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Using Stated-Preference Questions to Investigate Variations in Willingness to Pay for Preserving Marble Monuments: Classic Heterogeneity, Random Parameters, and Mixture Models

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Abstract. This paper investigates heterogeneity in the preferences/WTP (willingness to pay) to preserve marble monuments in Washington, D.C. This is done in the context of three different discrete-choice random-utility models. The main focus is to estimate a mixture model of choices over preservation programs. This model captures the best features of random-parameters models and models that assume preference parameters are deterministic functions of observable characteristics of the individual. The mixture model, and it alone, predicts that increased preservation is a bad for a significant proportion of young, non-Caucasians. That some proportion of the population might consider preservation a bad is a contingency that should be planned for in efforts to value cultural resources. Data and computer code are available at http://www.colorado.edu/economics/morey/dataset.html .

Key words: choice experiments, mixture models, preference heterogeneity, random parameters

1. Introduction

This paper investigates heterogeneity in the preferences/WTP (willingness to pay) to preserve 100 significant marble monuments in Washington, D.C. Cultural resources, such as this set of monuments, represent culture, history, institutions and artistic achievements, and opinions as to their value (positive or negative) are likely to differ. Using a number of different discrete-choice random-utility models, we find WTP to preserve these monuments varies significantly across individuals. In our most general model, a mixture model, estimated WTP for increased preservation is positive and significant for most individuals, but negative for a significant proportion of young, non-Caucasians. This possibility is suggested by the responses to the choice and attitudinal questions, but this prediction did not manifest itself in our simpler models. We did not adequately plan for the possibility that some individuals might prefer that these monuments not be preserved. Unfortunately, young, non-Caucasian were nonexistent in our focus groups. In retrospect, and given the historical events and people honored with this set of monuments, we should have anticipated this result.

The data are responses to pair-wise hypothetical choices. Each sampled individual was asked to choose between two monument preservation programs. For example:

Preservation Option B for $7 or *Preservation Option C for* $25.

The choice question was repeated ten times with varying costs and preservation levels across the alternatives. Three different "treatment" (preservation) programs, A, B, and C, were created. The different effectiveness levels were achieved using different coating and application techniques. The three options were distinguished by how they affected the injury time line. Option A increased by 25% the amount of time it would take for a given level of injury to occur, B by 50%, and C by 100%.

Implicit in our design of choice questions is the assumption that while preferences vary, all individuals prefer, at a zero cost, more to less preservation. Individuals were never explicitly asked whether increased preservation was a good or a bad.[1] For applications to cultural resources, the researcher must test and plan for the possibility that the scenario is a good for some and a bad for others.

The term WTP suggests positive value; it is awkward to discuss negative WTP. Given this, we will discuss valuation in terms of the compensating variation, CV. The CV is the amount of money that must be subtracted from the individual's income in the new state to make the individual indifferent between the new state, with the compensation, and the original state. If the scenario is an improvement, $CV > 0$ and it equals WTP to attain the new, improved state. For a deterioration, $CV < 0$ and its absolute value is the individual's willingness to accept, WTA, the new, inferior state.

A standard approach to modeling the answers to stated-choice questions is a discrete-choice random-utility model: multinomial logit (MNL), nested-logit, or probit. Here we adopt the general MNL framework. Utility, conditional on the choice of a state of nature, is a function of the cost and characteristics of that state, characteristics which the researcher can observe, and an additive term, an epsilon, that is known to the individual, but is a random variable from the researcher's perspective. The MNL specification is obtained by assuming the additive component has an Extreme Value distribution. Note that the individual is being asked to choose which program (state of the world) he prefers, not what he would do if an alternative were in place.[2] The epsilons vary both across individuals and across choice occasions for a given individual, a choice occasion occurring each time the individual makes a choice.[3]

In any discussion of heterogeneity, it is important to distinguish between individual i's CV for preserving monuments, CV_i, and the researcher's expectation of it, $E[CV_i]$. The two can be the same or differ for a number of reasons. In our simple MNL model that has only one alternative in each state of the world, there is no difference, $CV_i = E[CV_i]$, but this is not the case in random-parameters models or mixture models.[4] In those models, the *CV*s for a group of identical individuals (from the researcher's perspective) will have some distribution invoked by the variations in their preference parameters.[5]

A number of issues are important in any investigation of preference heterogeneity including: (1) the extent of the heterogeneity – that is, the magnitude of the variation across the individuals' *CV*s and $E[CV]$s; (2) whether the range for either the *CV*s or $E[CV]$s spans zero; and (3), the distribution of the *CV*s and $E[CV]$s. For example, are the distributions continuous or discrete?

One must also distinguish between heterogeneity that can and cannot be explained in terms of observed characteristics of the individual; we deem these *explained* and *unexplained* heterogeneity. For example, the variation in *CV*s across individuals caused by random variation in their preference parameters is unexplained variation. Variation explained in terms of age and gender, is explained variation.

The results presented here extend a study (Morey et al., 1997, 2002) undertaken to determine the benefits society would receive from a reduction in the rate of injury to 100 significant marble monuments in Washington, D.C. Marble monuments are injured by exposure to air pollutants such as sulfur dioxide (SO_2), which is being reduced by Title IV of the 1990 Clean Air Act Amendments. The issues are how society values this reduction in the rate of injury and how these values vary across individuals. Details on the focus groups, surveys, choice question, etc. can be found in Morey et al. (1997, 2002) which are available at http://www.colorado.edu/economics/morey/discuss.html.

Morey et al. (1997, 2002) incorporate preference heterogeneity into a MNL model by allowing variation in the preference parameters, β, across individuals by estimating β as a function of observable characteristics of the individuals. Conditional indirect utility is assumed a function of the level of preservation of alternative j, $Preservation_j$, and the amount of money the individual has left to spend on all other goods after choosing preservation alternative j, $(Income_i - Price_j)$. Classic heterogeneity is introduced by interacting these two choice-specific characteristics with *Gender*, *Age*, *Ethnicity*, and a dummy variable for *LowIncome*; the latter incorporates an income effect.[6] Specifically,

$$\begin{aligned} U_{jic} &= (\beta_1 + \beta_2 Gender_i + \beta_3 LowIncome_i)(Income_i - Price_{jc}) \\ &\quad + (\beta_4 + \beta_5 Age_i + \beta_6 Ethnicity_i) Preservation_{jc} \\ &\quad + (\beta_7 + \beta_8 Age_i + \beta_9 Ethnicity_i) Preservation_{jc}^{1/2} + \varepsilon_{jic} \end{aligned} \tag{1}$$

where U_{jic} is the utility individual i receives on choice occasion c if she chooses alternative j. The variables $Gender_i$ (1 for female), $LowIncome_i$ (1 if annual household income is less than \$12,000), and $Ethnicity_i$ (1 for non-Caucasian) are binary variables. $Preservation_j$ is 0 for the status quo, 0.25 for Option A, 0.50 for Option B, and 1.00 for Option C.

This is the specification of the Classic Model that provided the best fit.[7] The parameter estimates imply that the *CV* for preservation is positive and significant for all individuals, increases with age, and is lower for males, for low-income individuals, and for non-Caucasians. That is, these results say that no one considers increased preservation a bad. The models presented below reverse this finding.

However, while straightforward and common, this method of incorporating heterogeneity is highly restrictive. The researcher specifies a functional form that determines, up to the value of its parameters, how observable characteristics of the individual affect the preference parameters. While one is free to choose the functional form, most forms chosen are highly restrictive. In addition, the heterogeneity is assumed deterministic. That is, rather than assuming that observed characteristic levels of the individual increase or decrease the probability that one cares about preservation, the specification requires that everyone with the same characteristic levels has the exact same preference for preservation. This is unlikely. To assume, for example, that all old people care more than all young people is highly restrictive.

This paper explores other avenues for incorporating preference heterogeneity in models that value cultural resources. Random parameter models have become a popular method to model preference heterogeneity. MNL models are generalized to random parameters logit (RPL) by allowing the preference parameters to vary randomly over individuals (Ben-Akiva and Lerman, 1985). Recently developed techniques for simulating probabilities (McFadden and Ruud, 1994) have made it feasible to estimate such models. Applications include Train (1998), Revelt and Train (1998), Brownstone and Train (1999), Layton and Brown (2000), and Breffle and Morey (2000). Put simply, one assumes individual i's preference parameter on some characteristic is a random draw from some distribution where the family of the distribution is specified, but the mean and variance of the distribution are unknown, and so estimated. A typical assumption is that preference parameters are normally and independently distributed. This paper compares a RPL model of monument preservation with both the classic model in Morey et al. (2002) and a more general mixture model that combines classic heterogeneity and random parameters.

RPL models have the nice feature that they invoke correlation across choice occasions for a given individual; that is, the sequence of pair-wise choices for a given individual are correlated. So, the model accounts for the fact that two pair-wise choices, one from each of two individuals, contain more information than two choices from the same individual. Each individual's specific preference parameters are random draws from the chosen distributions, but the draws do not vary across choice occasions. For example, if your parameter on *Preservation* is above the mean, it is above the mean on all your choices, causing your choices to be correlated from the researcher's perspective. RPL models also relax the restrictive I.I.A. assumption of the MNL model (with or without classic heterogeneity): with RPL models the inclusion of or change to an alternative affects the ratio of the probabilities for any other two alternatives.

However RPL models are still quite restrictive. Estimating a RPL logit model requires that one assume a particular type of distribution for each random preference parameter.[8] All individuals have the same $E[CV]$ but the distributions on the preference parameters imply a range on the CVs across individuals. For example, if one assumes an individual's preference parameter is a draw from a normal distribution, the most common assumption, then the CV_is, by assumption, go from minus to plus infinity.[9] So, for any increase in preservation, the RPL model constrains some proportion of the population (possibly very small) to consider it a bad; that is, to have a negative CV. Put simply, the RPL model, unlike the Classic model, admits, in fact requires, that some proportion of the population will consider increased preservation a bad. Of course, one can assume a distribution with some finite range, but then one must specify that distribution and that range. Any chosen range is easy to criticize. Put simply, RPL models impose heterogeneity and typically wide-ranging heterogeneity. The data just determine the mean and variance of the specified distribution. RPL models make no attempt to explain the heterogeneity. Your preference parameters differ from mine only because each is an independent draw from the specified distribution.

As an intermediate step, we estimate a RPL model. In terms of Equation (1), the RPL model assumes $\beta_5 = \beta_6 = \beta_8 = \beta_9 = 0$; that is, it assumes no explained heterogeneity. Rather, it assumes that β_4 and β_7 are each normally distributed with means μ_4 and μ_7, variances σ_4^2 and σ_7^2, and covariance, $\sigma_{4,7}$. For example, picture the distribution of β_4 with $\mu_4 = 6$ and $\sigma_4^2 = 16$.

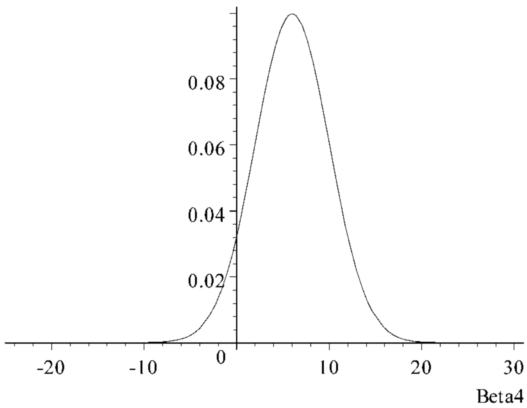

Figure 1.

The estimated means and variances of β_4 and β_7 will determine what proportion of the population feels increased preservation is a bad. Looking ahead, the RPL model predicts that 16% of the population feel that doubling the preservation time-line is a bad, but provides no information as to who is in this group.

Comparing a RPL model with a MNL model with no classic heterogeneity one typically finds, as we do here, that there is significant preference heterogeneity.

The main thrust of this paper is to estimate a MNL model that combines the better features of both RPL and classic heterogeneity. Put simply, the preference parameters are assumed random variables that are functions of observable characteristics of the individual. The resulting model is a *mixture* model: the population consists of a mixture of sub-populations.[10] In each of these subpopulations, the parameters on *Preservation* and *Preservation*$^{1/2}$ are random parameters; the means of the distributions are allowed to vary across sub-populations. For example, for the subpopulation of 22 year-old, non-Caucasians, the mean of their parameter on *Preservation* is $\mu_4 + \beta_5(22) + \beta_6$ and for 65 year-old Caucasians it is $\mu_4 + \beta_5(65)$. Statisticians refer to such models as mixture models because the distribution of a parameter in the population is a mixture of some finite number of continuous distributions. Picture, for example, the distribution of β_4 in a population consisting only of 22 year-old, non-Caucasians and 65 year-old Caucasians. If, for example, $\mu_4 = 6$, $\sigma_4^2 = 16$, $\beta_5 = 0.1$ and $\beta_6 = -5$, then the distribution of β_4 is

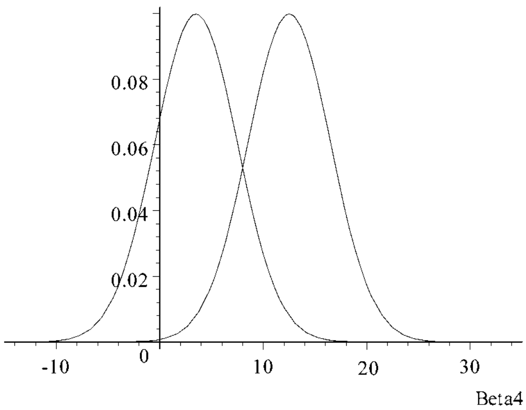

Figure 2.

For 22 year-old non-Caucasians, β_{4i} is a draw from the left distribution; for 65 year-old Caucasians, it is a draw from the right distribution.

Looking ahead, statistically the mixture model dominates both the RPL model and the model with only classic heterogeneity, indicating that age and ethnicity are important determinants of the variations in $E[CV]$ across individuals, but not in the deterministic manner implied by the classic only model. The estimated variances on the random parameters suggest that even though significant variation is explained by age and ethnicity, much of the variation remains unexplained. Possibly of most importance, the mixture model predicts that a significant proportion of individuals are made worse off by increased preservation and predicts that young non-Caucasians are most likely to be in this group.

2. A Mixture Model Combining RPL and Classic Heterogeneity

Assume the utility associated with alternative j for individual i on choice occasion c is:

$$\begin{aligned} U_{jic} &= \boldsymbol{\beta}_i' \boldsymbol{x}_{jc} + \varepsilon_{jic} \\ &= \beta_{ci}(Income_i - price_{jc}) + \beta_{pi}(Preservation_{jc}) + \beta_{ppi}(Preservation_{jc})^{1/2} + \varepsilon_{jic} \\ &= (\beta_1 + \beta_2 Gender_i + \beta_3 LowIncome_i)(Income_i - Price_{jc}) \\ &\quad + (\mu_4 + \mu_5 Age_i + \mu_6 Ethnicity_i + \eta_{1i})(Preservation_{jc}) \\ &\quad + (\mu_7 + \mu_8 Age_i + \mu_9 Ethnicity_i + \eta_{2i})(Preservation_{jc})^{1/2} + \varepsilon_{jic} \end{aligned} \tag{2}$$

where $\boldsymbol{\beta}_i \equiv (\beta_{ci}, \beta_{pi}, \beta_{ppi})$ and $\boldsymbol{\eta} \sim N(\boldsymbol{\mu}, \boldsymbol{\Omega}) \equiv N\left(\mu_1, \mu_2, \sigma_{\eta 1}^2, \sigma_{\eta 2}^2, \sigma_{\eta_1 \eta_2}\right)$. β_p and β_{pp} are natural candidates to be random variables; β_{ci}, the marginal utility of money, is assumed deterministic, as is common.

It is reasonable to expect that β_{pi} and β_{ppi} are correlated and thus the covariance between them, $\sigma_{\eta_1 \eta_2}$, is estimated. Its inclusion allows for differences in the curvature of marginal utility (and, thus, welfare) with respect to *Preservation*.

It is assumed that ε_i and $\boldsymbol{\eta}_i$ are independent. Note that, for individual i, correlation is induced across choice occasions by the common influence of $\boldsymbol{\eta}_i$.

Maximum likelihood estimation requires simulation. Conditional on $\boldsymbol{\beta}_i$, the probability of observing individual i's sequence of pair-wise choices is:

$$P\left(\boldsymbol{\beta}_i, \boldsymbol{x}_i\right) = \prod_{c=1}^{C} \left(\frac{e^{\boldsymbol{\beta}_i' \boldsymbol{x}_{ikc}}}{e^{\boldsymbol{\beta}_i' \boldsymbol{x}_{ikc}} + e^{\boldsymbol{\beta}_i' \boldsymbol{x}_{i(3-k)c}}} \right), \tag{3}$$

where k represents the chosen alternative from the pair of alternatives. Thus, the probability of observing the individual's sequence of pair-wise choices is:

$$P_i = \int_{-\infty}^{+\infty} \cdots \int_{-\infty}^{+\infty} P(\boldsymbol{\beta}, \boldsymbol{x}_i) N(\boldsymbol{\beta} | \mu, \boldsymbol{\Omega}) d\boldsymbol{\beta} \,. \tag{4}$$

Exact maximum likelihood estimation is not possible since this integral cannot be calculated analytically. P_i is simulated by summing over R random draws from $N(\boldsymbol{\beta} | \boldsymbol{\mu}, \boldsymbol{\Omega})$ using a pseudo-random number generator. The simulated probability is:

$$SP_i = \frac{1}{R} \sum_{r=1}^{R} P(\boldsymbol{\beta}_i^r, \boldsymbol{x}_i), \tag{5}$$

where $\boldsymbol{\beta}_i^r$ is the $\boldsymbol{\beta}$ from the rth random draw from $N(\boldsymbol{\beta} | \boldsymbol{\mu}, \boldsymbol{\Omega})$ for individual i.[11] Thus, the simulated log-likelihood function for the RPL is:

$$SL = \sum_{i=1}^{N} \ln \left[\frac{1}{R} \sum_{r=1}^{R} P(\boldsymbol{\beta}_i^r, \boldsymbol{x}_i) \right]. \tag{6}$$

Kenneth Train has a web site and a new book (Train, 2003) that provides software and instructions to estimate random-parameter models.[12]

3. Model Estimation and Results

Choice data are available for $N = 259$ individuals, and choices of preservation alternatives for up to ten choice occasions per individual, C_i, yielding a total of 2,568 choices. To estimate the model, we used a simulator for RPL in the Gauss programming language that was developed by Train, Revelt and Ruud. The data set and Gauss code are available at http://www.colorado.edu/economics/morey/dataset.html . We are happy to help with other applications.

Based on likelihood ratio tests, the Mixture Model explains the respondents' stated-choices significantly better than the Classic Model (with no random parameters). The Classic Model predicts significantly better than a model with homogenous preferences, and the homogenous model predicts significantly better than a random allocation. The Mixture Model also explains the choices significantly better than the RPL model. That is, classic heterogeneity and random parameters are both important components of the model.

A pseudo R^2 for the Mixture Model is 0.51. In 1,828 (71%) of the observed choices, the model makes a strong prediction as to which alternative the individual will choose (predicted probability at least 90%). In 79% of these choices, the predicted alternative is the chosen alternative. In contrast, for the 182 choices where the model makes only a weak prediction (neither alternative has a predicted probability greater than 60%), the actual choices split much more evenly: 44% for B and 56% for A.

The parameter estimates for the Mixture Model are reported in Table I. The estimate of the marginal utility of money, $(\beta_1 + \beta_2 Gender_i + \beta_3 LowIncome_i)$, is positive and constant for each respondent and is a step function of income.[13] Women have a significantly lower marginal utility of money than do men, and therefore a higher WTP for preservation.

The estimated expected marginal utility of preservation, $(-3.08 + 0.15 Age_i - 3.22 Ethnicity_i) + 0.5(9.55 - 0.01 Age_i - 3.74 Ethnicity_i)(Preservation_{jc}^{-0.5})$, is positive and declining for all respondents over the range of preservation levels considered ($Preservation = 0$ to 1), except for young, non-Caucasian respondents. For non-Caucasian respondents in their early twenties, the estimated expected marginal utility of preservation is negative at the higher levels of preservation. This suggests that these respondents, on average, view small amounts of preservation as a good but that it turns into a bad at higher levels. This finding contradicts the results of the Classic Model: the Classic Model predicted that all respondents view additional preservation over the range of preservation levels studied to be a good. The estimated standard deviations of the random parameters (σ_4 and σ_7) are highly significant, indicating that the parameters do indeed vary in the population; that is, significant heterogeneity exists beyond that captured by the classic heterogeneity.

Table I. Model parameter estimates

Variable	Estimate	Standard error
β_1: (*Income – Price*)	0.141	0.014 [b]
β_2: (*Income – Price*) $*$ *Gender*	–0.024	0.014 [a]
β_3: (*Income – Price*) $*$ *LowIncome*	–0.001	0.028
μ_4: *Preservation*	–3.077	2.887
μ_5: *Preservation* $*$ *Age*	0.149	0.063 [b]
μ_6: *Preservation* $*$ *Ethnicity*	–3.216	2.100
μ_7: $Preservation^{1/2}$	9.548	3.073 [b]
μ_8: $Preservation^{1/2} * Age$	–0.014	0.066
μ_9: $Preservation^{1/2} * Ethnicity$	–3.737	1.947 [a]
σ_4^2	90.332	26.766 [b]
σ_7^2	72.614	22.324 [b]
$\sigma_{4,7}$	–27.68	12.948 [b]
$\rho_{4,7}$	–0.34	

[a] Significant at 10% level of significance.
[b] Significant at 5% level of significance.

The estimated mean value of β_7, $\hat{\mu}_7$, is positive and significantly different than zero. The estimated mean value of β_4, $\hat{\mu}_4$, is negative though not significantly different than zero; that is, β_4 is negative for approximately half of the sample. The estimated covariance between β_4 and β_7 is negative and significant; the correlation coefficient is $\rho_{4,7} = \sigma_{4,7}/(\sigma_4 * \sigma_7) = -0.36$.

Estimating random parameters on both the linear and non-linear variable of an attribute allows the curvature of utility (but not expected utility) to vary across individuals of the same type. For example, marginal utility with respect to *Preservation* declines at a slower than average rate for individuals with a smaller than average β_7. The negative covariance indicates that such an individual will have a larger than average β_4 and, thus, a higher level of marginal utility. That is, the higher an individual's marginal utility, the slower its rate of decline. The effect of the negative correlation between β_4 and β_7 on welfare estimates is discussed below.

4. Welfare Measures

Consider the compensating variations, CV_i, associated with changes from the status quo level of SO_2 to states of the world with one of the preservation options.

$$\begin{aligned} CV_i \;=\; & 1/(\beta_1 + \beta_2 Gender_i + \beta_3 LowIncome_i)(Income_i - Price_{jc}) \\ & [(\mu_4 + \mu_5 Age_i + \mu_6 Ethnicity_i + \eta_{1i})(Preservation^I - Preservation^0) \\ & + (\mu_7 + \mu_8 Age_i + \mu_9 Ethnicity_i + \eta_{2i})((Preservation^I)^{1/2} - (Preservation^0)^{1/2})], \end{aligned} \tag{7}$$

Table II. Mixture Model estimated median and mean $E[CV]$ and confidence intervals

	Median	Mean	Confidence interval
Option A	\$40.47	\$37.53	(\$29.13–\$47.71)
Option B	\$60.44	\$56.45	(\$46.01–\$69.22)
Option C	\$93.94	\$86.58	(\$73.40–\$102.49)

where 0 denotes the status quo and I denotes the state with improved preservation. Note that η_{1i} and η_{2i} cause the CV_i to vary across individuals in a way the researcher cannot observe. The best the researcher can do is to calculate its expectation:

$$\begin{aligned} E[CV_i] \;=\; & 1/(\beta_1 + \beta_2 Gender_i + \beta_3 LowIncome_i)(Income_i - Price_{jc}) \\ & [(\mu_4 + \mu_5 Age_i + \mu_6 Ethnicity_i)(Preservation^I - Preservation^0) \\ & + (\mu_7 + \mu_8 Age_i + \mu_9 Ethnicity_i)((Preservation^I)^{1/2} - (Preservation^0)^{1/2})]\,. \end{aligned} \tag{8}$$

So, adding random parameters to the classic heterogeneity model significantly increases the variation in the CV_i but, in terms of its expectation, $E[CV_i]$, there is no more heterogeneity than in the classic only model (so that Equation (7) is the same in the Mixture Model and the Classic Model).

The estimated mean $E[CV]$ and its confidence intervals are shown in Table II for Options A, B and C.[14] The estimated $E\,[CV_i]$s are positive for all individuals, and significantly so for all but non-Caucasian individuals age 27 and younger. As in the Classic Model, the $E\,[CV_i]$s from the Mixture Model vary substantially as a function of the observed characteristics of the individual. Estimated $E\,[CV_i]$ for Option A varies across individuals from \$13 to \$54, from \$15 to \$88 for Option B, and from \$14 to \$145 for Option C. So, expectationally, no one is made worse off by any of the preservation programs. This not the case for the estimated *CV*s.

In terms of the expected *CV*s, women are willing to pay, on average, 21% more for preservation than are men. For each one year increase in age, $E\,[CV]$ increases by up to \$1.17 and up to 6%. Depending on the age and income level of the individual, a representative non-Caucasian's $E\,[CV_i]$ ranges from 24% to 60% of that of a Caucasian.

Estimating the correlation of the random parameters (on *Preservation* and $Preservation^{1/2}$) allows for differences in the curvature of CV_i with respect to level of preservation across individuals of the same type. The negative correlation between β_4 and β_7 indicates that, relative to other individuals of the same type, individuals with a higher marginal CV_i have a more linear than average CV_i function. Note that the slope of the marginal CV_i with respect to *Preservation* is a function of μ_7 but not μ_4. Given the negative covariance, an individual with a

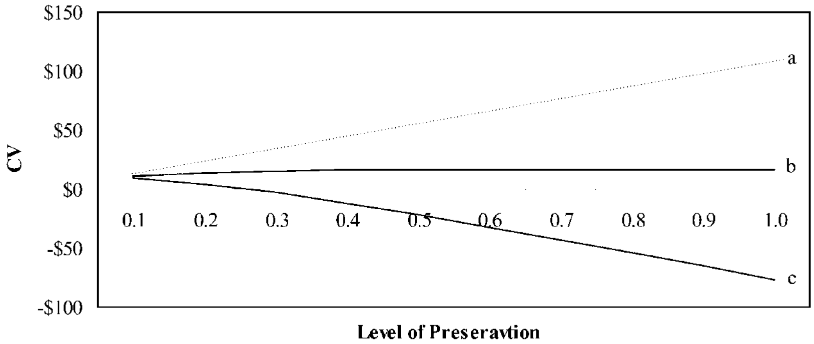

Figure 3. Estimated *CV* for different values of β_4 and $E[\beta_7|\beta_4]$.

higher than average β_4 is expected to have a lower than average β_7. This will cause this individual to have a CV_i that is higher than average, for his type, and increases as the level of preservation increases (e.g., path *a* in Figure 3). In contrast, an individual with a lower than average β_4 is expected to have a higher than average β_7, and so will have a CV_i that is lower than average and decreases as the level of preservation increases (e.g., path *c* in Figure 3). Figure 3 is an illustration for individuals who are 20 years old, male, low-income and non-Caucasian. The CV_i for an individual of this type is computed for three different possible values of β_4, ($\hat{\mu}_4 + 1.96\hat{\sigma}_4$, $\hat{\mu}_4$, and $\hat{\mu}_4 - 1.96\hat{\sigma}_4$), each combined with the expectation of β_7 conditional on β_4.

The individuals in this group have similar *CV*s for small amounts of preservation but the *CV*s quickly start diverging as the level of preservation increases. For those individuals who have a low, but positive, β_4, *CV* is negative for all preservation efforts that would extend the time-line by more than 25%. Not all young, low-income non-Caucasians have negative WTP but rather those with a below average β_4. The figure indicates that these individuals would *pay* approximately $20 to stop a preservation program that increased the time-line of preservation by 50%. One would not be able to see this if the model had assumed zero covariance ($\sigma_{4,7} = 0$). These results indicate that the change in utility and WTP – not just the level – can vary across individuals of the same type. In contrast, the assumption of zero covariance holds the slope of the marginal CV_i constant across individuals of the same type.

As explained earlier, it is important to note that the Mixture Model and the RPL Model both, by assumption, require that for every type of individual there is some probability that they will have a negative CV_i for preservation. It follows from the assumption that the random parameters are normally distributed. As noted earlier, the estimated RPL Model (with no classic heterogeneity) predicts that 16% of the population would be made worse off by a doubling of the preservation time-line, yet, unlike the Mixture Model, it does not provide information on the characteristics of that 16% (see Table III). In the Mixture Model, the probability that increased preservation is a bad varies by type of individual. For example, the Mixture Model

Table III. $E[CV]$s and % of CVs negative for two types of individuals

Increase in preservation timeline		Models					
		Classic	RPL	Mixture	Classic	RPL	Mixture
		20-year old, low-income, non-Caucasian male			75-year old, non-low-income, Caucasian female		
25%	$E[CV]$	\$9	\$38	\$14	\$60	\$38	\$54
	% CVs negative	0%	13%	32%	0%	13%	6%
50%	$E[CV]$	\$10	\$53	\$16	\$95	\$53	\$86
	% CVs negative	0%	14%	36%	0%	14%	5%
100%	$E[CV]$	\$11	\$88	\$16	\$153	\$88	\$144
	% CVs negative	0%	16%	42%	0%	16%	5%

predicts that only 5% of elderly Caucasian women will be made worse off by a doubling of the preservation time-line, while 42% of young, non-Caucasians will be made worse off.

5. Lessons Learned

In any valuation exercise, one should begin with the question of who benefits and who loses from the preservation of the resource. In some cases, everyone will benefit at a zero cost, but this is unlikely to be the case for many cultural resources.

Focus groups typically consist mostly of middle-age Caucasians. There were few non-Caucasians in our focus groups and none that were young, low-income and male; such individuals are difficult to recruit. Even if we had individuals of this type in the focus groups, individuals who might prefer less to more preservation would still be in the minority. In which case, their views might go unheard because of group pressure. Focus groups must be designed to find individuals with minority views and solicit their preferences, possibly in a separate focus group. If such individuals are identified, then efforts must be made to assure that they appear in sufficient numbers in the sample.

If the CV_i for some cultural policy is positive for some but negative for a significant proportion of the population, the valuation exercise becomes much more difficult. At a minimum, one must initially ask and probe as to whether the individual thinks implementation of the policy will make him better or worse off. One would ideally use an initial survey to allocate individuals to a positive or negative CV group.[15] One could then easily use choice questions of our type for the positive group. The negative CV group is more difficult. The choice questions for the negative group would need to be designed to illicit what they would pay to stop the policy and/or have to be paid to vote for the policy. The latter type of question is easier to ask and answer. For example, one might have the individual compare the status quo to preservation Option C combined with a tax reduction for that individual. This, of course, raises the question of why taxes should decline if expenditures on preservation increase.

In closing, we should mention that one could also use our data to estimate a latent-class model with covariates.[16] Latent-class models and random parameters models are similar in that both assume random parameters; latent-class models assume the parameters have discrete densities, RPL models assume the parameters are continuously distributed. Latent-class models assume a small number of classes/groups each with different preferences. Class membership is latent/unobserved. In this application, one would assume that the probabilities of membership in the different classes are functions of the covariates identified in the Classic Model and the Mixture Model, e.g. age, gender, and ethnicity.

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Notes

1. Unfortunately none of the attitudinal questions gave the respondent the opportunity to say that increased preservation is a bad (the range on the attitudinal questions went from "do not care" up through increasing levels of positive preference). In spite of this design flaw, the responses to these questions support the hypothesis that some individuals, at best, do not care about preservation, and non-Caucasians are more likely to be in this group. When asked to rate the importance of preserving this set of monuments, 33% of non-Caucasians indicated that such a program was not important to them, compared with 17% of Caucasians. When asked "how important is it to you that these monuments exist?" non-Caucasians were eight times more likely to say "not at all important" (8% vs 1%).
2. Choice studies, such as this one, that ask the individual to choose over different "states" with only one alternative in each state include Adamowicz et al. (1996), Roe et al. (1996), Johnson and Desvousges (1997), Stevens et al. (1997), Layton and Brown (2000) and Swait et al. (1998).
3. The epsilons for each choice occasion are known to the individual when that choice is made but the individual does not know what they will be in the future. The researcher never observes the epsilons.
4. When there is only one alternative in each state, there is only one epsilon and it cancels out. This is not the case in MNL models with multiple alternatives in each state. For details, see Morey and Rossmann (2003).
5. Note that this distribution is not invoked by estimation.
6. See Morey et al. (2003) for a discussion of this method of incorporating income effects.

7. The only other demographic data available were education level and household size. Neither was found to be a significant determinant of choice.
8. Typically only a few of the parameters are assumed random. In theory, one can specify any joint-density function, estimating, for example, variances and covariances for all of the parameters.
9. This can be observed by simulating thousands of *CV*s, each a separate draw from the joint normal distribution of the random preference parameters.
10. Titterington et al. (1985) is a classic introduction to mixture models. More recent theory and applications are expanded upon in Bartholomew and Knott (1999) and Wedel and Kamakura (2000). These references are also appropriate for the latent-class model discussed in the conclusion.
11. For each parameter vector, SP_i is calculated by taking R draws of $\boldsymbol{\beta}_i$, $\boldsymbol{\beta}_i^1, \ldots, \boldsymbol{\beta}_i^r, \ldots, \boldsymbol{\beta}_i^R$, calculating SP_i^r for each draw, and then averaging them.
12. A preview of the book can be found at http://emlab.berkeley.edu/books/choice2.html. An RPL simulator is available on Train's WWW site: http://elsa.berkeley.edu/~train/software.html .
13. The parameter on $LowIncome_i$ is not significant in the Mixture Model. To facilitate the comparison of this model to the same model but with only fixed parameters (the Classic Model) this variable is included. When estimating the Classic Model, β_3 is positive and significant.
14. Note that these are confidence intervals on the sample mean $E[CV]$s, not the range in $E[CV]$ across individuals in the sample. They are implied by the estimated variance and covariance of the estimated parameters.
15. With an online or phone survey, this could be done with branching. Branching is always difficult with written surveys.
16. Standard references to latent-class models include Bartholomew and Knott (1999), Titterington et al. (1985), and Wedel and Kamakura (2000).

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