ABSTRACT

YANG, MUYI. Accounting for Observed and Unobserved Preference Heterogeneity in Non-Market Valuation: An Application to Choice Experiments and Yellowstone National Park. (Under the direction of Professor Roger von Haefen).

This thesis is base on the sample from the 2002-2003 Yellowstone and Grand Teton National Parks winter visitor survey. Under a stated-preference experiment question design I estimate non-snowmobiler visitors' preferences for trip alternatives and welfare changes under different snowmobile restriction policies at YNP. I explore the statistical and welfare implications through the inclusion of observed preference heterogeneity into estimations while flexibly account for unobserved preference heterogeneity. The findings support the expectation that variation in parameters can be partially explained by incorporating visitors' demographics. The welfare analysis also shows that within the non-snowmobilers sub-population, visitors who possess particular characteristics are estimated to experience different utility improvement under proposed winter management policies.

Accounting for Observed and Unobserved Preference Heterogeneity in Non-Market Valuation: An Application to Choice Experiments and Yellowstone National Park

by
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DEDICATION

To My Parents

BIOGRAPHY

Muyi Yang was born on August 5th, 1985, in Chengdu, Sichuan, China. She went to Nanjing and studied at Nanjing University of Science and Technology University where she received her bachelor's degree in finance in 2007. She attended North Carolina State University to start her master's degree in economics in 2009. She started doing her second master degree in statistics at North Carolina State University in 2012.

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1. INTRODUCTION

Over the past two decades, there has been considerable interest in the non-market valuation literature with estimating rich econometric models that more fully account for unobserved preference heterogeneity. Examples of these innovative models include the random parameters or mixed logit models (Train, 1997) and, more recently, latent class models (Scarpa and Thiene, 2005). For recreation and choice experiment data across a large number of applications, considerable evidence has accumulated that these models tend to fit a given data set better and often provide qualitatively different policy implications. In the past, the computational demands of estimating these models has led many researchers to employ rather parsimonious specifications that often allow for little observable preference heterogeneity. The purpose of my thesis is to explore the statistical and welfare implications of incorporating observable preference heterogeneity in econometric models that flexibly account for unobserved preference heterogeneity. With continued advances in the speed of desktop computers, estimating flexible models that account for both unobserved and observed preference heterogeneity is feasible in a wide range of non-market valuation applications, so understanding what the statistical gains and welfare implications of estimating these more flexible models is an issue that may have wide interest amongst applied researchers.

To facilitate my investigation, I employ choice experiment data concerning alternative management strategies in Yellowstone National Park (YNP) related to snowmobile use. For the past decade, managing the congestion, noise, and emission externalities arising from snowmobile use in the park has been highly contentious. The data I use was collected by Mansfield et al. (2008) and designed to investigate the welfare implications of alternative snowmobile management policies in the park. Although these policies will affect different subpopulations of YNP visitors differentially, I focus on non-snowmobile visitors in my analysis.

My results suggest that both observed and unobserved preference heterogeneity play a statistically significant role in determining observed choices in the Yellowstone application. Moreover, the improved fits implied by the models that account for both observed and unobserved preference heterogeneity generate qualitative different welfare implication. For different segments of the non-snowmobile population, for example, visitors who belong to an environmental club show more emphasis on the ambient park conditions than those who are not a member of an environmental club, and therefore have the largest utility improvement on welfare changes from any snowmobile restriction policies. However, visitors from the local area do not have that preference and thus the welfare estimates are uniformly smaller under any management scenarios for this segment compared with others in the non-snowmobile population.

The rest of this thesis is structured as follows. Section 2 provides a brief introduction of 2002-2003 Yellowstone and Grand Teton National Parks winter visitor survey and the survey methodology. Section 3 summarizes the data statistics. Section 4 describes the econometric framework using in this thesis. Section 5 details the model specifications and presents the parameter estimates results. Section 6 describes the welfare analysis method and results.

Section 7 concludes.

2. BACKGROUND AND SURVEY METHODOLOGY

Yellowstone National Park was established in 1872 as the first national park in America. Located in Wyoming, Montana and Idaho, YNP is home to various wildlife including grizzly bears, wolves, bison, and elk. It is also known for its preserved active thermal features including Old Faithful Geyser and a collection of the world's most extraordinary hot springs and the Grand Canyon of the Yellowstone, a 24 mile long canyon on the Yellowstone River and up to 3 mile wide. Because of the profound history, meaningful culture, stunning scenery and valuable science aspects, YNP welcomes on average 3 millions visitors per year. The vast majority of them visit the YNP in summer, and about 150,000 visitors during the winter season. In addition to YNP, the Greater Yellowstone Area (GYA) as a whole serves as a popular destination for various winter recreation activities such as snowmobiling, cross-country skiing or snowshoeing, downhill skiing, snowcoach touring, car or bus touring, hiking and wildlife viewing. Among those activities, starting since 1992-1993, snowmobiling attracts more than 60% of winter visitors every year (National Park Service visitation records).

For the last decades, conflicts have risen concerning the multiple and competing uses of the park amongst visitors, especially on the appropriate uses of motorized activities in the park. Proponents of snowmobiles indicate that snowmobile activity is a safe, convenient and great way to see the Park’s wonderful winter landscape. Also, snowmobiling rental provides benefits for local businesses. However, visitors who would like to enjoy other recreational activities such as cross-country skiing, hiking, wildlife viewing oppose snowmobile access because the crowding, noise and emissions generated by the machines impose external costs on them and of course, disturb the wilderness ambience, threaten the Park's wild animals, and cause potential health risks on park staff and safety risks on non-motorized recreation visitors.

How to balance these conflicts requires a thorough benefit-cost analysis under different winter visitation management policies to determine the social welfare. Several proposals and agreements have been put forward, implemented and then discarded as potential winter management policies to address these conflicts on the use of snowmobiles in the GYA parks since 1990. Previous studies focus YNP use to assess the costs and benefits of changes in management policies to different types of park visitors including Mansfield et al. (2008) and Sung (2008). Both studies provide information needed to help resolve winter management issues at YNP and also addresses methodological issues in non-market valuation. The former analyzing the effects of different winter management policies on heterogeneous visitor's welfare based on a stated preference choice experiment using conditional logit models and nested logit models. The later examines 1) the effect of the temporary plan on heterogeneous snowmobile riders and guide service providers both theoretically and empirically, and 2) winter visitors' preferences and welfare impact of snowmobile policy changes at YNP using choice experiment data incorporating richer specification of the opt-out option. In their studies, they consider three sub-populations: non-snowmobilers, snowmobile riders (not owners) and snowmobile riders (owners). Both studies include park attributes and cost variable in their models, leaving out the observable preferences heterogeneity which might generate variation tastes among visitors on their choice behaviors.

The 2002-2003 Winter Visitor Survey for Yellowstone and Grand Teton National Parks was designed in part to provide information for a benefit-cost analysis of the winter management alternatives considered by the National Park Service (NPS). Three management policies were proposed: 1) banning snowmobiles, 2) capping the number of snowmobilers allowed in each day and requiring all snowmobilers to be on a guided tour, and 3) simply capping the number of snowmobilers each day. The survey used in this study obtains information on visitor's current recreational winter use of the parks, trip characteristics and trip related expenditures and winter recreation in 2001-2002. Specifically the survey includes questions to address the impact of different winter management policies on snowmobiles use and focuses on changes in visitor visitation in response to alternative management policies, which facilities estimating of the change in welfare or consumer surplus for day trips under different conditions. In conjunction with the survey, demographic information of respondents was collected. The survey was designed and implemented by RTI International (RTI).

The goal of Yellowstone visitor sampling design was to create a probability-based sample that could be weighted to reflect the true population of winter visitors to the park. Sampling began on December 23, 2002 and continued through March 3, 2003, with the sample of days stratified by entrance and type of day which means visitors were randomly chosen at the four entrances open in the winter (north, south, east, west) and on different types of days (weekdays, weekends and holiday). A total of 1960 main questionnaires were mailed out to visitors approached in YNP who agreed to participate in the survey and provided a valid contact address. Overall, 1532 completed surveys were returned, approximately 80% of the survey. 656 were non-riders, 297 respondents indicated they own a snowmobile and rode it in the park, and 579 snowmobile riders rent one for their trips. The same data set was used in previous studies including Mansfield et al. (2008) and Sung (2008).

The ultimate goal of the survey was to estimate visitors' willingness to pay for changes in key environmental and trip-related variables in the park that might change as a result of implementing alternatives management policies. The core of the survey was a series of stated-preference choice experiment questions aimed at gauging visitor's preference for attributes of YNP under different winter management alternatives (Mansfield, *et al.*, 2008). However, to avoid the potential for strategic behavior by survey respondents that may cause bias in welfare estimation, the choices were designed as a function of park attributes where each of them has two to four levels related to different management policies. These attributes focus on the conditions in the park (e.g., congestion, road conditions, noise and emission) rather than the rules/tools to achieve those alternative requirements. Respondents were asked to evaluate six choice experiments in which they chose from two hypothetical trips with different attributes and the option of not visiting the park. In each choice experiment, there are nine attributes that define each hypothetical trip, but to keep the cognitive burdens of the experiment down, only seven of the nine attributes varies.

The stated-preference choice experiment questions were designed to provide plausible attributes. Table 1 summarizes the nine attributes and levels of attributes used in the survey with detailed descriptions for each level of attribute. In the survey, nine attributes were used for choice experiment design, with no experiment containing a dominated alternative. Five of the nine attributes which are entrance crowding, destination crowding, road condition, level of noise and level of emissions are the park condition attributes described in qualitative terms. The activity attribute contains the four main winter recreation activities in YNP which are snowmobiling, coach touring, coach skiing and auto touring. Figure 1 is an example of the choice questions comparing the three trip alternatives.

3. BASIC DATA SUMMARY

3.1. Sample Demographics

In the survey, visitors are divided into two sub-samples, snowmobile riders and non-riders, with snowmobile riders further broken down by machine ownership status. Figure 2 summarizes the demographic information about the non-snowmobilers intercepted in YNP which is the sub-population analyzed in this thesis. The non-snowmobilers is one of the largest sub-populations which consist 42.8 percent of the total winter visitor during 2002 – 2003. Overall, non-snowmobilers to YNP for winter recreation are well educated, holding some college or graduate school degree, and have higher household annual income compared to the general U.S. population. Almost 77 percent of them have a bachelor’s degree or a post-graduate degree. Non-snowmobiling visitors are typically married, employed with an average age between 40 and 50 years. A large fraction of them have 1 to 3 kids at home and more than 50 percent of the non-riders come from the local area. Within the non-snowmobile riders, the most frequent income category is between $25,000 and $60,000, and the mean income is around $40,000 per year. Equal numbers of men and women were found among non-snowmobilers. Other observed demographic variables include winter equipment ownership and club membership status. Most of non-snowmobile riders are more likely to own one or more their own non-motorized winter recreation equipments such as cross-country skis, downhill skis and snowshoes. With respect to club membership, non-snowmobile visitors are likely to be a member of an environmental organization with about 33 percent of them belonging to an environmental organization.

3.2. Trip and Activity Characteristics

Table 1 describes detailed information about the trip and activity characteristics on the individual's most recent trips to GYA parks. The results show that non-snowmobilers spent on average 5 days in GYA, 1.68 days in YNP, while 4.18 days outside the park. 31.48% and 30.25% of non-snowmobilers entered the GYA parks through the Yellowstone North entrance and Grand Teton Moose entrances, respectively, and about 70% of them were in an unguided trip. For each of the rest of the park attribute, a large fraction of non-snowmobilers indicated they experienced for example no snowmobiles at the entrance, no snowmobiles at the most crowded area, bumpy road, low level noise and low level emission. In the warm-up choice question (Appendix A), 86.64% of the non-snowmobilers chose to stay with their current trip over other options. In terms of the activities on their most recent trip, respondents were asked to indicate all the activities they participated in on their most recent trip and the location of the activity. After that, they were asked to select one activity as their primary activity for the trip. For visitors who did not provide clear information in the activity column, a primary activity was determined based on the activity they took when intercepted in the park and the entrance where they were intercepted. The summarized statistics show that during the 2002-2003 winter, 59.91% of non-snowmobiler visitors drove cars to the YNP to participate in sightseeing, cross-county skiing or snowshoeing, and a majority of them indicated that cross-county skiing or snowshoeing were their primary park activities, while many visitors responded that they paid a visit to a ski area in the GYA during their trip. Snowcoach touring was the next most popular category, with 26.99% of non-snowmobiler visitors choosing to a participate it. The third most popular activity was to take a snow coach shuttle to a ski area to cross-county ski or snowshoe in YNP, which was taken by 6.24% of non-snowmobiler visitors. Table 2 contains the trip and activity variables used in this thesis and the corresponding description of those variables in terms of the qualitative levels of attributes

4. ECONOMETRIC FRAMEWORK

4.1. Random Utility Maximization Model

Discrete choice models in economic applications are typically derived using random utility maximization (RUM) theory (McFedden, 1974), which is useful when some aspects in the decision maker utility are unobserved by the researcher. Framework divides the utility into two parts, the deterministic component of utility which is observable and the stochastic part of utility that is unknown to the research. In general, the utility of individual *i* receives from choosing alternative *j* on choice occasion *t* is expressed in a discrete choice model as a function of individual specifics and the alternatives specifics:

$$U_{ijt} = V_{ijt}(X_{jt}, p_{jt}, Z_i, \lambda) + \varepsilon_{ijt}. \tag{4.1}$$

U_{ijt} is individual *i*'s utility for a trip, where *j*=0,1,2,denoting the three alternative trips in each choice set, and t = 1,…,6;

$V_{ijt}(\cdot)$ is the deterministic component of the utility function;

X_{jt} is a vector of attribute levels for the trip alternative *j*;

Z_i is a vector of observed demographics;

p_{jt} is the cost of the trip; is the only continuous variables in this model

λ is a vector of utility function parameters to be estimated

ε_{ijt} is the unobserved component of preferences.

For conventional purpose, I specify the utility to follow a liner specification such that the preferences for the three alternatives on a given choice occasion are

$$\begin{aligned} U_{i0t} &= V_{i0t} + \varepsilon_{i0t} = \alpha_0 + \varepsilon_{i0t} \\ U_{ijt} &= V_{ijt} + \varepsilon_{ijt} = X_{jt}\beta + p_{jt}\delta + \varepsilon_{ijt} \\ j &= 1,\ 2 \end{aligned} \tag{4.2}$$

Where U_{i0t} is the utility of the opt-out choice, which is in a simple model is just α_0 , an alternative-specific constant for the opt-out choice (Trip 0). α_0 is included to captures the average effect on utility of all factors that are not considered in the model. U_{i1t} and U_{i2t} denote the utility of Trip 1 and Trip 2, respectively. β is a vector of parameters associated with the alternative attributes, and δ is the parameter associated with price, which is also viewed as the negative of the marginal utility of income. The coefficient vector β itself does not have direct economic meaning, however, $-\beta/\delta$, the negative ratio of the attribute's coefficient to the price coefficient can be interpreted as the marginal willingness-to-pay for each attribute (Hanemenn, 1984).

In many applied settings, the research might expect the utility of an attribute to vary across the population. This preference heterogeneity may be correlated with observable demographics of the sample or unobserved random from the research's perspective. In my thesis, I develop econometric models that account for both observed and unobserved heterogeneity and ascertain their welfare implication. In a stated-preference choice experiment, observed demographics are the same for each respondent across alternatives and choices, thus they can not enter the model directly. A popular way to incorporate observed demographics is to multiply them by the opt-out alternative. In my thesis, I considered a more comprehensive specification of interaction terms of observed demographics with trip attributes. Thus a richer utility structure becomes:

$$U_{i0t} = \alpha_0 + \varepsilon_{i0t}, \;\; \alpha_0 = \bar{\alpha} + Z_i \eta$$
$$U_{ijt} = X_{jt}\beta + (X_{jt} * Z_i)\gamma + p_{jt}\delta + \varepsilon_{ijt}, \qquad (4.3)$$
$$j = 1, 2$$

where η is a vector of parameters associated with demographics-opt-out interaction terms, and γ is vectors of parameters associated with demographics-trip attributes interaction terms.

4.2. The Conditional Logit Model

By assumption, the stated-preference choice experiment response reflects the preferences of individual respondent. The choice among the three trip alternatives is unordered and we assume that individuals act in a rational way, maximizing their utility. Thus individual *i* will choose alternative *j* on a given choice set *t* if, and only if alternatives *j* provides a higher level of utility than all other alternatives. Hence, we can state the probability that individual *i* will choose alternative *j* on choice occasion t is

$$P_{ijt} = \mathrm{Pr}\,ob(U_{ijt} > U_{ikt} \quad for\ all\ \ j \neq k). \qquad (4.4)$$

Suppose the unobservable components, the scalar parameters $\varepsilon_{i1t}, \varepsilon_{i2t}, ..., \varepsilon_{ijt}$ follow a Type I extreme-value error distribution for each alternative with cumulative distribution function

$$F(\varepsilon_{ijt} < \varepsilon) = \exp\{-\exp(-\varepsilon)\} \qquad (4.5)$$

and probability density function

$$f(\varepsilon_{ijt}) = \exp\{-\varepsilon_{ijt} - \exp(-\varepsilon_{ijt})\}\,. \qquad (4.6)$$

The probability of choosing alternative *j* is then:

$$P_{ijt} = \mathrm{Prob}\,(\varepsilon_{ikt} < V_{ijt} - V_{ikt} + \varepsilon_{ijt} \quad for\ all\ \ j \neq k)$$

$$= \int_{-\infty}^{+\infty} \prod_{j \neq k} F(V_{ijt} - V_{ikt} + \varepsilon_{ijt}) \cdot f(\varepsilon_{ijt}) d\varepsilon_{ijt}$$

$$= \int_{-\infty}^{+\infty} \prod_{j \neq k} \exp\{-\exp[-(V_{ijt} - V_{ikt} + \varepsilon_{ijt})]\} \cdot \exp(-\varepsilon_{ijt}) \exp\{-\exp(-\varepsilon_{ijt})\} d\varepsilon_{ijt}$$

$$= \frac{\exp(V_{ijt})}{\sum_{k=0}^{2} \exp(V_{ikt})}$$

$$= \frac{\exp(X_{jt}\beta)}{\sum_{k=0}^{2} \exp(X_{jt}\beta)}, \tag{4.7}$$

which is the well-know logit choice probability.

Assuming that each individual's choice is independent of that of others, the likelihood function of each individual choosing the alternative that was observed is

$$L = \prod_{i=1}^{N} \prod_{j} (P_{ijt})^{d_{ijt}} \tag{4.8}$$

where $d_{jt}^{i} = 1$ if individual *i* chose *j* and zero otherwise and *N* is the total number of observations. The log-likelihood function is then

$$\ln L = \sum_{i=1}^{N} \sum_{j} d_{ijt} P_{ijt} \ . \tag{4.9}$$

The estimation is obtained by taking the derivative of the above log-likelihood function with respect to each parameter to be estimated and set it to zero. Thus, by maximizing the log-likelihood function, we get the first order condition

$$\sum_{i} \sum_{j} (d_{ijt} - P_{ijt}) X_{ijt} = 0, \tag{4.10}$$

Thus, the parameters show the relationship between the probability of selecting an alternative (a trip in this thesis) and the attributes of that alternative and interaction terms.

The conditional logit models specified by equation (4.2) to (4.3) are known to be subject to violate an important property "independent of irrelevant alternatives" (IIA), which assumes that the ratio of probabilities for any two alternatives be independent of the attributes of the third alternatives. If this assumption is violated, parameter estimates are biased. Second, the conditional logit models have limitation in fully representing the taste variation among individuals. When differences in tastes cannot be linked to observed variables, parameter estimates are biased (Train 2009). Third, the conditional logit models do not account for correlations within each individual's series of choices. More flexible specifications that address these concerns are the mixed logit model and latent class model.

4.3. The Mixed Logit Model

Revelt and Train (1998) proposed using the random parameters or mixed logit model for stated-preference data. Mixed logit is a highly flexible model that can approximate any RUM model (McFadden and Train, 2000). It does not exhibit the IIA restriction, allows random taste variation across individuals, accommodates correlation among alternatives by allowing common influence generated by individual's preference, and accounts for unobserved variables for alternatives with similar attributes.

When the coefficient vector β is no longer assumed to be fixed for individuals across alternatives, the conditional logit model needs be cast in the framework of a mixed logit model. Recall our utility function $U_{ijt} = V_{ijt} + \varepsilon_{ijt} = X_{jt}\beta + p_{jt}\delta + \varepsilon_{ijt}$, the mixed logit models assume that the coefficient vector β which is unobserved for each individual *i* varies in the population with density $f(\beta_i \mid \theta)$ where θ, the parameters are the ones to be estimated. ε_{ijt}, an unobserved random term that is still assumed to be distributed iid extreme value, and does not depend on β_i and X_{ijt}. The probability of individual *i* choose alternative *j* conditional on β^i is

$$L_{ijt}(\beta) = \frac{\exp(X_{ijt}\beta_i)}{\sum_{k=0}^{2}\exp(X_{ijt}\beta_i)}, \tag{4.11}$$

which is the logit formula as we obtained before. Since we only know the distribution of the coefficient vector β_i, the unconditional probability is the integration of the logit formula over the density function $f(\beta_i \mid \theta)$

$$P_{ijt}(\theta) = \int L_{ijt}(\beta_i) f(\beta_i \mid \theta) d\theta \tag{4.12}$$

Any models taking this form are called "mixed logit" because the choice probability is a mixture of logit at different β's with $f(\beta_i \mid \theta)$ as the mixing distribution. Note that, there are two sets of parameters, the coefficient vector β_i and the parameters in the density function of $f(\beta_i \mid \theta)$. The former characterize the choice preference of individual *i*, and the latter, are the density parameters determining the distribution of β_i, for example, the mean and covariance. In another word, $f(\beta_i \mid \theta)$ is a random term over individuals and alternatives whose distribution depends on density parameters and observed variables relating to individual *i* and alternative *j*.

The choice probability cannot be calculated exactly since the integral in equation (4.9) does not have a closed form. The probabilities can, however, be approximated through simulation. For any given value of θ, a value of β_i, say $\beta_{i,r|\theta}$ is drawn from $f(\beta_i \mid \theta)$. Using this draw, the logit formula $L_{ijt}(\beta_i)$ is calculated. Repeating this process for many draws and averaging the results to get the simulated probabilities that approximate the choice probabilities, i.e.

$$\hat{P}_{ijt} = 1/R\sum_{r=1}^{R} L_{ijt}(\beta_{i,r|\theta}) \approx P_{ijt} \tag{4.13}$$

where R is the number of draws. $\hat{P}_{ijt}$, the simulated probability of individual *i* chooses alternative *j* is an consistent estimator of P_{ijt}. Its variance decreases as R increases. It is strictly positive for any finite R, such that $\ln \hat{P}_{ijt}$ is defined.

P_{ijt} is smooth (twice differentiable) in the parameters and variables, which helps the numerical search for the parameter values that maximize the likelihood function. The log-likelihood function $\ln L = \sum_{i=1}^{N}\sum_{j} d_{ijt}P_{ijt}$ is approximated by the simulated log-likelihood function $S\ln L = \sum_{i=1}^{N}\sum_{j} d_{ijt}\hat{P}_{ijt}$. The maximum simulated likelihood estimator (MSLE) is the value of θ that maximizes $S\ln L$. Lee (1992) and Hajivassiliou and Ruud (1994) derive the asymptotic distribution of the maximum simulated likelihood estimator based on smooth probability simulators with the number of repetitions increasing with sample size. Under regularity conditions, the estimator is consistent and asymptotically normal.

In empirical work, different types of mixed logit models can be applied through specifying the structure of $f(\beta_i \mid \theta)$. The random-coefficients interpretation is useful when considering models of repeated choices by the same decision maker. The most straightforward version is a model for which the same draws of random coefficient vectors are used for all repeated choices (Brownstone, Bunch and Train, 1999). The random coefficient specification is used in this paper where the coefficients on price and the interaction terms of demographics with attributes of the alternatives are specified to be fixed while other non-price coefficients are allowed to vary across individuals. Including the subject-specific stochastic components for each element in the coefficient vector β, the utility function in (4.2) is modified to

$$\begin{aligned}
&U_{i0t} = V_{i0t} + \varepsilon_{i0t} = \alpha_0 + \varepsilon_{i0t} \\
&U_{ijt} = V_{ijt} + \varepsilon_{ijt} = X_{jt}\beta_i + p_{jt}\delta + \varepsilon_{ijt} \quad j = 1,\ 2 \\
&\beta_i = \bar{\beta} + e_i \\
&where\ (e_i) \sim\ f(e_i \mid \sigma_e^2 I).
\end{aligned} \tag{4.14}$$

Now $\beta_i = \bar{\beta} + e_i$ is a random coefficient vector. $\bar{\beta}$ is the mean estimate of β_i. The random vector e_i is the deviation from mean and is assumed to follow an independently normal distribution with mean zero and variance σ_e^2. I is an identity matrix. Note that here are two sets of parameters needed to be estimated: $\bar{\beta}$ and a covariance matrix $\sum$. In the new utility function, different types of tastes among individuals placed on alternatives that are related to observable attributes are now captured through the normally disturbed function. Comparing to the conditional logit models, the stochastic part of the utility is now heteroskedastic and may be correlated over alternatives and across the sequence of choices. This is because e_i is the same for all alternatives/choice sets meaning that each individual's preferences are used to value alternatives/choice sets, thus we could derive:

$$Cov(X_{jt}e_i + \varepsilon_{ijt}, X_{kt}e_i + \varepsilon_{ijs}) = \text{var}(e_i) X_{jt} X_{kt} , \qquad (4.15)$$

to access the willingness to pay under the specified models in which parameters on attributes is normally distributed with mean $\bar{\beta}$ and standard deviation σ_e , the marginal willingness to pay for the attribute also follows normal distribution with mean $-\bar{\beta} / \delta$ and standard deviation σ_e / δ (recall that δ is the fixed parameter on price).

Similarly, if I expand my estimations by incorporating demographic variables, the richer specifications of utility functions where demographic variables are interacted with opt-out alternative is

$$\begin{aligned} & U_{i0t} = \alpha_{0i} + \varepsilon_{i0t}, \quad \alpha_{0i} = \bar{\alpha} + Z_i \eta + v_i \\ & U_{ijt} = X_{jt}\beta_i + p_{jt}\delta + \varepsilon_{ijt}, \quad j = 1, 2 \\ & \beta_i = \bar{\beta} + e_i \\ & \textit{where } (e_i, v_i) \sim f(e_i, v_i \mid \Sigma). \end{aligned} \qquad (4.16)$$

Where v_i is the random deviation from mean estimate $\bar{\alpha}$ with mean zero and variance σ_v^2 and is assumed to have an independently normal distribution. Σ is the covariance matrix of the two error terms. Assume e_i and v_i are independent with $Cov(e_i, v_i) = 0$.

The utility function of a more comprehensive specification where selected demographic variables are interacted with selected trip attributes is

$$
\begin{aligned}
&U_{i0t} = \alpha_{0i} + \varepsilon_{i0t}, \quad \alpha_{0i} = \bar{\alpha} + Z_i \eta + v_i, \\
&U_{ijt} = X_{jt}\beta_i + p_{jt}\delta + (X_{jt} * Z_i)\gamma + \varepsilon_{ijt}, \quad j = 1, 2 \\
&\beta_i = \bar{\beta} + e_i \\
&where\ (e_i, v_i) \sim f(e_i, v_i \mid \Sigma).
\end{aligned}
\tag{4.17}
$$

Again, the two random terms e_i and v_i are jointly normally distributed with mean zero and covariance Σ.

Depending on expectations about the behavior of random coefficients in a given application, one can also specify random coefficients to follow other distributions. The most popular distributions used in previous researches including log-normal, triangular and uniform. The log-normal is applied when it is reasonable to expect that the coefficients on variables need to have a specific (non-negative) sign. A uniform distribution with a (0, 1) bound is sensible when we have dummy variables (Hensher and Greene, 2001). In this paper, we expect that individuals (non-riders) have a variety of tastes for the coefficients of trip attributes, so I allow coefficients of both signs.

4.4. The Latent Class Model

Mixed logit model does not subject to the IIA assumption, but limitations with the continuous mixed logit model are that 1) the researcher has to make specific assumptions about the distributions of random deviations from the mean trends $\bar{\beta}$, 2) the probability densities for β_i is assumed to have a continuous distribution and 3) β_i describes only relationships between the observed variables. However, researchers have found that the distribution specification does affect the sensitivity of parameters and welfare estimation (Revelt and Train 1998, Hensher and Greene 2003, Hess and Rose 2006).

Latent class model includes one or more discrete unobserved variables, also known as latent classes to address the above issue. Individuals are implicitly sorted into *Q* classes, each class represents a homogeneous population and different regressions are estimated for each class (McFadden and Train, 2000, Greene and Hensher, 2002). To ascertain the optimal number of classes, diagnostic statistics such as Bayesian Information Criterion (BIC)[1] (Roeder *et al*., 1999), Akaike Information Criteria (AIC)[2] (Akaike, 1974), consistent AIC[3] (Bozdogan, 1987a, 1994a_1994c) and corrected AIC[4] (Hurvich & Tsai, 1989) are typically used to determine the value for *Q*[5]. Demographic variables and other external variables (covariates) can be used to predict class membership.

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1. BIC=ln(n)k-2lnL, where k is the number of parameters in the statistical model, and L is the maximized value of the likelihood function for the estimated model, n is the number of data points in x, the number of observations, or equivalently, the sample size. Small BIC indicates appropriate fit of the model.
2. AIC=2k-2lnL, where k is the number of parameters in the statistical model, and L is the maximized value of the likelihood function for the estimated model. Small AIC indicates appropriate fit of the model.
3. Consistent AIC=AIC+k(ln(N)-1)
4. Corrected AIC=AIC+2k(k+1)/(n-k-1). Burnham & Anderson (2002) strongly recommend using AICc, rather than AIC, if *n* is small or *k* is large.
5. Overfitted models can be selected by only using AIC or BIC (Hynes et al. 2008). Models with many parameters can generate parameter estimates and standard errors that are unstable or implausibly large (Domanski and von Haefen, 2011, unpublished).

The choice probability equation now becomes

$$P_{ijt|q}(\beta) = \frac{\exp(X_{ijt}\beta_q)}{\sum_{k=0}^{2}\exp(X_{ijt}\beta_q)}, \tag{4.18}$$

Where $P_{ijt|q}(\beta)$ is the probability of choice alternative *j* by individual *i* on choice occasion *t* conditional on class *q*. The probability densities for β_q can be specified to follow a discrete mixing distribution. Let y_{it} denote the specific choice made, so that the model provides

$$P_{it|q} = \Pr ob(y_{it} = j \,|\, class = q). \tag{4.19}$$

Assume that within each class, individual *i* chooses alternative *j* in choice set *t* independently. (In fact, in the application of stated choice experiment sampling design where individual answers a sequence of survey questions. There might be correlation in the stochastic components of utilities.) Thus, the likelihood of individual *i* over choice sets is *a* joint probability of the sequence $\boldsymbol{y}_{\mathrm{i}} = [y_{i1}, y_{i2},\ldots, y_{i6}]$:

$$P_{i|q} = \prod_{t=1}^{6} P_{it|q}. \tag{4.20}$$

Since the class assignment is unknown, a prior probability S_{iq}, the probability for individual *i* being in class *q* is assumed to follow a typical logit structure

$$S_{iq} = \frac{\exp(Z_i\gamma_q)}{\sum_{q=1}^{Q}\exp(Z_i\gamma_q)},\ \ q = 1,\ldots,Q,\ \ \gamma_Q = 0, \tag{4.21}$$

where S_{iq} is assumed to depend on the observable demographic variables, and $\sum_{q=1}^{Q} S_{iq} = 1$.

The unconditional probability is the expectation of logit choice probability given by equation (4.18) weighted by the probability of being in class *q*:

$$P_i = \sum_{q=1}^{Q} S_{iq} P_{i|q} \tag{4.22}$$

The log likelihood for all the individuals in the sample is

$$\ln L = \sum_{i=1}^{N} \ln P_i = \sum_{i=1}^{N} \ln[\sum_{q=1}^{Q} S_{iq} P_{i|q}] = \sum_{i=1}^{N} \ln[\sum_{q=1}^{Q} S_{iq} (\prod_{t=1}^{6} P_{it|q})]. \tag{4.23}$$

Comparing to more familiar maximum likelihood problems, maximization of the log likelihood with respect to *Q* sets of parameter vectors β_q and *Q-1* latent class parameter vectors γ_q encounters computational difficulty. Recursive expectation-maximization (EM) algorithm (Dempster *et al*., 1977) provides an alternative estimation method to reduce the computationally burdensome estimation by transforming the maximization of a log of sums (4.23) into a simpler recursive maximization of the sum of logs, and then estimate parameters and the choice probability for each class separately at each recursive step (Train 2008). The EM algorithm can work with estimation limitations including incomplete data (McLachlan and Krishnan 1997) as well as mixture estimation (Bhat 1997; Train 2008).

Recall that the prior probability S_{iq} is a function of parameters γ_q , and the likelihood joint probability $P_{i|q}$ is a function of β_q . Define $\overline{\phi}^m = (\beta_q^m, \gamma^m)$ as some fixed set of starting values for the parameters. The EM algorithm iteratively calculates a new set of values for the parameters:

$$\phi^{m+1} = \arg\max_{\phi} \sum_{i=1}^{N} \sum_{q=1}^{Q} h_{iq}(\overline{\phi}^m) \ln(S_{iq} P_{i|q}), \tag{4.24}$$

where *m* is the iteration number. Rewrite the right hand side of the equation as:

$$\ln(S_{iq}P_{i|q}) = \ln S_{iq} + \ln P_{i|q}. \qquad (4.25)$$

Beginning with the expectation (E) step at iteration *m* which computes the expectation of the log-likelihood evaluated with the current parameter estimates, using multiple starting values, the probability (weight) of individual *i* belonging to class *q* conditional on the parameters β_q^m and γ^m is:

$$h_{iq}(\phi^m) = \frac{S_{iq}P_{i|q}}{\sum_{q=1}^{Q} S_{iq}P_{i|q}}. \qquad (4.26)$$

Then a maximization (M) step, which computes parameters maximizing the expected log-likelihood found on the “E” step is performed. “M” step treats the weights from the previous step as given and independent for each class, then updates individual class probability dependent on demographics and the conditional probability parameters:

$$\begin{aligned} \gamma^{m+1} &= \arg\max_{\delta} \sum_{i=1}^{N}\sum_{q=1}^{Q} h_{iq}(\phi^m)\ln S_{iq} \\ \beta_q^{m+1} &= \arg\max_{\delta} \sum_{i=1}^{N}\sum_{q=1}^{Q} h_{iq}(\phi^m)\ln P_{i|q}. \end{aligned} \qquad (4.27)$$

The EM iteration alternates between performing an expectation step and maximization step and updates the weights using the new parameter values. The entire process is repeated until convergence. EM algorithm transforms the complex mixed logit estimations into s series of conditional logit estimations for each class and choice probability, and independently maximizes the conditional logit likelihood function for each class. One potential drawback for latent class models is that the estimation may not be the maximum likelihood solution because the unconditional likelihood is not globally concave. Thus employing the EM algorithm may lead convergence to a local instead of to a global maximum. Using multiple starting values or randomized starting values can address this issue.

Utility functions for latent class models under different specifications are the same as those for mixed logit models ((4.16) and (4.17)) except that the random coefficients now have some discrete distribution that will depend not only on the covariance matrix Σ, but also on demographic variables Z_i:

$$(e_i, v_i) \sim f(e_i, v_i \mid \Sigma, Z_i) \tag{4.28}$$

5. Empirical Investigation

Effects coding are used to model the qualitative trip attributes levels, while traditional dummies are used to model the individual-specific variables, *no snowmobiles* and *opt-out* variables. There are 13 individual-specific variables in the dataset which provide enough observed heterogeneity to examine the different preferences within non-snowmobile visitors. This section specifies how I incorporate demographic variables into estimations and compare estimated results from different models for each of the three specifications:

1. Specification with trip attributes only
2. Specification with demographic variables interacted with the opt-out alternative;
3. Specification with demographic variables interacted with selected trip attributes.

5.1. Observable Demographics Interacted with the Opt-out Alternative

Several preliminary specifications for mixed logit models with trip attributes only were run to determine which parameters should be specified as randomly distributed. Returns from these runs suggested that the mean estimates for nine of the eighteen parameters associated with trip attributes are statistically significant different from zero and have significant error components. Therefore, those nine parameters were kept as random. The standard deviations for those nine coefficients are quite large indicating heterogeneity in taste for those attributes which suggests that models including demographic interactions might perform better. Previous studies on stated-preference experiments applications give us a rational reason to investigate the degree to which additional variation in coefficients can be captured through the inclusion of demographic characteristics. Revelt and Train (1998) estimated the impact of rebates and loans on customers' choice of efficiency level for refrigerators and found that the willingness to pay for each attribute of choice alternatives varies with income and education. Their specification follows Atherton and Train (1995), which was obtained after extensive testing with the demographic variables that were available from the survey.

There are three trip alternatives in each of the six choices sets. The first two alternatives are the ones with attributes consistently changing for each choice experiment. It is very likely that a certain amount of visitors will choose neither of those two trip alternatives, so visitors are always given a third alternative which is the opt-out choice in any choice set. The opt-out option is constant across all the six choice sets, and there might be something systematic that will lead a person to repeatedly choose to not going for a trip, thus the opt-out dummy is a good candidate to be interacted with demographic variables.

To identify if observable preference heterogeneity generate statistically significant impact on individuals' choice decision suggests a search across several specifications so as to determine which of the demographic variables should be included. After running several preliminary conditional logit specifications with different combination of interaction terms, I found that there exists heterogeneity within non-snowmobilers that can be captured by observable demographics. 11 demographics were included which form the baseline model, and the likelihood ratio test (Roeder et al. 1999) shows that the inclusion of the 11 interaction terms generated a significant improvement in fit.

Table 4.1 reports the results from conditional logit and mixed logit estimations with demographics interacted with the opt-out alternative. The first two columns contain the conditional logit parameters estimations, while the rest of the columns show the results for the mixed logit. The conditional logit results are very much like the results from Mansfield et al. (2008) and have the expected signs. The mixed logit provides an estimate of both the mean and the standard deviation of each random parameter. In total, there are 11 demographics included in the baseline model. As expected, not all of these 11 interaction terms are statistically significant, especially those demographics included in typically choice experiment applications. However, it can be seen that from the mixed logit results the five interaction terms (marked with two asterisks) which generate statistically significant effects at 0.05 level are *equipment*opt-out*, *clubsenvir *opt-out*, *local*opt-out*, *highincome*opt-out* and *childernat*opt-out*. Those demographics are of interest and exploited further in the next specification interacting with the selected trip attributes.

Latent class models with class number 2, 3 and 4 were estimated to arrive at the preferred one. The trip cost attributes were defined as fixed parameters across all classes, while other park attributes were random. Table 3 presents the information criteria summary for model selection. Consistent AIC shows that three or four classes were optimal, while corrected AIC suggests two classes was optimal. However, large number of parameters might cause over-fitting of the model, and based on the parameter estimates from three and four classes, the parameters for one class for particular variables vary dramatically while small latent class probability was obtained for each class. Hynes, Hanley and Scarpa (2008) suggested that the more appropriate decision criterion is the corrected AIC, which incorporates the greatest penalty for an increased number of parameters. Thus 2 latent classes were selected as the best fit from 2, 3 and 4 classes.

Table 4.2 presents the results from the latent class model. There are two sets of parameter estimates associated with 18 trip attributes for each of the class, along with 11 interaction terms and six parameter estimates associated with demographics in the latent class index. The coefficients for trip attributes diverge across classes indicating that there exists preference heterogeneity captured by the hidden classes. Most of the trip attributes coefficients for the two classes have the expected signs except for *crwd_low* and *smooth* in class one, and coefficients on *ems_nnotice* in both classes have negative signs which were estimated positive in both conditional logit and mixed logit. However, overall, it seems to suggest some preference for avoiding high noise and emissions. Interaction terms show that observable preference heterogeneity such as age, gender, club membership status and live in locality can capture some of the variations in individual's choice decision of trip alternatives. In the set of the latent class index, all the demographic parameter estimates are significantly different from zero. Cost coefficient is less in magnitude comparing with that in the mixed logit model as it is less precisely estimated in the latent class model.

5.2. Observable demographics interacted with trip attributes

In the next step, I ran four additional conditional logit models to reach the most preferred specification for incorporating demographics interacted with selected trip attributes into estimations. The five demographic variables mentioned in section 5.1 were taken to be interacted with every qualitative level of four selected trip attributes: entrance crowding, destination crowding, noise and emission, respectively. Each attribute has three qualitative levels, and only the low and moderate levels are included, leaving out the third (high level) as the base line. Thus each specification has 10 new interaction terms. After investigating several specifications with different interactions, 11 significant interaction terms: *Local*ent_low*, *Clubsenvir*ent_mod*, *Equipment*crwd_low*, *Clubsenvir*crwd_low*, *Equipment*nois_low*, *Clubsenvir*nois_mod*, *Local*nois_low*, *Clubsenvir*ems_low*, *Equipment*ems_mod*, *Clubsenvir*ems_mod* and *Local*ems_low* stand out as they generate statistically significant improvements in fit comparing to others. This gives strong evidence that the observed demographics are capable of explaining additional variation in preferences among the non-snowmobilers sub-population. The final specification containing theose 11 significant interaction terms was estimated using different models. The conditional logit model results are presented in the first two columns of Table 5.1, along with the mixed logit model results in the last two columns. The likelihood ratio tests indicate that incorporating demographics gives better fitting conditional and mixed logit models. Table 5.2 gives the estimates for the two-classes latent class model.

In Table 5.1, the mixed logit results show that estimated standard deviations on entrance attribute such as *west*, guided status attribute such as *guided*, noise level such as *nois_low*, emission level such *ems_nnotice*, and opt-out alternative are highly significant, indicating that those trip attributes increases visitors' utility on average, but the large and significant standard deviation indicates that experiencing those attributes provides positive utility to only a portion of the sample. Note that all non-snowmobilers have a positive preference for smooth road condition. The opt-out alternative has positive mean coefficient and positive and highly significant coefficient on its standard deviation. The opt-out coefficient is large comparing to other coefficients, suggesting that there exists a large propensity for the non-snowmobilers to choose to not visit the park in the sample given other trip alternatives. Again, it varies across the sample.

The estimates for interaction terms in both conditional and mixed logit models indicate that individual characteristics such as environmental club membership status and winter non-motorized equipment ownership status generate the most attention. The statistically significant coefficients associated with the interaction terms show that visitors who have those two characteristics seem to be more sensitive to trip attributes such as park entrance crowding level, trip destination crowding level, noise and emission levels. Also, it can be seen that in both models visitors who live in locality show negative preference on low levels of entrance crowding, noise and emission. This can be interpreted as that although in general visitors prefer low congestion, noise and emission, there might existing external benefits among local visitors such that they might own small business related to the local tourism thus they might explain those attributes more broadly such that higher level of those park attributes indicating more popularity of this area. However, statistical significance can be found only on the coefficient of the *local*nois_low* in the mixed logit model. Comparing with the estimates in the previous specification in Table 4.1, the magnitudes of the estimated standard deviations on *ent_low*, *nois_low* and *ems_nnotice* become relatively smaller when each of them is interacted with demographic variables *equipment* and *clubsenvir* respectively. This indicates that variations in those three random parameters are partially related to the observed visitor characteristics.

Random parameter models can account for taste variation and in some cases provide an improved fit over the conditional logit model. However, when the choice set is large, the continuous distribution estimation cannot provide consistent estimates when sampling from alternatives. The relative choice probabilities in a random parameter mixed logit model are not independent across alternatives and IIA does not hold. Latent class models allow discrete distribution of parameters and address this issue by breaking the mixed logit non-IIA model into a series of conditional logit IIA models, sampling of alternatives can be reintroduced at each recursive step (Domanski and von Haefen, 2012).

After a series of searching for the preferred latent class model, I end up with incorporating four interaction terms into estimation: *equipment*crwd_low*, *equipment*nois_low,* *clubsenvir*ems_low* and *clubsenvir*ems_mod* into latent class estimation. The latent class estimates presented in Table 5.2 give us a consistently results regarding the role of demographics. Again, coefficients associated with trip attributes vary across the two classes indicating variation in taste among non-snowmobilers. Coefficients on activity variables are consistent in signs across the two classes as each class places negative coefficients on snowmobiling and coach skiing. While coefficients on other trip attributes such as entrance, crowding at destination, road condition, noise level and emission level are not consistent in signs such that the same attribute brings positive effect on one class, but negative effect on the other one. One notable feature of the results from the latent class model is that the magnitude of the coefficients on opt-out alternative across the two classes is quite different. The first group has a very positive and significant coefficient of 2.771, while the coefficient is just 0.685 for the second group which means that visitors in the second class are less likely to choose the opt-out alternative indicating that no-trip alternative does not generate the same amount of positive utility as it does in the first class. This makes sense as the latent class model incorporates demographic variables and other hidden covariates to classify sampled population. The diverse parameter estimates are the evidence of taste variation. The parameter estimates on interaction terms are highly significant suggesting that preference heterogeneity can capture some of the taste variation. For example, visitors who belong to environmental clubs have a strong preference on low emission level; visitors who own winter non-motorized equipments are less likely to prefer low level of destination crowding and low level of noise. The findings are consistent with that in the conditional logit model. Some possible explanations for negative preference on low level crowding and noise among equipment-owner visitors are: non-snowmobiler visitors who own their own non-motorized equipments are actively engage in other winter recreation activities other than snowmobile, so they might enjoy seeing others doing the same sports in the slopes, or they may be interpreting the variable more broadly, for example, more people meaning more popularity of this place. Interactions of demographics with the opt-out alternative show that individual characteristics such as age and gender, equipment ownership status, club membership status and high annual household income all place important roles among non-snowmobilers in determining their choice decision.

6. WELFARE ANALYSIS

6.1. Method

Once we have estimated the utility function, we can monetize the effects of changes in different trip attributes on the utility of a representative agent according to various winter management policies at YNP. Welfare impacts of the snowmobile policy change in YNP on heterogeneous non-snowmobile visitors can be estimated by measure the changes in consumer surplus, which is also the willingness to pay (WTP). Mansfield *et al*. (2008) assumed that the current snowmobile policy results in high crowding, bumpy road, and high noise and emission levels. In this thesis, I consider two assumed park condition baselines: 1) *baseline high* with high crowding conditions and 2) *baseline moderate* with moderate crowding conditions. I consider two baseline scenarios because in the absence of policy, crowding conditions in YNP will vary depending on weekdays, weekend, holidays and the weather. Therefore, if we assume that under any circumstance, visitors perceive the park condition as high crowding, bumpy road, and high noise and emission levels, the welfare analysis will be bias upward in terms of improvement in the park condition by alternative winter management policies.

The *ex ante* expected utility on a choice occasion of a representative visitor is calculated as follows (Hanemann, 1984):

$$E(U_p^i) = \ln\{\sum_{j=1}^{J_p} \exp[V_j^i(q_p^i)]\},$$

where U_p^i is the utility a visitor *i* receives from a choice occasion under snowmobile policy *p*, J_p denotes the set of choice alternatives available under policy *p*. V_j^i is the deterministic part of utility for trip alternative *j*, q_p is the conditions in the park that are expected to received by visitor *i* under the policy *p*. The welfare change of a representative visitor *i* caused by the policy change from baseline *b* to *p* is given by

$$WTP = -\frac{1}{\delta}[E(U_p^i) - E(U_b^i)],$$

where δ is the marginal utility of income (negative of the price coefficient).

To calculate the *ex ante* expected utility, I assume that visitors can choose from a complete set of choice alternatives on their trip. The set of choice alternatives includes the different combinations of activity, entrance, and guide status, while they cannot influence the park ambient conditions such as crowding, road conditions, noise and emissions, which are fixed under the winter management policies in paces. Table 6 lists all the twenty-one feasible combinations of choice alternatives along with an option of not visiting the park. Prices for each of these alternatives were obtained from current entrance fees, guided tour service price, and rental costs of equipments. Based on the NPS proposed policies and previous studies, I consider the same management scenarios used in Mansfield *et al*. (2008) except for the one that imposes 4-stroke technology restriction on all snowmobiles entering the park since only the non-snowmobiler subpopulation is considered in here. The non-snowmobilers are more likely to be concerned with the presence of snowmobiles in the park than the noise and emission problems. The followings are the three management scenarios:

1. Snowmobiles are banned from the park (*ban*);
2. All snowmobile riders must be guided by commercial guide (*guided tour*);
3. A daily cap on the number of snowmobiles entering the park is put in place (*cap*);

These policies will affect non-snowmobile visitors by decreasing the congestion, noise, emissions experienced in the park. Table 7 presents the proposed management policies and the assumed impact each could have on park conditions. For the guided tour policy, the management intervention scenario improves the park condition only partially by reducing the noise and emission levels but does not affect the number snowmobiles in the park. For the cap policy, I assumed the policy would result in low congestion levels. The table also includes the assumed baseline conditions when there is no restriction on snowmobile access to the park.

Each of the management policies reduces the choice set in a particular way. Under the snowmobile ban all choices including the snowmobile activities are removed from the choice set. Under the guided tour requirement choices with unguided options are eliminated. For the cap policy the choice set remains unchanged from baseline conditions but will face improved park conditions from the reduced number of snowmobiles in the park.

6.2. Results

To estimate the changes in welfare under sampled management scenarios for the non-snowmobilers, I use the parameter estimates from Table 4.1 and Table 4.2 where the model specification is the one with demographics interacted with the opt-out alternative (specification 2 defined in section 5), and Table 5.1 and Table 5.2 where the model specification is the one that additional interactions of selected demographic variables with selected trip attributes are added (specification 3 defined in section 5). WTP estimates are calculated for all three models: conditional logit, mixed logit and latent class model, respectively under each specification. However, the WTP estimates show that only the outcomes from the mixed logit model give us a precise welfare values with standard errors that are smaller compared to the mean estimates. This can be explained as that since in the conditional logit model, coefficients are not capable of representing the true values of parameters as they are all specified as fixed for all visitors, thus no variation in taste is allowed which result in large Krinsky and Robb standard errors. As for the latent class model, because the cost variable is not precisely estimated, it will give us unreliable point estimates of WTP along with large standard errors. Hereafter I will refer to the mixed logit results in the following discussion. To assess the distributional effects these policy interventions across different demographic groups, non-snowmobilers were further divided into eight groups by the following three individual characteristics and their interactions: *equipment* (own non-motorized winter equipments including cross country skis, downhill skis and snowshoes), *clubsenvir* (belong to an environmental club), and *local* (live in locality). Including demographic dummy variables in welfare analysis allow us to see how the WTP varies with respect to observed preference heterogeneity for each policy scenario.

Table 8 presents the point estimates and Krinsky-Robb (1986) standard errors from mixed logit model for several welfare scenarios for each of the eight non-snowmobilers group under assumed baseline conditions *Baseline high* and *Baseline moderate*. Before I discuss the effects of demographics on the welfare changes, an overall picture can be seen that under both specifications non-snowmobile riders experience a welfare gain from any changes in the snowmobile regulation except for the guided tour requirement policy which will result in moderate snowmobile crowding level in the park (moderate congestion, emission level and noise, and smooth road). When snowmobiles are banned from the park they experience the most utility gains, followed by the cap on entrance policy which results in low snowmobile crowding level in the park (low congestion, emission level and noise, and smooth road). Non-snowmobilers face considerably less welfare gains when a guided policy which results low snowmobile crowding level in the park is in place compare to the cap scenario. This finding indicates that snowmobile-free park is preferred by non-snowmobilers even though the resulting ambient conditions are identical between the two policies. One notable thing is that it is expected to see greater welfare gain (or smaller welfare loss) when using *Baseline high* comparing with using *Baseline moderate*, however, the results I get under specification 2 do not follow that pattern. One possible explanation is that when incorporating interactions of demographics with the opt-out alternative, parameter estimates associated with trip attributes alone are impacted by the interaction terms such that they are subjected to be underestimated. In the following section, I will refer to the second part (specification 3) in Table 8 when I discuss the results.

Three individual characteristics: *Equipment*, *Clubsenvir* and *Local* are included in the welfare analysis which further divided non-snowmobilers into eight groups where the first group is viewed as a baseline which has none of these characteristics. It can be seen that observable heterogeneity plays an important role in a way such that a representative visitor who possesses some specific characteristics is predicted to have welfare changes from management policies that are different from those who (group 1) do not have these particular characteristics. I will discuss and compare the effect of a single demographic, and then move on to the joint effects.

Visitors who belong to an environmental club (Group 3) benefit the most utility gains under any management scenarios with welfare estimates ranging from -\$3.33 to \$644.57 from baseline I and -\$17.87 to \$630.04 from baseline II. It makes sense as those people are more likely place an emphasis on the ambiance condition in the park when they make trips decisions. Thus any policies that will improve the park condition will make them better of in a larger portion compared to visitors who do not belong to any environmental clubs. The second individual characteristic of interest is equipment ownership status. Comparing to the Group 1, visitors who own their own non-motorized winter recreation equipments (Group 2) benefit more under any management policies except for guided tour requirement with moderate congestion prediction. The snowmobile ban ($521.92 from *Baseline high* and $468.51 from *Baseline moderate*) provides a much larger improvement than guided tour requirement with low congestion prediction ($242.05 from *Baseline high* and $250.75 from *Baseline moderate*), followed by a relatively smaller improvement than a simple cap ($342.70 from *Baseline high* and $351.40 from *Baseline moderate*). While guided tour requirement with moderate congestion prediction gives a less clear directions where visitors who own equipments will suffer larger welfare loss ($30.91) than visitors in Group 1 ($7.25) from *Baseline high*, while they are predicted to have smaller welfare loss ($22.21) than visitors in Group 1 ($46.04) from *Baseline moderate*. The third individual characteristic is living in locality (Group 4). The welfare estimates are uniformly smaller under any management scenarios for this group than that of in Group 1. As I discussed in section 5 about the parameter estimates results, local visitors place negative signs on low levels of entrance crowding, noise and emission, thus they are expected to receive the smallest improvement on welfare change from any snowmobile restriction policies among the eight groups.

Group 5 to Group 8 are the ones that involve two or three individual characteristics. Several insights can be seen from the estimates. Not surprisingly, visitors who own equipments and belong to an environmental club (Group 5) experience on average larger welfare gain (smaller welfare loss) from any policy comparing to Group 1, but slightly smaller improvement than visitors who belong to an environmental club but do not own equipment (Group 3). This can be explained as that visitors who own equipments are expected to actively engage in non-motorized in park activities, so they might relate crowding level to the popularity of a recreation spot and place less emphasis on the park ambience condition. This finding is consistent with the parameter estimates results discussed in section 5 as those visitors place negative signs on low level destination crowding and low level noise. The welfare estimates for group 6, group 7 and group 8 are clear. Any group that involves demographic variable *Clubsenvir* experience greater improvement on welfare under any winter management policy compared to the baseline group, while the groups that have *local* characteristic gain less, however, the negative effect from local is proportionally offset by the positive effect from other characteristics.

7. CONCLUSION

This thesis has investigated the advantages of flexibly accounting for observed and unobserved heterogeneity in the estimations of discrete choice models. The 2002-2003 Yellowstone and Grand Teton National Parks winter visitor survey is a series of stated-preference choice experiment questions survey collects detailed information on respondents' demographics and choices with regard to hypothetical recreation sites which allow us to gauge visitors preferences for attributes of YNP under different winter management policies.

To examine the importance of observed and unobserved preference heterogeneity in discrete choice modeling in the YNP implication, I estimated the YNP winter non-snowmobile visitors' preference for hypothetical trip alternatives using three discrete choice models each under two specifications of interaction terms, and calculated welfare impact of snowmobile restriction policy changes in YNP under two assumed park condition as the baselines.

I estimate visitors' preference function parameters with random utility maximization (RUM) models in the framework of three different discrete choice models: 1) a conditional logit model specifies fixed parameters for all individuals in the sample, 2) a mixed logit model allows taste variation among individuals that cannot be explained by observed variables by specifying randomly distributed parameters, and 3) a latent class model classifies non-snowmobilers into groups using demographics and other covariates and estimates utility functions for each group. All of these models indicate large heterogeneity in preference for trip alternatives. Although fundamental uncertainty could be one of the explanations, it is also likely that some preference heterogeneity could be due to the demographics of respondents. To account for the role of observable preference heterogeneity in determining respondents' choice decisions, I incorporated demographics of surveyed respondents into estimation under two specifications of interaction terms 1) interactions of demographics with the opt-out alternative and 2) additional interactions of demographics with trip attributes using each model. Accounting for both observed and unobserved preference heterogeneity improves statistical fitting of the models and generates qualitatively different policy implications both in aggregate and across the distribution of the target population. Even though utility function parameter estimates from the three models are different in magnitude and some time the signs, the results from all the three different models evidence the assumption that to some degree, additional variation in coefficients can be captured through the inclusion of demographic characteristics. All three models indicates that demographics such as *Clubsenvir* (non-snowmobile visitors who belong to an environmental club), *Equipment* (own winter non-motorized recreation equipments) and *Local* (come from local area) generate statistically significant impacts on visitors' choice preference on trip alternatives. Welfare analysis results from mixed logit model indicate that non-snowmobile visitors who belong to an environmental club show uniformly positive utility gains on low level of park attributes such as entrance crowding, destination crowding, noise and emission. However, it is not always the case for visitors who own winter non-motorized recreation equipments and visitors from local area.

I used parameter estimates from the mixed logit to calculate welfare changes under proposed snowmobile restriction policies in YNP. Even though utility function parameter estimates between the two specification of interaction terms are very similar to each other, and in both cases the rankings of different policies' effect are unaffected by the specification of interactions, the additional demographics-attributes interactions allows us to detect the taste variation in trip attributes related to individuals' characteristics, which could not be captured with just the demographics-opt-out interactions. Also, when parameter estimates from the two different interactions specifications are used in welfare calculation, clear distinctions can be seen that welfare changes calculated with more comprehensive interactions are overall larger ($10 ~ $168 per choice occasion) than the ones with just demographics-opt-out interactions. Observable preference heterogeneity effects welfare changes in a way such that compared with the base group visitors with no demographics involved, visitors who belong to an environmental club experience much more utility gains (or least utility loss) for proposed winter management policies in place, while visitors who own non-motorized winter recreation equipments follow a slightly larger utility improvement. However, the utility of visitors who come from local areas improve less under any snowmobile restriction policies than visitors in the base group. One possible explanation is that there might exists external benefits associated with snowmobiling activity for local non-snowmobile visitors, another possible reason is that local visitors are more flexible than other visitors in terms of choosing substitute winter recreation sites if policies were changed at YNP.

A few limitations here are that the sample is based on visitors who came to the YNP during the winter season 2002 – 2003, it can not predict the preferences of potential visitor if management policies were changed. Second, without accounting for the reasons of choosing the opt-out alternative, in the current set up of welfare analysis, it cannot be determined that how much of the estimated WTP can be explained by the use values of visitors such as reduced snowmobile access and improved park conditions, and how much is due to potential non-use values such as the beliefs that snowmobile activity might threaten the wildlife in the park, the noise and emissions are bad for the environment. Finally, the sample in my thesis only consider the non-snowmobile subpopulation, expanding the sample by including snowmobile visitors in future research that examine an overall welfare impacts is of interest.

22. CHOICE 1: Which do you prefer—Trip A, Trip B or "Not Visit"? Please check ONE box at the bottom of the table to indicate whether you prefer Trip A, Trip B or Not Visit.

		Trip A	**Trip B**	**Not Visit**
Activity		Take a guided snowcoach tour to see park sights in Yellowstone starting at the South entrance (near Flagg Ranch)	Take an unguided snowmobile trip in Yellowstone starting from the West entrance (near West Yellowstone)	**I would not enter Yellowstone or Grand Teton National Park if these were my only choices**
Conditions during day trip	**Daily snowmobile traffic at the entrance where you started**	High (800 to 1,500 snowmobiles)	Moderate (300 to 600 snowmobiles)	
	Snowmobile traffic at most crowded part of the trip	High (800 to 1,500 snowmobiles)	Moderate (300 to 600 snowmobiles)	
	Condition of snow on the road or trail surface for all or most of the trip	Smooth	Bumpy and rough	
	Highest noise level experienced on trip	Loud (Like a gas-powered lawn mower or a busy highway)	Loud (Like a gas-powered lawn mower or a busy highway)	
	Exhaust emission levels	Very noticeable	Very noticeable	
	Total Cost for DAY per person	$230	$75	
I would choose… (check only one)		If you planned a trip doing just this activity, how many days would you spend on the trip? __________ days	If you planned a trip doing just this activity, how many days would you spend on the trip? __________ days	**go to Question 22b below**

Figure 1 Example Choice Question

Variable	*Description*	*Mean (St.Dev.)*
Age	Age of respondent	47.0 (14.0)
Female	Equals 1 if female, 0 otherwise	0.483
Income		
Less than $25,000		0.112
$25,000 to $59,999	2002 gross household annual income	0.277
$60,000 to $124,999	(Income > $65.000 ⇔ highincome)	0.355
More than $125,000		0.256
Collegedeg	College 2 or 4yr degree	0.765
Childernat	Having some children under 18 at home	0.356
Retired	Employment status is retired	0.171
Student	Employment status is student	0.518
Local	Living locally	0.508
Married	Marriage status	0.761
Equipment	Winter Equipment ownership status	
Own snowmobiles		0.038
Own cross-country skis		0.548
Own downhill skis		0.473
Own snowshoes		0.367
Clubssnowm	Belong to a snowmobile club	0.005
Clubsxc	Belong to a cross-county skiing club	0.089
Clubsenvir	Belong to an environmental organization	0.326

Figure 2 Sample Demographics for Non-Snowmobilers (N = 656)

Table 1. Trip and Activities Characteristics on Visitor's (Non-snowmobiler) Recent Trip to GYA Parks

Length of Trip	Days
Days spent in GYA	5.09
Days spent in YNP	1.68
Days spent outside the parks	4.181
Features of Trip	Percentage
Activity	
Snowmobiler	1.87%
Snowcoach tour	26.99%
Snowcoach shuttle to ski or snowshoe	6.24%
Drive car to sightsee, ski or snowshoe	59.91%
Entrance	
Yellowstone West near West Yellowstone, MT	22.53%
Yellowstone East near Cody, WY	0.31%
Yellowstone North near Gardiner, MT	31.48%
Yellowstone South near Flagg Ranch	10.80%
Grand Teton Moose entrance near Jackson Hole, WY	30.25%
Guided tour	
Yes	30.93%
No	69.07%
Snowmobile traffic at the entrance	
I did not see any snowmobile	50.08%
Low	29.00%
Moderate	12.51%
High	8.40%
Snowmobile traffic at the most crowded area	
I did not see any snowmobile	42.02%
Low	27.80%
Moderate	18.80%
High	11.37%
Condition of snow on road surface	
Bumpy and rough for at least some of the trip	46.51%
Smooth	53.48%
Level of Noise	
Low	71.20%
Moderate	17.72%
High	11.08%

Table 1. Continued

Level of emission	Percentage
I did not notice	63.41%
Noticeable	28.55%
Very noticeable	8.04%
Very noticeable	8.04%
Cost	
Per person for day	$55.68
Choice	
Your trip	86.64%
Trip B	8.49%
Not Visit	4.87%

Table 2. Levels of Attributes and Variables

Variables	Attributes
Activity	***Activity***
Snowmobiling	• Snowmobile
Coach touring	• Snow coach tour
Coach Skiing	• Snowmobile snow coach shuttle to cross-country skiing
Auto touring	• Drive car to auto-tour
Entrance	***Entrance where trip starts***
West	• Yellowstone West near West Yellowstone, MT
North	• Yellowstone North near Gardiner, MT
South	• Yellowstone South near Flagg Ranch
Grand Teton	• Grand Teton National Park
Guided tour	***Guided tour or not***
Guided	• Guided tour
Unguided	• Unguided tour
Entrance crowding	***Daily snowmobile traffic at the entrance where you start***
No_snowmobile	• I did not see any snowmobiles near the entrance where my trip started
Ent_low	• Low, 200 or fewer snowmobiles (typical North and East Entrances on all days and South Entrance on most weekdays and weekends)
Ent_mod	• Moderate, 300 to 600 snowmobiles (typical West Entrance on weekdays and South Entrance on busy holiday weeks)
Ent_high	• High, 800 to 1.500 snowmobiles (typical West Entrance on holiday or crowded weekend)
Destination crowding	***Snowmobile traffic at the most crowded part of trip***
No_snowmobile	• I did not see any snowmobiles on my most recent trip
Crwd_low	• Low, 200 or fewer snowmobiles (very uncrowned days at Old Faithful)
Crwd_mod	• Moderate, 300 to 600 snowmobiles (typical Old Faithful on less crowded weekdays and weekends)
Crwd_high	• High, 800 to 1500 snowmobiles (typical Old Faithful on holiday and busy weekends or weekdays in late January and February)
Road condition	***Condition of snow on the road or trail surface for all or most of the trip***
Smooth	• Smooth
Bumpy	• Bumpy and rough
Level of noise	***Highest noise level experienced on trip***
Nois_low	• Low noise, occasional
Nois_mod	• Moderate, you would need to raise your voice to talk to someone standing next to you, noise like a busy city street
Nose_high	• Loud, standing next to the road you could not converse with someone standing next to you, noise level similar to standing next to a gas-powered lawn mower or a busy high way

Table 2. Continued

Level of emission	***Exhaust emission levels***
Ems_nnotice	• Exhaust emissions are not noticeable
Ems_notice	• Exhaust emissions are noticeable for some of the trip
Ems_verynotice	• Exhaust emissions are very noticeable for most of all the trip
Cost	***Total cost for day per person***
Cost	• Out-of-pocket costs that vary depend on types of trip
Choice	***Choice of not visiting the park***
Opt-out	• No trip dummy

Table 3. Latent Class (LC) Models Information Criteria Summary[1]

# of classes	Specification	Parameter[2]	Log Likelihood	Consistent AIC	Corrected AIC
2	Baseline[3]	38	-3021.3	6327.1	6311.1
2	Baseline + Demographics & LC Probability Interaction	49	-2998.7	6364.2	6508.4
2	Baseline + Demographics & Opt-out Dummies	49	-3004.6	6376.1	6520.3
2	Baseline + Demographics & Trip Attribute Dummies	54	-2963.6	6331.4	6589.6
3	Baseline[3]	57	-2888.5	6203.7	6544.4
3	Baseline + Demographics & LC Probability Interaction	79	-2854.1	6299.6	7646.8
3	Baseline + Demographics & Opt-out Dummies	68	-2873.4	6255.9	7003.8
3	Baseline + Demographics & Trip Attribute Dummies	73	-2838.0	6222.4	7216.6
4	Baseline[3]	76	-2812.4	6193.8	7356.3
4	Baseline + Demographics & LC Probability Interaction	109	-2748.1	6312.1	10598.1
4	Baseline + Demographics & Opt-out Dummies	87	-2799.2	6249.7	8175.9
4	Baseline + Demographics & Trip Attribute Dummies	92	-2771.5	6231.8	8589.2

[1] Total number of observations is 625.
[2] In all specifications, there is only one parameter in the LC index which is the LC Probability
[3] Baseline model only includes trip attribute variable

Table 4.1. Parameters of Conditional and Mixed Logit Models with Demographics Interacted with Opt-out Alternative

	Conditional Logit Model		Mixed Logit Model	
	Estimates	Std. err.	Estimates	Std. err.
Log-likelihood	-3376.7		-2810.9	
Activity				
Snowmobiling	-0.462***	0.105	-0.656***	0.199
Std. dev			1.346***	0.181
Coach tour	-0.137	0.100	-0.140	0.202
Std. dev			0.884***	0.205
Coach Skiing	0.177***	0.080	0.278*	0.151
Std. dev				
Auto tout[a]	0.422		0.518	
Entrance				
West	0.059	0.077	0.059	0.162
Std. dev			0.489**	0.235
North	0.008	0.070	-0.023	0.126
Std. dev				
South	-0.090	0.101	-0.023	0.182
Std. dev			0.239	0.196
Grand Teton[a]	0.023		-0.013	
Guided Status				
Guided	0.071	0.070	0.118	0.132
Std. dev			1.019***	0.117
Unguided[a]	-0.071		-0.118	
Crowding at Entrance				
Ent_low	0.324***	0.086	0.511***	0.144
Std. dev			-0.382	0.388
Ent_mod	-0.043	0.075	-0.084	0.141
Std. dev				
Ent_high[a]	-0.281		-0.427	
Crowding at Destination				
Crwd_low	0.444***	0.095	0.788***	0.178
Std. dev				
Crwd_mod	-0.022	0.075	-0.110	0.135
Std. dev				
Crow_high[a]	-0.422		-0.678	
Road Condition				
Smooth	0.077*	0.041	0.279***	0.089
Std. dev				
Bumpy[a]	-0.077		-0.279	

Table 4.1. Continued

	Conditional Logit Model		Mixed Logit Model	
	Estimates	Std. err.	Estimates	Std. err.
Noise Level				
Nois_low	0.147**	0.074	0.239*	0.140
Std. dev			-0.648	0.383
Nois_mod	-0.117*	0.060	-0.075	0.103
Std. dev				
Nois_high[a]	-0.030		-0.164	
Emission Level				
Ems_nnotice	0.064	0.118	0.575***	0.213
Std. dev			-1.059***	0.370
Ems_notice	0.110	0.074	0.143	0.140
Std. dev				
Ems_verynotice[a]	-0.174		-0.718	
Cost	-0.004***	0.001	-0.013***	0.002
No_snowmobile	1.295***	0.170	2.287***	0.349
Std. dev			-2.773	0.344
Opt-out	1.090*	0.590	1.586	1.589
Std. dev			2.881***	0.174
Interaction terms with Opt-out alternative				
Age*opt-out	-3.785	2.647	-9.989	6.954
Age^2* opt-out	3.602	2.912	9.227	7.363
Female*opt-out	0.017	0.117	0.047	0.287
Collegedeg*opt-out	0.093	0.146	0.614	0.378
Retired*opt-out	-0.205	0.212	-0.692	0.497
Married*opt-out	0.139	0.147	0.251	0.399
Equipment*opt-out	0.235	0.146	0.778**	0.370
Clubsenvir *opt-out	0.229*	0.125	0.807**	0.334
Local*opt-out	0.307***	0.120	0.766**	0.326
Highincome*opt-out	-0.239*	0.135	-0.593**	0.302
Childernat*opt-out	-0.154*	0.084	-0.420**	0.191

[a] Omitted effects-coded variable.
*** Statistically different from 0 at the 0.01 level of significance.
** Statistically different from 0 at the 0.05 level of significance.
* Statistically different from 0 at the 0.1 level of significance.

Table 4.2. Parameters of Latent Class Models with Demographics Interacted with Opt-out Alternative

	Class 1		Class 2	
	Estimates	Std. err.	Estimates	Std. err.
Log-likelihood			-2985.0	
Activity				
Snowmobiling	-0.071	0.272	-0.210	0.148
Coach tour	-1.380***	0.342	-0.296***	0.123
Coach Skiing	-0.629**	0.307	0.225	0.169
Auto tout[a]	2.080		0.281	
Entrance				
West	4.220***	0.575	0.312	0.530
North	0.417*	0.279	-0.146	0.151
South	0.102	0.214	0.087	0.098
Grand Teton[a]	-4.739		-0.253	
Guided Status				
Guided	0.597**	0.237	0.114	0.121
Unguided[a]	-0.597		-0.114	
Crowding at Entrance				
Ent_low	0.056	0.251	0.312***	0.099
Ent_mod	0.214	0.323	0.288***	0.110
Ent_high[a]	-0.270		-0.600	
Crowding at Destination				
Crwd_low	-0.298	0.241	0.076	0.127
Crwd_mod	0.740***	0.258	0.286*	0.165
Crow_high[a]	-0.442		-0.362	
Road Condition				
Smooth	-0.240 *	0.258	0.115	0.123
Bumpy[a]	0.240		-0.115	
Noise Level				
Nois_low	0.012	0.130	0.009	0.073
Nois_mod	0.189	0.295	0.177	0.152
Nois_high[a]	-0.201		-0.186	
Emission Level				
Ems_nnotice	-0.018	0.207	-0.075	0.104
Ems_notice	0.146	0.288	0.002	0.171
Ems_verynotice[a]	-0.128		0.073	

Table 4.2. Continued

	Class 1		Class 2	
	Estimates	Std. err.	Estimates	Std. err.
Cost	-0.002***	0.0006	-0.002***	0.0006
No_snowmobile	0.522	0.327	0.143	0.137
Opt-out	2.519***	0.580	0.799***	0.281
Interaction terms with opt-out alternative				
Age*opt-out	-0.553***	0.181		
Age^2* opt-out	-5.565**	2.263		
Female*opt-out	5.323**	2.552		
Collegedeg *opt-out	0.034	0.088		
Retired*opt-out	-0.178	0.110		
Married*opt-out	0.182	0.166		
Equipment*opt-out	0.134	0.110		
Clubsenvir *opt-out	-0.219*	0.114		
Local*opt-out	-0.472***	0.107		
Highincome*opt-out	0.114	0.096		
Childernat*opt-out	0.044	0.102		
Latent class probability and Demographics in each latent class index				
Latent probability	0.829***	0.286		
Collegedeg	-0.463*	0.246		
Retired	0.564**	0.266		
Equipment	-0.665***	0.257		
Clubsenvir	-1.021***	0.237		
Local	-0.431**	0.213		
Highincome	0.519**	0.255		

[a] Omitted effects-coded variable.
*** Statistically different from 0 at the 0.01 level of significance.
** Statistically different from 0 at the 0.05 level of significance.
* Statistically different from 0 at the 0.1 level of significance.

Table 5.1. Parameters of Conditional and Mixed Logit Models with Demographics Interacted with Selected Trip Attributes

	Conditional Logit Model		Mixed Logit Model	
	Estimates	Std. err.	Estimates	Std. err.
Log-likelihood	-3302.4		-2769.8	
Activity				
Snowmobiling	-0.456***	0.108	-0.631***	0.314
Std. dev			-1.281***	0.154
Coach tour	-0.130	0.101	-0.032	0.185
Std. dev			0.833***	0.193
Coach Skiing	0.192***	0.081	0.271*	0.168
Std. dev				
Auto tout[a]	0.394		0.392	
Entrance				
West	0.083	0.076	0.007	0.208
Std. dev			-0.272**	0.767
North	-0.019	0.070	-0.026	0.128
Std. dev				
South	-0.070	0.100	0.019	0.209
Std. dev			0.002	0.853
Grand Teton[a]	0.006		0.000	
Guided Status				
Guided	0.056	0.070	0.112	0.168
Std. dev			1.071***	0.140
Unguided[a]	-0.056		-0.112	
Crowding at Entrance				
Ent_low	0.423***	0.100	0.587***	0.181
Std. dev			0.125	3.259
Ent_mod	-0.121	0.081	-0.177	0.148
Std. dev				
Ent_high[a]	-0.302		-0.410	
Local*ent_low	-0.125	0.096	-0.146	0.177
Clubsenvir*ent_mod	0.347***	0.110	0.524***	0.209
Crowding at Destination				
Crwd_low	0.683***	0.115	1.112***	0.213
Std. dev				
Crwd_mod	-0.040	0.074	-0.096	0.124
Std. dev				
Crow_high[a]	-0.639		-1.016	
Equipment*crwd_low	-0.276***	0.098	-0.485***	0.186
Clubsenvir*crwd_low	0.240***	0.103	0.298	0.199

Table 5.1. Continued

	Conditional Logit Model		Mixed Logit Model	
	Estimates	Std. err.	Estimates	Std. err.
Road Condition				
Smooth	0.080*	0.041	0.308***	0.087
Std. dev				
Bumpy[a]	-0.080		-0.308	
Noise Level				
Nois_low	0.187*	0.110	-0.152*	0.223
Std. dev			-0.603*	0.404
Nois_mod	-0.109*	0.061	-0.064	0.122
Std. dev				
Nois_high[a]	-0.078		-0.216	
Equipment*nois_low	-0.433***	0.110	0.756***	0.250
Clubsenvir*nois_mod	0.454***	0.121	0.588***	0.235
Local*nois_low	-0.113	0.104	-0.403**	0.186
Emission Level				
Ems_nnotice	0.050	0.135	0.459***	0.275
Std. dev			-1.020*	0.574
Ems_notice	0.294	0.102	0.456	0.274
Std. dev				
Ems_verynotice[a]	-0.344		-0.915	
Clubsenvir*ems_low	0.209***	0.093	1.036***	0.374
Equipment*ems_mod	0.256***	0.103	-0.372**	0.189
Clubsenvir*ems_mod	-0.239*	0.135	-0.415*	0.247
Local*ems_low	-0.151	0.109	-0.177	0.233
Cost	-0.005***	0.001	-0.013***	0.002
No snowmobiles	1.195***	0.175	1.955***	0.384
Std. dev			-2.136***	0.688
Opt-out	1.008*	0.560	1.465	1.367
Std. dev			2.864***	0.306

Table 5.1. Continued

	Conditional Logit Model		Mixed Logit Model	
	Estimates	Std. err.	Estimates	Std. err.
Interaction terms with Opt-out alternative				
Age*opt-out	-3.811	2.667	-10.356	6.105
Age^2* opt-out	3.560	2.945	10.347	6.734
Female*opt-out	0.021	0.119	0.033	0.280
Collegedeg *opt-out	0.103	0.146	0.314	0.415
Retired*opt-out	-0.198	0.216	-0.601	0.532
Married*opt-out	0.148	0.148	0.244	0.347
Equipment*opt-out	0.277	0.151	0.750**	0.363
Clubsenvir *opt-out	0.471***	0.145	0.768***	0.324
Local*opt-out	0.227*	0.131	0.719**	0.344
Highincome*opt-out	-0.240*	0.138	-0.432	0.453
Childernat*opt-out	-0.156*	0.086	-0.351*	0.205

[a] Omitted effects-coded variable.
*** Statistically different from 0 at the 0.01 level of significance.
** Statistically different from 0 at the 0.05 level of significance.
* Statistically different from 0 at the 0.1 level of significance.

Table 5.2. Parameters of Latent Class Models with Demographics Interacted with Selected Trip Attributes

	Class 1		Class 2	
	Estimates	Std. err.	Estimates	Std. err.
Log-likelihood			-2949.1	
Activity				
Snowmobiling	-0.090	0.271	-0.159	0.148
Coach tour	-1.343***	0.330	-0.380***	0.125
Coach Skiing	-0.706***	0.289	0.096	0.176
Auto tout[a]	2.139		0.443	
Entrance				
West	3.802***	0.601	-0.112	0.562
North	0.508*	0.271	-0.061	0.165
South	0.115	0.205	0.078	0.102
Grand Teton[a]	-4.425		0.095	
Guided Status				
Guided	0.455**	0.215	0.128	0.128
Unguided[a]	-0.455		-0.128	
Crowding at Entrance				
Ent_low	0.167	0.241	0.194*	0.106
Ent_mod	0.152	0.311	0.290***	0.120
Ent_high[a]	-0.319		-0.484	
Crowding at Destination				
Crwd_low	-0.455*	0.241	0.095	0.138
Crwd_mod	1.155***	0.258	0.652***	0.197
Crow_high[a]	-0.700		-0.720	
Equipment*crwd_low	-0.198***	0.064	-0.198***	0.064
Road Condition				
Smooth	-0.228	0.246	0.048	0.132
Bumpy[a]	0.228		-0.048	
Noise Level				
Nois_low	0.025	0.127	-0.008	0.076
Nois_mod	-0.248	0.289	-0.116	0.164
Nois_high[a]	-0.223		0.124	
Equipment*nois_low	-0.437***	0.126	-0.437***	0.126
Emission Level				
Ems_nnotice	0.060	0.199	-0.066	0.110
Ems_notice	-0.237	0.303	0.076	0.177
Ems_verynotice[a]	0.177		-0.010	
Clubsenvir*ems_low	0.400***	0.083	0.400***	0.083
Clubsenvir*ems_mod	0.740***	0.110	0.740***	0.110

Table 5.2. Continued

	Class 1		Class 2	
	Estimates	Std. err.	Estimates	Std. err.
Cost	-0.003***	0.0001	-0.003***	0.0006
No_snowmobile	0.791**	0.359	0.125	0.146
Opt-out	2.771***	0.564	0.685***	0.287
Interaction terms with Opt-out alternative				
Age*opt-out	-0.483***	0.186		
Age^2* opt-out	-6.165**	2.406		
Female*opt-out	5.726**	2.710		
Collegedeg *opt-out	-0.036	0.094		
Retired*opt-out	-0.164	0.114		
Married*opt-out	-0.033	0.181		
Equipment*opt-out	0.321***	0.115		
Clubsenvir *opt-out	0.344***	0.131		
Local*opt-out	0.053	0.134		
Highincome*opt-out	0.373***	0.103		
Childernat*opt-out	-0.411	0.114		
Latent class probability and Demographics in each latent class index				
Latent probability	0.205	0.262		
Collegedeg	-0.410*	0.235		
Retired	0.266	0.249		
Equipment	-0.103	0.240		
Clubsenvir	-0.596***	0.237		
Local	-0.089	0.208		
Highincome	-0.053**	0.230		

[a] Omitted effects-coded variable.
*** Statistically different from 0 at the 0.01 level of significance.
** Statistically different from 0 at the 0.05 level of significance.
* Statistically different from 0 at the 0.1 level of significance.

Table 6. Choice Alternatives for Welfare Analysis[a]

Activity	Entrance	Guide Status	Price
Snowmobile	West	Guided	$200
Snowmobile	West	Unguided	$15
Snowmobile	South	Guided	$230
Snowmobile	South	Unguided	$15
Snowmobile	North	Guided	$200
Snowmobile	North	Unguided	$15
Snowmobile	Grand Teton	Guided	$200
Snowmobile	Grand Teton	Unguided	$15
Snow Coach Tour	West	Guided	$100
Snow Coach Tour	South	Guided	$120
Snow Coach Tour	North	Guided	$100
Ski or Hike	West	Guided	$110
Ski or Hike	West	Unguided	$20
Ski or Hike	South	Guided	$110
Ski or Hike	South	Unguided	$20
Ski or Hike	North	Guided	$110
Ski or Hike	North	Unguided	$20
Ski or Hike	Grand Teton	Guided	$110
Ski or Hike	Grand Teton	Unguided	$20
Car Tour	North	Unguided	$20
Car Tour	Grand Teton	Unguided	$20
Opt-Out	NA	NA	NA

[a] Other attributes such as crowding, road condition, emissions and noise are determined by the management policies in effect during the baseline or policy intervention states.

Table 7. Park Conditions and Welfare Scenarios[a]

	Baseline high	*Baseline moderate*	*Snowmobile Ban*	*Guided Tours Required low*	*Guided Tours Required Mod*	*Cap on Entrants*
Attribute	*Unrestricted snowmobile access*	*Unrestricted snowmobile access*	*Snowmobiles banned from the park*	*Snowmobiles in park must be on guided tour*	*Snowmobiles in park must be on guided tour*	*Daily cap on the number of snowmobiles in the park*
Crowding - entrance	High	Moderate	None	Low	Moderate	Low
Crowding - destination	High	Moderate	None	Low	Moderate	Low
Road Condition	Bumpy	Bumpy	Smooth	Smooth	Smooth	Smooth
Noise	High	Moderate	Low	Low	Moderate	Low
Emissions	High	Moderate	Low	Low	Moderate	Low
Cost	I	I	I	I	I	I

[a] The cost for all options remaining in the choice set is the same as under baseline conditions for all scenarios labeled I

Table 8. Per Choice Occasion Welfare Analysis – Mixed Logit Model[a]

	Baseline high = bumpy road and high congestion, noise and emissions				*Baseline moderate= bumpy road and moderate congestion, noise and emissions*			
	Snowmobile ban	Guided tour required w/ low CNE	Guided tour required w/ moderate CNE	Cap on entrants w/ low CNE	Snowmobile ban	Guided tour required w/ low CNE	Guided tour required w/ moderate CNE	Cap on entrants w/ low CNE
Random coefficient model w/ demographics interacted with opt-out alternative (Specification 2)								
1. Equipment = 0, Clubsenvir = 0, Local = 0	$497.01	$245.54	-$32.37	$330.31	$501.75	$250.28	-$27.63	$335.04
	(119.2)	(67.2)	(27.31)	(75.7)	(124.2)	(78.3)	(12.6)	(86.3)
2. Equipment = 1, Clubsenvir = 0, Local = 0	$473.31	$222.77	-$21.82	$306.87	$476.70	$226.15	-$18.43	$310.26
	(115.2)	(63.0)	(19.4)	(71.6)	(118.7)	(71.6)	(9.8)	(79.8)
3. Equipment = 0, Clubsenvir = 1, Local = 0	$476.52	$225.83	-$22.98	$310.04	$480.06	$229.37	-$19.43	$313.58
	(116.2)	(64.2)	(20.4)	(72.8)	(119.8)	(72.9)	(10.5)	(81.2)
4. Equipment = 0, Clubsenvir = 0, Local = 1	$476.19	$225.51	-$22.86	$309.71	$479.72	$229.04	-$19.33	$313.24
	(116.3)	(64.6)	(20.4)	(73.1)	(119.8)	(73.0)	(10.54)	(81.1)
5. Equipment = 1, Clubsenvir = 1, Local = 0	$440.82	$192.10	-$13.17	$274.92	$442.96	$194.25	-$11.02	$277.06
	(109.9)	(58.0)	(12.5)	(66.9)	(112.2)	(64.0)	(7.3)	(72.6)
6. Equipment = 1, Clubsenvir = 0, Local = 1	$440.34	$191.65	-$13.07	$274.45	$442.47	$193.79	-$10.94	$276.58
	(109.4)	(57.8)	(12.3)	(66.4)	(111.6)	(63.5)	(7.1)	(71.9)
7. Equipment = 0, Clubsenvir = 1, Local = 1	$444.86	$195.87	-$14.00	$278.88	$447.13	$198.14	-$11.73	$281.15
	(111.8)	(60.7)	(13.8)	(69.4)	(114.0)	(66.5)	(8.1)	(74.9)
8. Equipment = 1, Clubsenvir = 1, Local = 1	$398.11	$153.30	-$7.01	$233.39	$399.29	$154.48	-$5.83	$234.58
	(101.9)	(51.1)	(7.1)	(60.1)	(103.1)	(54.7)	(4.7)	(63.5)

[a] These sample WTP estimates are point estimates calculated using coefficient means.
Krinsky-Robb (1986) standard errors in parentheses.

Table 8. Continued

	Baseline high = bumpy road and high congestion, noise and emissions				*Baseline moderate= bumpy road and moderate congestion, noise and emissions*			
	Snowmobile ban	Guided tour required w/ low CNE	Guided tour required w/ moderate CNE	Cap on entrants w/ low CNE	Snowmobile ban	Guided tour required w/ low CNE	Guided tour required w/ moderate CNE	Cap on entrants w/ low CNE
Random coefficient model w/ demographics interacted with opt-out alternative & trip attributes (Specification 3)								
1. Equipment = 0, Clubsenvir = 0, Local = 0	$507.30	$226.92	-$7.25	$327.95	$468.51	$188.13	-$46.04	$289.16
	(110.2)	(69.50)	(37.47)	(75.17)	(115.9)	(89.15)	(16.44)	(93.19)
2. Equipment = 1, Clubsenvir = 0, Local = 0	$521.92	$242.05	-$30.91	$342.70	$530.62	$250.75	-$22.21	$351.4
	(138.8)	(78.48)	(21.91)	(39.18)	(142.8)	(87.1)	(11.9)	(97.4)
3. Equipment = 0, Clubsenvir = 1, Local = 0	$644.57	$363.61	-$3.33	$465.07	$630.04	$349.08	-$17.87	$450.54
	(176.7)	(116.4)	(20.5)	(127.0)	(179.6)	(125.5)	(13.1)	(134.8)
4. Equipment = 0, Clubsenvir = 0, Local = 1	$413.66	$135.65	-$7.37	$234.91	$374.42	$96.40	-$46.62	$195.67
	(111.2)	(63.5)	(41.2)	(71.0)	(118.1)	(87.2)	(17.0)	(92.2)
5. Equipment = 1, Clubsenvir = 1, Local = 0	$627.68	$346.97	-$6.41	$448.25	$630.01	$349.29	-$4.09	$450.57
	(172.8)	(111.0)	(7.5)	(122.3)	(174.5)	(113.7)	(4.3)	(124.8)
6. Equipment = 1, Clubsenvir = 0, Local = 1	$429.24	$152.80	-$31.96	$250.90	$438.20	$161.75	-$23.01	$259.86
	(114.4)	(59.3)	(22.0)	(69.1)	(119.5)	(70.5)	(11.78)	(79.8)
7. Equipment = 0, Clubsenvir = 1, Local = 1	$553.01	$ 273.18	-$3.48	$373.80	$537.91	$258.08	-$18.59	$358.70
	(151.7)	(94.4)	(21.8)	(104.6)	(155.6)	(106.2)	(13.4)	(114.7)
8. Equipment = 1, Clubsenvir = 1, Local = 1	$ 536.7	$ 257.69	-$6.76	$357.74	$539.20	$260.13	-$4.31	$360.18
	(146.9)	(86.9)	(7.5)	(98.0)	(148.9)	(90.2)	(4.4)	(101.1)

[a] These sample WTP estimates are point estimates calculated using coefficient means.
Krinsky-Robb (1986) standard errors in parentheses

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