MODELLING THE EFFECT OF HEALTH RISK PERCEPTION ON PREFERENCES AND CHOICE SET FORMATION OVER TIME: RECREATIONAL HUNTING SITE CHOICE AND CHRONIC WASTING DISEASE

Thuy Truong, Resource Economics and Environmental Sociology, University of Alberta

W. L. (Vic) Adamowicz, Resource Economics and Environmental Sociology, University of Alberta

Peter C. Boxall, Resource Economics and Environmental Sociology, University of Alberta

DRAFT October 2011

ABSTRACT

Chronic wasting disease (CWD) is a prion disease that affects deer, elk and other cervid wildlife species. CWD is essentially the cervid 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 consumption of meat from CWD infected animals.

In this paper we model hunter response to the knowledge that deer in a wildlife management unit (WMU) have been found to have CWD in Alberta, Canada. We examine hunter site choice over two hunting seasons using revealed and stated preference data. We model preferences, choice set formation, and scale (variance) as a function of attributes, time period and demographics. The availability function approach (Cascetta and Papola, 2001) is applied to approximate choice set formation or endogenous choice set analysis. We also compare this approximation to a fully endogenous choice set model using the Independent Availability Logit model (Swait, 1984). We find that CWD incidence affects choice set formation and preferences. Availability of an alternative in a choice set is negatively affected by CWD and this effect appears to be increasing over time. Thus modeling CWD in terms of its effect on preferences only would result in biased estimates of impact. Furthermore, the error variance is increasing over time, possibly arising from additional uncertainty about the impact of CWD and the spread / prevalence of the disease. However, our comparison between the availability function approach and the fully endogenous choice set formation model suggests differences between these two approaches.

Modelling the effect of health risk perception on preferences and choice set formation over time: recreational hunting site choice and chronic wasting disease

INTRODUCTION

In this paper we examine consumer (hunter) response to potential health risks that arise from the prevalence and spread of Chronic Wasting Disease. Chronic Wasting Disease (CWD) is a prion disease that affects elk, deer and moose and was recently found in Alberta. CWD 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 consumption of meat from CWD infected animals. The Government of Alberta has implemented several activities to prevent the spread of CWD which confounds the impact of the disease (see Zimmer et al 2011). In our analysis we attempt to untangle these components. It could be the case that hunters may initially ignore the potential risk of CWD and (dis)like CWD prevention activities, but may change their preferences and behaviors later on through learning. Our data include two years of hunter activity, thus offering a chance to examine changing behavior over time. Our analysis is intended to measure the economic impact of CWD on recreational hunting, and contribute to the analysis of behaviors in the presence of risk.

The economics of recreation demand was initially analyzed using the travel cost model (Hotelling 1949 and Clawson 1959), in which the demand for trips to a specific site decreases with price (travel cost). The application of random utility models (RUM) to recreation site choice allows for the analysis of the effect of attributes other than price on recreation demand (including potential health risks at sites), and to more fully examine substitution patterns between options. The site choice model was proposed by Hanemann (1978), in which every trip is considered a choice where an individual is assumed to choose the site that maximizes his utility, given the constraint of income and time.

The application of RUMs for recreation site choice allows analysis of the response to health risks by considering this risk as an attribute of the sites. Some researchers have examined the response of recreation demand to risk perceptions. Diana et al (1993) and May and Burger (1996) examined anglers' compliance with health advisories and found most anglers ignored consumption advisories. Jakus et al (1997), however, found anglers were less likely to visit a reservoir with an advisory. Jakus and Shaw (2003) proposed a two-level nested multinomial logit (MNL) model to analyze the behavior of keeping fish from sites simultaneously with site choice behavior. The probability of not keeping fish from a site is considered a proxy of hazard perception and this was found to drive anglers away from a site. Zimmer et al. (2011) analyzed the effect of Chronic Wasting Disease (CWD), a degenerative wasting disease that affects deer, moose and elk, on hunting site choice in Alberta using a nested MNL model and found that the prevalence of the disease as well as wildlife management disease mitigation efforts affect site choice.

One of the key components of the RUM approach is the definition of the choice set, the set from which the consumer chooses their preferred option. The choice set is often defined exogenously by the researcher, based on rules or data availability. Increasingly, however, it is being recognized that choice set formation, or endogenous choice set determination, is an important component of consumer behavior (Swait 1984, 2001). This applies in the recreation demand case that we study, as well as in cases of transportation mode choice, food product choice, housing choice, and other areas where random utility models are employed.

To the best of our knowledge, none of the previous research examining health risks and recreation choice analyzed response to risk in a two-stage decision process to account for the process of choice set formation. If there are a large number of possible sites, decision makers may narrow their choice sets using some specific criteria, and make the choice within those in their individual choice sets. Mis-specification of individual choice sets might result in biased estimates of the utility function and incorrect prediction of individuals' choices (see, for example, Swait and Ben-Akiva, 1987a).

Several attempts have been made to deal with the issue of choice set formation in the RUM. Peters, Adamowicz and Boxall (1995) asked respondents to specify the alternatives to be considered before making final 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) have explicitly modeled choice set formation based on the two-stage choice process as formulated by Manski (1977). Swait (2001) developed a model that does not consider choice set generation as a separate construct, but another expression of utility.

The explicit modeling of choice set formation is challenging when there are large choice sets, and models approximating the choice set formation process have been developed. Cascetta and Papola (2001) introduced the implicit availability perception function as an extension of the standard MNL model to allow decision makers to have an individual degree to which an alternative is considered for final decision. The model is extended by Martinez et al. (2009). While this approach is an approximation, it does provide a tractable method for incorporating choice set formation into RUM models that have many alternatives.

This study applies the availability model of Cascetta and Papola (2001) to analyze the response of hunters to potential health risk in both stages of choice set formation and site choice evaluation; specifically the responses of hunters to CWD prevalence in Alberta. We also attempt to compare the Cascetta and Papola approach to a fully specified Independent Availability Model (IAL) that accounts for choice set formation.

It is also possible that individual choice sets, and evaluation of alternatives, may change over time with changes in information. The psychology literature suggests that people are more likely to repeat an action if it produced favourable outcomes (the law of effect), that the learning effect is initially higher (the power law of practice), and that recent experience has higher impact (recency) (Erev and Roth 1998, Nicolaisen *et al* 2001, Bunn and Oliveira 2001). In general, people will adjust their behaviours in order to maximize their utility along with the process of learning. 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 occurrence 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.

This study uses a dataset that includes two years of stated and revealed preference data of site choices of Albertan hunters. The data allow for analysis of the effect of learning on choice set formation and preference over the two time periods.

An availability function is introduced to the standard RUM to analyze the process of choice set formation. Including CWD and time period variables into the availability function can help investigate the CWD effects on choice set formation, which is assumed to be a result of the learning process. Changes in hunting site preference can be investigated by examining the utility function. The marginal (dis)utility of the attribute CWD could change over time as the disease spreads and management to arrest its spread and prevalence are implemented. In addition, scale parameters are also estimated for SP and RP part of the data set each year to account for differences in error variances over time and between stated and revealed preference data sources (Swait and Louviere, 1993). 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. We also assess the importance, in terms of statistical performance and welfare impacts, of the inclusion of these aspects of choice.

LITERATURE REVIEW

As mentioned, there are some studies about responses of recreation site choice 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 tend to drive anglers away from that reservoir. Jakus and Shaw (2003) introduced the perceived hazard function to the site choice model. The perceived hazard function estimates the probability of keeping fish from a site. Because keeping fish caught is assumed to be for eating, it could be considered a risk perception function. The perceived hazard function is then introduced to the site choice model as an attribute. Jakus and Shaw did not find a significant effect of advisory awareness on the probability of keeping fish, but found that higher risk perceptions for a site drive anglers away from the site.

Zimmer et al. (2011) analyzed the hunting site choices of Albertan hunters, focusing on responses to CWD risk and prevention activities. Zimmer found that hunters were less likely to visit a site with higher CWD prevalence. In addition, one CWD management activity (culling) was found to have a negative effect on site demand, while another one (extra tags – licenses allowing additional deer harvest) was found to have a positive effect. Data from Zimmer et al. are part of the data used in this study.

Some alternatives may not be in a choice set of an individual for several reasons. For example, the individual may not know about some recreational sites, or rule out some sites using some criteria. Although ignoring the choice set formation process might result in biases (see Haab and Hicks 1999 for a review), choice set formation was not modeled explicitly in the above mentioned risk perception research. In Jakus et al (1997), distance was the main factor used to identify the choice sets. A reservoir located far away from an angler’s origin was eliminated from the choice set of anglers of 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 faced a choice set of 12 major reservoirs. Zimmer et al. (2011) analyzed the choice model with a two-level nested random parameter logit model, but this does not capture the choice set generation processes.

Choice set definition

Researchers have been using survey responses or exogenous information to define choice set. Peters, Adamowicz and Boxall (1995) estimated two models, one with all sites known to researchers as the choice set and one with choice sets that only include sites actually visited or known to individuals. Their results show that using all available sites as a choice set might result in biased estimates of preferences and welfare. Parsons and Hauber (1998) analyzed day-trip fishing demand in Maine and defined choice sets using spatial boundaries. Choice sets available to an individual included 12 randomly drawn sites within the range of 0.8 hours from the individual's home. They also vary the boundary from 0.8 up to 4 hours by 0.2 hour increments, and found that estimates change when the boundary changes. This implies that choice set mis-specification 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 are 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. They found that models that omit relevant alternatives included in the choice sets will result in biased utility functions and incorrect welfare measures.

Besides identifying the choice sets using survey responses or certain rules such as distance or familiarity, choice set formation can also be modeled in different ways. Swait (1984), Swait and Ben-Akiva (1987a) and Ben-Akiva and Boccara (1995) developed a formal two-stage model where the first stage is for 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, which will be presented in the next section. Cascetta and Papola (2001) proposed a RUM with an implicit availability perception function, which allows us to estimate the degree to which an alternative is available for consideration of an individual. The next section briefly introduces these two models.

Explicit modeling of choice set generation

In Haab and Hicks' (1997) model, the probability of choosing alternative j is

$$p_j = \sum_{C_k \subseteq C_m} P\left(j \mid j \in C_k\right) P\left(j \in C_k\right) \qquad (1)$$

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 and C_k is the choice set in C_m, which is the set of subsets of the universal set M. Considering all possible subsets from the universal set of J alternatives, the probability is

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

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 Manski's (1977) two-stage decision process, the probability of choosing alternative j is

$$p_j = \sum_{C_k \subseteq C_m} P\left(j \mid C_k\right) Q\left(C_k\right) \qquad (3)$$

where $Q\left(C_k\right)$ is the probability that C_k is the true choice set and $P\left(i \mid C_k\right)$ is the probability of choosing alternative j, conditional on the given choice set C_k. Note that this is different from Haab and Hicks (1997). The latter term in Haab and Hicks' model is the probability of an alternative belonging to a choice set, while it is the probability of a choice set being the true choice set in Manski's approach.

Swait (1984), Swait and Ben-Akiva (1987a) and Ben-Akiva and Boccara (1995) construct choice set formation based on Manski's framework. The probability that C_k is the true choice set is given by

$$Q\left(C_k\right) = \frac{\prod_{j \in C_k} A_j \prod_{l \notin C_k}\left(1-A_l\right)}{1-\prod_{h \in C_m}\left(1-A_h\right)} \qquad (4)$$

where A_j is the probability of alternative j in choice set C_k, which can be modeled as a binary logit model $A_j = \frac{1}{1+e^{-\gamma Z_{ij}}}$. This is the Independent Availability Logit model, which assumes that the probability of being considered for each alternative is independent of that of other alternatives.

Swait (2001) proposes the GenL model that models choice set generation as another expression of preferences, not a separate construct. The probability of choice set C_k being considered is defined as a monotonic transformation of the expected utility of all alternatives in the choice set

$$Q(C_k) = \frac{e^{\mu I_k}}{\sum_{r=1}^{K} e^{\mu I_r}} \text{ where } I_k = \frac{1}{\mu_k} \ln\left(\sum_{j \in C_k} e^{\mu_k V_j} \right) \qquad k = 1,\ldots,K \qquad (5)$$

where μ is the scale parameter for the choice set formation stage, I_k is the inclusive value of choice set C_k, and μ_k is the scale parameter. Note that Haab and Hicks and the IAL model 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 quite large for choice problem with a large number of alternatives J. The GenL model does not require enumeration all choice sets. However there is no obvious logical rule to limit the number of choice sets to the choice problem under consideration in this paper, which has 11 alternatives within the CWD management area.

In a recent development, von Haefen (2008) applied a Kuhn-Tucker demand system to model latent consideration sets. The model is attractive because it is tractable for large choice sets and can be estimated using standard econometric techniques. However, the model is not applied in this paper as we do not employ the Kuhn-Tucker approach.

Cascetta and Papola's Implicit Availability and Perception model

The models constructed above were on the basis of Manski's (1977) two-stage choice process and the number of possible choice sets is very large for large scale choice problems. If the number of alternatives is 11 (as in our case), the number of possible choice sets is 2,047. This makes those models challenging to apply for large choice problems. Several alternative models that approximate the choice set generation process have been proposed (Bierlaire et al 2010), one of which is the implicit availability and perception model by Cascetta and Papola (2001) (we refer to this as the CP model from now on). This model is expanded on by Martinez et al (2009) (the constrained multinomial logit model - CMNL).

The CP 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 modelled by a continuous variable in the domain of $[0,1]$. The probability of choosing alternative j becomes

$$p_{ij} = \frac{A_j e^{\mu V_{ij}}}{\sum_{k=1}^{J} A_k e^{\mu V_{ik}}} \qquad \text{or} \qquad p_{ij} = \frac{e^{\mu V_{ij} + \ln A_j}}{\sum_{k=1}^{J} e^{\mu V_{ik} + \ln A_j}} \tag{6}$$

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, the alternative j is less likely to be considered. To satisfy $0 \le A_{ij} \le 1$, the availability function can be defined as

$$A_{ij} = \frac{1}{1 + e^{-\alpha Z}} \tag{7}$$

where Z is a set of variables that affect choice set formation and α a vector of corresponding parameters. Note that the formulation above is slightly different from Cascetta and Papola (2001) since the availability factor $\ln A_j$ is not multiplied by the scale factor. For the model in equation (6), the function $G(y) = \sum_{j \in C} A_j y_j^{\mu}$ is a valid GEV generating function. Also note that the availability factor 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

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

and $\frac{1}{\mu} \ln A_{ij}$ can be considered a penalty since it is negative. Martinez et al (2009) expanded this model to model cutoffs or noncompensatory preferences in a random utility framework.

Applications

Some researchers have applied the explicit approaches of modelling choice set formation, but these are limited to cases with small choice sets. Swait (1984) applies the IAL model to transportation mode choice with four alternatives. Haab and Hicks (1997) applied their model to two cases. The first is with 5 alternatives, the second is 12 alternatives. For the second example, the number of possible choice sets is obviously large. However Haab and Hicks eliminate 6 among the 12 alternatives using some logical rules. This obviously helps reduce computational complexity.

Bovy (2009) provides a review of choice set generation modelling approaches, specifically applied to route choice in transportation networks. Başar and Bhat (2004) applied the IAL model to analyze choice set generation, applying it to an airport choice problem with three airports. Swait and Erdem (2007) applied the IAL model to investigate the brand effect on choice and choice set formation with two case studies, one with 6 alternatives and one with up to 10 alternatives. Hicks and Schnier (2010) analyze fishing zone choice with Manski's two-stage model, but group zones to macro-regions to reduce the complexity of the choice set generation stage, while retaining micro-regions at the choice stage. This approach is useful but may not be applicable to all choice problems.

Bierlaire et al (2010) compared the two approaches (CMNL and Manski's) using synthetic data (with a 3 alternative choice problem) and found that while Manski's model is unbiased, the CMNL is sometimes a poor approximation. The Martinez et al (2009) model is also discussed by Bierlaire et al (2010) as an alternative formulation of the problem.

DATA

Data for this study come from the survey discussed by Zimmer (2009). The data used in this present study come from two different years. The first hunting season trip information comes from 2007 and is used in the study by Zimmer et al. (2011). The second year of trip data (2009) were collected from a subset of respondents who provided information in the first year. Thus, the information from the two periods arises from the same sample of individuals - which is relatively rare in the recreation demand literature. The dataset consists of demographics and hunting site (WMU) choice of Albertan hunters and the four attributes described above for the two years. The hunting sites include those within CWD surveillance zones including WMUs 148, 150, 151, 162, 163, 200, 234, 236, 256, 500. Those outside of CWD surveillance zones are coded as 999.

WMUs were originally created based on geographic and ecological variations by Alberta Sustainable Resource Development (SRD) to manage wildlife populations. Culling and extra tags are part of the strategy by SRD to combat the threat of CWD spread that might affect hunting activities, which generate annual revenue of $71 million (Federal-Provincial-Territorial Task Force 2000) in Alberta. Culling was done to reduce the deer herds in areas where infected animals were identified. Extra tags were provided as an incentive to hunters who submit their harvested deer heads for testing and to reduce deer populations.

The data set has both revealed preference (RP) and stated preference (SP) choices in two hunting seasons, with a total of 4,362 observations or choices. Table 1 describes the structure of the data.

Hunters were sampled by postal code from the hunting license database. Hunters were contacted by telephone and invited to take the survey online. A total of 84 hunter surveys were usable in 2007 and 37 in 2009.[1] Each survey first asked hunters how many hunting trips they made in 2007 and locations (WMUs) for the RP data. Then for the SP part, the survey asked again where and how many trip they would go for hunting in new (hypothetical) situations where CWD occurrence and the presence of extra tags and culling program were altered such that they are not correlated as they were in RP data. For a complete experimental design, see Zimmer (2009).

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

EMPIRICAL MODEL

Our empirical analysis examines choices from 11 alternative hunting sites over two time periods. Because of the confounding between CWD and management programs use to combat CWD (culling and allocation or additional hunting tags) revealed preference data alone cannot identify the effect of CWD on site choice. Therefore, a set of stated preference questions about site choice was included in the survey of hunters. The stated preference data are included with the revealed preference data. Using these data we model site choice, availability (choice set formation) and scale. The effect of time on preferences, availability and scale is examined using dummy variable interactions. For the problem under consideration, the *cwd* attribute, and its interaction with a time dummy variable can be included in the utility function and the availability function. In this case, if learning over time heightens the perception of risk, the interaction term is expected to have a negative impact on the availability of the alternative, implying that in the second year, hunters are less likely to include sites with higher occurrence of CWD in their choice sets, and also have higher marginal disutility of CWD.

The scale function $\mu_i = \mu(z)$, which is inversely related to the variance (Ben-Akiva and Lerman 1985), is also estimated, where z is a set of relevant variables, including a time dummy and a dummy variable

[1] 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.

indicating whether the data are stated or revealed. The detailed model is described below. This formulation allows for time elements and data types to affect the variance of the error component.

Attributes and variables

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 has four levels: none (0), low (1 to 5), medium (6 to 10), and high (>10). Midpoints are used, so the levels are 0, 2.5, 7.5 and 12.5 percent. The travel cost tc is calculated using travel time, distance and hunters' income (see Zimmer et al. 2011) so it is continuous and individual specific. 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. Table 2 summarizes the attributes and levels.

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

Several individual characteristics are used:

- $yr2$: 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).
- $yrshunt$: number of years the hunter has been hunting.
- age : age of the hunter of the time of survey.

Utility function

A utility function is assumed to have alternative specific constants (ASCs), attributes and selected interactions:

- ASC for hunting sites, which are Wildlife Management Units (WMUs) including those in the CWD surveillance zones j = 148, 150, 151, 162, 163, 200, 234, 236, 256, 500, and all those outside of the zones, coded as 999. The ASCs are assumed to capture all unobserved attributes relevant to the alternatives (Murdock, 2006).
- Attributes: cwd , $tags$, $cull$, tc

- Interactions: $cwd \times yr2$ (to test for the change in the effect of CWD risk perception on preferences), $tc \times urban$ (to allow for the difference in sensitivity to travel cost between rural and urban hunters), $tags \times urban$ (to allow for a difference in response to the extra tags program between urban and rural hunters), $cwd \times urban$ (to test whether urban hunters are more sensitive to CWD than rural hunters) and $cull \times yrshunt$ (to test whether more experienced hunters are more sensitive to culling program).

The utility function is defined as

$$V_{ij} = ASC_j + \beta X_{ij} \qquad \text{for } j \neq 999$$

$$V_{ij} = ASC_j \qquad \text{for } j = 999$$

Where X_{ij} includes all attributes and interactions listed above and ASC_{500} is fixed at 0.

Availability function

The availability function is $A_{ij} = \frac{1}{1+e^{-\alpha Z_{ij}}}$ where Z includes a constant, cwd, $cwd \times yr2$ (interaction of cwd and $yr2$, to test for the difference in effect of cwd between two years), age, $urban$, and $yrshunt$.[2] We apply this specification for CP models as well as Independent Availability Logit model.

Scale function

The scale parameter for a data set cannot be identified, but the ratio of the scale parameter of one data set relative to another can be identified (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 values of scale parameter. So the scale parameter is estimated for four groups: Group 1 ($yr2$=0 and sp=0) has scale parameter μ_1, Group 2 ($yr2$=1 and sp=0) μ_2, Group 3 ($yr2$=0 and sp=1) μ_3 and

[2] We also estimated the model as specified in Martinez et al (2009). This model produced very similar results in terms of the parameters of the utility function and the welfare measures. The results of this model are available upon request. In the Martinez et al model the availability function is $\phi\left(cwd_j\right) = \frac{1}{1+e^{-\omega \times cwd_j + \rho}}$ where ρ and ω are estimated and individual characteristics are introduced by setting $\omega_i = \omega_0 + \omega_1 \times yr2 + \omega_2 \times age + \omega_3 \times urban + \omega_4 \times yrshunt$.

Group 4 ($yr2$ =1 and sp =1) μ_4. Fixing the scale parameter of Group 1 at 1, the scale function is $\mu_g = e^{\gamma_1 yr2 + \gamma_2 sp + \gamma_3 sp \times yr2}$.

ESTIMATION

A scale function is also included, and together with a utility and availability function, these components make the model highly nonlinear. The models are estimated using BIOGEME (Bierlaire, 2003) and MATLAB. A likelihood ratio test is applied to test for statistical significance of coefficients of utility and the availability function as well as the scale function.

A random component can be introduced into the utility function to allow for heterogeneous utility across hunters. We include this type of model for the Cascetta and Papola (CP) models, but not the Independent Availability Logit Models. The deterministic part of the utility function becomes

$$V_{ij} = ASC_j + \beta X_{ij} + \gamma_{ij} \qquad (9)$$

Where γ_{ij} is the individual and alternative specific random component which is assumed to be normally distributed $N\left(0, \delta_{ij}^2\right)$. The random component is allowed to vary not only across hunters but also across SP and RP decisions. The reason is that, although the choice is made by the same hunter, the RP decision was made in the past while the SP one is made at the time of survey, and preferences may have changed between the two points of time. However, the random component does not vary across choices made by the same hunters in a data set. As a result, data for the random parameter models are treated as panel data.

In the random parameter logit model, the probability of choosing alternative j is

$$\psi_{ij} = \int p_{ij}\left(\gamma\right) f\left(\gamma\right) d\gamma \qquad (10)$$

where $f\left(\gamma\right)$ is appropriate distribution density function. The model can be estimated by maximizing the following simulated log-likelihood function

$$SLL\left(\beta\right) = \sum_i \sum_j Y_{ij} \ln \left(\frac{\sum_{h=1}^{H} \psi_{ij}\left(\gamma_h\right)}{H} \right) \qquad (11)$$

where β_h is randomly drawn from the density function $f\left(\beta\right)$ with H replications. H = 500 is applied to this paper.

RESULTS

Results of seven models are presented in Table 3. The first three models are fixed parameter models. Model MNL1 is the basic model with a utility function only. Model MNL2 adds the scale function and model MNL3 further adds the availability function. Similarly, the next three models (RPL1-3) are random parameter models with a normally distributed random component added to the utility function. The final model is the IAL model. Note that all the models involve pooled SP and RP data for the two years.

We first discuss the MNL and RPL models using the Cascetta and Papola (CP) approach. We compare these to the IAL model later in this section.

In both MNL and RPL models, the scale and availability functions improve log-likelihood values. To test the hypothesis that the scale factors are identical for all data sets, likelihood ratio test rejects the null hypothesis that all coefficients of the scale functions are equal to zero in both models MNL2 and RPL2.

Log-likelihood values further improve when accounting for choice set formation. Testing model MNL3 against model MNL2, as well as model RPL3 against model RPL2, a likelihood ratio test again rejects the null hypothesis that the availability factor is unity. 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 MNL models have expected signs. Coefficients on travel costs are negative and consistent across models of MNL and RPL. The coefficient *tc x urban* is positive, indicating that urban hunters are less sensitive to travel costs. The effects of travel cost are underestimated if the scale factor and choice set formation are ignored.

In the MNL models, *tags* has a positive coefficient while *tags x urban* have negative coefficients. This means hunters are motivated by the extra tags program, but urban hunters are less motivated. In addition, it is observed that models without scale and availability functions underestimate the effect of the extra tags program. This result changes in RPL models. In these RPL models, the extra tags program does not encourage hunter choice, but urban hunters prefer sites with this program.

The culling program drives hunters away from the sites but more experienced hunters are less likely to dislike culling programs. When random components are included in the utility functions of models with scale and availability functions, more experienced hunters are no longer less affected by the culling program. Again, it can be observed that ignoring scale and availability would underestimate the effect of the culling program, because the coefficient of this variable is much smaller in the full model.

CWD prevalence has different effects on site choice formation and site choice evaluation. In the utility function, its effect varies across models. The effects found in RPL models differ from MNL models, and the effect even varies among RPL models.

Although CWD has the expected effect on choice set formation, that is, higher CWD prevalence reduces the availability of the sites, it has unexpected signs in some of the utility functions. MNL models indicate that rural hunters prefer sites with higher CWD prevalence. This may be based on habits and attachments to place, relative to urban hunters. However in the second year, hunters are less likely to prefer those sites as expected. Also note that urban hunters appear to dislike sites with CWD prevalence. In model MNL3, the coefficient on *CWD x urban* is large enough to outweigh that of *CWD*, implying that urban hunters dislike sites with higher CWD prevalence.

These results change in the RPL models. In model RPL1, hunters dislike sites with high CWD prevalence, which is contrary to the results from the MNL models. In addition, urban hunters do not have different tastes toward CWD risk in comparison to rural hunters.

In comparison to model MNL2, in model RPL2 both *CWD* and *CWD x yr2* are insignificant, but urban hunters dislike sites with higher CWD prevalence. Comparing MNL3 and RPL3, while *CWD* and *CWD x urban* are consistent between the models, the coefficient of *CWD x yr2* changes sign and is significant in both models.

CWD prevalence affects the availability of site, in a very different way than utility is affected. The variables *CWD* and *CWD x yr2* have negative coefficients and are statistically significant. This implies the higher CWD prevalence reduces the availability factor of a site, and reduces in magnitude in the second year. As a result, hunters are less likely to consider sites with higher CWD prevalence and this effect is stronger in the second year. This result is consistent between the MNL and RPL models.

Other individual specific variables including age, urban and hunting years are significant in the availability function. Including these variables, together with alternative specific variables, causes an effect on the availability factor. Figures 1 and 3 illustrate the effect of age and hunting years on the availability factor.

Table 3: Estimation Results

	Fixed parameter models						Random parameter models						Independent Availability Logit Model (IAL)	
Model	**Base: MNL1**		**Scale: MNL2**		**Full: MNL3**		**Base: RPL1**		**Scale: RPL2**		**Full: RPL3**			
Log-likelihood	-7,583.41		-7,500.26		-7,375.68		-5,067.19		-4,960.45		-4,937.84		-7402.643	
Rho-square	0.275		0.283		0.295		0.516		0.526		0.528		0.292	
Utility function														
Travel cost	-15.1	(0.442)	-23.8	(1.09)	-23.2	(1.08)	-15.3	(0.718)	-27.5	(2.57)	-29.7	(2.92)	-59.608	(4.909)
CWD	0.04	(0.012)	0.053	(0.018)	0.627	(0.087)	-0.05	(0.017)	***0.037***	***(0.026)***	0.616	(0.127)	-0.148	(0.053)
Tags	0.436	(0.065)	0.706	(0.109)	0.572	(0.105)	***0.053***	***(0.087)***	***0.129***	***(0.12)***	***0.161***	***(0.142)***	1.929	(0.282)
Cull	-0.444	(0.075)	-0.867	(0.129)	-0.961	(0.129)	-0.874	(0.113)	-1.06	(0.2)	-1.46	(0.228)	-2.48	(0.260)
Tc x urban	6.67	(0.427)	10.6	(0.774)	11.1	(0.776)	3.82	(0.657)	16.2	(1.97)	15.3	(1.84)	26.472	(2.855)
Tags x urban	-0.441	(0.084)	-0.671	(0.133)	-0.265	(0.136)	***0.195***	***(0.123)***	0.639	(0.187)	0.529	(0.211)	-1.676	(0.345)
CWD x urban	-0.053	(0.013)	-0.113	(0.022)	-0.655	(0.083)	***-0.00***	***(0.02)***	-0.284	(0.040)	-0.781	(0.129)	-0.203	(0.110)
Cull x hunt years	0.011	(0.003)	0.020	(0.004)	0.014	(0.005)	0.013	(0.005)	***0.009***	***(0.009)***	***0.013***	***(0.009)***	0.0455	(0.012)
CWD x year 2	-0.051	(0.013)	-0.101	(0.023)	-0.054	(0.027)	-0.071	(0.023)	***0.037***	***(0.038)***	0.115	(0.047)	-0.164	(0.066)
ASC 148	0.915	(0.172)	1.54	(0.284)	1.3	(0.266)	0.76	(0.394)	-2.47	(0.479)	-2.45	(0.558)	2.250	(0.468)
Std(ASC 148)	-		-		-		1.84	(0.186)	4.04	(0.444)	4.15	(0.518)	-	
ASC 150	1.08	(0.172)	2.01	(0.295)	1.7	(0.277)	1.4	(0.396)	0.763	(0.369)	***0.6***	***(0.431)***	3.121	(0.492)
Std(ASC 150)	-		-		-		2.51	(0.203)	3.82	(0.395)	4.12	(0.51)	-	
ASC 151	1.64	(0.158)	2.83	(0.287)	2.4	(0.267)	2.75	(0.344)	2.21	(0.353)	1.79	(0.373)	4.461	(0.543)
Std(ASC 151)	-		-		-		2.09	(0.124)	4.05	(0.391)	4.27	(0.477)	-	
ASC 162	0.756	(0.163)	1.21	(0.269)	1.11	(0.253)	1.91	(0.317)	-1.33	(0.361)	-1.42	(0.436)	1.871	(0.360)
Std(ASC 162)	-		-		-		0	(fixed)	3.29	(0.327)	3.74	(0.447)	-	
ASC 163	1.3	(0.155)	2.13	(0.266)	2.02	(0.25)	0.73	(0.374)	***-0.139***	***(0.312)***	***0.097***	***(0.372)***	4.486	(0.526)
Std(ASC 163)	-		-		-		2.74	(0.151)	3.74	(0.333)	4.15	(0.43)	-	
ASC 200	1.42	(0.148)	2.28	(0.259)	2.17	(0.243)	***-0.158***	***(0.367)***	-1.38	(0.301)	-1.54	(0.425)	4.920	(0.511)
Std(ASC 200)	-		-		-		3.23	(0.163)	4.91	(0.384)	6.05	(0.599)	-	
ASC 234	1.71	(0.152)	2.87	(0.277)	2.11	(0.26)	2.51	(0.327)	1.66	(0.287)	1.89	(0.347)	5.345	(0.567)
Std(ASC 234)	-		-		-		2.03	(0.09)	2.77	(0.246)	3.6	(0.336)	-	
ASC 236	1.43	(0.149)	2.24	(0.257)	2.1	(0.242)	1.63	(0.323)	0.498	(0.264)	1.05	(0.323)	5.634	(0.626)
Std(ASC 236)	-		-		-		2.55	(0.117)	4.6	(0.41)	4.81	(0.467)	-	
ASC 256	***0.248***	***(0.168)***	***0.301***	***(0.277)***	***0.38***	***(0.261)***	2.12	(0.345)	***-0.064***	***(0.267)***	***0.138***	***(0.329)***	1.146	(0.546)
Std(ASC 256)	-		-		-		2.68	(0.216)	1.69	(0.224)	2.1	(0.26)	-	
ASC 500	0	(fixed)	0	(fixed)	0	(fixed)	0	(fixed)	0	(fixed)	0	(fixed)	0	(fixed)
Std(ASC 500)	-		-		-		2.45	(0.235)	0	(fixed)	0	(fixed)	0	(fixed)
ASC 999	***0.181***	***(0.16)***	***0.211***	***(0.262)***	***0.315***	***(0.249)***	-0.82	(0.358)	-2.16	(0.344)	-2.73	(0.42)	2.089	(0.361)
Std(ASC 999)	-		-		-		3.52	(0.162)	4.96	(0.418)	4.22	(0.407)	-	

Availability function							
Constant			4.59 (0.594)			3.92 (0.828)	***-0.068*** ***(0.267)***
CWD			-0.768 (0.062)			-0.705 (0.079)	1.176 (0.364)
CWD x year 2			-0.116 (0.054)			-0.362 (0.073)	-0.747 (0.254)
Age			-0.077 (0.015)			-0.048 (0.02)	***-0.001*** ***(0.008)***
Urban			10 (2.31)			7.92 (1.03)	0.356 (0.186)
Hunting years			0.12 (0.012)			0.091 (0.019)	***-0.004*** ***(0.007)***
Scale function							
Year 2		-0.303 (0.070)	-0.305 (0.068)		***-0.144*** ***(0.136)***	***-0.157*** ***(0.125)***	-1.377 (0.074)
SP		-0.518 (0.043)	-0.468 (0.045)		-0.391 (0.085)	-0.56 (0.097)	-0.782 (0.104)
Year2 x SP		0.177 (0.083)	0.3 (0.09)		***0.178*** ***(0.149)***	0.423 (0.143)	0.676 (0.113)

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

As mentioned above, a site with CWD risk is less likely to be considered, compared to a site without CWD. This discrepancy in availability factor is widened when age increases. Figure 1 illustrates the availability factor, calculated for two sites: with CWD (=2.5) and no CWD, of urban and rural hunters of the two years. Availability factors are calculated using estimates from model MNL3, and average hunting years is used. It is hard to see the increasing difference in the availability function for urban hunters. For urban hunters, the availability factors are very close to 1 in all cases and it is difficult to differentiate them in Figure 1. This is because the coefficient of urban in the availability function is relatively large. However, it is easy to see that the difference in availability factors of sites with and without CWD widens as age increases for rural hunters, in both year 1 and year 2. Therefore, older hunters are less likely to consider sites with CWD risk.

Figure 1: Availability factor by ages

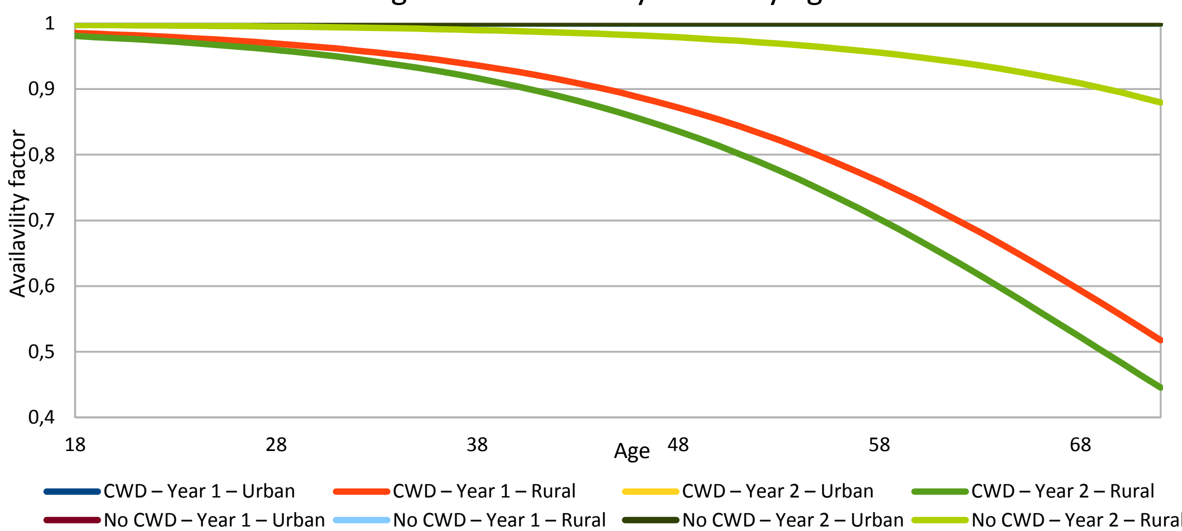
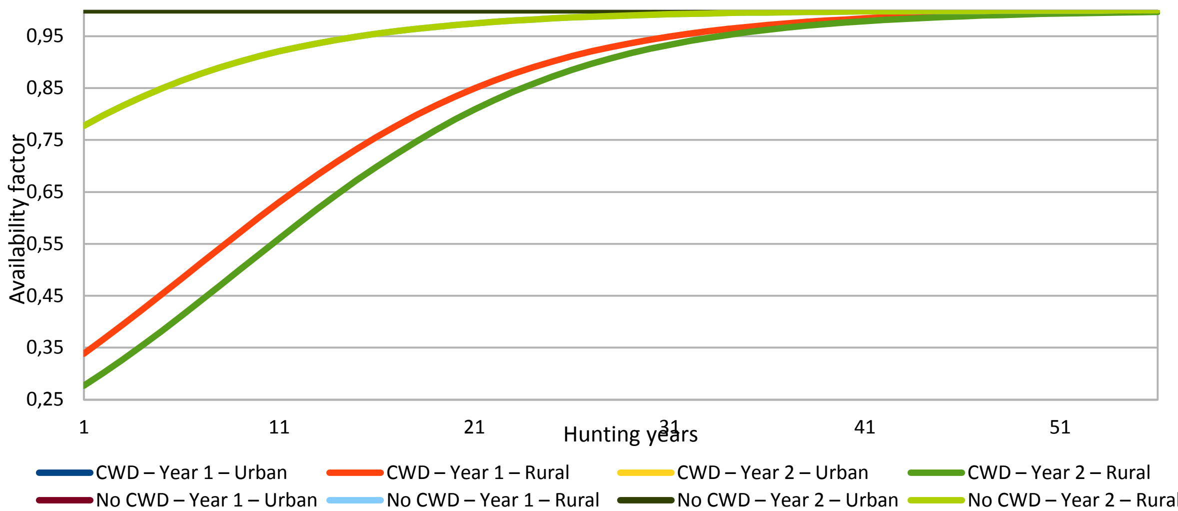


Figure 2 presents changes in the availability factor by years of hunting experience. Average age was used to calculate the availability factors. Contrary to the case of age, the difference in availability factors between sites with and without CWD is narrowed when experience increases. Again it is difficult to see the differences of urban hunters because availability factors (of sites with and without CWD) of urban hunters are very close to 1. However it is easy to compare availability factors of rural hunters. In all cases, availability factors increase with hunting years, meaning that more experienced hunters are less sensitive to CWD risk in choice set formation. Here it can also be observed that rural hunters are much less likely to consider sites with CWD.

Figure 2: Availability factor by hunting years



In the scale function, in MNL models, all variables are 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. When random components are included, some scale parameters become statistically insignificant. In model RPL2, only sp is significant, implying that the scale factor is smaller for SP data, but not for the second year data. This means SP data has higher variance. In model RPL3, the scale factor of SP data is smaller than that of RP data, and increases from year 1 to year 2 within SP data sets. This implies SP data has higher variance, and the variance of SP data in year 2 is higher than that in year 1.

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" (see Zimmer et al 2011 for more details). This latter case also has no management actions taking place. We examine the welfare impact on rural hunters, urban hunters, and an 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.

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 β_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 and V_{ji}^1 is the corresponding utility at the worst case scenario and μ_i is the scale factor. Note that utility function is defined as in equation (8).

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 as mentioned, no management activity. Table 4 presents simulated welfare change for this "worst case" scenario.

Table 4: Welfare changes of moving to the "worst case" scenario ($/trip)

4A: WELFARE MEASURES – FROM MODEL MNL1 (BASE MNL) AND MNL2 (MNL MODEL WITH SCALE)

	Year 1		Year 2	
	Rural	Urban	Rural	Urban
Base MNL	15.37 (3.75)	-4.24 (4.38)	-11.23 (3.66)	-40.67 (4.74)
MNL with scale	15 (5.18)	-18.35 (4.73)	-23.07 (6.28)	-49.93 (15.78)

Note: Welfare change $/trip of moving to the worst case scenario. Standard deviations are in parentheses.

4B: WELFARE MEASURES – FROM THE MODEL MNL3 (with availability and scale)

	Year 1		**Year 2**	
	Rural	**Urban**	**Rural**	**Urban**
Utility function	248.49 (30.51)	-7.26 (3.41)	248.98 (0.63)	-28.45 (8.39)
Availability factor	-81.41 (32.7)	-0.35 (1.03)	-116.05 (3.4)	-0.69 (2.82)
Total	**68.33** **(21.17)**	**-7.69** **(2.71)**	**-38.36** **(1.98)**	**-29.04** **(8.52)**

Note: Standard deviations are in parentheses.

Table 4A outlines 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 model that includes availability (Table 4B) changing from current situation to the worst case also reduces welfare of both rural and urban hunters in year 2. The reduction is higher for rural hunters ($38.36/trip) than urban hunters ($29.04/trip). The welfare reduction in year 2 is higher than that in year 1. In year 1, the reduction is only \$7.69/trip for urban hunters. The welfare increases for rural hunters in year 1, because the positive coefficient of CWD in the utility function for rural hunters.

In Table 4B 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 availability factor change, holding the utility fixed at the current management. The contribution of availability function to welfare change is small, especially for urban hunters. In all cases, it is less than half of the contribution generated by the utility function. This is consistent with the results from Figure 1 and 2: CWD affect choice sets of rural hunters much more than it affects that of urban hunters. Urban hunters all sites with a high probability, and thus there is relatively little change associated with the availability component for them. For rural hunters, however, the availability function plays a significant role in the welfare decomposition as availability is not close to 1 (in probability terms) and is affected by CWD.

COMPARISON WITH THE IAL MODEL

The last column of table 3 presents the results of the IAL model that includes scale effects[3]. In Table 5 below we also present the implied probabilities of choice set sizes for the sample. If the CP model and the IAL model are similar, that provides some confidence in the use of the CP model as a practical method of incorporating consideration sets. We focus on model MNL3 (Full:MNL3, column 4 in Table 3) and the IAL model.

Examining the scale function parameters, we see that the two models provide qualitatively similar results. 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. CWD has negative effects on rural hunters, larger negative effects on urban hunters, and are more negative in year 2. In the MNL3 model year 1 impacts of CWD are positive for rural hunters, negative for urban hunters and the year 2 interaction is negative. Other parameters are qualitatively similar. Thus, the two methods provide somewhat different

[3] Note – these results are tentative as we have not completed all the diagnostics on this model.

measures of the utility function parameters associated with CWD, although the most of the parameters are qualitatively similar.

Finally, some of the parameters affecting availability are different. The most prominent difference is the impact of Urban on choice set formation. In the MNL3 model the urban dummy variable is large and positive, effectively meaning that urban hunters have a very high probability of considering all sites. In the IAL model, however, this parameter is much smaller, generating smaller probabilities of consideration. Table 5 below shows that a small fraction of the sample is likely to have choice sets of size 10 or 11. The MNL model, however, would imply that all urban hunters have a high probability of choice sets of size 10 or 11, because of the dominance of the urban dummy variable. The CWD parameters are also different in the IAL and MNL3 models. In the IAL the impact of CWD is positive in year 1, but decreases in year 2. In the MNL model the effect is negative for both years. Age and years of hunting are not significant explanators of choice set formation in the IAL model, while they are in the MNL model.

The conclusion from this comparison is somewhat mixed. While the CP model appears to mimic the IAL model in some ways, it also differs in other ways. Perhaps the most apparent difference is the way that the demographic variable "Urban" enters the availability function. This variable generates a very strong consideration effect in the CP model, while its effect in the IAL model, while positive, is not as large. In both models, however, the increasing negative impact of CWD, on utility and choice set formation, is maintained.

Table 5: Implied Probabilities of Choice Set Size

# alternatives	Q (probability)
1 alt	0.00
2 alts	0.00
3 alts	0.01
4 alts	0.03
5 alts	0.08
6 alts	0.15
7 alts	0.21
8 alts	0.22
9 alts	0.18
10 alts	0.10
11 alts	0.03

CONCLUSIONS

This paper applies the Implicit Availability and Perception model of Cascetta and Papola (2001) to analyze the response of Albertan hunters to CWD risk, in both stages of site choice evaluation and choice set formation. 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, but found strong effects of CWD on choice set formation.

Models estimated using the Cascetta and Papola approach suggest that CWD prevalence makes a site less likely to be considered. Hunters are even less likely to consider sites with CWD in the second year in our case study. In terms of choice set formation, rural hunters are more sensitive to CWD risk than urban hunters. In addition, older hunters are more cautious toward CWD risk, while more experienced hunters are less sensitive to CWD risk.

The welfare measures show that for urban hunters, the change in welfare that can be attributed to the choice set formation process is very small. For rural hunters the choice set formation contribution is larger, but is never more than 50% the size of the utility function impact. Therefore, in this case study, the importance of modeling choice set formation in terms of welfare measures is not substantial, especially for urban hunters.

In terms of the impact of CWD on hunters, there is clearly a change between year 1 and year 2. The impact of CWD in the first year is minimal while the impact is more substantial in year 2. Recreational demand models are usually based on a single year of data. Our results show the impact of changing conditions of time. The availability function, utility function and scale (variance) component have all changed over the time period.

Finally, our comparison of the MNL models with availability, and a fully specified IAL model provides mixed 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. Bierlaire et al (2010) pointed out that the Cascetta and Papola model is sometimes a poor approximation of the formal choice set formation model. Our results show that there are differences between the two models suggesting caution in the use of the CP approximation. However, this conclusion is subject to further testing of specifications and evaluation, and is based only on this data set. Further efforts should be made to apply the formal choice set formation models to compare with and validate the CP model and the Martinez model.

REFERENCES

Andrews, R. and T.T. Srinivasan. 1995. Studying consideration effects in empirical choice models using scanner panel data. *Journal of Marketing Research*. 32: 30-41.

Başar, G. and C. Bhat. A Parameterized Consideration Set Model for Airport Choice: An Application to the San Francisco Bay Area. *Transportation Research B*. 38:889-904.

Ben-Akiva M. and B. Boccara. 1995. Discrete choice models with latent choice sets. *International Journal of Research in Marketing*. 12: 9-24.

Ben-Akiva, M. and S. R. Lerman. 1985. Discrete Choice Analysis: Theory and Application to Travel Demand. MIT, Cambridge.

Bierlaire, M. 2003. BIOGEME: A free package for the Estimation of Discrete Choice Models. Proceedings of the 3rd Swiss Transportation Research Conference. Ascona. Switzerland.

Bierlaire, M., R. Hurtubia and G. Flötteröd. 2010. Analysis of Implicit Choice Set Generation Using a Constrained Multinomial Logit Model. *Transportation Research Record*. 2175: 92-97.

Bovy, P.H. 2009. On Modelling Rout Choice Sets in Transportation Networks: A Synthesis. *Transport Review*. 29(1): 43-68.

Bunn, D.W. and F.S. Oliveira. 2001. Agent-based simulation: An application to the new electricity trading arrangements of England and Wales. *IEEE transactions on Evolutionary Computation* 5:493-503.

Cascetta, E., A. Papola, 2001. Random utility models with implicit availability/perception of choice alternatives for the simulation of travel demand. *Transportation Research Part C*, 9 (4): 249–263.

Chiang, J., S. Chib and C. Narasimhan. 1999. Markov chain Monte Carlo and model of consideration set and parameter heterogeneity. *Journal of Econometrics*. 89: 223-248.

Clawson, M. 1959. Method for Measuring Demand for and the Value of Outdoor Recreation*.* Reprint No. 10. Washington, D.C.: Resources for the Future.

Diana, S.C. and C.A. Bisogni. 1993. Understanding anglers' practices related to health advisories for sport-caught fish. *Journal of Nutrition Education.* 25(6): 320-328.

Erev, I. and A.E. Roth. 1998. Predicting how people play games with unique, mixed strategy equilibria. *American Economic Review*, 88: 848-81.

Federal-Provincial-Territorial Task Force on the Importance of Nature to Canadians. 2000. *The importance of nature to Canadians: the economic significance of nature related activities*. Minister of the Environment: Ottawa, Canada.

Haab, T.C. and R.L. Hicks. 1997. Accounting for choice set endogeneity in random utility models of recreation demand. *Journal of Environmental Economics and Management* 34(2): 127-147.

Haab, T.C. and R.L. Hicks. 1999. Choice Set Considerations in Models of Recreation Demand: History and Current State of the Art. *Marine Resource Economics* 14: 271-281.

Hanemann, W.M. 1978. A Methodological and Empirical Study of the Recreation Benefits from Water Quality Improvement. *Ph.D. Dissertation*. Department of Economics. Harvard University.

Hicks, R.L. and K.E. Schnier. 2010. Spatial Regulations and Endogenous Consideration Sets in Fisheries. *Resource and Energy Economics*. 32: 117-134.

Hicks, R.L. and I.E. Strand. 2000. The Extent of Information: Its Relevance for Random Utility Models. *Land Economics*. 76(3): 374-385.

Hotelling, H. 1949. Letter to the National Park Service. In *An Economic Study of the Monetary Evaluation of Recreation in the National Parks.* Washington, D.C.: U.S. Department of the Interior, National Park Service and Recreational Planning Division.

Jakus, P.M., M. Downing, M.S. Bevelimer, and J.M. Fly. 1997. Do sportfish consumption advisories affect reservoir anglers' choice? *Agriculture and Resource Economics Review*. 26(2): 196-204.

Jakus, P.M. and W.D. Shaw. 2003. Perceived hazard and product choice: An application to recreational site choice. *Journal of Risk and Uncertainty.* 26(1): 77-92.

Jones, C. and F. Lupi. 1999. The effect of modelling substitute activities on recreational benefit estimates: Is more better? *Marine Resource Economics*, 14: 357-74.

Manski, C.F. 1977. The Structure of Random Utility Models, *Theory and Decision*, 8: 229-254.

Martinez, F., F. Aguila and R. Hurtubia. 2009. The constrained multinomial logit: A semi-compensatory choice model. *Transportation Research Part B*, 43: 365-377.

May, H. and J. Burger. 1996. Fishing in a polluted estuary: fishing behaviour, fishing consumption, and potential risk. *Risk Analysis.* 16(4): 459-471.

Murdock, J. 2006. Handling unobserved site characteristics in random utility models of recreation demand. *Journal of Environmental Economics and Management.* 51 (1), 1–25.

Nicolaisen, J., V. Petrov, and L. Tesfatsion. 2001. Market power and efficiency in a computational electricity market with discriminatory double-auction pricing. *IEEE transactions on Evolutionary Computation*, 5: 504-23.

Parsons, G. and A. Hauber. 1998. Spatial boundaries and Choice Set Definition in a Random utility model of Recreation Demand. Land Economics, 74(1): 32-48.

Peters, T., W. Adamowicz and P. Boxall. 1995. The Influence of choice set consideration in modelling the benefits of improved water quality. *Water Resources Research*, 613: 1781-7.

Roberts, J., J. Lattin. 1991. Development and testing of a model of consideration set composition. *Journal of Marketing Research*. 28: 429-440.

Swait, J. 1984. Probabilistic choice set formation in transportation demand models. Unpublished Ph.D. Thesis. Department of Civil Engineering, MIT, Cambridge, MA.

Swait, J. 2001. Choice set generation within the generalized extreme value family of discrete choice models. *Transportation Research Part B* 35(7): 643-666.

Swait, J. and M. Ben-Akiva. 1986. An analysis of the effects of captivity on travel time and cost elasticities. *Annals of the 1985 International Conference on Travel Behaviour. April 16-19, 1985*. Noordwijk, Holland. pp 113-128.

Swait, J. and M. Ben-Akiva. 1987a. Incorporating random constraints in discrete choice models of choice set generation. *Transportation Research B.* 21(2): 91-102.

Swait, J. and M. Ben-Akiva. 1987b. Empirical test of a constrained choice discrete model: mode choice in Sao Paulo Brazil. *Transportation Research B.* 21(2): 103-115.

Swait, J. and T. Erdem. 2007. Brand Effects on Choice and Choice Set Formation Under Uncertainty. *Marketing Science*. 26(5): 679-697.

Swait, J. and J.J. Louviere. 1993. Role of the scale parameter in the estimation and comparison of multinomial logit models. *Journal of Marketing Research.* 30(3): 305-314.

von Haefen, R.H. 2008. *Latent consideration sets and continuous demand systems*. Environmental and Resource Economics 41(3): 363-379.

Zimmer, N.M.P. 2009. The Economic Impacts of Chronic Wasting Disease on Hunting in Alberta. *Thesis*. Department of Rural Economy. University of Alberta.

Zimmer, N.M.P., P.C. Boxall, and W.L. Adamowicz. 2011. The Impacts of Chronic Wasting Disease and its Management on Recreational Hunters. Accepted for Publication in the Canadian Journal of Agricultural Economics.