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Using Actual and Contingent Behavior Data with Differing Levels of Time Aggregation to Model Recreation Demand

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A model of recreation demand is developed to determine the role of water levels in determining participation at and frequency of trips taken to various federal reservoirs and rivers in the Columbia River Basin. Contingent behavior data are required to break the near-perfect multicollinearities among water levels at some waters. We combine demand data for each survey respondent at different levels of time aggregation (summer months, rest of year, and annual), and our empirical models accommodate the natural heteroskedasticity that results. Our empirical results show it to be quite important to control carefully for survey nonresponse bias.

Key words: contingent behavior, recreation demand, travel cost model

Introduction

Due to public concern about anadromous fish species in the Columbia River system, policies which help such species to migrate are being considered. Some of these policies involve substantial seasonal changes in water levels behind Columbia River dams. Policies which help salmon migrate will reduce the quality of reservoir recreation. These reservoir recreation opportunities, at least for some people, are likely more valued than salmon enhancement.

This study was designed to meet the needs of the federal agencies that manage the waters in the Columbia River Basin. These are (*a*) to estimate how often individuals would take trips to *each* of several federal waters under various patterns of water levels (either actual or proposed), and (*b*) to estimate recreational values of each of these waters under current conditions and with changes in the pattern of water levels.

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We derive recreational values with an individual travel cost model (TCM).[1] Other studies have investigated reservoir management issues similar to the ones faced here (Cordell and Bergstrom; Bendel and Stratis; Ward). Our approach contributes to recreation valuation methodology by using contingent behavior data as a supplement to actual behavioral data and correcting for possible sample selection bias. Our study uses panel data and corrections for heteroskedasticity are included in both the probit and the continuous models that make up our demand specification. Few recreation studies have used panel data (some exceptions are Cole et al. and Englin and Cameron 1996.) No previous recreation studies employ observations for each individual at different levels of time aggregation.

The Data and Key Modeling Considerations

We develop the recreation demand model for each of nine specific federal waters in the Columbia River Basin: Hungry Horse, Dworshak, and Lower Granite reservoirs; Roosevelt, Umatilla, Koocanusa, and Pend Oreille lakes; and the Kootenai and Clearwater Rivers. We estimate our models using data collected through a mail survey administered in the fall of 1993.[2] For each person, we potentially have four time-series observations on actual water-based recreational trips to each project for May, June, July, and August of 1993 (along with the actual water levels for each project for each of these months and total annual trips to each water). We also have two additional observations, called contingent behavior (CB) data (eg., Cameron; Englin and Cameron 1996).

CB responses are elicited with the aid of computer-enhanced photographs and graphical and verbal depictions of possible water level changes.[3] An individual is allowed to state that he would or would not (or does not know if he would) take a different number of trips to each regional project under a set of hypothetical, as opposed to the actual, water levels in 1993. If he would take a different number of trips, he is asked how many more or fewer trips he would take to each regional water. CB questions are important here for two main reasons. First, some of the water level policies that must be analyzed represent drastic departures from the relatively small variations in water levels that prevailed during 1993 (a relatively dry year, as compared with the historical average). By extending the domain of our model through the use of contingent scenarios, we alleviate the inherent problem of out-of-sample forecasting that will plague any attempt to predict behavior under several plausible policy scenarios. The contingent scenarios let us anchor these forecasts in part upon stated behaviors, rather than leaving the forecasting results to depend entirely upon the effects of small variations in water levels simply propagated through the particular functional form of the model.

Second, while observed actual monthly water levels at the various waters could in

[1] In our study it is imperative that trips and values be estimated for each, not just one, of the waters. In addition, the model must accommodate all types of water-based recreation. For recent reviews of recreation demand modeling see Bockstael, McConnell, and Strand.

[2] Four versions of the survey were designed and implemented following parts of Dillman's total design method. Professor Dillman's survey center at Washington State University assisted in survey design, including conducting focus groups to develop survey materials. While Dillman's total method calls for several follow up or reminder steps to maximize response rates, the research project schedule and budget did not allow this. Other survey design, implementation, and model details are provided in Callaway et al.

[3] A copy of the survey insert, including the color computer-enhanced photographs, is available on request. Thanks go to Matt Rae and other key *ACE* members for these photographs.

principle be used to explain monthly demands, these monthly water levels have been highly collinear across waters in the historical data.[4] Using the actual 1993 data alone, it would be impossible to discern the separate effects of varying each water level independently while holding the others constant. Since possible policy scenarios involve departures from the usual contemporaneous geographical pattern of water levels, it is imperative to isolate these separate effects.

We handle the large number of possible reallocations of trips (substitution) between waters by assuming that survey respondents choose a destination from a set of federal waters (or an aggregate of other waters) in a large region. The water levels at the chosen destination and at other waters are considered when choosing that destination. We collect trip information (travel costs) to each of the projects and to "all other" waters in the same region. (Data previously collected indicated that the vast majority of trips taken by those that live in the Columbia River Basin are to nearby or regional waters.) Some waters are included in as many as three of these different survey regions. Responses regarding any particular water are pooled across regional versions of the survey. Thus, the demand for a particular water can be estimated as a function of responses and characteristics of all the individuals in the sample who had an opportunity to report a trip to that project.[5] Lastly, to accommodate different types of recreators, we use intercept dummy variables for the type of recreator each individual appears to be (holder of fishing license, boat owner, or both).

The Sample

Our sample includes several categories of respondents. We drew an approximately random sample of members of the general population of the Pacific Northwest (PNW) whose addresses were obtained from local telephone listings. This group was drawn from because we wanted to allow nonrecreators in this group to recreate in response to increasing water levels and because we wanted to be able to explore possible differences between the general population and known recreators. An oversampled pool of residents from counties adjacent to the nine federal waters considered in the analysis were used to increase survey response rates. Actual recreators were intercepted while at the federal waters and asked to participate in the study by mailing in a postcard containing their addresses. This group was surveyed so that some individuals in the sample were known to have actually seen the waters and existing conditions at them. Finally, a random sample of willing volunteers from an earlier survey effort (Callaway, Shaw, and Ragland) was taken, also to increase response rates.

Some possible biases from these four sample groups could exist if not accommodated

[4] As a preview, this multicollinearity was evidenced by its classic symptoms, namely, drastically changing parameters as alternative water levels are dropped in and out of the model, and insignificance in the "own" water level when accompanied by these alternatives. Further, simple correlation coefficients showed evidence of a strong linear positive or negative relationship between water levels in several instances. For example, the correlation coefficient for actual water levels at Albeni Falls and Hungry Horse is 0.98. Using the hypothetical levels posed in the questions for version 1 and coupled with the actual water levels decreases this correlation coefficient to 0.26.

[5] An anonymous referee points out that waters which appear multiple times because they are on different surveys could lead to visitors/trips being overrepresented in an analysis. This might be especially problematic if one aggregated results across the waters. However, as will be seen below, we adjust for this using survey version specific variables in our selectivity model. In addition, we have separate demand models for each water and the main effect in our analysis of having different numbers of visitors/trips is that some models are estimated for larger subsamples and thus have smaller sample variances for the parameters, ceteris paribus. We do not attempt to aggregate trips or consumer's surplus across water demand functions.

for explicitly, as we do. We had limited means of using other methods to increase response rates (see footnote 2). For example, because of their level of interest in the topic, we expected nonrecreators in the general population group to be less likely to return the survey than people who visited the waters. We adjust for systematic differences in response rates between our general population sample and the other specialized samples by explicitly modeling response/nonresponse decisions for our full intended sample.

The Theoretical Model

The focus of our analysis is the average individual monthly summer season (May through August) demand for a recreational water, measured in number of trips, and corrected for nonresponse bias.[6] The rest-of-year demand is incorporated solely to complement the set of disaggregated summer monthly demands and thereby to facilitate combining (for each individual) the four actual monthly observations with the three actual and contingent annual observations also employed for estimation of our model.

The Basic Model

Begin by establishing some notational conventions. Let $t = 5, 6, 7, 8$ denote monthly data for May, June, July, and August, respectively. For annual data, let $T = A, B, C$ denote actual 1993 conditions, the first contingent water level scenario, and the second contingent scenario, respectively. Let r denote "rest of year." Let X be a vector of individual-specific socioeconomic determinants of demand (including travel costs) that do not vary over time during the summer months.[7] Z_t is a vector of socioeconomic or other determinants of demand that do vary over time during the summer months, and W_t is a vector of monthly water levels at all nine main waters in each of May through August.

Individual summer monthly demands (q_t) can thus be expressed as

$$q_t = X'\beta_x + Z_t'\beta_z + W_t'\beta_w + \epsilon_t, \qquad t = 5, 6, 7, 8. \tag{1}$$

Rest-of-year demand (q_r) can be expressed as

$$q_r = X_r'\gamma_x + \epsilon_R. \tag{2}$$

This specification is used because off-season water levels are not available and, in any event, are not likely to vary as dramatically across policy scenarios as will summer season water levels. Annual demand (q_T) can be expressed as the sum of the four summer monthly demands and rest-of-year demands:

$$q_T = (\Sigma_{t=5}^{8} (X'\beta_x + Z_t'\beta_z + W_t'\beta_w)) + (X_r'\gamma_x) + \epsilon_T, \qquad T = A, B, C. \tag{3}$$

When $T = A$, we have actual annual demand. We also have analogous contingent annual demands from the two contingent behavior questions, denoted q_B and q_C.

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[6] An alternative approach to ours, with a focus on water level changes at several different reservoirs was implemented by Ward. In Ward's application however, the water level change modeled is a *total removal* of water, which is actually simulated by changing the site price until zero visits occur at the site. Our approach differs mainly because we examine less severe reductions (and increases) in water levels using a water level variable within the model.

[7] Callaway et al. provides details on construction of the travel costs or implicit travel prices.

Adjustments to the Basic Theoretical Model

Note that we have trip and water level information on a month-by-month basis for only the summer months. To be able to express annual demand as a function of average peak-use season water levels, we divide the sum of the water levels in May through August by 4: $(W_5 + W_6 + W_7 + W_8)/4$. Thus, we need to use $q_A/4$ for actual 1993 annual demand (and $q_B/4$ and $q_C/4$, analogously).[8]

Annual demands can therefore be expressed as a function of average summer water levels as follows:

$$q_A/4 = X'\beta_x + (\Sigma Z_t/4)'\beta_z + (\Sigma W_t/4)'\beta_w + (X_r/4)'\gamma_x + \epsilon_A/4. \tag{4}$$

The simplification of the first term is possible because X is time invariant. The same equation holds for $q_B/4$ and $q_C/4$. Thus, the same parameters, β_x, β_z, β_w, and γ_x, appear in all eight demand equations.[9] Arrayed similarly, the correspondences between the parameters are clear. The four monthly observations are

$$q_5 = X'\beta_x + Z_5'\beta_z + W_5'\beta_w + 0'\gamma_x + \epsilon_5,$$

$$q_6 = X'\beta_x + Z_6'\beta_z + W_6'\beta_w + 0'\gamma_x + \epsilon_6,$$

$$q_7 = X'\beta_x + Z_7'\beta_z + W_7'\beta_w + 0'\gamma_x + \epsilon_7,$$

and

$$q_8 = X'\beta_x + Z_8'\beta_z + W_8'\beta_w + 0'\gamma_x + \epsilon_8.$$

The rest-of-year observations are

$$q_r = 0'\beta_x + 0'\beta_z + 0'\beta_w + X_r'\gamma_x + \epsilon_r,$$

and the three annual observations are

$$q_A/4 = X'\beta_x + (\Sigma Z_t/4)'\beta_z + (\Sigma W_t/4)'\beta_w + (X_r/4)'\gamma_x + \epsilon_A/4,$$

$$q_B/4 = X'\beta_x + (\Sigma Z_t/4)'\beta_z + (\Sigma W_t/4)'\beta_w + (X_r/4)'\gamma_x + \epsilon_B/4,$$

and

$$q_C/4 = X'\beta_x + (\Sigma Z_t/4)'\beta_z + (\Sigma W_t/4)'\beta_w + (X_r/4)'\gamma_x + \epsilon_C/4.$$

For us to combine these different observations in a single model, summer monthly plus rest-of-year demands must sum to annual demand. This places strong restrictions on viable functional forms for the demand equations: they must be linear in qt (or $qT/4$) and linear in parameters. Note also that the information in $q_A/4$ is redundant with the information in q_5 through q_8 plus q_r, so q_A data will be dropped from the estimating models.

[8] If we combine data at two different levels of time-aggregation, without appropriate scaling, the estimated parameters cannot be directly compared—not if it is just a linear transformation as in (4).

[9] Some respondents, who declined to answer the contingent behavior questions, have only six pieces of demand information each.

The Empirical Model

In this section we discuss how the theoretical model above is adapted so that it can be estimated using our data. First, we discuss corrections for nonresponse bias. Then we discuss the intuition behind our two-stage recreation demand model.

Survey Response/Nonresponse Sample Selection Model

Use of missing socioeconomic data and econometric tests for selection bias is not new (e.g., Little and Rubin; Dubin and Rivers), but most previous tests for bias in valuation studies require data on nonrespondents obtained in a follow-up survey (Whitehead, Groothuis, and Blomquist; Mattsson and Li). By merging on the basis of five-digit zip codes, we combine 1990 census data with the rest of the known characteristics for all the origins in our targeted sample. We use these data to estimate the probabilities that each targeted household provides a complete response to each of the two crucial sections of our survey. The inverse Mill's ratios (IMRs) for these probabilities are then used to effect selectivity corrections in our subsequent set of recreation demand models (Heckman; Dubin and Rivers).

For each regional version of the survey, two preliminary probit models explain the probability that the individual returned the survey with enough information to model actual trips and trips under the contingent scenarios. We use the pair of IMR variables from the response/nonresponse models—one for the actual demand information and one for the contingent demand information—as additional explanatory variables to control for heterogeneity in propensities to return or complete the survey.

In rigorous joint models, the coefficients on these IMR variables are usually interpreted as the product of the error correlation (between the latent propensity-to-respond variable and the observed demand variable) and the error standard deviation of the demand variable. Since the standard deviation is necessarily positive and nonzero, a statistically significant coefficient estimate implies the sign of the error correlation. Simulating the expected demand under true random sampling is accomplished by simulating a zero error correlation (which amounts to zeroing out the IMR terms in the demand model).

Empirical Demand Specification

We estimate the demand for trips to each project in two stages. In the first stage, the probability that the individual recreator takes positive trips to a particular project j is estimated. In the second stage, the continuous model of number of trips to project j is estimated, conditional on an individual having taken at least one trip to project j. This specification is somewhat like a common maximum likelihood estimation (MLE) tobit model, generalized to allow for two different "indexes": $G'\beta_g$ explains the zero-trips/positive-trips choice, and $H'\beta_h$ explains the number of trips, given that trips are positive.

The probability of taking some positive number of trips is $\Phi(G'\beta_g)$. Thus, the inverse Mill's ratio for positive trips is $\lambda^G = \phi(G'\beta_g)/[1-\Phi(G'\beta_g)]$. The expression for expected trips, given that positive trips are taken, is $H'\beta_h$. Thus, the appropriate expression for *unconditional* expected trips is $\Phi(G'\beta_g)\ [(H'\beta_h + \rho\sigma\lambda^G)]$.

The variables and parameters in $G'\beta_g$, the index that determines zero versus positive trips, are $G = (X, Z_t, W_t, X_r)$ and $\beta_g = (\beta_x, \beta_z, \beta_w, \gamma_x)$. Descriptions of the elements of

Table 1. Variables in Recreation Demand Models

Variable Name	Description
R_INT, R_IMR-ACTUAL, R_VERSION1	Rest-of-year demand models variables; form link between monthly and annual demands
R_VERSION4	Analogous to similarly named variables for monthly and annual observations, below
OWN PRICE	The own price of the water visit, equal to round-trip distance calculated using the program ZIPFIP,[a] multiplied by the DOT estimate of 29 cents per mile for operating a vehicle, plus lodging costs, plus the opportunity cost of time in travel[b]
FISH-LICENSE, OWN BOAT, FISH & BOAT	These are the intercept shifter dummy corresponds: 1 if the individual had a fishing license in 1993, owned a boat, had a fishing license *and* owned a boat
PRICE_1–PRICE_9	Cross price terms for each of the nine other waters
WTRLVL1–WTRLVL9	The own water level for water *x* is reported as *Wx* for each of the models, the others from *W1–W9* are the potential cross project water levels
HAVE-DIST	1 if distance data were available for this individual; else 0
HAVE-INC, INCOME	1 if income reported for this individual; else 0, and annual income for 1993, if income data reported
DIST-OTHER	Average price or distance for the other five closest waters ????
VERSION1–VERSION4	Intercept shifter dummy for different survey versions when data are pooled
IMR-ACTUAL and *IMR-CONT*	Inverse Mill's ratios from the initial probit survey response models (revealed preference and stated preference response/nonresponse sample selection)
NE TRIPS	The total number of water-based recreation trips reported in each month for the Northeast (controls for seasonal trip-taking behavior independent of historical water-level management in Pacific Northwest)

Note: Models also include intercept terms and dummy variables for whether the trips are taking place in the main summer months or during the remainder of the year.
[a] ZIPFIP calculated the road distance between two places using the latitude and longitude of the centroids for the respective zip codes. Comparison with the distances published in the AAA road atlas showed ZIPFIP estimates to be reasonably accurate.
[b] Lodging costs are the sample average reported for each project by distance zone (<25 miles, 26–149 miles, and >149 miles). Opportunity cost of time is calculated for each individual by multiplying round-trip distance divided by 40 mph assumed average speed, multiplied by the reported hourly wage rate (Shaw).

the variable vectors are presented in table 1. X includes the price (travel cost) to the project in question and to alternative water recreational opportunities, income, and other individual-specific variables. For some waters, Z_t includes a July/August month dummy variable and an independent measure of the tendency to take trips in peak summer months (calculated using average monthly water-based recreation trips from data for the northeastern U.S.).[10]

[10] The July/August dummy was not important for some of the separate empirical model specifications. We thank Dr. George Parsons for providing estimates of the total number of trips by month from his New England recreation data set. We use these estimates to proxy any unobservable U.S. cultural tendency to take a trip in May, June, July, or August. We also note that this variable will not be correlated with water levels in the Columbia River Basin, whereas use of the obvious choice of historical trip data, from the same actual region of the Pacific NW, might create a problem of endogeneity bias.

Our specifications allow the variables in H to be different from those in G and also allow the elements of β_h to differ from those of β_g, which is more general than in the traditional tobit specification, where H and G are identical and $\beta_h = \beta_g$.

Correction for Heteroskedasticity. We have been careful to scale all of our data so that the effective unit of observation is either a summer month or a summer monthly average. Still, the error terms can be expected to be heteroskedastic due to the presence in the estimating specification of trip data pertaining to three different time intervals: monthly, rest of year, and annual. All error variances in our specifications are therefore modeled as differing systematically across these three data types. For tractability, however, we assume that the errors are homoskedastic within each of these categories. The correction for heteroskedasticity is fairly general when viewed in the context of the maximum-likelihood estimation method, and both are discussed in the next section.

The Likelihood Function

It will facilitate exposition of our estimation method to review a conventional tobit log-likelihood function under homoskedasticity. Let $I_i = 1$ if $q_i > 0$, $I_i = 0$ if $q_i = 0$. With a *single* index, $G'\beta_g$, this function is

(5)
$$\max_{\beta_g, \sigma_g} \log \mathcal{L} = \sum_{I=0} \log\{1 - \Phi(G'\beta_g/\sigma_g)\}$$
$$\sum_{I=1} -(1/2)\{\log(2\pi) + \log \sigma_g^2 + [(q_i - G'\beta_g)^2/\sigma_g^2]\}.$$

Heteroskedasticity across the three different data types (i.e., monthly, rest of year, and annual) and the use of two different indexes, $G'\beta_g$ and $H'\beta_h$, in the discrete and continuous portions of the model requires a more general specification.

It is very difficult to estimate the objective function for the requisite nonlinear optimization problem, so we use a two-stage estimation process. The first stage is a heteroskedastic probit model, with different error variances for monthly, rest-of-year, and annual observations:

(6)
$$\max_{\beta_g, \delta_r, \delta_T} \log \mathcal{L} = \sum_i^t I_i \log\{\Phi(G'\beta_g)\} + (1 - I_i)\log\{1 - \Phi(G'\beta_g)\}$$
$$+ \sum_i^r I_i \log\{\Phi(G'\beta_g/\exp(\delta_r))\} + (1 - I_i)\log\{1 - \Phi(G'\beta_g/\exp(\delta_r))\}$$
$$+ \sum_i^T I_i \log\{\Phi(G'\beta_g/\exp(\delta_T))\} + (1 - I_i)\log\{1 - \Phi(G'\beta_g/\exp(\delta_T))\},$$

where Σ_i^t signifies the sum over all monthly observations; Σ_i^r signifies the sum over all rest-of-year observations; and Σ_i^T signifies the sum over the annual observations, which are both contingent since the redundant actual annual data have been dropped.[11] The error standard deviation for the monthly data is normalized to unity (or, equivalently, β_g is actually β_g^*/σ_g). Defining the indicator variables $D_r = 1$ for rest-of-year data, 0 oth-

[11] All actual data are revealed in the notation by summing over the monthly summer data and the rest-of-year data—it would therefore be redundant to include the actuals in the summation from i to T.

erwise, and $D_T = 1$ for annual data, 0 otherwise, allows the index to be generalized to $G'\beta_g/\exp(\delta_r D_r + \delta_T D_T)$. From this, we save the fitted inverse Mill's ratio: $\lambda_G = \phi(G'\beta_g/\exp(\delta_r D_r + \delta_T D_T))/[1 - \Phi(G'\beta_g/\exp(\delta_r D_r + \delta_T D_T))]$.

The second stage is heteroskedastic least squares by maximum likelihood on *only* those observations with positive trips:[12]

$$(7) \qquad \max_{\beta_h, \sigma, \delta_r^*, \delta_T^*} \log \mathcal{L} = \sum_{I=1} -(1/2)\{\log(2\pi) + \log(\sigma^2 \exp(\delta_r^* D_r + \delta_T^* D_T)) + [(q_i - H'\beta_h)^2/(\sigma^2 \exp(\delta_r^* D_r + \delta_T^* D_T))]\},$$

where H includes λ_G interacted with dummies for monthly, rest-of-year, and annual data types. This is because the coefficient on this inverse Mill's ratio is interpreted as the product of an error correlation and the demand-equation error standard deviation. Since the error standard deviation will differ according to observation type, the coefficient on λ_G must also differ by observation type. Likewise, the usually constant σ^2 again differs across the three data types to accommodate the heteroskedasticity in our data.[13]

Derivation of Approximate Consumer's Surplus (WTP)

An individual's WTP to bring about a change in water levels can be defined in terms of expected consumer's surplus ($E[CS]$). The $E[CS]$ for an individual facing a change in water levels is

$$(8) \qquad E[CS] = \int_{W_0}^{W_1} Q^*(P \mid \epsilon)\, dF(\epsilon)\, dW,$$

where $Q^*(\cdot)$ is the observed demand at initial water level W_0 (conditional on ϵ), and W_1 is the water level after the change.

Because of complexities associated with actually calculating $E[CS]$ for each individual (Hellerstein) and for every water level change that needs to be considered, we actually approximate $E[CS]$ for a given water level by estimating the area under the *unconditional expected trip demand function* from individual *observed* price up to the individual's *choke* price. To derive $E[CS]$ for a change in water levels, we repeat this for a different water level and subtract the difference between the two areas to estimate the $E[CS]$ for the water level change.

From the above, we know that unconditional expected trips are

[12] While there are no $I=0$ limit observations in the log-likelihood function in (7), we use the tobit procedure in LIMDEP for the second stage because this algorithm conveniently allows for heteroskedastic errors and permits us to take advantage of the higher-level language of LIMDEP. The one problem with relying on this packaged algorithm is that the LIMDEP output for this second stage reports t-test statistics that do not correct for the presence of estimated regressors (the λ_G variables). While we report the t-statistics from the LIMDEP output, we note that these are derived from a variance-covariance matrix has not been corrected.

[13] We have programmed a full information maximum-likelihood algorithm that allows simultaneous estimation of the two sets of slope and intercept parameters, β_g and β_h, as well as the conditional heteroskedastic error variance parameters, δ_r, δ_T, σ, δ_r^*, and δ_T^*, and the correlation between the latent probit dependent variable and the observed continuous trips variable (given that trips are positive). This correlation parameter is ρ. However, it is very difficult to push this algorithm to convergence for specifications as complex as those employed here. We tried this for one of our waters, using the converted two-stage point estimates as starting values, but could not achieve convergence in this optimization. This algorithm ran under GQOPT on a UNIX system. The initial DFP portion of the optimization, with a convergence criterion of 10^{-6} ran for an elapsed time of eight days without convergence, although these were "good" iterations.

$$(9) \qquad E[q] = \Phi(G'\beta_g/\exp(\delta_r D_r + \delta_T D_T))[(H'\beta_h + \rho\sigma_t\lambda_t^G + \rho\sigma_r\lambda_t^G + \rho\sigma_T\lambda_T^G)].$$

This form complicates the calculation of the choke price needed for the consumer's surplus calculation, since water levels appear in *G, H,* and the λ terms. Details of how this was accomplished are described in Callaway et al.

Estimated Models

We obtain coefficients for (*a*) the two basic response/nonresponse probit models for each of the four survey versions, (*b*) the heteroskedastic probit models for the participation decision at each of the nine federally managed waters, and (*c*) the continuous heteroskedastic models for each of these nine projects. Due to the sheer number of parameter estimates involved in our nine models, we only briefly summarize the results in this article.[14]

Survey Response/Nonresponse Model

Two probit models were estimated for each of the four regional survey versions. One model captures the effects of sample type and different sociodemographic, distance, and census zip code data on the respondent's probability of responding with revealed preference information sufficient to allow their responses to be included in the estimating sample. The second probit model uses identical variables to explain the probability of responding with contingent preference information sufficient to allow these responses to be included in the estimating sample. Two separate probit models were estimated for each region because noticeably more respondents provided revealed preference than contingent preference data. The processes leading to actual (versus contingent) response completion are assumed to be independent.

The results of the first of these probit models are reported here (table 2) and are revealing.[15] While the specifications are not the most parsimonious, multicollinearities do exist between some of the explanatory variables, so we would not rely entirely upon individually statistically significant *t*-ratios in the process of model selection. Maximizing "fit" is relatively more important in this context. Variables that tend, in most cases, to be significant determinants of survey response propensity include (*a*) the distance to the different waters included on that survey version, (*b*) the survey sample strata group, and (*c*) various zip code demographic variables. In cases where one might have strong priors regarding the sign of a coefficient, most estimates confirm the expected influence of the associated variable on the probability of an individual returning the survey questionnaire and providing usable responses.

Demand Models: Heteroskedastic Probit First Stage

Our demand modeling uses a subsample limited to respondents who reported taking at least *some* trip (actual or contingent) to one of the federal waters or any one of the "other

[14] All coefficient estimates are available in Callaway et al.

[15] Results of the second are reported in Callaway et al., but note that the IMRs from this second model do appear in the demand models as the variable *IMR-CONT*.

Table 2. Probit Models for Nonresponse Selectivity-Correction Inverse Mill's Ratios (Models for Presence of *Actual* Trip Data)

Variable	Description	Region 1 (n = 1428) 547/881	Region 2 (n = 1432) 513/919	Region 3 (n = 2092) 746/1346	Region 4 (n = 1994) 744/1250
HAVDIS	1 if distance data available; else 0	0.1921	5.796	8.026	9.903
		(0.656)	(3.164)**	(2.693)**	(1.901)*
HAVOTH	1 if distances to other waters available; else 0	0.2428	−3.269	−4.377	−6.299
		(0.783)	(−1.412)	(−1.305)	(−1.187)
HAVCEN	1 if census data available; else 0	0.5078	−0.7529	0.2017	0.4726
		(1.330)	(−1.680)*	(0.6570)	(1.308)
P2	1 if population 2; else 0 (adjacent counties)	−0.5667	−0.06077	−0.1000	−0.03542
		(−4.424)	(−0.184)	(−0.369)	(−0.088)
P3	1 if population 3; else 0 (Phase 1A)	0.3188	0.2497	0.2027	0.3278
		(2.316)**	(1.908)*	(2.322)**	(3.052)**
P4	1 if population 4; else 0 (postcard sample)	0.1770	0.3877	0.7593	1.457
		(1.232)	(1.959)*	(4.628)**	(2.453)**
P5	1 if population 5; else 0 (Canada)	−0.7784	−0.07165	0.2068	0.1533
		(2.448)**	(−0.030)	(0.071)	(0.02985)
DIST1	Distance to water 1	0.4901	−0.01533	−0.2211	−0.7500
		(3.821)**	(−0.048)	(−1.245)	(−2.165)**
DIST2	Distance to water 2	0.01589	−0.7563	−0.1570	0.3835
		(0.611)	(−1.044)	(−0.682)	(0.3946)
DIST3	Distance to water 3	−2.394	0.3996	−0.09249	−0.7575
		(−5.061)**	(0.603)	(−0.631)	(−0.716)
DIST4	Distance to water 4	1.675	0.1628	—	0.1144
		(4.749)**	(1.335)		(0.287)
MIN1	Distance to nearest other water	1.310	−0.5921	0.6213	0.6391
		(2.620)	(−1.608)	(1.158)	(0.746)
MIN2	Distance to second nearest other water	−0.4602	1.368	−0.005089	−1.566
		(−0.371)	(1.814)*	(−0.010)	(−1.392)
MIN3	Distance to third nearest other water	−3.556	0.5580	−0.5410	1.624
		(−3.221)**	(0.993)	(−0.707)	(2.292)**
MIN4	Distance to fourth nearest other water	−0.1560	−1.611	−0.04339	−0.6860
		(−0.165)	(−2.470)**	(−0.113)	(−0.800)
MIN4	Distance to fifth nearest other water	2.824	0.5227	0.4801	0.8660
		(4.015)**	(0.886)	(1.234)	(1.737)**
PURBAN	Zip code proportion urban	0.09663	−0.1389	0.1433	0.2734
		(0.503)	(−0.727)	(1.097)	(1.910)*

Table 2. Continued

Variable	Description	Region 1 (n = 1428) 547/881	Region 2 (n = 1432) 513/919	Region 3 (n = 2092) 746/1346	Region 4 (n = 1994) 744/1250
PBLACK	Zip code proportion Black	−8.925	1.642	−0.25804	−0.8250
		(−1.623)*	(0.244)	(−0.428)	(−1.037)
PAMIN	Zip code proportion American Indian	−1.490	−4.225	4.091	−1.004
		(0.820)	(−1.972)**	(1.724)*	(−0.6956)
PASIAN	Zip code proportion Asian	−1.113	−4.619	−6.821	0.2582
		(−0.266)	(−1.041)	(−2.979)**	(0.185)
POTHER	Zip code proportion other ethnicity	−8.291	−1.548	−1.726	−0.9552
		(−2.227)**	(−1.018)	(−1.454)	(−0.272)
PLANGIS	Zip code proportion language-isolated	−18.20	13.29	25.45	−3.003
		(−0.664)	(0.864)	(2.378)**	(−0.274)
PCOLL	Zip code proportion college grad and above	3.924	0.764	0.7393	0.4776
		(3.372)**	(0.815)	(1.404)	(0.795)
PAGIND	Zip code proportion in ag, forestry, fisheries industries	−43.012	2.326	−2.038	−2.134
		(−3.798)**	(0.314)	(−0.424)	(−0.288)
PAGOCC	Zip code proportion in ag, forestry, fisheries occupations	45.638	−3.893	0.6255	0.3508
		(3.543)**	(−0.444)	(0.109)	(0.046)
PPUBINC	Zip code proportion on public income assistance	2.895	5.040	−3.340	−9.817
		(0.616)	(0.3945)	(−1.000)	(−2.360)**
PSSINC	Zip code proportion on social security income	1.260	−2.098	−2.178	0.6271
		(0.376)	(−0.815)	(−1.269)	(0.291)
PRETINC	Zip code proportion on retirement income	−9.699	8.940	1.326	2.245
		(−1.866)*	(2.186)**	(0.531)	(0.761)
INCM	Zip code median income	−0.020633	0.01568	0.002658	−0.01060
		(−4.670)*	(2.273)**	(0.490)	(−1.800)*
RENT	Zip code median gross rental	−0.2180	1.084	0.2038	−0.2524
		(−0.339)	(2.032)**	(0.549)	(−0.531)
VALUE	Zip code median house value	0.14280E−03	−0.008981	−0.003215	0.68629E−03
		(0.064)	(−3.601)**	(−1.872)*	(0.614)
CONSTANT	Intercept term	−0.4277	−2.623	−3.491	−3.667
		(−1.836)*	(−1.112)	(−4.346)	(−0.732)
Log L		−850.93	−869.31	−1298.5	−1225.0

Note: The numbers in parentheses are t-values. One asterisk denotes significance at the 10% level. Two asterisks denote significance at the 5% level. Distances *DIST1–4*, refer to numbering of waters within each REGION and differ from numberings overall; different coefficients are allowed for each of the four different surveys, although the coefficients on the resulting inverse Mill's ratio terms will be constrained to be identical for each type of data.

waters." Almost no respondent who did not take trips during the season under actual conditions was induced to take trips under the contingent scenarios, so, for the general water users we focus on the allocation of trips among the different waters in the regional choice set. Any specific federal project will still have many water recreators with zero trips to that particular water, but these respondents will have reported at least one actual or contingent trip to some other water.

For purposes of illustration, table 3 reports these results for three of the waters, Hungry Horse Reservoir, Lake Pend Oreille, and Lake Koocanusa.[16] For each water, there are two columns of results. The first column is a probit model to predict whether the respondent took any trips to that particular water. The second column is the tobit portion of the model, to be discussed below. For the probit models, the own prices are negative and significantly different from zero (this is true in most of the nine models), and the own water-level variable was most often positive and significantly different from zero. The cross-price and cross-water-level terms are mixed in sign and significance. The apparent complementarity of some waters in terms of water levels could reflect a type of complementarity not ordinarily considered by economists, who typically focus upon the cross effects of prices.[17]

The nonprice and nonwater-level variables—income, the water-based activity dummy variables (fishing license, boat ownership, or both), the exogenous seasonal visitation rate control variable (*NE TRIPS*)—are most often of the expected sign, but their statistical significance varies from water to water.

Demand Models: Heteroskedastic (Continuous) Second Stage

The set of candidate explanatory variables in the second-stage models are essentially the same as for the first-stage models, except we include the λ_t, λ_r, and λ_T inverse Mill's ratio terms from the first-stage heteroskedastic probit participation model. These results are again quite mixed. While the price and own water-level variables often have coefficients with the expected sign and these coefficients are significantly different from zero in the first-stage models, they are seldom statistically significant in the second-stage models. For these three waters, own price is negative and significant in the Pend Oreille and Hungry Horse demand equations only. This seems to indicate that the major influence of these variables may be in the participation decision itself; once an individual decides that a particular water is usable for his or her purposes, he pays little attention to the price and water level in determining the frequency of his monthly visits.

The cross-price and cross-water-level terms in the second-stage models are again mixed in sign and significance. Intuition suggests that these waters should be substitutes, and our models do indeed identify some substitutes. However, a negative cross-price coefficient, or positive cross-water-level coefficient on an alternative water may again indicate some complementarity. Such complementarity is unlikely unless it is an artifact of multiple-site trip taking, but we do not distinguish between single- and multiple-

[16] Space constraints preclude reporting both the probit and second-stage demand parameters for all nine waters, for models which use some or all of the explanatory variables described in table 1.

[17] This apparent relationship may be due simply to remaining collinearity between water levels. The actual historical water levels are sometimes highly correlated across waters. Our augmentation with contingent scenarios unties these correlations in some instances but not in all. To have used the contingent scenarios to completely orthogonalize the various water levels would have been extremely helpful to the empirical analysis but was beyond the scope of the research project.

Table 3. First-Stage Probit and Second-Stage Tobit Parameter Estimates (Waters 1, 2, 3)

	Water 1—Hungry Horse		Water 2—Lake Pend Oreille		Water 3—Lake Koocanusa	
Variable	Probit (n = 1723)	Tobit (n = 399)	Probit (n = 4741)	Tobit (n = 648)	Probit (n = 1723)	Tobit (n = 419)
R_INT	0.89209	1.2546	0.79977	−1.2951	0.79977	−1.1202
	(3.103)**	(1.085)	(3.450)**	(−0.906)	(3.450)**	(−1.255)
R_IMR-ACTUAL	−1143.0	−1.5244	−848.0	9.2049	−848.00	5.3601
	(−0.003)	(−0.610)	(−0.007)	(1.609)	(−0.007)	(0.913)
OWN-PRICE	−8.2493	−38.633	−13.107	−18.339	−13.107	−34.351
	(−5.098)**	(−2.432)**	(−5.771)**	(−2.422)**	(−5.771)**	(−2.549)**
INTERCEPT	−30.656	−129.84	−100.05	−100.09	−100.05	4.9706
	(−5.590)**	(−2.232)**	(−1.170)	(−0.203)	(−1.170)	(2.483)**
IMR-ACTUAL	−0.45949E−02	−0.52688	−0.34608	−3.1044	−0.34608	−2.0123
	(−0.028)	(−1.195)	(−2.063)**	(−4.201)**	(−2.063)**	(−1.795)*
IMR-CONT	−0.16408	−0.94794	−0.28555	−2.4868	−0.28555	−0.57610
	(−0.807)	(−2.199)**	(−1.958)*	(−3.681)**	(−1.958)*	(−0.520)
VERSION2						
VERSION3				0.34247		
				(0.193)		
VERSION4				0.95677		
				(0.945)		
HAVE-DIST	0.31101	1.3196	−0.27614	0.63147	−0.27614	−2.6869
	(1.109)	(1.513)	(−1.188)	(0.130)	(−1.188)	(−2.972)**
PRICE_1			8.1113	−10.095	8.1113	14.796
			(6.177)**	(−0.858)	(6.177)**	(1.773)*
PRICE_2	−6.7632	−31.694			7.9179	−0.56485
	(−3.565)**	(−2.190)**			(6.227)**	(−0.057)
PRICE_3	−1.9091	−8.0547	7.9179	31.011		
	(−0.658)	(−0.749)	(6.227)**	(1.118)		
PRICE_4	14.966	68.472	−2.8495	−11.127	−2.8495	17.495
	(4.328)**	(2.145)**	(−1.418)	(−0.576)	(−1.418)	(1.309)
PRICE_5				10.771		
				(0.945)		

Table 3. Continued

Variable	Water 1—Hungry Horse Probit (n = 1723)	Water 1—Hungry Horse Tobit (n = 399)	Water 2—Lake Pend Oreille Probit (n = 4741)	Water 2—Lake Pend Oreille Tobit (n = 648)	Water 3—Lake Koocanusa Probit (n = 1723)	Water 3—Lake Koocanusa Tobit (n = 419)
PRICE_6				8.0158 (1.864)*		
PRICE_7				−8.5776 (−0.708)		
PRICE_8				10.453 (1.880)*		
PRICE_9						
DIST-OTHER	0.46007 (0.431)	2.3306 (0.303)	−0.89741 (−0.641)	13.103 (1.267)	−0.89741 (−0.641)	3.512 (0.433)
HAVE-INCOME	−0.14441 (−0.764)	−0.15744 (−0.249)	−0.24670 (−1.755)*	−1.7673 (−2.856)**	−0.24670 (−1.755)*	0.5215 (0.073)
INCOME	3.1031 (1.332)	6.5722 (0.742)	−1.2527 (−0.666)	0.70318 (0.064)	−1.2527 (−0.666)	25.57 (3.258)
FISH-LICENSE	0.40769 (2.740)**	1.7474 (2.552)**	0.35034 (2.568)**		0.35034 (2.568)**	0.9498 (1.991)
OWN BOAT	0.40394E−01 (0.341)	0.31488 (1.448)	0.51254 (4.478)**		0.51254 (4.478)**	1.869 (2.476)
FISH & BOAT	−0.61982 (−3.103)**	−2.3064 (−2.239)**	−0.41468 (−2.169)**		−0.41468 (−2.169)**	
WTRLVL_1	5.9381 (4.408)**	26.927 (2.561)**				
WTRLVL_2			44.598 (1.047)	51.514 (0.217)	44.598 (1.047)	
WTRLVL_3	3.7086 (2.968)**	12.439 (1.608)	3.2562 (2.351)**		3.2562 (2.351)**	
WTRLVL_4						
WTRLVL_5						
WTRLVL_6						

Table 3. Continued

Variable	Water 1—Hungry Horse		Water 2—Lake Pend Oreille		Water 3—Lake Koocanusa	
	Probit (n = 1723)	Tobit (n = 399)	Probit (n = 4741)	Tobit (n = 648)	Probit (n = 1723)	Tobit (n = 419)
WTRLVL_7						
WTRLVL_8						
WTRLVL_9						
NE TRIPS	0.14071	0.56754	0.21575E−01	−0.13249	0.21575E−01	−0.1667
	(1.946)*	(1.817)*	(0.233)	(−0.432)	(0.233)	(−0.058)
λ_M		4.8651		0.38699		−0.2681
		(2.064)**		(0.175)		(−0.190)
λ_R		0.96481E−01		−0.98536		−0.2059
		(1.410)		(−0.431)		(−0.127)
λ_A		6.0796		0.72960		−1.141
		(2.016)**		(0.288)		(−0.495)
DUMMY_RST	5.0704	−0.89447	4.7825	−0.67981	4.7825	−0.8210
	(0.016)	(−4.347)**	(0.034)	(−4.145)**	(0.034)	(−2.885)
DUMMY_ANN	0.38654E−01	−0.21890	−0.27129	−0.35862	−0.27129	−0.1766
	(0.288)	(−3.999)**	(−1.854)*	(−8.257)**	(−1.854)*	(−0.322)
σ		1.4172		3.7088		2.826
		(21.206)**		(30.856)**		(20.988)
Log L	−685.64	−643.87	−1423.0	−1625.6	−729.08	

Note: The numbers in parentheses are t-values. One asterisk denotes significance at the 10% level. Two asterisks denote significance at the 5% level.

destination trips in our models, so it is not possible to sort this out within the current framework.

Policy: Expected Trips and Consumer's Surplus

As part of the overall project for the federal agencies, we have employed our calibrated model to evaluate several hypothetical water-level scenarios, pegged to a set of system operating strategies (SOSs) that might potentially be part of some plan to more effectively flush the salmon smolts out to the ocean. Sample average expected trips and sample average fitted consumer's surplus can be calculated for baseline, actual 1993 water levels and then recalculated for any given change from these baseline levels to a set of alternative hypothetical water levels.

We illustrate two resource planning strategies below: a reservoir recreation (RR) and fishery (F) strategy. The former would aim to protect and enhance recreation opportunities by filling reservoirs by the end of June, maintaining the reservoirs at full pool through the end of August. These conditions are considered to be more or less optimum for reservoir recreators. The objective of the F strategy is to assist downstream fish migration and enhance conditions for salmon spawning. The water levels and flow rates embodied in this strategy are *not* considered to be optimal for reservoir recreationists.

Expected Trips and Changes in Expected Trips

For each of the nine waters, we estimate the individual's expected trips (May through August) for specified patterns of water levels. The sample average of expected monthly trips over all nine waters under conditions in 1993 (our baseline) is sometimes quite small. For example, fitted trips for Lake Pend Oreille vary from 0.5 in May to 1.06 trips in August. Across all waters, sample average expected trips under 1993 conditions are lowest at John Day (0.09 in July) and highest at the Kootenai River (1.7 in July).

Comparing expected trips under the RR and F strategies, there is a tendency for average expected trips to be lower at all nine waters under the fishery strategy, as would be expected. For example, simulations assuming water levels that are otherwise consistent with the average levels over the past 50 years but controlled to enhance reservoir recreation, produce average expected June trips to Hungry Horse of 0.81. Under management for the F strategy, average expected June trips fall to 0.44, or by about half.

The number of expected trips falls with the types of changes in water levels under the F strategy, but in some cases, not by a large or statistically significant amount. As another example, average expected trips to Dworshak Lake under the RR strategy are 1.37 for July (again assuming otherwise 50-year-average water level conditions). For the F strategy, average expected trips in that month are 1.19.

Expected Consumer's Surplus and Changes in Expected Surplus

Baseline sample, average expected consumer's surplus (*CS*) is calculated for actual water levels in 1993. This measure can be interpreted roughly as the average expected monthly willingness to pay (WTP) rather than do without these reservoir recreation opportunities, given 1993 water levels. For all nine waters, the *CS* estimates have magnitudes that seem intuitively plausible, varying from about $13 (each summer month) for Lake Koocanusa to $99 (August) for Lake Roosevelt. These monthly welfare amounts cannot easily be compared with other extant welfare estimates for water recreation opportunities because most other estimates are typically either annual or per-trip measures. (A crude range of the value per outing for water-based recreation is from about $20 to $60, with some estimates being higher for more exotic recreation such as fishing for salmon in Alaska.) We could only attempt to convert our monthly *CS* estimates to annual measures by assuming no intermonth substitution of trips—rather a strong assumption for some recreators. Alternatively, conversion of our monthly to per-trip measures is possible by dividing the monthly WTP by the individual's estimated monthly trips, but this can create confusion, as one's interpretation of such per-trip measures varies depending on whether one uses baseline trips or trips predicted under one of the strategies.[18]

Expected consumer's surplus ($E[CS]$) under the RR and F strategies are also simulated. Assuming the 50-year-average levels otherwise obtain, the July average $E[CS]$ for Hungry Horse under the RR strategy is approximately $72. Under the F strategy, this falls to $40, slightly more than half the monthly WTP under optimum recreation conditions. For other waters at other times during the summer, this change is less dramatic. This is due to different estimated demand functions for other waters, as well as different simulated water level conditions for the other waters under these two scenarios.

Summary and Conclusions

At the outset of this research project, it was not even *qualitatively* clear to what extent water levels at reservoirs really matter to recreators in the Columbia River Basin. Based on our analysis, we conclude that water levels at a particular water (the own water levels) do strongly contribute to the probability that an individual will visit a federal water. This influence diminishes in the model that explains the frequency of trips taken.

The use of the mixed actual and CB data for the recreation demand model in this study spans the range of possible scenarios concerning the full set of water levels at several different locations. It would not have been sufficient to model any single water in isolation; substitution possibilities with respect to alternative site characteristics (not just their prices) had to be accommodated. CB data are required to break the near-perfect multicollinearities among water levels at some sets of waters in the actual historical data. We combine several types of demand information from each survey respondent, using demand data for each person at different levels of time aggregation in an innovative way.

Our study has shown that it is important to control carefully for survey nonresponse bias (separately for actual and contingent behavior responses, which exhibit different nonresponse rates). Controlling for nonresponse propensities in the estimation of our demand models helps to achieve demand parameter estimates that, in theory, more closely reflect the preferences of the entire relevant population, as opposed to simply considering the preferences of those survey recipients who were interested enough to complete the different sections of the survey instrument.

While not every valuation problem can involve such clear potential for differences in

[18] See other issues about per-trip *CS* measures in Morey.

values for respondents and nonrespondents, we suggest that this possibility be considered carefully. If the potential is there, the investigators might consider using our approach to control for such differences. Future research might attempt to devise schemes to examine more about the nonrespondents than can be obtained using other census variables and other public data sources, as well as by using follow-up surveys. The latter may be accomplished by implementing a second survey, designed with this initial nonresponse target group in mind so as to ensure better response rates than the original survey accomplished.

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