Economic Valuation of Multi-Attribute Beach Erosion Control Programs

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Abstract:

Natural resource benefit analysis of a proposed policy should take into account both the features of the resource and the characteristics of the people affected by potential changes to the resource. In this study, we incorporate a choice-based conjoint survey design to elicit individual choices of beach erosion control programs that consider multiple effects on beach environment. Three empirical choice models which incorporate individual heterogeneity, are used to analyze and compare the elicited individual choices of erosion control programs. Our results show that to a typical individual, both the positive and negative impacts of the programs affect their choices. We find the economic benefit of an erosion control program to preserve a stretch of sand beach can be exaggerated if potential negative impacts on the coastal environment from the same program are not considered. This study demonstrates feasible comparisons of programs that account for the erosion program effects as well as the demographics of program locations.

Key Words: Beach Erosion Control, Choice Based Conjoint Analysis, Individual Specific Welfare Measures, Mixed Logit Model, Multinomial Logit Latent Class Model

JEL Classification: Q26, H41

1. Introduction

Welfare measures can and should vary with individual characteristics. Typically, when conducting empirical welfare analysis of public goods, the average per-person benefit estimates are derived with no account for the heterogeneity across individuals. The issue of heterogeneity becomes even more important if the estimated value of benefits is going to be used to describe benefits of the same or a similar policy being implemented in other areas. It is well recognized that benefit analysis of a proposed public policy regarding the management of a natural resource, should take into account both the features of the natural resource under consideration and the characteristics of the people who are directly or indirectly affected by any resulting changes to the resource (Smith et al., 1999).

In this paper we study beach erosion control programs in terms of the economic values associated with their multiple effects on the coastal environment. Via a household survey, we use choice based conjoint analysis to ask survey participants to compare erosion control programs which vary in terms of their multiple impacts on the beach and coastal environment. Through individuals' choices of programs, we investigate the perceived tradeoffs of both positive and negative effects of erosion control programs. Three empirical choice models, namely the multinomial logit, mixed logit, multinomial logit latent class models, are employed to incorporate individual heterogeneity into the program choice analysis. The three empirical models are compared in terms of the Hicksian welfare measures they imply. We confirm that preferences for erosion control programs are indeed affected by both program attributes and household/individual characteristics, and subsequently the welfare measures that are derived. We also find that the mixed logit model seems to produce more stable welfare measures in this case study.

The remainder of this paper is organized as follows. Section 2 reviews previous valuation research on beach protection/nourishment, as well as attribute based stated choice methods for non-market valuation. Section 3 discusses three alternative choice models for analyzing multi-attribute products. Section 4 presents the welfare measures of product attributes implied by the three empirical choice models. Section 5 describes the survey design for valuing beach erosion control and data collection. Section 6 discusses the empirical model specifications and estimation issues. Section 7 presents the results of the data analysis. Some concluding remarks are given in Section 8.

2. Valuation of Shoreline Protection

The majority of the research on beach valuation estimates recreation demand for a site using the travel cost method and deriving the corresponding consumer surplus measure. Some studies focus on the impact that protection enhanced beach quality has on property values and development in coastal areas (e.g., Parsons, 1992; Cordes and Yezer, 1998). There are recent studies of beach recreation site choices that use the random utility framework (e.g., Parsons et al., 2000). Some studies have employed the contingent valuation method (CVM) to estimate both the use and passive use values of beach nourishment and protection (e.g., Silberman et al., 1992). In the sizeable literature of beach valuation, it is rarely emphasized the potential multiple effects of erosion control methods on the coastal environment and the associated tradeoffs. Freeman (1995) concludes in his review of the empirical literature on the economic value of marine recreation, that very few economic valuation studies have been done which focus on the role of qualitative attributes of beaches. An economic valuation of erosion control programs in terms of their multiple effects on beaches will provide policy makers with important program evaluation information.

The multiple effects of a beach erosion control program can be viewed as the "attributes" of the control program. As such, different control methods can generate different levels of these attributes. By valuing the attributes of various erosion control programs, the benefits of these programs can be estimated. This type of analysis is common for comparing market goods in an effort to understand the tradeoffs that consumers are willing to make, with respect to a product's attributes. This so called conjoint analysis has recently gained popularity for valuation of non-market goods because of its intuitive applicability when comparing policy alternatives. Furthermore, the National Oceanic and Atmospheric Administration (NOAA) reissued its proposed rule in 1995, for natural resource damage assessments (NRDA) which states that the lost value and associated services are to be compensated by providing in-kind resource services. Perceivably conjoint analysis can provide one means of assessing the equivalence of lost and gained services to assist in NRDA work (Mathews et al. 1995).

There are various forms of conjoint analysis (Green et al., 2001). A large number of non-market valuation applications employ the traditional conjoint analysis survey format that derives preference ratings or the strength of preferences for products (e.g., Mackenzie, 1993; Roe et al., 1996). Alternatively, survey respondents can be asked to rank all products according to the associated attribute levels (e.g., Garrod and Willis, 1996). The more recent applications focus on a single choice among two or more alternatives with or without a "none of the above" option (e.g., Opaluch et al. 1993; Adamowicz et al. 1994; Blamey et al., 1999; Cameron et al., 2002). Despite the increasing popularity of conjoint analysis amongst researchers, there is little evidence of which format is preferred in terms of producing the most accurate and precise welfare measures. In a split sample study, Boyle et al. (2001) elicit ratings, ranks, and single choices each from a separate random sample and find that the welfare estimates for changes in attribute levels from these three samples are significantly different. They conclude that the single choice format with an opt-out option (status quo) might be preferred. In contrast to the cardinal utility assumption for ratings, the single choice format only requires the ordinal assumption of choice preferences, and the status quo option allows "no change" so that individuals are not forced to accept changes which might bias the results upward. We adopt the choice-based conjoint analysis with an opt-out option, for our study. Individuals are asked to review the attributes of two erosion control programs at a time, and then indicate their preference for one of these programs or the status quo (no program); hence, for each choice decision three alternatives (two proposed programs and no program) are presented to each survey respondent. [1] This method allows multiple beach attributes induced by erosion control programs to be evaluated as bundles. Subsequently the erosion control programs can be valued based on the estimated, combined attribute values that they induce.

3. Discrete Choice Models

In this paper, we choose three empirical models to illustrate the alternative modeling strategies to take into account individual heterogeneity in analyzing choice decisions. The three models are the conditional logit model, mixed logit model, and multinomial logit latent class model (LCM, Greene and Hensher, 2002). The conditional logit model is the standard model for choice analysis. The mixed logit model and LCM are chosen because these models are specifically designed to allow parameter heterogeneity across individuals, which is the focus of this paper. [2]

The Standard Discrete Choice Model

The common analytical model underlying the analysis of discrete choice data derived from consumer choices is the random utility framework, popularized by McFadden (1973). Assume that an individual, i, has J possible multi-attribute products from which to choose. The model assumes that once individual i decides on one product, he/she does not care about the quality attributes of the other, excluded products. Given these assumptions, individual i's indirect utility function, conditional on his/her choice to consume the jth good, is as follows.

$$U_{ij} = V(q_{ij}, I_i\text{-}p_{ij}; s_i) + \varepsilon_{ij} = V_{ij} + \varepsilon_{ij} \tag{1}$$

where; the vector, q_{ij}, represents a set of attributes corresponding to the consumed good j; I_i is income; the cost (fee) to consume good j is p_{ij}, as a reduction of income; s_i is a vector of individual characteristics. The random variables, ε_{ij}'s, follow a joint distribution defined as $f_\varepsilon(\varepsilon_{i1},..., \varepsilon_{iJ})$. It is assumed that for each individual, one and only one of the J goods is chosen, thus choice decision follows a multinomial distribution, $f(x_{i1},...x_{iJ})= A\pi_{i1}^{x_{i1}} \cdot \pi_{i2}^{x_{i2}} \cdot ... \cdot \pi_{iJ}^{x_{iJ}}$, where π_{ij} is the probability that individual i chooses the good j; x_{ij}=1 if good j is chosen and x_{ij}=0 otherwise; A is some constant that does not depend on the probability π_{ij}. Given a sample of n individuals, the log-likelihood function which represents the corresponding set of n choice decisions, can be written as follows:

$$L = \sum_{i=1}^{n} (x_{i1} \log(\pi_{i1}) + x_{i2} \log(\pi_{i2}) + ... + x_{iJ} \log(\pi_{iJ})) \tag{2}$$

If the random errors, the ε's, are assumed to be independently and identically distributed (i.i.d.) with a type one extreme value distribution, the probability π_{ij} can be derived by integrating the density function and the widely used logistic function for π_{ij} results.

$$\pi_{ij} = \frac{e^{V_{ij}}}{\sum_{k=1}^{J} e^{V_{ik}}} = \frac{e^{\beta' w_{ij}}}{\sum_{k=1}^{J} e^{\beta' w_{ik}}} \tag{3}$$

The V_{ij} is commonly assumed to be linear in parameters such that $V_{ij} = \beta' w_{ij}$, where w_{ij} is a vector of explanatory variables including q_{ij} , the product attributes, p_{ij}, the cost to consume product j and possibly household/individual characteristics (included through choice specific intercept terms or variable interactions); and β is a vector of variable coefficients that are usually assumed constant across individuals and product choices. Substituting (3) into the log-likelihood function (2), the parameters in V_{ij} can be estimated by maximizing the function.

The Mixed Logit Model

The mixed logit model assumes that the parameters in the indirect utility function V_{ij} vary randomly across individual and can be correlated (Revelt and Train, 1998). The random parameters can also be functions of variables such as individual characteristics. Let β_{ik} be the coefficient associated with the kth explanatory variable in V_{ij}, which depends on individual characteristics (s_i) and varies randomly across i.

$$\beta_{ik} = \beta^*_{ik} + u_{ik} = \alpha_k + \lambda_k' s_i + u_{ik} \qquad i = 1,...,n \quad k=1,...,K \tag{4}$$

The vector of parameters λ_k indicates the impact of individual characteristics on β_{ik}. The u's are random errors with zero means and a joint distribution of $g(u_1,...,u_K|\theta)$ where θ is a vector of parameters including variances and correlation coefficients of the u's. Let λ be the vector of parameters (α_k, λ_k). The joint density function of β_k, k=1,...,K can be written as $f(\beta_1,...,\beta_K|\lambda,\theta)$. As seen in (2), the log-likelihood function is derived using the probabilities π_{ij}'s, conditional on the assumption that the β_{ik}'s are constant and the same across individuals (i’s). With the assumption of random β_{ik}, the unconditional probability of π_{ij} is derived by integrating the conditional probability over β_k, k=1,...,K, and can be written as:

$$\pi_{ij}^* = \int_{\beta_k} \pi_{ij}(\beta_k) f(\beta_k \mid \lambda, \theta) d\beta_k \tag{5}$$

If a multivariate normal distribution is assumed for β_k, then π_{ij}^* involves multiple integrals of a multivariate normal distribution, as does the unconditional log-likelihood function. Consequently the mixed logit model, also called the random-parameters logit model or error-components logit model, derives its choice probabilities with a mixture of logistic and normal distributions. In addition to the explicit incorporation of individual heterogeneity in parameter estimation, the mixed logit model also relaxes the assumption of independence of irrelevant alternatives (IIA) that is embedded in the standard conditional logit model. [3] McFadden and Train (2000) show that under certain regularity conditions, any discrete choice model derived from the random utility maximization has choice probabilities that can be approximated by a mixed logit model. [4] The applicability of the mixed logit model is well perceived amongst the IIA free discrete choice models, due to its known properties and the availability of routine estimation procedures.

The Multinomial Logit Latent Class Model

The LCM can be viewed as a semi-parametric extension of the conditional logit model or a “distribution free” mixed logit model (Greene and Hensher, 2002). It was initially used for market segmentation in marketing research (Swait, 1994). There are a few applications in non-market valuation (e.g., Boxall and Adamowicz, 2002; Provencher et al., 2002, Provencher and Bishop, 2004). Instead of continuous distributional assumptions for parameters, it assumes discrete changes in parameters across different classes that are distinguished by individual heterogeneity. Given a class assignment, parameters are the same for all individuals. The probability of choice j by individual i within the class c is exactly the same as equation (3) except that it is conditional on the class c.

$$\pi_{ij|c} = \frac{e^{\beta_c' w_{ij}}}{\sum_{k=1}^{J} e^{\beta_c' w_{ik}}} \tag{6}$$

Let the prior probability for class c for individual i be denoted P_{ic} that it can also be determined by a conditional logit model.

$$P_{ic} = \frac{e^{\delta_c' s_i}}{\sum_{l=1}^{C} e^{\delta_l' s_i}} \tag{7}$$

where s_i is a vector of individual characteristics and C is the number of classes. The expected probability of choice j for individual i is the weighted sum of choice probabilities in the C classes, $\pi_{ij} = \sum_{c=1}^{C} P_{ic} \cdot \pi_{ij|c}$. The log-likelihood function for the LCM with n individuals can be written as follows.

$$L = \sum_{i=1}^{n} \ln\left[\sum_{c=1}^{C} P_{ic} \cdot (\pi_{i1|c}^{x_{i1}} \cdot \pi_{i2|c}^{x_{i2}} \cdot \ldots \pi_{iJ|c}^{x_{ij}})\right] \tag{8}$$

where x_{ij}=1 if alternative j is chosen and x_{ij}=0 otherwise. The number of classes, C, is pre-specified in the log-likelihood function. The choice of C value can be determined by the Bayesian Information Criterion (Roeder et al. (1999)). Once the parameters in the likelihood function are estimated, the individual specific posterior class probabilities can be computed using the Bayes rule.

$$\hat{P}_{c|i} = \frac{\hat{\pi}_{ij|c} \cdot \hat{P}_{ic}}{\sum_{c=1}^{C} \hat{\pi}_{ij|c} \cdot \hat{P}_{ic}} \tag{9}$$

Note that if there is no covariate, then the prior class probabilities are the same across individuals (P_{ic}=P_c). However, the estimated posterior class probabilities are still individual specific because the choice probabilities for a given class assignment ($\pi_{ij|c}$) are individual specific. The individual specific posterior parameter estimates can be computed as the weighted average of the parameters over classes, $\hat{\beta}_i = \sum_{c=1}^{C} \hat{P}_{c|i} \cdot \hat{\beta}_c$.

The mixed logit model has gained much popularity in non-market valuation analysis for its flexibility and LCM is also getting more attention. [5] Provencher and Bishop (2004) compare standard logit, mixed logit, and LCM for their abilities to forecast trip behavior, and find that mixed logit model and LCM forecast equally well but they do not always outperform the standard logit model. In this study, we will compare these choice models in terms of the Hicksian welfare measures that they imply.

As seen, both mixed logit and LCM are designed to account for individual heterogeneity. In fact, individual characteristics can be incorporated as part of the model specification in all choice models including the standard conditional logit model. For example, choice specific intercept terms can depend on individual characteristics. Individual characteristics can also be interacted with choice attributes so the impact of choice attributes is individual specific. The additional advantage of mixed logit model and LCM is that they also allow parameters in the model to vary with individuals.

4. Welfare Measures for Changes in Choice (Program) Attributes

The welfare measure for a change in a choice attribute (e.g., improved catch rate at a fishing site) based on a standard conditional logit model, with a linear specification for the conditional indirect utility function (the V's), is the log-sum formula (Bockstael et al. 1991):

$$W_i = \frac{\ln(\Sigma_j e^{V(q_{ij})}) - \ln(\Sigma_j e^{V(q_{ij}^0)})}{-\beta_p} \tag{10}$$

where q_{ij}^0 is the vector of levels of product attributes associated with the initial state and β_p is the coefficient of p_{ij} such that $-\beta_p$ is the marginal utility of income. The β_p can be a function of individual characteristics. Based on the estimated conditional utility function and the formula in (10), we can derive the individual welfare measure associated with any changes in the choice (program) attributes. The average welfare measure is the average over individuals. Note that the formula in (10) can be used to compute the welfare measure for a change in one choice attribute for one choice alternative, or it can be used to compute the welfare measure for simultaneous changes in more than one attribute across partial or all choice alternatives. [6]

In the mixed logit model, some of the β's are random. The expected welfare measure can be derived by integrating the formula in (10) with respect to the random βs, $\int W_i(\beta)d\beta$. A simulation approach of random draws from the estimated distribution of βs is employed to compute the multiple integrals (Train, 1998). In the case of LCM, the β's vary across classes. The expected welfare measure based on the LCM can be computed as the weighted sum of welfare measure in all classes, weighted by the posterior individual specific class probabilities, $\sum_{c=1}^{C} P_{c|i} W_{ic}$ (Boxall and Adamowicz, 2002). As seen, the expression in (10) is the core of computing the welfare measures for all three empirical models.

In this study we apply the choice based conjoint analysis to examine generic, non-site specific erosion control programs that are characterized by their resulting impacts on the beach environment. Unlike the recreation site choice models in which the welfare measure is typically derived for altering the level of a site attribute for a particular site, (or for the elimination of a site), the same welfare measure is not meaningful when comparing alternative erosion control programs, unless it is derived in comparison to a status quote. As pointed out by Freeman (1991), the conjoint ratings of alternative housing bundles cannot be used to derive welfare measures for housing characteristics unless a numeraire good is used for comparison in deriving the ratings. Roe et al. (1996) concur and propose to analyze the rating differences between the suggested attribute bundles of an environmental commodity and the status quo to derive valid welfare measures from conjoint ratings. In this study, to enable welfare analysis, the opt-out "no program" option is necessarily provided as a choice within the choice set of J choices, so individuals have the option of choosing no erosion control to avoid any possible negative impact on beach environment that may result from erosion control activities. To compute the welfare measure for preserving one mile of beach by any of the J-1 erosion control programs, in comparison to the "no program" choice with no beach preservation, we start by invoking one unit increase in the beach preservation attribute for the J-1 program choices in the expression (10), then integrate over random βs for the mixed logit model and compute weighted sum over classes for the LCM.

For the qualitative choice attributes, it might be interesting to examine the welfare change if the J-1 program alternatives would result in the same (negative or positive) qualitative impact on beach environment; that is to compute the welfare measure by setting an impact attribute to a certain level for all program alternatives, except for the "no program" option for which the impact attribute is set to zero. In other words, the opt-out "no program" choice is again used as the baseline for comparison to derive welfare gains and losses of beach impacts universally caused by the J-1 alternative erosion control programs. The computation of this welfare measure again follows the formula in (10) with changes in an impact attribute necessary to achieve the same attribute level across J-1 program alternatives in the choice set.

One welfare measurement that can be of interest involves a common change in a choice attribute for all the J choice alternatives in the choice set. (Imagine that a proposed government policy will result in the same level change of a choice attribute for all choice alternatives.) Let q_{ijk} be the new level of attribute k induced by the choice alternative j, and q_{ijk}^{0} be the originally proposed level of attribute k. Now, suppose that the same new level of attribute k is applied to all J choice alternatives, such that $\Delta q_{ijk} = q_{ijk} - q_{ijk}^{0} = \Delta q_{ik}$ for all j. Based on the formula in (10) and assuming a linear specification for V, the welfare measure of a common change in attribute k for all choice alternatives based on a conditional logit model can be simplified as follows:

$$W_i = \frac{\Delta q_{ik} \beta_{ik}}{-\beta_{ip}} \tag{11}$$

where β_{ik} is the coefficient on the attribute k. Similar to (10), the expression (11) serves as the core that integration or weighted sum of (11) can be applied to derive the welfare measures for the mixed logit model and LCM. The expression in equation (11) gives the welfare measure for a common change in attribute k for all choice alternatives in a multiple choice model, which turns out to be similar to the typical welfare measure formula for the binary choice random utility model. It follows that if more than one attribute is changed simultaneously for all choice alternatives, the welfare measure is just the expression (11) summed over k. [7] Note that any of the coefficients (the β's) can depend on the individual characteristics, thus the welfare measures can be allowed to vary across individuals.

5. Survey Design and Data

An empirical study of the economic valuation of beach erosion control in New Hampshire (NH) and Maine (ME) is conducted. In this section, the survey design and data collection processes are presented.

Mail Survey Questionnaire and Implementation

There are approximately 18 miles of coastline in NH and about 70 miles of sand beaches in ME, located primarily in southern Maine from York north to Cape Elizabeth. This region provides a wide variety of uses and contributes significantly to the two States' economic and environmental resource base. The survey instrument design was initiated with two focus group meetings conducted in Londonderry (NH) and Wells (ME) in May, 2000. The results of the focus group meetings showed that in general, participants in both groups were well informed on the subject and concerns of beach erosion, as well as familiar with erosion control devices. In terms of evaluating specific erosion control programs, participants favored programs that would create "less destruction" to the natural environment. The information gleaned from these focus groups was an important component in determining the final set of attributes used to describe the impacts of different programs for comparison.

Based on the focus group results, we identify eight resulting impacts of erosion control programs. Each program can be described by the varying levels of the eight program effects on the beach environment along with its cost to a household. The eight impact attributes are: beach preservation, property protection, visible structure, restricted beach access, hazards to swimmers, alteration of wildlife habitat, erosion of a neighboring beach, and water quality deterioration. A hypothetical erosion control program can be created by randomly combining levels (values) of these attributes and program cost. The levels of attributes designed for this study are reported in

Table 1. Two attributes (beach preservation in miles and property protection in million dollars) and the program cost to a household (in dollars) have multiple levels. The remaining attributes are simplified to two levels (yes or no), and empirically, these qualitative program impact attributes are coded as 1 if a suggested erosion control program results in such impact and 0 otherwise. The program cost to a household serves as the payment vehicle in the survey design and is described as additional annual license plate renewal fees. [8] Given the fairly large number of attributes, it is not feasible to present all possible combinations of the levels of attributes to survey respondents. Instead, an orthogonal main effect design that investigates only the main attribute effects with no interactions is implemented in the survey. [9]

The questionnaire, along with a brochure describing beach erosion and erosion control in NH and ME, was sent to a randomly selected sample of 1200 households (600 in NH and 600 in ME) in August 2000. An initial introductory letter was mailed to each household within the sample, followed by the questionnaire and brochure. [10] Each potential survey respondent was first asked to rate and then rank erosion control program characteristics in terms of their perceived importance. The respondent was then presented with four pairs of hypothetical erosion control programs, one pair at a time, and asked to compare them. A sample pair of hypothetical erosion control programs used in the survey questionnaire is given in Table 2. The opt-out choice, no erosion control, as describe in the survey (see Table 2 for an example) states clearly that none of the erosion control program attributes will be realized if no erosion control is preferred to the two erosion control program alternatives. Hence, numerically we assign the value of 0 (no impact) to all program impact attributes for the status quo choice.

There were 89 undeliverable questionnaires due to incorrect mailing names and/or addresses, and 255 completed and returned questionnaires yielding an effective response rate of

23%. Recall that within each questionnaire, there were four pairs of erosion control programs to compare, along with the option to choose the status quo or "don't know." Subtracting the respondents with no choices or "don't know" answers yielded an unbalanced panel data set. The total number of program choices included in our quantitative analysis is 839. The characteristics of respondents are summarized in Table 3. The median income of the responded households is $52,500 for the NH households and $37,500 for the ME households, which is very close to the median income in both states according to the 2000 US Census. The demographics of the responded households are also close to those of the general population in NH and ME.

6. Model Specification and Estimation Issues

For the comparison of erosion control programs across locations, an important element in the model specification is to allow individual heterogeneity to affect choice decisions, and subsequently affect welfare measures. As discussed in Section 3, individual heterogeneity can be modeled by including variables of individual characteristics in the choice models and/or by allowing individual specific parameters. We first interact individual characteristics with erosion control program attributes to determine whether the effects of program attributes are affected by individual characteristics. The only attribute whose effect on choice decisions is consistently affected by individual characteristics, especially gender and work status, is the program cost (additional license plate renewal fee). Hence, in our basic conditional logit model, the program cost variable is interacted with the gender and work status dummies. In other words, we allow the marginal utility of income to vary with two individual characteristics, which means that different scaling factors for different individuals are applied to derive welfare measures. In addition, higher income households (households with income approximately twice the States' median household income or more) are found to be more likely to choose erosion control over no control at all. [11] Interestingly, those who live in coastal counties are on average less likely to support erosion control. [12] Based on the preliminary results, we determine the common, basic specification for the three empirical models; that is to interact the program cost variable with gender and work status dummy variables, and include choice specific intercept terms as functions of income level and living location. In addition, individual specific parameters are allowed in the mixed logit model and LCM.

All coefficients in the mixed logit model can be assumed random. However, specifying a complete set of random coefficients as functions of individual characteristics in a mixed logit model might not be estimable due to a potentially flat likelihood function (Greene, 2000; Ruud, 1996). Additional, but somehow arbitrary assumptions about the random coefficients might be necessary. As suspected, the full specification of the mixed logit model (assuming that all coefficients are random and are functions of individual characteristics) does not converge in this application. Allowing the cost variable to be random is especially troublesome. There are difficulties with estimating a random coefficient for the cost variable. Difficulties in addition to the convergence problems, include the determination of the plausible distribution, incorrect signs for some observations, and unreasonably large welfare measures when the estimated individual specific price coefficient is close to 0. To avoid these difficulties, some researchers recommend fixing the coefficient of the price variable in the mixed logit model (e.g., Revelt and Train, 1998; Goett et al., 2000). We adopt this strategy. We then try various subsets of random coefficients and examine the corresponding variance estimates. We find consistently significant variance estimates for two random coefficients associated with property protection and visible structure, indicating that survey respondents might have divergent views of these two erosion control program attributes. Hence, we present a mixed logit model with two random (normally distributed) coefficients, property protection and visible structure. The correlation between these two random coefficients is set to zero because it is not significantly different from zero. [13, 14]

The basic specification of the LCM follows the conditional logit model. In this paper, a LCM with two classes is presented. We find that the prior class probabilities are not affect by individual characteristics. Nevertheless, the posterior class probabilities are still individual specific as shown in Equation (9). [15]

7. Estimation Results

The estimation results of the three empirical models are presented in Table 4. The regression results show that most of the erosion control program attributes are significant except for property protection and the presence of a visible structure in the conditional logit model. The coefficients of these two attributes are assumed random with a normal distribution in the mixed logit model, and the standard errors of the two random coefficients are significant. We found in the focus group meetings, property protection to rank low on the priority of erosion control by most participants, even though it is one of the key determinants by policy makers for beach erosion control. Some people do not like to see erosion control related devices on beaches yet some visible structures such as jetties, can actually be appealing to certain beach goers such as fishermen. The significant randomness of these two coefficients in the mixed logit model seems to match with our observation of a wide range of opinions regarding these two attributes of erosion control.

The potential negative aspects of an erosion control program such as impact on wildlife habitat, erosion of a neighboring beach, and deterioration of water quality play important roles in the choice decisions. The constant marginal utility of income is rejected in all three models since the overall program cost coefficient (β_p) varies significantly with male and retire dummy variables (male=1 if male; retire=1 if retired). The marginal utility of income is larger for a male and/or a retiree. The high income households tend to support erosion control regardless the impacts to the beach environment. Those who live in coastal counties tend not to support erosion control programs—the sentiment also found in the focus group participants who live near the coast but not on the coast. The significant choice specific intercept terms indicate that on average, any erosion control can be preferred or disliked over the status quo of no erosion control regardless its impact on beach environment.[16] The coefficient estimates in the first class in the LCM are similar to the other empirical models and the estimated prior class probability for the first class is higher. However, some coefficient estimates in the second class in the LCM are noticeably larger in magnitude than those in the first class. The variation of welfare measures based on the LCM is thus expected to be larger.

The welfare measures for each impact attribute can be computed by invoking a change in one attribute at a time. The welfare measure of a common one unit change in an impact attribute for both erosion control program alternatives is computed for each of the two quantitative attributes, beach preservation and property protection. For each of the qualitative impact attributes such as whether to disturb wildlife habitat, we compute the welfare change so both erosion control program alternatives have the same qualitative impact on beach environment. The mean welfare measures (across individuals) for each impact attribute based on the three estimated models are reported in Table 5. The numbers in the brackets are the bootstrapped standard errors.[17]

The welfare measures associated with the insignificant coefficients are indicated with square brackets. The mean welfare measures based on the three empirical models are similar in magnitude and the confidence intervals of welfare measures across three models in general overlap. However, the welfare measures based on the LCM have noticeably much larger standard errors. All three models show large negative values associated with certain impacts of erosion control. Individuals incur large losses when an erosion control program has negative impact on wildlife habitat, and causes erosion of neighboring beaches and water quality deterioration. The estimated mean of the random coefficient of visible structure is insignificant in the mixed logit model. Note that the welfare measure for visible structure based on the mixed logit model has its sign reversed. It is because the expression of welfare measure is essentially an exponential function of a normal random parameter. The positive values of the random draws from the estimated parameter distribution are scaled heavier than the negative values such that the simulated expected welfare measure becomes positive even though the estimated mean of the random parameter is negative. This sign reversal in welfare measurement based on mixed logit models can also happen when the estimated mean of the random parameter is significant (Zhao, 2004). This is an issue that has not been addressed in the literature and a potential drawback to apply mixed logit models to choice analysis in non-market valuation.

Within the empirical models the marginal utility of income varies significantly with individual characteristics, in particular with respect to the male and retired dummy variables. Table 6 reports the mean welfare measures for specific groups of individuals based on the results of the conditional logit and mixed logit models. [18] The benefit estimates associated with the insignificant coefficients are again indicated with square brackets, and the bootstrapped standard errors are reported in the brackets. In general, welfare measures are lower (in absolute value) for retirees and for men, although some of the differences are not significant and the welfare measures for women vary noticeably in re-sampling. The welfare estimates in Tables 5 and 6 indicate that individuals value beach preservation but do not like certain impacts on beach environment caused by erosion control programs. Benefits of beach preservation alone cannot determine the optimal choice of erosion control programs in that the negative impact of an erosion control program on a beach environment can offset the positive economic values of its intrinsic purpose.

8. Remarks and Future Work

We design a choice-based conjoint analysis to value beach erosion control programs based on the effects induced by the programs. The method can be used to evaluate any public program or policy with multiple positive and negative effects. We find that to a typical individual, choices of erosion control programs are affected by both the positive and negative impacts of the programs. The economic benefit of an erosion control program to preserve a stretch of sand beach should take into account the potential negative impact on the coastal environment caused by the same program. It must be emphasized that the conjoint analysis of the erosion control programs in this study does not directly include recreation value since the recreation demand is site specific, and is thus difficult to include in the experimental design as a generic program attribute of erosion control. We acknowledge that a full comparison of erosion control programs at different sites should indeed incorporate recreation values at the sites. In the future, detailed information of household beach recreation activities can be collected along with erosion control program choices so that a joint determination of household beach recreation and erosion control program choices can be analyzed.

As seen the qualitative results and program choices are similar regardless empirical model choices. In our application, the conditional logit model provides similar individual specific welfare estimates as those based on mixed logit model. The bootstrapped confidence intervals are slightly tighter for the welfare measures based on mixed logit model. The point estimates of welfare measures based on LCM are similar to the other two models. However, the bootstrapped standard errors of welfare measures from LCM are noticeably larger. In contrast, the mixed logit model provides the most stable results in our application. As known, welfare measures are nonlinear functions of coefficient estimators. Further investigation of the small sample properties of the welfare estimators based on these discrete choice models is needed.

Estimated benefits and costs from existing studies are sometimes used to infer the benefits and costs for new regulations by government agencies for limited budget. A benefit transfer, as defined by Boyle and Bergstrom (1992), is the transfer of existing estimates of non-market values to a new study that is different from the study for which the values were originally estimated. The advantages of transferring benefit and cost measures are apparent. However, the results of benefit transfers can be misleading due to the quality of the existing studies, the similarity of the existing and new studies, and the method used to transfer values. Smith et al. (1999) note that benefit transfer analysis must be conducted within a policy framework that allows for changes in both the features of the natural resource under consideration as well as the characteristics of the people who care about it. In this study, erosion control programs are evaluated through a set of identified generic impact attributes and the values of attributes are allowed to be correlated and vary across individual characteristics. The comparison of erosion control programs to account for program effects and the demographics of program locations is feasible and future research to validate and ensure the transferability is warranted.

Notes

1. Following the recommendation by the NOAA panel (Arrow et al., 1993), in addition to the three program alternatives, the "don't know" option was also provided in our empirical study of New Hampshire and Maine beaches. There were however, only a few respondents that chose the "don't know" option and subsequently these observations were omitted from the data analysis.

2. We also tried the heteroscedastic extreme value model, which is an extension of the conditional logit model with non-constant variances. The results were similar to those for the conditional logit and the estimated variances were all very close to 1. The multinomial probit model also showed similar results as the conditional logit model. These models are designed to relax the assumption of independence from irrelevant alternatives (IIA) embedded in the standard conditional logit model and can be formulated to incorporate individual heterogeneity. In this paper, we present the simple conditional logit model as the baseline model for comparison with mixed logit model and LCM that are specifically designed to derive individual specific parameter estimates.

3. The random coefficients in the indirect utility functions across choice alternatives induce the correlation of choice alternatives to relax the IIA assumption. However, in the standard mixed logit model, the correlation induced by a random coefficient is the same between any of the two choice alternatives because the same random coefficient appears in all indirect utility functions associated with the choice alternatives. The induced correlation can be strict and unrealistic. Additional treatments such as including choice dummy variables are required to allow specific correlation structure among choices.

4. See Greene (2000, pp. 871-875) for the description and an empirical comparison of the conditional (multinomial) probit and mixed logit models.

5. A similar random-parameters discrete choice model that assumes normality for both ε's and β's, has also been applied to non-market valuation (Layton, 2000).

6. von Haefen (2003) suggests an alternative approach to welfare measurement from the multiple choice random utility model that uses an individual's estimated utility of the actual choice as the baseline utility to derive the conditional welfare changes. The proposed welfare measure can also be computed for either a change in quality of a particular site choice or the loss of a site.

7. Johnson et al. (1999) propose to use a similar formula to derive the welfare measure for product j:

$$W_{ij} = \frac{\sum_k (q_{ijk} - q_{ijk}^0)\, \partial V^i / \partial q_{ijk}}{-\, \partial V^i / \partial P}$$

Their formula of welfare measure of changes in choice attributes for the specific choice alternative j is inconsistent with the random utility framework for the multiple choice models as described in (10). Nonetheless, by dropping the subscript j the formula is pertinent if it is used to describe the welfare measure for common changes of choice attributes across all choice alternatives.

8. Given that there is no broad based tax structure in New Hampshire, the choices of a payment vehicle applicable to all households are limited.

9. In the focus group meetings, we presented two sets of program comparisons. In one comparison, the erosion control programs were described based on four impact attributes and costs. In the other, programs were described using eight attributes and costs. The focus group participants acknowledged the difficulties of comparing programs based on eight impact

attributes. However, the majority of the participants still preferred the program description of eight attributes over four for its more thorough presentation of the actual program effects.

10. A reminder card was sent following the survey packet. Due to budget constraints, we were unable to conduct the second mailing.

11. Instead of the actual income, we chose to use an income dummy variable to distinguish the higher income households from the others. This specification allows simple comparison of WTP estimates of two income groups. According to the US 2000 Census, the median household income is $37,240 in Maine and $48,928 in New Hampshire. We used the average median income in two States multiplied by 2 to define the higher income households. We also tried two other grouping criteria. Results were very similar.

12. The choice specific intercept terms are meaningless in the case of unlabeled choice alternatives. However, in the presence of a status quo of no program as the reference choice alternative, choice specific intercept terms for any erosion control program indicate a preference of any program over no program. Technically we can restrict the choice specific intercept terms to be the same for the two erosion control program choices.

13. Other rules for reducing the number of random coefficients in the estimation were attempted. The qualitative results of most coefficients were very stable with expected signs, regardless of the model specification. Certain coefficients (wildlife habitat and erosion of a neighboring beach) became insignificant when their coefficients were assumed random. We also tried random intercepts models to mimic the random effects models but the estimation did not always converge and the standard deviations for the random intercepts were often insignificant.

14. As shown in Train (1999), the estimation time of mixed logit models can be significantly shortened by Halton draws. We employ 150 Halton draws instead of regular random draws in the estimation.

15. In this paper, the number of classes is not determined by information criteria such as BIC because the results associated with higher number of classes are unreasonable and often un-estimable in our application. We acknowledge that due to this arbitrary choice regarding the number of classes, the results of LCM can be seen as disadvantaged in comparison to the other two models.

16. Note that the magnitude of the intercepts of the two erosion control program choices is similar since the erosion control programs are not systematically ordered in the survey. For generality, we do not restrict the intercept terms to be the same between two program choices in the estimation.

17. There are different methods to derive standard errors for the welfare measures based on discrete choice models. One method is to approximate the variance analytically by Taylor series expansion of the welfare measure (Cameron, 1991). Another method is to draw from a multivariate distribution based on the estimated coefficients and the associated covariance matrix (Krinsky and Robb, 1986). The other method is to bootstrap from the estimated choice probabilities and re-estimate the models. This method is originally proposed by Duffield and Patterson (1991) for the binary choice models. The computation of any of these methods is non-trivial especially for the mixed logit model because the associated welfare measure must be derived via simulation. In this paper, we adopt the method by Duffield and Patterson (1991) and extend it for the multiple choice models.

18. The individual specific welfare measures based on LCM are omitted from Table 6 to conserve space. Note that the welfare measures by individual characteristics based on the LCM have similar magnitude as those based on the other two models. However, the standard errors are much larger, as seen in Table 5. The estimated coefficient of the cost variable in LCM varies significantly between two classes and across re-sampling, which can result in large variation in welfare measures.

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Table 1
Erosion Control Effects in the Choice Design
(Orthogonal Main Effect Design with 4 Blocks)

Attributes of an Erosion Control Program	Levels of Each Attribute
Sand beach preservation (miles)	1, 2, 3, 4
Property protection ($million)	1, 2, 3
Annual cost to a household ($)*	($3, $7, $11, $15) × #cars in a household
Visible structure on beach	Yes, No
1/1000 chance of minor injury to swimmers	Yes, No
Restricted beach access and swimming area	Yes, No
Disturbance to wildlife habitat (no threat of extinction)	Yes, No
Erosion on neighboring beach	Yes, No
Deterioration (10%) of salt water quality near beach	Yes, No

*The proposed annual cost to a household is an additional license plate renewal fee times the number of cars in the household.

Table 2
An Example of Conjoint Choice of Beach Erosion Control Programs

Program 1	Program 2
<u>Impacts</u>: 1. 4 mile stretch sand beach preserved 2. $7 collected at each license plate renewal for beach preservation 3. Total $1 million worth of properties protected 4. No visible structure/device 5. No danger to swimmers 6. No restriction on beach access 7. Disturbance to wildlife habitat (no threat of extinction) 8. Causing some erosion on neighboring beach 9. Slight deterioration (10%) of salt water quality near beach due to reduced water circulation	**<u>Impacts</u>**: 1. 2 mile stretch sand beach preserved 2. $15 collected at each license plate renewal for beach preservation 3. Total $2 million worth of properties protected 4. Visible (permanent) structure/device on beach 5. Slight chance (1/1000) of minor injury to swimmers 6. Restricted beach access and swimming areas 7. No impact on wildlife habitat 8. No causing erosion on neighboring beach 9. No impact on salt water quality near beach

Based on the impacts of Programs 1 and 2, which program would you prefer? (CIRCLE ONE ANSWER)

1. Program 1 → WHY? ____

2. Program 2 → WHY? ____

3. Prefer no erosion control program over Programs 1 and 2 (i.e., no beach preservation, no property protection, no cost, and no human activities to alter beach attributes).

4. Don't know → WHY? ____

Table 3
Summary Statistics of Respondents in NH and ME

NH residents	54%	
Living in a coastal county	36%	
Male	63%	
Married	67%	
College degree	51%	
Children under 18 in the household	32%	
Non-White	2%	
Retired	18%	
Primary residence ocean front	1%	
	Mean	Std Dev
Age	48.69	15.83
Household Income ($)	56133	28155
# Cars in the household	1.92	0.82

Table 4
Three Empirical Models

Variables	Model 1 Conditional Logit	Model 2 Mixed Logit	Model 3 Latent Class	
			Class 1	Class 2
Program Cost to a Household (Unit: $)[a]				
α_p	-0.019***b	-0.031***	-0.019**	-0.022**
	(0.007)	(0.010)	(0.008)	(0.010)
MALE	-0.028***	-0.032***	-0.040***	-0.031***
	(0.008)	(0.012)	(0.010)	(0.011)
RETIRE	-0.048***	-0.035*	-0.016	-0.086***
	(0.013)	(0.019)	(0.016)	(0.021)
Beach Preservation	0.174***	0.284***	0.406***	-0.329***
(Unit: mile)	(0.050)	(0.067)	(0.067)	(0.088)
Property Protection	-0.094	-0.378***	-0.093	-0.118
(Unit: $million)	(0.065)	(0.124)	(0.074)	(0.114)
Visible Device on Beach	-0.017	-0.025	-0.053	0.449***
(Yes=1)	(0.092)	(0.131)	(0.104)	(0.160)
1/1000 Chance Swim Hazard	-0.250***	-0.340***	-0.370***	-0.181
(Yes=1)	(0.090)	(0.118)	(0.103)	(0.165)
Restrict Access	-0.261***	-0.384***	-0.408***	0.090
(Yes=1)	(0.091)	(0.118)	(0.107)	(0.160)
Impact on Wildlife Habitat	-0.588***	-0.722***	-0.567***	-0.893***
(Yes=1)	(0.093)	(0.117)	(0.106)	(0.175)
Erosion of Neighboring Beach	-0.473***	-0.572***	-0.433***	-1.018***
(Yes=1)	(0.092)	(0.130)	(0.103)	(0.171)
10% Deterioration of Water Quality	-0.531***	-0.772***	-0.429***	-1.055***
(Yes=1)	(0.091)	(0.134)	(0.102)	(0.172)
Intercept1	2.245***	3.810***	3.432***	2.368***
	(0.274)	(0.421)	(0.371)	(0.401)
Intercept1_Coastal County	-0.562***	-0.447	0.800*	-1.250***
	(0.204)	(0.399)	(0.415)	(0.305)
Intercept1_High Income	0.524*	0.618	-1.671***	2.000***
	(0.280)	(0.528)	(0.381)	(0.411)
Intercept2	2.160***	3.749***	3.418***	2.417***
	(0.250)	(0.389)	(0.350)	(0.384)
Intercept2_Coastal County	-0.687***	-0.684*	0.630	-1.239***
	(0.202)	(0.382)	(0.419)	(0.255)
Intercept2_Hign Income	0.890***	1.141**	-1.628***	2.670***
	(0.272)	(0.512)	(0.389)	(0.389)
$\sigma_{Homesave}$		1.218***		
		(0.132)		
$\sigma_{SeeDevice}$		0.936***		
		(0.217)		
Prior Class Probability			0.649***	0.351***
			(0.041)	(0.041)
Log-Likelihood	-760.998	-670.342	-693.147	

[a]The overall coefficient of the program cost variable is $\beta_p = \alpha_p + \lambda_1 * MALE + \lambda_2 * RETIRE$.

[b]Standard errors are in the parentheses. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively. The correlation of the two random coefficients in Models 2 is insignificant and set to zero.

Table 5
Estimated Mean Benefit/Loss for Each Program Attribute

Attribute	Model 1	Model 2	Model 3
Beach saved (per mile)	5.25 (3.57)	5.84 (3.06)	4.21 (98.10)
Home saved (per million dollars)	[-2.85] (2.66)	-7.76 (2.35)	[-2.79] (127.59)
Visible structure on beach	[-0.19] (1.32)	[1.12] (1.05)	0.88 (176.18)
1/1000 chance of minor injury to swimmers	-3.81 (3.19)	-3.57 (1.63)	-4.69 (110.58)
Restricted beach access and swimming areas	-3.18 (2.98)	-3.40 (1.50)	-3.06 (65.82)
Disturbance to wildlife habitat	-4.75 (4.72)	-4.29 (1.49)	-4.88 (89.21)
Causing some erosion on neighboring beach	-5.74 (7.95)	-4.74 (2.48)	-6.30 (493.80)
10% deterioration in salt water quality near beach	-4.13 (4.76)	-4.56 (1.55)	-4.49 (639.46)

Note: The benefit estimates associated with insignificant coefficients (at 0.1 level) are indicated with square brackets. Bootstrapped standard errors are in the brackets.

Table 6
Estimated Mean Benefit/Loss for Each Program Attribute by Groups of Individuals

Attributes	Model 1				Model 2			
	Non-retiree		Retiree		Non-retiree		Retiree	
	Male	Female	Male	Female	Male	Female	Male	Female
Beach saved (per mile)	3.71 (1.23)	9.28 (10.04)	1.84 (0.62)	2.62 (1.06)	4.52 (1.28)	9.21 (8.21)	2.90 (0.95)	4.31 (2.42)
Home saved (per million dollars)	[-2.01] (1.40)	[-5.04] (6.22)	[-1.00] (0.70)	[-1.42] (1.08)	-5.97 (1.54)	-12.28 (4.84)	-3.88 (1.08)	-5.69 (2.29)
Visible structure on beach	[-0.12] (0.72)	[-0.37] (2.95)	[-0.04] (0.23)	[-0.07] (0.43)	[0.89] (0.72)	[1.76] (1.95)	[0.52] (0.39)	[0.69] (0.84)
1/1000 chance of minor injury to swimmers	-2.73 (1.03)	-6.67 (9.09)	-1.16 (0.48)	-2.32 (1.03)	-2.80 (1.05)	-5.46 (3.73)	-1.82 (0.76)	-3.20 (1.87)
Restricted beach access and swimming areas	-2.49 (0.92)	-5.12 (8.52)	-1.25 (0.50)	-2.12 (0.95)	-2.83 (0.97)	-4.86 (3.40)	-1.97 (0.80)	-3.15 (2.31)
Disturbance to wildlife habitat	-3.49 (0.73)	-8.27 (14.19)	-1.55 (0.36)	-2.06 (0.65)	-3.37 (0.66)	-6.74 (4.04)	-2.07 (0.51)	-2.82 (1.37)
Causing some erosion on neighboring beach	-3.31 (0.86)	-11.80 (24.07)	-1.01 (0.32)	-1.82 (0.72)	-3.22 (0.85)	-8.54 (7.06)	-1.63 (0.62)	-2.70 (2.02)
10% deterioration in salt water quality near beach	-3.09 (0.59)	-7.10 (14.31)	-1.38 (0.30)	-1.82 (0.53)	-3.64 (0.61)	-7.05 (4.30)	-2.23 (0.49)	-3.05 (1.64)
#Individuals	112	74	29	10	112	74	29	10

Note: The benefit estimates associated with the insignificant coefficients (at 0.1 level) are indicated with square brackets. Bootstrapped standard errors are in the brackets.