

Panel Estimators to Combine Revealed and Stated Preference Dichotomous Choice Data

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Combining stated and revealed preference data often involves multiple responses from the same individual. Panel estimators are appropriate to jointly model the decision to actually visit at current trip costs, the intention to visit at hypothetically higher trip costs, and the intention to visit at proposed quality levels. To incorporate data on all three choices, the random effects probit model is used to estimate the economic value of changes in instream flow. This model illustrates how the complementarity of revealed and stated preference data allows including of instream flow as a covariate in the model and calculating value under alternative flow regimes.

Key words: contingent valuation, instream flow, recreation, travel cost

Introduction

A recent improvement in estimating consumer demand involves combining data on actual and intended behavior. For example, combining data on the quantity of trips actually taken with stated preference responses on *intended* number of trips at alternative prices (Englin and Cameron) has been shown to have several advantages. As noted by Adamowicz, Louviere, and Williams, pooling these two types of data allows evaluating the consumer's response to quality levels outside the range of existing quality that may nevertheless be policy relevant. Second, strategic design of quality levels in the intended behavior portion of the survey may reduce the multicollinearity between quality characteristics often present in observed data (Adamowicz, Louviere, and Williams). Combining stated willingness-to-pay (WTP) questions may allow more precise estimation of the choke price or vertical intercept portion of the demand curve when there is minimal variation in prices in the observed data. Finally, combining the travel cost (TC) method and contingent valuation (CV) data allows the researcher to impose consistency between the two types of responses when estimating WTP (Cameron).

Combining revealed preference information and intended behavior responses frequently involves obtaining multiple responses from the same individual. These responses are likely correlated within an individual due to individual specific but unobservable taste parameters. Standard statistical models fail to account for the correlation across multiple responses from the same individual and are therefore inefficient. Panel estimators such as bivariate probit, fixed effects, and random effects/error-component models are candidate models that account for the possible correlation of multiple responses of the same

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individual. Englin and Cameron apply a fixed-effects ordinary least squares and Poisson models to test for differences in price elasticities and consumer surplus from separate demand equations estimated with observed number of trips and intended number of trips with three hypothetical cost increases. Adamowicz, Louviere, and Williams compared site-selection choices estimated from actual data versus hypothetical scenarios.

Bivariate Probit and Random Effects Probit Models

Contingent valuation surveys often involve a series of dichotomous responses. For example, questions such as "Do you currently visit?" "Would you visit if quality were higher?" "Would you visit if costs were higher?" The first response is an actual behavior response while the other two are contingent visitation and valuation, respectively. When combining dichotomous responses to stated and actual behavior questions the appropriate model depends on several factors. A bivariate probit model would be an appropriate statistical model if the analyst believes any of the following is true: (a) the determinants (e.g., X s) of these choices are different; or (b) the determinants are the same but the size of the coefficients (β s) may be different; or (c) the unobservable or random effect (ϵ) is different across these choices. The bivariate probit model is

$$(1) \quad Z_{i1} = \beta_1'X_{i1} + \epsilon_{i1}, Y_{i1} = 1 \text{ if } Z_{i1} > 0, Y_{i1} = 0, \text{ otherwise,}$$

and

$$(2) \quad Z_{i2} = \beta_2'X_{i2} + \epsilon_{i2}, Y_{i2} = 1 \text{ if } Z_{i2} > 0, Y_{i2} = 0, \text{ otherwise,}$$

where Z_{i1} , Z_{i2} are unobserved latent variables and Y_{i1} and Y_{i2} are indicator variables. $[\epsilon_{i1}, \epsilon_{i2}]$ is distributed bivariate normal with zero mean, unit variance, and correlation ρ . ρ is the correlation coefficient between responses to the first dichotomous choice question (e.g., have you visited the site) and the second dichotomous choice question (e.g., would you visit if quality were Q^* instead of Q_0 or Trip Costs were $TC_0 + \$X$ instead of TC_0). Cameron and Quiggin discuss why two responses might be less than perfectly correlated and hence the rationale for a bivariate probit estimator. The log likelihood of the bivariate probit model is given by Greene (1995, p. 464):

$$(3) \quad \ln L = \sum_i \ln \Phi_2[q_{i1}\beta_1'X_{i1}, q_{i2}\beta_2'X_{i2}, q_{i1}q_{i2}\rho],$$

where $q_{ij} = 2Y_{ij} - 1$, $j = 1, 2$; and Φ_2 is used to signify the bivariate normal CDF.

The bivariate probit limits the number of responses per individual to two. When an individual is asked to respond to several questions about higher trip costs and changed quality levels, the bivariate probit model's inability to handle more than two related responses is a serious drawback. The random effects probit model can handle multiple responses, but it does involve its own set of restrictive assumptions.

Alberini, Kanninen, and Carson noted that a random effects/error-component model may be appropriate for analyzing the multiple dichotomous-choice responses at different bid levels for the same program (e.g., the double-bounded approach). We believe such a modeling approach is also useful where the same person responds to a series of dichotomous questions regarding current visitation, intended visitation, and WTP. In particular, stated and revealed preference responses are often dichotomous, for example,

when the site is visited at most once a year (e.g., the Grand Canyon) or where a majority of households interviewed do not visit the site at all. In these settings, the random effects panel estimator may be more appropriate than the fixed effects model for a number of reasons. As noted by many authors (Greene 1990; Maddala), the random effects model has more intuitive appeal and greater external generalizability for panel data of a sample of individual consumers drawn from a large population than fixed effects. The fixed effects model would be appropriate if the researcher were interested in the specific sample units, rather than simply generalizing the sample to the population. Further, Maddala suggests that coefficients on individuals' demographics cannot be identified with a fixed effect model, but can with a random effects model. The ability to incorporate variables on demographics can be useful for at least two reasons. First, if the sample characteristics do not perfectly match the population and the population values of the demographic variables are known, the population levels can be multiplied by the coefficients to obtain an estimate of the probabilities more representative of the population. Second, to facilitate transfer of the WTP function to different geographic areas which may have different demographics, including demographic variables, facilitates such benefit transfers. A final advantage of random effects over fixed effects is that, with typical panel data sets including hundreds of cross sections (e.g., individuals) but few responses per individual, fixed effect probit models give inconsistent parameter estimates, while random effect probit models are consistent (Maddala).

Equation 4 illustrates the basic structure of the random effects model:

$$(4) \quad Z_{it} = \beta X_{it} + u_i + \epsilon_{it}, Y_{it} = 1 \text{ if } Z_{it} > 0, Y_{it} = 0 \text{ otherwise,}$$

where Z_{it} , Y_{it} , X_{it} and β are vectors of latent, indicator, explanatory variables, and vector of coefficients, respectively; i indexes individuals in the sample and t indexes the number of responses per person or visitor; and u_i is an unobservable characteristic specific to individual i . The u_i are the random disturbances that are common to and constant over a given individual's responses and assumed to be uncorrelated with the other regressors (Greene 1990; Maddala). The ϵ_{it} are the transitory errors due to random response shocks across individuals (Alberini, Kanninen, and Carson).

Equation (4) could be estimated as a random effects probit or logit model (Maddala; Greene 1990). The random effects logit model constrains the correlations between responses (ρ) to be 0.5 (Maddala), while the random effects probit model allows estimating the correlation coefficient between responses. By evaluating the size of ρ one can determine whether most of the variability in responses is due to the unobservable individual specific differences or from the transitory error that varies across individuals. In particular, if ρ is low, then the variance associated with ϵ_{it} is large relative to the individual specific variance (u_i) and vice versa (Alberini, Kanninen, and Carson). The log likelihood of the random effects probit model is given by Greene (1995) as:

$$(5) \quad \ln L = \sum_i \ln \left\{ \int_{-\infty}^{\infty} \frac{1}{(2\pi)^{1/2}} e^{-\epsilon^2/2} \Pi_i \Phi(r_{it} z_{it}) d\epsilon_{it} \right\},$$

where $r_{it} = 2y_{it} - 1$ and $z_{it} = [\beta' X_{it} + [\rho/(1-\rho)]^{1/2} \epsilon_{it}]$. Thus, the random effects probit model offers a new tool for analyzing data sets that combine multiple stated and actual dichotomous choices. The disadvantage of this modeling structure is it implicitly restricts the model to having the same coefficients (β s) and variables (X s) to explain all the dichotomous choices. However, one could add a dummy variable that could be coded as

being applicable for a particular type of dichotomous choice (e.g., visitation vs valuation decisions). In addition, the random effects probit model assumes that each person's error-generating process is the same for all their dichotomous choices (although it does vary across individuals). While on the surface this assumption of the same βX and error-generating process may seem overly restrictive, as shown below, this may not necessarily be the case. The actual trip decision and intended visitation responses can be cast in a utility difference framework that is nearly identical to the dichotomous choice CVM framework. Thus, these different dichotomous choice questions (e.g., would you visit if quality was Q_1 instead of Q_0) are simply different ways of representing the same valuation behavior. Economic theory would suggest the same utility structure or demand behavior should explain the decision to visit at higher costs and qualities (Cameron). However, in some cases the β s for intended and revealed preference may not appear to be equal, but the differences are due to differences in the scale parameter (i.e., the inverse of the variance) between intended and actual behavior. Unfortunately, probit estimates of the coefficients in (4) are really β/σ , where σ is the scale parameter. As noted by Swait and Louviere, the scale factor cannot be separately identified in most data sets. Separate identification of β and σ is essential if the researcher wishes to determine if differences in estimated coefficients between actual and intended behavior are really due to mean differences in responses or simply differences in the variances between the two types of behavior. Several past studies have found that, once differences in variances between actual and intended behavior have been accounted for, mean response behavior is quite similar (Louviere).

Another potential drawback of random effect probit models is the requirement that the random effect (u_i) is uncorrelated with the explanatory variables X_{it} . If the analyst believes this requirement is likely to be seriously violated, Chamberlain provides a random effects probit model that allows for correlation between u_i and X_{it} .¹

When the research objective is to *test* whether the same variables and coefficients equally explain actual behavior responses and intended behavior responses, the bivariate probit model makes testing these hypotheses more direct. Testing could be performed by determining whether the same independent variables in the valuation function have a statistically significant effect on the two choices or whether there is equality of β/σ of the same variables. In any case, the analyst is essentially testing whether $(\beta_1/\sigma_1) = (\beta_2/\sigma_2)$, where 1 represents actual and 2 represents intended behavior, to determine if there is consistency between actual behavior and intended behavior responses. As Swait and Louviere point out, if this hypothesis is accepted, it implies equality of both the coefficients (β s) and the scale parameter (σ) or variance. Of course, if we reject the hypothesis of equality, the source of this divergence could be either the coefficients or, as has been found more frequently, the differences in the scale parameter. Swait and Louviere provide a likelihood ratio testing procedure to determine which of the two factors is the source of the difference. It is also possible to test for differences between actual and intended behavior in the random effects probit model by including shifter and interaction dummy variables to test for differences in stated preference versus revealed preference responses. The same caveat regarding whether the source of any divergence is due to the coefficient or the scale parameter applies here as well. That is, since only β/σ is estimated, the β s

¹ At present the author is not aware of any commercially available statistics package that can implement the Chamberlain model. For example, the feature is not available in the latest (version 7) of LIMDEP.

could be equal for actual and intended behavior but different variances could result in rejecting the equality of β/σ . In some cases it may not be possible to implement Swait and Louviere's likelihood ratio test since the test requires sufficient data to estimate separate actual behavior and intended behavior models.

The next section adapts the utility difference framework to provide a combined stated and revealed preference dichotomous choice model and then use the random effects probit model to analyze the recreation benefits of maintaining instream flow.

Stated and Revealed Preference Dichotomous Choice Model

Hanemann's (1984) utility difference formulation of the discrete choice CVM problem can be recast as a visit/no-visit decision at current trip costs, higher trip costs, and/or improved quality. Consider first the decision to actually visit the site. Let utility of individual i (U_i) be defined as the sum of deterministic (V_i) and random components (ϵ_i), where ϵ_i is an independently and identically distributed random variable with zero mean that reflects components of the utility function unobservable to the analyst (Hanemann 1984). Following McConnell, Weninger, and Strand, let $V_{i1}(Y_i - TC_i, Q = 1)$ be the deterministic utility from taking a trip when site quality is good (i.e., $Q = 1$), where Y_i is income and TC is travel costs. If the individual does not make the trip, the deterministic part of utility is $V_{i0}(Y_i)$ assuming weak complementarity, that is, site quality does not matter when the site is not visited (Freeman).

If we observe the individual at the recreation site, then it must be the case that the utility difference must satisfy

$$(6) \quad V_{i1}(Y_i - TC_i, Q = 1) - V_{i0}(Y_i) > \epsilon_{i0} - \epsilon_{i1}.$$

This utility difference is driven by the observable trip choice and hence may be considered revealed preference information, although it is still subject to some of the criticisms levelled by Randall regarding observability of the actual travel cost variable, TC , faced by the respondent.

Suppose that this visitor is now asked a rather standard dichotomous choice CVM question of the form, "If everything else about this trip were the same, including the site quality, but the trip costs to make this visit were $\$X$ higher, would you still have made this visit?" If the individual answers yes, we can infer that the utility difference must also satisfy:

$$(7) \quad V_{i1}[Y_i - (TC_i + \$X), Q = 1] - V_{i0}(Y_i) > \epsilon_{i0} - \epsilon_{i1}.$$

Of course if the answer is no, then

$$(8) \quad V_{i1}[Y_i - (TC_i + \$X), Q = 1] - V_{i0}(Y_i) < \epsilon_{i0} - \epsilon_{i1}.$$

If these are the only two questions asked, there are several possible modeling frameworks that recognize the interrelationship of the responses to the trip decision and dichotomous choice CVM question. One could model the two responses as a bivariate probit if one had data on visitors and nonvisitors. The first equation would be the visit/no-visit at the individual's TC (which would need to be inferred or calculated for nonvisitors). Those that visit would be asked a dichotomous choice CVM question involving a $\$X$ increase in TC at existing quality. Those not currently visiting would be asked if they intended

to visit if the cost were $\$X$ lower. Alternatively, McConnell, Weninger, and Strand suggest that the Hanemann, Loomis, and Kanninen double-bounded framework could be adopted. In this framework TC is treated as the first bid and $(TC \pm \$X)$ treated as the second bid. Of course the random effects probit model could also be estimated.

This simple two-response model can be extended in several directions. For example, combining the discrete trip choice in (6) with a true double-bound dichotomous choice question, yields three possible responses per person. This could be modeled using the multiple-bounded approach suggested by Welsh and Bishop.

Another important extension relates to modeling the value of site quality improvements. There may be situations of great policy relevance where the analyst wishes to know how WTP changes with a policy-induced change in quality. It may not be possible to rely solely on revealed preference techniques to estimate $\partial WTP/\partial Q$ due to one of four reasons: (a) quality does not currently vary at this site; (b) there are no similar sites with differing quality levels so that a varying parameters type TCM approach is ruled out; (c) the change in quality proposed is so large as to be outside the current range of quality variation at the given site or even similar sites; or (d) quality varies but is so correlated with other nonpolicy site characteristics that it is difficult to estimate the effect of interest.

In this case an intended visitation approach (Loomis) can be appended to the model developed so far to allow estimation of $\partial WTP/\partial Q$. In particular, the individual can be asked if he or she would visit under different quality conditions. For example, existing visitors could be asked if they would continue to visit if site quality deteriorated (i.e., $Q = 1 - \gamma$). Alternatively, in a household survey, visitors and nonvisitors could be asked if they would visit if quality improved ($Q = 1 + \gamma$). This latter question would provide valuable information on the participation effects associated with improvement in environmental quality.

If the reduction in quality ($-\gamma$) results in a large enough reduction in the utility of taking a trip relative to the travel costs the individual may now stay home since

$$(9) \quad V_{i1}(Y_i - TC_i, Q = 1 - \gamma) - V_{i0}(Y_i) < \epsilon_{i0} - \epsilon_{i1},$$

while for a large enough increase in quality ($+\gamma$), one might expect

$$(10) \quad V_{i1}(Y_i - TC_i, Q = 1 + \gamma) - V_{i0}(Y_i) > \epsilon_{i0} - \epsilon_{i1},$$

for all current visitors and possibly some previously nonvisiting households.

It should be noted that the actual behavior question in (6) may be ex post, while the intended behavior questions in equations (9)–(10) are usually ex ante in nature. Therefore, this differing time perspective could lead to different answers even though the underlying utility function is the same.

While there are several error structures that allow for correlation of responses across individuals, one that accommodates more than two responses per person is the random effects model in (4). The following empirical model uses the random effects probit model to analyze four responses per person. These responses include the actual trip decision, a dichotomous choice CVM response to higher trip costs, and two contingent visitation responses at different site quality levels.

Empirical Model Combining Actual Trip Decision, Dichotomous Choice CVM, and Intended Visitation at Alternative Quality Levels

The empirical model has four observations per individual. The first observation is the actual trip visitation decision. Following (6), if the individual chooses to incur his own specific travel cost (TC) to visit ($VISIT = 1$) with the currently good site quality ($F = 15$ million gallons daily of instream flow), then utility difference is (where subscript i has been suppressed for notational simplicity) as follows:

$$(11) \quad V_1(Y - TC, F = 15) - V_0(Y) > \epsilon_0 - \epsilon_1.$$

The first intended visitation question asks whether the individual would visit if site quality deteriorated to $F = 5$ million gallons daily (mgd). If he would continue to visit then the utility difference is

$$(12) \quad V_1(Y - TC, F = 5) - V_0(Y) > \epsilon_0 - \epsilon_1.$$

The second intended visitation question asks whether the individual would visit if instream flows fell to $F = 3$ mgd. If he would continue to visit, this utility difference is similar to (12):

$$(13) \quad V_1(Y - TC, F = 3) - V_0(Y) > \epsilon_0 - \epsilon_1.$$

Finally, the individual is asked whether they would continue to visit the site with existing site quality ($F = 15$) if trip costs were $\$X$ higher, where $\$X$ varies across individuals. If he would visit then the utility difference is

$$(14) \quad V_1[Y - (TC + \$X), F = 15] - V_0(Y) > \epsilon_0 - \epsilon_1.$$

Equations (11)–(14) form our panel of four responses per person. Treating the responses as a panel reveals more about valuation than treating each observation as independent. Differences in individual preferences will result in some individuals switching from visit to nonvisit status when instream flow falls from 15 mgd to 5 mgd or to 3 mgd. Precision in estimated values is enhanced since we have both variation in TC s across individuals as a result of differences in their residential location and randomly varying $\$X$ in the dichotomous choice CVM portion of the survey. We will compare the estimates from treating the responses as a panel with an equivalent probit model that pools all of the responses but treats each observation as independent.

Applying a random effects probit model provides coefficient estimates of the bid amount (β_1) and a constant term (β_0), as well as making possible estimation of an instream flow variable (β_2). In this contingent behavior model, β_0 can be interpreted as the utility of choosing to visit the site (independent of the cost or flow rate) relative to the utility of not visiting the site. However, WTP does depend upon the flow rate and thus the overall constant ($\beta_0 + \beta_2 F_r$) is also determined by the flow coefficient and the magnitude of flow. Hanemann (1989) shows that with a linear utility difference model the unrestricted mean and median WTP of a trip to the river with each of the three flow levels would be

$$(15) \quad WTP(F_r) = (\beta_0 + \beta_2 F_r)/\beta_1,$$

where $F_r = 15, 5, 3$ mgd. If one desired to know the marginal value of flow, this could be obtained as:

$$(16) \quad \text{Marginal Value of Flow} = \beta_2/\beta_1.$$

If instead of a probit model specification that is linear in the dollar bid amount, one uses the natural log of the bid amount to avoid potential prediction of negative benefits that is permitted in (15), *WTP* is given by

$$(17) \quad WTP(F_r) = \exp[(\beta_0 + \beta_2 F_r)/\beta_1].$$

The validity of all of these valuation measures, of course, depends on the consistency of the maintained hypotheses embedded in the structure of the utility functions and as well as the functional form of the probit model.

Data Collection

The empirical problem deals with recreation at a river in Puerto Rico. The Rio Mameyes is threatened by a proposal to reduce its virgin flows in half, while at the same time increasing the sewage treatment discharges into the river. Several agencies were interested in how the aggregate value of recreation would change with differing levels of diversion. Prior to formally developing the survey instrument a focus group was held in the town closest to the river and consisted only of people who recreate in the river. Following this focus group, a complete survey script was developed. A cadre of interviewers were trained in the proper techniques to conduct a personal interview and then the survey was pretested on a small sample ($n=30$) of visitors. During the pretest interviews we repeatedly probed the respondent to determine if any portions of the survey or questions were confusing or unclear. Finally, the pretest was used to refine the range of bid amounts for the dichotomous choice *WTP* questions.

In the economic section of the survey, visitors were first asked their trip cost (*TC*). This provides the information for (11). They were then asked their willingness to pay higher trip costs to visit the Rio Mameyes at current flows. Specifically, they were asked if they would still visit the Rio Mameyes today, if their cost were \$*X* higher than they already spent on that visit. This provides the dichotomous choice *CVM* information for (14). The bid amounts were \$5 per trip to \$120 per trip at the high end. These bid amounts were based on responses to discussion in the focus groups and pretesting of the survey questionnaire.

Visitors were then shown a graph of the water level in the river by month of the year. The graph showed the current average flow and the seven-day minimum flow as reference points. This graph also showed what the flow in the river would be in each month with the maximum daily extraction planned by the water authority. This graph showed that the Rio Mameyes could be dry seven days each month during the months of April, June, and December, as well as having very low flows during May, July, and October (the overall recreation season average being 3 mgd, hereafter $F = 3$). A second graph had the same two reference curves plus what the river flows would be like each month with water withdrawals subject to a 5 mgd minimum instream flow (hereafter, $F = 5$). The graph indicated the river would be at this 5 mgd minimum seven months a year.

The contingent behavior questions asked whether they would (a) increase, (b) decrease, or (c) not change their visitation if the river flows were as shown on the graph for $F = 3$. If they said they would change their visitation, they were asked to state the change

in number of trips (ΔT_1). This question was repeated for $F = 5$ (withdrawals with a 5 mgd minimum).

We computed the new number of trips (T_1 or T_2) with $F = 3$ and $F = 5$, respectively, by subtracting the decreased trips (ΔT_1 or ΔT_2) from their current trips (T_0). With $F = 3$ completely drying up the river in several months, decreased trips equalled current trips for about 148 out of 199 visitors, suggesting that about 70% would no longer visit the site ($T_0 - \Delta T_1 = 0$). For the purposes of demonstrating how to combine the dichotomous choice CVM response with contingent behavior responses, any positive visitation was coded as one (e.g., if T_1 or $T_2 > 0$, T_1 or $T_2 = 1$). We recognize that number of trips is integer data and could be modeled along the lines suggested by Cameron or Englin and Cameron. However, to illustrate analysis of a site where the majority of individuals visit at most once a year (e.g., the Grand Canyon, Yellowstone) and the random effects probit model, positive visits were simply coded to one. Therefore the recoded contingent behavior responses provide the information for (12) and (13).

Model Specifications

Three different probit model specifications are estimated. Equation (18) is a simple probit model that pools all individual responses without accounting for the panel nature of the data:

$$(18) \quad Y_{ir} = \beta_0 + \beta_1(TC_i + BID_i) + \beta_2(FLOW_r) + \epsilon_i,$$

where $Y_{ir} = 1$ if the person does or would visit with the particular river flow scenario (r) and zero, otherwise; TC is travel cost to the site and BID is bid amount the respondent was asked to pay, which in the change in flow scenarios is equal to zero; $Flow$ is the river flow level associated with the specific alternative, $r = 15, 5$, and 3 mgd; and $\epsilon_i \sim N(0, 1)$.

Equation (19) presents the standard random effects probit model which ignores any difference in revealed and stated behavior:

$$(19) \quad Y_{irt} = \beta_0 + \beta_1(TC_{it} + BID_{it}) + \beta_2(FLOW_r) + U_i + V_{it},$$

where $i = 1, \dots, 200$ and $t = 1, 2, 3, 4$; U_i is the unobservable characteristic specific to each individual; V_{it} is the transitory error across individuals; and r is the particular river flow level, where $r = 3, 5, 15$.

To allow testing of consistency of revealed and stated preference responses, we test whether $\beta_3 = 0$ and $\beta_4 = 0$ in the following equation:

$$(20) \quad Y_{irt} = \beta_0 + \beta_1(TC_{it} + BID_{it}) + \beta_2(FLOW_r) + \beta_3(SPDUM_{it}) \\ + \beta_4(SPDUM_{it}(TC_{it} + BID_{it})) + U_i + V_{it},$$

where $SPDUM = 1$ if response is stated preference and zero if equal to actual behavior.

Equation (21) provides the log of cost model. This specification has the advantage of ruling out the possibility of negative benefits or WTP.

$$(21) \quad Y_{irt} = \beta_0 + \beta_1(\ln(TC_{it} + BID_{it})) + \beta_2(FLOW_r) + U_i + V_{it},$$

and the corresponding model for testing differences in stated versus actual behavior is

$$(22) \quad Y_{irt} = \beta_0 + \beta_1(\ln(TC_{it} + BID_{it})) + \beta_2(FLOW_r) + \beta_3(SPDUM_{it}) \\ + \beta_4(SPDUM_{it}(\ln(TC_{it} + BID_{it}))) + U_i + V_{it}.$$

Sampling

Recreation users were sampled at two locations, at the mouth of the river and at a site that will be referred to as the restaurant site as it is next to a closed restaurant. Surveys at the restaurant site were performed on half the weekends in July and August as well as two holidays and weekdays for a total of twelve days during 1995. Surveys at the mouth of the river were conducted on half the weekends in July as well as two holidays and two weekdays for a total of nine days during 1995. Recreation users were interviewed on site. One person from every group present at the site during the survey period (10 A.M. to 5 P.M.) was interviewed. Visitors were screened for minimum age of 16 (i.e., driving age so they could make their own trip decisions). In addition, we did not interview visitors who had been previously interviewed at the recreation site. Our use of on-site sampling would likely result in endogenous stratification, namely, a greater probability of sampling more frequent users. To the extent that endogenous stratification may affect our estimates in our probit models, our absolute benefit estimates may be overstated.² A total of 274 recreation users were contacted and 200 agreed to be interviewed, resulting in a response rate of 73%.

Results

Comparison of Estimated Random Effects Probit Model to Binary Probit Model

LIMDEP'S panel data, random effects probit model, were used to estimate equations (19) through (22) as well as the standard binary probit model estimated by assuming all of the observations are independent (18). We are not able to implement Swait and Louviere's likelihood ratio test, since a separate probit model for the actual behavior responses cannot be estimated. This is due to the sample design, which while cost effective in identifying visitors to the Rio Mameyes results in all observations of the dependent variable in the actual behavior model being one.

As can be seen in table 1, the bid amount in the simple binary probit model is insignificant in both the linear and log cost model. In contrast, both specifications of the cost variable are significant in the panel probit model, with the linear being significant at the 0.10 level and the log cost being significant at the 0.01 level. Explicit modeling of the panel nature of the responses makes a noticeable change in the size and significance of the bid coefficient. One possible reason for this marked improvement is that the base

² Shaw as well as Englin and Shonkwiler provide techniques for addressing this within the context of trip frequency models such as the Poisson model. It is not clear that the same magnitude of concern regarding endogenous stratification in trip frequency models is warranted in a binary response model. Unlike a demand curve where the number of trips is the dependent variable and hence endogenous stratification would result in overstating the dependent variable, with a binary response model the dependent variable is simply whether the individual visited or would visit the site or not. Thus, the degree of bias from endogenous stratification in a binary response model may be less.

Table 1. Estimates of Binary and Random Effects Probit Models for Probability Would Pay Increased Trip Cost

Variable	Binary Probit		Random Effects Probit	
	Coefficient	<i>t</i> -Statistic	Coefficient	<i>t</i> -Statistic
Linear Model				
Constant	-0.93577	-9.168	-1.0019	-9.816
<i>TC + BID</i>	-0.00065	-0.043	-0.00262	-1.723
<i>Flow</i>	0.14488	14.288	0.16490	16.877
<i>LogL</i>	-397.27		-392.26	
Log Cost Model				
Constant	-0.8211	-4.474	-0.6841	-3.728
$\ln(\text{TC} + \text{BID})$	-0.0452	-0.836	-0.1373	-2.538
<i>Flow</i>	0.1460	14.824	0.1692	17.180
<i>LogL</i>	-397.02		-391.33	

Note: The number of observations is 796.

travel cost variable is measured with a substantial amount of error or noise. Explicit incorporation of the random effects accounts for this measurement error across individuals, whereas the simple binary probit does not.

The *SPDUM* and (*SPDUM*(TC + BID)*) variables in equation (20) and *SPDUM* and (*SPDUM*(ln(TC + BID))*) in equation (21) were all insignificant ($t = -0.092$ and $t = -0.037$, respectively, for the linear model and $t = -0.042$ and $t = -0.001$, respectively for the natural log of cost model). This suggests no differences between stated preference and revealed preference behavior using either the linear in bid or the log of bid specification of the random effects probit model.

Benefit Estimates from Random Effect Probit Models as a Function of Flow

Using (15), the panel probit model (with the linear bid specification) estimates WTP at current flow levels of \$565 per group trip or \$118 per person. With the 5 mgd minimum flows, the value per trip is -\$13.58. This suggests that the substantial water withdrawals reduces each visitor's well being by \$132 if negative values are allowed. Alternatively, truncating the WTP distribution at zero, visitors lose \$118 and most visitors essentially stop visiting the site even if minimum flows are 5 mgd. Since the random effects probit model allows for stream flow as a covariate, the estimated probit equation can be manipulated to determine the flow at which the average person in our sample would no longer visit because net benefits are negative. When the stream flow averages less than 6 mgd, the typical person in our sample would no longer visit the Rio Mameyes as net benefits ($WTP - TC_0$) becomes negative. This seems reasonable as the upstream portion of the river near the restaurant site can be shallow in places even with current flows of 10–15 mgd. The advantage of the log cost specification is that negative benefits are ruled out. Using the expression for WTP from (17) for the log cost model, benefits at 5 mgd flow are \$3.22 and drop to 27 cents at 3 mgd. This latter number suggests the benefits of visiting the river are essentially zero at the lowest flows.

Pooling the three types of behavior (e.g., actual visitation at 15 mgd, dichotomous

choice valuation at 15 mgd, and intended visitation at 5 mgd and 3 mgd) allows calculating welfare effects that reflect valuation and visitation arising from one common model of behavior. Traditional analysis would be to multiply a separately estimated dichotomous choice WTP per day value times the separately calculated change in days from the intended visitation responses. This misses the opportunity to estimate a valuation function that explicitly incorporates flow as a variable and allows predicting of visitation decisions based on the net benefits per trip. Since flow is a variable, (16) can be used to estimate the marginal value of flow. The linear in cost, random effects probit model estimates this at \$63 per mgd of flow.

Conclusion

Many recreation surveys provide numerous opportunities to pool revealed and stated preference data. Two possibilities are (a) combining revealed preference data on actual visitation levels with intended visitation levels at alternative qualities and (b) combining revealed preference information on whether a site is visited at the current travel cost with dichotomous choice questions regarding the willingness to pay higher trip prices.

In both situations, the resulting data sets involve multiple responses from a given individual, namely, not all of the observations are independent. Ignoring the correlation across responses may result in inefficient estimates. When the dependent variable is dichotomous (i.e., would you visit, would you pay \$X) there are at least two possibilities. If there are only two responses per individual, a bivariate probit approach provides a less restrictive structure than the random effects probit model. However, the bivariate probit model does not allow the analyst to estimate coefficients on quality that vary only across a given individual's responses. Panel probit models incorporating random effects can be used to model these quality changes and can be applied to surveys where there are more than two observations per person. In our empirical example this arose when combining the actual trip visitation decision, a dichotomous choice CVM question using higher trip costs (but current quality) and two intended visitation questions at two different quality levels. Since our interest was in how the value of recreation changed with the hypothetical but policy relevant changes in instream flow, the panel nature of the random effects probit model was best able to use the revealed and stated information to estimate the value of trips with different quality levels. In particular, we were able to estimate the value per trip as a function of stream flow and identify the flow at which they would stop taking trips.

The modeling framework and empirical example provides additional support for Cameron's and Adamowicz, Louviere, and Williams's suggestion that actual and stated behavior can often more productively be viewed as complementary rather than purely competitive. This suggests that recreation surveys would be improved by asking both actual behavior and intended behavior questions. Addition of counterfactual scenarios regarding quality can help to reduce multicollinearity among recreation site attributes allowing the analyst to better isolate the site characteristic that may be of policy significance. In addition, such counterfactual scenarios may provide some information on intended responses to quality changes that are outside the range of quality differences currently experienced. The synergistic use of stated and revealed preference data suggests the whole is greater than the sum of the parts.

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