EFFICIENT ESTIMATION METHODS FOR "CLOSED-ENDED" CONTINGENT VALUATION SURVEYS

by

Trudy Ann Cameron*
University of California, Los Angeles

and

Michelle D. James
Department of Fisheries and Oceans, Canada

Department of Economics
University of California, Los Angeles
Working Paper #404
September, 1985
(revised June, 1986)

Version: 06-06-86

* We would like to acknowledge the helpful comments of Luc Anselin, Neil Bruce, Arnold Harberger, Jack L. Knetsch, Edward E. Leamer, Lee Lillard, Mark W. Plant, Kenneth Sokoloff, Michael Waldman and the participants in UCLA's Workshop in Labor Economics. The authors are solely responsible for any remaining errors.

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Abstract

Policymakers are often faced with the need to assign an economic value to a non-market resource. Experimental techniques have demonstrated the usefulness of "closed-ended contingent valuation" surveys, where respondents merely state whether they would accept or reject a hypothetical threshold amount, either as payment for giving up access to the resource, or as a fee for use of the resource. The "yes/no" responses make discrete choice techniques appropriate for analysis. We develop a maximum likelihood estimation technique which exploits the variation in the threshold values suggested to each respondent to allow direct and separate point estimates of slope coefficients and error standard deviations in units comparable to the underlying unobserved valuation. The formulation incidentally reveals that ordinary probit analysis, with the threshold value as an explanatory variable, would yield the desired *point* estimates as simple functions of the probit parameters. To illustrate our estimation method, we use 4161 responses to an in-person survey of recreational sport-fishermen. We examine factors which influence individual willingness-to-pay and which therefore affect the aggregate social value of the resource.

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T.A. Cameron and M.D. James

1. Introduction

Policymakers are often faced with the need to assign an economic value to a non-market resource; likewise, market planners and product developers frequently need to assess the market potential for a commodity which is not yet available for actual trial marketing. The methods to be described below are equally appropriate in either situation. However, we will focus on the problem of valuing a non-market resource.

There are two basic methods for indirectly determining the economic value of a non-market resource. The "travel cost" method uses observed travel costs per visit to a site (from different origin points) and per-capita visitation rates from each origin to deduce the "demand" relationship between individuals' willingness-to-pay for a visit and the number of visits at each possible level of travel cost (see Clawson (1959), Burt and Brewer (1971) and Cicchetti, Fisher and Smith (1976)). While variations have been developed which will take into account changes in value resulting from quality alterations (see Brown and Mendelsohn (1984)), it is sometimes difficult to apply these methods, especially if consumption is not confined to discrete identifiable sites. In addition, the travel cost method does not measure compensation demanded, an important consideration if policymakers are concerning with determining the social costs accompanying a reduction in some quality attribute or the loss of access to the resource.

A second method for indirectly valuing a non-market resource is called "contingent valuation." Individual respondents are asked hypothetical questions about how much they would be willing to pay (WTP) for access or conversely, how much compensation they would demand (CD) to be induced to give up their access. There are three approaches to asking these questions: (i.) "open-ended", where the respondent is simply asked to name the sum, (ii.) "sequential bids", where respondents are asked whether or not they would pay or accept some specified sum (the question is then repeated using a higher or lower amount, depending on the initial response); and (iii.) "closed-ended", where the respondent is asked only whether or not they would pay or accept a single specific sum. In this third method, the sum is varied across respondents.

The third contingent valuation approach is often preferred, since it generates a scenario similar to that encountered by consumers in their usual market transactions. A hypothetical price is stated and the respondent merely decides whether to "take it or leave it," relieving him of the need to come up with a specific dollar value. It also avoids the pitfalls uncovered by Knetsch and Kahneman (1984) and Boyle *et al.* (1985), where the results from sequential bidding experiments are shown to be strongly biased by the "starting point" (the initial amount quoted). There was no noticeable bias with closed-ended questions. A variety of experimental studies have supported the superiority of contingent valuation methods over other approaches, including the travel-cost method, "costs and prices of substitutes" methods, and "property value" methods. (See comparison studies by Knetsch and Davis (1966), Desvouges, Smith and McGivney (1982), Sellar, Stoll and Chavas (1985), Thayer (1981) and studies cited in Schulze, D'Arge, and Brookshire (1981) plus Brookshire, Thayer, Schulze, and d'Arge (1982).)

An outline of the paper is as follows. In Section 2, we describe the estimation methods which have been used in the empirical literature until now. In Section 3, we explain a new maximum likelihood estimation technique for determining parameter values and mean conditional valuations for either marginal or total willingness-to-pay. Section 4 suggests some logical candidate specifications for use with total or marginal valuation questions. Section 5 describes our illustrative example, and Section 6 summarizes.

2. Existing Empirical Approaches

Earlier analyses of closed-ended contingent valuation data include Bishop, Heberlein, and Kealy (1983) and a pair of papers by Sellar, Chavas, and Stoll (1985, 1986). Both applications use logit analysis to derive fitted choice probabilities for the "yes" ($y_i = 1$) and "no" ($y_i = 0$) responses to the valuation questions.[1]

Recall that in both logit and probit analysis, a linear "index," $x_i'\beta^*$, captures the influence of the explanatory variables on choice probabilities. In the logit model, the choice probability is given by:

$$\text{(1)} \qquad \pi_i = P(y_i = 1) = (1 + \exp(x_i'\beta^*))^{-1}.$$

In the probit model, the choice probability is given by:

$$\text{(2)} \qquad \pi_i = P(y_i = 1) = 1 - \Phi(-x_i'\beta^*)$$

where Φ is the cumulative normal density function, and the index enters with a negative sign. Note that in both of these cases, the underlying coefficients and standard error, β and σ, cannot be separately identified. The parameter β^* in (2) is actually β/σ. Consequently, it is not possible to determine fitted values for the underlying implicit dependent variable, Y_i, because this requires $x_i'\beta$. It is only possible to construct fitted values for the choice probabilities.

These earlier studies typically perform an initial estimation with the threshold value, y_i^*, as the sole explanatory variable for their binary choice

[1] There seems to be no compelling reason (other than computational convenience) for selecting logit methods over probit methods, since it is well known that the density functions involved are quite similar except in the tails.

model. They then interpret the fitted choice probabilities, π_i, as the probability that a randomly selected respondent would agree to pay the stated fee (or would reject the offered compensation) as a function of the dollar amount tendered--the "upper tail" cumulative probability in the distribution of valuations. In a second step, these cumulative probabilities are used to estimate the "expected value" of the resource in question. Essentially, the process involves computing the value of $\mu = \Sigma Y_i \Pr(Y_i)$, but only values of Y_i between zero and $y_i{*}^{max}$ are included. The authors are careful to acknowledge the potential for a serious problem with truncation bias because the offered amounts always have an upper limit (Bishop, Heberlein, and Kealy (1983), p. 623).

An alternative approach, adopted by Sellar, Chavas, and Stoll (1985, 1986), does not use the specific computed values of the fitted probabilities, but instead leaves them in the form of the algebraic expressions. While the parameters are fitted on the basis of the discrete levels of Y_i (the $y_i{*}$) proposed in the survey questions, these investigators prefer to determine the marginal expected value of Y (either WTP or CD) essentially by numerical integration over a continuum of values from zero to the maximum level of $y_i{*}$ used on the questionnaires:

$$(3) \qquad E(Y) = \int_0^{y_i{*}_{max}} Y_i \Pr(Y_i)\, dY_i$$

However, there will still be the problem with truncation bias in this method of computing the marginal mean of Y in the sample.

When other explanatory variables are available, they are included among the right-hand side variables, x_i. However, the strategy still has a major deficiency. It is not possible in this modeling framework to compute the *marginal* contribution of any of these other variables to the underlying valuation, $\partial Y_i / \partial x_i$. Although these additional variables may improve the goodness-of-fit of the discrete choice model, these investigators are still left only with the fitted choice probabilities,

π_i, (or the fitted logit formula for these probabilities) and therefore can only compute the overall approximate marginal distribution of valuations. These two-step methods (logit, followed by discrete or continuous marginal mean computations) do not allow recovery of *conditional* distributions of valuation which control for heterogeneity among the respondents.

Important policy decisions may depend on the extent to which certain *attributes* of a non-market resource contribute to its overall social value. This information is particularly valuable when enhancement measures are being considered, or when the authorities plan (or anticipate) reductions in the levels of *some* of the amenities which make up the resource. The "value" to users is certainly derived from the levels of, and interactions between, a wide variety of site characteristics (such as scenery, fresh air, clean water, wildlife) as well as the characteristics of the users themselves (i.e. income, age, and individual tastes). Therefore, it is essential to know the marginal contributions to value of all these factors in order to be able to predict the consequences for aggregate social value of (a.) changes in the resource itself, or (b.) changes in the composition of the user group.

In Sellar, Stoll, and Chavas (1985), the survey questionnaire was designed to elicit estimates of the *total* valuation of an entire season of access to a resource. The variables entering into the logit index thus include not only the threshold value, y_i*, but also the number of days the respondent planned to use the resource. They acknowledge that a simple model with only y_i* in the logit index would ignore the effect on total value of variations in the number of planned days of use. Therefore, they appropriately include the number of days in the vector of explanatory variables. They are able to show (by differentiating through their integral expressions) that in order for the implied per-day willingness-to-pay function to have a negative slope, the estimated parameters of the logit model must lie between certain limits. Once again, however, this model does not incorporate any individual-specific characteristics, and neither can it capture the effects on valuation of variations in the levels of different amenities. While the differentiation with respect to number of days in such a model may yield reasonable approximations of the overall value of a marginal day's resource use (and will permit this value to vary inversely with the number of days consumed), it is not very useful for policy simulations. The resulting "demand" curves are fixed; there is no provision for them to *shift* in response to any of the myriad of factors understood to affect the demand for most commodities (i.e. income, prices of substitutes and complements, sociodemographic factors, tastes, etc.).

A further limitation is the authors' reliance on a specific functional form within the logit index. They utilize $\pi_i = (1 + \exp(-(\ln \alpha + \beta \ln y_i^* + \delta \ln q_i))$, where q_i is the number of usage days. The choice of logarithms seems quite arbitrary; this functional form simply offers algebraic convenience while simultaneously facilitating downward-sloping estimated underlying "demand" curves. These authors go to considerable lengths to derive the plausible range of fitted values for the coefficient δ, to ensure that the fitted model is consistent with downward-sloping demand, but surely, other functional relationships ought to be entertained.

In contrast to the usual assumption of a logit model, the maximum likelihood estimation method developed in the present paper is directly related to the probit model. At the end of the next section, after we have described this new approach, we will show explicitly how our method is intimately related to the probit analog to the above procedure. In preview, these earlier applications could have used the parameter estimates from simple probit analysis to compute point estimates for the parameters of *any* arbitrarily specified valuation function. Approximate standard error estimates, however, are somewhat tedious to compute, and will be different from the asymptotic standard errors produced directly by our new one-stage method.

3. Empirical Methodology

Of course, if we knew the precise dollar figure each individual would be willing to pay or would demand as compensation, then any theoretically consistent model (or even a completely *ad hoc* specification) which yielded inverse demand functions which were linear-in-parameters would make straightforward linear regression analysis quite satisfactory as an estimation technique. However, with the yes/no responses to "closed-ended" contingent valuation surveys, some variant of a qualitative choice model is clearly necessary. Because the offered amounts are varied over individuals, the yes/no responses convey some diffuse information about the amount of dispersion in the presumed underlying continuous dependent variable, valuation. Rather than using the familiar but limiting logit estimation methods described in the last section, we propose an innovative[2] "censored" dependent variable technique which exploits this information.

Assume that the unobserved continuous dependent variable is the respondent's true valuation of the resource, Y_i. Each individual is confronted with a threshold value, y_i*, and by his (yes/no) response, we conclude that his true valuation is either greater than or less than y_i*. If we assume that the distribution of Y_i, conditional on a vector of explanatory variables, x_i, has some known distribution with a mean of $x_i'\beta$, maximum likelihood techniques can be employed. An individual will respond in a manner which suggests that his valuation is more than y_i* (i.e. be willing to pay y_i*, or will reject compensation y_i*) if the difference between his true valuation and its conditional expected value $u_i = (Y_i - x_i'\beta)$ is greater than the difference $(y_i* - x_i'\beta)$. For willingness-to-pay questions, let an acceptance of y_i* be denoted by $y_i = 1$, and a rejection by $y_i = 0$. (For compensation-demanded

[2] To our knowledge, the only paper adopting a strategy remotely similar to ours is Lerman and Kern (1983). In their model, however, the observable information on the dependent variable is in the form of a maximum bid. They argue that if the transaction price actually paid for a house is the maximum bid price in the population, and if the distribution of potential bid prices is Gumbel, the transaction price can be used to identify the shape parameter of that distribution.

questions, a rejection of y_i* will imply $y_i = 1$, and an acceptance will imply $y_i = 0$. This preserves the generality of the estimation procedure.) We can then write:

(4) $\Pr(y_i = 1 \mid x_i) = \Pr(u_i > y_i^* - x_i'\beta)$

We know that the random error term u_i has a mean of zero and the same variance as the conditional distribution of Y given x.[3]

We might choose to assume a normal distribution for this conditional density function,[4] which yields:

$$(5) \qquad \Pr(y_i = 1 \mid x_i) = \Pr(u_i/\sigma > (y_i^* - x_i'\beta)/\sigma) = \Pr(z_i > (y_i^* - x_i'\beta)/\sigma)$$

where z_i is the standard normal random variable. Hence

$$(6) \qquad \Pr(y_i = 1 \mid x_i) = 1 - \Phi((y_i^* - x_i'\beta)/\sigma)$$
$$\Pr(y_i = 0 \mid x_i) = \Phi((y_i^* - x_i'\beta)/\sigma)$$

For a given sample of n independent observations, the joint density function for the data, $f(y \mid y^*, x_1, \ldots, x_p, \beta, \sigma)$, can then be reinterpreted as the likelihood function:

$$(7) \qquad L = f(\beta, \sigma \mid y, y^*, x_1, \ldots, x_p)$$

$$= \prod_{i=1}^{n} \left[\left[1 - \Phi\left[\frac{y_i^* - x_i'\beta}{\sigma} \right] \right]^{y_i} \left[\Phi\left[\frac{y_i^* - x_i'\beta}{\sigma} \right] \right]^{1-y_i} \right]$$

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[3] Homoscedasticity of the errors will be assumed in this development. In our example, we will utilize a logarithmic transformation of the implicit dependent variable to accommodate a certain amount of systematic heteroscedasticity in the implicit dependent variable.

[4] The following formulation could be cast in terms of an analog to the familiar logit model with its hyperbolic secant-squared distributions. However, the normal density and cumulative probability density functions are more in keeping with the usual regression assumptions.

Taking logs, we have

$$\text{(8)} \qquad \log L = \sum_{i=1}^{n} \left[y_i \log\left[1-\Phi\left[\frac{y_i^* - x_i'\beta}{\sigma}\right]\right] + (1-y_i)\log\left[\Phi\left[\frac{y_i^* - x_i'\beta}{\sigma}\right]\right]\right]$$

Nonlinear optimization techniques may then be employed to maximize the value of this function with respect to the vector of coefficients, β, and the standard deviation of the conditional distribution of valuations, σ. For most such optimization algorithms, the estimation process can be facilitated by the provision of analytical first (and often second) derivatives.

Using the notation established above, we first define the following simplifying abbreviations:

$$z_i = (y_i^* - x_i'\beta)/\sigma$$

$$\Phi_i = \Phi(z_i)$$

$$\phi_i = \phi(z_i)$$

$$\phi'_i = \phi'(z_i) = -z_i\,\phi(z_i)$$

$$R_i = x_{ir}x_{is}\,\phi'_i$$

$$S_i = x_{ir}x_{is}\,\phi^2_i$$

$$T_i = x_{ir}z_i\,\phi'_i$$

$$U_i = x_{ir}z_i\,\phi^2_i$$

$$V_i = z^2_i\,\phi'_i$$

$$W_i = z^2_i\,\phi^2_i$$

The gradient vector for this model is then given by:

$$\frac{\partial \log L}{\partial \beta_r} = \frac{1}{\sigma} \sum \left[\frac{y_i x_{ir} \phi_i}{1 - \Phi_i} - \frac{(1 - y_i) x_{ir} \phi_i}{\Phi_i} \right] \qquad r = 1,\ldots,p$$

$$\frac{\partial \log L}{\partial \sigma} = \frac{1}{\sigma} \sum \left[\frac{y_i z_i \phi_i}{1 - \Phi_i} - \frac{(1 - y_i) z_i \phi_i}{\Phi_i} \right] \qquad r = 1,\ldots,p$$

The elements of the Hessian matrix can be simplified if we define the function:

$$G(P,Q) = \sum \left[\frac{y_i (P_i[\Phi_i - 1] - Q_i)}{[\Phi_i - 1]^2} + \frac{(1 - y_i)(P_i \Phi_i - Q_i)}{\Phi^2_i} \right]$$

Then we can specify:

$$\frac{\partial^2 \log L}{\partial \beta_r \partial \beta_s} = \frac{1}{\sigma} G(R,S) \qquad r,s = 1,\ldots,p$$

$$\frac{\partial^2 \log L}{\partial \beta_r \sigma} = \frac{-1}{\sigma} \frac{\partial \log L}{\partial \beta_r} + \frac{1}{\sigma^2} G(T,U) \qquad r = 1,\ldots,p$$

$$\frac{\partial^2 \log L}{\partial \sigma^2} = \frac{-1}{\sigma} \frac{\partial \log L}{\partial \sigma} + \frac{1}{\sigma^2} G(V,W)$$

Use of these analytic derivatives, instead of numerical approximations to the required derivatives, can reduce computational costs considerably.

Hypotheses testing in this framework is the same as in any maximum likelihood context. Asymptotic t-tests statistics can be used to assess individual parameters; Likelihood Ratio tests (or Wald, or Lagrange multiplier tests) can be used to test restrictions on subsets of the coefficients in the model).

Once the optimization process has yielded the required parameter estimates, an empirical investigator will usually be interested in determining the goodness-of-fit of the estimated model. Here, we can employ the same sorts of measures which are traditionally used with logit or probit models. The standard measures are (a.) individual prediction success, and (b.) aggregate prediction success.

In computing individual prediction successes, one counts up the number of observations for which the model predicts a probability exceeding 0.5 that the respondent should be willing to pay (or should not accept) the suggested fee (compensation) when the individual is observed to respond that he *would* pay (reject) the specified amount. This is a prediction success. A *conflict* between the individual's choice probability and the qualitative response to the valuation question indicates a prediction failure. The number of successes as a proportion of the total sample is one measure of the accuracy of the model in explaining individual choices. However, as with other discrete choice models, this can be an overly stringent criteria for judging goodness-of-fit because it ignores "near misses", attaching an equal degree of accuracy to a probability of 0.505 and to 0.995 (and likewise penalizing as harshly for a probability of 0.495 as for a probability of 0.005).

An alternative measure of prediction success is "aggregate prediction success." In this case, each respondent is assumed to represent some large equal number of respondents with identical characteristics, so that the choice probability for this one individual can be viewed equivalently as the proportion of his identical cohort which would be willing to pay (or would not accept) the offered amount. The individual fitted probabilities for the accept and reject responses can therefore be summed and compared to the actual frequencies of response in the data. Typically, this aggregate measure yields a prediction success rate much higher than in the individual case.

We promised at the end of Section 2 that a simple relationship between our method and the results of simple probit estimation could be identified. This is easily seen by comparing the choice probability in equation (2) with that in equation (5). Clearly, the expression $(y_i^* - x_i'\beta)/\sigma$ can be rewritten as the inner product:

$$(9) \qquad (y^*, x')\,(-1/\sigma, \beta/\sigma) = -x_a'\beta_a$$

and the augmented vectors of variables, x_a, and coefficients, β_a, may be treated as one would treat the explanatory variables and coefficients in an ordinary probit estimation. In fact, this relationship between the conventional probit model and our new estimation method demonstrates that if previous researchers had utilized probit techniques, they would have had at their fingertips a set of point estimates of the underlying β parameters which (a) describe the incremental contribution to value of an extra unit of each explanatory variable and (b) are required for determining fitted values of the underlying willingness-to-pay or compensation demanded measures. Specifically, if the threshold value y_i^* is included among the explanatory variables in an ordinary probit model, its coefficient yields an estimate of $\alpha = -1/\sigma$. The coefficients on the other variables are $\gamma_j = \beta_j/\sigma$, so the desired βs may be found by dividing the other coefficients by the coefficient on y_i^*, and changing the sign. The σ itself is of course easy to compute.[5]

Having identified this relationship between the two methods, it is evident that the elaborate second-stage numerical integration techniques employed by Sellar, Stoll, and Chavas (1985) are not required, even if simple probit estimation is used, since the computed β and σ parameters can be interpreted in the same way as one would interpret the coefficients of a common multiple regression model.

The point estimates of the individual parameters should be identical by either technique, but it is accurate standard error estimates we seek. Ordinary probit

[5] Ordinary probit analysis can therefore be employed to produce excellent starting values for the estimation process described in the previous section.

analysis will generate asymptotic standard error estimates for the parameters $\alpha = -1/\sigma$ and $\gamma_j = \beta_j/\sigma$. While the point estimates for β_j and σ are easily computed, it is only possible to compute approximations for the standard error estimates. For rough estimates, one might use a first-order Taylor series approximation. In contrast, accurate asymptotic standard error estimates are produced directly by our new estimation procedure. This facilitates hypothesis testing regarding the signs and sizes of individual β_j parameters, an important objective of the modeling process.

4. Candidate Specifications for Valuation Models

The manner in which the survey questions relating to valuation are posed will determine whether the model should assume that Y is the value of a single marginal unit of the non-market resource, or whether Y is the total value of the total number of units consumed during a specified period of time. We might distinguish three types of variables: q_i, the number of units of the resource being valued, x_i, characteristics of the resource being valued; and z_i, characteristics of the individual being asked to make the valuation.

In practice, considerable attention must be paid to the consistency of the valuation questions with the underlying economic theory. There is often some question whether the valuation function can be interpreted as a "demand" curve or not (but this is an entirely separate issue). For the purposes of this analysis, we will loosely describe the valuation function as an inverse demand curve.

a.) Valuing a Marginal Day of Access

With rich enough data on the circumstances under which the respondent is making a valuation decision, one could adopt any functional form for the inverse demand relationship which was consistent with the microeconomic theory of consumer optimization. In practice, however, most analyses will be constrained by deficient data to working with plausible *ad hoc* specifications for the valuation function. Reasonable first-generation models might include variants of the following two basic forms:

(10) linear: $Y_i = \beta_0 + \beta_1 q_i + \beta_2 x_i + \beta_3 z_i + \epsilon_i$;

(11) log-linear: $\log(Y_i) = \beta_0 + \beta_1 q_i + \beta_2 x_i + \beta_3 z_i + \epsilon_i$.

However, virtually any transformation of Y_i can be considered.

b.) Valuing Total Days of Access

As with marginal valuations, we should certainly adhere to formal theoretical specifications whenever the data can support them. However, we will typically have to be satisfied with sensible *ad hoc* specifications. To be consistent with our conviction that demand curves ought to slope downward, the first derivative (with respect to q_i) of any proposed total valuation function must vary with q_i. Some possibilities, with their associated marginal valuation functions, are as follows:

(12) quadratic:

$$Y_i = \beta_0 + \beta_1 q_i + \alpha_1 q_i^2 + \beta_2 x_i + \beta_3 z_i + \epsilon_i$$

$$\partial Y_i / \partial q_i = \beta_1 + \alpha_1 q_i$$

Fitted marginal valuations need not always be positive, but if β_1 is positive and α_1 is negative, they will be positive for at least some levels of q_i, and they will be linear and downward-sloping. This model would allow site amenities and personal characteristics to affect total valuation, but not marginal valuations, which is somewhat restrictive. As an alternative, we might consider:

(13) quadratic with interaction terms:

$$Y_i = \beta_0 + \beta_1 q_i + \alpha_1 q_i^2 + \beta_2 x_i + a_2 x_i q_i + \beta_3 z_i + \alpha_3 z_i q_i + \epsilon_i$$

$$\partial Y_i / \partial q_i = \beta_1 + \alpha_1 q_i + \alpha_2 x_i + \alpha_3 z_i$$

This specification *will* allow site amenities and personal characteristics to shift the marginal valuation curve in (Y,q)-space.

When using quadratic specifications, however, it is important to check the fitted marginal valuation function to ascertain whether the model predicts that particular respondents have negative marginal valuations at their current number of days. This is a distinct possibility, given the diffuse nature of the actual sample information on Y. If the investigator is unwilling to argue that negative marginal valuations are plausible, it will probably be advisable to consider alternative specifications which constrain the marginal valuation to be positive. One such alternative is:

(14) linear in logarithms:

$$\log Y_i = \beta_0 + \beta_1 \log q_i + \beta_2 x_i + \beta_3 z_i + \epsilon_i$$

$$\partial Y_i/\partial q_i = (\beta_1/q_i)(\beta_0 + \beta_1 \log q_i + \beta_2 x_i + \beta_3 z_i)$$

where we substitute the fitted value of Y_i in the derivative because the actual value is of course unobserved. This marginal valuation will be positive as long as $\beta_1 > 0$, and downward-sloping as long as $(\beta_0 + \beta_1 \log q_i + \beta_2 x_i + \beta_3 z_i) > \beta_1$. Site effects and respondent characteristics will shift the marginal valuation curve due to their presence in the fitted valuation.

5. An Empirical Illustration: Marginal Willingness-to-Pay for a Recreational Fishing Day

This paper emphasizes our new methodology for estimating models using closed-ended contingent valuation data, so the empirical example described below will receive a somewhat cursory interpretation of its results. Readers interested specifically in the valuation of a recreational fishery are referred to our comprehensive related study, Cameron and James (1986). In that paper, we develop a household-production based theory wherein the demand for recreational fishing days is specifically related to the quality of those fishing days, to the prices of associated market goods, and to per-day user fees. The model is similar to that proposed by Cicchetti, Fisher and Smith (1977). The derived demand for chronological fishing days is argued to result from the individual's constrained utility maximization. This theoretical development suggests that the demand for fishing days will be inversely related to the magnitude of per-day user fees; however, the possibility of quality/quantity substitutability in the utility function means that the effect of fishing-day quality on number of days demanded is an empirical question.

Our raw data consist of 4161 responses to an in-person survey of recreational fisherman conducted between July and early December, 1984, on the south coast of the province of British Columbia, Canada. A substantial proportion of marine sportfishing effort in the province is expended in this area, and sportfishing anglers account for a significant fraction of the total catch of Chinook and Coho (the salmonid species which are the preferred game fish).

The data are described in greater detail in our other paper, so only a limited description will be provided here. One set of questions in the survey first established the cost of the current day's fishing (bait, gasoline, boat rentals, but not equipment costing more than $100). The respondent was then asked whether he would still have gone fishing if the cost of the fishing trip had been some specific (randomly-chosen) number of dollars higher. This is a "willingness-to-pay" (WTP) question. It was designed specifically to allow examination of the effects of the current day's quality variables upon valuation.

Our model assumes that WTP depends upon a variety of factors, including the characteristics of the individual and the circumstances of the current fishing trip. The survey provides highly detailed information about the times and locations where the party fished, the species caught, their numbers, and how many fish of each type were released. Date and location were used to merge the survey data with meteorological records so that weather could also be modeled explicitly. Table 1 summarizes the means and standard deviations of variables which were available either directly from the survey responses, or were constructed from these responses.[6]

On the presumption that valuation should be a non-negative random variable, our example will assume that the relationship between Y and $x'\beta$ is log-linear (meaning that we simply replace y_i* with log(y_i*) in the estimation process).[7] In this formulation, the fitted coefficients are interpreted (as in ordinary regression analyses) as the percent change in valuation for a one unit change in the explanatory variable.

One of the main points in this paper is that estimates of the desired coefficients and approximate standard errors can be obtained even if a conventional probit algorithm is the only software available. To simplify the notation, use $\alpha = (-1/\sigma)$ for the conventional probit coefficient on y_i*, the threshold level of the implicit dependent variable. Also, use $\gamma_j = (\beta_j/\sigma)$ for the conventional probit coefficient on the j^{th} "explanatory" variable. Once the probit model is estimated, we can compute $\sigma = -1/\alpha$ and $\beta_j = -\gamma_j/\alpha$. Standard errors for these functions of the

[6] One misfortune in the data is that the pilot survey indicated the impossibility of gathering accurate income data. Many respondents in the pilot survey became downright hostile when questioned about their income levels. Since 33% of the responses were by anglers who had been interviewed previously, there was also substantial resistance to questions which did not pertain to the current fishing trip (i.e. personal data).

[7] While a "change of variables" in maximum likelihood estimation typically requires that terms in the Jacobian of the transformation be appended to the log-likelihood, this procedure is not required in this case. The underlying probability density functions pertain to y_i (the discrete outcome), not Y_i (the underlying continuous valuation). Since only y_i* has been transformed (an "explanatory" variable), the density for y_i remains unchanged.

Table 1

Descriptive Statistics for Weighted* Sample
(n - 4161)

VARIABLE	DESCRIPTION	MEAN (PROPORTION)	STANDARD DEVIATION
CHARACTERISTICS OF RESPONDENTS:			
GUIDED	guided/not guided	0.09326	
RESROC	resides Canada (not B.C.)	0.06808	
RESOTH	resides outside Canada	0.2029	
SOLO	fished alone	0.1189	
WKND	fished on weekend/holiday	0.4855	
NDAYS83	days fished in 1983	18.82	25.04
MONTH OF OBSERVATION:			
JULY		0.3679	
AUG		0.3916	
SEPT		0.1964	
OCT		0.03000	
NOV	(or first days of DEC)	0.01411	
MAJOR SURVEY AREA:			
SITE1	Victoria	0.1904	
SITE2	Port Alberni	0.1018	
SITE3	Campbell River	0.4831	
SITE4	Sechelt	0.2247	
CHARACTERISTICS OF CATCH:			
NKCN	# chinook salmon kept	0.4955	0.9977
NKCO	# coho salmon kept	0.7696	1.534
LBS	weight largest fish (lbs)	5.154	6.550
WEIGHTS OF LARGEST FISH (IF LARGEST IS EACH SPECIES)			
LGSTSALM	(1895 OBS) salmon	9.324	6.324
LGCN	(1334 OBS) chinook	12.42	6.759
LGCO	(495 OBS) coho	5.608	2.552
LGOS	(66 OBS) other salmon	9.412	5.106
LGOF	(268 OBS) other fish	5.817	5.888
WEATHER:			
MEANTEMP	mean temperature (C)	15.44	3.316
TOTPREC	total precipitation (mm)	1.068	4.128
HRSUN	hours of sunshine	8.797	4.584
RESPONDENTS' SUBJECTIVE ASSESSMENTS:			
EVERY	enjoyed "very much"	0.6728	
EREAS	enjoyed "reasonably"	0.2301	
ESOME	enjoyed "some"	0.06680	
ENONE	enjoyed "not at all"	0.03030	
VALUATION INFORMATION:			
FEXP	today's marginal expenses	30.35	41.61
ADFEXP	proposed extra expense	22.06	18.79
STILLFSH	would still fish with ADFEXP	0.7243	

* Since the sample is not exactly representative of the population, we must employ exogenously determined weights with our likelihood function. These weights are based on a 60-cell crosstabulation (RESIDENCE by SITE by MONTH) of both the relevant population and the sample. Fishing "effort" (in total days) and salmonid catch rates are available. We have chosen to weight our sample observations according to the proportion of total annual effort in each of these 60 cells.

estimated parameters[8] are computed using Kmenta's approximation formulas for their variances (Kmenta, 1971, p. 444):

$$\mathrm{Var}(\sigma) = \mathrm{Var}(-1/\alpha) = [1/\alpha^2]^2\ \mathrm{Var}(\alpha)$$

$$\mathrm{Var}(\beta_j) = [\gamma_j/\alpha^2]^2\ \mathrm{Var}(\alpha) + [-1/\alpha]^2\ \mathrm{Var}(\gamma_j) + 2\ [\gamma_j/\alpha^2][-1/\alpha]\ \mathrm{Cov}(\alpha,\gamma_j)$$

Indeed, if the sample being utilized is representative of the population about which the investigator wishes to make inferences, the conventional probit algorithms in any one of a number of statistical packages may well be adequate. Problems arise, however, when (as is the case here) it is necessary to devise weights for each observation so that it will more-accurately reflect the true frequency of each type of respondent in the population. If the packaged probit routine does not allow weights on the observations, it will be necessary either to modify the source code for the packaged routine, or to write new code which allows weights. If this much effort is to be invested, it is probably preferable to go directly to the algorithms proposed in Section 3.

The first column of numbers in Table 2A gives results[9] derived from a weighted conventional probit estimation (with corresponding approximate asymptotic t-ratios). The second column gives the results for the same model estimated in one step by our new method, so that the t-ratios reflect actual asymptotic standard errors for each coefficient. For this application, it seems that the conventional probit method

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[8] To make these approximated quantities comparable to the output for the maximum likelihood approach, we will take the corresponding standard errors and use them to compute approximate t-test statistics for each parameter.

[9] Estimation of the censored dependent variable model described above was accomplished using the Fortran-based non-linear optimization subroutine package GQOPT. While various econometrics computer software packages can now perform conventional probit and logit estimations, the more-complex techniques explored in this study require a more general program.

TABLE 2A

Comparison of MLE Method Estimates and Transformed Ordinary Probit Estimates (n = 4161)

Variable	transformed Probit β (approx. t-test)	weighted MLE β (asy. t-test)	$\partial WTP/\partial x_j$ wtd mean (std.dev)* (C$ 1984)
intercept	3.104 (10.11)	3.113 (9.795)	
GUIDED	0.5498 (3.879)	0.5503 (3.864)	28.06 (22.56)
RESROC	0.2420 (1.302)	0.2472 (1.334)	12.61 (10.13)
RESOTH	0.3101 (2.636)	0.3118 (2.649)	15.90 (12.78)
SOLO	-0.1047 (-1.167)	-0.1054 (-1.176)	-5.372 (4.318)
WKND	0.07081 (1.204)	0.07038 (1.1870)	3.589 (2.885)
NDAYS83	0.0005292 (0.4108)	0.0005354 (0.4160)	0.02730 (0.02194)
FEXP	0.0008499 (0.8348)	0.0008311 (0.8171)	0.04238 (0.03406)
NKCN	0.2569 (5.556)	0.2569 (5.497)	13.10 (10.53)
NKCO (given NKCN>0)	-0.1912 (-6.188)	-0.1904 (-6.077)	-9.709 (7.803)
NKCO (given NKCN=0)	-0.04538 (-1.291)	-0.04528 (-1.285)	-2.309 (1.856)
LGCN	0.01013 (1.503)	0.01002 (1.489)	0.5111 (0.4108)
LGCO	0.07931 (4.406)	0.07916 (4.363)	4.037 (3.244)
MEANTEMP	-0.02664 (-1.789)	-0.02727 (-1.841)	-1.391 (1.118)
TOTPREC	-0.01125 (1.669)	-0.01127 (-1.672)	-0.5746 (0.4618)
HRSUN	-0.02822 (-3.618)	-0.02821 (-3.603)	-1.438 (1.156)
EVERY	0.8007 (4.895)	0.8013 (4.865)	40.86 (32.84)
EREAS	0.4051 (2.437)	0.4065 (2.446)	20.73 (16.66)
AUG	-0.4496 (-5.675)	-0.4522 (-5.645)	-23.06 (18.53)
SEPT	-0.7070 (-5.477)	-0.7101 (-5.447)	-36.21 (29.10)
OCT	-0.8085 (-3.760)	-0.8147 (-3.775)	-41.54 (33.39)
NOV+	-0.4780 (-1.425)	-0.4780 (-1.430)	-24.38 (19.59)
SITE 2	1.448 (10.86)	1.453 (10.43)	74.09 (59.55)
SITE 3	0.6729 (8.197)	0.6742 (8.010)	34.38 (27.63)
SITE 4	0.8157 (8.839)	0.8179 (8.609)	41.70 (33.52)
σ	1.187 (24.98)	1.186 (25.01)	

* weighted means and standard deviations across all observations of the fitted quantities $\partial Y_i/\partial x_{ji} = \beta_j(x_i'\beta)$

TABLE 2B

Goodness-of-Fit Measures for Efficient MLE Model
(weighted sample, n = 4161)

Individual Prediction Success (maximum probability):

		Observed*		
		Would Pay	Would Not	Total
	Would Pay	2813.19	570.62	3383.81
Fitted	Would Not	200.46	576.73	777.19
	Total	3013.65	1147.35	4161.00

Aggregate Prediction Success (summed probabilities):

Predict Would Pay:	3001.04	Actually Would Pay:	3013.65
Predict Would Not:	1159.96	Actually Would Not:	1147.35

* Fractional values for actual choices reflect weighting of sample observations to reflect population relative frequencies.

with approximate standard errors gives results which are very close to the one-step maximum likelihood results.

For ease of interpretation, Table 2A also provides some descriptive statistics for the fitted incremental contributions of each explanatory variable to WTP, in dollar terms, in the third column. (We use the point estimates from the one-step method, but these estimates should theoretically be identical, due to the invariance property of maximum likelihood estimates.) Bear in mind that in the log-linear model, $\partial Y/\partial x_{ij} = \beta_j(x_i'\beta)$, so heterogeneity among the anglers will result in some quite widely differing incremental contributions for each explanatory variable. Consequently, we will use the exogenously weighted means in the second column of Table 2A to summarize the results.

Other things held constant, WTP is substantially higher when the present trip has been guided, and when the respondent's residence is either in Canada (outside B.C.) or outside Canada. If the respondent was fishing alone, WTP is lower, although not significantly. For weekend days, the valuation appears to be higher, probably reflecting the fact that a larger proportion of weekend anglers are engaged in full-time employment during the week. For them, opportunities to fish are fewer, and hence probably valued more highly.

The variable NDAYS 1983 (number of days fished in 1983) is intended to serve as a proxy for either the level of experience of the respondent, or their dedication to the sport. People who fish more frequently seem to value the days' fishing more highly. However, this effect is not statistically significant.

One theoretically-important determinant of the demand for fishing days is the price of market goods used to "produce" a fishing day. We have only an inadequate proxy for this variable: the current day's fishing expenses, FEXP.[10] This variable has a small and insignificant, but nevertheless positive effect upon WTP extra for the current fishing day. This may suggest that these market goods are complementary inputs to the "fishing day" which we are attempting to value. (Cross-price elasticities of substitution would appear to be negligible, however.)

It is interesting to note that the numbers of fish caught or kept of each type seem to offer considerable explanatory power. On average, an extra Chinook salmon caught and kept appears to add $13.10 to WTP. These are the preferred sportfish. The results for Coho seem counterintuitive, until one realizes that anglers face a per-day limit on the total number of salmon which can be kept. If a Coho is perceived as reducing the number of Chinook which could potentially be kept, they may indeed reduce utility. In an attempt to examine the "interaction effect" between these different types of salmon, we allowed a distinction between the impact of an extra Coho with and without Chinook being caught. Plausibly, when no Chinook were caught, an extra Coho appears to detract considerably less from WTP. (It is still possible, of course, that the implications regarding the number of Coho caught are an artifact of misspecification in $x_i'\beta$. Our related paper, emphasizing the fishery, rather than the estimation technique, explores a variety of alternative specifications.)

Interestingly, however, if the largest fish caught is a Coho, the weight of this fish (LGCO) does seem to increase WTP by an average of $4.04 per pound (where the mean weight of the largest fish when it is a Coho is on the order of 5.6 pounds). On the other hand, if the largest fish caught was a Chinook, its weight seems to be much less important to the angler's WTP. These results together tend to

[10] FEXP is actually the inner product of both the prices and the quantities of these market goods. If either prices or quantities are approximately constant across observations, the explanatory power could be attributed to the varying component. However, without further evidence, no such assumption can reliably be made.

support the possibility that the typically much larger Chinook are valued for sport, while Coho are valued much less, but moreso if they are relatively large.

Among the climatic variables, only HRSUN is statistically significant, but all three enter with a negative sign. Bearing in mind the hypothesis that fishing tends to be better on overcast days when bright sunlight does not force the fish to greater depths, it is not surprising that WTP varies inversely with the number of hours of sunlight and likewise with a correlated variable, the mean temperature recorded for the specific fishing area on the day of the interview. Whether or not there is much rain is probably irrelevant to the fish, but it could diminish the angler's comfort during the fishing day.

As anticipated, the extent to which the respondent perceives the day's fishing experience as enjoyable makes a substantial and very significant contribution to the amount they would be willing to pay. The two enjoyment dummy variables, EVERY and EREAS, make a strong contribution.[11] The average marginal contributions tell how many more dollars a respondent would be willing to pay if their subjective experience fell into either of these categories (compared to a base category where respondents claimed that they enjoyed the fishing trip only somewhat or not at all). Note that their relative influence is plausible.

The set of monthly dummy variables with base month July all exhibit negative coefficients. (November data were only recorded for one of the four fishing areas, and the coefficient on NOVEMBER is insignificant.) It is difficult to interpret the relative sizes of the coefficients on the monthly dummy variables. That their signs are all negative, however, may reflect not only the weather, but also seasonality in

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[11] Early in the estimation phase, a binary discrete choice model was estimated with EVERY as the dependent variable. As expected, the probability that a particular fisherman enjoys the current fishing trip "very much" can also be predicted quite well by the fishing trip's characteristics. However, *perfect* collinearity is not a concern because different sets of variables appear to explain enjoyment and valuation. Nevertheless, it would be interesting to extend this analysis to examine the interrelationship between these variables.

the availability of fish. The SITE dummies may also reflect the "supply" of fish, since different areas have systematically different catch rates.

The locational dummies for three of the sites (SITE 1 (Victoria) = 0) indicate that sportfishermen in the Port Alberni area seem willing to pay an average of about $74.09 more than Victoria anglers. To a certain extent, the greater time costs required to gain access to these more remote areas will imply that only very serious anglers will be fishing there. Anglers will pay $34.38 more in Campbell River, and $41.70 more in the Sechelt area.

The weighted "within sample" goodness-of-fit measures[12] described in Section 3 have been computed for this model and appear in Table 2B.

The ability to determine the incremental contributions to total value of each explanatory variable is the clear advantage of this new approach. Nevertheless, policy-makers will probably still be interested in the marginal mean of the distribution of valuations in the population. (As outlined above, earlier models could determine *only* this quantity.) It is a simple matter to compute the weighted marginal distribution of WTP predicted by this model. Conditional upon our maintained hypothesis that the true underlying valuation is distributed log-normally, some descriptive statistics are: mean = $50.99, standard deviation = $40.98, median = $55.02, first quartile = $28.17, third quartile = $88.69, 90th percentile = $132.17. Of course, the marginal mean depends entirely upon the distribution of the x_j in the sample. If planned policy measures affect the x_j values represented in the sample (i.e. increase the number of each species caught), one must know the incremental contribution of this variable to valuation before it is possible to simulate the effects of such a change on the marginal mean

[12] As emphasized by Efron (1985), however, these rates of "prediction success" cannot be extrapolated to new data, since the accuracy is biased by the use of the same data both to fit the parameters and to assess "predictive" ability.

distribution of values. An ability to do this makes our model superior to its predecessors.

6. Summary

In this paper, we have developed an efficient estimation method for fitting models which use "closed-ended" contingent valuation survey data. These survey instruments are becoming increasingly popular for assessing the value of non-market resources; they have also shown considerable promise for assessing the market potential for products which have not yet been developed, or are not yet being produced in quantities large enough to allow actual test marketing.

Any model of valuation must of course be based upon valid theoretical foundations. It is still up to the individual investigator to specify a theoretically plausible relationship between the underlying unobserved valuation, Y, and the explanatory variables, x, appropriate to the application at hand. In the past, empirical work has been limited by the fact that we do not have an opportunity to observe Y directly. Use of inappropriate estimation methods limited the generality of the valuation functions unnecessarily. With the algorithms described in this paper, however, any specification which could be estimated by multiple regression techniques if Y were known can now be estimated with only contingent valuation responses, and the estimated coefficients can be interpreted in exactly the same way as in those regression models.

As an illustrative example, we have undertaken to estimate the marginal social value of a sport-fishing day. One of the most important contributions of this research is the development of a model which explicitly estimates the *marginal* contribution of catch characteristics to the value of a fishing day. Recreational anglers consistently claim that there is a lot more to fishing than just catching fish. To our knowledge, ours is the first empirical analysis which distinguishes the contribution of the fish from other factors which interact to generate utility for anglers. Further results, simulations, and qualifications are contained in Cameron and James (1986). In that paper, we also estimate a model for total compensation demanded and derive fitted values for marginal compensation demanded, and compare the fitted values of WTP and compensation demanded. We also examine a model wherein the two types of valuation are jointly estimated (in order to increase the efficiency of the estimation process by taking advantage of any correlation in the error terms, as in a seemingly unrelated regressions (SUR) model).

Analysts need no longer be limited merely to the estimation of approximate mean valuations over an entire sample. Instead, it is possible to distinguish the incremental contributions to resource valuations made by site amenities and due to individual users' characteristics. Furthermore, now that easily-interpreted results can be achieved, contingent valuation surveys should become even more attractive, not only for valuing non-market resources, but also for the assessment of consumer demand in other very general product-marketing situations where the commodity itself is not yet available for real marketing experiments.

REFERENCES

Bishop, Richard C., Thomas A Heberlein, and Mary Jo Kealy, "Contingent Valuation of Environmental Assets: Comparisons with a Simulated Market," *Natural Resources Journal* 23, July 1983, pp. 619-633.

Bishop, Richard C., and Thomas A. Heberlein, "Measuring Values of Extramarket Goods: Are Indirect Measures Biased?" *American Journal of Agricultural Economics*, 61(5) December 1979, pp. 926-930.

Boyle, Kevin J., Richard C. Bishop, and Michael P. Welsh, "Starting Point Bias in Contingent Valuation Bidding Games," *Land Economics*, 61(2) May 1985 pp. 188-195.

Brookshire, David S., Mark A. Thayer, William D. Schulze, and Ralph C. D'Arge, "Valuing Public Goods: A Comparison of Survey and Hedonic Approaches," *American Economic Review*, 72(1), March 1982, pp. 165-177.

Brown, Gardner, Jr., and Robert Mendelsohn, "The Hedonic Travel Cost Method," *Review of Economics and Statistics*, 66(3), August 1984, pp. 427-433.

Burt, Oscar, and Durwood Brewer, "Estimation of Net Social Benefits from Outdoor Recreation," *Econometrica* 39 (Sept. 1971), 813-828.

Cameron, Trudy Ann, and Michelle D. James, "The Determinants of Value for a Recreational Fishing Day: Estimates from a Contingent Valuation Survey," unpublished working paper (1986), Department of Economics, University of California, Los Angeles.

Cicchetti, Charles, Anthony Fisher, and V. Kerry Smith, "An Econometric Evaluation of a Generalized Consumer Surplus Measure: The Mineral King Controversy," *Econometrica* 44 (Nov. 1976), 1259-1296.

Clawson, Marion, "Methods of Measuring the Demand for the Value of Outdoor Recreation," Resources for the Future Reprint no. 10 (1959).

Davis, Robert K., "The Value of Big Game Hunting in a Private Forest," *Transactions of the Twenty-Ninth North American Wildlife and Natural Resources Conference*, March 9, 10, and 11, 1964. Washington: Wildlife Management Institute, 1964.

Desvouges, Smith and McGivney, "A Comparison of Alternative Approaches for Estimating Recreation and Related Benefits of Water Quality Improvements," Draft Report to the U.S. EPA (July, 1982)

Efron, Bradley, "How Biased is the Apparent Error Rate of a Prediction Rule?", working paper, 1985.

Kmenta, J. *Elements of Econometrics*, New York: Macmillan, 1971.

Knetsch, J.L., and Davis, "Comparison of Methods for Recreational Evaluation," in *Water Research*, A. Kneese and S.C. Smith, eds., 1966.

Knetsch, J.L., and D. Kahneman, "Assessing Non-Pecuniary Environmental Value: A Further Report on Anchoring, Additivity, Question Format Bias, and Fairness Tests," unpublished working paper, 1985.

Lerman, S.R., and C.R. Kern, "Hedonic Theory, Bid Rents, and Willingness-to-Pay: Some Extensions of Ellickson's Results," *Journal of Urban Economics*, 13 (1983), pp. 358-363.

Schulze, W.D., R.C. d'Arge, and D.S. Brookshire, "Valuing Environmental Commodities: Some Recent Experiments", *Land Economics*, 68 (1981), pp. 151-172.

Sellar, C., J. Stoll and J. Chavas, (1985) "Validation of Empirical Measures of Welfare Change: A Comparison of Nonmarket Techniques," *Land Economics*, 61(2) May 1985, pp. 156-175.

Sellar, C., J. Chavas, and J.Stoll, (1986) "Specification of the Logit Model: The Case of Valuation of Nonmarket Goods," forthcoming, *Journal of Environmental Economics and Management*

Thayer, Mark A., "Contingent Valuation Techniques for Assessing Environmental Impact: Further Evidence," *Journal of Environmental Economics and Management*, 8, (1981) pp. 27-44.