

MODELING HUNTERS PREFERENCES USING DISCRETE CHOICE
EXPERIMENTS

by

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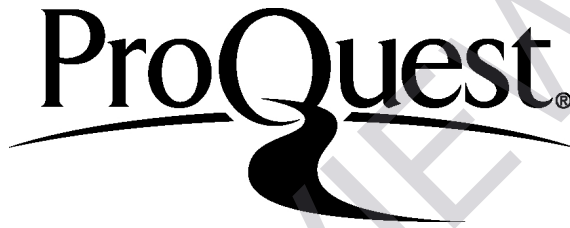
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MODELING HUNTERS' PREFERENCES USING DISCRETE CHOICE EXPERIMENTS

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University of Nebraska, 2015

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Careful utilization of natural resources to meet human demands is the pivotal concern of the evolving discipline of “human dimensions of natural resources”. In the USA, government agencies such as the Nebraska Game and Parks Commission (NGPC) regularly offer state-wide programs to manage wildlife, such as controlling the abundance of deer species through licensed hunting. Hunting is an outdoor activity for all kinds of citizens, and generates revenue to support management of game species. Agencies often conduct surveys to better understand stakeholders’ perceptions for planning better management strategies.

An online survey included a discrete choice experiment (DCE) was planned to elicit hunters’ preferences who hunt in Nebraska on publicly accessible land for hunting. The current research describes the design and analysis of the DCE portion of the survey.

Discrete choice experiments (DCEs) are based on random utility theory. In DCEs, distinct choice sets, each with at least two alternatives, were constructed. Every alternative is based on some combination of attributes, where each attribute is measured and/or observed with different levels. A group of choice sets is offered to every respondent to choose the alternative which he/she likes the most. This multivariable approach better describes tradeoffs between attributes than uni-dimensional approaches

such as nominal and/or Likert-scale questions. Two approaches for designing discrete choice experiments, Yong Method (2-Level design) and Street-and-Burgess Method (3-Level design), were compared. Further, three commonly used analysis approaches for analyzing the discrete choice data are briefly reviewed. These are Multinomial Logit Models (MNL), Mixed Logit Models (MXL), and Latent Class Models (LCM).

DCEs generated from the 2 and 3 level designs were analyzed with each of MNL, MXL and LCM. Design and analysis methods of DCEs suggest that careful consideration of both is necessary to effectively address the research objectives.

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PREVIEW

Acknowledgments

فَبِأَيِّ آلَاءِ رَبِّكُمَا تُكَذِّبَانِ (Fabi-ayyi ala i rabbikuma tukazziban) translation,

Then which of the favors of your Lord will you deny?

All praise to Allah WHO blesses me with countless blessings and provided me the opportunity and strength to come to the stage of completion of PhD degree at University of Nebraska Lincoln (UNL), USA.

I'm thankful to my doctoral committee for allowing me to complete my PhD degree. This novel expertise provided me lifelong opportunity for employing all sort of statistical methods for modeling and understanding human behaviors towards natural resources as, to me, human capital is supreme of all such resources.

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Table of Contents

List of Tables	ix
List of Figures	xii
Chapter 1 - discrete choice experiments for natural resources	1
Introduction.....	1
Importance of Discrete Choice Experiments	5
Literature Review of the Design of Discrete Choice Experiments.....	11
Literature Review of the Analysis of Discrete Choice Experiments	18
Multinomial Logit (MNL)	19
Mixed Logit (MXL)	20
Latent Class Models (LCM)	20
Proposed Study for using Discrete Choice Experiments	22
Figures & Tables.....	23
Chapter 2 - Analysis of discrete choice experiments with homogeneity assumption	30
Introduction.....	30
Methods	33
Design	33
Sampling	33
Variables of Study.....	35
Software	36
Methods for Designing DCEs	37
Designing DCEs using Street and Burgess Method.....	38
Designing of DCEs using Yong Method	40
Model Estimation and Selection	42
Results.....	46
Demographic Facts	46
Model fitted with MNL for 2-Level Design (Yong Method)	47
Model fitted with MNL for 3-Level Design (Street and Burgess Method)	51

Discussion.....	57
Figures & Figures	63
Chapter 3 - Analysis of discrete choice experiments with heterogeneity assumption.....	84
Introduction.....	84
Purpose of Discrete Choice Experiments	86
Methods	90
Sampling	90
Variables of study	90
Mixed Logit (MXL)	90
Latent Class Models.....	91
Model selection within each Analysis approach.....	92
Model selection for mixed logit model (MXL)	94
Model selection for latent class model (LCM)	95
Model comparison across three Analysis approaches	96
Results.....	97
Demographic Facts	97
Model selection for mixed logit model (MXL)	97
Model fitted with Mixed Logit (MXL) for 2 Level Design.....	97
Mixed Logit (MXL) with correlated random parameters for 2 Level Design	102
Model fitted with Mixed Logit (MXL) for 3 Level Design.....	103
Mixed Logit (MXL) with correlated random parameters for 3 Level Design	106
Model selection for latent class model (LCM)	108
Model fitted with Latent Class Modeling (LCM) for 2 Level Design.....	109
Model fitted with Latent Class Modeling (LCM) for 3-Level Design	113
Discussion.....	119
Comparing Model Fitted with MNL, MXL and LCM for 2-Level Design	119
Comparing Model Fitted with MNL, MXL and LCM for 3-Level Design	126
Comparing 2-Level and 3-Level Designs across Analyses (MNL, MXL and LCM)	133

Figures & Tables.....	137
References.....	156
Appendix A - Survey	165

PREVIEW

List of Tables

Table 1-1. List of articles, published in 2014, used OMEP and/or Bayesian D-efficient for designing DCEs in the respective study.	23
Table 1-2. List of articles, published in 2014, studied main effects and interaction for analyzing DCEs in the respective study.	24
Table 1-3. List of articles, published in 2014, did not specify designing method and type of interaction for DCEs in the respective study.	25
Table 2-1. Attributes and their associated levels used for constructing choice sets with both 2-Level design and 3-Level design	63
Table 2-2. Demographic characteristics (age, gender, marital status, # of children and home ownership) of Respondents who were licensed hunters for the year 2014	64
Table 2-3. Demographic characteristics (ethnicity, education and income) of respondents who were licensed hunters for the year 2014	65
Table 2-4. Demographic characteristics (community, residence, where did hunt, preferred species) of respondents who were licensed hunters for the year 2014	66
Table 2-5. Cross table for State of Residence by Gender.	67
Table 2-6. Cross table of preferred species by helping to recruit new individuals.	68
Table 2-7. Age distribution from mean.	69
Table 2-8. Parameter Estimates (Est.), Standard Errors (SE) and p-values for 2-Levels design with MNL for main effects only. Each estimate is difference from base (i.e., first) level.	70
Table 2-9. Parameter Estimates (Est.), Standard Errors (SE) and p-values for 2-Levels design with MNL with 2-way interactions of attributes with demographic variables.	71
Table 2-10. Parameter Estimates (Est.), Standard Errors (SE) and p-values for 3-Levels design with MNL when preferred species are Upland, and Big game. Each estimate is difference from base (i.e., first) level.	72

Table 2-11. Parameter Estimates (Est.), Standard Errors (SE) and p-values for 3-Levels design with MNL when preferred species are Turkey, and Squirrel-and-Rabbit. Each estimate is difference from base (i.e., first) level.	73
Table 2-12. Parameter Estimates (Est.), Standard Errors (SE) and p-values for 3-Levels design with MNL when preferred species are Waterfowl, and Dove & Crow. Each estimate is difference from base (i.e., first) level.	74
Table 3-1. Likelihood Ratio Test (LRT) with degree of freedom (df) and p-value showed that MXL with correlated random parameters is better to use for 2-Level design.	137
Table 3-2. Likelihood Ratio Test (LRT) with degree of freedom (df) and p-value showed that MXL with correlated random parameters is better to use for 3-Level design.	138
Table 3-3. Parameter Estimates (Est.), Standard Errors (SE) and p-values for 2-Levels design with MXL for main effects only. Each estimate is difference from base (i.e., first) level.	139
Table 3-4. Parameter Estimates (Est.), Standard Errors (SE) and p-values for 2-Levels design with MXL with 2-way interactions of attributes with demographic variables.	140
Table 3-5. Estimated coefficients of correlation between the effects for 2-Level design.	141
Table 3-6. Parameter Estimates (Est.), Standard Errors (SE) and p-values for 3-Levels design with MXL	142
Table 3-7. Estimated coefficients of correlation between the effects for 3-Level design.	143
Table 3-8. AIC values across and within each Q for 2-Level design, and minimum value is underlined.	144
Table 3-9. Parameter Estimates (Est.), with corresponding Standard Errors (SE) underneath it, and P-values of class estimates for 2-Level design with LCM.	145
Table 3-10. Parameter Estimates (Est.), with corresponding Standard Errors (SE) underneath it, and P-values of class coefficients for 2-Level design with LCM.	146

Table 3-11. AIC values across and within each Q for 3-Level design, and minimum value is underlined.	147
Table 3-12. Parameter Estimates (Est.), with corresponding Standard Errors (SE) underneath it, and P-values of class estimates for 3-Level design with LCM.	148
Table 3-13. Parameter Estimates (Est.) of 1 st , 2 nd , & 3 rd attributes, with corresponding Standard Errors (SE) underneath it, and P-values (p) of class coefficients for 3-Level design with LCM.	149
Table 3-14. Parameter Estimates (Est.) of 4 th , 5 th , & 6 th attributes with corresponding Standard Errors (SE) underneath it, and P-values (p) for 3-Level Design, of the class coefficients for 3-Level design with LCM	150

List of Figures

Figure 1-1. Yearly published articles with DCE in the field “Natural Resources”, as per the chosen search key words from 1995 through 2014.....	26
Figure 1-2. An example of questions using nominal scale, in a typical (or traditional) survey.....	27
Figure 1-3. An example of questions using Likert scale, in a typical (or traditional) survey.....	28
Figure 1-4. An example of choice set with two alternatives, each alternative has one of the three levels of each of 3 attributes.....	29
Figure 2-1. Screen shot of a choice set appeared on screen for respondent. It is one of the eight choice sets constructed using either of 2-Level or 3-Level design.	75
Figure 2-2. Age distribution of recruiters and non-recruiters in hunters.	76
Figure 2-3. Comparing age for different type preferred game.....	77
Figure 2-4. Community of current living is distributed with age. The minimum age is 19.	78
Figure 2-5. Probability of choice of the hunters with respect to their ages for travel time and reservation predicted from worst to best possible case using MNL. This interaction is studied for all ages (19 years old and above), community where currently living: Urban, helped as recruiter: Yes and type of preferred species to hunt: Upland Birds.....	79
Figure 2-6. Probability of choice of the hunters with respect to their community of live for travel time from worst to best possible case using MNL. This interaction is studied for average-aged hunters (51 years), helped as recruiter: Yes and type of preferred species to hunt: Upland Birds.....	80
Figure 2-7. Probability of choice of the hunters with their recruitment status for access days, travel time and reservation from worst to best possible case using MNL. This interaction is studied for average-aged hunters (51 years), community where	

currently living: Urban, helped as recruiter: Yes and type of preferred species to hunt: Upland Birds.....	81
Figure 2-8. Probability of choice of the hunters with their hunting type for travel abundance, travel time and reservations from worst to best possible case using MNL. This interaction is studied for average-aged hunters (51 years), community where currently living: Urban and helped as recruiter: Yes.	82
Figure 2-9. Probability of choice of the hunters based on 3-Level design using MNL. Probability of choice for worst, base and best sites are respectively represented by solid black straight line, small dashed straight line (in the middle of graph), and large dashed dotted straight line. Each of preferred species is represented by unique line type and plotting character.	83
Figure 3-1. Probability of choice of the hunters with respect to their ages for travel time and reservation predicted from worst to best possible case using MXL. This interaction is studied for all ages (19 years old and above), community where currently living: Urban, helped as recruiter: Yes and type of preferred species to hunt: Upland Birds.....	151
Figure 3-2. Probability of choice of the hunters with respect to their community of live for travel time from worst to best possible case using MXL. This interaction is studied for average-aged hunters (51 years), helped as recruiter: Yes and type of preferred species to hunt: Upland Birds.....	152
Figure 3-3. Probability of choice of the hunters with their recruitment status for access days, travel time and reservation from worst to best possible case using MXL. This interaction is studied for average-aged hunters (51 years), community where currently living: Urban, helped as recruiter: Yes and type of preferred species to hunt: Upland Birds.....	153
Figure 3-4. Probability of choice of the hunters with their hunting type for travel abundance, travel time and reservations from worst to best possible case using MXL. This interaction is studied for average-aged hunters (51 years), community where currently living: Urban and helped as recruiter: Yes.	154

Figure 3-5. Probability of choice of the hunters based on 3-Level design using MXL.

Probability of choice for worst, base and best sites are respectively represented by solid black straight line, small dashed straight line (in the middle of graph), and large dashed dotted straight line. Each of preferred species is represented by unique line type..... 155

PREVIEW

CHAPTER 1 - DISCRETE CHOICE EXPERIMENTS FOR NATURAL RESOURCES

Introduction

Humans live in and interact with their environment in diverse ways, and it is unlikely that each person has exactly the same attitude toward natural resources. Human preferences for natural resources vary across demographic characteristics and different geographies, affecting how humans respond to management actions. For example, people living near a forest would have certain preferences toward the forest resource. If their preference is to consume trees for fire (heating purposes) rather than using other energy sources such as hydro, wind, or gas, then more forest management actions such as restrictions on tree cutting and fines may be required. On the other hand if a community cares for the resource using conservation approaches, different management actions will be required. The study of human preferences for natural resource management is an aspect of “human dimensions of natural resources.” It is important to understand variation in human preferences toward natural resources for effective planning (Gibson et al. 2000).

Social scientists have developed methods and approaches for effectively measuring human preferences. To understand people’s preferences about a certain issue, e.g. wildlife hunting opportunities, researchers typically use a survey and ask yes/no or Likert scale questions. For example, a Likert scale ranging from 1 to 5 (strongly disagree to strongly agree) asking “how likely would you prefer a hunting area close to home?” and “how likely would you prefer a hunting area with many target species?” Most people

would answer 5, strongly agree, for both of these questions. However, this would not really tell us how people tradeoff these preferences, i.e. when forced to choose between the two which do they prefer. Understanding tradeoffs is important because managers may not be able to provide hunting opportunities close to everyone with many target species. Therefore, scale-based questions of this sort are less helpful for planning.

There are two ways to determine tradeoffs among people's preferences, by either measuring stated or revealed preferences. In a stated preference (SP) survey, respondents are usually asked to choose a scenario or attributes of a scenario that they prefer the most – before they actually experienced the product or service. In contrast, a revealed preference (RP) survey asks for respondents' behavior after they have used and/or experienced a certain good and/or service. Both SP and RP are about the type of data used and when it's collected, rather than indicating a specific elicitation technique (Carson and Louviere 2011). For example, Windle and Rolf (2014) applied two commonly used elicitation methods: Contingent Valuation Method (CVM) and Discrete Choice Experiment (DCE) for estimating the visitors' stated preferences about off-beach facilities and beach maintenance likely to be provided at a beach in Australia. Kempen et al. (2009) used a RP survey to investigate willingness of households in rural Guatemala to abstain (an indirect way to measure about willingness to pay) from buying illegal firewood. Often researchers used both SP and RP in the same study. Earnhart (2001) combined both approaches to study household preferences for environmental amenities of coastal wetlands in Fairfield, Connecticut.

Advanced countries, such as the USA and Canada, have different research institutes and government agencies for planning and implementing wildlife management. In Nebraska, one of these agencies is the Nebraska Game and Parks Commission (NGPC), and one of their main goals is to provide opportunities for and manage recreational hunting. Recreational hunting is an important management tool for keeping populations of game species (e.g., deer) in check. The agency collaborates on a regular basis with university social scientists, ecologists, and statisticians to estimate the public's perceptions (general and/or specific) toward wildlife, predict population dynamics of wildlife, such as white tailed deer (*Odocoileus virginianus*), and other projects.

Unfortunately, there is a decline in hunting and angling participation across the United States (Kendall et al. 2013). This declining trend is an important issue for agencies like NGPC for whom hunting and angling license fees are a significant source of revenue, in addition to the value of recreational hunting as an important management tool. From 1990 to 2006, there was a decline in hunting from 14.1 million to 12.5 million people across the US (USFWS, 2006, 2011). This national trend is also reflected in hunting participation in Nebraska, where hunting participation declined approximately 23% from 1990 to 2006. The reasons why individuals participate in hunting mainly include getting a trophy (trophy in this case refers to a head or skin or other artifact from an animal, not a reward in a competition), and obtaining high quality meat (Perea et al. 2014). Hunting activities also contribute to the economic welfare of local communities (Pennisi and Kill 2012). One postulated reason for the decline in hunting participation is difficulty in finding land on which to hunt (Holzinger II 2009). In Nebraska, 97% of the

land is privately owned, so hunters need to get permission prior to hunting on a particular piece of land. The small amount of public land available for hunting receives a high level of hunting pressure as a result.

In 2011, a two-year program was started by NGPC and Pheasants Forever, called Open Fields and Waters (OFW). The objective of this initiative is to increase public access for hunting on privately owned land. The OFW is an important program not only for hunters who hunt in Nebraska, but it also provides benefits for local landowners. With this in mind, NGPC conducted an online survey in 2011 to learn about hunters who hunted on OFW land in Nebraska during 2011. The objective of this survey was to estimate the impact of OFW on hunters' recruitment and retention. This survey measured hunters' attitude/preferences using Likert and Likert-like scales: 2-point e.g., YES/NO; 5-point e.g., options from strongly-disagree to strongly-agree or choosing option(s) from a given range of possible offers. The Likert-scale based survey showed strong preferences for most items but all preferences were considered as isolated preferences, i.e. asked as individual items. Therefore there is no information about how hunters would tradeoff preferences such as a large areas to hunt or a site closer to home. Thus, it is difficult to decide what the best possible set of practices is for management because hunters choose the best for every given question provided through "Likert scale" based items. The hunters emphasized that maintaining OFW program was important for retention and recruitment, especially for promoting upland bird hunting (Pennisi and Kil 2012).

To better understand tradeoffs among preferences, a survey based on a discrete choice experiment (DCE) can provide multi-attribute information. DCEs are mainly used

in the field of marketing research, environmental economics, and medical health facilities (Louviere et al. 2010; Bekker-Grob et al. 2012). The purpose of this research is to implement a DCE for getting better estimates of hunters' preferences, which will be helpful for NGPC to more effectively plan future hunting land investments for improving the OFW program and hunter recruitment and retention. The focus of the present research is to review approaches to design and analyze SP data obtained through a DCE, and empirically compare two DCE design approaches to see which method works best to elicit preferences. This will be done using a study of hunters' preferences in Nebraska.

Importance of Discrete Choice Experiments

This section is helpful to understand the mechanism of discrete choice experiments as compared to nominal and Likert scales. To decide more realistic and practical approaches for future hunting policies while optimizing available resources, officials need to understand how hunters tradeoff their preferences among various combinations of possibilities. The approach suitable to this endeavor is to provide each respondent with a set of choices and ask them to select one. There are different terms used in the literature, such as “forced choice preferences,” “stated preference” or “choice experiment”. In this manuscript, the term “discrete choice experiment (DCE)” will be used (Carson and Louviere 2011). The usage of DCEs is increasing in the field of natural resources and environmental management. There were only 5 published articles using DCE until 2000, with publications increasing in the coming years (Figure 1-1).

The difference between a Likert scale survey and a DCE based survey can be explained with a simple example. Consider there are three attributes of interest and each

has three different levels (there could be any number of attributes and each attribute can have any number of levels). For example, the first attribute “number of individual target species present” could have 3 levels of presence: “very few target species present,” “average number of target species present” and “enough target species present to fill bag limit”. The second attribute, “access-days” has 3 levels: “limited to 2-3 designated days per week,” “limited to 2-6 days to hunt per month” and “unlimited days to hunt at a given site.” The third attribute “number of sites” has levels: “4-8 other sites within a 20 miles radius,” “more than 10 sites within a 20 mile radius of the site” and “no other sites within a 20 mile radius.” When asking about these attributes using nominal scale approach, a respondent has to choose the preferred option for each item. This makes it difficult to precisely estimate the relative importance of the chosen response within respondent and between respondents across all the attributes, in other words, it makes it difficult to weigh the relative importance of each response compared to the others (Figure 1-2). Similarly, the questionnaire could be based on Likert scale items (Figure 1-3). Here, respondents can provide their level of preference for each item but it is still be difficult to estimate the relative importance of all options within a respondent and between respondents across all attributes.

In DCE, the same case can be presented in a multidimensional style, where plausible combinations of all levels of the given attributes are arranged in sets called alternatives or options. Two or more of these alternatives are then grouped together where each group of alternatives makes up a choice set. Respondents are presented each choice set and asked to choose the most preferred alternative within a given choice set (Figure 1-

4). Now, respondents are required to make tradeoffs to choose the most preferred alternative. For example, a choice set with two alternatives, Site A and Site B (Figure 1-4), Site A has more than 10 other hunting sites nearby but has fewer target species. A respondent who places greater value on having other sites nearby over target abundance would likely prefer Site A over Site B. Data collected in this way will provide better understanding of how and which respondents' selections maximize their underlying desire. This type of data collection is more likely to provide insights for effective policy making to accommodate a majority of respondents (hunters) as per available resources (species' presence, pressure, and number of sites) in a collective manner.

DCEs help to find reasonable estimates of the respondents' perceptions about their tradeoffs among the attributes in the given set of alternatives. However, failure to carefully construct choice sets can lead to problems with excessive respondent burden and imprecise estimates of utility variance. Respondent burden mainly increases with increasing number of attributes and/or by the number of levels per attribute, as well as the number of choice sets presented to respondents (Witt et al. 2009). This is problematic mainly because respondents have to read, compare and contrast much more than what is usually required in a traditional survey questionnaire, thus increasing respondent fatigue or burden.

Johnston et al. (2003) examined relationships among preferences of rural residents and policy implications in southern New England using both Likert-scale assessments and stated preferences. Their findings explained key limitations for eliciting preferences based on Likert-scale. For instance, they found that support based on Likert-

scale estimates for land use policy options does not assure about enhancing welfare. As an example, they found strong support that housing developers should “conserve open space as part of residential development” by using mean rating of Likert-scale. They also revealed lower preferences for “open space located adjacent to residential development.” Therefore, this study told that discrete choice models are better for eliciting information about the marginal utility of management outcomes such as public’s preferences toward open space in residential area.

Discrete choice experiments (DCEs) are based on well-established behavioral theory called random utility theory (RUT), proposed by Thurstone (1927). RUT states that “an individual derives utility by choosing an alternative” (Walker and Ben-Akiva, 2002). So RUT “models a respondent’s preferences on alternatives by drawing a real-valued score on each alternative (typically independently) from a parameterized distribution, and then ranking the alternatives according to scores” (Soufiani et al. 2012).

Decisions by different individuals are not necessarily weighted (or rated) the same even when each person has the same number of available alternatives. Such variability is referred to as heterogeneity. To understand the latent choices of individuals, behavioral economics emphasizes the behaviors of individual for choosing their preferences. For example, one can prefer personal conveyance rather than riding on public transport. There could be more than one conveyance type (e.g., bicycle, car) and means of transport (e.g., bus, train), and there could be many reasons for choosing such alternatives. The challenge of a choice analyst is to set up the procedure that maximizes the amount of measured variability or observed heterogeneity and minimizes the amount of unmeasured