Title: Using the Random Parameters Logit Model to Combine Revealed and Stated Preference Data

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Abstract: Recent literature has combined Revealed (RP) and Stated Preference (SP) data in the Multinomial Logit Model (MNL) to estimate the value of environmental goods. However, emerging research has identified that a limitation of the MNL is the assumption of Independently and Identically Distributed (IID) errors, resulting in inaccurate model predictions and inconsistent utility parameters. Our analysis applies an alternative method to combine RP and SP data that takes into account the heterogeneity in both the observable and unobservable components of utility. This allows us to test whether such heterogeneity has an important effect on predicting behavioral choices.

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1. Understanding the Problem

During the past 30 years or so, economists have developed several methods for estimating the non-market value of environmental goods, but obtaining reliable and robust estimates has proved to be a challenging task. Broadly speaking, nonmarket valuation methods can be divided into stated preference (SP) and revealed preference (RP) approaches. Both of these approaches have been used extensively but are subject to several limitations.

Among the SP techniques, the Contingent Valuation Method (CVM) has evolved as perhaps the most popular of all nonmarket valuation methods but also the most controversial. Critics of CVM have pointed out several difficulties. A transparent problem is that survey questions may differ from situations where respondents make real choices. The potential resolution to this problem is to ask a question that more closely mimics an agent's actual choices, and for this reason the dichotomous choice format was introduced as an improvement over open-ended questions. But respondents may also have difficulty answering dichotomous choice questions, since they are not generally accustomed to placing bids on single goods.

In order to address the problem that CVM may not reflect the pricing behavior of the consumer in the marketplace, Choice Experiments (CE) have emerged form the marketing literature to more closely mimic the resource allocation of economic agents for both market and non-market goods. In this method, survey respondents are asked to select from a set of goods with varying attributes. Louviere et al. (2000) summarized CE as the "…richest form of behavioral data for studying the phenomenon of choice (p.14)." Recent literature has also incorporated the consumer's intensity of preferences in CE.

Kuperis et al. (1999) used CE to estimate the demand for milk products by designing stated choice experiments to identify the type of milk chosen, as well as the quantity demanded for each type.

Our analysis combined RP and SP data with the Conjoint framework, as described above. One advantage of these methods is that both RP and SP data may be collected. Prior literature that has combined RP and SP with choice based methods has achieved this by rescaling one data set relative to the other in the Multinomial Logit (MNL) of choice to make parameter estimates comparable.[1] The MNL has been used extensively in recent years to predict consumer choice and has grown in popularity due to the ease of estimation, accessibility to software, the speed of delivery of robust estimates, overall goodness-of-fit, and accuracy of predictions.

However, in emerging literate has identified that a limitation of the MNL is the assumption of Independently and Identically Distributed (IID) errors, resulting in inaccurate model predictions and inconsistent utility parameters. Hence, the purpose of this study is to illustrate an alternative method to combine RP and SP data that takes into account the unobservable components of choice on utility.

While Swait and Louviere's (1993) method is useful because it takes into account error variance differences between data sets, the limitation of the approach is that it ignores error variance differences among individuals. The Random Parameters Logit (RPL) is one modeling approach that relaxes the assumption of IID errors, and allows all unobserved components of utility to predict choice. Train (2003) explained that the RPL

[11] See Amadowicz, W., J. Louviere, and M. Williams. (1994). "Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities." *Journal of Environmental Economics and Management.* 26: 271-292; Amadowicz, W., J. Swait, P. Boxall, J. Louviere, and M. Williams . (1997). "Perceptions versus Objective Measures of Environmental Quality in Combined Revealed and Stated Preference Methods of Environmental Valuation." *Journal of Environmental Economics and Management.* 32: 64-84; Swait, J. and J. Louviere. (1993). "The Role of Scale Parameter Estimation in the Estimation and Comparison of Multinomial Logit Models." *Journal of Marketing Research*, 30: 304-314; Earnhart, D. (2001). "Combining Revealed and Stated Preference Methods to Value Environmental Amenities at Residential Locations." *Land Economics*. 77(1):12-29.

model is useful for empirical research because "It obviates three limitations of the standard logit model by allowing for random taste variation, unrestricted substitution patters, and correlation of unobserved factors over time (p. 138)". Essentially, the model allows the variance of the response distribution, as well as the means, to predict consumer choice.

The plan of the discussion is as follows. The role of an unrestricted variance-covariance matrix in discrete choice models is first discussed. Next, recent literature that dissects the random component of utility is identified. A conceptual model of the RPL model follows, as well as the econometric estimation procedure. Discussion focuses on not only the heterogeneity captured by the model, but also all unobserved effects captured from free-variance.

2. Background and Prior Work

Louviere (2001) discussed the role of response variability as a behavioral phenomenon, investigating if consumer experiments impact variance as well as means. According to the author, response variability is rarely viewed as a behavioral phenomenon and is more likely to be viewed as a nuisance. The IID based models further assume that these effects are constant, and do not vary among individuals. However, since probability distributions have more than one moment, clearly it is reasonable to investigate the role of the unobservable component of utility on choice.

The author further described that the mean of responses in the Random Utility Model (RUM) is inversely related to response variability, and "such means and variances are perfectly confounded, and no single study can determine whether either or both are impacted (p.1)." The inverse relationship means that smaller (larger) response variability leads to larger (smaller) response means. Hence, models that display lower variances predict more consistently since more information is explained in the systematic component of utility. Dellaert et al. (1999) and Louviere et al. (2000) find similar results, such that models which display lower response variabilities result in models with greater explanatory power, more statistically efficient parameter estimates, and higher consistency of choice for consumer experiments.

As explained by Louviere et al. (2000), Louviere (2001), and Louviere et al. (2002), parameter estimates in the RUM are confounded with a scale factor. The scale factor is the parameter ofthe EV1 distribution of errors and is inversely related to the error variance. Hence, models with higher scales (i.e., lower error variances) predict more consistently than models with lower scales. Researchers are therefore not estimating the means of response distributions in models with the assumption of IID errors. Actually, the researcher is estimating $\beta / \sigma_{\varepsilon}^{2}$, where $\beta =$ mean of the utility parameter, and $\sigma_{\varepsilon}^{2} =$ the response variability. Louviere et al. (2001) noted that "…unless one designs research to separate response means from response variability effects, one cannot determine whether one or the other or both moments are affected, which raises the question about how to interpret past inferences about consumer behavior based on the means of response distributions (p.2)."

Louviere et al. (2002) noted several practical considerations for researchers in business and the social sciences when taking into account the effect of unobserved effects on consumer choice. First, the authors made it transparent that one cannot simply assume that error variances across data sets are identical when combining preference data. It is necessary to rescale one data set relative to the other such that parameter estimates are comparable. Second, variability in the stochastic component of utility is associated with numerous factors, and it is naïve to lump all unobserved effects into a single error term, assuming these differences are due solely to heterogeneity between individuals. Third, response variability is as much a behavioral phenomenon as response means. As noted, coefficient estimates are confounded with error variance in the RUM, and empirical parameter estimates may actually be due to the mean of the response, the variability of the response, or both.

It is obvious that each individual in a sampled population has a unique deterministic and stochastic component of their respective utility function. The RPL model allows not only for heterogeneity across individuals but also heterogeneity of all unobserved components (data collection method, interviewer quality, type of preference data, etc.). Modeling the unobserved component of choice is hypothesized to increase the explanatory power of our modeling capabilities, as well as our insights into the behavioral choice process.

Prior literature has combined RP and SP data (see Adamowitcz 1994, 1997; Earnhart 2001; Swait et al. 1993) by rescaling one data set relative to the other in the MNL of choice to make parameter estimates comparable. As noted, this procedure corrects for group-wise heteroskedastocity between data sets. However, a limitation to this approach is that it ignores the effect of heterogeneity and all unobserved effects between individuals. If heteroskedasticity between individuals is present, parameter estimates are distorted and the researcher may lead to erroneous conclusions.

This research identifies how a RPL may be used to combine RP and SP data, accounting for all unobservable components in the choice process. By allowing for Free-Variance, the model provides a more realistic method to observe consumer decisions. The following section provides a conceptual framework identifying the role of the scale factor when combining SP and RP data in the RPL model.

3. Conceptual Framework

Consider a simple case where there is only one variable that can affect utility. The estimated utility functions from the combined SP and RP data sets are:

$$\hat{U}_{SP} = \beta_1 X_1 \tag{0.1}$$

$$\hat{U}_{RP} = \lambda \beta_1 X_1 \tag{0.2}$$

where, $\hat{U}_{SP}$ and $\hat{U}_{RP}$ are the utility functions for the stated and revealed preferences, respectively, and $\beta_1 's$ are the utility parameters and λ is the relative scale parameter. In the RPL model suppose that *D*=1 is a dummy variable indicating the observation is in the revealed data set and *D*=0 indicates the observation is in the stated data. As such, utility coefficients are a function of *D*, which varies across observations. Letting η represent the estimated parameter for *D:*

$$\beta_1 = \mu + \eta D \tag{0.3}$$

In equation (0.6), if the utility function is from the SP data, then *D*=0, and (0.5) collapses to the utility function:

$$\hat{U} = \eta X_1 \tag{0.4}$$

In equation (0.7), if the utility function is from the RP data, then *D*=1, and collapses to the utility function:

$$\hat{U}_{RP} = (\mu + \eta) X_1 \tag{0.5}$$

Now imposing the restriction that the utility functions in RP and SP are data equivalent (Cameron, 1992) we obtain the expressions (0.8) and (0.9):

$$\beta_1 X_1 = \eta X_1 \tag{0.6}$$

$$\lambda \beta_1 X_1 = (\mu + \eta) X_1 \tag{0.7}$$

(0.8) implies that $\eta = \beta_1$, substituting into (0.9) we obtain the expression

$$\lambda \eta X_1 = (\mu + \eta) X_1 \tag{0.8}$$

$$\therefore \lambda = 1 + \frac{\mu}{\eta} \tag{0.9}$$

Thus, the scale factor λ can be represented by the parameters η and μ. Now suppose there were several variables such that

$$\beta_k = \mu_k + \eta_k D \tag{0.10}$$

where $k = 1,...,K$.

and $\mu_1 = \beta_1, \mu_2 = \beta_2, \mu_3 = \beta_3, ..., \mu_K = \beta_K$. The expression can now be generalized to obtain,

$$\lambda = 1 + \frac{\mu_k}{\eta_k} \tag{0.11}$$

$$\begin{aligned} &and, \lambda = 1 + \frac{\mu_1}{\eta_1} = 1 + \frac{\mu_2}{\eta_2} = 1 + \frac{\mu_3}{\eta_3} = ... = 1 + \frac{\mu_K}{\eta_K} \\ &\therefore \frac{\mu_1}{\eta_1} = \frac{\mu_2}{\eta_2} = \frac{\mu_3}{\eta_3} = ... = \frac{\mu_K}{\eta_K} \end{aligned} \tag{0.12}$$

Equation (0.14) represents the scale factor for the MNL model of choice. Here we are showing the scale factor for MNL, which is constant. But in the RPL this is not constant, should we show this? Louviere (2001, p.2) shows that $U_{in} = V_{in} + \varepsilon_{1in} + \varepsilon_{2in} + \varepsilon_{3in} + ... + \varepsilon_{pin}$ where p is the subcomponents of the random component ε_{in} that refers to the within-subjects, between-subjects, etc., sources of response variability. Should we adopt something like this or explain this in our model?

As noted, the error variance is constant across individuals for the method proposed by Swait and Louviere (1993). However, the RPL allows (1.14) to vary across individuals in the population. The Simulated Maximum Likelihood estimation procedure is next discussed for the RPL model.

4. Econometric Estimation Procedure

According to Train (1998), the RPL model is a special case of the MNL model. The RPL allows for parameters to vary across individuals in the population with the same characteristics. In contrast, the MNL assumes that different people with the same characteristics are expected to have the same tastes. Another interesting characteristic of the RPL is the relaxing of the assumption of IID errors, implying a completely unrestricted variance-covariance matrix.

Following Morey et al. (1993), β_q is a vector of taste parameters for the q^{th} individual, and is independently drawn from $N(\mu,\Omega)$. In this case, preferences are observable to the individual but are random to the researcher. That is, tastes are known to the individual but unknown to the researcher and are a vector of random variables. By allowing for "free-variance", individual taste parameters differ from person to person.

Hence, for the q^{th} individual and the k^{th} parameter, the utility coefficient may be expressed as β_{qk}. The population mean and individual deviation are given as μ_k and η_{qk}, respectively. The utility for the q^{th} individual, and the j^{th} alternative is given by:

$$\begin{aligned} &U_{qj} = \beta_q^{'} X_{qj} + \varepsilon_{qj} = \mu^{'} X_{qj} + \eta_q^{'} X_{qj} + \varepsilon_{qj} \\ &where, \\ &q = 1, 2, ..., n. \\ &j \in C_q \end{aligned} \qquad (0.13)$$

where $\eta \sim N(\mu,\Omega)$, ε_{qj} is a random draw from EV1 distribution of errors, and η_q is the correlation across choices for the q^{th} individual. If the individual q was observed to choose alternative i, the probability if this choice conditional on β_q is:

$$P_{qi}(\beta_q, X_q) = \frac{e^{\beta_q^{'} X_{qi}}}{\sum_{j \in C_q} e^{\beta_q^{'} X_{qj}}} \tag{0.14}$$

The unconditional probability of choosing alternative i is therefore:

$$\pi_q = \int_{-\infty}^{\infty} P_{qi}(\beta, X_q) N(\beta | \mu, \Omega) d\beta \tag{0.15}$$

where $N(\beta | \mu, \Omega)$ is the normal cdf with parameters (μ, Ω).

In this model, a closed solution is not possible and π_q is generated by a randomly drawn process. Let the number of simulated random draws from $N(\mu, \Omega)$ for the q^{th} individual. The simulated probability for R random draws is given as:

$$SP_q = \frac{1}{R} \sum_{r=1}^{R} P_q(\beta_q^r, X_q) \tag{0.16}$$

where for the random draw r for the q^{th} person from $N(\beta | \mu, \Omega)$, the coefficients are given as β_q^r. The estimator is simulated Maximum Likelihood and is given as:

$$SL = \sum_{q=1}^{N} \ln \left[\frac{1}{R} \sum_{r=1}^{R} P(\beta_q^r, X_q) \right] \tag{0.17}$$

Although the model is useful in identifying heterogeneity between and unobserved effects between individuals, the expensive computational procedure limits practical applications of the model.

5. Data and Survey

Data for this analysis were obtained by interviewing 216 random patrons at 16 parks in Topeka, Kansas. Survey questions were designed to identify amenity value of environmental services by identifying the respondent's travel costs and visitation choices among Topeka parks. Table I in the appendix presents summary statistics and variable definitions for the survey.

Since the purpose of this analysis was to combine RP and SP data, the on site survey was required to obtain both observed as well as hypothetical visitation data. While many prior studies collect this type of information via the mail format, Hanley et al. (2000) point out that the on-site survey format is more reliable than mail surveys since the interviewer actually witnesses the respondent's choice of resource site. See appendix for the complete survey.

The following sections discuss RP and SP question formats for the survey instruments. Since the literature offers advice on optimal question formats, we follow closely the experimental designs of prior studies.

RP Elicitation-The Travel Cost Method

Although the studies of choices to different recreational sites are ubiquitous in the literature, few studies entirely address the problems of substitute sites, multiple purpose visits, and opportunity cost of time (See Section 1). Here, an attempt was made to control these issues through a detailed questionnaire format. As well as observed park choice on the day of the survey, each respondent was asked to list the other parks he or she chooses to visit. The travel cost to each site is also recorded. Each person's choice set is then defined as the parks that are available to the respondent in his/her respective area.

Also, the agent's opportunity cost of leisure time is determined through standard calculations in Fugitt and Wilcox (1999).

SP Elicitation-The Choice Experiment

A hypothetical CE was used to mirror the observed travel decision of the respondent. While prior studies have combined CE data with the travel cost decision, this CE approach is unique in that it closely complements the SP and RP travel decision of respondents. In particular, the survey elicits each respondent's intensity of preferences for each hypothetical park, rather than simply the choice of one park over another. This follows recent literature that has incorporated the consumer's intensity of preferences in CE. Kuperis et al. (1999) used CE to model the demand for milk products by designing stated choice experiments to identify the types of milk chosen, as well as the quantity demanded for each choice of milk. Figure I (appendix) illustrates that the respondent is faced with several resource allocation decisions for park sites. For example, a given consumer was told that there were only three parks in his/her area and asked to choose how often he or she would visit each park with certain amenities.

The CE offers several benefits to our analysis of combining RP and SP data. First, this approach mirrors the observed travel decision for respondents since in the observed data the agent chooses which site to visit as well as the number of times to visit. Second, as discussed in an earlier section of this paper, hypothetical data are beneficial to researchers since the data matrix may be constructed to be orthogonal by design. In the literature this is called the Orthogonal Main Effects experimental design, where the park attributes are varied independently so that the columns of the data matrix are linearly independent. In our case this is accomplished by designing seventy-two surveys, each of which contains two choice sets with three parks, where each park has a unique combination of attributes.

6. Results

It is intuitive for each individual in a sampled population to have unique taste parameters. In effect, this flexibility in the RPL model also accounts for heterogeneity of all unobserved components (data collection method, interviewer quality, type of preference data, etc.).

Results are presented in Tables II(a) and II(b) in the appendix. The RPL model estimation improved the goodness-of-fit slightly over the MNL model. As shown in Table II(a), the random parameters in the utility functions were all statistically significant at the 1% level with the exception of INCOME.

Table II(b) presents the derived standard deviations of parameter distributions in our estimated choice function. As noted, we hypothesized that by allowing for the distribution of utility parameters to vary across decision makers we would also more accurately capturing the behavioral process of modeling choice. In effect, such flexibility would improve model fit and correct for inconsistent parameters estimates. Contrary to our expectations, the derived standard deviations of parameter distributions were all statistically insignificant in our model. This suggests that allowing for the distribution of utility parameters to vary over decision makers did not have a statistically significant effect on choice.

[2] Starting points for the RPL were generated from the MNL model. McFadden's R-SQUARE improved slightly with the RPL compared to the MNL model.

The RPL model is useful in identifying heterogeneity between and unobserved effects between individuals, however, the expensive computational procedure limited the practical applications of the model in our case. The unrestricted covariance matrix[3] could not be estimated due to convergence difficulties; estimation of the completely unrestricted model posed convergence problems and the results were unstable.

7. Discussion

Historically, empirical RUM research has solely considered the effect of the consumer choice process on behavioral means, but not response variability. However since coefficient estimates in the RUM are perfectly confounded with error variance, it is transparent that response variability matters. In the limit, where response variability is infinite, Louviere (2000) indicates that "…if the are J discrete outcomes, the probabilities will exactly equal 1/J and there will be no reliable, systematic, statistical behavioral information contained in choices (p. 2)."

Our model addresses the limitations of traditional methods of combining preference data, and may give researchers a better understanding of the behavioral process of choice. As noted, response variability is as much a behavioral phenomenon as response means (Louviere, 2001). Coefficient estimates are confounded with error variance in the RUM, and empirical parameter estimates may actually be due to the mean

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[3] The unrestricted model posed convergence problems and the results were unstable. As such our restricted model reduces the covariance matrix to:

$$\begin{pmatrix} \sigma_{11}^{2} & 0 & 0 \\ 0 & \sigma_{22}^{2} & 0 \\ 0 & 0 & \sigma_{33}^{2} \end{pmatrix}$$

The restricted case does not allow for unrestricted substitution patterns and correlation of unobserved effects over time. Our results suggest that the distribution of utility parameters did not vary over decision makers, supporting true the IIA assumption in the MNL model.

of the response, the variability of the response, or both. The RPL model is useful in identifying heterogeneity between and unobserved effects between individuals, however, the expensive computational procedure limited the practical applications of the model in our case.

An interesting extension of this analysis would be to test is the accuracy of RPL predictions both in and out-of sample. Gelso (2002) compared the prediction accuracy of fully and partially combined RP and SP models in the MNL model of choice and found that combined models predict more accurately compared to separate models. However, we have discussed that a limitation of the MNL is the assumption of Independently and Identically Distributed (IID) errors, resulting in inaccurate model predictions and inconsistent utility parameters. As such, accounting for all sources of heterogeneity via the RPL would be hypothesized to increase model prediction accuracy. Further dissecting the role of the scale factor would indeed prove to be an interesting and fruitful research.

9. Appendix

TABLE I: Summary Statistics and Variable Description

Variable	Description	Stated Data	Revealed Data	Combined Data
I. Park Amenities:				
Athletic Field	if present (=1), otherwise (=0)	0.484 (0.499)	0.897 (0.303)	0.666 (0.472)
Water Feature	if present (=1), otherwise (=0)	0.459 (0.499)	0.386 (0.487)	0.427 (0.495)
Tree Density	if high (=1), otherwise (=0)	0.496 (0.500)	0.296 (0.456)	0.408 (0.492)
Garden	if present (=1), otherwise (=0)	0.538 (0.498)	0.378 (0.485)	0.468 (0.499)
Playground	if present (=1), otherwise (=0)	0.493 (0.500)	0.953 (0.212)	0.696 (0.460)
II. Demographic Characteristics Interacted with Price:				
Education	years of education	15.131 (2.66)	15.154 (2.681)	15.142 (2.673)
Sex	gender (1=Male)	0.406 (0.491)	0.382 (0.486)	0.396 (0.489)
Adults	number of adults	1.920 (0.627)	1.911 (0.649)	1.916 (0.637)
Children	number of children	1.320 (1.215)	1.327 (1.185)	1.323 (1.201)
Urban	residential location (1=Urban)	0.783 (0.412)	0.785 (0.411)	0.784 (0.412)
Income	dollars of income per annum	51285.71 (33785.11)	51237.92 (32836.14)	51264.64 (33361.21)
Age	years of age	30.360 (10.059)	30.260 (9.87)	30.311 (9.974)
III. Price of Resource Site and Observed Park Attributes				
Price	price of travel plus opportunity cost of leisure time	8.98 (6.37)	15.53 (15.57)	11.871 (11.84)
IV. Characteristics Unique to Observed Parks				
Center	presence of community center	---------	0.395 (0.489)	0.174 (0.379)
Gage	very large park	---------	0.170 (0.376)	0.075 (0.263)
Small Park	small park	---------	0.171 (0.377)	0.075 (0.264)
Size	size of park in acres	---------	123.854 (221.322)	54.606 (159.265)
No. of Observations		1050	828	1878

Figure I: Example of Intensity of Preferences and Orthogonal Main Effects of Conjoint Experiment

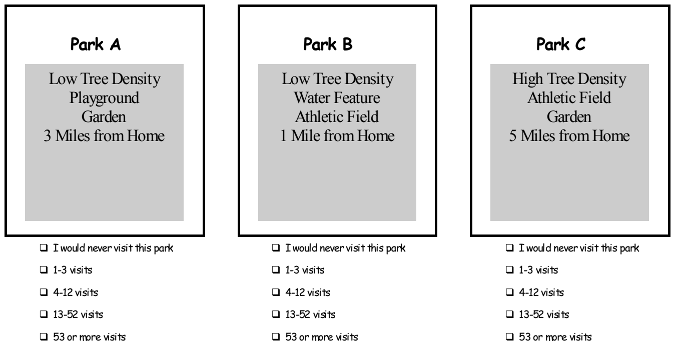

Figure I: The diagram illustrates the CE experimental design for this analysis. Each respondent faces a choice set of three parks with combinations of park amenities. The so-called Orthogonal Main Effects design results in a data matrix reduces multicollinearity. As mentioned earlier in this analysis, the benefit of stated preference data is that it may be designed to have several desirable statistical qualities. Conversely, observed data for environmental explanatory variables are often highly related and therefore collinear. As such, if preference equality exists, the stated data may be combined with the observed data to result in parameter estimates that are statistically efficient. Indeed, statistical efficiency is a desirable quality to researchers, as it provides more stable parameter estimates.

TABLE I(a): RPL Model Estimation Results

Variable	Coefficient	St. Error	b/St.Er.	|P[|Z|>z]
I. Random Parameters in Utility Functions				
Athletic Field	0.387***	0.016	22.788	0.000
Water Feature	0.246***	0.016	15.549	0.000
Tree Density	0.167***	0.018	9.397	0.000
Garden	0.102***	0.016	6.317	0.000
Playground	0.491***	0.016	29.691	0.000
Education	0.004***	0.0009	4.279	0.000
Sex	-0.048***	0.006	-8.415	0.000
Adults	0.023***	0.004	5.727	0.000
Children	0.005***	0.003	2.164	0.030
Urban	0.036***	0.008	4.736	0.000
Income	0.008E-05	0.008E-05	0.988	0.323
Age	0.002***	0.003	6.457	0.000
Price	-0.250***	0.019	-12.909	0.000
Gage	-0.452***	0.035	-12.760	0.000

No. of Observations	1377
Log-Likelihood at Zero	-29639.71
Log-Likelihood at Convergence	-55322.37
McFadden's ρ^2	0.46424
Replications for Simulated Probabilities =	500
Chi-squared	51365.31
Degrees of freedom	28
Significance level	0.0000000

TABLE II(b): RPL Model Estimation Results (Continued)

Variable	Coefficient	St. Error	b/St.Er.	|P[|Z|>z]
II. Derived Standard Deviations of Parameter Distributions				
Athletic Field	0.003	0.016	0.189	0.849
Water Feature	0.002	0.014	0.162	0.871
Tree Density	0.0001	0.015	0.010	0.992
Garden	0.0004	0.014	0.030	0.976
Playground	0.007	0.016	0.473	0.636
Education	0.00002	0.0001	0.169	0.866
Sex	0.0002	0.002	0.096	0.923
Adults	0.00006	0.0008	0.070	0.944
Children	0.00004	0.002	0.022	0.983
Urban	0.0003	0.002	0.148	0.882
Income	0.009E-06	0.002E-05	0.360	0.719
Age	0.00002	0.00005	0.364	0.716
Price	0.0003	0.002	0.122	0.903
Gage	0.013	0.027	0.476	0.634

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Park & Environmental Awareness Survey

Section 1: Traveling to Parks in Topeka…

QUESTION 1:

My first question is how often per year do you generally visit this park?

❑ almost never ❑ 1-3 visits ❑ 4-12 visits ❑ 13-52 visits ❑ 53 or more visits

(i) How many miles did you travel to this park, i.e., how far is the park from your home? _______

(ii) How much time do you generally spend in this park? _______

(iii) Did you drive to this park? _______

QUESTION 2:

2. Do you visit any other parks? ❑ yes ❑ no

Alternate park list,

Park Name	Frequency	Travel	Time	Drive (1 or 0)

QUESTION 3:

3. What if there was a $1 admission fee to enter this park. Would you pay it or would you pass? ❑ yes ❑ no

A. If there was a $3 admission fee to enter this park, would you pay it or would you pass? ❑ yes ❑ no

B. If there was a $0.5 admission fee to enter this park, would you pay it or would you pass? ❑ yes ❑ no

Section 2: Choice of Parks in Topeka…

QUESTION 4: *Okay, on to the next question. The next 2 questions consider how you value parks in Topeka. First, lets suppose that each park is the only park available to you in Topeka. Given the park characteristics in the three following profiles, how often would you visit each park?*

Park A	Park B	Park C
Low Tree Density Playground Garden 3 Miles from Home	Low Tree Density Water Feature Athletic Field 1 Mile from Home	High Tree Density Athletic Field Garden 5 Miles from Home
❑ I would never visit this park ❑ 1-3 visits ❑ 4-12 visits ❑ 13-52 visits ❑ 53 or more visits	❑ I would never visit this park ❑ 1-3 visits ❑ 4-12 visits ❑ 13-52 visits ❑ 53 or more visits	❑ I would never visit this park ❑ 1-3 visits ❑ 4-12 visits ❑ 13-52 visits ❑ 53 or more visits

QUESTION 5: The next 2 questions also consider how you value parks in Topeka. Please remember that each park is the only parks available to you in Topeka. Given the park characteristics in the three subsequent profiles, how often would you visit each park?

Park A	Park B	Park C
Low Tree Density Playground Garden 3 Miles from Home	Low Tree Density Water Feature Athletic Field 1 Mile from Home	High Tree Density Athletic Field Garden 5 Miles from Home
❑ I would never visit this park ❑ 1-3 visits ❑ 4-12 visits ❑ 13-52 visits ❑ 53 or more visits	❑ I would never visit this park ❑ 1-3 visits ❑ 4-12 visits ❑ 13-52 visits ❑ 53 or more visits	❑ I would never visit this park ❑ 1-3 visits ❑ 4-12 visits ❑ 13-52 visits ❑ 53 or more visits

Section 3: Environmental Opinions...

QUESTION 6:

What should be taken into account when legislators are creating environmental laws, RIGHT versus WRONG or BENEFITS versus COSTS(Give spotted owl example)?

- ❑ Right versus wrong.
- ❑ Benefits versus costs.

QUESTION 7:

When legislators are creating environmental laws, should they take into account ONLY HUMANS or ALL LIVING THINGS(Give spotted owl example)?

- ❑ All living things
- ❑ Only Humans.

QUESTION 8:

Now lets consider an endangered species, such as humpback whales.

Would you be willing to pay $20 to protect an endangered species of humpback whale?	❑ yes	❑ no
Would you be willing to pay $35 to protect an endangered species of humpback whale?	❑ yes	❑ no
Would you be willing to pay $10 to protect an endangered species of humpback whale?	❑ yes	❑ no

Section 4: About you….

9. Gender ❑ Male ❑ Female 10. Adults ____ 11. Children ____

12. Would you say you live in primarily a rural or urban area of Topeka? ❑ Urban ❑ Rural

13. What is the highest level of education that you have completed?
❑ Less than high school ❑ High school or equivalent ❑ Some college or technical training
❑ Bachelor's degree ❑ Some graduate school ❑ Graduate degree

14. Which of the following income categories best describes your total expected household income for 2001?
❑ Under $15,000 ❑ $15,000—$25,000 ❑ $25,000—$50,000
❑ $50,000—$80,000 ❑ $80,000-$120,000 ❑ over $120,000

15. What is your age? ❑ 18-29 ❑ 30-35 ❑ 18-29 ❑ 36-50❑ 51-70 ❑ greater than 70

16. Which of the following best describes your employment situation?
❑ Employed (salaried) ❑ Employed (wage) ❑ Self employed ❑ Not employed
❑ Homemaker ❑ Student ❑ Retired ❑ Other________.