for rural hunters. Second, the effect of CWD in year 2 is not statistically different from that of year 1. In general, the overall effect of CWD on availability is not different between year 1 and year 2, but is different between rural and urban hunters. The choice set formation contributions to total welfare changes are considerable in most cases.

However, CWD shows different effects in the utility function. Both the CPA and IAL models suggest that rural hunters appear to dislike CWD while urban hunters appear to prefer sites with CWD. The CWD effect in the utility function appears to be different between year 1 and year 2 and seems to generate a strong welfare impact. Particularly, hunters appear to be less likely to like sites with higher CWD prevalence in year 2.

These analyses can be helpful for making decisions on management strategies to combat CWD in Alberta. Zimmer *et al*. (2012a), when analyzing hunter behaviors with data of the first hunting season of this study, found that the impact of CWD on hunter behavior was not significant. However, Zimmer *et al*. (2012b) compared welfare measures of avoiding CWD in Alberta with the cost of the CWD management program, and found that the cost of the program was likely greater than the benefit. Yet they argued that in the long run, if CWD was no longer present and no management was needed, the benefit of control would continue to accrue and would outweigh the costs that are experienced in early years. As hunters are found to be more likely to dislike CWD in year 2 in our analysis, they may be more likely to dislike CWD beyond this second period. As a result, the benefits of stopping the spread and prevalence of CWD will become larger over time. This implies that the benefit not only accrues but may also become larger if hunters change their preferences for CWD over time.

Finally, our comparison of the CPA and a fully specified IAL model provides some similar results. While the models are qualitatively similar for many parameters, it appears that the Cascetta and Papola approach generates a somewhat different set of parameters for the availability function or choice set formation. This is probably consistent with Bierlaire *et al*. (2010), who pointed out that the Cascetta and Papola model is sometimes a poor approximation of the formal choice set formation model.

The choice set formation models outperform models without choice set formation. They generate welfare measures that are quite different than models that do not include choice set formation. As a result, choice set formation processes should be included in recreation choice models – particularly when there

are factors that may significantly affect choice set formation such as health risks. Since the CPA model appears to be a poor approximation using our data, the IAL model may be more desirable despite its complexity in estimation. In addition, the CPA model sometimes generated very high welfare measures (in absolute values) contributed by the utility and/or availability functions, implying that the CPA model may be fragile. This suggests that additional investigation of the structure of choice set formation, and the capability of choice set formation models to capture such processes, is required.

A number of conceptual and empirical questions arise from our investigation. These include:

1. Is it possible to construct a good a theory of choice set formation? Why do people form choice sets and can knowledge of this process inform the specification of choice set formation functions and analysis? Is formation of choice sets a mechanism for maintaining flexibility (Kreps 1979) or is limiting choice set size a mechanism to avoid regret (Sarver 2008), suggesting that empirical representations of regret should focus on choice set structure rather than utility?

2. There is a relationship between choice set formation and non-compensatory preference structures (e.g. Swait 2001b; Hauser 2010). Further research aimed at untangling the difference between these two representations of choice processes and between "hard" and "soft" choice set boundaries is required.

3. What are the welfare implications of changes in attributes that affect choice set formation as well as utility, and monetary measures (such as travel costs) that enter choice set formation and utility? (see Manrai and Andrews (1998) for a discussion of similar issues in a marketing context).

Investigation of these issues will require theoretical and empirical analyses that include analyses of actual and simulated data, as well as experimental research. What is clear, however, is that including choice set formation improves the statistical properties of choice models, and generates welfare measures that differ from choice models that exclude choice set generation. Therefore additional investigation into choice set formation properties appears warranted.

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**Figures**



Figure 1: Probability of choosing WMU 148 when its CWD prevalence changes
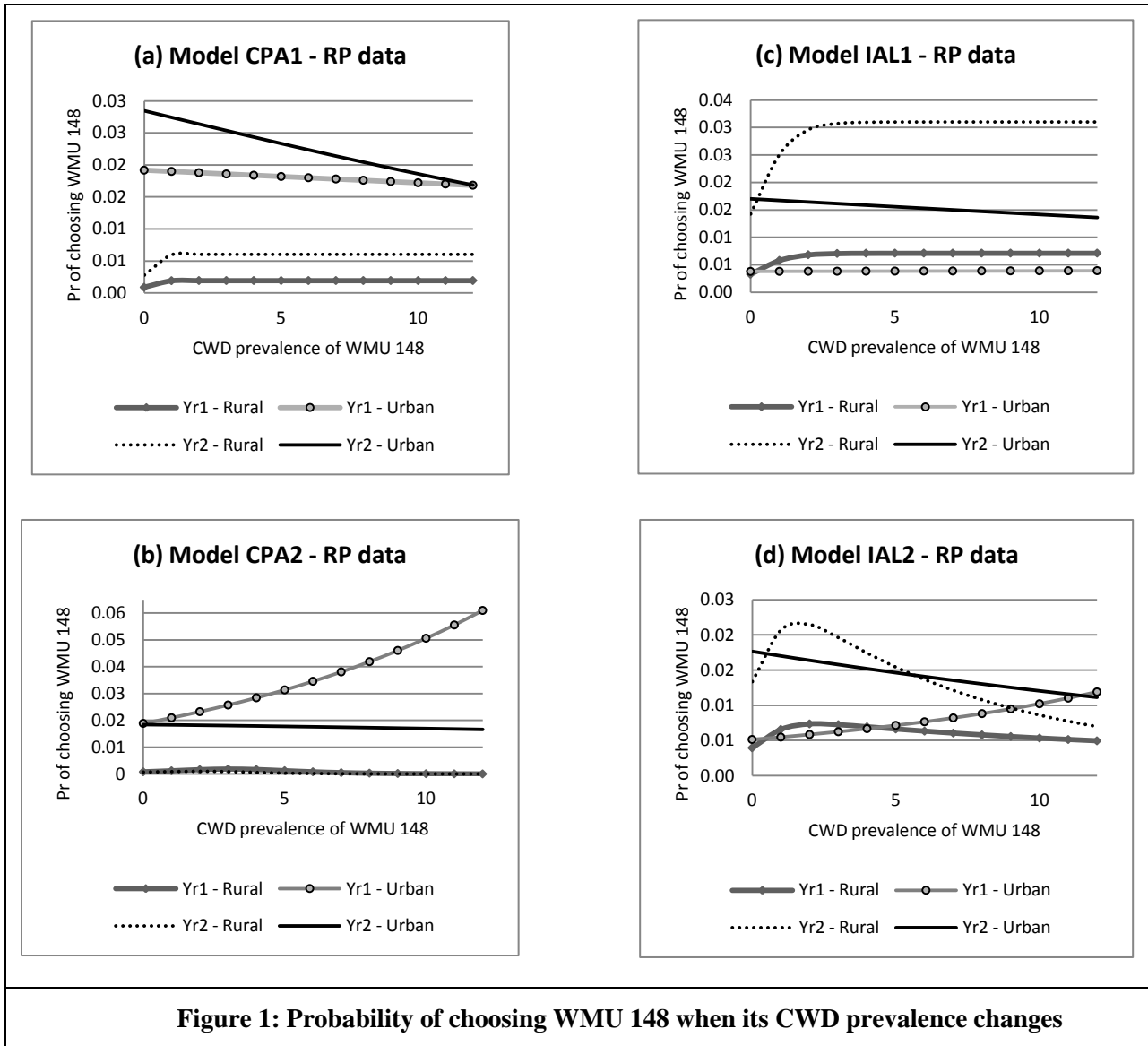
**Tables**

**Table 1: Data structure – number of choices**

|  | **Year 1 (2007): 84 hunters** | **Year 2 (2009): 37 hunters** | **Total** |
|---|---|---|---|
| Revealed preference | 748 | 308 | 1,056 |
| Stated preference | 2,532 | 774 | 3,306 |
| Total | 3,280 | 1,082 | 4,362 |

**Table 2: Attributes and levels**

| Attributes | Description | Levels |
|---|---|---|
| *tc* | Travel cost, computed from distance & income | Continuous, mean=238, min=0, max=648 |
| *cwd* | CWD level – percent of deer population infected with CWD | None 0, low 1-5, medium 6-10, high >10. Midpoints are used 0, 2.5, 7.5 and 12.5. |
| *tags* | Presence of an extra tags program | 0, 1 |
| *cull* | Presence of culling | 0, 1 |

**Table 3: Estimation Results: MNL, CPA and IAL Models of Site Choice**

| Model | MNL1 | MNL2 | CPA1 | CPA2 | IAL1 | IAL2 |
|---|---|---|---|---|---|---|
| Log-likelihood | -7,583.41 | -7,500.26 | -7,472.54 | -7,429.78 | -7,383.03 | -7,372.73 |
| Rho-square | 0.275 | 0.283 | 0.286 | 0.290 | 0.294 | 0.295 |
| **SCALE FUNCTION** | | | | | | |
| SP | | -0.518 (0.043) | -0.445 (0.035) | -0.445 (0.101) | -1.409 (0.402) | -1.252 (0.046) |
| Year 2 | | -0.303 (0.070) | -0.197 (0.047) | *0.035 (0.055)* | -1.05 (0.448) | -0.834 (0.117) |
| Year2 x SP | | 0.177 (0.083) | *0.087 (0.058)* | -0.166 (0.09) | 0.917 (0.166) | 0.76 (0.087) |
| **AVAILABILITY FUNCTION** | | | | | | |
| Constant | | | -0.158 (0.072) | -3.115 (0.384) | *-0.166 (0.209)* | -0.157 (0.053) |
| CWD | | | 4.814 (0.459) | 0.975 (0.07) | 1.64 (0.673) | 1.604 (0.079) |
| CWD x YR2 | | | *-0.05 (0.046)* | *0.127 (0.124)* | *-0.037 (0.135)* | *0.018 (0.045)* |
| CWD x URBAN | | | -4.834 (0.465) | -1.223 (0.213) | -1.635 (0.687) | -1.653 (0.082) |
| **UTILITY FUNCTION** | | | | | | |
| CWD | 0.04 (0.012) | 0.053 (0.018) | | -0.515 (0.082) | | -0.133 (0.044) |
| CWD x year 2 | -0.051 (0.013) | -0.101 (0.023) | | -0.24 (0.058) | | -0.24 (0.07) |
| CWD x urban | -0.053 (0.013) | -0.113 (0.022) | | 0.861 (0.212) | | 0.315 (0.078) |
| Travel cost | -15.1 (0.442) | -23.8 (1.09) | -22.344 (0.555) | -22.229 (0.628) | -55.629 (21.508) | -49.976 (4.059) |
| Tags | 0.436 (0.065) | 0.706 (0.109) | 0.547 (0.051) | 0.846 (0.162) | 1.672 (0.987) | 1.666 (0.071) |
| Cull | -0.444 (0.075) | -0.867 (0.129) | -0.831 (0.06) | -1.19 (0.079) | -2.723 (1.406) | -2.654 (0.187) |
| Tcost x urban | 6.67 (0.427) | 10.6 (0.774) | 10.362 (0.619) | 10.774 (0.604) | 9.972 (1.996) | 12.623 (1.548) |
| Tags x urban | -0.441 (0.084) | -0.671 (0.133) | -0.393 (0.066) | -0.664 (0.14) | -1.168 (0.65) | -1.448 (0.112) |
| Cull x hunt years | 0.011 (0.003) | 0.020 (0.004) | 0.02 (0.004) | 0.022 (0.009) | *0.062 (0.076)* | 0.056 (0.013) |
| ASC 148 | 0.915 (0.172) | 1.54 (0.284) | 1.519 (0.088) | 1.46 (0.117) | 2.3 (0.649) | 2.166 (0.14) |
| ASC 150 | 1.08 (0.172) | 2.01 (0.295) | 1.624 (0.09) | 1.905 (0.222) | 2.167 (0.477) | 2.402 (0.112) |
| ASC 151 | 1.64 (0.158) | 2.83 (0.287) | 2.402 (0.086) | 2.564 (0.185) | 4.077 (1.069) | 4.138 (0.165) |
| ASC 162 | 0.756 (0.163) | 1.21 (0.269) | 1.275 (0.062) | 1.239 (0.1) | 2.106 (0.727) | 1.931 (0.237) |
| ASC 163 | 1.3 (0.155) | 2.13 (0.266) | 2.189 (0.098) | 2.207 (0.079) | 5.208 (1.982) | 4.456 (0.133) |
| ASC 200 | 1.42 (0.148) | 2.28 (0.259) | 2.278 (0.063) | 2.289 (0.084) | 5.992 (2.269) | 5.142 (0.127) |
| ASC 234 | 1.71 (0.152) | 2.87 (0.277) | 2.287 (0.074) | 2.448 (0.135) | 5.993 (2.421) | 5.608 (0.159) |

| | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| ASC 236 | 1.43 | (0.149) | 2.24 | (0.257) | 2.25 | (0.063) | 2.161 | (0.078) | 7.202 | (3.159) | 5.964 | (0.183) |
| ASC 256 | *0.248* | *(0.168)* | *0.301* | *(0.277)* | 0.608 | (0.059) | 0.539 | (0.098) | 1.802 | (0.985) | 1.173 | (0.051) |
| ASC 500 | 0 | (fixed) | 0 | (fixed) | 0 | (fixed) | 0 | (fixed) | 0 | (fixed) | 0 | (fixed) |
| ASC 999 | *0.181* | *(0.16)* | *0.211* | *(0.262)* | 0.532 | (0.045) | 0.601 | (0.107) | 3.028 | (1.63) | 2.173 | (0.125) |

*Note: coefficients in bold and italic are NOT significant at 10%. Standard errors are in parentheses.*

**Table 4: Implied Probabilities of Choice Set Size from the IAL Model**

| | Q (Probability) | |
|---|---|---|
| Number of alternatives | **IAL1** | **IAL2** |
| 1 | 0.01 | 0.01 |
| 2 | 0.02 | 0.03 |
| 3 | 0.06 | 0.07 |
| 4 | 0.12 | 0.12 |
| 5 | 0.16 | 0.16 |
| 6 | 0.18 | 0.18 |
| 7 | 0.17 | 0.16 |
| 8 | 0.12 | 0.12 |
| 9 | 0.09 | 0.09 |
| 10 | 0.05 | 0.05 |
| 11 | 0.01 | 0.01 |
| Total | 1.00 | 1.00 |

**Table 5: Welfare Changes of Moving to the "Worst Case" Scenario**

| Model | | MNL1 | MNL2 | CPA1 | CPA2 | IAL1 | IAL2 |
|---|---|---|---|---|---|---|---|
| Year 1 – Rural | Utility | | | 0.49 (4.3) | -127.29 (30.41) | 10.21 (4.98) | -10.32 (1.95) |
| | Availability | | | 21.76 (7.15) | 101.18 (11.89) | 26.87 (25.48) | 25.26 (23.97) |
| | **Total** | **15.37 (3.75)** | **15 (5.18)** | **21.98 (8.48)** | **-27.15 (28.49)** | **32.47 (21.77)** | **12.96 (24.72)** |
| Year 1 – Urban | Utility | | | 2.7 (4.42) | 237.21 (22.35) | 10.41 (5.19) | 43.25 (7.74) |
| | Availability | | | -4.61 (0.59) | -91.15 (10.39) | 1.48 (0.22) | -14.88 (2.17) |
| | **Total** | **-4.24 (4.38)** | **-18.35 (4.73)** | **-2.06 (4.3)** | **66.76 (11.09)** | **11.95 (5.28)** | **26.19 (6.91)** |
| Year 2 – Rural | Utility | | | 0.03 (6.27) | -221.92 (12) | 15.05 (4.16) | -51.58 (1.69) |
| | Availability | | | 11.03 (8.82) | 111.71 (30.67) | 9.41 (9.1) | 10.17 (10.26) |
| | **Total** | **-11.23 (3.66)** | **-23.07 (6.28)** | **9.93 (12.93)** | **-61.66 (13.36)** | **20.67 (0.07)** | **-42.88 (8.71)** |
| Year 2 – Urban | Utility | | | 0.57 (3.13) | 51.58 (13.27) | 8.85 (4.13) | 3.64 (5.35) |
| | Availability | | | -22.27 (7.71) | -60.08 (20.38) | -9.59 (2.94) | -9.2 (2.97) |
| | **Total** | **-40.67 (4.74)** | **-49.93 (15.78)** | **-21.95 (7.75)** | **-25.98 (9.24)** | **-1.01 (5.6)** | **-5.86 (6.85)** |

*Note: Measures are in $/trip. Standard deviations are in parentheses.*