Economic Valuation of Beach Erosion Control*

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October 19, 2006

* The opinions expressed here are those of the authors, and do not necessarily express the views of the United States Environmental Protection Agency.

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Abstract:

In this study, we employ a choice-based conjoint survey design to elicit individual choices of beach erosion control programs that can potentially cause multiple effects on beach environment. Two 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 his/her choices. We find that the economic benefit of an erosion control program to preserve a stretch of sand beach can be grossly exaggerated if potential negative impacts on the coastal environment from the same program are not considered. This study demonstrates feasible comparisons of beach erosion control programs that account for their multiple effects as well as the demographics of program locations.

Key Words: Beach Erosion Control, Choice Based Conjoint Analysis, Individual Specific Welfare Estimates

JEL Classification: Q26, H41

Introduction

According to the United States Army Corps of Engineers, close to half of the United States beaches are experiencing significant erosion problems. Beach erosion can be caused by a combination of human-induced development, global rising of the sea level, occasional violent weather systems, and chronic sediment transport by waves. Some of the negative impacts associated with beach erosion include losses of recreational beaches, tourist-related business, ocean front properties, land for aquaculture, and wildlife habitat. Government involvement in erosion control is justified due to the public goods characteristics of most coastal beaches. Various erosion control programs/plans have been implemented in the coastal regions of the United States (U.S.). There are many erosion control methods (e.g., http://www.nicholas.duke.edu/psds/Stabilization/Categories.htm), of which most have multiple effects, both positive and negative, on the beach and surrounding environment. For example, erosion control programs that require maintenance and adjustments can restrict use of beaches over a period of time. Some such programs require installation of visible structures that can affect both the aesthetics of beaches and the overall experience of the beach trip itself. Yet other erosion control methods can initiate or accelerate erosion on neighboring beaches or affect coastal wildlife habitat. If these effects are not considered when developing erosion control programs, non-optimal program choices can result.

The particular coastal areas studied in this paper include the states of New Hampshire (NH) and Maine (ME). 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 beach nourishment experience in these two states is relatively limited. A summary of the beach nourishment projects in these areas from 1935 to 1996 can be found in Haddad and Pilkey (1998). In February 1997, the Maine State Planning Office and the Maine Department of Environmental Protection established a stakeholders group with the goal of developing policy recommendations essential to the management and use of beaches in Maine. The five key issues reported by the stakeholders group in their April 1998 report included: beach erosion; property at risk; wildlife habitat; public use of beaches; and regulation of activities in sand dunes. In order to provide cost effective management of this resource it is crucial to estimate both the benefits and costs associated with various management alternatives. The NH/ME Sea Grant Offices presented specific future objectives in their 1996 publication "Sustaining a Sea Beside the Sea." They acknowledged the need to produce socioeconomic information to assist decision makers who must weigh the impacts of various types of coastal improvement and the cost of beach protection/restoration.

The purpose of this study is to derive welfare estimates that are adjustable according to individual heterogeneity and the varying effects of different erosion control programs. A mail survey of randomly selected NH and ME households is conducted. We employ choice based conjoint analysis and ask survey participants to compare erosion control programs which vary according to 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. Two empirical choice models, namely the conditional logit and mixed logit models, are employed to incorporate individual heterogeneity into the program choice analysis. We confirm that preferences for erosion control programs are indeed affected by both program attributes and household/individual characteristics, as are the subsequently derived benefit estimates.

In the next section, we review previous valuation research on beach protection/nourishment, as well as attribute-based stated choice methods for non-market valuation. We then describe the survey design for valuing beach erosion control and data collection process. The empirical models to analyze individual choices of erosion control programs and the associated welfare measures are presented, followed by the discussion of model specification and estimation issues, and the results of the data analysis. Some concluding remarks are then presented.

Valuation of Beach Erosion Control

The majority of the research on beach valuation, estimates recreation demand for a site using the travel cost method and then derives 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; Kriesel and Friedman 2003). There are recent studies of beach recreation site choices that use the random utility framework (e.g., Parsons, Massey, and Tomasi 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, Gerlowski, and Williams 1992). In the sizeable literature on 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 erosion 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 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, Krieger, and Wind 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, Boyle, and Teisl 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 (e.g., Opaluch et al. 1993; Adamowicz, Louviere, and Williams 1994; Blamey, Gordon, and Chapman 1999; Cameron et al., 2002). 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.

Survey Design and Data Summary

The survey instrument design was initiated with two focus group meetings conducted in Londonderry (NH) and Wells (ME) in May, 2000. 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. 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.[2] Given the fairly large number of attributes, it is not feasible to present all possible combinations of the levels of attributes to survey respondents.[3] Instead, an orthogonal main effect design that investigates only the main attribute effects with no interactions is implemented in the survey.

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.[4] 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.

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 each survey respondent was asked to compare four pairs of erosion control programs. Subtracting the missing values or "don't know" answers yielded an unbalanced panel data set with a total of 797 program choices. The characteristics of respondents by state are summarized in Table 3. Most of the demographic variables are comparable between the two states. The ones that differ noticeably are the percentage living in a coastal county, average number of trips to beaches, and mean household income. To capture the differences between the two states, these variables will be included in the analysis of erosion control program choices.

Discrete Choice Models and Welfare Measures

In this paper, we choose two empirical models to illustrate the alternative modeling strategies to take into account individual heterogeneity in analyzing choice decisions. These models are the conditional logit model and mixed logit model. The conditional logit model is the standard model for choice analysis. The mixed logit model is selected because it is designed to allow preference heterogeneity across individuals, which is the focus of this paper.[5]

The general log-likelihood function that represents the corresponding set of n choice decisions can be written as follows.

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

where x_{ij}=1 if good j is chosen by individual i and x_{ij}=0 otherwise; π_{ij} is the probability that individual i chooses the good j. J equals the total number of choice alternatives including J-1 erosion control programs plus the no-program option. The conditional logit model is to assume a logistic function for π_{ij} as a function of the utility level (McFadden (1973)).

$$\pi_{ij} = \frac{e^{V_{ij}}}{\sum_{k=1}^{J} e^{V_{ik}}} = \frac{e^{\beta' w_{ij}}}{\sum_{k=1}^{J} e^{\beta' w_{ik}}} \quad (2)$$

The indirect utility function 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); β is a vector of variable coefficients that are usually assumed constant across individuals and product choices.

The mixed logit model assumes that the parameters in the indirect utility function V_{ij} vary randomly across individuals 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.

$$\beta_{ik} = \beta^*_{ik} + u_{ik} = \alpha_k + \lambda_k ' s_i + u_{ik} \qquad i = 1,...,n \quad k=1,...,K \tag{3}$$

The vector of parameters λ_k indicates the impact of individual characteristics on β_{ik}. The u's are random errors with zero means. Since π_{ij} depends on β_{ik}, with the assumption of normally distributed β_{ik}, the unconditional probability of π_{ij} in the log-likelihood function of the mixed logit model is derived by integrating over β_k, k=1,...,K (Haab and McConnell (2002)). The applicability of the mixed logit model is well perceived amongst the IIA free discrete choice models for its known properties and the availability of routine estimation procedures (McFadden and Train (2000)).[6] In general, 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 is that it also allows parameters in the model to vary with individuals.

The welfare measure for a change in a choice attribute 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, McConnell, and Strand 1991):

$$W_i = \frac{\ln(\Sigma_j e^{V(q_{ij})}) - \ln(\Sigma_j e^{V(q^0_{ij})})}{-\beta_p} \tag{4}$$

where q^0_{ij} 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 (4), we can derive the individual benefit/loss estimates associated with any changes in the choice (program) attributes. Note that the formula in (4) can be used to compute the welfare estimate for a change in one choice attribute for one choice alternative, or it can be used to compute the welfare estimate for simultaneous changes in one (or more than one) attribute across partial or all choice alternatives.[7]

In the mixed logit model, some of the β's are random. The mean welfare estimate can be computed by integrating the formula in (4) 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). As seen, the expression in (4) is the core of computing the welfare estimates for both empirical models. In the case study, we compute the willingness to pay for preserving one mile of beach by any of the erosion control programs in the choice set. For the qualitative choice attributes, we examine the welfare changes by setting an impact attribute to a certain level for each program alternative. To demonstrate the joint effects of program attributes, the overall welfare changes of some combinations of attributes are also computed.

Estimation and Results

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 benefit estimates. As discussed previously, individual heterogeneity can be modeled by including variables of individual characteristics and/or by allowing individual specific parameters in the choice models. We first interact individual characteristics with erosion control program attributes to investigate 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 monetary welfare estimates. Individual characteristics can also impact program choices directly. For example, the choice of erosion control program may be affected by the frequency of beach use. Avid users might want erosion control more than casual users. High income households are more likely to support erosion control programs that can be costly. Those who live in coastal counties may view erosion control differently than those who live further away from the coast. Further, as seen in the summary statistics in Table 3, these individual characteristics differ between the two states that including these variables also help discern the differences between states. Hence, we present a common, basic specification for both conditional and mixed logit models; that is to interact the program cost variable with gender and work status dummy variables, and estimate choice specific intercept terms as a function of individual characteristics including the coastal county dummy variable, high income level dummy variable, and frequency of beach use.[8]

The other estimation issue is to determine random coefficients in the mixed logit model. Technically all coefficients in the mixed logit model can be assumed random. However, specifying a complete set of random coefficients as a function of individual characteristics might not be estimable due to a potentially flat likelihood function (Greene, 2000; Ruud, 1996).[9] Allowing the coefficient of the program cost variable to be random is especially troublesome since it is the (negative) marginal utility of income that its value directly affects the computation of welfare measures. It is recommended by researchers to fix the coefficient of the cost variable (e.g., Revelt and Train 1998; Goett, Hudson, and Train 2000) and we adopt the 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.[10, 11]

Our idea is to capture the differences between states through demographic variables and individual characteristics so that the estimation results can be applied to choices of erosion control programs in states other than NH and ME. To examine and test whether our empirical choice models capture the differences between the two states, we first estimate models separately with NH and ME data; then we estimate a model with the pooled data; finally we estimate a pooled model with a state dummy variable. In the estimation, we set the status quo of no program as the reference choice, so the (positive) choice specific intercept terms for any erosion control program indicate a preference of the program over no program.

The estimation results of the conditional and mixed logit models are presented in Tables 4 and 5, respectively. Each table contains four estimated models that differ by the data sets: NH, ME, pooled, and pooled with a state dummy variable. All estimated models are numbered consecutively with Models 1 – 4 in Table 4 and Models 5 – 8 in Table 5. Most of the erosion control program attributes are significant except for property protection in the conditional logit model and the presence of a visible structure in both empirical models. (The swim hazard attribute is insignificant for the NH data.) The coefficients of the property protection and visible structure attributes are assumed random with a normal distribution in the mixed logit model, and the standard errors of the two random coefficients are significant (Table 5). 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. Further, the constant marginal utility of income in general is rejected in both conditional logit and mixed logit models since the overall program cost coefficient (β_p) varies significantly with male and/or 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 NH high income households tend to support erosion control regardless of the impacts to the beach environment. Trip frequency does not significantly impact program choices that those who visit beaches more frequently are not more likely to choose to control erosion. 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 (except for the NH data), positive choice specific intercept terms indicate that on average, any erosion control is preferred over the status quo of no erosion control regardless of its impact on the beach environment.[12]

We conduct likelihood ratio (LR) tests for data pooling based on Models 1, 2, and 3 in Table 4, and Models 5, 6, and 7 in Table 5. The LR test statistics are respectively 29.7 based on the conditional logit models and 29.1 based on the mixed logit models. Data pooling is rejected at α=0.1 but it cannot be rejected at α=0.05 for the conditional logit models [$\chi^2_{19,0.1} = 27.2$, $\chi^2_{19,0.05} = 30.1$]; and data pooling cannot be rejected for the mixed logit models [$\chi^2_{21,0.1} = 29.6$, $\chi^2_{21,0.05} = 32.7$]. Further, the NH state dummy variable is insignificant in both conditional and mixed logit models (Models 4 and 8). The test results lend support to the specification of the empirical models for deriving welfare estimates that can be adjusted according to individual characteristics and choice attributes, regardless of states. The demographic variables included in the empirical models seem to capture most of the differences between the two states. Hence, in the welfare analysis, we present the mean benefits/losses of erosion control program attributes based only on the pooled models 3 and 7. We also present the welfare estimates by individual characteristics based on the same pooled models to show the impact of individual heterogeneity on welfare measurement. Welfare estimates based on the other estimated models are available upon request.

The mean welfare estimates for each impact attribute by states based on the pooled models 3 and 7 are reported in Table 6.[13] The numbers in the brackets are the bootstrapped standard errors.[14] The welfare estimates associated with the insignificant attribute coefficients are indicated with square brackets. As seen in Table 6, the ME residents have slightly higher welfare estimates than the NH residents, but the differences are not statistically significant. The mean welfare estimates based on the conditional logit and mixed logit models are similar in magnitude, although the welfare estimates based on the mixed logit models appear to be more precise with tighter confidence intervals. In general, 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 overall value of an erosion control program depends on its combined effects. Note that the overall welfare change of multiple impacts is not simply the sum of welfare changes from the individual impacts because of the nonlinearity in the formula of welfare measure as seen in (4).[15] For example, suppose an erosion control program is designed to preserve 5 miles of beach but it will cause a slight chance of injury to swimmers, disturbance to wildlife habitat, and deterioration of water quality. Based on the mean results of the pooled mixed logit model, this erosion control program has an estimated annual value of $4.45 per household. If another potential erosion control program preserves only one mile of beach but it will cause erosion on the neighboring beach and deterioration of water quality, then the overall value of this program is estimated to be -$3.65 per household. In this case, the benefit of the erosion control is outweighed by its negative effects on the beach environment. In a hedonic property value study, Kriesel and Friedman (2003) find that shoreline stabilization can benefit ocean front property owners but it has adverse effects on the broader community. Our findings are consistent with theirs.

Table 7 reports the mean welfare estimates for specific groups of individuals based on the results of the pooled conditional logit and mixed logit models 3 and 7. The benefit estimates associated with the insignificant attribute coefficients are again indicated with square brackets, and the bootstrapped standard errors are reported in the brackets. In general, welfare estimates are lower (in absolute value) for retirees and for men, and the welfare estimates among women have larger variation. The welfare estimates in Tables 6 and 7 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 impacts of an erosion control program on a beach environment can offset the positive economic values of its intrinsic purpose.

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, and derive empirical models to be used to derive welfare estimates that can be adjusted according to individual characteristics and choice attributes. The method can be used to evaluate any public program or policy with multiple positive and negative effects facing different stakeholders.

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 can be grossly exaggerated without taking into account the potential negative impacts on the coastal environment caused by the same program. The total number of all beach trips is included as an explanatory variable in the choice models as one way to investigate the impact of frequency of beach use on the choice of erosion control program. As seen in Tables 4 and 5, the variable of total trips is not significant in all models. We also try other specifications, and the trip frequency is consistently insignificant. As a future extension, 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.

This analysis shows that the qualitative results and program choices are similar regardless of the choice of empirical model. In our application, the conditional logit model provides similar individual specific welfare estimates as those based on the mixed logit model. The bootstrapped confidence intervals are tighter for the welfare estimates based on mixed logit model (in Table 6). Given that 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. 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. Given that there is no broad based tax structure in New Hampshire, the choices of a payment vehicle applicable to all households are limited.
3. 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.
4. An initial introductory letter was mailed to each household within the sample, followed by the questionnaire and brochure. A reminder card was sent following the survey packet. Due to budget constraints, we were unable to conduct the second mailing.
5. We also tried a few other empirical choice models. The heteroscedastic extreme value model, which is an extension of the conditional logit model with non-constant variances, produced results similar to those for the conditional logit model, and the estimated variances were all very close to 1. The multinomial probit and the multinomial logit latent class models also gave similar estimates 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 the popular mixed logit model which is specifically designed to derive individual specific parameter estimates.

6. 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 for the same individual. 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.
7. 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.
8. Instead of the actual income, we chose to use an income dummy variable to distinguish the higher income households from the others. 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. There was no qualitative difference whether the actual income or income dummy was used, but the model with the income dummy was more significant and it allowed simple comparison of

WTP estimates of two income groups. We also tried two other grouping criteria. Results were very similar. The results employing the actual income variable are available upon request.

9. In the preliminary estimation, the full specification of the mixed logit model (assuming that all coefficients are random and are functions of individual characteristics) does not converge. Estimation difficulties other than the convergence problems include determination of the plausible distribution, incorrect signs for some observations, and unreasonably large welfare estimates when the estimated individual specific price coefficient is close to 0.

10. 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.

11. 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.

12. 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.

13. Welfare estimates of program attributes for each of the two program alternatives are computed, and the average estimates of the two programs are reported. In the pooled models,

even though parameters are the same for the two states, the values of explanatory variables differ to result in different welfare estimates between the two states.

14. 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 (Huang, 1994).

15. Nevertheless, the direct sum of welfare changes from each of the multiple impacts can provide a quick approximation for the overall value of an erosion control program with multiple impacts.

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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	Attribute Levels
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

	All		**New Hampshire**		**Maine**	
NH residents	54%		--		--	
Living in a coastal county	37%		28%		46%	
Primary residence ocean front	1%		1%		2%	
Living with children under 18	32%		29%		35%	
Male	63%		69%		58%	
Married	65%		66%		64%	
College degree	51%		55%		48%	
Non-white	2%		3%		1%	
Retired	18%		18%		18%	
	Mean	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
# trips to NH/ME beaches in 1999	7.52	12.41	6.09	10.22	9.18	14.37
# trips to all beaches in 1999	8.66	13.92	7.64	13.29	9.83	14.53
Household income ($)	56156	28271	61458	27381	50036	28058
Household income > $84000	0.18	0.39	0.22	0.41	0.14	0.35
Age	48.97	15.88	49.6	15.63	48.26	16.13
# Cars in the household	1.93	0.83	1.97	0.85	1.88	0.8
# Respondents	213		114		99	
# Observations (# Program Choices)	797		427		370	

Table 4
Conditional Logit Models

	Model 1 NH	Model 2 ME	Model 3 Pooled	Model 4 Pooled
Program Cost to a Household (Unit: $)[a]				
α_p	-0.006	-0.036***	-0.018***	-0.018***
	(0.010)[b]	(0.011)	(0.007)	(0.007)
MALE	-0.047***	-0.008	-0.027***	-0.028***
	(0.011)	(0.012)	(0.008)	(0.008)
RETIRE	-0.023	-0.082***	-0.044***	-0.044***
	(0.016)	(0.022)	(0.013)	(0.013)
Beach Preservation	0.154**	0.244***	0.197***	0.198***
(Unit: mile)	(0.071)	(0.078)	(0.051)	(0.051)
Property Protection	-0.070	-0.130	-0.091	-0.090
(Unit: $million)	(0.092)	(0.102)	(0.067)	(0.067)
Visible Device on Beach	0.141	-0.182	0.009	0.012
(Yes=1)	(0.134)	(0.148)	(0.095)	(0.095)
1/1000 Chance Swim Hazard	-0.076	-0.410***	-0.234**	-0.232**
(Yes=1)	(0.127)	(0.140)	(0.092)	(0.092)
Restrict Access	-0.293**	-0.174	-0.240***	-0.242***
(Yes=1)	(0.127)	(0.143)	(0.093)	(0.093)
Impact on Wildlife Habitat	-0.703***	-0.463***	-0.589***	-0.588***
(Yes=1)	(0.132)	(0.144)	(0.095)	(0.095)
Erosion of Neighboring Beach	-0.502***	-0.400***	-0.444***	-0.448***
(Yes=1)	(0.131)	(0.151)	(0.094)	(0.095)
10% Deterioration of Water Quality	-0.587***	-0.440***	-0.503***	-0.505***
(Yes=1)	(0.130)	(0.144)	(0.094)	(0.094)
Intercept1	1.932***	2.285***	1.986***	1.846***
	(0.378)	(0.450)	(0.284)	(0.308)
Intercept1_Coastal County	-0.154	-0.823***	-0.605***	-0.551**
	(0.338)	(0.311)	(0.216)	(0.221)
Intercept1_High Income	0.913**	-0.212	0.566**	0.516*
	(0.421)	(0.437)	(0.287)	(0.290)
Intercept1_# Total Beach Trips	0.009	0.005	0.010	0.011
	(0.013)	(0.011)	(0.008)	(0.008)
Intercept1_NH Dummy Variable				0.244
				(0.208)
Intercept2	1.955***	2.133***	1.943***	1.774***
	(0.343)	(0.417)	(0.259)	(0.283)
Intercept2_Coastal County	-0.417	-0.921***	-0.744***	-0.681***
	(0.338)	(0.310)	(0.215)	(0.219)
Intercept2_High Income	1.270***	0.312	0.933***	0.876***
	(0.414)	(0.411)	(0.280)	(0.281)
Intercept2_# Total Beach Trips	0.005	0.012	0.007	0.008
	(0.014)	(0.011)	(0.008)	(0.008)
Intercept2_NH Dummy Variable				0.294
				(0.206)

Log-Likelihood	-376.107	-338.475	-729.461	-728.352
McFadden's R^2	0.161	0.154	0.142	0.143
LR test stat for data pooling			29.758*	

[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 brackets. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

Table 5
Mixed Logit Models

	Model 5 NH	Model 6 ME	Model 7 Pooled	Model 8 Pooled
Program Cost to a Household (Unit: $)[a]				
α_p	-0.021 (0.014)[b]	-0.045*** (0.016)	-0.031*** (0.010)	-0.031*** (0.010)
MALE	-0.057*** (0.018)	-0.004 (0.019)	-0.032*** (0.012)	-0.032*** (0.012)
RETIRE	0.012 (0.026)	-0.092** (0.037)	-0.026 (0.020)	-0.027 (0.020)
Beach Preservation (Unit: mile)	0.267*** (0.098)	0.390*** (0.105)	0.327*** (0.070)	0.328*** (0.070)
Property Protection (Unit: $million)	-0.337* (0.178)	-0.531** (0.209)	-0.421*** (0.134)	-0.419*** (0.134)
Visible Device on Beach (Yes=1)	0.185 (0.204)	-0.209 (0.194)	0.011 (0.135)	0.018 (0.135)
1/1000 Chance Swim Hazard (Yes=1)	-0.180 (0.168)	-0.439** (0.186)	-0.320*** (0.122)	-0.317*** (0.122)
Restrict Access (Yes=1)	-0.431** (0.170)	-0.274 (0.184)	-0.368*** (0.122)	-0.369*** (0.122)
Impact on Wildlife Habitat (Yes=1)	-0.905*** (0.174)	-0.550*** (0.178)	-0.736*** (0.121)	-0.737*** (0.121)
Erosion of Neighboring Beach (Yes=1)	-0.641*** (0.201)	-0.438** (0.191)	-0.546*** (0.135)	-0.550*** (0.135)
10% Deterioration of Water Quality (Yes=1)	-0.924*** (0.210)	-0.630*** (0.193)	-0.752*** (0.138)	-0.750*** (0.138)
Intercept1	3.495*** (0.600)	3.981*** (0.706)	3.577*** (0.443)	3.470*** (0.518)
Intercept1_Coastal County	0.372 (0.673)	-1.014 (0.630)	-0.403 (0.435)	-0.361 (0.446)
Intercept1_High Income	1.290* (0.766)	-0.606 (0.910)	0.810 (0.566)	0.774 (0.573)
Intercept1_# Total Beach Trips	0.006 (0.028)	0.004 (0.022)	0.006 (0.016)	0.007 (0.016)
Intercept1_NH Dummy Variable				0.160 (0.421)
Intercept2	3.526*** (0.546)	3.901*** (0.674)	3.570*** (0.411)	3.411*** (0.484)
Intercept2_Coastal County	-0.085 (0.640)	-1.186* (0.617)	-0.662 (0.415)	-0.599 (0.427)
Intercept2_High Income	1.997*** (0.748)	0.004 (0.898)	1.350** (0.548)	1.294** (0.554)
Intercept2_# Total Beach Trips	0.001 (0.027)	0.012 (0.022)	0.003 (0.016)	0.003 (0.016)
Intercept2_NH Dummy Variable				0.248 (0.407)

$\sigma_{Homesave}$	1.264*** (0.193)	1.392*** (0.232)	1.300*** (0.146)	1.294*** (0.146)
$\sigma_{SeeDevice}$	1.119*** (0.300)	0.668* (0.390)	0.928*** (0.228)	0.926*** (0.229)
Log-Likelihood	-329.461	-292.505	-636.492	-636.287
McFadden's R^2	0.265	0.269	0.251	0.252
LR test stat for data pooling			29.052	

[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 brackets. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively. The correlation of the two random coefficients is insignificant and set to zero.

Table 6
Estimated Mean Benefit/Loss for Each Program Attribute

	NH		ME		Pooled	
Attribute	Conditional Logit	Mixed Logit	Conditional Logit	Mixed Logit	Conditional Logit	Mixed Logit
Beach saved (per mile)	2.78 (3.72)	2.53 (1.03)	3.15 (5.00)	2.74 (1.23)	2.95 (4.31)	2.62 (1.12)
Home saved (per million dollars)	[-1.25] (1.94)	-1.36 (1.01)	[-1.42] (2.53)	-1.48 (1.18)	[-1.33] (2.21)	-1.42 (1.09)
Visible structure on beach	[0.06] (0.78)	[0.04] (0.58)	[0.06] (0.93)	[0.04] (0.64)	[0.06] (0.85)	[0.04] (0.61)
1/1000 chance of minor injury to swimmers	-1.63 (1.45)	-1.38 (0.73)	-1.81 (1.87)	-1.46 (0.83)	-1.72 (1.64)	-1.41 (0.78)
Restricted beach access and swimming areas	-1.64 (1.95)	-1.74 (0.87)	-1.89 (2.65)	-1.91 (1.06)	-1.76 (2.28)	-1.82 (0.96)
Disturbance to wildlife habitat	-4.53 (5.69)	-3.33 (1.47)	-4.98 (7.42)	-3.49 (1.75)	-4.74 (6.49)	-3.40 (1.60)
Causing some erosion on neighboring beach	-3.03 (2.87)	-2.55 (1.06)	-3.46 (3.86)	-2.82 (1.29)	-3.23 (3.33)	-2.67 (1.16)
10% deterioration in salt water quality near beach	-3.49 (4.44)	-3.17 (1.36)	-4.05 (6.08)	-3.52 (1.72)	-3.75 (5.20)	-3.33 (1.53)
Beach saved (5 miles), 1/1000 chance of injury to swimmers, disturbance to wildlife habitat, and 10% deterioration in salt water quality near beach	3.49 (8.19)	4.26 (3.96)	4.06 (10.72)	4.68 (4.41)	3.75 (9.36)	4.45 (4.17)
Beach saved (1 mile), causing some erosion on neighboring beach, and 10% deterioration in salt water quality near beach	-4.05 (4.29)	-3.48 (1.68)	-4.65 (5.84)	-3.86 (2.07)	-4.33 (5.01)	-3.65 (1.86)
# Respondents	114	114	99	99	213	213
# Observations (# Program Choices)	427	427	370	370	797	797

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 7
Estimated Mean Benefit/Loss for Each Program Attribute by Groups of Individuals

Attributes	Conditional Logit				Mixed Logit			
	Non-retiree		Retiree		Non-retiree		Retiree	
	Male	Female	Male	Female	Male	Female	Male	Female
Beach saved (per mile)	1.79 (0.55)	5.93 (13.41)	0.78 (0.26)	1.37 (0.51)	1.94 (0.58)	4.16 (2.46)	1.40 (0.50)	2.99 (8.89)
Home saved (per million dollars)	[-0.78] (0.58)	[-2.72] (6.58)	[-0.35] (0.26)	[-0.61] (0.49)	-1.02 (0.61)	-2.29 (2.35)	-0.73 (0.47)	-1.67 (5.25)
Visible structure on beach	[0.04] (0.41)	[0.12] (2.11)	[0.02] (0.19)	[0.03] (0.38)	[0.03] (0.43)	[0.06] (1.03)	[0.03] (0.33)	[0.06] (1.12)
1/1000 chance of minor injury to swimmers	-1.06 (0.44)	-3.42 (4.90)	-0.46 (0.20)	-0.74 (0.37)	-1.04 (0.46)	-2.28 (1.66)	-0.73 (0.35)	-1.47 (4.23)
Restricted beach access and swimming areas	-1.08 (0.48)	-3.50 (6.94)	-0.48 (0.22)	-0.81 (0.40)	-1.35 (0.51)	-2.89 (2.21)	-0.98 (0.41)	-1.99 (4.73)
Disturbance to wildlife habitat	-2.82 (0.65)	-9.64 (20.30)	-1.22 (0.31)	-2.18 (0.71)	-2.46 (0.60)	-5.52 (3.92)	-1.75 (0.56)	-3.85 (11.44)
Causing some erosion on neighboring beach	-2.07 (0.52)	-6.26 (10.35)	-0.90 (0.26)	-1.71 (0.59)	-2.03 (0.54)	-4.08 (2.61)	-1.47 (0.48)	-3.41 (9.89)
10% deterioration in salt water quality near beach	-2.34 (0.54)	-7.39 (16.30)	-1.04 (0.28)	-1.91 (0.65)	-2.49 (0.57)	-5.17 (3.63)	-1.83 (0.56)	-4.10 (12.35)
# Respondents	107	68	28	10	107	68	28	10
# Observations (# Program Choices)	401	253	105	38	401	253	105	38

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.