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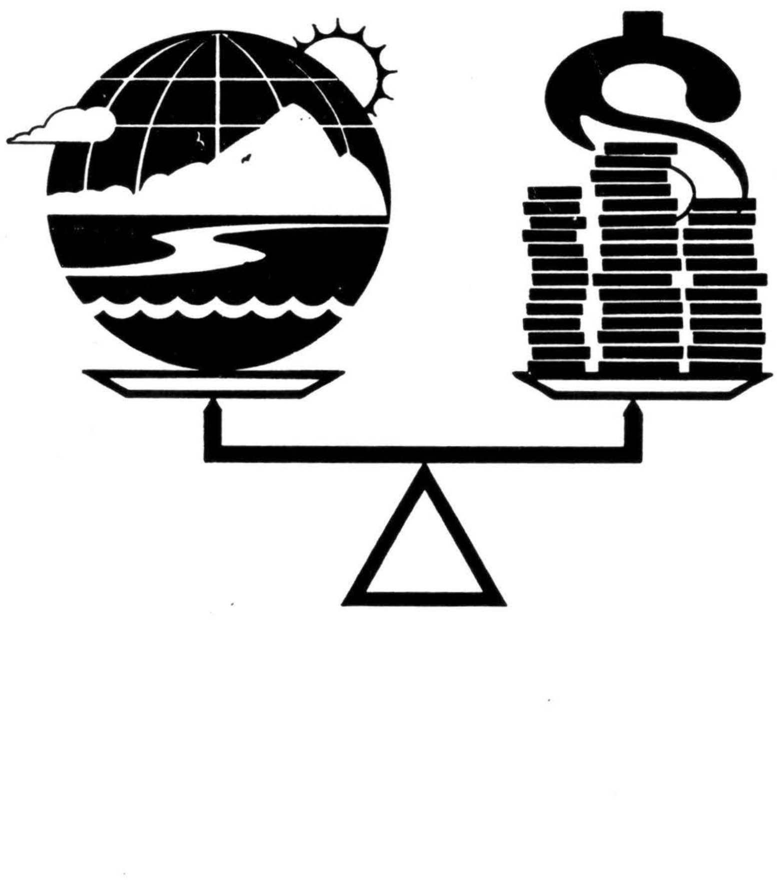

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Contingent Valuation Assessment of The Economic Damages of Pollution to Marine Recreational Fishing

Submitted to:

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CONTINGENT VALUATION ASSESSMENT OF THE ECONOMIC DAMAGES OF POLLUTION TO MARINE RECREATIONAL FISHING

(EPA Cooperative Agreement # CR-814656-01-0)

Trudy Ann Cameron

Executive Summary

The research performed under this cooperative agreement is summarized in the contents of four papers. These are described in the following sections.

1. **"The Determinants of Value for a Marine Estuarine Sportfishery: The Effects of Water Quality in Texas Bays," (also Working Paper #523, Department of Economics, University of California at Los Angeles).**

This paper gives a detailed description of the data collected in the socioeconomic portion of the Texas Parks and Wildlife Creel Survey of over 10,000 recreational anglers between May and November of 1987. It also summarizes the auxiliary data sources used to augment these data, which include gamefish abundance estimates we have calculated from the data collected in the Texas Parks and Wildlife Resource Monitoring Program, water quality data from the Texas Department of Water Resources, and five-digit zip code sociodemographic averages from the 1980 Census.

The objective in this first paper is to formulate special statistical models that produce estimates of each individual survey respondent's willingness to pay for access to the recreational fishery in the eight major bays along the Texas Gulf Coast. In this paper, no attempt is made to force these models to conform with formal economic theories. Instead, minimally sophisticated discrete choice econometric models are used in an attempt to establish the apparent systematic relationships between willingness to pay and whatever explanatory factors are available. These factors include: characteristics of the individual, their current catch, location and time of the interview, typical gamefish abundance, and coarse measures of several dimensions of water quality by time and location collected both by survey personnel and separately by the Department of Water Resources.

The econometric methods used in this analysis are specially designed to accommodate the "limited dependent variable" nature of the data. The paper describes the method by which maximum likelihood logit estimates can be transformed to yield the implied parameters of an approximation to the demand function for recreational fishing access. In particular, we are interested in price and income elasticities of demand. But we also focus in this study on the extent to which water quality, geographical and seasonal dummy variables, socioeconomic and other variables act as shifters of this demand function.

For this portion of the study, there are mixed findings concerning the effects of water quality on the value of the recreational fishery. A wide variety of meteorological data and data on water quality is available. In most cases, however, it was necessary to aggregate these data up to the level of each of the eight major bays and for each month of the sample period. For example, we know about average temperature, dissolved oxygen, turbidity, etc., as well as nitrogen nitrate levels, phosphate levels, non-filterable residues, oil and gas in bottom deposits, and a wide array of other qualities.

While several of our water quality variables appear to make statistically significant contributions to explaining willingness to pay for fishing access, many of them have counter-intuitive signs. It can be inferred that water quality probably varies *inversely* with other unmeasured attributes of anglers and the fishing resource that *directly* affect the value of the fishery. For example, if there are fewer substitute recreational opportunities in the Houston area, recreational fishing opportunities may be valued very highly, but simultaneously, the water quality may be very low. The reverse may be true in more remote areas of the coast. If we include water quality, but omit alternative recreational opportunities (for lack of data), then, it will appear that lower water quality implies higher social values of the fishery. I suspect that something like this is precisely what is happening.

This study represents an heroic effort to assemble the most appropriate water quality data for the Texas Gulf Coast available from many different sources. Countless hours went into matching and merging all of this information with the survey responses. Unfortunately, it is an empirical issue whether or not the anticipated relationships will show up in these data. This paper concludes that it will be necessary to control for other important determinants of value before the residual variation attributed to measured water quality can be unambiguously identified. However, there is definite evidence that respondents *perceptions* regarding environmental quality are more immediate determinants of value than the actual *measured* quality of the water.

While water quality apparently cannot be considered in this much detail with the current dataset, other coarser sociodemographic variables, such as income, appear to have strong and intuitively plausible effects on values. The apparent price elasticity of demand for fishing days (if a market existed) appears to be roughly -2.2, meaning that if access cost anglers 1% more, demand would decrease by 2.2%. The income elasticity appears to be just less than unity, implying that recreational fishing opportunities are borderline between being necessities and luxuries.

There are other implications of these models, also conditional on the quality of the data. For example, geographical heterogeneity in the demand for recreational fishing days does seem to exist. The water quality variables, collectively, seem to explain quite a lot of this geographic variation, even if multicollinearity among these variables limits our ability to attribute value differences to specific individual dimensions of water quality.

The Vietnamese, as opposed to other cultural groups, seem to have markedly different preferences for fishing than the population as a whole. Money spent on associated market goods, once thought to be a reasonable proxy for the non-market value of a fishery, is positively related to the value of a fishing day (but typically completely unrelated to catch rates). Importantly, many other explanatory variables make strong contributions to explaining the annual value of fishing day access; reliance solely upon market expenditures could severely misstate resource values.

The preliminary specifications explored in detail in this paper produced results that were sufficiently provocative to warrant further analysis of these data. It was decided that placing a little more structure on the model might help. Hence the next paper.

2. "Combining Contingent Valuation and Travel Cost Data for the Valuation of Non-market Goods," (a retitled major revision of Working Paper #503, Department of Economics, University of California at Los Angeles).

This second paper takes advantage of the general sense of the data derived from the extensive exploratory modeling described in the first paper. It has been determined that there are several apparently robust systematic relationships between willingness to pay for access to the fishery and other measurable variables. With this established, one can be more confident that it is worthwhile to undertake further modeling that is more solidly founded upon neoclassical microeconomic principles.

I am *very* pleased with the quality of this paper. It develops a new methodology, employing novel and very sophisticated econometric techniques appropriate to the special features of the data. The analysis is particularly careful and rigorous and many tangential issues are considered thoroughly.

The simplest model of consumers' utility maximization posits that consumers have preferences defined over two types of commodities: the good in question (sportfishing days) and a composite of all other goods and services. More of both of these things makes them happier, but they are constrained by their budgets. They must trade off other goods and services in order to consume an additional fishing day, and vice versa. They allocate their limited budgets between fishing days and other things so as to maximize their level of happiness.

All models of this type are, of course, dramatic simplifications of the real world, but they frequently provide very useful insights into the essential features of consumer behavior. Individuals with different sociodemographic characteristics, under different resource conditions, will make different consumption decisions. This type of variation allows us to calibrate a model which can then be used to simulate the likely responses of particular types of individuals if their decision making environment changes. While these models cannot be expected to do very well in predicting the actual response of a specific individual to some change, they can perform fairly well in the aggregate.

Earlier research employing these "utility-theoretic" models for the valuation of a non-market good such as sportfishing access occasionally used a technique known as the travel cost method. If fishing days can be considered as a single homogeneous good, information on the cost of a single trip and the number of trips taken can be combined to yield a model of demand for fishing days. This is the relationship between the implicit price of access and the number of days demanded, with accommodation for whatever shift factors (income, resource quality, etc.) can be quantified.

Other attempts to value recreational fishing days have relied upon "contingent valuation" survey techniques, where survey participants are queried about the decisions they think they would make if a hypothetical market for fishing days existed (i.e. if they had to pay a per-day entrance fee or purchase a season's pass to fish). The discrete choice form of contingent valuation question was posed on the Texas Parks and Wildlife Creel Survey. Respondents' answers about whether or not they would be willing to pay an arbitrarily selected annual fee to continue fishing were analyzed in ad hoc models in the first paper discussed above.

In the paper being described here, however, the mathematical form of the discrete choice model is carefully selected to conform to an underlying family of consumer preference functions with desirable properties from the point of view of economic theory. By doing this, the calibrated models can ultimately be solved to yield corresponding estimates of the formal welfare measures of value, including equivalent variation and compensating variation.

The primary methodological innovation in this paper is to combine both travel cost and discrete choice contingent valuation data in one comprehensive model. Both methods of eliciting valuation information from survey respondents should provide insights regarding the *same* preference structure. We can combine the two different perspectives for a more thorough characterization of consumer behavior.

In the basic model in this paper, all fishing days are treated as homogeneous and consumer choices regarding fishing access depend only upon their taste for fishing, their incomes, and the price of access to a fishing day. When this model is explored thoroughly and shown to be relatively successful, the assumption that all fishing days are identical is relaxed.

The illustrative generalization explored in this paper is to allow preferences for fishing days (versus all other goods and services) to vary systematically with the zip code proportion of people reporting Vietnamese heritage on the 1980 Census. This is an imperfect measure of the respondent's own sociodemographic category, but we anticipate at least some correlation. The proxy turns out to be a significant shifter of preferences. The higher the proportion Vietnamese, the less willing is a representative consumer to trade off fishing days for other goods. Likewise, the greater will be their demand for fishing days at any relative price and the greater would be the cost to them of having to forgo some or all of their fishing access.

The paper provides detailed empirical estimates of the welfare values associated with changes in fishing access. However, these dollar values are conditional upon the extent to which the data we are using actually capture the concepts prescribed by the microeconomic theory underlying the specification. The data are far from ideal. Consequently, it would not be appropriate in this summary to uphold the dollar values as unambiguous. The Texas data are by far the best I had encountered up until that time. But it is crucial that this set of papers be regarded as *demonstrations* of the types of analyses that can be conducted. If results as satisfying as these can be achieved with mediocre ingredients, then subsequent surveys can be conceived and implemented to take maximum advantage of the methodological framework. These future studies will undoubtedly produce final empirical value estimates which can more confidently be used as a basis for policy making.

With these qualifications, and others described carefully in the paper, some of the welfare estimates can be mentioned. For example, according to the basic model, if fishing days were curtailed by 10%, the average survey respondent would lose an amount of satisfaction roughly equivalent to the loss of $35 of income per year (although individual losses range from $19 to $52). A 20% curtailment would match an income loss of $139, on average. Simulating a complete loss of access is riskier and less realistic, but the model suggests that the average respondent would be hurt by about $3400.

Generalizing the model to accommodate sociodemographic heterogeneity (proportion Vietnamese in zip code) shows how the fitted preference function is markedly different (for an otherwise typical respondent) when this proportion ranges from 0 to 2%. Plots of the estimated "indifference curves" and budget constraints make these differences particularly obvious.

The paper also breaks new ground by freeing up certain parameter restrictions within the jointly estimated model so that the travel cost and contingent valuation data are allowed to imply different preferences. A scheme is also developed for allowing differential weightings in the pooling of these data, according to the perceived relative reliability of these two types of information.

3. "Using the Basic 'Auto-Validation' Model to Assess the Effect of Environmental Quality on Texas Recreational Fishing Demand: Welfare Estimates," (also Working Paper #522, Department of Economics, University of California at Los Angeles)

The initial exploratory study described above (which employed all of the available data and used ad hoc models) suggested that measured *objective* dimensions of water quality did not always have clear cut and intuitively plausible effects on willingness to pay for access to sportfishing opportunities. An alternative possibility is that people's preferences for sportfishing are affected by their *perceptions* of environmental quality, not by what is actually out there. (What you don't know won't hurt you?) The creel survey asked respondents' subjective opinions about whether they were able to enjoy "unpolluted natural surroundings." Answers were recorded on a scale of one to ten. In this supplemental paper, we allow preferences to take on systematically different configurations depending upon these answers.

Various welfare implications can be derived from the fitted model, again with the same caveats mentioned in the above two summaries. The amount of income loss that would be equivalent to a 10% cutback in access to the fishery is roughly $29 per year at the mean level of the subjective variable (8.07).

If environmental quality is perceived to be a 10, the loss would be about $37 per year. In contrast, if the quality is only 6, the loss of access would be only $23. For a complete loss of access, the decrease in value at the mean, at 10 and at 6 would be about $2400, $3000, and $1900 respectively. (Note that only a smaller subsample of the data could be used for these models, since not all respondents were queried regarding environmental quality.)

Thus, we find that perceptions of environmental quality do affect preferences for fishing days as opposed to all other goods and services, and thus the value of access to the fishery will almost certainly be influenced by perceptible variations in water quality. Furthermore, we can show that respondents' answers to the "unpolluted natural surroundings" questions are statistically related to several of the measured water quality attributes examined in the first paper described above. However, it is clear that more research will be necessary to establish how objective water and environmental quality data can be translated into individual perceptions.

With infinite and free computing resources, it would be desirable to allow preferences to differ systematically according to the levels of a whole range of shift variables. At present, however, there was no budget for such an elaborate model, so we were limited to exploring single shift variables independently. (Each shift variable adds five new unknown model parameters to be estimated.)

4. "The Effects of Variations in Gamefish Abundance on Texas Recreational Fishing Demand: Welfare Estimates."

Keeping in mind the limitations on complexity, a second supplemental paper was also developed. Whether or not the value of this recreational fishery is dependent upon the abundance of gamefish is another question of vital interest to policy makers. Ideally, one would measure all of the major gamefish species (there are seven or eight, described in the first paper, above). For this illustration, however, we opt to concentrate upon red drum.

As a measure of red drum abundance, we could have used each individual's reported catch of red drum on the fishing trip when they were surveyed, but this catch is dependent upon skill levels, which will be related to the individual's resource value. This is undesirable. Consequently, we rely upon data produced by the Parks and Wildlife Resource Monitoring program. We used data from the thousands of official samples collected by this program and aggregated up to average abundance measures by bay system and by month. These data are only proxies for the actual local abundance of red drum experienced by recreational anglers in each area and month, but they are completely unrelated to angler skill. Thus we hope to avoid simultaneity bias in the resulting estimates.

This model, augmented to control for red drum abundance, lets us explore the likely changes in the social value of access to the fishery when the abundance of red drum changes. Again subject to extensive caveats, we find that the income loss that would be equivalent to a 10% reduction in fishing access is roughly $35 at mean abundance of red drum. If abundance was higher by 20%, the same reduction would hurt anglers by an average of $40. If abundance was lower by 20%, the decrease in access would be equivalent to about a $32 decrease in income. A total loss of access would imply a loss of about $2800 at mean abundance, a loss of $3200 if abundance was 20% higher and of $2600 if abundance was 20% lower. If red drum abundance went to zero, a complete loss of access would still imply a loss of about $1800, presumably because there are several other gamefish species which can be sought.

If anglers do not care directly about water quality, except to the extent that it affects catch rates of their preferred species, this type of model may be the most fruitful to pursue. Future studies might rely upon expert biological opinion regarding the expected effects on gamefish of changes in different attributes of water quality. Calibrated utility models such as those used in this series of studies could then be used to simulate the ultimate effects of these changes on social welfare.

Again, all of these studies *do* undertake to provide point estimates of the dollar value of changes in consumer welfare corresponding to limitations on their access to recreational fishing or to changes in the quality of the fishing experience. However, due to the tenuousness of the data's ability to capture the theoretical concepts employed in these models, I elect *not* to cite all of these specific numbers outside the context of the papers, where the full range of caveats is laid out. Conditional upon the data available, I am confident of the validity of the findings. However, extensive detailed simulation sensitivity analyses would be required to put "true" confidence bounds on these estimates. The simple statistical precision of the estimates reported in the paper (as is usual in empirical work) presume that the data are exact measures of the desired quantities.

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ABSTRACT

We use a large number of responses to an in-person creel and contingent valuation survey of recreational anglers collected in the bays along the Texas Gulf Coast between May and November of 1987, supplemented by concurrent and independently gathered water quality data and 1980 Census data. Using empirical techniques recently developed by this author (censored logistic regression by maximum likelihood), these data are employed to fit implied (non-market) demand functions for fishing days which incorporate shift variables for water quality, perceived pollution levels, ethnic heterogeneity, expenditures on related market goods, and catch rates. The price elasticity of demand for fishing days (if a market existed) appears to be roughly -2.2; the income elasticity appears to be just less than unity. Geographical heterogeneity in the demand for recreational fishing days is partially explained by water quality variables. The Vietnamese seem to have *markedly* different preferences for fishing than the population as a whole. Money spent on associated market goods, once thought to be a reasonable proxy for the non-market value of a fishery, is indeed positively related to the value of a fishing day (but typically completely unrelated to catch success). Importantly, *many* other explanatory variables make strong contributions to explaining the annual value of fishing day access; reliance solely upon market expenditures could severely misstate resource values.

The Non-market Value of Water Quality Attributes: Estimates for Texas' Marine Estuarine Sportfishery

by

Trudy Ann Cameron

1. Introduction

Decisions regarding the expenditure of public funds to enhance or restore environmental assets have frequently been made on the basis of purely normative arguments. Until recently, the non-market benefits enjoyed collectively by the consumers of environmental resources have been difficult to determine. The objective in this paper is to quantify the effects of variations in water quality upon the non-market value of the marine recreational fishery along the Texas Gulf Coast. Knowing how water quality affects the social value of this fishery will allow us to simulate changes in that value as a consequence of policies which improve water quality (or as a result of decisions to allow water quality to deteriorate).

The "travel cost" method (TCM) for valuing non-market resources has been widely used but is frequently inappropriate for a marine sportfishery because the point-to-point distance for these fishing trips is often poorly defined. Destinations are diffuse and true opportunity costs for access are difficult to measure. These problems with the travel cost method have made hypothetical or "contingent" market surveys popular for eliciting resource values.

In contingent valuation (CV) surveys, it seems to be particularly difficult for respondents to state the precise value they would place on the resource. Consequently, a variety of value elicitation techniques are employed. Different strategies are suitable depending upon whether the investigation relies upon personal interviews, telephone interviews, or mailed questionnaires.

One method is verbal "iterative bidding." An elaboration of this method, useful for in-person interviews or mail surveys, is the "payment card," where the respondent is merely asked to scan a card and to indicate the highest amount willingly paid (or lowest compensation willingly accepted) for access to the resource. An extreme form of the iterative bidding strategy involves only the first iteration: a single randomly assigned value is proposed and the respondent decides whether to "take it or leave it," much as in ordinary day-to-day market transactions. This "closed-ended CV" or "referendum" question format economizes greatly on respondent effort and minimizes strategic bias, but reduces estimation efficiency. The single offered sum is varied across respondents, which allows the yes/no responses to these questions to imply both the location and the scale of the conditional distribution of valuations. Many more responses are required to generate equally statistically significant parameter estimates for the valuation function, but it is suspected that this value elicitation technique minimizes the wide array of biases which have been argued to plague the other CV elicitation methods.

At present, contingent valuation investigations are probably the most practical way to quantify the economic benefits to a recreational fishery of pollution control activities. CV questions can often be appended quite easily to regular creel survey instruments, so the marginal cost of gathering CV data is relatively modest.

In CV valuation models, respondents' valuations of the resource are presumed to depend upon (a.) characteristics of the respondent and (b.) attributes of the resource (in this case, including the level of pollution and indirect manifestations of pollution levels such as the degree of urbanization and catch rates). A calibrated CV model can be used to simulate both (a.) the *direct* effects of changes in pollution levels--by imposing counterfactual changes in the quantities of pollutants and recomputing the fitted individual valuations; and (b.) *indirect* effects of changes in pollution levels--for example, by imposing predicted changes in catch rates and recomputing individual valuations. The difference in the population weighted sums of these individual valuations before and after the simulated reductions in pollution levels is a measure of the social benefit of the hypothesized clean-up program. This overall change in social value can be added to estimates of other relevant benefits (i.e. for market activities) and the total can be compared to the costs of the program in order to determine its economic advisability.

For our Texas fishery, there is some concern at present about the proposed widening and deepening of the Houston Ship Channel, which is anticipated to have a substantial negative environmental impact. If statistically discernible effects of water quality upon the value of this recreational fishery can be found, our fitted models can simulate the changes in value resulting from changes in water quality due to projects such as this.

Section 2 of this paper reviews the intuition and the details of the statistical model which we will use to fit valuation functions. Section 3 outlines the data. Section 4 considers "naive" specifications of the "valuation function" and explains how implied demand functions can be extracted from the estimated models. Section 5 presents some preliminary empirical results. Section 6 digresses to evaluate the determinants of catch success, an issue which is important to our ability to assume exogeneity of the explanatory variables in the valuation function. Section 7 examines respondents' claimed motivations for going fishing and their subsequent satisfaction levels, issues which are fundamental to the form of the basic utility functions which underlie the demand for fishing days. Section 8 takes advantage of explicit questions regarding perceived pollution levels to address whether pollution levels enter directly or indirectly into people's utility functions. We conclude with some tentative findings and a preliminary set of recommendations for improving subsequent surveys which might be used to assess the effects of water quality on the non-market value of recreational fishing.

2. Censored Logistic Regression Models for Referendum Valuation Data

Before addressing this specific empirical project, it is helpful to outline the econometric estimation procedure which will be used to calibrate our model of valuation for this fishery. In Cameron and James (1987), and in a forthcoming paper (Cameron, 1988) I have made the argument that initial estimates of utility-theoretic models of valuation in the spirit of Hanemann (1984) (or even entirely data-driven *ad hoc* valuation models) using referendum data can be obtained quite simply using packaged logit or probit maximum likelihood algorithms. Since the numbers of observations in the models explored in this study are large, and since the specifications involve a wide array of potential explanatory variables, I opt here to perform initial estimations using censored *logistic* regression models. The computations necessary to optimize the likelihood function underlying these models does *not* involve myriad evaluations of the non-closed-form integral for the cumulative normal density function. The optimization is faster and cheaper than it would be for a censored normal regression model. Furthermore, since the parameters of the censored logistic regression model can be solved-for from the parameter estimates produced by conventional packaged maximum likelihood logit models, and the SAS computer package provides ML logit routines in its MLOGIT module, we find it expedient to pursue initial trial specifications in the context of the SAS package. This also allows us to take advantage of the superior data-manipulation capabilities of this program.

Based my earlier studies, the implicit valuation function parameter estimates produced by either the censored normal (probit-type) or censored logistic (logit-type) estimation procedures are very similar. The slight differences in the shape of the conditional density function for the regression errors makes only modest differences in the fitted values of the ultimate "regression" model. Hence it is safe to presume that explanatory variables which make a statistically significant contribution to the valuation function in the context of a simple logit specification will also be important under alternative distributional hypotheses.

2.1 *Review of Censored Regression Models for Referendum Data*

Since the censored logistic model is not yet in the public domain, I will briefly reproduce the derivation of the model.

"Referendum" surveys have recently become very popular as a technique for eliciting the value of public goods or non-market resources. Numerous applications of these methods now exist. (For comprehensive assessments of these survey instruments and detailed citations to the seminal works and specific applications, the reader is referred either to Cummings, Brookshire, and Schulze (1986), or to Mitchell and Carson (1988).

The referendum approach first establishes the attributes of the public good or the resource, and then asks the respondent whether or not they would pay or accept a single specific sum for access. (It is *crucial* that the arbitrarily assigned sums be varied across respondents.) This questioning strategy is attractive because it generates a scenario for each consumer which is similar to that encountered in day-to-day market transactions. A hypothetical price is stated and the respondent merely decides whether to "take it or leave it." This is less stressful for the respondent than requiring that a specific value be named, and circumvents much of the potential for strategic response bias. The challenge for estimation arises *only* because the respondent's true valuation is an *unobserved* random variable. We must infer its magnitude through an indicator variable (the consumer's "yes/no" response to the offered threshold sum) that tells us whether this underlying value is greater or less than the offered value.

In formulating appropriate econometric methodologies for analyzing these data, it is important to begin by imagining how valuation might be modeled if we could somehow readily elicit from each respondent their true valuation. If valuation could be measured like other variables (i.e. continuously), we would simply regress it on all the things that we suspect might affect its level. The econometrically interesting complication with referendum data arises from the fact that we don't know the exact magnitude of the individual's valuation; we only know whether it is greater than or less than some specified amount.

2.2 *Log-likelihood Function for Censored Logistic Regression*

Referendum data are *not* discrete choice data in the conventional sense (see McFadden, 1976, or Maddala, 1983). The procedure developed below is based upon the premise that if we *could* measure valuation exactly, we would use it *explicitly* in a regression-type model.[1] The censoring of valuation to be "greater than or less than" a known threshold is a mere statistical inconvenience to be worked around.

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[1] Here, we would be using it explicitly in a "non-normal" regression model, namely, a regression model incorporating a two-parameter logistic density function. But that would be nothing special--econometric researchers have for several years been using maximum likelihood methods to explore Poisson regression, Weibull regression, and a host of other distributional assumptions as alternatives to the familiar normal model.

Assume that the unobserved continuous dependent variable is the respondent's true willingness-to-pay (*WTP*)[2] for the resource or public good, Y_i. We can assume that the underlying distribution of Y_i, conditional on a vector of explanatory variables, x_i (with elements $j=1,\ldots,p$), has a logistic (rather than a normal) distribution, with a mean of $g(x_i,\beta) = x_i'\beta$.

In the standard maximum likelihood binary logit model, we would assume that:

$$(1) \qquad Y_i = x_i'\beta + u_i$$

where Y_i is unobserved, but is manifested through the discrete indicator variable, I_i, such that:

$$(2) \qquad \begin{aligned} I_i &= 1 \text{ if } Y_i > 0 \\ &= 0 \text{ otherwise.} \end{aligned}$$

If we assume that u_i is distributed according to a logistic distribution with mean 0 and standard deviation b (and with alternative parameter $\kappa = b\surd 3/\pi$, see Hastings and Peacock (1975)), then

$$(3) \qquad \begin{aligned} \Pr(I_i = 1) = \Pr\,(Y_i > 0) &= \Pr(u_i > -x_i'\beta) \\ &= \Pr(u_i/\kappa > -x_i'\beta/\kappa) \\ &= 1 - \Pr(\psi_i < -x_i'\gamma), \end{aligned}$$

where $\gamma = \beta/\kappa$ and we use ψ to signify the standard logistic random variable with mean 0 and standard deviation $b = \pi/\surd 3$. The formula for the cumulative density up to z for the standard logistic distribution is

$$(4) \qquad F(z) = 1 - \{1 + \exp[z]\}^{-1}.$$

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[2] These models can be adapted very simply to accommodate willingness-to-accept (*WTA*).

Therefore the log-likelihood function can be written as:

$$\text{(5)} \qquad \log L = \Sigma - I_i \log\{1 + \exp[-x_i'\gamma]\} + (1 - I_i) \log\{\exp[-x_i'\gamma]/(1 + \exp[-x_i'\gamma])\}.$$

Simplification[3] yields:

$$\text{(6)} \qquad \log L = \Sigma (1 - I_i)(-x_i'\gamma) - \log[1 + \exp(-x_i'\gamma)].$$

It is *not* possible in this model to estimate β and κ separately, since they appear everywhere as β/κ. The model must therefore be evaluated in terms of its estimated probabilities, since the underlying valuation function, $x_i'\beta$, cannot be recovered.

With referendum data, however, each individual is confronted with a threshold value, t_i. Earlier researchers have included t_i as one of the x_i variables in the conventional logit model described above. In our new model, we conclude by the respondent's (yes/no) response that his true *WTP* is either greater than or less than t_i. We can assume a valuation function[4] as in (1) with the same distribution for u_i, but we can now make use of the variable threshold value t_i as follows--in a new model which might be described as special form of "censored logistic regression":

$$\text{(7)} \qquad \begin{aligned} I_i &= 1 \text{ if } Y_i > t_i \\ &= 0 \text{ otherwise,} \end{aligned}$$

so that

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[3] Note that many textbooks (e.g. Maddala, 1983) exploit the symmetry around zero of the standard logistic distribution to simplify these formulas even further. We simplify this way to preserve consistency with the next model where we estimate k explicitly.

[4] However, it is now straightforward to make the mean of the conditional distribution any arbitrary function $g(x_i,\beta)$.

$$(8) \qquad \Pr(I_i = 1) = \Pr(Y_i > t_i) = \Pr(u_i > t_i - x_i'\beta)$$
$$= \Pr(u_i/\kappa > (t_i - x_i'\beta)/\kappa)$$
$$= 1 - \Pr(\psi_i < (t_i - x_i'\beta)/\kappa).$$

With this modification, the log likelihood function can now be written as:

$$(9) \qquad \log L = \Sigma - I_i \log\{1 + \exp[(t_i - x_i'\beta)/\kappa]\}$$
$$+ (1 - I_i) \log\{\exp[(t_i - x_i'\beta)/\kappa]/(1 + \exp[(t_i - x_i'\beta)/\kappa])\}.$$

As before, this can be simplified to yield:

$$(10) \quad \log L = \Sigma (1 - I_i)[(t_i - x_i'\beta)/\kappa] - \log\{1 + \exp[(t_i - x_i'\beta)/\kappa]\}.$$

The presence of t_i allows κ to be identified, which then allows us to isolate β so that the underlying fitted valuation function can be determined. Note that if $t_i = 0$ for all i, (10) collapses to the conventional logit likelihood function in (6).

The log-likelihood function in (10) can be optimized directly using the iterative algorithms of a general nonlinear function optimization computer program[5] and this is undeniably the preferred strategy when the option is readily available. There exist function optimization algorithms which will find the optimal parameter values using only the function itself (and numeric derivatives). However, analytic first (and second) derivatives can sometimes reduce computational costs considerably. See Appendix I for a description of

[5] We used a program called GQOPT - A Package for Numerical Optimization of Functions, developed by Richard E. Quandt and Stephen Goldfeld at Princeton University (Department of Economics). Roughly optimal parameter values are first achieved using the DFP (Davidon-Fletcher-Powell) algorithm; these values are then used as starting values for the GRADX (quadratic hill-climbing) algorithm to achieve refined estimates (i.e. to a function accuracy of 10^{-10}). We understand that the programs GAUSS and LIMDEP can also be adapted to optimize arbitrary functions.

the gradient and Hessian components helpful in nonlinear optimization of this log-likelihood function.

Maximization of the log-likelihood function in (10) will yield separate estimates of β and κ (and their individual asymptotic standard errors). However, estimates of $-1/\kappa$ and β/κ can, in the case of $g(x_i, \beta) = x_i'\beta$, be obtained quite conveniently from conventional maximum likelihood "packaged" logit algorithms, although we emphasize that this is merely a handy "short-cut" to be used if a general function-optimization program is not available. If we simply include the threshold, t_i, among the "explanatory" variables in an ordinary (maximum likelihood) logit model (as has typically been done by earlier researchers using referendum data), it is easy to see that:

$$- (t, x') \begin{bmatrix} -1/\kappa \\ \beta/\kappa \end{bmatrix} = -x^{*\prime}\gamma^{*}, \tag{11}$$

The augmented vectors of variables, x^* and coefficients, γ^*, may be treated as one would treat the explanatory variables and coefficients in an ordinary logit estimation. From γ^*, it is possible to compute point estimates of the desired parameters β and κ. If we distinguish the elements of γ^* as $(\alpha, \gamma) = (-1/\kappa, \beta/\kappa)$ then $\kappa = -1/\alpha$ and $\beta_j = -\gamma_j/\alpha$, $j = 1, \ldots, p$. However, accurate asymptotic standard errors for these functions of the estimated parameters are not produced automatically. If the conventional logit algorithm used allows one to save the point estimates and the variance-covariance matrix estimates for subsequent calculations, there are some alternative, relatively simple, methods for calculating approximate standard errors using *only* the information gleaned from a conventional logit model. (See the second portion of Appendix I.)

3. <u>Data</u>

The Texas Parks and Wildlife Coastal Fisheries Branch has conducted a major creel survey of recreational fishermen from the Mexican border to the Louisiana state line during the period of May to November, 1987. The survey records detailed catch information, and appends a list of "socioeconomic" questions which make up the contingent valuation portion of questionnaire. Over 10,000 responses were collected; our admissibility criteria reduce the usable sample to 5526, which is still a very large number of responses. Hydrological data are collected simultaneously at each investigation site along with the CV investigation. We merge these survey data with an assortment of data drawn from other sources, notably the Texas Department of Water resources and the 1980 Census. Extensive documentary information on variable construction is contained in Appendix II. The reader is referred to that section for details.

4. <u>Specifications</u>

4.1 *"Naive" Models*

As always, the very simplest model of fisheries valuation could presume that we only wish to know the marginal mean of the value of a year's fishing. If we include only the offered threshold as an explanatory variable in a logit model to explain the yes/no response, the fitted model will yield the marginal mean and marginal standard deviation of values (ignoring heterogeneity among respondents). This number is valuable if we can safely assume that the interview sample is a truly random sample of the "use" population, and if we know the size of the sample relative to the entire population. Under these limited circumstances, we can extrapolate from these per-person estimates to the total fitted "use" value of the fishery at the time of the survey and under the current conditions of the fishing population and the resource itself.

If we were *not* concerned with forecasting the effects of changes in the fishing population or changes in resource attributes, this single point estimate and its standard deviation would tell us most of what we need to know. However, resource valuation models can be extremely useful for forecasting the anticipated effects upon resource values of changes in resource *attributes*. In this study, we are primarily concerned with changes in species abundance and changes in water quality. We will control for cross-sectional heterogeneity in anglers and in resource attributes. Having calibrated a model acknowledging this heterogeneity, we will have a fitted model which will be useful for predicting the effects on the value of the resource of a wide range of policy-induced changes in our explanatory variables.

Where resource values are sensitive to water quality "parameters," we can determine the effect of a change in the level of each parameter on the social resource value of the resource. Comparing the social benefits of pollution control, for example, with the social costs of a cleanup program can provide a useful assessment of the economic efficiency implications of cleanup proposals. If resource values are sensitive to species abundance or size (either overall or by individual species), there will be important implications for fisheries management. Likewise, if access values are sensitive to the day of the week interacted with respondent characteristics, these valuation models could indicate how fishing licenses and closures could be decided in order to optimize both the resource base and the aggregate social value of access.

One initial problem observed in the data concerns the distinction between willingness to pay and actual ability to pay. "Demand" in the economic sense might be limited to "effective" demand, not just wishful thinking. This distinction is unresolved at present, but must be addressed at some point during this study.

The reason for raising this issue is that we observe in our sample that many of the people who claim to be willing to pay $20000 to continue fishing over the year come from zip codes where $20000 exceeds the median household income. While it may be that the respondent's household income is substantially larger than their zip code median, these responses cast some doubt on the accuracy of "effective" demands implied by responses to the $20000 referendum value. Fortunately, however, we have a very large sample, by contingent valuation standards. The referendum threshold values were assigned randomly to different respondents. Therefore, we will lose little except some estimation efficiency by dropping all respondents who were offered this extremely high threshold. It is quite possible that many of the respondents who respond that they would be willing to pay $20000 for a year's access to the recreational fishery are responding strategically, rather than realistically. Strategic biases from these responses can be quite high, so the results reported here exclude the $20000 offers, regardless of their yes or no response. (Current plans for the continuation of the survey call for this threshold to be dropped anyway. All specifications will eventually be estimated with the full sample, with $20000 threshold respondents deleted, and with thresholds exceeding $500, 2000, and $1500 deleted. This allows us to assess the sensitivity of the valuation function parameter estimates to survey design.)

4.2. *Derivation of "Demand Functions" Underlying the Valuation Data*

In this survey, the underlying continuous dependent variable Y is the respondent's total valuation of a full year's access to the fishery, which we will designate as "total willingness to pay," *TWTP*. We can still estimate models for *TWTP* using censored logistic (or censored normal) regression implicitly via an ordinary MLE logit (or probit) algorithm. We can manipulate the estimated discrete choice coefficients to uncover the individual coefficients (β) for any arbitrary underlying linear-in-parameters fitted total *TWTP* relationship, $x_i'\beta$. However, the *TWTP* function must then be solved to yield the corresponding implicit demand function.

To illustrate, suppose that our explanatory variables included only the number of fishing days per year, q, and other shift variables which we will denote by the "generic" variable X. Then the fitted quantity log(*TWTP*) will be $\beta_1 + \beta_2 \log(q) + \beta_3 X$, where the parameters are now their estimated values and we ignore the stochastic component. The price willingly paid for a year's access is the total amount willingly paid for *all* trips. To determine the marginal *WTP* for one additional trip, we need to find the expression for the derivative: $\partial TWTP/\partial q$. Since $\partial \log TWTP/\partial \log(q)$ is just β_2, $\partial TWTP/\partial q$ can be assumed to be β_2 times the ratio of *fitted TWTP* ($= \exp[\beta_1 + \beta_2 \log(q) + \beta_3 X]$) to q. (To be strictly correct in treating this exponentiated fitted value of log(TWTP) as the fitted conditional mean of TWTP, we would scale this quantity by $\Gamma(1+\kappa)\Gamma(1-\kappa)$, but this term affects only the intercept of the resulting demand expression, so will will suppress it for simplicity of exposition.) If we consider $\partial TWTP/\partial q$ to be p(q), the presumed demand relationship can be expressed as:

$$(12) \qquad \log p(q) = \log \beta_2 - \log(q) + \beta_1 + \beta_2 \log(q) + \beta_3 X.$$
$$= (\beta_1 + \log \beta_2 + \beta_3 X) + (\beta_2 - 1) \log(q)$$

We can rearrange these formulas to isolate log(q) on the left-hand side:

$$(13) \qquad \log(q) = [(\beta_1 + \log(\beta_2))/(1-\beta_2)] - [1/(1-\beta_2)] \log p(q)$$
$$+ [\beta_3/(1-\beta_2)] X$$
$$= \alpha_1{*} + \alpha_2{*} \log p(q) + \alpha_3{*} X.$$

We have thus arrived at *point estimates* for the implicit demand function corresponding to a log-log functional form for *TWTP*. The coefficients on log(p) have the straightforward interpretation of price elasticities of demand for fishing trips. If the X variables contain the logarithm of income, then the corresponding coefficient in the $\alpha_3{*}$ vector gives the income elasticity of demand. Other variables making up the X vector will include respondent and resource attributes which shift the demand function.

Of course, the β parameters in the above formulas are transformations of the original MLE logit parameters. It will certainly be possible to "automate" the computation of all of the $\alpha{*}$ parameters of the implied demand function if we use software which allows us to save the fitted logit parameters to be used in subsequent computations (e.g. SHAZAM). Our initial exploratory models focus on the estimation of the β parameters, indirectly via the ordinary MLE logit approach. However, once promising specifications have been identified, and if one is willing (and able) to estimate a censored regression log-likelihood function directly, using non-linear optimization algorithms, it would be straightforward to reparameterize the censored regression likelihood function described above so that the elasticity parameter $\alpha_2{*}$ and the other $\alpha_3{*}$ parameters could be estimated directly. Note that $\beta_1 = -\log[\alpha_2{*}/(1+\alpha_2{*})] - \alpha_1{*}/\alpha_2{*}$ (plus an additional term in Γ functions of κ) and $\beta_2 = (1+\alpha_2{*})/\alpha_2{*}$ and $\beta_3 = -\alpha_3{*}/\alpha_2{*}$. The expression $x_i'\beta$ in the likelihood function should therefore be replaced by:

$$(14) \qquad g(x_i,\beta) = -\log[\alpha_2{*}/(1+\alpha_2{*})] - \alpha_1{*}/\alpha_2{*} + (1+\alpha_2{*})/\alpha_2{*} \log(q_i) + (-\alpha_3{*}/\alpha_2{*})\, X = g(\alpha_1{*},\alpha_2{*},\alpha_3{*},q_i,X_i).$$

The log-likelihood function to be optimized will now be:

$$(15) \qquad \log L = \Sigma\, (1 - I_i)[(t_i - g(\alpha_1{*},\alpha_2{*},\alpha_3{*},q_i,X_i))/\kappa] - \log\{1 + \exp[(t_i - g(\alpha_1{*},\alpha_2{*},\alpha_3{*},q_i,X_i))/\kappa]\}.$$

Since the individual parameters $\alpha_1{*}$, $\alpha_2{*}$, and $\alpha_3{*}$ are fully identified, the nonlinear function optimizing program will produce the desired results. (The analytical gradient and Hessian formulas will be different and much more complicated, but as noted, many programs will compute their own numeric derivatives.) This model would produce not only direct point estimates of the demand elasticities, $\alpha_2{*}$, and the other demand function derivatives, but also their *directly* estimated asymptotic standard errors. By the invariance property of maximum likelihood, the point estimates should be identical, so extremely accurate starting values for these nonlinear algorithms can be generated by transforming the ordinary logit point estimates. The nonlinear optimization of the likelihood function in (15), however, will yield asymptotic standard error estimates (and therefore t-ratios for hypothesis testing) which could only be approximated with considerable difficulty from the asymptotic variance-covariance matrix produced automatically for the ordinary logit parameter estimates.

5. Preliminary Empirical Results

5.1 *Unspecified Geographic Heterogeneity in Demand*

If we assume geographic homogeneity to begin with and estimate a TWTP model in log form simply as a function of the log of the total number of fishing trips (LTRIPS), the log of median zip code household income (LINC), and market expenditures (MON), we get the ordinary logit point estimates in Table 1a. To determine whether there exists systematic geographical variation in the demand function for fishing days, we then extend this model to include a set of qualitative dummy variables, one for each major bay system:

MJ1 - Sabine-Neches
MJ2 - Trinity-San Jacinto (Galveston Bay)
MJ3 - Lavaca-Tres Palacios (Matagorda Bay)
MJ4 - San Antonio-Espiritu Santo
MJ5 - Mission-Aransas
MJ6 - Corpus Christi-Neuces
MJ7 - Upper Laguna Madre
MJ8 - Lower Laguna Madre

Since the Galveston Bay area accounts for Houston, we arbitrarily make MJ2 the omitted category when we enter sets of major bay dummy variables. Coefficients on the other dummies therefore represent shifts in the dependent variable relative to the values for MJ2.

Individually, several of these dummy variables are statistically significant. Collectively, a likelihood ratio test for the incremental contribution of the complete set of dummy variables indicates that geographical variation in demand is statistically significant at the 10% level.

If we take the ordinary logit parameter estimates from Table 1b and transform them to yield the parameters of the log-log demand function corresponding to this *TWTP* function (shown in the last column of Table 1b), we find that the price elasticity of demand for a fishing day, controlling for qualitative geographical variation via the set of major bay dummy variables,

Table 1a

Extremely Simple Model: Geographic Homogeneity of Demand

Variable	Est. Coeff.	Asy. t-ratio
LOFFER	-0.5608	-24.631
LTRIPS	0.3077	12.05
LINC	0.2488	2.316
MON	0.001734	6.167
constant	1.718	1.625

max LogL = -2550.6.

Table 1b

Augmented Simple Model: with Geographic Heterogeneity (dummies)

Variable	Est. Coeff.	Asy. t-ratio	Demand f^n q
LOFFER	-0.5638	-24.68	-
LTRIPS	0.3095	12.08	-
LINC	0.1278	1.058	0.5024
MON	0.001801	6.234	0.0071
MJ1	-0.1827	-0.7526	-0.7185
MJ3	-0.2589	-1.796	-1.018
MJ4	-0.03043	-0.1706	-0.1197
MJ5	-0.1167	-0.9230	-0.4587
MJ6	-0.3405	-2.819	-1.339
MJ7	-0.2878	-2.149	-1.131
MJ8	-0.3184	-2.478	-1.252
constant	3.119	2.563	-
log(p)	-	-	-2.217

max LogL = -2544.2 (LR test statistic for the set of seven major bay dummy variables is 12.8. $\chi^2(.05)$ critical value = 14.07; $\chi^2(.10)$ critical value = 12.01.

is -2.217. The income elasticity of demand is 0.5024. the change in the log of fishing days for a one dollar increase in market expenditures is 0.0071. The seven bay dummies shift the log of fishing days by -0.72, -1.02, -0.12, -0.46, -1.34, -1.13, and -1.25, respectively.

5.2 *Quantifying Geographical Heterogeneity in Demand*

The evidence therefore suggests that geographical variation exists in the demand function for recreational fishing days in Texas. But in the model in the last section, the *reasons* for this geographical variation are *non-specific*. Demand could differ by bay system for a variety of reasons. First, systematically different types of people, with different preferences or constraints, might be utilizing each different bay system. (This is suggested by the drop in significance of the LINC variable when bay dummies are included.) The quality attributes of the resource could also vary across bay systems. If fish abundance affects *TWTP*, then variations in species abundance across bays could be captured by these dummy variables. If fishing conditions (weather and water conditions) vary systematically across bays, this effect could also be manifested in the dummy coefficients. In particular, however, we are curious to see whether measurable variations in water quality "parameters" exert any statistically discernible influence on *TWTP*. In lieu of a set of simple bay dummy variables, then, we begin to consider specifications employing variables which *quantify* the inter-bay differences in resource attributes.

Table 2a augments the model in Table 1a by including a variable, TOTAL, for the total number of fish actually caught on the interview day. (In subsequent models, we will consider exogenous measures of abundance for individual species, by month and bay.) TOTAL current catch is not statistically significant, but it bears the anticipated sign, so we will

Table 2a

Simple Model with Current Total Catch, No Water Quality

Variable	Est. Coeff.	Asy. t-ratio
LOFFER	-0.5617	-24.64
LTRIPS	0.3064	11.99
LINC	0.2504	2.331
MON	0.001735	6.156
TOTAL	0.003109	1.090
constant	1.718	1.625

max LogL = -2549.9.

Table 2b

Augmented Model: Geographic Heterogeneity in Water Quality

Variable	Est. Coeff.	Asy. t-ratio	Demand f^n q
LOFFER	-0.5637	-24.63	-
LTRIPS	0.3132	12.19	-
LINC	0.2299	1.888	0.9177
MON	0.001675	5.953	0.00669
TOTAL	0.003603	1.243	0.01438
RESU	0.005401	2.138	0.02156
PHOS	1.076	2.685	4.296
CHLORA	0.02313	2.725	0.09233
LOSSIGN	0.005420	1.359	0.02163
CHROMB	-0.009027	-0.969	-0.03603
LEADB	-0.006231	-1.160	-0.02487
constant	3.119	2.563	-
log(p)	-	-	-2.250

max LogL = -2536.9 (LR test statistic for the set of six water quality variables is 26.0. $\chi^2(.05)$ critical value = 12.59.

retain it in the model as a rudimentary control for "catch success." TOTAL will vary with individual fishing skill or effort, but it will also vary across major bays as species abundance varies. Of primary interest for the purposes of this study, of course, is the potential influence of water quality measures on *TWTP*, and hence on the demand function for recreational fishing days.

Our supplementary data from the Texas Department of Water Resources provides sufficient sample on several common water quality parameters to allow us to generate monthly averages for each bay system. For others, however, the limited number of samples only allows reliable estimates of annual averages for each bay system. (This is particularly true for metals found in bottom deposits. We are awaiting further supplementary data on bottom deposits from the shellfish division of the Health Department.) In our first pass through the data, we examined pairwise correlations between species abundance and a wide range of water quality measures and selected several which seemed to have an obvious relationship to species abundance. (We have tangentially explored regressions of actual catch and monthly abundance of each species on all reliably measured water quality attributes, described in Section 6.)

To illustrate the potential for water quality to affect *TWTP* for fishery access, we display in Table 2a some preliminary results for a rudimentary model incorporating a selection of water quality variables. (We emphasize that this model is by no means our last word on the subject. We have barely "scratched the surface" of a wide variety of potential specifications.)

The water quality variables we include in Table 2b which are available as monthly averages for each bay system are RESU (total non-filterable residue, dried at 105C, in mg/l), PHOS (phosphorous, total, wet method, mg/l as P), and CHLORA (chlorophyll-A, μg/l, spectrophotometric acid method).

Variables which can at present only be used as annual averages for each bay system are LOSSIGN (loss on ignition, bottom deposits, scaled to g/kg), CHROMB (chromium, total, in bottom deposits, mg/kg, dry weight), and LEADB (lead, total, in bottom deposits, mg/kg as PB dry weight).

Transforming the ordinary logit parameter point estimates in Table 2b according to the formulas suggested above for solving such a model for the corresponding log-log demand function yield the demand parameters given in the last column of Table 2b. The price elasticity of demand for fishing days is now -2.250. The income elasticity of demand is now 0.9177. (The increase is probably attributable to the fact that we are not longer implicitly controlling for geographic income variation via the set of major bay dummy variables, so that this measure is probably more reliable.) A one dollar increase in market expenditures corresponds to a 0.0067 increase in the log of the number of fishing days demanded, suggesting that market goods associated with the fishing day (if typical) are complementary goods. An extra fish caught *on the interview day* affects demand by increasing the log of days demanded by 0.0144. Demand is higher where non-filterable residues are higher, where phosphorous concentrations are higher, where loss on ignition is greater, and where there are greater concentrations of chlorophyll-A. However, the presence of metals in bottom deposits, such as chromium and lead, corresponds to lesser demand for fishing days.

5.3 *Controlling for Demographic Heterogeneity Among Respondents*

Having determined that there will be some water quality measures which appear to have a statistically significant impact upon the value of access to this recreational fishery, we now introduce three variables designed to control for interregional variations in demographics. We use PSPNOENG, PVIETNAM, and PURBAN. To the extent that the demographic characteristics of anglers are correlated with the water quality in the areas where they fish, it will be important to allow for demographic effects in any attempt to identify the *distinct* effects on resource values of water quality measures.

Table 3 gives the ordinary MLE logit parameter estimates with these additional explanatory variables. The last column of the table gives the point estimates of the parameters of the corresponding log-log demand function (and its shift variables). None of these three variables make statistically significant contributions to explaining resource values, but this may be an artifact of collinearity among the variables, so we retain them out of interest in determining point estimates of their effects on the demand function.[6] The proportion of unassimilated Hispanic residents in the respondent's zip code (PSPNOENG) tends to decrease the log of fishing days demanded by about 1.5; the proportion of Vietnamese (PVIETNAM) has a *dramatic* effect on values (which persists through a variety of alternative specifications)--this variable increases the log of fishing days demanded by 31.8! People from relatively more urbanized areas apparently demand fewer fishing days.

5.4 *Introducing Variations in Species Catch Rates, Species Abundance*

The total number of fish caught on the interview day has been included as an explanatory variable in several of the specifications discussed above.

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[6] Bear in mind that just because a particular variable is not statistically significantly different from zero for a particular sample of data does not imply that it *is* zero. We retain variables for which the coefficient estimates are stable across alternative specifications. With better data (e.g. with a more equal distribution of "yes" and "no" responses) there might have been enough information in this sample to reduce the sizes of the standard errors. Likewise, the error distribution may have an apparent dispersion larger than the actual dispersion because we are using group averages as proxies for several of our explanatory variables, including income. What could be an excellent "fit" with the true data could be converted to a poorer "fit" by the use of group averages.

Table 3

Augmented Model: Demographic Variables

Variable	Est. Coeff.	Asy. t-ratio	Demand f^n q
LOFFER	-0.5637	-24.63	-
LTRIPS	0.3132	12.09	-
LINC	0.2281	1.512	0.9068
MON	0.001632	5.731	0.006488
PSPNOENG	-0.3915	-0.5880	-1.556
PVIETNAM	8.000	1.237	31.80
PURBAN	-0.1190	-1.400	-0.4732
TOTAL	0.003624	1.250	0.01441
RESU	0.005333	2.106	0.02120
PHOS	1.142	2.819	4.541
CHLORA	0.02235	2.631	0.08884
LOSSIGN	0.007762	1.686	0.03085
CHROMB	-0.01300	-1.194	-0.05169
LEADB	-0.004626	-0.8354	-0.01839
constant	1.404	0.9377	-
log(p)	-	-	-2.241

max LogL = -2534.9

Given that we have a wealth of data on the catch and on overall abundance, by individual species, it seems worthwhile to experiment with valuation models which discriminate among the effects of individual species on the annual value of access to the fishery.

Perplexing results emerge as we include variables relating to the catch of individual species. There are seven major species in our working data set: REDS, TROUT, CROAK, SAND, BLACK, SHEEP, and FLOUND (See Appendix II for detailed descriptions). We have experimented with:

a.) actual current day catch rates;
b.) monthly average actual catch rates by bay system;
c.) "annual" average actual catch rates by bay system;
d.) monthly average abundance indexes by bay system from the TPW resource monitoring program;
e.) annual average abundance indexes by bay system from thr TPW resource monitoring program

For all of these measures of catch rates, we find that for at least some species, often important ones, the coefficients in MLE logit models imply that greater catch rates or greater abundance decreases the value of the resource. This seems highly implausible, and points to the existence of important unmeasured variables, negatively correlated with catch rates, which are positively correlated with resource values and (by their omission) leave the catch rate variables with counterintuitive signs.

Logically, since we are asking respondents to value a year's access to the fishery, it should be *expected* annual catch which influences their values. But anglers may be myopic. Actual average catch rates or abundance may be discounted in favor of current perceptions of catch rates. A variety of models have been estimated, but for illustration, we report our findings for one which uses monthly bay average catch rates. It is our inclination that *average* catch rates should be preferred to *individual* current catch rates because the latter does not control for individual expertise or fishing intensity. The monthly averages reflect the catch of the "average" angler, abstracting from individual differences in skill or enthusiasm.

Results for a specification which replaces the TOTAL current catch variable with the full set of monthly catch averages for each bay system are presented in Table 4. The coefficients on MATROUT, MASAND, and MABLACK are negative, and the point estimate for the coefficient on MABLACK is relatively large. The set of catch variables collectively results in an improvement of only 3.0 in the log-likelihood function, which is not sufficient to reject by an LR test the hypothesis that the catch data should be excluded from the model. But perhaps we are not measuring the desired variables correctly.

It is unfortunate that the survey did not collect information from post-trip respondents regarding their target species. If you only ever fish for one particular species, then the abundance if other species will not affect your value of access to the resource. In fact, of other species compete for the same biological niche as your preferred species, their abundance might detract from your value of the fishery. This angle will need to be explored. At one point, we made the heroic assumption that observed target proportions in each bay and month for pre-interview respondents carry over to the population as a whole (which is tenuous). Including these target proportions directly in a logistic regression model had no discernible effect, however, probably because the information was not specific to individual anglers (a severe errors in variables problem).

Further investigation of the observable (and unobserved) correlates of catch rates is clearly warranted. At the time of this writing, we have not yet uncovered and explanation for these counterintuitive findings. The following section addresses catch rates explicitly, and describes the search

Table 4

Augmented Model: Monthly Average Catch Rates (by bay system)

Variable	Est. Coeff.	Asy. t-ratio	Demand f^n q
LOFFER	-0.5636	-24.62	-
LTRIPS	0.3129	12.09	-
LINC	0.2158	1.432	0.8604
MON	0.001647	5.725	0.006566
PSPNOENG	-0.3705	-0.5479	-1.477
PVIETNAM	7.421	1.142	29.58
PURBAN	-0.1149	-1.343	-0.4580
MAREDS	0.05111	0.4234	0.2037
MATROUT	-0.02823	-0.6157	-0.1125
MACROAK	0.001740	0.05004	0.006935
MASAND	-0.02808	-0.5756	-0.1119
MABLACK	-0.2094	-0.6973	-0.8346
MASHEEP	0.4165	1.331	1.660
MAFLOUND	0.06694	0.5238	0.2669
RESU	0.006257	2.328	0.02494
PHOS	1.185	2.671	4.723
CHLORA	0.02056	2.244	0.08195
LOSSIGN	0.006621	1.289	0.02639
CHROMB	-0.009143	-0.7001	-0.03645
LEADB	-0.005987	-0.9940	-0.02387
constant	1.5419	1.030	-
log(p)	-	-	-2.247

max LogL = -2532.7

for potential reasons for the results in Table 4 (and similar results for other models not reported in this paper).

6. Actual Current Catch versus Species Abundance: Regression Models

It is not intuitively obvious whether exogenously measured species abundance, or actual catch rates by the respondent, should be the more appropriate determinant of valuation for the fishing season. Unfortunately, it is rarely easy to extract from respondents a reliable (retrospective) total of each species caught over the past year. We only have the current day's catch of each species in our present survey data. But exogenously measured abundance of each species is not necessarily a good predictor of variations in expected catch from the point of view of the individual who is being asked to value a year of access to the fishery. One reason is that Parks and Wildlife Resource Monitoring controlled samples are not "caught" using the same technology available to recreational fishermen. If fish are present, but are not "biting," they may still be swept up in the nets used by the Monitoring Program. Ideally, we would like to know the success rates (for each species) for a "standardized" recreational angler (with given skills and effort level). If we use individual respondents' actual catch rates, unobservable differences in skill will potentially bias the coefficients on the catch rate in the valuation equations.

To determine what factors affect individual respondents' current catch rates, we ran a set of ordinary least squares regressions of each respondent's actual catch of each species (REDS, TROUT, CROAK, SAND, BLACK, SHEEP, and FLOUND) against the corresponding monthly and annual abundance indexes for that species, current market expenditures related to the fishing day (MON), specific fishing experience (SITETRIP, the annual number of trips to the site where the respondent was interviewed), non-specific fishing experience

(NSWTRIP, annual trips to other saltwater fishing sites in Texas), and a number of demographic variables. The demographic variables reflect zip code average or median data drawn from the 1980 Census, so they do not necessarily capture *concurrent* demographics, but we will assume they are close. We include PRETIRED (the proportion of people in your zip code who are retired), PSPANISH (the proportion of people of Hispanic origin), PSPNOENG (the proportion speaking Spanish at home and little or no English--unassimilated immigrants), PVIETNAM (the proportion indicating Vietnamese origin, PURBAN (the proportion living in areas designated as urban), PTEXNATV (the proportion born in Texas--reflecting familiarity with the fishery or the environment), PFFFISH (the proportion working in forestry, fishing, or farming), and HHLDINC (median household income).

These variables may affect catch rates for several reasons. First, demographic differences may influence the target species chosen. Alternatively, these variables may serve as proxies for fishing experience or skill. They may also proxy whether or not the objective of the fishing trip is purely recreational, or whether the catch is a significant supplement to the angler's diet. Demographic measures may also covary systematically with geographical regions and therefore with species abundance.

Table A.1 (at the back of this paper) displays the results of the seven OLS regressions. Interestingly, the exogenous abundance indexes (MMxxxxx and Axxxxx, computed from the Resource Monitoring data) are frequently significantly negatively related to the actual catch. Only for sand seatrout (SAND) do both abundance indexes enter positively. This result requires further investigation. In any event, if the fish are there, but you cannot catch them using legal recreational fishing gear, they may contribute considerably less to your value of the resource.

For several species, money spent on market goods related to the fishing day is *negatively* related to the catch. (And it is interesting that MON is markedly uncorrelated, at 0.03, with zip code median household income.) Site-specific fishing experience (SITETRIP) significantly increases one's catch of red drum (REDS), spotted seatrout (TROUT), and black drum (BLACK). Non-specific fishing experience (NSWTRIP) significantly increase one's catch of sheepsheads (SHEEP) and southern flounder (FLOUND), but significantly diminishes one's catch of croakers (CROAK).

PRETIRED insignificantly decreases the TROUT, CROAK, BLACK and SHEEP catch, significantly decreases the SAND catch, but has an insignificant positive effect on the FLOUND catch. People from zip codes with relatively large numbers of Vietnamese catch significantly (and substantially) fewer of several species, notable REDS, and SAND, but they catch dramatically larger numbers of CROAK. People from urbanized areas catch fewer REDS, but more CROAK, SAND, and FLOUND. Texas natives (or at least people from areas where relatively more people are Texas natives) catch significantly fewer REDS, but more TROUT, CROAK, BLACK, and FLOUND. If more of your neighborhood is employed in fishing, farming or forestry, you tend to catch significantly more REDS, SAND, and SHEEP, but significantly fewer CROAK. Higher neighborhood incomes mean higher REDS catch, but significantly lower CROAK and SAND catch rates. These differing results undoubtedly reflect the "sport" versus "food" values of different species.

These tendencies might still reflect regional variations in fishing location, which might be correlated with demographic factors. To identify non-specific geographical and seasonal variations in catch rates, we also estimate OLS regressions of actual catch rates on a set of major bay dummies, MJ1 - MJ8, and a set of monthly dummies, MN5 - MN11 (where MN5 is May 1987, etc.). The results of these regressions are displayed in Table A.2. Clearly, there is considerable qualitative geographical and seasonal variation in catch rates for all species. Table A.3 therefore includes the quantitative variables from Table A.1 (with the exception of Axxxxx, which takes on only one value per bay system), as well as the set of dummy variables MJ1 - MJ8. Geographical variation in resource stocks does not seem to explain completely the observed variations in catch rates. Tastes (demographics) still seem to matter in many cases.

Since the abundance indexes derived from the Resource Monitoring data set do not seem to be a very good proxy for expected annual catch, we revert to using the information present in the contingent valuation sample. With over 5000 usable responses, we can average the actual current catch data for each respondent across all fishing trips to a particular bay system in a particular month. Likewise, we can generate annual average actual catch rates in each bay system. Tables A.4a through A.4c describe catch data based on the CV sample information. Table A.4a displays the differences in mean catch rates across bay systems for each species (AAxxxxx). Table A4.b explains the actual individual catch for each species using *both* monthly average catch rates and "annual" (May through November) catch rates, plus a variety of demographic variables. The monthly average catch is clearly the preferred indicator when both are included. (Its coefficient is always near one and highly significant.) However, if *only* annual catch rates are included, as in Table A.4c, these do an excellent job of explaining current individual catch. But sociodemographic, "experience," and market expenditure variables still contribute significantly to explaining individual catch rates for several species. In words, you don't just catch what everybody else catches--who *you* are makes a difference too.

In subsequent work, we will contemplate using regression models like these to generate fitted reduced form estimates of individual catch to be used as explanatory variables in the logistic regression models for the demand equation. Purging catch rates of components which might be correlated the error term may improve the accuracy of the estimated coefficients.

7. Explicit Trip Motivation, Trip Goal Satisfaction

The main objective of this project is to determine whether water quality has any statistically discernible effect upon the value of access to a recreational fishery. For a subset of respondents--those who were interviewed prior to embarking on their fishing trip--respondents were actually asked *explicitly* about how important it was to them to be able to "enjoy natural and unpolluted surroundings" on a fishing trip. The responses warrant investigation.

In the pre-trip interviews, the TPW survey actually asked direct questions about a whole variety of potential motivations for going fishing. All respondents were asked to respond on a 10-point Likert scale (with 10 being "extremely important" and 0 being "not at all important") the importance they place upon recreational fishing as a way to:

A - Relax (PRERELX)
B - Catch Fish (PRECAT).

The third motivation question was drawn at random from a selection of alternatives, including:

C - Get away from crowds of people (NOPEOPLE),
D - Experience unpolluted natural surroundings (NOPOLLUT),
E - Do what you want to do (DOWHTWNT),
F - Keep the fish you catch (KEEPFISH),
G - Have a quiet time to think (QUIETIME),
H - Experience good weather (GOODWTHR),
I - Spend time with friends or family (FRNDFMLY), and
J - Experience adventure and excitement (ADVNEXCT).

Since the latter eight goals were not asked of everyone, it was necessary to focus on the subsamples to which each question was posed. For pre-trip interviews which were not matched with post-trip interviews of the same anglers, we have a very limited amount of information. It is not possible to include demographic data, because zip codes were not collected. We therefore rely on whether the professed target species was red drum, trout, or flounder (TARGR, TARGT, or TARGF), upon major bay dummies, monthly dummies, and upon a dummy variable for weekend days. We use OLS regression of the recorded Likert scale response on these variables in an effort to detect factors affecting angler's objectives in going fishing. The results are contained in Table A.5.

From Table A.5, we see that target species, geographic dummies, and seasonal dummies do not help at all to explain the NOPOLLUT motivation for going fishing. However, the target species do affect the NOPEOPLE motivation, the KEEPFISH motivation (red drum anglers seem to fish for sport; flounder anglers fish for food), and the GOODWTHR motivation (trout anglers enjoy the weather more; red drum and flounder anglers are less inclined to go out for the nice weather...they must be more serious). Red drum anglers are less likely to go fishing for its social aspects (FRNDFMLY).

More weekend anglers claim to be strongly motivated by the desire for adventure and excitement (ADVNEXCT). Geographical and seasonal dummies occasionally make significant differences in the objectives of anglers. However, the values of the F-test statistics corresponding to these regression suggest that none of the models have particularly good explanatory power.

Unfortunately, people who were interviewed prior to their fishing trips were not a random sample of anglers. Interviewing personnel did not begin to collect data until 10:00 a.m. in general, so pre-trip interviews sample individuals who do not embark on fishing trips until relatively late in the day. These are probably less avid fishermen. Consequently, what we learn from this sample cannot be reliably extrapolated to the entire sample. (It would have been helpful if the pollution question, in particular, had been posed to everyone, both pre- and post-trip.) Nevertheless, with this caveat in mind, we can examine the apparent relationships between attitudes and other variables.

For the pre-trip interview sample which could be *matched* with corresponding post-trip interviews, we have both the attitudinal variables and the crucial zip code data which allow us to splice in data (by zip code) on our primary Census variables: median household income (HHLDINC), proportion of the population over 65 (PRETIRED), proportion of the population with birthplace in Texas (PTEXNATV), the proportion living in urban areas (PURBAN), the proportion of the population reporting Vietnamese origin (PVIETNAM), and proportion of the population speaking Spanish at home and speaking English not well or not at all (PSPNOENG). If we assume that zip code areas are relatively homogeneous, we can use median household income and these demographic proportions to control for a certain extent for the respondents demographic characteristics. To determine the extent to each motivation depends upon the characteristics of the respondent, we can attempt to interpret a number of OLS regressions. Other included explanatory variables are: number of fishing trips to the interview site over the last year (SITETRIP), number of saltwater fishing trips to other sites (NSWTRIP), and money spent on market goods during this fishing trip (MON). The results are presented in Table A.6.

In the post-trip interviews, the TPW survey asked some direct questions concerning respondents' ability to *achieve* certain goals in going fishing.

Again, all respondents were asked to respond on a 10-point Likert scale (with 10 being "completely" and 0 being "not at all") the extent to which they were able to achieve the same set of goals (A through J). All respondents were offered the first two goals, and one question from the remaining eight was asked of each respondent.

In subsequent research, we may devote attention to the other attitudinal questions in the post-trip surveys, but for the present we will focus on the NOPOLLUT question, since this is most relevant to the issue at hand. For post-trip respondents' answers to the question "To what extent were you able to experience unpolluted natural surroundings," we obtained the regression results summarized in Table A.7. This OLS regression demonstrates that *who* you are (the demographic variables) has little to do with your perception of your ability to enjoy unpolluted surroundings. The only exception may be the PVIETNAM variable. On the other hand, geographic and seasonal dummies occasionally make a statistically significant contribution to explaining peoples responses. Anglers do seem to have differing perceptions of the level of pollution, especially across bay systems. The northern bays are perceived to be more polluted than are southern bays.

It is unfortunate that this attitude question (NOPOLLUT) was not asked of the entire sample, so that this variable could be employed as a potential explanator for annual resource values. Nevertheless, we can experiment will a logistic regression specification based upon the 830 respondents who were posed *both* the NOPOLLUT question and the contingent valuation question. Table 5 summarizes the results of an ordinary logit model (*without* water quality variables or catch data) which includes the Likert scale value for the NOPOLLUT variable as a potential shift variable for the demand function.

Since only a tiny subsample of the full dataset is being used in this case, we might expect some differences in the implication of the fitted models (especially if there was anything non-random regarding the choice of whom to ask each of the trip satisfaction questions--a factor which has not yet been investigated). However, the implied demand derivatives in Table 5 are highly consistent with those derived using the full dataset, except for the fact that the coefficient on PSPNOENG changes sign. The price elasticity of demand is typical, at -2.66; the income elasticity of demand is somewhat higher than in the full sample, at 1.589. However, in this subsample, the level of significance of LINC has dropped somewhat.

Of particular interest is the coefficient on NOPOLLUT. This variable is statistically significant at the 10% level in the logit model. Adjustments in aspects of environmental quality (including water quality) which would increase a respondents' Likert scale choice by 1 unit (on the scale of 1 to 10) would therefore seem to increase the log of fishing days demanded by 0.28. Since the mean Likert scale value is approximately 8.2, this implies that the "elasticity of fishing day demand with respect to environmental quality" is roughly 2.2--an elastic response.

8. Perceptions of Pollution versus Measured Water Quality

When we choose to specify a resource valuation model using water quality measures as explanatory variables, we are not being specific about whether water quality affects valuation of the recreational fishery *directly* or *indirectly*. For example, anglers may have no conscious perception of the dimensions of water quality when they go fishing, but water quality may be closely related to fish abundance and therefore to catch rates, so that water quality variables are proxies for other variables which *do* enter directly into individuals' utility functions. (At present, we are exploring OLS regression models for catch rates which include water quality variables.)

To determine whether perceptions of environmental quality reflect actual levels of measured dimensions of water quality, we can select the subsample of respondents who were queried regarding their ability to enjoy unpolluted natural surroundings. We can then regress the NOPOLLUT variable on a range of water quality variables to see whether any statistically significant relationships emerge. If anglers appear to perceive water quality directly, then we can argue that water quality probably enters directly into their utility functions as a detectable resource attribute. If not, we would be inclined to say that appreciation of water quality variables is implicit, acting through other variables which are manifestations of water quality.

Results for this experiment are given in Table A.8. There are 695 observations for which complete data exist for the initial set of explanatory variables we use here. Once again, monthly or annual averages for each bay system are used for the water quality variables, rather than conditions actually existing in the area on the specific day when the NOPOLLUT survey response was collected. This averaging process may considerably obscure an underlying close relationship between the date- and site-specific values of the water quality variables, had we been able to collect this information simultaneously with the creel survey. Consequently, the standard error for the parameter estimates may well be larger than they would be with more accurate data. Therefore t-tests for the statistical significance of coefficients are probably not conclusive.

Table A.8 shows that several water quality measures bear estimated coefficients with t-values greater than unity. The two different measures of dissolved oxygen, MDO and DISO (from different data sources) enter oppositely

Table 5

Alternative Strategy: Use Reported Pollution Perceptions to Explain Value
(n = 830)

Variable	Est. Coeff.	Asy. t-ratio	Demand f^n q
LOFFER	-0.6639	-10.22	-
LTRIPS	0.4145	5.946	-
LINC	0.3966	0.9774	1.590
MON	0.004663	3.901	0.01869
TOTAL	0.003468	0.2962	0.01390
PSPNOENG	0.2828	0.1820	1.134
PVIETNAM	4.228	0.2686	16.95
PURBAN	-0.2009	-0.8602	0.8051
NOPOLLUT	0.07043	1.753	0.2823
constant	0.08104	0.02007	-
log(p)	-	-	-2.661

max LogL = -357.53

and relatively significantly. Water transparency (TRANSP) significantly improves perceptions of low pollution. NH4 and PHOS and CHLORA are positively correlated with these perceptions; NITR is negatively related. CHROMB and LEADB detract from perceived environmental quality. (Other specifications reveal the consequences of the high correlations between OILGRS and LEADB: one or the other used alone is strongly negatively significant, but not both.)

A tentative conclusion from these initial models is that people do seem to have perceptions of environmental quality that are somewhat related to actual measured dimensions of water quality. Loosely, then, policy actions designed to change the levels of arguments which probably figure significantly in regressions like that in Table A.8 will change anglers' perceptions of pollution levels. The censored logistic regression reported in Table 5 could then be used crudely in a "second stage" to infer the effects of such policies on the demand for fishery access and on the total social value of the fishery.

9. Tentative Findings and Directions for Continuing Research

At this stage, of course, the results we have obtained reflect only our "first pass" through the data, to determine whether statistically discernible relationships among the variables of interest will assert themselves. Having achieved some success, it is now necessary to go back over all the data to verify the plausibility of the observed values and to "clean" the sample of additional influential observations which may be causing varying degrees of mischief in the estimation process. Occasional questionable values emerged during the work thus far. Usually, the statistical fit of the models is improved by correction of these problems.

Some remarkable outliers among the water quality data on bottom deposits from the Department of Water Resources need to be examined before these "parameters" are included in the model. We also need to splice in the water quality data obtained from the Texas Water Development Board. Due to the absence of a crucial map, we are not able at present to distinguish accurately between the data for the Upper and Lower Laguna Madre areas. With that problem resolved, we will have at our disposal a number of other important dimensions of water quality.

With tighter data, we will be able to employ the more refined econometric methods described in sections 2.2 and 4.2 of the paper. For now, we have been satisfied to obtain point estimates of the demand function parameters and to rely upon the statistical significance of the underlying MLE logit parameters to imply the significance of the corresponding demand function parameters.

As is typical with survey analyses, the process of utilizing a data set reveals many ways in which the questionnaire could be improved from the point of view of using its results for particular tasks. We find that these data would have been much more useful if the range of offered threshold values had been manipulated during the course of the survey to ensure that fairly even proportions of "yes" and "no" responses were elicited. The efficiency of the estimation process is greater when one is better able to discriminate the shape of the distribution in the vicinity of the marginal mean of the distribution of implicit valuations. This sample has a disproportionate number of "no" responses, which means that the information we have frequently concentrates on the upper tail of the distribution, which is less helpful.

For the pollution aspect of this study, our objectives would have been helped by asking all respondents *direct* questions about their water pollution perceptions and explicitly whether these perceptions affect their enjoyment of the fishing day (today or over the course of the year).

It would have been desirable to elicit retrospective information from respondents on their approximate total annual catch of each species, their self-assess fishing ability, and especially, their target species (this was only asked in pre-trip interviews).

We need to know more about the econometric literature on utilization of group means in lieu of individual values for explanatory variables. Since some of our earlier work with San Francisco Bay area data (Cameron and Huppert, 1988a, 1988b, and 1988c) has implied that individual income, for example, is correlated with Census median zip code income only at a level of roughly 0.3 to 0.4, much information may be lost by using these medians as proxies. On the other hand, there may be some valid arguments for treating zip code median income as a reasonable measure of "permanent income," or the operational level of total consumption for the individual relative to neighbors. This methodological issue still need to be explored. As we have pointed out in the paper, if information is being obscured by the use of group means or medians, the standard errors of the point estimates in our models could be artificially amplified, making parameters appear to be statistically insignificant at any of the typical (arbitrary) levels. With "real" data, the proxied variables might be strongly statistically significant. We don't know.

A major unresolved issue, which has confounded us for some time, is the apparent negative effect of catch rates for some species on resource values. This is counterintuitive, since we have strong priors that better catch rates should imply a more desirable resource. We are confident that some explanation can be found. Certainly, five thousand Texans cannot be wrong.

Effort thus far has been focused on determining the parameters of the demand functions corresponding to the fitted total valuation functions for a year of fishing access. The basic implications of microeconomic theory for the parameters of a log-log demand specification are readily satisfied. The price elasticity of demand for fishing days (if a market existed) appears to be roughly -2.2; the income elasticity appears to be just less than unity, implying that recreational fishing is borderline between being a necessity and a luxury. It is unfortunate that the lack of specific demographic data on our respondents prevents us from unambiguously identifying respondent characteristics which would let us segregate the sample and estimate separate demand functions for each group. We must content ourselves with using zip code averages as "shift" variables for a common demand specification.

Geographical heterogeneity in the demand for recreational fishing days does seem to exist. Water quality variables seem to explain quite a lot of this geographic variation. The Vietnamese seem to have *markedly* different preferences for fishing than the population as a whole. Money spent on associated market goods, once thought to be a reasonable proxy for the non-market value of a fishery, is positively related to the value of a fishing day (but typically completely unrelated to catch success). Importantly, *many* other explanatory variables make strong contributions to explaining the annual value of fishing day access; reliance solely upon market expenditures could severely misstate resource values.

APPENDIX I

NONLINEAR OPTIMIZATION OF THE CENSORED LOGISTIC REGRESSION MODEL

a.) *Gradients and Hessian Elements for Nonlinear Optimization*

For the simplest version of the model, with $g(x_i,\beta) = x_i'\beta$, we can write out these derivatives by first defining the following simplifying abbreviations:

$$(1) \quad \psi_i = (t_i - x_i'\beta)/\kappa \qquad R_i = 1/(1+\exp(-\psi_i)) \qquad S_i = R_i^2\exp(-\psi_i)$$

The gradient vector for this model is then given by:

$$(2) \quad \partial log\ L/\partial\beta_r = \Sigma\ (x_{ij}/\kappa)\ \{(I_i - 1) + R_i\ \} \qquad r = 1,\ldots,p$$

$$\partial log\ L/\partial\kappa = \Sigma\ (\psi_i/\kappa)\ \{\ (I_i - 1) + R_i\ \}$$

The elements of the Hessian matrix are:

$$(3) \quad \partial^2 logL/\partial\beta_r\partial\beta_s = -(1/\kappa^2)\ \Sigma\ x_{ir}x_{is}\ S_i \qquad r,s = 1,\ldots,p$$

$$\partial^2 logL/\partial\beta_r\partial\kappa = -(1/\kappa)^2\ \Sigma\ x_{ir}\ \{\ (I_i - 1) + R_i(1 + \psi_i)\ \} \qquad r = 1,\ldots,p$$

$$\partial^2 logL/\partial\kappa^2 = -(1/\kappa^2)\ \Sigma\ (2\psi_i)\ \{\ (I_i - 1) + R_i\ \} + \psi_i^2 S_i$$

The expectation of I_i is $[1/(1+\exp(\psi_i))]$. The negatives of the expectations of the Hessian elements are as follows:

$$(4) \quad -E(\partial^2 logL/\partial\beta_r\partial\beta_s) = (1/\kappa^2)\ \Sigma\ x_{ir}x_{is}\ S_i \qquad r,s = 1,\ldots,p$$

$$-E(\partial^2 logL/\partial\beta_r\kappa) = (1/\kappa^2)\ \Sigma\ x_{ir}\psi_i\ S_i \qquad r = 1,\ldots,p$$

$$-E(\partial^2 logL/\partial\kappa^2) = (1/\kappa^2)\ \Sigma\ \psi_i^2\ S_i$$

For models with more general forms of the valuation function, $g(x_i,\beta)$, the gradient vector and Hessian matrix will have different formulas. In these situations, it may prove easier to substitute computing time for programming effort by using numeric derivatives in the optimization process.

b.) *Standard Error Estimate for Logistic Regression Parameters from Ordinary MLE Logit Algorithms*

One alternative is to use Taylor series approximation formulas for the variances of the desired parameters (Kmenta (1971, p. 444)):

$$\text{(5)} \qquad \mathrm{Var}(\kappa) = \mathrm{Var}(-1/\alpha) = [1/\alpha^2]^2\ \mathrm{Var}(\alpha)$$

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

A second possibility is to use the analytical formulas for the Hessian matrix given in (3) in conjunction with the optimal values of β and κ derived from γ^*. The negative of the inverse of this matrix can be used to approximate the Cramer-Rao lower bound for the variance-covariance matrix for β and κ. Alternately, the *expected values* of the Hessian matrix elements are sometimes used in this process.[7]

Whichever way the point estimates are obtained, and by whatever method the asymptotic standard errors are determined, these ingredients are necessary for hypothesis testing regarding the signs and sizes of individual β_j parameters. These can frequently be interpreted as derivatives (or as elasticities) of the inverse demand function (or ad hoc "valuation" function), and assessments of their probable true values are can be an important objective in many empirical investigations.[8]

[7] The outer product of the gradient vector evaluated at the optimum is also sometimes used. However, since the expectation of the Hessian has simple formulas, it is probably preferred in this application.

[8] Of course, if estimates are achieved by optimization of (10), hypothesis testing regarding the βs (individually or jointly) is the same as in any maximum likelihood context: by likelihood ratio tests.

APPENDIX II

CONSTRUCTION OF ESTIMATING SAMPLE DATA

1. Observations from the Texas Parks and Wildlife Survey

The "high use" season data set from the survey covers primarily the period from May 1987 to November 1987, although a few observations are included for December, 1987 and for January and February, 1988. We begin our analysis with the 9413 responses collected in post-trip interviews alone. Relatively fewer respondents were interviewed before their outings, since survey interviewers arrived later in the morning than most anglers leave for fishing trip. Also included are the 1094 respondents who were interviewed both before and after their fishing trip. These respondents were also posed the contingent valuation question; they will also be systematically different types of individuals because all are characterized by departing typically later in the day. This may be related to their implicit resource values.

Variables from the survey which are available for use in this study include the following:

MAJOR	which of eight major bay systems (1 -north; 8-south)
HOLIDAY	whether the survey day was a holiday
DAYTYPE	1st digit (holiday) 2nd digit (day of week)
MONDAY	year/month/day
MINOR	code identifying minor bay where survey was conducted
STAT	numerical code identifying survey site
ID	boat ID number
INTTIME	interview time
TRIP	
ACT	activity- recreational fishing or partyboat fishing
PEOPLE	number of people in the party
COUNTY	code for county or state of residence
MINBAY	minor bay where most fish were caught
GEAR	type of fishing gear used by party
BAIT	type of bait which caught the majority of fish
REDS	number of red drum landed
LRED	largest specimen landed and measured
MLRED	average length of <=6 specimens landed and measured
TROUT	number of spotted seatrout landed
LTROUT	"

MLTROUT	"
CROAK	number of croakers landed
LCROAK	
MLCROAK	
SAND	number of sand seatrout landed
LSAND	
MLSAND	
BLACK	number of black drum landed
LBLACK	
MLBLACK	
SHEEP	number of sheepshead landed
LSHEEP	
MLSHEEP	
FLOUND	number of South Atlantic flounder landed
LFLOUND	
MLFLOUND	
TOTAL	total landed, all species
LTOTAL	
MLTOTAL	
SWTRIP	number of saltwater fishing trips made in the last 12 months
SITETRIP	number of trips to the survey sight in last 12 months
FWTRIP	number of freshwater fishing trips in last 12 months
SATISFY	overall grade given to the fishing trip (0-10)
POSTRELX	answer to the post-trip question on extent person was able to relax
POSTCAT	answer to the post-trip question on extent person was able to catch fish;
POSTVAR	answer to alternating questions on other dimensions of fishing trip
ZIP	five-digit zip codes which will be used to merge survey data with census tract information on zip code areas for the approximately 90% of the sample with Texas residency implied. "What is the zip code where you currently live?"
MON	dollars spent on the fishing trip for non-capital market purchases: "How much will you spend on this fishing trip from when you left home until you get home?"
CONTVAL	conveys the arbitrarily assigned threshold value proposed to each respondent and their yes/no response to the question: "If the total cost of all your saltwater fishing last year was _____ dollars more, would you have quit fishing completely?" A "no" response therefore implies that the resource value is greater than the threshold.

While the data set was quite well checked for consistency prior to our receipt of it, several unusable observations had to be deleted. Criteria for deletion were:

- missing data on the contingent valuation question;
- erroneous codes for the relaxation or catch satisfaction questions;
- inadmissible codes for the post-trip varying satisfaction-oriented questions;
- inadmissible levels for the relaxation or catch satisfaction questions;
- inadmissible values for the response to the contingent valuation question;
- more than 365 reported saltwater or freshwater fishing trips reported over the last year;
- fractional numbers of salt- or freshwater fishing trips reported;
- negative or greater than 365 trips per year;
- satisfaction Likert scale values outside the 0-10 integer range;
- trout catch greater than 300, total catch greater than 300;
- zip codes greater than 99999;
- no average abundance figures for this month or bay system.

If preliminary specifications on this data set indicate that certain variables appear to have no statistically discernible effect on valuations, the presence or absence of valid values for these variables will be irrelevant, and some of these observations can be reinstated.

Initial specifications do not incorporate sampling weights to offset any bias in estimated valuations which could result from systematic deletions of observations upon criteria which are correlated with resource values. If necessary, weights will be incorporated in subsequent specifications.

2. Controlled Catch Rate Data: Resource Monitoring Data Set

Another requirement of this study is some measure of "expected" catch rates by time and location. Actual catch associated with the fishing excursion during which the survey responses were collected are at best an imperfect indicator of catch expectations. Contemporaneous catch effects are also confounded by the possibility that the angler's expertise is unmeasured, and this expertise will simultaneously affect both their valuation of the resource and their current catch. This will result in misleadingly large estimates of the impact of catch rates on the total value of the year's access to the sportfishery if expertise, catch and resource valuation are all positively correlated (which seems likely).

In order to avoid the omitted expertise variable's biasing effect on the catch rate coefficient, we take advantage of a supplementary data source which can be merged with the survey data. The Texas Department of Parks and Wildlife regularly collects information on individual species abundance, sizes, tagging, and other information. We elect to use this resource monitoring data for the period 1983 to 1986, for which 23,729 samples are available. Since we seek to reproduce a proxy for anglers' *expectations* about catch rates, the 1983-86 period would seem to provide a proxy for recent experience.

Each observation in this large data file conveys information collected during a particular controlled harvest. Variables include, gear type (3 kinds), location, date, effort (which depends on gear type), meteorological data (including winds, cloud cover, rain, fog, water temperature, water depth, turbidity (TURB), salinity (SAL), dissolved oxygen (DO), barometric pressure, tide information, and wave height. The gear is applied to the fishery for a measured period of time. At the end of the sample period, the gear is removed and a count is taken of each type of organism collected. Mean lengths are also available. We focus on information for the major recreational target species of finfish: red drum (REDS), croaker (CROAK), black drum (BLACK), spotted seatrout (TROUT), sheepshead (SHEEP), sand seatrout (SAND), and southern flounder (FLOUND).

In distilling this information into a catch expectation variable for each species, several manipulations are required. First, we standardize the catch using each of the three gear types to the mean number of effort units for each gear type. This controls for variations in catch rates due solely to differing sampling durations, yielding catch per unit effort (CPUE) for each type of gear, for arbitrary effort units.

Once these "catch per unit effort" (CPUE) figures have been obtained, we compute overall means and standard deviations in CPUE for each species *by gear type*. We then use these means and standard deviations to "standardize" the individual CPUE figures for each species and each gear type. The resulting quantities are "indices" of CPUE. The different gear types do not necessarily yield additive estimates of catch rates, since they differ in effectiveness for any given number of hours of application. Therefore, we must resort to the standardized indices, which are unit-free (i.e. we subtract the overall mean CPUE for each gear type, and divide through by the overall standard deviation in CPUE for that gear type).

The next step is to aggregate these indices across gear types to come up with a weighted average (across gear types) of the three indices of standardized CPUE. Our objective, initially, is to create indices of expected catch rates for each major species for each sample month and each major bay system along the Texas Coast.

The weights we use are therefore the proportion of *samples* collected by each type of gear in each month and each major bay system. This implies that if one type of gear was only infrequently used in a given month or bay system, the CPUE index for this type of gear will receive a very low weight in the aggregation across gear types. Averages CPUE indices derived from large numbers of samples are presumed to be more reliable, and therefore receive larger weights. (DATA.CTCHIND2)

In addition to the weighted average abundance indices by major bay and month, we also computed annual average catch rates for each major bay. (DATA.ANCATCH2) Since the survey of recreational anglers asked whether they would have given up fishing *entirely* if the access cost had been a particular specified amount, it will also be important to consider whether annual average expected catch is a better explanatory variable for resource valuation than actual catch on the current fishing trip or even monthly expected catch around the time when the survey response was elicited. However, various different measure of catch rates will be included in the valuation models, to determine which measure, statistically, seems to have the greatest effect of resource value.

Bear in mind that the constructed abundance variables (MMxxxxx for monthly averages by bay system; Axxxxx for annual averages by bay system) are measured in standard deviation units. When these variables are used in regressions or logit analyses, the coefficient reflects the consequences of a *one standard deviation* change in abundance.

We may also take advantage of some of the dimensions of water quality collected along with the resource monitoring data. The 23,729 observations provides a rich quantity of information on turbidity, salinity, and dissolved oxygen. We compute average values of these measures for each month and each bay system, MTURB, MSAL, and MDO (DATA.TURSALDO), to be employed in regressions of pollution perceptions on measured water quality levels.

3. <u>Texas Department of Water Resources Water Quality Data</u>

Dave Buzan and Patrick Roque of the Texas Department of Water Resources were kind enough to allow us to utilize information on the characteristics of a large number of water samples taken at diverse locations throughout the Texas estuarine/bay system for the purpose of monitoring water quality.

We use only those observations on water quality measures for which a precise quantity is given. We excluded all observations for which it was only recorded that the amount of the substance was *greater* than a certain amount.

For a few hundred observations, it was reported that the measured amount was less than a certain amount. For these cases, the threshold amount was very small, so we opted to record "zero" for these measures, so as not to bias upwards the mean quantities of these substances.

While occasional water samples were taken on an incredible variety of water quality "parameters," consistent sampling focuses on transparency (TRANSP), dissolved oxygen (DISO), nonfilterable residues (RESU), nitrogen/ammonia (NH4), nitrate nitrogen (NITR), total phosphorous (PHOS), and chlorophyll-A (CHLORA). There were from 816 to 3884 observations on these quality measures; the other parameters all had fewer than 100 measurements, so that monthly averages by bay system were deemed to be less reliable. For these other water quality measures (having from 90 to 100 observations), we generate annual average levels for each bay system. These measures include "loss on ignition, bottom deposits" (LOSSIGN), oil and grease (OILGRS), and organic nitrogen (ORGNITR). In bottom deposits, a few records are available for *each* bay system on phosphorous (PHOSB), arsenic (ARSENB), barium (BARIUMB), cadmium (CADMIUMB), chromium (CHROMB), copper (COPPERB), lead (LEADB), manganese (MANGANB), nickel (NICKELB), silver (SILVERB), zinc (ZINCB), selenium (SELENB) and mercury (MERCURB). These metals contamination data can be employed investigate whether *amounts* or *perceptions* of metal contamination appear to be statistically related to resource values.

Locational information for these samples is recorded at the level of "stations," which we identified on maps and aggregated into each of the eight major bay/estuary systems along the Texas gulf coast. Subsequent research may disaggregate further, but for now, we rely on the presumption that each bay is a reasonably isolated aquatic system. There is considerable variation across bay systems in the average levels of these "parameters." [Early models use only those "parameters" which do not seem to involve questionable "outliers" among the samples. Further investigation of these outliers will be necessary before we can be confident about using bay average levels of contamination as accurate measures of true levels.]

In sum, we have determined average levels for each of these basic water quality parameters for each bay system and for each month (DATA.DWRPARM). We also aggregate to determine annual averages for each bay system. (DATA.ANDWRPAR) For the metals and other parameters for which there are fewer observations, we have only eight observations, by major bay system. (DATA.HVYMETAL).

4. Hydrological and Meteorological Data Collected at Survey Sites

For each day at each survey site, TPW personnel recorded fairly detailed information about weather and surface conditions in the vicinity of the survey site. Both beginning of "day" and end of "day" values were recorded. We begin by considering only the beginning conditions (bearing in mind that this was approximately 10:00 a.m.). These data can be merged with the actual survey responses according to major bay, date, minor bay, and station numbers. Information from this data set which may prove pertinent includes:

BWINDSP - beginning wind speed;
BCLOUD - midpoints of cloud cover categories;
BARO - beginning barometer reading;
BRAIN - whether it was raining (0 = no, 1 = yes);
BFOG - whether there was fog (0 = no, 1 = yes);
BTEMP - temperature in Celsius;

The temperature data contained obvious reporting errors, where temperatures had clearly been recorded in Farenheit instead of Celsius. Fortunately, there is very little potential for overlap in the two scales. We discredited any supposedly Celsius temperature over 40, presumed it was Farenheit, and converted it to the corresponding Celsius measure. Consistency checks confirmed that the corrected data were feasible, give the location and times of year.

We merged these data (DATA.MDMETEOR) directly with the survey response records, based on day and location. We also constructed mean monthly levels of each of these weather and sea condition variables for each bay system (DATA.MMETEOR), as well as annual average levels for each bay system (DATA.AMETEOR).

5. Texas Water Development Board Water Quality Data

David Brock of the Texas Water Development Board has been very helpful in providing us with some of his agency's data on water quality. At the time of this writing, we are still seeking additional information necessary for merging this information with the other data sets. The original merge criteria contained an error.

The TWDB data measures many of the same water quality "parameters" as does the DWR data, plus some additional ones. The included data are:

Water temperature (C)
Turbidity (jksn ju)
Transparency (secchi cm)
Conductivity field @25 C-mmh
Conductivity lab @25 C - micromh
Dissolved oxygen mg/l
pH su
Ammonia NH_3-N mg/l
Nitrite NO_2-N mg/l
Nitrate NO_3-N mg/l
NitrogenT kjeldl mg/l
Phos-T P-wet mg/l
Phos-D ortho mg/l
Organ. carbon toc mg/l
Sulfate SO_4 mg/l
Chlorophyll-A mg/l

These data will be incorporated with the main data set as soon as the geographical definitions can be conformed accurately.

6. <u>Health Department Data</u>

In February 1988, during a visit to Austin to confer with the other agencies mentioned in this Appendix, I met with Texas State Health Department data management personnel with Maury Osborn of the TPW Coastal Fisheries Branch. The Health Department maintains detailed historical records of water contamination, in particular for the purpose of determining shellfish "closures." We were informed that if a request for this data was issued by Jerry Clark of TPW directly to the Health Department, these data could be released to us. This formal request was made, but as yet, no data have materialized. We are not sure what accounts for this lack of cooperation, but we will persist.

7. <u>Census Data (1980) for Texas, by 5-Digit Zip Code</u>

The Inter-University Consortium for Political and Social Research (ICPSR) provided at nominal cost a tape containing detailed information about Texas residents aggregated to the level of 5-digit zip codes. Since all post-trip interviews attempted to collect the respondent's home zip code, we have a rich source of supplementary demographic data which we can exploit to reduce (to a certain extent) heterogeneity in valuation responses.

By far the majority of respondents (over 90% of the sample) gave zip codes within Texas. For these respondents, then, we can augment our array of potential explanatory variables for the valuation models with Census information. It is extremely important to keep in mind that zip code proportions or medians for these variables are by no means identical to the respondents' actual characteristics. At best, we might assert that since 5-digit zip codes are very small areas, geographically, it is more plausible to use zip code demographic averages than, say, county or state averages, to control for demographic heterogeneity.

The Census data which we suspect may be relevant to explain valuation responses were extracted from the Census tape and assembled in a file called DATA.TEXCENS1. Our variables are:

HHLDINC - median household income in 1980 (TABLE69);
FAMINC - median family income in 1980 (TABLE74);
MEDINC - median individual income in 1980 (TABLE82);
PURBAN - proportion inside urbanized areas (TABLE1);
PRETIRED - proportion of individuals in zip code over the age of 65 (computed from TABLE15);
PSPANISH - proportion of individuals in zip code claiming hispanic background (computed from TABLE13);
PSPNOENG - proportion of over-18 individuals in zip code claiming to speak Spanish at home and to speak little or no English (computed from TABLE27);
PVIETNAM - proportion stating "race" as Vietnamese (TABLE12);
PFFFISH - proportion of individuals in zip code reporting to work in "forestry, fishing, or farming" sectors (TABLE66);
PTEXNATV - proportion of individuals in zip code reporting birthplace outside Texas (TABLE33).

We anticipate that household income (HHLDINC) will be the most appropriate explanatory variable reflecting income levels, although the other income measures will be explored. Since retired persons' opportunity costs of time for going fishing are smaller, we expect that if you come from a community with a large proportion of retired persons (PRETIRED), your likelihood of being retired yourself is larger, and your valuation of the fishery may be systematically different. The proportion of people in your zip code living in a designated urban area may also affect your motivations for going fishing, and hence your value of access.

Cultural differences in tastes and preferences (for different species of game fish, or for recreation in general) may affect valuations. Especially since some people significantly supplement their diets with "game" fish, we would like to control for these differences. The PSPANISH variable includes people who have lived in the US or Texas for several generations; the PSPNOENG variable is intended to capture the proportion of recent immigrants from Mexico, since this is by far the most prominent immigrant group in the state.

If PSPNOENG is significant where PSPANISH is not, this may reflect assimilation of the immigrant group, at least in terms of preferences regarding fish and recreation. Although this is 1980 Census data, significant numbers of Vietnamese immigrants had already settled in Texas by that time. PVIETNAM will be slightly outdated, but may nevertheless be important. Unfortunately, the Census tapes do not seem to identify individuals which consider themselves to be a member of the prevalent "Cajun" ethnic group. PTEXNATV is the proportion of the community which reports being born in Texas, versus elsewhere. This variable ignores the cultural background of individuals, and simply discriminates the proportion of the community which may have less familiarity with Texas recreational resources, fish species, angling techniques, etc.

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A. SUPPLEMENTARY TABLES

Table A.1 - Regressions of current catch on monthly and annual abundance measures for the species, market expenses, trip frequencies, and demographic variables by zip code.

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.55995251	0.30007121	1.866
MMREDS	0.36847595	0.23700779	1.555
AREDS	-0.10965756	0.04224035	-2.596
MON	-0.000016971	0.000118226	-0.144
NSWTRIP	0.000788784	0.000874304	0.902
SITETRIP	0.005368462	0.000797330	6.733
PRETIRED	0.85482835	0.72060800	1.186
PSPANISH	0.75937497	0.26831368	2.830
PSPNOENG	0.65719318	0.83394446	0.788
PVIETNAM	-9.52181432	4.10336572	-2.320
PURBAN	-0.18475126	0.06936814	-2.663
PTEXNATV	-0.69407659	0.27218848	-2.550
PFFFISH	4.39061789	1.80245578	2.436
HHLDINC	0.000012134	0.0000073043	1.661

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.32098798	0.96852747	0.331
MMTROUT	0.46025045	0.55181825	0.834
ATROUT	-0.10727163	0.08659900	-1.239
MON	0.000344210	0.000391106	0.880
NSWTRIP	0.000856360	0.002804431	0.305
SITETRIP	0.008488526	0.002555053	3.322
PRETIRED	-2.23625648	2.31717300	-0.965
PSPANISH	2.50439916	0.90968459	2.753
PSPNOENG	-4.76702938	2.65016291	-1.799
PVIETNAM	-10.54180776	13.22176053	-0.797
PURBAN	0.007574193	0.22341404	0.034
PTEXNATV	1.61013946	0.92900808	1.733
PFFFISH	4.43354471	5.80127597	0.764
HHLDINC	0.000016170	0.000023415	0.691

Table A.1, continued

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	3.30401254	0.98231253	3.364
MMCROAK	-1.23508097	0.45744060	-2.700
ACROAK	0.08828395	0.09482006	0.931
MON	-0.001526458	0.000391878	-3.895
NSWTRIP	-0.006019254	0.002894183	-2.080
SITETRIP	-0.001736803	0.002636454	-0.659
PRETIRED	-3.96485185	2.37842920	-1.667
PSPANISH	-9.44617850	0.91612331	-10.311
PSPNOENG	16.61375283	2.78349049	5.969
PVIETNAM	34.13699452	13.59965826	2.510
PURBAN	1.00645150	0.22970427	4.382
PTEXNATV	4.46549691	0.89550728	4.987
PFFFISH	-26.83794821	5.96099955	-4.502
HHLDINC	-0.000175471	0.000024158	-7.263

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	2.60203861	1.27890185	2.035
MMSAND	0.13525806	0.62965032	0.215
ASAND	0.34725560	0.12388076	2.803
MON	0.003049747	0.000506331	6.023
NSWTRIP	0.000772157	0.003762673	0.205
SITETRIP	0.002321740	0.003427697	0.677
PRETIRED	-6.69928574	3.10020622	-2.161
PSPANISH	-5.55781967	1.15362653	-4.818
PSPNOENG	8.36237511	3.52678402	2.371
PVIETNAM	-37.14203944	17.67071748	-2.102
PURBAN	1.00236870	0.29815854	3.362
PTEXNATV	1.47548162	1.15738569	1.275
PFFFISH	18.26459246	7.73754036	2.361
HHLDINC	-0.000122238	0.000031442	-3.888

Table A.1, continued

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.21504911	0.15372003	-1.399
MMBLACK	-0.03098885	0.11983304	-0.259
ABLACK	0.02454022	0.01586489	1.547
MON	-0.000098978	0.000060809	-1.628
NSWTRIP	-0.000610036	0.000452134	-1.349
SITETRIP	0.000872498	0.000411767	2.119
PRETIRED	-0.51376786	0.37191902	-1.381
PSPANISH	-0.88597982	0.13901951	-6.373
PSPNOENG	2.70210744	0.42860428	6.304
PVIETNAM	-0.11057677	2.12731804	-0.052
PURBAN	0.04845612	0.03601018	1.346
PTEXNATV	0.66908968	0.13901599	4.813
PFFFISH	0.23180632	0.93050578	0.249
HHLDINC	-.0000017218	.00000377165	-0.457

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.06836968	0.21828737	0.313
MMSHEEP	0.12234247	0.15810969	0.774
ASHEEP	-0.04147377	0.03175789	-1.306
MON	0.000139507	0.000087330	1.597
NSWTRIP	0.002547533	0.000636643	4.002
SITETRIP	0.000655088	0.000579990	1.129
PRETIRED	-0.22178639	0.52319454	-0.424
PSPANISH	0.06904953	0.19867934	0.348
PSPNOENG	-0.55274431	0.60979506	-0.906
PVIETNAM	-2.34572452	3.01854217	-0.777
PURBAN	0.02545117	0.05043334	0.505
PTEXNATV	-0.002006479	0.20671267	-0.010
PFFFISH	2.93979145	1.31880893	2.229
HHLDINC	-.0000027911	.00000531521	-0.525

Table A.1, continued

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.01970803	0.32426667	-0.061
MMFLOUND	-0.61281021	0.20575268	-2.978
AFLOUND	-0.15836960	0.03617201	-4.378
MON	-0.000077295	0.000129670	-0.596
NSWTRIP	0.007868546	0.000943887	8.336
SITETRIP	-0.000819604	0.000860134	-0.953
PRETIRED	1.13867584	0.78206752	1.456
PSPANISH	-0.98520829	0.30517406	-3.228
PSPNOENG	2.04588931	0.91854214	2.227
PVIETNAM	1.06771366	4.44847267	0.240
PURBAN	0.16953815	0.07518352	2.255
PTEXNATV	0.63002837	0.30251588	2.083
PFFFISH	-1.23657529	1.94501820	-0.636
HHLDINC	-.0000037847	.00000789691	-0.479

Table A.2 - Regressions of current catch on major bay and monthly dummy variables

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.05034214	0.07581144	0.664
MJ1	0.09586074	0.16287253	0.589
MJ3	0.47034606	0.09943735	4.730
MJ4	0.41556795	0.12293509	3.380
MJ5	0.19918153	0.08094287	2.461
MJ6	0.19034190	0.07985535	2.384
MJ7	0.39698000	0.09674908	4.103
MJ8	0.87774944	0.08008518	10.960
MN5	0.04357481	0.09756501	0.447
MN6	0.04480128	0.09810146	0.457
MN8	0.20531995	0.08224176	2.497
MN9	0.38649084	0.08346977	4.630
MN10	0.39501347	0.08322912	4.746
MN11	0.26375298	0.10148514	2.599

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	2.02945978	0.24217103	8.380
MJ1	-0.30959043	0.52027779	-0.595
MJ3	0.60509801	0.31764131	1.905
MJ4	1.48200534	0.39270218	3.774
MJ5	-0.45785320	0.25856281	-1.771
MJ6	-0.23295552	0.25508884	-0.913
MJ7	1.81081777	0.30905394	5.859
MJ8	0.77603162	0.25582300	3.033
MN5	-0.19569724	0.31166034	-0.628
MN6	-0.61720332	0.31337396	-1.970
MN8	-0.37767862	0.26271195	-1.438
MN9	-0.51615104	0.26663468	-1.936
MN10	-0.43755749	0.26586596	-1.646
MN11	-0.08592488	0.32418277	-0.265

Table A.2, continued

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	1.80420655	0.25440856	7.092
MJ1	0.15435967	0.54656879	0.282
MJ3	-1.44501071	0.33369255	-4.330
MJ4	-0.96835590	0.41254645	-2.347
MJ5	-1.22670089	0.27162867	-4.516
MJ6	0.12211734	0.26797915	0.456
MJ7	-0.80625121	0.32467124	-2.483
MJ8	-1.77502414	0.26875041	-6.605
MN5	-0.52584969	0.32740935	-1.606
MN6	-0.52478913	0.32920957	-1.594
MN8	1.30543161	0.27598747	4.730
MN9	0.54887768	0.28010843	1.960
MN10	0.24721955	0.27930087	0.885
MN11	-0.73844884	0.34056457	-2.168

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	1.49360615	0.32742378	4.562
MJ1	-1.75665494	0.70343395	-2.497
MJ3	-1.55240358	0.42946227	-3.615
MJ4	-1.25885186	0.53094723	-2.371
MJ5	-1.05708742	0.34958605	-3.024
MJ6	-1.56950545	0.34488913	-4.551
MJ7	-2.36323791	0.41785184	-5.656
MJ8	-1.87517327	0.34588174	-5.421
MN5	0.39706249	0.42137579	0.942
MN6	-0.32002563	0.42369266	-0.755
MN8	0.63333692	0.35519583	1.783
MN9	0.43997674	0.36049951	1.220
MN10	0.84778208	0.35946017	2.358
MN11	2.84404560	0.43830655	6.489

Table A.2, continued

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.20731884	0.03932264	5.272
MJ1	-0.02152089	0.08448036	-0.255
MJ3	-0.12508682	0.05157716	-2.425
MJ4	-0.12285552	0.06376521	-1.927
MJ5	-0.15597693	0.04198426	-3.715
MJ6	-0.11956589	0.04142017	-2.887
MJ7	-0.13773178	0.05018278	-2.745
MJ8	-0.15204360	0.04153938	-3.660
MN5	-0.07209143	0.05060600	-1.425
MN6	-0.04345460	0.05088425	-0.854
MN8	-0.01226179	0.04265798	-0.287
MN9	0.02200455	0.04329494	0.508
MN10	0.14766722	0.04317011	3.421
MN11	0.05904913	0.05263933	1.122

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR HO: PARAMETER=0
INTERCEP	0.12359373	0.05514031	2.241
MJ1	-0.19739614	0.11846289	-1.666
MJ3	-0.01479838	0.07232426	-0.205
MJ4	-0.06177563	0.08941499	-0.691
MJ5	-0.07825227	0.05887258	-1.329
MJ6	-0.14568843	0.05808159	-2.508
MJ7	-0.24692556	0.07036899	-3.509
MJ8	-0.15689291	0.05824875	-2.693
MN5	0.05152056	0.07096245	0.726
MN6	-0.007780611	0.07135262	-0.109
MN8	0.03604168	0.05981731	0.603
MN9	-0.004137654	0.06071048	-0.068
MN10	0.05014380	0.06053545	0.828
MN11	0.47535803	0.07381370	6.440

Table A.2, continued

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.82159657	0.08199456	10.020
MJ1	-0.31496533	0.17615627	-1.788
MJ3	-0.30390463	0.10754737	-2.826
MJ4	-0.63615308	0.13296157	-4.784
MJ5	-0.79315402	0.08754450	-9.060
MJ6	-0.79126378	0.08636828	-9.162
MJ7	-0.73886256	0.10463985	-7.061
MJ8	-0.63585291	0.08661686	-7.341
MN5	0.06951967	0.10552233	0.659
MN6	0.13816270	0.10610253	1.302
MN8	0.15535632	0.08894932	1.747
MN9	0.05658948	0.09027749	0.627
MN10	0.23391866	0.09001721	2.599
MN11	0.78029069	0.10976219	7.109

Table A.3 - Regressions of current catch on monthly abundance index, demographic variables, and major bay dummy variables

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.08249090	0.30620085	0.269
MMREDS	0.31460321	0.24591373	1.279
MON	-0.000126631	0.000119475	-1.060
NSWTRIP	0.000997362	0.000871506	1.144
SITETRIP	0.005338593	0.000792004	6.741
PRETIRED	0.40792992	0.72216553	0.565
PSPANISH	0.94774237	0.29027646	3.265
PSPNOENG	-1.92730218	0.94335117	-2.043
PVIETNAM	-6.30008634	4.13511627	-1.524
PURBAN	-0.17926668	0.06960719	-2.575
PTEXNATV	-0.35985526	0.28079594	-1.282
PFFFISH	4.06562241	1.79684467	2.263
HHLDINC	0.000014557	.00000727471	2.001
MJ1	0.22117083	0.16308096	1.356
MJ3	0.41258319	0.10128207	4.074
MJ4	0.29340746	0.11918553	2.462
MJ5	0.11045001	0.08697339	1.270
MJ6	0.14403815	0.08637686	1.668
MJ7	0.36564235	0.09914413	3.688
MJ8	0.80571613	0.09778452	8.240

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.32926072	0.98058040	0.336
MMTROUT	0.72672191	0.51692313	1.406
MON	0.000418306	0.000383818	1.090
NSWTRIP	0.001301984	0.002790464	0.467
SITETRIP	0.009021724	0.002535271	3.558
PRETIRED	-1.40101257	2.31274943	-0.606
PSPANISH	2.38954617	0.93836731	2.546
PSPNOENG	-6.87307423	3.02935838	-2.269
PVIETNAM	-5.11369468	13.24493296	-0.386
PURBAN	-0.08751728	0.22300185	-0.392
PTEXNATV	1.51843888	0.90477954	1.678
PFFFISH	1.66646879	5.76057977	0.289
HHLDINC	0.000014731	0.000023296	0.632
MJ1	-0.12522173	0.51372014	-0.244
MJ3	0.46603374	0.32238217	1.446
MJ4	1.42956747	0.38169115	3.745
MJ5	-0.73896336	0.29216032	-2.529
MJ6	-0.56608140	0.27586664	-2.052
MJ7	1.58614179	0.30245190	5.244
MJ8	0.62707082	0.32306103	1.941

Table A.3, continued

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	2.66756373	1.00525808	2.654
MMCROAK	-3.98638283	0.40759600	-9.780
MON	-0.001477013	0.000392887	-3.759
NSWTRIP	-0.006107054	0.002860786	-2.135
SITETRIP	-0.001945570	0.002599357	-0.748
PRETIRED	-2.84572618	2.37166305	-1.200
PSPANISH	-10.44237560	0.96981335	-10.767
PSPNOENG	21.96652769	3.12265143	7.035
PVIETNAM	42.50799742	13.57571203	3.131
PURBAN	0.88205153	0.22857272	3.859
PTEXNATV	4.60465670	0.92367915	4.985
PFFFISH	-25.60229589	5.90128326	-4.338
HHLDINC	-0.000159420	0.000023899	-6.671
MJ1	-1.32428223	0.52467711	-2.524
MJ3	-1.26997939	0.32994369	-3.849
MJ4	-1.09222587	0.39260972	-2.782
MJ5	-0.23015884	0.28546340	-0.806
MJ6	2.96516199	0.32860335	9.024
MJ7	-0.10117965	0.31440281	-0.322
MJ8	-0.30969034	0.32172324	-0.963

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	3.49528262	1.33092771	2.626
MMSAND	0.72768171	0.58049126	1.254
MON	0.003208116	0.000516215	6.215
NSWTRIP	0.000111362	0.003769108	0.030
SITETRIP	0.002300422	0.003424049	0.672
PRETIRED	-6.18159589	3.12377497	-1.979
PSPANISH	-4.92447442	1.25551174	-3.922
PSPNOENG	8.32102379	4.07928230	2.040
PVIETNAM	-43.08458320	17.88205173	-2.409
PURBAN	0.98033470	0.30113908	3.255
PTEXNATV	1.59438668	1.21376362	1.314
PFFFISH	20.77898656	7.76855507	2.675
HHLDINC	-0.000125297	0.000031474	-3.981
MJ1	-1.26918171	0.70113740	-1.810
MJ3	-1.80970744	0.44122254	-4.102
MJ4	-1.69999347	0.55660418	-3.054
MJ5	-0.93288233	0.41761009	-2.234
MJ6	-1.51242967	0.37264711	-4.059
MJ7	-1.47083745	0.46585384	-3.157
MJ8	-1.88560063	0.44713447	-4.217

Table A.3, continued

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.06527348	0.15959629	-0.409
MMBLACK	-0.03127245	0.12061281	-0.259
MON	-0.000069184	0.000062054	-1.115
NSWTRIP	-0.000675180	0.000452805	-1.491
SITETRIP	0.000844350	0.000411388	2.052
PRETIRED	-0.38407660	0.37526227	-1.023
PSPANISH	-0.81824332	0.15091174	-5.422
PSPNOENG	2.86581250	0.49012528	5.847
PVIETNAM	-1.20317407	2.14842043	-0.560
PURBAN	0.04742877	0.03617276	1.311
PTEXNATV	0.58276254	0.14602230	3.991
PFFFISH	0.39924427	0.93388199	0.428
HHLDINC	-.0000024413	.00000378035	-0.646
MJ1	-0.04210067	0.08343432	-0.505
MJ3	-0.12673404	0.05401686	-2.346
MJ4	-0.15692987	0.06429929	-2.441
MJ5	-0.11390689	0.04643952	-2.453
MJ6	-0.06697295	0.04542878	-1.474
MJ7	-0.10752456	0.04999241	-2.151
MJ8	-0.21494500	0.05137572	-4.184

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.18397633	0.22424085	0.820
MMSHEEP	0.19706534	0.16868340	1.168
MON	0.000146931	0.000087682	1.676
NSWTRIP	0.002501075	0.000638205	3.919
SITETRIP	0.000654810	0.000579796	1.129
PRETIRED	-0.10899880	0.52896178	-0.206
PSPANISH	0.18634607	0.21297531	0.875
PSPNOENG	-0.98841053	0.69064803	-1.431
PVIETNAM	-3.18386372	3.02844868	-1.051
PURBAN	0.02463802	0.05097815	0.483
PTEXNATV	0.03107763	0.20624852	0.151
PFFFISH	2.90768177	1.32049588	2.202
HHLDINC	-.0000038586	.00000532886	-0.724
MJ1	-0.11879970	0.11723539	-1.013
MJ3	-0.08906114	0.07379417	-1.207
MJ4	-0.18881993	0.09180317	-2.057
MJ5	-0.11501370	0.06391136	-1.800
MJ6	-0.16932811	0.06321095	-2.679
MJ7	-0.21894058	0.06971473	-3.141
MJ8	-0.22701709	0.08198620	-2.769

Table A.3, continued

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	0.21204966	0.33183132	0.639
MMFLOUND	-0.49321815	0.21939866	-2.248
MON	-0.000066724	0.000129246	-0.516
NSWTRIP	0.007551138	0.000943757	8.001
SITETRIP	-0.000819620	0.000857429	-0.956
PRETIRED	1.36027395	0.78225188	1.739
PSPANISH	-0.71324691	0.31584173	-2.258
PSPNOENG	0.81296362	1.02514679	0.793
PVIETNAM	0.52069004	4.47714546	0.116
PURBAN	0.16554232	0.07538672	2.196
PTEXNATV	0.93747057	0.30394040	3.084
PFFFISH	-0.37430053	1.94690673	-0.192
HHLDINC	-.0000050267	.00000787969	-0.638
MJ1	-0.35044016	0.17397636	-2.014
MJ3	-0.43350722	0.10925459	-3.968
MJ4	-0.80589558	0.12901976	-6.246
MJ5	-0.65223380	0.10370180	-6.290
MJ6	-0.63117761	0.09957913	-6.338
MJ7	-0.55085946	0.10597766	-5.198
MJ8	-0.42631471	0.10855894	-3.927

Table A.4a - Average "Annual" Actual Catch Rates by Sample Respondents (for May-Nov 1987); by Major Bay System

MAJOR	AAREDS	AATROUT	AACROAK	AASAND	AABLACK	AASHEEP	AAFLOUND
1	0.35000	1.44286	1.63571	0.75714	0.214286	0.064286	0.785714
2	0.21942	1.68155	1.92039	1.93689	0.219417	0.172816	0.982524
3	0.70226	2.34292	0.46612	0.19713	0.117043	0.119097	0.603696
4	0.57912	3.36027	0.99663	0.36364	0.090909	0.060606	0.202020
5	0.42059	1.29244	0.75575	1.05586	0.062432	0.118291	0.205915
6	0.45898	1.45691	2.21288	0.63344	0.115265	0.055036	0.236760
7	0.62898	3.56847	1.31051	0.15446	0.057325	0.007962	0.340764
8	1.16386	2.48221	0.33708	0.23034	0.086142	0.014045	0.331461

Table A.4b - OLS Regressions of Actual Individual Catch Rates on Average Rates for Sample Anglers (for each bay and month, MAxxxxxx, and for each bay, AAxxxxxx).

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.12266561	0.29823802	-0.411
MAREDS	0.95085659	0.08092220	11.750
AAREDS	-0.05043007	0.12278424	-0.411
MON	-0.000092812	0.000115702	-0.802
NSWTRIP	0.000923382	0.000857973	1.076
SITETRIP	0.005093002	0.000781527	6.517
PRETIRED	0.45725770	0.70551913	0.648
PSPANISH	0.72133204	0.26179804	2.755
PSPNOENG	-1.22854525	0.82771249	-1.484
PVIETNAM	-4.92451856	4.04183705	-1.218
PURBAN	-0.18016933	0.06794174	-2.652
PTEXNATV	-0.34731022	0.26481849	-1.312
PFFFISH	2.72013126	1.76799000	1.539
HHLDINC	0.000013987	.00000716232	1.953

Table A.4b, continued

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-1.36523478	0.94998077	-1.437
MATROUT	0.98197610	0.10033556	9.787
AATROUT	0.006042790	0.14070736	0.043
MON	0.000286035	0.000370669	0.772
NSWTRIP	0.001863515	0.002757012	0.676
SITETRIP	0.008918273	0.002511557	3.551
PRETIRED	-1.43720691	2.26629296	-0.634
PSPANISH	1.43940886	0.84354198	1.706
PSPNOENG	-3.82852658	2.58495718	-1.481
PVIETNAM	-2.07403981	12.94627157	-0.160
PURBAN	-0.07554478	0.21864170	-0.346
PTEXNATV	1.53446304	0.84795042	1.810
PFFFISH	-1.98870119	5.68333396	-0.350
HHLDINC	0.000010671	0.000023018	0.464

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	1.81057461	0.97371072	1.859
MACROAK	0.83774972	0.06864557	12.204
AACROAK	0.11396771	0.13693499	0.832
MON	-0.001215592	0.000383033	-3.174
NSWTRIP	-0.005338101	0.002844955	-1.876
SITETRIP	-0.001572947	0.002590113	-0.607
PRETIRED	-1.90685717	2.34453169	-0.813
PSPANISH	-8.60976875	0.88171963	-9.765
PSPNOENG	18.04502300	2.73232498	6.604
PVIETNAM	31.27438550	13.34679054	2.343
PURBAN	0.82502684	0.22594926	3.651
PTEXNATV	3.72817129	0.87567771	4.257
PFFFISH	-21.13769899	5.86344930	-3.605
HHLDINC	-0.000159098	0.000023783	-6.690

Table A.4b, continued

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	1.04106408	1.26437786	0.823
MASAND	0.98233478	0.07436923	13.209
AASAND	0.11303100	0.18715312	0.604
MON	0.003017771	0.000497673	6.064
NSWTRIP	-0.001733434	0.003701859	-0.468
SITETRIP	0.000968215	0.003369551	0.287
PRETIRED	-5.89965190	3.04239513	-1.939
PSPANISH	-4.58440729	1.14376694	-4.008
PSPNOENG	7.47884232	3.46885734	2.156
PVIETNAM	-46.01016400	17.40831290	-2.643
PURBAN	0.91626869	0.29301929	3.127
PTEXNATV	1.94350416	1.13489728	1.712
PFFFISH	18.23397447	7.61793262	2.394
HHLDINC	-0.000110765	0.000030901	-3.585

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.29092946	0.15268688	-1.905
MABLACK	0.96665317	0.09114036	10.606
AABLACK	-0.09573732	0.25278827	-0.379
MON	-0.000071042	0.000060670	-1.171
NSWTRIP	-0.000674880	0.000447214	-1.509
SITETRIP	0.000671392	0.000407375	1.648
PRETIRED	-0.26273281	0.36938636	-0.711
PSPANISH	-0.61890961	0.14299078	-4.328
PSPNOENG	2.06309845	0.43075110	4.790
PVIETNAM	-0.74833926	2.10625389	-0.355
PURBAN	0.04133539	0.03551921	1.164
PTEXNATV	0.53988053	0.13864906	3.894
PFFFISH	0.35225404	0.92028645	0.383
HHLDINC	-5.35967E-07	.00000374053	-0.143

Table A.4b, continued

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.09047019	0.20353089	-0.445
MASHEEP	0.99441736	0.03670434	27.093
AASHEEP	0.04962667	0.31134446	0.159
MON	0.000051587	0.000080557	0.640
NSWTRIP	0.002201864	0.000597400	3.686
SITETRIP	0.000382545	0.000544200	0.703
PRETIRED	0.05006948	0.49119093	0.102
PSPANISH	0.01381854	0.18550590	0.074
PSPNOENG	-0.32208556	0.55982006	-0.575
PVIETNAM	-3.32365172	2.82850803	-1.175
PURBAN	0.04434566	0.04734667	0.937
PTEXNATV	0.04907053	0.18406197	0.267
PFFFISH	2.55337512	1.22902375	2.078
HHLDINC	-.0000014707	.00000499508	-0.294

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.61623401	0.31048537	-1.985
MAFLOUND	0.97594742	0.05182762	18.831
AAFLOUND	-0.02153132	0.10986631	-0.196
MON	-0.000030626	0.000124319	-0.246
NSWTRIP	0.006652809	0.000914079	7.278
SITETRIP	-0.001277307	0.000831043	-1.537
PRETIRED	1.44956602	0.75447296	1.921
PSPANISH	-0.43520381	0.29352799	-1.483
PSPNOENG	0.72106186	0.88677081	0.813
PVIETNAM	-1.86240792	4.30327459	-0.433
PURBAN	0.09270761	0.07250692	1.279
PTEXNATV	0.70903598	0.28266255	2.508
PFFFISH	-0.33088056	1.87895111	-0.176
HHLDINC	-4.07689E-07	.00000763403	-0.053

Table A.4c - OLS Regressions of Actual Individual Catch Rates on "Annual" Average Catch Rates (by bay system, AAxxxxxx)

DEP VARIABLE: REDS

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.17221294	0.30189259	-0.570
AAREDS	0.88499989	0.09463395	9.352
MON	-0.000142307	0.000117054	-1.216
NSWTRIP	0.001071111	0.000868480	1.233
SITETRIP	0.005384716	0.000790784	6.809
PRETIRED	0.33591552	0.71415935	0.470
PSPANISH	0.82939290	0.26486900	3.131
PSPNOENG	-1.50245838	0.83760654	-1.794
PVIETNAM	-6.08247392	4.09055782	-1.487
PURBAN	-0.17038106	0.06877599	-2.477
PTEXNATV	-0.32388801	0.26808275	-1.208
PFFFISH	4.01044819	1.78637790	2.245
HHLDINC	0.000014969	.00000725031	2.065

DEP VARIABLE: TROUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-1.46919676	0.95805247	-1.534
AATROUT	0.97625433	0.10071020	9.694
MON	0.000416560	0.000373599	1.115
NSWTRIP	0.001431302	0.002780255	0.515
SITETRIP	0.009029381	0.002533030	3.565
PRETIRED	-1.53660877	2.28566892	-0.672
PSPANISH	2.05603824	0.84838605	2.423
PSPNOENG	-5.21985591	2.60313817	-2.005
PVIETNAM	-4.62037204	13.05445151	-0.354
PURBAN	-0.07380018	0.22051315	-0.335
PTEXNATV	1.39479051	0.85508754	1.631
PFFFISH	1.56510528	5.72027055	0.274
HHLDINC	0.000015985	0.000023209	0.689

Table A.4c, continued

DEP VARIABLE: CROAK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	2.28572714	0.98589955	2.318
AACROAK	0.91638532	0.12171787	7.529
MON	-0.001416135	0.000387781	-3.652
NSWTRIP	-0.006336075	0.002881682	-2.199
SITETRIP	-0.001620966	0.002624632	-0.618
PRETIRED	-2.73498544	2.37478506	-1.152
PSPANISH	-10.42514263	0.88066463	-11.838
PSPNOENG	22.06274250	2.74857122	8.027
PVIETNAM	35.64921090	13.51980165	2.637
PURBAN	0.87878673	0.22891726	3.839
PTEXNATV	4.15492950	0.88664122	4.686
PFFFISH	-26.48857430	5.92496424	-4.471
HHLDINC	-0.000177231	0.000024053	-7.368

DEP VARIABLE: SAND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	1.41489731	1.28379481	1.102
AASAND	1.08298286	0.17483291	6.194
MON	0.003137767	0.000505358	6.209
NSWTRIP	0.000235592	0.003756601	0.063
SITETRIP	0.002220311	0.003420799	0.649
PRETIRED	-6.59692145	3.08942598	-2.135
PSPANISH	-4.84730866	1.16144683	-4.174
PSPNOENG	7.61299788	3.52299589	2.161
PVIETNAM	-43.06236011	17.67862787	-2.436
PURBAN	0.98954192	0.29754040	3.326
PTEXNATV	1.73664712	1.15250486	1.507
PFFFISH	20.49016673	7.73491401	2.649
HHLDINC	-0.000123535	0.000031368	-3.938

Table A.4c, continued

DEP VARIABLE: BLACK

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.26300398	0.15420014	-1.706
AABLACK	0.84957965	0.23893440	3.556
MON	-0.000073271	0.000061280	-1.196
NSWTRIP	-0.000649917	0.000451707	-1.439
SITETRIP	0.000826483	0.000411208	2.010
PRETIRED	-0.40638490	0.37285190	-1.090
PSPANISH	-0.70453147	0.14419906	-4.886
PSPNOENG	2.21811495	0.43483440	5.101
PVIETNAM	-1.10922521	2.12716746	-0.521
PURBAN	0.04450246	0.03587531	1.240
PTEXNATV	0.59054447	0.13996088	4.219
PFFFISH	0.35238792	0.92954552	0.379
HHLDINC	-.0000025102	.00000377348	-0.665

DEP VARIABLE: SHEEP

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.03535211	0.21662870	-0.163
AASHEEP	1.14481671	0.32859181	3.484
MON	0.000147038	0.000085663	1.716
NSWTRIP	0.002511729	0.000635759	3.951
SITETRIP	0.000648276	0.000579156	1.119
PRETIRED	-0.16218767	0.52276013	-0.310
PSPANISH	0.14164609	0.19738974	0.718
PSPNOENG	-0.72252764	0.59566819	-1.213
PVIETNAM	-3.27210423	3.01068062	-1.087
PURBAN	0.03013284	0.05039299	0.598
PTEXNATV	0.01242447	0.19591140	0.063
PFFFISH	2.98360822	1.30807122	2.281
HHLDINC	-.0000038444	.00000531597	-0.723

Table A.4c, continued

DEP VARIABLE: FLOUND

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	-0.59237667	0.32028494	-1.850
AAFLOUND	0.92591610	0.10075174	9.190
MON	-0.000037291	0.000128243	-0.291
NSWTRIP	0.007522444	0.000941733	7.988
SITETRIP	-0.000864638	0.000856981	-1.009
PRETIRED	1.39301161	0.77828601	1.790
PSPANISH	-0.65905648	0.30254645	-2.178
PSPNOENG	1.15633766	0.91445592	1.265
PVIETNAM	-0.40499133	4.43841383	-0.091
PURBAN	0.16577954	0.07468882	2.220
PTEXNATV	0.77931103	0.29156099	2.673
PFFFISH	-0.12527303	1.93823814	-0.065
HHLDINC	-.0000051086	.00000787083	-0.649

Table A.5 - Pretrip Motivation Questions: OLS Regressions

DEP VARIABLE: NOPEOPLE

F-TEST	0.943
OBS	603

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	7.59185247	0.44738621	16.969
TARGR	0.52836370	0.24653310	2.143
TARGT	-0.34403082	0.24382515	-1.411
TARGF	0.47487337	0.47290029	1.004
MJ1	0.64433020	0.41974765	1.535
MJ3	0.84117457	0.46032060	1.827
MJ4	0.23616653	0.44200330	0.534
MJ5	0.34060028	0.46624780	0.731
MJ6	0.27210277	0.50602718	0.538
MJ7	0.27241992	0.54607083	0.499
MJ8	0.46534192	0.41754746	1.114
MN5	-0.04077979	0.38895224	-0.105
MN6	-0.04905820	0.34417911	-0.143
MN8	-0.37063712	0.35045962	-1.058
MN9	0.32841948	0.39216770	0.837
MN10	-0.19742662	0.36166775	-0.546
MN11	-0.09581740	0.44172970	-0.217
WKND	-0.01828012	0.21044572	-0.087

DEP VARIABLE: NOPOLLUT

F-TEST	0.791
OBS	429

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	9.28862007	0.32744825	28.367
TARGR	-0.06010503	0.19483745	-0.308
TARGT	0.02721384	0.18658810	0.146
TARGF	-0.18077773	0.37549661	-0.481
MJ1	0.13636153	0.30518053	0.447
MJ3	0.06243266	0.36528564	0.171
MJ4	-0.18281956	0.27396226	-0.667
MJ5	-0.40245959	0.35735465	-1.126
MJ6	-0.14210375	0.33100665	-0.429
MJ7	0.02401744	0.32870964	0.073
MJ8	0.08025961	0.27896454	0.288
MN5	-0.007657418	0.31921439	-0.024
MN6	0.08823009	0.32933579	0.268
MN8	0.19207957	0.25276985	0.760
MN9	0.25429200	0.27247807	0.933
MN10	-0.39582402	0.27040307	-1.464
MN11	-0.28337536	0.32430722	-0.874
WKND	0.10035740	0.19787569	0.507

DEP VARIABLE: DOWHTWNT

F-TEST 1.385
OBS 503

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	7.70993748	0.44125530	17.473
TARGR	-0.19641401	0.21523229	-0.913
TARGT	0.10541805	0.21296736	0.495
TARGF	0.26082970	0.39672252	0.657
MJ1	0.80886667	0.48840354	1.656
MJ3	1.33626023	0.43315279	3.085
MJ4	0.77824468	0.43810012	1.776
MJ5	0.80050893	0.42618053	1.878
MJ6	0.48155068	0.40874203	1.178
MJ7	1.08142499	0.43207201	2.503
MJ8	0.89569917	0.44663572	2.005
MN5	0.50210737	0.40968952	1.226
MN6	0.09873351	0.31592841	0.313
MN8	0.60081590	0.37690952	1.594
MN9	-0.13628211	0.31189957	-0.437
MN10	0.002551616	0.35379013	0.007
MN11	0.19458545	0.39803834	0.489
WKND	0.14459588	0.25298011	0.572

DEP VARIABLE: KEEPFISH

F-TEST 2.619
OBS 536

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	8.09163143	0.39754566	20.354
TARGR	-0.63493893	0.28813687	-2.204
TARGT	-0.03000512	0.28608262	-0.105
TARGF	1.16005118	0.51360011	2.259
MJ1	-0.67785857	0.48409302	-1.400
MJ3	-0.89785739	0.42731459	-2.101
MJ4	-0.21607825	0.51354355	-0.421
MJ5	-1.01361087	0.52192311	-1.942
MJ6	-1.04931986	0.49730779	-2.110
MJ7	-0.41688883	0.45091149	-0.925
MJ8	-0.25730722	0.45696247	-0.563
MN5	-0.14119910	0.54846485	-0.257
MN6	0.22085293	0.39028515	0.566
MN8	-0.63595454	0.36390967	-1.748
MN9	1.45515992	0.48851570	2.979
MN10	0.18826575	0.36217584	0.520
MN11	-0.67293081	0.44317159	-1.518
WKND	0.21160550	0.26132905	0.810

DEP VARIABLE: QUIETIME

F-TEST 1.579
OBS 482

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	8.33047553	0.58638878	14.206
TARGR	-0.14268653	0.29999957	-0.476
TARGT	-0.18754912	0.30534004	-0.614
TARGF	0.03336624	0.48896232	0.068
MJ1	-0.73609622	0.69983581	-1.052
MJ3	-0.70451833	0.71501660	-0.985
MJ4	-0.56445054	0.70372958	-0.802
MJ5	-1.14804492	0.69315901	-1.656
MJ6	-1.34006483	0.68904331	-1.945
MJ7	-0.29360849	0.69167542	-0.424
MJ8	0.04573877	0.74465338	0.061
MN5	-0.81118400	0.47981448	-1.691
MN6	-0.09321641	0.41382943	-0.225
MN8	0.08157845	0.44580404	0.183
MN9	-0.10180406	0.53428439	-0.191
MN10	0.22701246	0.40778226	0.557
MN11	-0.45980224	0.53274809	-0.863
WKND	-0.05979884	0.32476937	-0.184

DEP VARIABLE: GOODWTHR

F-TEST 2.759
OBS 381

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	7.09707233	0.43106770	16.464
TARGR	-0.48646878	0.32599391	-1.492
TARGT	0.51229235	0.33760558	1.517
TARGF	-1.49302896	0.49194356	-3.035
MJ1	0.40571747	0.49441812	0.821
MJ3	1.09149043	0.56904719	1.918
MJ4	0.72597107	0.44476911	1.632
MJ5	0.48019072	0.58953742	0.815
MJ6	1.23645655	0.46327764	2.669
MJ7	-0.26498057	0.44679878	-0.593
MJ8	0.22708658	0.46512018	0.488
MN5	-0.31701387	0.38871104	-0.816
MN6	1.28035717	0.60295514	2.123
MN8	0.14411618	0.46022680	0.313
MN9	1.14428728	0.46974240	2.436
MN10	0.49489729	0.43572265	1.136
MN11	0.57428481	0.45843956	1.253
WKND	0.34439790	0.25591639	1.346

DEP VARIABLE: FRNDFMLY

F-TEST 1.233
OBS 406

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	8.54110823	0.46254806	18.465
TARGR	-0.59800573	0.25565774	-2.339
TARGT	0.15487751	0.25328885	0.611
TARGF	0.46287229	0.40689201	1.138
MJ1	0.20963175	0.44760664	0.468
MJ3	0.66950705	0.46462665	1.441
MJ4	0.25996020	0.42541605	0.611
MJ5	0.46650183	0.43289498	1.078
MJ6	0.60614119	0.55775904	1.087
MJ7	-0.09825039	0.43264822	-0.227
MJ8	0.17366924	0.40604008	0.428
MN5	-1.35708719	0.70293279	-1.931
MN6	0.35442366	0.34017854	1.042
MN8	0.09749444	0.32599378	0.299
MN9	0.15200115	0.39173057	0.388
MN10	0.45811705	0.33971443	1.349
MN11	0.19319351	0.47315411	0.408
WKND	0.13095893	0.23814544	0.550

DEP VARIABLE: ADVNEXCT

F-TEST 1.267
OBS 443

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	7.25608143	0.61347890	11.828
TARGR	0.23528665	0.31342257	0.751
TARGT	-0.26195517	0.30524996	-0.858
TARGF	-0.14838342	0.47233401	-0.314
MJ1	0.03723037	0.54138594	0.069
MJ3	-0.92314231	0.71890424	-1.284
MJ4	-0.04891245	0.51960706	-0.094
MJ5	1.01363017	0.56859825	1.783
MJ6	-0.83621541	0.60606846	-1.380
MJ7	0.03118484	0.49129926	0.063
MJ8	0.49056525	0.53133745	0.923
MN5	-0.01289834	0.53358967	-0.024
MN6	0.04472742	0.49114189	0.091
MN8	-0.34816497	0.46015875	-0.757
MN9	-0.55696234	0.54623163	-1.020
MN10	-0.20256002	0.52433722	-0.386
MN11	0.49999921	0.52655699	0.950
WKND	0.44184453	0.26438608	1.671

Table A.5, continued

DEP VARIABLE: PRERELX
F-TEST 1.585
OBS 3722

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	8.78987067	0.13274228	66.218
TARGR	-0.08702046	0.08311952	-1.047
TARGT	-0.02271869	0.08253455	-0.275
TARGF	-0.05306643	0.14142803	-0.375
MJ1	-0.009755689	0.13606929	-0.072
MJ3	-0.25145705	0.14111326	-1.782
MJ4	-0.36764056	0.13622517	-2.699
MJ5	0.03227412	0.14489392	0.223
MJ6	0.008712145	0.14303434	0.061
MJ7	0.05884559	0.13821775	0.426
MJ8	-0.003183858	0.13112852	-0.024
MN5	0.01144559	0.12708450	0.090
MN6	-0.02560113	0.11183769	-0.229
MN8	0.13506010	0.10587769	1.276
MN9	0.01645299	0.12161881	0.135
MN10	0.12827553	0.10739298	1.194
MN11	0.08320163	0.13371926	0.622
WKND	-0.01423466	0.06462206	-0.220

DEP VARIABLE: PRECAT
F-TEST 2.063
OBS 3722

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	6.56236349	0.17428059	37.654
TARGR	0.09004818	0.10912966	0.825
TARGT	0.12237258	0.10836163	1.129
TARGF	0.52153433	0.18568432	2.809
MJ1	0.15331075	0.17864870	0.858
MJ3	-0.17609374	0.18527106	-0.950
MJ4	0.17431650	0.17885337	0.975
MJ5	0.15514299	0.19023478	0.816
MJ6	0.54007251	0.18779330	2.876
MJ7	0.15005384	0.18146947	0.827
MJ8	0.30449474	0.17216185	1.769
MN5	-0.10320669	0.16685235	-0.619
MN6	-0.22755882	0.14683444	-1.550
MN8	0.04694627	0.13900941	0.338
MN9	-0.14802188	0.15967631	-0.927
MN10	-0.10164869	0.14099887	-0.721
MN11	0.05654611	0.17556329	0.322
WKND	0.11237509	0.08484389	1.324

Table A.6 - For sample interviewed both before and after fishing trip; demographic, geographic, and seasonal variables and their effects on extent to which "unpolluted natural surroundings are a motivation for going fishing.

DEP VARIABLE: NOPOLLUT
F-TEST 1.569
OBS 85

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	19.31015380	26.92078701	0.717
HHLDINC	-0.000493022	0.000514831	-0.958
PRETIRED	-42.07217646	41.08032759	-1.024
PTEXNATV	-1.35518067	28.42559659	-0.048
PSPNOENG	6.58063295	39.05040280	0.169
PVIETNAM	-109.12039	406.35400	-0.269
PURBAN	0.18671766	5.03175573	0.037
SITETRIP	0.04004085	0.01082416	3.699
NSWTRIP	0.02132592	0.10230115	0.208
MON	0.005535399	0.01279516	0.433
MJ1	-4.17274793	8.79692225	-0.474
MJ3	-9.84498903	9.81685770	-1.003
MJ4	1.22590283	8.62253424	0.142
MJ5	-2.43125737	8.03930377	-0.302
MJ6	4.13690974	6.64660300	0.622
MJ7	-5.69727465	6.63558981	-0.859
MJ8	-15.01756379	8.27448287	-1.815
MN5	9.44642008	7.95520190	1.187
MN6	4.20898200	7.25488897	0.580
MN8	8.30827846	6.19106440	1.342
MN9	4.44008039	6.23858464	0.712
MN10	0.94326577	5.99986399	0.157
MN11	11.91217331	6.72034145	1.773
WKND	2.07968018	4.75885531	0.437

Table A.7 - Extent to which respondents were able to "Experience Unpolluted Natural Surroundings." (n=858)

DEP VARIABLE: NOPOLLUT

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	8.42190686	1.00903630	8.346
HHLDINC	-0.000011214	0.000022673	-0.495
PRETIRED	1.58102890	1.96850152	0.803
PTEXNATV	-0.61188444	0.85289639	-0.717
PSPNOENG	-1.28938826	1.51495547	-0.851
PVIETNAM	19.42599903	11.87295215	1.636
PURBAN	0.08369006	0.19819351	0.422
MJ1	-0.86422020	0.36986443	-2.337
MJ3	0.32246599	0.38965319	0.828
MJ4	0.64005519	0.25369335	2.523
MJ5	1.01771109	0.35532066	2.864
MJ6	0.10662209	0.31278854	0.341
MJ7	0.46076012	0.29608459	1.556
MJ8	0.88094389	0.32441647	2.715
MN5	0.22148059	0.35923225	0.617
MN6	-0.69695574	0.29829741	-2.336
MN8	-0.02393900	0.22370082	-0.107
MN9	-0.18379131	0.27529979	-0.668
MN10	-0.02430656	0.26243870	-0.093
MN11	0.45402552	0.35517060	1.278
WKND	-0.16900558	0.19266161	-0.877

Table A.8 - OLS Regression of "Ability to Enjoy Unpolluted Natural Surroundings" on Measured Water Quality Variables

DEP VARIABLE: NOPOLLUT
F-TEST 4.192
OBS 695

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	7.65156764	1.88693837	4.055
MTURB	0.000064889	0.01043748	0.006
MSAL	0.01185356	0.01791982	0.661
MDO	-0.22131054	0.13894215	-1.593
TRANSP	0.02299990	0.01366888	1.683
DISO	0.26350825	0.10926245	2.412
RESU	0.009595514	0.007438127	1.290
NH4	3.99552741	3.69437706	1.082
NITR	-1.40780844	1.18960581	-1.183
PHOS	0.14529883	1.41691553	0.103
CHLORA	0.009712722	0.02752364	0.353
LOSSIGN	-0.01482662	0.02449996	-0.605
CHROMB	-0.003165001	0.01881366	-0.168
LEADB	-0.04634034	0.01468208	-3.156

Combining Contingent Valuation and Travel Cost Data for the Valuation of Non-market Goods

by

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ABSTRACT

Contingent valuation (CVM) survey methods are now being used quite widely to assess the economic value of non-market resources. However, the implications of these surveys have sometimes met with a degree of skepticism. Here, hypothetical CVM data are combined with travel cost data on actual market behavior (exhibited by the same consumers) to internally validate the implied CVM resource values. We estimate *jointly* both the parameters of the underlying utility function and its corresponding Marshallian demand function. Equivalence of the utility functions implied by the two types of data can be tested statistically. Respondent and/or resource heterogeneity can be accommodated readily. A sample of Texas recreational anglers illustrates the technique.

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Combining Contingent Valuation and Travel Cost Data for the Valuation of Non-market Goods

Economists have long been skeptical about the reliability of consumers' stated intentions, as opposed to their actions in the marketplace. The notion that "actions speak louder than words" underlies much of the criticism of survey methods as a basis for demand forecasting. In some situations, however, market demand activity cannot be directly observed. Surveys and other indirect methods are the only glimpses of demand relationships we have. In these circumstances, it is valuable to explore methods by which researchers can combine survey responses and other available information to formulate the best possible characterization of demand when actual market observations "in the field" are unattainable.

For a wide variety of environmental resources and public goods, the absence of markets makes it extremely difficult to establish a monetary value for access to these commodities. Whenever a proposed change in policy affects the quality or availability of these non-market goods, either explicit or implicit cost-benefit analysis must be undertaken at some point in the decision process. For some time, economists have experimented with alternative methods of eliciting or inferring the social value of these non-market goods.

The familiar travel cost method (TCM) popularized by Clawson and Knetsch (1966) has been widely applied in an extensive array of empirical studies. This method interprets variation in travel costs to a particular site where a non-market good is consumed as equivalent to the effect of a per-trip entrance fee to the same location. Subsequent research has provided numerous extensions and qualifications to the original travel cost method.

A somewhat newer, competing approach to valuation involves directly *asking* individual consumers of the non-market good about its value. A hypothetical market scenario is described to each respondent and their professed behavior under that scenario is recorded. To avoid the connotations of hypotheticality, this has been dubbed the "contingent valuation method" (CVM). Despite the potential for a variety of biases in *poorly* designed CVM surveys (described in detail in surveys by Cummings, Brookshire, and Schulze, 1986, or Mitchell and Carson, 1988) there are still many situations where more realistic methods (such as market simulations or actual market experiments) are prohibitively difficult, and where some of the other potential methods, such as hedonic housing price models or hedonic wage models, are inappropriate. In these cases, it has generally been conceded that CVM surveys, when interpreted cautiously, can provide useful information about the characteristics of demand for a good not presently priced and traded in a real market. The CVM technique has also been widely applied.

Despite the semantic care in naming the CVM, the data it produces have still been criticized as "hypothetical answers to hypothetical questions." Consequently, "external validation" of empirical applications of CVM has received considerable attention in the literature. Some of these compare CVM and TCM; others compare CVM with other valuation methods.

For example, Bishop and Heberlein (1979) and Bishop, Heberlein and Kealy (1983) pit CVM estimates against TCM and the results of simulated market experiments. They conclude that CVM mechanisms produce "meaningful--albeit inaccurate--economic information." CVM and TCM are also compared by Sellar, Stoll and Chavas (1985), who conclude that the two methods do provide comparable estimates of consumer surplus, and that whenever possible, *both* methods should be used in future studies as a validity check on the results.

Schulze, d'Arge, and Brookshire (1981) determine that "all evidence obtained to date suggests that the most readily applicable methodologies for evaluating environmental quality--hedonic studies of property values or wages, travel cost, and [CVM] survey techniques--all yield values well within one order of magnitude in accuracy. Such information...is preferable to complete ignorance." Brookshire, Thayer, Schulze, and D'Arge (1982) compare CVM estimates with a hedonic property value study. Regarding CVM, they conclude that "[a]lthough better accuracy would be highly desirable, in many cases where no other technique is available for valuing public goods, this level of accuracy is certainly preferable to no information for the decision-making process."

Brookshire and Coursey (1987), on the other hand, compare hypothetical non-market CVM responses with market-like elicitation processes (Vernon Smith's public good auction experiments in the laboratory and in the field). Compared to CVM, the marketplace appears to be "a strong disciplinarian" in terms of limiting the tendency for certain types of inconsistencies in valuation responses.

In *all* these previous studies aimed at external validation of the values for non-market goods produced by CVM, the alternative measures of value were obtained either by *indirect* methods (the travel cost approach or hedonic wage or rent functions) or by small *simulated market* experiments. The point estimates of value produced by each technique are generated by *completely separate* models which are sometimes even applied to completely separate samples of data. This makes rigorous statistical comparisons of the different value estimates impossible.

The new joint models introduced in this paper also appeal to the marketplace to "discipline" contingent valuation estimates, while at the same time, the CVM information provides insights into the probable behavior of respondents under conditions which are far removed from the current market scenario. The innovation is that the validation occurs in the context of a *single* joint model applied to a *single* sample of respondents. Since we collect both CVM and TCM information from each respondent, the joint model can be estimated both with and without restrictions, allowing the consistency of the CVM information and TCM information to be tested in a statistically rigorous fashion. [1]

The new joint models described in this paper will be appropriate for a whole spectrum of non-market resource valuation tasks wherever CVM or TCM have been used separately before. For concreteness in this paper, however, we concentrate on an empirical application concerning the non-market demand for access to a recreational fishery. The U.S. Fish and Wildlife Service estimates that economic activity associated with recreational fishing generated $17.3 billion in 1980 and $28.1 billion in 1985, and there are at least 60 million Americans who fish regularly (reported in *Forbes*, May 16, 1988, pp. 114-120). Recreational fisheries valuation has therefore attracted considerable policy-making interest over the past few years.[2] There are many

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[1] The conceptual framework for the econometric implementation is similar to models of discrete/continuous choice employed by Hanemann (1984) and by Dubin and McFadden (1984), but in the present case, the discrete choices are purely hypothetical.

[2] Among current related policy issues, for example, is the quantification of the social costs of acid precipitation (which kills fish and decreases the consumer surplus associated with recreational fishing). These costs are

theoretical examinations and empirical attempts at valuation extant.[3] One factor accounting for the proliferation of empirical analyses is the availability of vast quantities of survey data collected regularly for fisheries management purposes.

Section I of this paper develops the logic whereby a discrete-choice direct utility function can be modified into an *indirect utility difference* function (defined over fishing days and a composite of all other goods). Then this function and the corresponding Marshallian demand function for fishing access days can be modeled jointly. Section II describes a sample of CVM and TCM data used to demonstrate this technique. Section III describes alternative stochastic specifications. Section IV provides a general outline of the types of results these models generate. Section V goes into detail regarding the specific empirical results for a basic model and some useful extensions.

I. THE JOINTNESS OF CONTINGENT VALUATION AND TRAVEL COST RESPONSES

A rigorous utility-theoretic tradition in the analysis of "discrete-choice" CVM data was initiated by Hanemann (1984b), who elaborated substantially upon earlier estimation procedures used by Bishop and Heberlein (1979). The discrete choice (or "referendum") format for CVM survey questions is often argued to be less subject to some of the usual CVM biases than are other formats. Rather than asking the respondent to place his own specific

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generally considered to be one of the most substantial components of acid rain damages.

[3] To cite only a few of the more recent recreational fisheries studies: McConnell, 1979, Anderson, 1980, Samples and Bishop, undated, McConnell and Strand, 1981, Vaughn and Russell, 1982, Morey and Rowe, 1985, Rowe, Morey, Ross, and Shaw, 1985, Samples and Bishop, 1985, Donnelly, Loomis, Sorg, and Nelson, 1985, Morey and Shaw, 1986, Cameron and James, 1986, 1987, Thomson and Huppert, 1987, Cameron 1988a, Cameron and Huppert, 1988, 1989, Agnello, 1988, and McConnell and Norton, undated.

dollar value on access to the resource, a single threshold value is offered and the respondent is asked to indicate whether his personal valuation is greater or less than this amount.

For the survey available for this study, the referendum CVM question seems most easily interpreted as asking whether the respondent would entirely cease to use the resource if the annual access fee ("tax") were equal to T.[4] Let Y be the respondent's income, let q be the current number of trips per year to the recreation site, and let M be the respondent's typical travel costs (i.e. market cost of access and incidental expenses on complementary market goods associated with one trip).[5]

With cross-sectional data, it is convenient to begin by assuming a common utility function wherein access to the recreational resource can be traded off against a composite of all other goods and services, z, for which the price can be normalized to unity. If market goods (travel, etc.) are consumed *in fixed proportions* with the number of recreation trips, then only the number of trips appears separately in the utility function: $U(z,q) = U(Y-Mq,q)$.

Suppose a respondent to the CVM question indicates that he *would* continue fishing under the hypothetical two-part tariff with fixed tax T and marginal price M. This implies that his maximum attainable utility when paying the tax and enjoying access *exceeds* his utility when forgoing all trips

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[4] A possible alternative interpretation of the question is addressed in Appendix I.

[5] These data do not allow accurate imputation of the opportunity costs of travel time. Rather than invoking a completely arbitrary guess about time costs, we opt to ignore this component while acknowledging that the empirical results will certainly reflect this decision. To the extent that time costs are important, the social values of access implied by the travel cost portion of the model will be underestimated.

and thereby avoiding both the tax and the travel costs associated with each trip:

$$\Delta U(Y,M,T) = \max_q U(Y\text{-}Mq\text{-}T,q) - U(Y,0) > 0, \text{ or} \tag{1}$$

$$\Delta V(Y,M,T) = V(Y\text{-}T,M) - V(Y) > 0,$$

where U signifies the direct utility function and V the corresponding indirect utility. Crucially, as pointed out by McConnell (1988), the optimal quantity demanded in the first term of the direct utility formulation in (1) would be *endogenously* determined and is presently unobserved.

The TCM question, however, concerns the respondent's optimal quantity demanded under existing conditions. If the utility surface implied by the discrete-choice CVM response truly describes the configuration of individuals' preferences, then it should also be consistent with the current *observed* behavior, namely demand for access days in an environment where per-day specific access prices (beyond M) are currently zero.[6] The Marshallian demand function, q(Y,M), corresponding to the same utility function will be given by the maximization of the Lagrangian:

$$\max_q U(Y\text{-}Mq,q) \qquad \text{s. t.} \qquad Y = z + Mq. \tag{2}$$

Theoretically, the utility maximizing decisions of economic agents, whether real or hypothetical, should reflect the *same* underlying structure of preferences. Conditional on the extent to which the functional form chosen

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[6] Except for the hypothetical nature of the discrete choice question in the contingent valuation context, the models used in this paper have much in common with the strategies employed in King (1980) and in Venti and Wise (1984), where consumer choices are modeled explicitly as the result of utility maximization. In contrast, earlier empirical discrete choice/demand models accommodated the choice process in a "reduced form" manner similar to the approaches used in the literature on switching regressions or sample selection.

for U(z,q) is an *adequate* representation of the preferences of individuals in this sample, this supposition will be used to impose parameter constraints across the two parts of the model. Requiring that respondents' professed behavior in a hypothetical context be consistent with their observed behavior in real markets should attenuate the degree of bias due to the hypothetical nature of the CVM question. In turn, the CVM information allows the researcher to "fill in" some information about demand that is not captured by the range of the currently observable demand data and it can temper biases in the travel cost information due to underestimation of the true opportunity costs of access.

One key question to be addressed in this study is whether CVM and TCM data do indeed elicit the same preferences. When parameter constraints are imposed across two models, it is also possible to allow the corresponding parameters to differ, taking on any values the data suggest. This option allows for a rigorous statistical comparison of the different utility configurations implied by the CVM and the TCM data. Contingent on the validity of the assumption of quadratic utility, one can test statistically the hypothesis that the corresponding parameters in the two models are the same. This is implicitly a test of whether professed behavior in the hypothetical market is consistent with observed behavior in a real market. If utility parameter equivalence is rejected, then one might suspect that the contingent valuation technique and/or the travel cost method might be unreliable in this specific application.

Travel cost models seem to enjoy broader acceptance than CVM models, although rudimentary travel cost models like the one employed here can also have serious deficiencies. Fortunately, if the researcher harbors prior opinions regarding the relative or absolute reliability of these two types of information, these priors can be readily incorporated into the estimation process. Consequently, even if parameter equivalence is rejected initially, there will be some recourse.

In addition to these basic issues, this paper describes a number of extensions which demonstrate the flexibility of this model as a prototype for subsequent work in non-market resource valuation.

II. AN ILLUSTRATIVE EXAMPLE

Between May and November of 1987, the Coastal Fisheries Branch of the Texas Department of Parks and Wildlife conducted a major in-person survey of recreational fishermen from the Mexico border to the Louisiana state line. The "socioeconomic" portion of the survey is most pertinent here. The specific CVM question asked of respondents was: "If the total cost of all your saltwater fishing last year was ____ more, would you have quit fishing completely?" At the start of each survey day, interviewers randomly chose a starting value from the list $50, $100, $200, $400, $600, $800, $1000, $1500, $2000, $5000, and $20,000. On each subsequent interview, the next value in the sequence was used. Therefore, offered values can be presumed to have no correlation whatsoever with the characteristics of any respondent. In addition to this question, respondents were asked "How much will you spend on this fishing trip from when you left home until you get home?" The survey also established how many trips the respondent made over the last year to all saltwater sites in Texas.[7] Five digit zip codes were collected, which allows establishment of residency in Texas.

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[7] Unfortunately, the duration of each trip is unknown, so it must be assumed that the majority are one-day trips, which may or may not be entirely plausible. Here, the term "trip" is used synonymously with "fishing day."

Income data were not collected from each respondent, but the five-digit zip codes allow merging of the data with 1980 Census median household incomes for each zip code. Zip codes cover relatively homogeneous "neighborhoods," at least when compared to income data on the county level, for example. Individuals' consumption patterns tend to conform somewhat to those of their neighbors, so median zip code income may be a better proxy for "permanent" disposable income than actual current self-reported income. There is high variance in median incomes across zip codes, so the Census income variable may actually make a substantial and accurate contribution to controlling for income heterogeneity among the survey respondents.[8]

In other work utilizing the entire dataset (Cameron, Clark, and Stoll, 1988) it has been determined that subsets of individuals in the sample exhibit extreme behavior. The full sample has therefore been filtered somewhat for use in this demonstration study. Since the initial models presume identical underlying utility functions for all individuals, those who report more than sixty fishing trips per year are discarded from the sample. It is relatively likely that these individuals are atypical, since 90% of usable sample reports fewer than this number of days. The median number of trips reported is between eleven and twelve. This research is therefore clearly directed at "typical" anglers.

It is also the case in the full usable sample from the survey that some individuals respond that they would keep fishing if the cost had been $20,000 higher when $20,000 exceeds the median household income of their zip code.

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[8] While the use of group averages instead of individual income information undeniably involves errors-in-variables complications in the estimation process, the distortions may in fact be not much greater than they would be with the use of self-reported income data in an unofficial context. It is well known that many individuals have strong incentives to misrepresent their incomes if they do not perceive a legal requirement to state them correctly.

Since the assignment of value thresholds was completely exogenous, the estimating sample includes only those respondents who were posed values up to and including the $2000 offer. Everyone offered values greater than this was excluded, regardless of their answer to the CVM question.

The final criterion for inclusion in the sample for this study was that a respondent should not report spending more than $100 on this fishing trip. Again, a very large proportion of the sample passes this criterion. When market expenditures are reported to be much larger than this, it seems reasonable to suspect that capital items have been included, so that it would be invalid to treat these costs as "typical" for a single fishing trip. Current expenditures over $2000 were reported by several respondents.

Descriptive statistics for the variables used in this paper are contained in Table I.

III. THE STOCHASTIC SPECIFICATION

It may be helpful to think of the model developed in the following sections as a nonlinear analog to a more familiar econometric model. The conceptual framework is similar to a system of two equations with one right-hand side endogenous variable, cross-equation parameter restrictions, and a non-diagonal error covariance matrix. However, one of the dependent variables is continuous and one is discrete, both equations are highly nonlinear in parameters, and the simultaneity in the model involves an endogenous variable which is not observed directly, but must be counterfactually simulated.

In order to have the option of constraining the coefficients of the utility function (and hence the indirect utility function) as well as those of the corresponding Marshallian demand function to be identical, the discrete choice model and the demand equation must be estimated simultaneously. To fix

Table I

Descriptive Statistics for the Variables
(n = 3366)

Acronym	Description	Mean	Std. dev.
Y	median household income for respondent's 5-digit zip code (in $10,000)[a] (1980 Census scaled to reflect 1987 income; factor=1.699)	3.1725	0.6712
M	current trip market expenditures, assumed to be average for all trips (in $10,000)	0.002915	0.002573
T	annual lump sum tax proposed in CVM scenario (in $10,000)	0.05602	0.04579
q	reported total number of salt water fishing trips to sites in Texas over the last year	17.40	16.12
I	indicator variable indicating that respondent would choose to keep fishing, despite tax T	0.8066	0.3950
PVIET	proportion of population in respondent's 5-digit zip code claiming Vietnamese ancestry	0.002497	0.006217

[a] Dollar-denominated quantities are expressed in $10,000 units throughout the study, so that squared income and squared net income do not become too large, resulting in extremely small probit coefficient estimates which thwart the optimization algorithm.

ideas, it is helpful to begin by considering the two components of the joint model completely separately, ignoring any potential error correlation.

A. *A Separate CVM Choice Model*

The decision to work within the framework of direct, rather than indirect, utility functions buys easy characterization of the shapes of consumer indifference curves. Under the hypothetical CVM scenario, the respondent is asked to choose between ceasing to use the resource and paying no lump-sum tax, or continuing to consume a *revised* optimal quantity of access q(Y-T,M) at a new lower net income. Unless one can assume that there is no income effect, q(Y-T,M) will probably be less than the current optimal quantity, q(Y,M). But if, for the initial exposition, it is *temporarily* assumed that the income elasticity of demand for access is zero, one can begin by considering how the CVM component of the joint model should be estimated.

It will be convenient to model the discrete choice elicited by the CVM question using conventional maximum likelihood *probit* (rather than logit) techniques, where the underlying distribution of the implicit dependent variable, the true utility difference, is presumed to be Normal. Since $\Delta U(Y,M,T)$ in equation (1) can at best be only an approximation, assume that for the i^{th} observation, $\Delta U_i = \Delta U_i^* + \epsilon_i$, where ϵ_i is a random error term distributed $N(0, \sigma^2)$. ΔU_i^*, the systematic portion of the utility difference on the right hand side of equation (1) will be represented in what follows as $f(x_i,\beta)$.

In conventional probit models, ΔU_i is unobserved, but if ΔU_i is "large" (i.e. $\Delta U_i > 0$), one observes an indicator variable, I_i (the "yes/no" response), taking on a value of one. Otherwise, this indicator takes the value zero. In constructing the likelihood function for this discrete response variable, the following algebra is required:

$$(3) \qquad Pr(I_i = 1) = Pr (\Delta U_i > 0) = Pr (\epsilon_i > - f(x_i,\beta)).$$

Since ϵ_i has standard error σ, dividing through by σ will create a standard normal random variable, Z, with cumulative density function Φ.

$$(4) \qquad \begin{aligned} Pr(\epsilon_i > - x_i'\beta) &= Pr (Z > - f(x_i,\beta)/\sigma) \\ &= Pr (Z < f(x_i,\beta)/\sigma) \\ &= \Phi (f(x_i,\beta)/\sigma), \end{aligned}$$

by the symmetry of the standard normal distribution.

At best, in cases where $f(x_i,\beta)$ is linear-in-parameters, the vector β can only be identified up to a scale factor, since it only ever appears in ratio to σ. (However, this is quite acceptable, because the solutions to the consumer's utility maximization problem are invariant to monotonic transformations of the utility function.) The probability of observing $I_i = 0$ is just the complement of $Pr(I_i = 1)$, namely $1 - \Phi (f(x_i,\beta)/\sigma)$, so the log-likelihood function for n observations will be:

$$(5) \quad \log L = \Sigma_i \; I_i \log [\Phi (f(x_i,\beta)/\sigma)] + (1 - I_i) \log \{ 1 -[\Phi (f(x_i,\beta)/\sigma)] \}$$

If $f(x_i,\beta)$ was linear in β, and if q(Y-T,M) could be observed or assumed to be equal to q(Y,M), this separate discrete choice model could readily be estimated by any number of maximum likelihood routines in packaged statistical programs (such as SAS or SHAZAM). For compatibility with what follows, however, when q(Y-T,M) is made endogenous, this application requires a general MLE algorithm. (In this paper, the GQOPT nonlinear function optimization package is used). The endogenous demands, q(Y-T,M) will be functions of the same parameters appearing in (5). When the formulas for these demands are substituted into $f(x_i,\beta)$, these functions will usually no longer be linear functions of the β parameters.

B. A Separate Demand Model

The systematic portion of the TCM Marshallian demand function resulting from the optimization problem in (2) will be denoted by $g(x_i,\beta)$. In estimating this model separately, one might assume that $q_i = g(x_i,\beta) + \eta_i$, where η_i $N(0, \upsilon^2)$. This suggests that nonlinear least squares (by maximum likelihood) is an appropriate estimation method.

The log-likelihood function associated with the demand model is therefore:

$$(6) \qquad \log L = -(n/2)\log(2\pi) - n \log \upsilon - (1/2)\ \Sigma_i\{\ [q_i - g(x_i,\beta)]/\upsilon\}^2$$

Again, there exist packaged computational routines to estimate such nonlinear models, but this application requires a general function optimization program to allow for subsequent constrained joint estimation of this model and the utility difference model.

C. Constrained Joint Estimates, Independent Errors

To impose the requirement that the two decisions (one real and one hypothetical) reflect the *identical* underlying utility function, the CVM and TCM models must be estimated simultaneously. With independent errors, it is simple to combine the two specifications by summing the two separate log-likelihood functions and constraining the corresponding β_j coefficients in each component to be the same:

$$(7) \quad \log L = -(n/2)\log(2\pi) - n \log \upsilon - (1/2)\ \Sigma_i\ \{\ [q_i - g(x_i,\beta)]/\upsilon\}^2$$
$$+\ \Sigma_i\ \{\ I_i \log [\Phi\ (f(x_i,\beta)/\sigma)] + (1 - I_i) \log \{\ 1 - [\Phi\ (f(x_i,\beta)/\sigma)]\ \}\ \}.$$

D. Constrained Joint Estimates, Correlated Errors

Realistically, unobservable factors which affect respondents' answers to the CVM discrete choice question are simultaneously likely to affect their actual number of fishing days demanded. To accommodate the influence of unmeasured variables, one can allow for a correlation, ρ, between the ϵ_i error terms in the discrete choice model and the η_i error terms in the demand model.[9] Assume that these errors have a bivariate normal distribution, $BVN(0,\ 0,\ \sigma^2,\ \upsilon^2,\ \rho)$.

In empirical discrete/continuous choice models, it is frequently more convenient *not* to work directly with the joint distribution of the errors. Instead, one can take advantage of the fact that the joint density can be represented equivalently as the product of a conditional density and a marginal density. In order to derive the model with nonzero ρ, one can exploit the fact that for a pair of standardized normal random variables, say W_1 and W_2, the conditional distribution of W_2, given $W_1 = w_1$, is univariate Normal with mean $(\rho\ w_1)$ and variance $(1 - \rho^2)$.

When allowing for nonzero values of ρ, then, the term $\Phi(f(x_i,\beta)/\sigma)$ in the discrete-choice portion of equation (7) will be replaced by:

$$(8) \qquad \Phi\ \{\ [(f(x_i,\beta)/\sigma) + \rho\ Z_i]\ /\ (1 - \rho^2)^{1/2}\ \}$$

where $Z_i = [q_i - g(x_i,\beta)]/\upsilon$, the standardized fitted error in the demand function, evaluated at the current parameter values. Clearly, if $\rho = 0$, this model collapses to the model with independent errors described in the previous section.

IV. AN EXPLICIT FUNCTIONAL FORM AND CLASSES OF RESULTS

The basic model proposed in this paper (and its variants) uses a quadratic *direct* utility specification for $U(z,q)$. Other discrete/continuous

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[9] If the estimated value of the error correlation, ρ, is substantial and statistically significant, one probably ought to generalize the specification, if possible, to accommodate systematic heterogeneity across respondents. Section V will address this issue.

modeling exercises have begun with an *indirect* utility function, since commodity prices (rather than quantities) are more plausibly assumed to be exogenous for the typical consumer. In the present context, however, we desire to maintain the geometric intuition behind direct utility functions and their associated indifference curves.[10] We have selected the quadratic form for the direct utility function because of its simplicity and because a number of other familiar specifications are unsuitable for the derivation of associated Marshallian demand functions (also discussed in Appendix II).

For identical consumers, the simplest quadratic direct utility specification is:

$$U(z,q) = \beta_1 z + \beta_2 q + \beta_3 z^2/2 + \beta_4 zq + \beta_5 q^2/2 \tag{9}$$

Under the current scenario for the respondent, consumption of the Hicksian composite good z is (Y - Mq) and q will be non-zero for anyone being interviewed, so the utility function in (9) is really a function of Y and q.[11]

$$U(Y,q) = \beta_1 (Y-Mq) + \beta_2 q + \beta_3 (Y-Mq)^2/2 + \beta_4 (Y-Mq)q + \beta_5 q^2/2. \tag{9'}$$

The specific form of the utility difference which dictates a respondent's answer to the CVM question will be linear in the same parameters as U:

$$\begin{aligned}\Delta U(Y,M,T) = f(x_i,\beta) = \; & \beta_1 \{[Y-Mq-T] - Y\} + \beta_2 q \\ & + \beta_3 \{[Y-Mq-T]^2 - Y^2\}/2 + \beta_4 [Y-Mq-T]q + \beta_5 (q)^2/2.\end{aligned} \tag{10}$$

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[10] A quadratic indirect utility version of the model is discussed in Appendix II. Unfortunately, the calibrated model does not satisfy the regularity conditions for valid indirect utility functions.

[11] In-person CVM surveys typically sample only current users of the resource. When access price increases (or simply positive access prices) are being contemplated, this does not pose much of a problem. However, when projected scenarios involved improved resource attributes, one must really survey potential users as well as current users to elicit an accurate measure of aggregate demand responsiveness.

The first order conditions for the Lagrangian in equation (2) yield a corresponding Marshallian demand for q of:

$$(11) \qquad q(Y,M) = g(x_1,\beta) = [\ \beta_2 + \beta_4\ Y - \beta_1\ M - \beta_3\ Y\ (M)\ ]\ /\ [\ 2\beta_4\ (M) - \beta_3\ M^2 - \beta_5\ ].$$

Since every additive term in both the numerator and denominator of this expression contains a multiplicative β coefficient, the demand function is of course invariant to the scale of the β vector. Consequently, it is necessary to adopt some normalization of the demand function parameters (for example, $\beta_2 = 1$, an entirely arbitrary and inconsequential choice). Thus the form of the demand function actually estimated will be:

$$(12) \qquad q(Y,M) = [\ 1 + (\beta_4{*})\ Y - (\beta_1{*})(M) - (\beta_3{*})\ Y\ (M)\ ]\ /\ [\ 2(\beta_4{*})(M) - (\beta_3{*})\ (M)^2 - \beta_5{*}\ ].$$

where $\beta_j{*} = \beta_j/\beta_2$. This demand function is highly non-linear in M.

Crucially, when we endogenize the q in equation (10) by substituting the formulas for q(Y-T,M) based on the calibrated demand models in (11) or (12), we are effectively converting the direct utility specification into an indirect utility specification! But if the indirect utility function V(Y-T,M) = U(Y-T,q(Y-T,M)) were to be written out in full, it would be a complex and unappealing formula. Instead, we will describe our results in terms of the implied direct utility function U(z,q).

The central empirical results in this study are the estimates of the β parameters of the assumed underlying quadratic direct utility function. All of the economically interesting empirical measurements in this paper are derived from this calibrated utility function. Throughout, the empirical utility function should exhibit properties which are consistent with economic intuition about plausible shapes for these functions.

First, the derivatives of the underlying direct utility function are:

$$(13) \qquad \partial U/\partial z = \beta_1 + \beta_3 z + \beta_4 q \qquad \partial^2 U/\partial z^2 = \beta_3$$
$$\partial U/\partial q = \beta_2 + \beta_4 z + \beta_5 q \qquad \partial^2 U/\partial q^2 = \beta_5$$
$$\partial^2 U/\partial z \partial q = \beta_4$$

The marginal utilities of the composite good z and of access days q will depend on the local values of z and q. Whether or not each marginal utility is increasing or decreasing will be revealed by the signs of β_3 and β_5.

If both β_3 and β_5 are negative, the fitted utility function will be globally concave, and a globally optimal combination of z and q will be implied. The budget constraint will be binding unless the implied global optimum is attainable inside the budget set. The formulas for the global optimum will be strictly in terms of the estimated coefficients:

$$(14) \qquad q^{\max U} = [-\beta_2 + (\beta_1\ \beta_4/\beta_3)] \ / \ [\beta_5 - (\beta_4{}^2/\beta_3)]$$
$$z^{\max U} = (-\beta_1 - \beta_4 q^*)/\beta_3$$

Admissible fitted quadratic utility functions are not necessarily strictly concave, however. The bundle at which both marginal utilities go to zero may correspond to a saddle point of the complete fitted utility function. But only quasi-convexity in the positive orthant is required. To assess compliance with this regularity condition, one can easily examine the configuration of the fitted utility function's indifference curves.

An indifference curve through any arbitrarily chosen bundle (z',q') can be identified by first determining the level of utility this bundle represents:

(15) $$U' = \beta_1 z' + \beta_2 q' + \beta_3 z'^2/2 + \beta_4 z'q' + \beta_5 q'^2/2.$$

To find all other bundles (z,q) which provide utility U', one merely sets up the quadratic formula for z:

(16) $$(\beta_3/2)z^2 + (\beta_1 + \beta_4 q)z + [\beta_2 q + (\beta_5/2)q^2 - U'] = 0$$

Plots of empirical indifference curves are highly intuitive and relatively novel and will be used throughout the discussion to highlight the differences in estimated preference structures.

Once the corresponding Marshallian demand function has been calibrated by joint estimation of the utility parameters, we are usually curious about the implied price and income derivatives:

(17) $$\partial q/\partial M = [\ -(2\beta_4 M-\beta_3 M^2-\beta_5)(\beta_1+\beta_3 Y) - 2(\beta_2+\beta_4 Y-\beta_1 M-\beta_3 MY)(\beta_4-\beta_3 M)\ ] \ / \ [2\beta_4 M-\beta_3 M^2-\beta_5]^2$$

$$\partial q/\partial Y = [\beta_4-\beta_3 M] \ / \ [2\beta_4 M-\beta_3 M^2-\beta_5]^2 .$$

From the demand curves, policy makers are also sometimes interested in estimates of the reservation price. One simply sets q = 0 in equation (11) and solves the resulting quadratic formula for (M). Given the current level of M, the reservation level of any *additional* potential per-day access charge can readily be determined.

One of the ultimate empirical objectives of this research concerns estimation of the total social value of recreational access to this fishery. One measure of value is the equivalent variation, E, which can be viewed as the fixed tax which would make these anglers just indifferent between paying the tax and continuing to fish, or not paying the tax and forgoing their fishing opportunities. Algebraically, E is given by the equation $\max_q U(Y-Mq-E,q) = U(Y,0)$.

But completely depriving everyone of access to the resource is an extremely drastic proposition. So we also consider the equivalent variation formulas that give the social costs of limiting access to a proportion α of current (fitted) access levels, where $0 < \alpha < 1$. The equivalent variation for such partial restrictions is given by $\max_q U(Y-Mq-E,q) = U(Y-\alpha Mq,\alpha q)$. Letting $D = (2\beta_4 M - \beta_3 M^2 - \beta_5)$, $R = (\beta_2+\beta_4 Y-\beta_1 M-\beta_3 MY)/D$ and $S = (\beta_4-\beta_3 M)/D$, the value of E is the solution of the quadratic formula:

$$
\begin{aligned}
(18)\quad 0 = {} & [\ (\beta_3/2)(MS-1)^2 - \beta_4 S(MS-1) + (\beta_5/2)S^2\ ]\ E^2 \\
& + [\ \beta_1(MS-1) - \beta_2 S + \beta_3(Y-MR)(MS-1) + \beta_4\{R(MS-1) - (Y-MR)S\} - \beta_5 RS\ ]\ E \\
& + [\ -\beta_1(1-\alpha)MR + \beta_2(1-\alpha)R + (\beta_3/2)\{(Y-MR)^2 - (Y-\alpha MR)^2\} \\
& + \beta_4\{(Y-MR)R - (y-\alpha MR)(\alpha R)\} + (\beta_5/2)(1-\alpha^2)R^2\ ].
\end{aligned}
$$

When $\alpha=0$, the formula produces the equivalent variation for a complete loss of access. While it would be desirable to compute Taylor's series approximations to the standard errors of the value of E computed from the estimated β parameters, this would clearly be a daunting task.

An alternative measure of value (the compensating variation, C) asks what amount of money would have to be given to a respondent who has been denied some or all of his access in order to leave him equally well off as before the intervention. Algebraically, this C is given by $\max_q U(Y-Mq,q) = U(Y+C,0)$. For a complete loss of access, C is the root of the quadratic formula:

$$
\begin{aligned}
(19)\quad 0 = {} & -(\beta_3/2)\ C^2 - (\beta_1 + \beta_3 Y)\ C \\
& -\beta_1 Mq + \beta_2 q + (\beta_3/2)[\ (Y-Mq)^2 - Y^2] + \beta_4(Y-Mq)q + (\beta_5/2)q^2.
\end{aligned}
$$

A general formula for partial loss of access could easily be devised, but this paper will focus on the equivalent variations.

V. SPECIFIC EMPIRICAL ESTIMATES

A. The Basic Model

The "basic model" constrains the quadratic direct utility parameters and the corresponding parameters in the Marshallian demand function for fishing days to be identical. The model initially assumes equal reliability of the two types of information (CVM and actual market demand), and allows the post-tax quantity demanded in the discrete choice model to be determined endogenously according to the same demand function. The model also allows for correlated errors in the two decisions. The *first* pair of columns in Table II give these results (the second pair of columns will be discussed later). Both the estimated quadratic direct utility function parameters and the corresponding implied (normalized) Marshallian demand parameters are provided.

The utility function implied by these parameter estimates is globally concave, with a slightly positively sloped principal axes for the ellipses that form its level curves. (The relevant lower left portions of these curves are interpreted as indifference curves). Of course, the quadratic form is merely a local approximation to the true utility function. Nevertheless, if the entire surface of the true utility function was quadratic, the apparent global optimum of that function would be located at 28.4 fishing days and $289,823 in median zip code income (compared to sample means of 17.4 fishing days and $31,725 in income). Thus the utility function is well-behaved in the relevant region. At the means of the data, the two marginal utilities are positive. The implied price elasticity of demand at the means of the data is -0.074 and the income elasticity is 0.078, although these elasticities change substantially with deviations away from the sample mean values. To establish

Table II

Fitted Quadratic Direct Utility Parameters
(with and without parameters constrained to be identical
for CVM and TCM portions of model)

Parameter	Constrained βs: Point Est. (Asymp. t-ratio)	Constrained βs: Implied $\beta^* = \beta/\beta_2$	Unconstrained βs: Point Est. (Asymp. t-ratio)	Unconstrained βs: Implied $\beta^* = \beta/\beta_2$
β_1 (z)	3.309 (8.237)[a]	27.76	1.276[b] (0.7457)	0.04530
β_2 (q)	0.1192 (19.55)	1.0	28.17 (2.573)	1.0
β_3 ($z^2/2$)	-0.1167 (-1.836)	-0.9790	1.498 (2.834)	0.05318
β_4 (zq)	0.002579 (2.006)	0.02164	2.263 (2.147)	0.08033
β_5 ($q^2/2$)	-0.006837 (-22.80)	-0.05736	-502.3 (-1.311)	-17.83
$\beta_1^* = \beta_1/\beta_2$	-		75.89 (5.756)	
$\beta_2^* = \beta_2/\beta_2$	-		1.0 -	
$\beta_3^* = \beta_3/\beta_2$	-		-10.89 (-2.428)	
$\beta_4^* = \beta_4/\beta_2$	-		-0.01749 (-0.9029)	
$\beta_5^* = \beta_5/\beta_2$	-		-0.04739 (-14.97)	
υ	16.01 (81.98)		15.97 (82.04)	
ρ	0.2315 (9.086)		0.2505 (9.749)	
max Log L	-15708.17		-15640.61[c]	

[a] Asymptotic t-ratios in parentheses.

[b] CVM utility parameters do not satisfy regularity conditions.

[c] Likelihood ratio test statistic for four parameter restrictions = 115.12. Equivalence of utility parameters is soundly rejected.

a visual benchmark for this basic model, for an individual with mean income and travel costs, an indifference curve for the empirical quadratic utility function, the budget constraint through $(\mu_Y, 0)$, and the fitted maximum attainable indifference curve are shown in Figure 1.

Using the basic constrained model that assumes one common utility function for all respondents, it is possible to use equation (18) to compute fitted values for the equivalent variation (either for each respondent, or at the means of the data). Across the 3366 respondents in this sample, the fitted values of E for a complete loss of access appear in the first row of Table III ($\alpha = 0$).[12] Over the estimating sample, the average point estimate for the equivalent variation for a complete loss of access is $3451 (or, alternatively, at the means of the data, it is $3423). Minimum and maximum values in the sample are also provided.

Table III also gives the model's estimates for the equivalent variation associated with successively smaller restrictions on days of access (α denotes the proportion of current consumption to which each individual's access days are restricted).[13] For an across-the-board 10% reduction in fishing days, for example, the average calculated utility loss by these respondents would be only $35, although values as high as $52 and as low as $19 can obtain, due solely to different incomes and travel costs faced by different respondents.

The main policy interest in equivalent variations for partial restrictions on access stems from the need to make optimal allocations of finite fish stocks between recreational anglers and commercial harvesters. If

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[12] For the single individual with average characteristics in Figure 1, this quantity would be determined by taking the parallel downward shift in the budget constraint which would leave the new constraint just tangent to the lower indifference curve.

[13] The computed equivalent variation, plotted as a function of α, is convex when viewed from below.

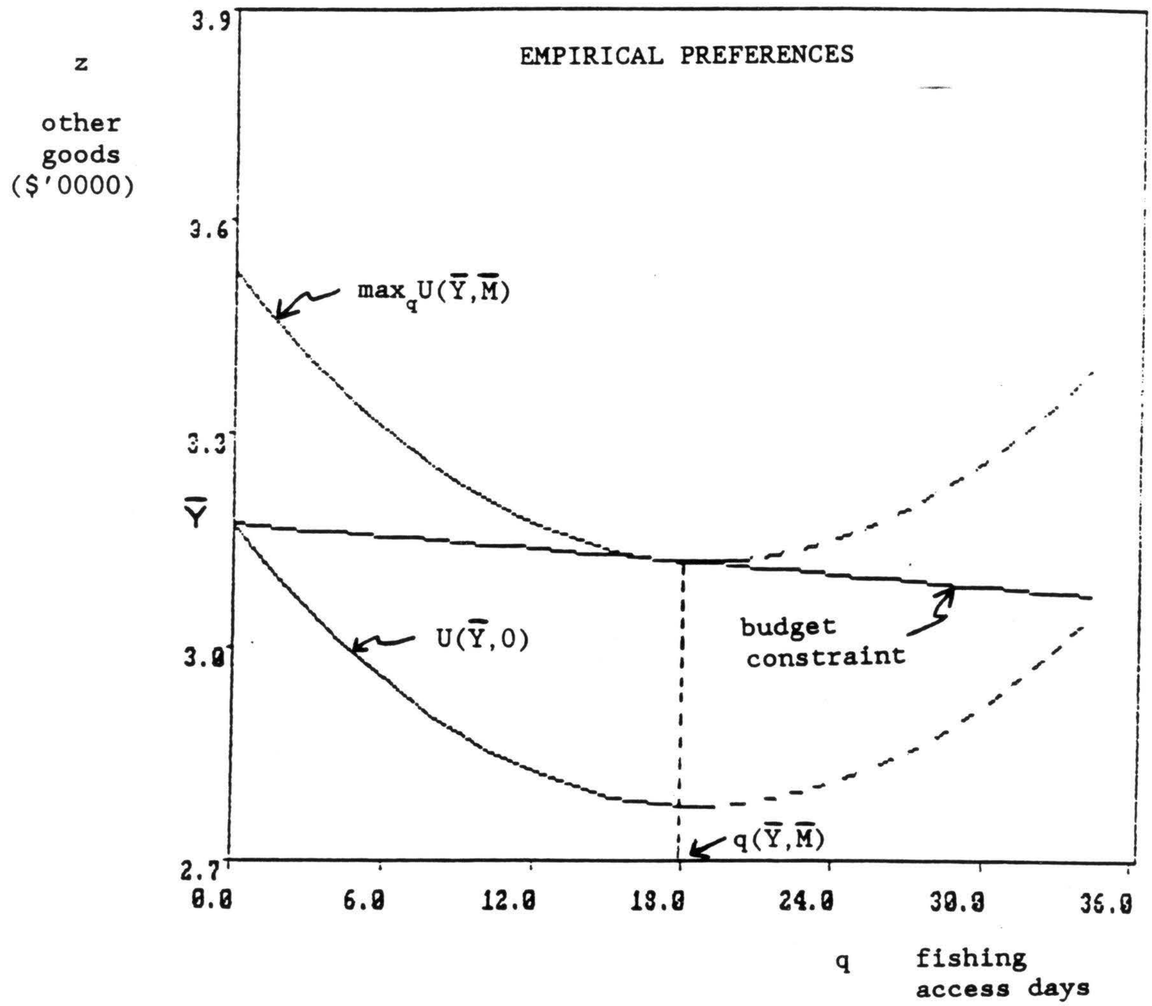

Figure 1 - Indifference curves at optimum and at zero access days, for respondent with mean income and travel costs.

Table III

Fitted Individual Equivalent and Compensating Variation Estimates[a] for the Basic (Constrained) Model (Table II)

Valuation Measure:	mean	max	min
Equivalent Variation			
$\alpha = 0.0$[b]	\$ 3451	\$ 5132	\$ 1857
$\alpha = 0.1$	2799	4166	1505
$\alpha = 0.2$	2214	3298	1190
$\alpha = 0.3$	1697	2529	912
$\alpha = 0.4$	1248	1861	670
$\alpha = 0.5$	867	1294	465
$\alpha = 0.6$	555	829	298
$\alpha = 0.7$	313	467	168
$\alpha = 0.8$	139	207	75
$\alpha = 0.9$	35	52	19
Compensating Variation			
$\alpha = 0.0$	\$ 3560	\$ 5361	\$ 1899

[a] Since the same utility function is presumed for all respondents, individual variations in these quantities stem solely from differences in income and travel costs.

[b] For access days restricted to the fraction α of fitted current access days.

faced with a proposal to cut back on recreational access, it would be necessary to quantify the social losses to recreational anglers, compare these losses to the anticipated gains accruing to commercial harvesters, and then to argue that such a redistribution of the catch would result in a potential Pareto improvement.[14]

The final row of Table III provides, for comparison, the corresponding compensating variation for a complete loss of access (i.e. for $\alpha = 0$ only). As is typical, the compensating variation for the loss is larger than the equivalent variation for the same loss. Here, however, the difference is largely an artifact of the quadratic form chosen for the utility function. The concentric ellipses which form the level curves of a globally concave utility function can be expected to have this relationship.

B. Different Preferences Implied by Real versus Contingent Data

We require both a constrained and an unconstrained specification if we plan to use a formal likelihood ratio test statistic to determine whether the utility parameters implied by the CVM data alone are consistent with those estimated jointly using both CVM and TCM data. The *constrained* specification (the basic model just described) appears in the first pair of columns in Table II.

For the unconstrained model, the demand information necessary to compute the endogenous quantity in the CVM discrete choice model is calculated using only the utility function parameters for the CVM portion of the model. We therefore allow the discrete choice CVM model exclusively to imply values for

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[14] In a richer specification, with enough shift variables to more closely capture the variations in quantity demanded, it would be an interesting exercise to assess total aggregate losses due to restrictions of access to specific numbers of days. The present data are not appropriate for simulating these policy changes.

β_1, β_2, β_3, β_4, and β_5. The observed TCM demand decisions will imply separate values for β_1*, β_3*, β_4*, and β_5*.

The second pair of columns in Table II displays results for an unconstrained model corresponding to the first pair of columns in the same table. The point estimates do not bode well for the consistency of the preferences elicited by the two types of responses. First of all, it is especially unsettling to note that the quadratic direct utility function implied by the CVM data alone does not even conform to the regularity conditions expected of a valid utility function. At the means of the data, the implied marginal utility from an additional access day is negative; there is also increasing marginal utility with respect to the composite good. The TCM quadratic direct utility parameters, however, are thoroughly acceptable. (The only link between the two submodels is the estimated error correlation, ρ.)

Nevertheless, there must still be some information about preferences in the CVM data, and the recorded responses on these surveys dictate these particular parameter values. We can certainly still compare the maximized value of the log-likelihood in the constrained and unconstrained models in order to assess whether the imposition of cross-equation parameter restrictions is tenable. A likelihood ratio test for the set of four parameter restrictions embodied in the "basic" model soundly rejects these restrictions.[15] For this quadratic specification, the CVM- and TCM-elicited preference functions are different.

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[15] It may be suspected that the TCM estimates systematically *understate* the true value of access (due to underestimates of the actual opportunity costs of access) and that the CVM estimates systematically *overstate* the true value of access (due to the incentives embodied in the way the question was posed). If data deficiencies make it too implausible to force compatibility of these responses with a *common* underlying set of preferences, the researcher would of course be free to report the two types of value estimates separately.

For a respondent with mean characteristics, Figure 2 shows the empirical indifference curves passing through the bundle (0,Y) for (i.) the "basic" constrained model and (ii.) the demand portion of the unconstrained model. The greater curvature of the indifference curve for the restricted parameters implies that E (the equivalent variation) based on the joint model, will be substantially larger than E based on observed TCM market demand behavior alone. For the unrestricted TCM demand parameters, the fitted equivalent variation at the means of the data is only $1686 (versus about $3451 for the constrained model).

The implied *inverse* demand functions corresponding to the different sets of preferences implied by the joint model and by the unconstrained TCM model are shown in Figure 3. When the CVM responses and observed TCM demand behavior are constrained to reflect the same set of quadratic preferences, the reservation price is about $409. The unrestricted TCM demand behavior implies a much lower reservation price. Thus the CVM (i.e. hypothetical market) scenario *does* seem to invite respondents to overstate the strength of their demand for resource access, as one might suspect (and/or the TCM indirect market data understates the strength of demand).

C. Differing Reliability for Real versus Contingent Data

The basic model (with or without the utility parameters constrained across the two sub-models) reflects the presumption that the decisions which respondents claim they would make under the hypothetical scenario proposed in the CVM question deserve to be treated as *equally credible* when compared to their actual market behavior regarding number of fishing days demanded. This need not be the case.

In other research on CVM (Cameron and Huppert, 1988), Monte Carlo techniques were used to demonstrate the wide range of referendum CVM value

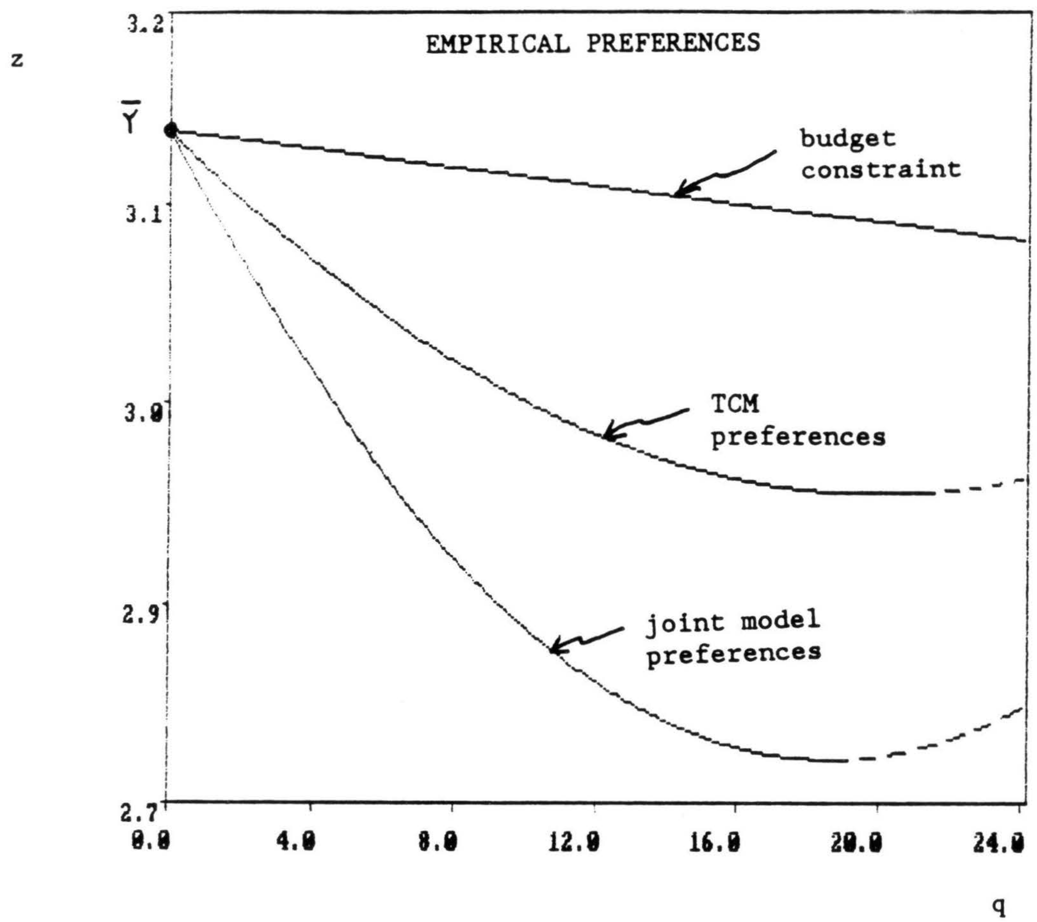

Figure 2 - $U(\bar{Y},0)$ for respondent with mean travel costs, according to constrainted joint model preference parameters and according to TCM portion of model with separate sets of preference parameters (CVM parameters fail to satisfy regularity conditions and are not shown).

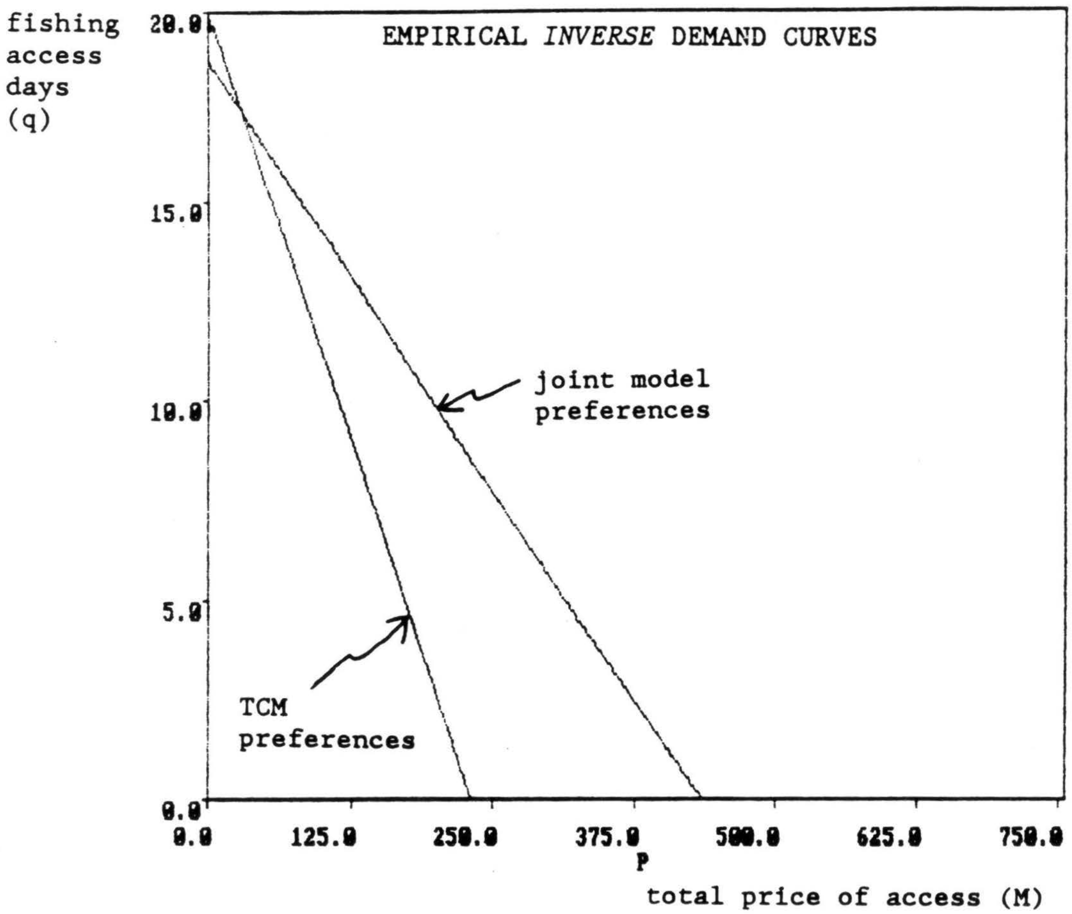

Figure 3 - Inverse demand curves corresponding to constrained joint model preference parameters, and according to TCM parameters from unconstrained model, for respondent with mean income and travel costs. (CVM parameters do not satisfy regularity conditions and are not shown.)

estimates which can result simply as an artifact of the arbitrary assignment of the threshold values on the questionnaires. One conclusion in that study was that researchers should probably insist on vastly larger samples for referendum CVM data, in order to offset the inefficiencies in estimation which result from the highly diffuse information in referendum responses. By itself, this property of referendum data might be sufficient to warrant a discounting of its credibility when it is combined with "point" information from the same sized sample.

Fortunately, researchers are free to use their own prior opinions to adjust the relative credibility of each type of information. This can be done in an *ad hoc* fashion, by employing non-unitary weights on the respective terms in the log-likelihood function (see Appendix IV). Alternately, it can be done more rigorously, by making assumptions about the variances of the distributions of the estimated β parameters around the "true" mean of the β vector.[16]

In the discussion that follows, we assume that CVM data are presumed to be *less* reliable than travel cost data, since this has been a typical sentiment among researchers in this area. However, the demand information inferred from the travel cost data is *also* likely to be unreliable, especially since TCM applications often assume that the opportunity cost of access is constant as access days increase. If opportunity costs rise, as they most likely do, TCM will underestimate the implicit value of access, perhaps severely.[17] Also recall that we do not impute an arbitrary value of travel

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[16] We owe this helpful suggestion to Ed Leamer.

[17] If increasing opportunity costs of access can be captured in the data, there exist econometric strategies for dealing with non-linear budgets sets which could undoubtedly be adapted to this type of problem. (See Hausman, 1985.)

time in this study. Depending upon the relative qualities of the two types of data, then, appropriate discounting of each type of information can be decided *ex ante*.

*Utilizing Explicit Priors on the Distributions of β and β**

Let β continue to denote the utility parameter estimates derived from the CVM data, and let β^* be the utility parameter estimates from the TCM data. Let β^T signify the true but unknown utility parameter vector. (Without loss of generality, we can normalize the second element, β_2, to unity in all three cases.) Now assume that conditional on the true β^T, β and β^* are statistically independent and that the elements of β/β^T are distributed $N(1,\sigma^2)$ and the elements of β^*/β^T are distributed $N(1,\sigma^{*2})$. (These σs are distinct from the unidentifiable probit regression variance employed in section III.)

The researcher is free to make prior assumptions about the magnitudes and relative sizes of σ^2 and σ^{*2}, and this prior information can be incorporated into the log-likelihood function in (7) as follows. Note that β^T, β and β^* are now all estimated separately, so the parameter space is increased. The additional log-likelihood term will be:

$$(20) \quad -n \log 2\pi - n(\log \sigma + \log \sigma^*) - (1/2)\, \Sigma\, \{\, [(\beta/\beta^T)-1]^2/\sigma^2 + [(\beta^*/\beta^T)-1]^2/\sigma^{*2}\, \}.$$

Maximization of the augmented log-likelihood with respect to the vectors of variables β, β^*, β^T, υ, and ρ, given preselected values of σ^2 and σ^{*2} will yield, for the model with identical consumers, fifteen distinct parameter estimates.[18]

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[18] It is not possible to optimize this likelihood function also with respect to σ and σ*. The algorithm will drive these values to zero.

What are the consequences for our ultimate estimates of the equivalent variation for a complete loss of access? In Table IV, the first column, reproduced from Table II, reflects an implicit assumption that $\sigma = \sigma^* = 0$. (The implied Marshallian demand parameters corresponding to the CVM portion of the model are given in the second column.) Nothing is "tying together" the two sets of estimates for the utility parameters, so they are very different indeed.

In contrast, for arbitrarily selected standard errors $\sigma = 1.0$ and $\sigma^* = 1.0$, the third column of Table IV displays the revised estimates of β and β^*, along with the additional, separate, estimates of the true β^T. (The fourth column again shows the Marshallian demand parameters implied by the CVM β estimates.) Ultimately, of course, we are interested in the value implications of the estimates. At the means of the data, these "true" β^T parameters imply an equivalent variation for a complete loss of access of \$3378 (which is very little different from the \$3423 at the means of the data for the basic model).

To illustrate a more-extreme case, we also include another pair of columns in Table IV. In this case, the assumed standard error of β/β^T (for the CVM parameters) is increased to 3.0. A standard error this large would seem to discredit the CVM data substantially. The assumption of poorer-quality information has the anticipated effect upon the precision of the three sets of utility parameters in the model. The asymptotic t-ratios for all of the different β parameters drop substantially, with the coefficients on z^2 and zq becoming insignificant in all three cases. However, the resulting equivalent variation according to β^T shrinks only to \$3124.

To assess the sensitivity of the parameter estimates and the welfare implications to different assumptions about the distributions of β and β^*

Table IV

Joint Models with Separate CVM and TCM Parameters
(CVM and TCM discounted by disproportionate variances)

Parameter	no σ, σ*, β^T		$\sigma_1 = 1.0$, $\sigma_2 = 1.0$		$\sigma_1 = 3.0$, $\sigma_2 = 1.0$	
	Point Est.	Implied β*	Point Est.	Implied β*	Point Est.	Implied β*
β_1 (z)	1.276	0.04530	3.421	28.11	3.930	30.07
	(0.7457)		(8.361)		(2.989)	
β_2 (q)	28.17	1.0	0.1217	1.0	0.1307	1.0
	(2.573)		(16.67)		(13.18)	
β_3 $(z^2/2)$	1.498	0.05318	-0.1383	-1.136	-0.2572	-1.968
	(2.834)		(-1.883)		(-0.5393)	
β_4 (zq)	2.263	0.08033	0.002157	0.01772	0.002038	0.01559
	(2.147)		(1.909)		(0.7828)	
β_5 $(q^2/2)$	-502.3	-17.83	-0.007072	-0.05811	-0.007873	-0.06024
	(-1.311)		(-14.36)		(-6.875)	
$\beta_1^* = \beta_1/\beta_2$	75.89		28.48		32.56	
	(5.756)		(9.323)		(2.679)	
$\beta_2^* = \beta_2/\beta_2$	1.0		1.0		1.0	
	-		-		-	
$\beta_3^* = \beta_3/\beta_2$	-10.89		-1.135		-1.945	
	(-2.428)		(-1.846)		(-0.5421)	
$\beta_4^* = \beta_4/\beta_2$	-0.01749		0.02069		0.01561	
	(-0.9029)		(1.793)		(0.7751)	
$\beta_5^* = \beta_5/\beta_2$	-0.04739		-0.05714		-0.05596	
	(-14.97)		(-25.74)		(-14.74)	
$\beta_1^T = \beta_1^T/\beta_2^T$	-		28.30		32.33	
			(9.484)		(2.707)	
$\beta_1^T = \beta_1^T/\beta_2^T$			1.0		1.0	
			-		-	
$\beta_3^T = \beta_3^T/\beta_2^T$	-		-1.136		-1.947	
			(-1.845)		(-0.5418)	
$\beta_4^T = \beta_4^T/\beta_2^T$	-		0.02068		0.01560	
			(1.794)		(0.7751)	
$\beta_5^T = \beta_5^T/\beta_2^T$	-		-0.05763		-0.05641	
			(-23.35)		(-13.87)	
υ	15.97		16.01		16.00	
	(82.04)		(81.95)		(81.87)	
ρ	0.2505		0.2317		0.2331	
	(9.749)		(9.120)		(9.090)	

(relative to β^{T}), one can perform a grid search across different values of σ and $\sigma*$ to produce a range of values for the "true" β^{T} coefficients and for the implied equivalent variations. These are summarized in Table V. (Since these functions are extremely expensive to optimize, we provide results only for combinations of σ and $\sigma*$ where $\sigma > \sigma*$. It seems likely, a priori, that the CVM data are at least as noisy as the TCM data, although both may be questionable.) The implied equivalent variations, EV, for each set of error assumptions, appear in bold print, implying a surprising robustness of the value estimates to differing reliabilities of the two types of data.

What conclusion is implied? A very wide range of different assumptions can be made about the relative reliability of CVM and TCM data, without producing too much difference in the ultimate welfare implications of the fitted preference functions. This result should be greatly reassuring, although it is conditional upon the maintained hypotheses of quadratic direct utility and has been demonstrated for this one sample only.

D. *Accommodating Respondent and/or Resource Heterogeneity*

The models described above have presumed that these respondents are homogeneous on all dimensions other than income, Y, proposed tax, T, number of fishing days, q, and typical market expenditures, M. It is a simple matter, however, to relax this assumption.

For example, one can explore the effects of allowing the utility parameters to vary continuously with the level of a sociodemographic variable. In the *ad hoc* valuation models explored in Cameron, Clark, and Stoll (1988), it was found that the Census proportion of people in the respondent's zip code who report themselves as being of Vietnamese origin, PVIET, seemed to be

Table V

Results of Grid Search across Different Error Assumptions
For the Distribution of the CVM and the TCM Parameter Vectors

Contingent Valuation Information: σ =		Travel Cost Information: σ^* = 0.5	1.0	1.5	2.0	2.5	3.0
0.5	β_1^T	27.90					
	β_3^T	-1.021					
	β_4^T	0.02139					
	β_5^T	-0.05742					
	EV at means:[a]	**$3412**					
1.0	β_1^T	28.15	28.30				
	β_3^T	-1.070	-1.134				
	β_4^T	0.02108	0.02070				
	β_5^T	-0.05735	-0.05763				
	EV at means:	**$3395**	**$3378**				
1.5	β_1^T	28.64	28.75	29.01			
	β_3^T	-1.177	-1.224	-1.335			
	β_4^T	0.02043	0.02013	0.01944			
	β_5^T	-0.05720	-0.05750	-0.05796			
	EV at means:	**$3364**	**$3348**	**$3320**			
2.0	β_1^T	29.39	29.53	29.74	30.10		
	β_3^T	-1.331	-1.391	-1.482	-1.636		
	β_4^T	0.01947	0.01910	0.01852	0.01852		
	β_5^T	-0.05698	-0.05725	-0.05773	-0.05773		
	EV at means:	**$3317**	**$3300**	**$3272**	**$3233**		
2.5	β_1^T	30.53	30.64	30.84	31.10	31.51	
	β_3^T	-1.566	-1.614	-1.702	-1.820	-1.998	
	β_4^T	0.01802	0.01770	0.01712	0.01633	0.01516	
	β_5^T	-0.05665	-0.05692	-0.05738	-0.05805	-0.05892	
	EV at means:	**$3245**	**$3229**	**$3202**	**$3165**	**$3116**	
3.0	β_1^T	32.17	32.32	32.51	32.77	32.96	33.08
	β_3^T	-1.887	-1.945	-2.025	-2.142	-2.247	-2.347
	β_4^T	0.01600	0.01561	0.01506	0.01427	0.01350	0.01270
	β_5^T	-0.05617	-0.05642	-0.05686	-0.05749	-0.05840	-0.05963
	EV at means:	**$3141**	**$3125**	**$3099**	**$3062**	**$3019**	**$2970**

[a] The values for EV may or may not be statistically significantly different. They are the solutions of the elaborate quadratic formulas given in equation (18) in the body of the paper.

influential in a wide range of models.[19] Allowing this variable to shift the parameters of the quadratic utility function, one can replace the constant β_j by the varying parameter ($\beta_j + \gamma_j PVIET_i$) for j = 1,...,5. Table VI demonstrates that the PVIET variable does indeed make a statistically significant difference to the overall fit of the model and to the parameters of the utility function.[20] Individually, only γ_5, reflecting the additional curvature of the utility function with respect to fishing access days, is statistically significantly different from zero. However, the whole set of shift terms is jointly significant according to the likelihood ratio test statistic value of 28.40 (where $\chi^2_{.05}(5) = 11.07$).

A visual display of the effect on preferences of allowing for heterogeneity with respect to the PVIET variable is displayed in Figure 4. As benchmark levels, PVIET=0 and PVIET=.02 are selected. (Maximum PVIET in the sample is 0.0649). Other than this distinction, the indifference curves pertain to individuals both having the overall sample's mean income and travel costs.

The higher the proportion of individuals of Vietnamese ancestry in the respondent's zip code, the greater the curvature of the indifference curves, and the larger the implied equivalent variation for a loss of access to the fishery. Current optimal numbers of days are similar for the two representative anglers, so the large discrepancy between the vertical intercepts of the two empirical indifference curves suggests that while the two socioeconomic groups exhibit similar current behavior, they respond

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[19] This is consistent with anecdotal evidence which suggests than many people in this socioeconomic group supplement their diets with "recreationally-caught" fish.

[20] Both the income and PVIET variables are certainly measured with a degree of error due to reliance on Census zip code means. With specific data at the individual level, the following results would certainly be somewhat different.

Table VI

Jointly Estimated Model;
Heterogeneous Utility Function
(varies with proportion Vietnamese)

Coefficient and Variable	Estimate (asy. t-ratio)
β_1 (z)	2.897 (2.761)
β_2 (q)	0.1195 (14.87)
β_3 ($z^2/2$)	0.1210 (0.3711)
β_4 (zq)	0.003829 (1.800)
β_5 ($q^2/2$)	-0.007125 (-21.84)
γ_1 (zPVIET)	96.64 (0.7534)
γ_2 (qPVIET)	-0.08279 (-0.09106)
γ_3 (z^2PVIET/2)	-58.89 (-1.467)
γ_4 (zqPVIET)	-0.3573 (-1.395)
γ_5 (q^2PVIET/2)	0.08352 (6.583)
υ	15.95 (81.93)
ρ	0.2302 (8.971)
Max. logL	-15693.97[a]

[a] Compare to basic model in Table II.

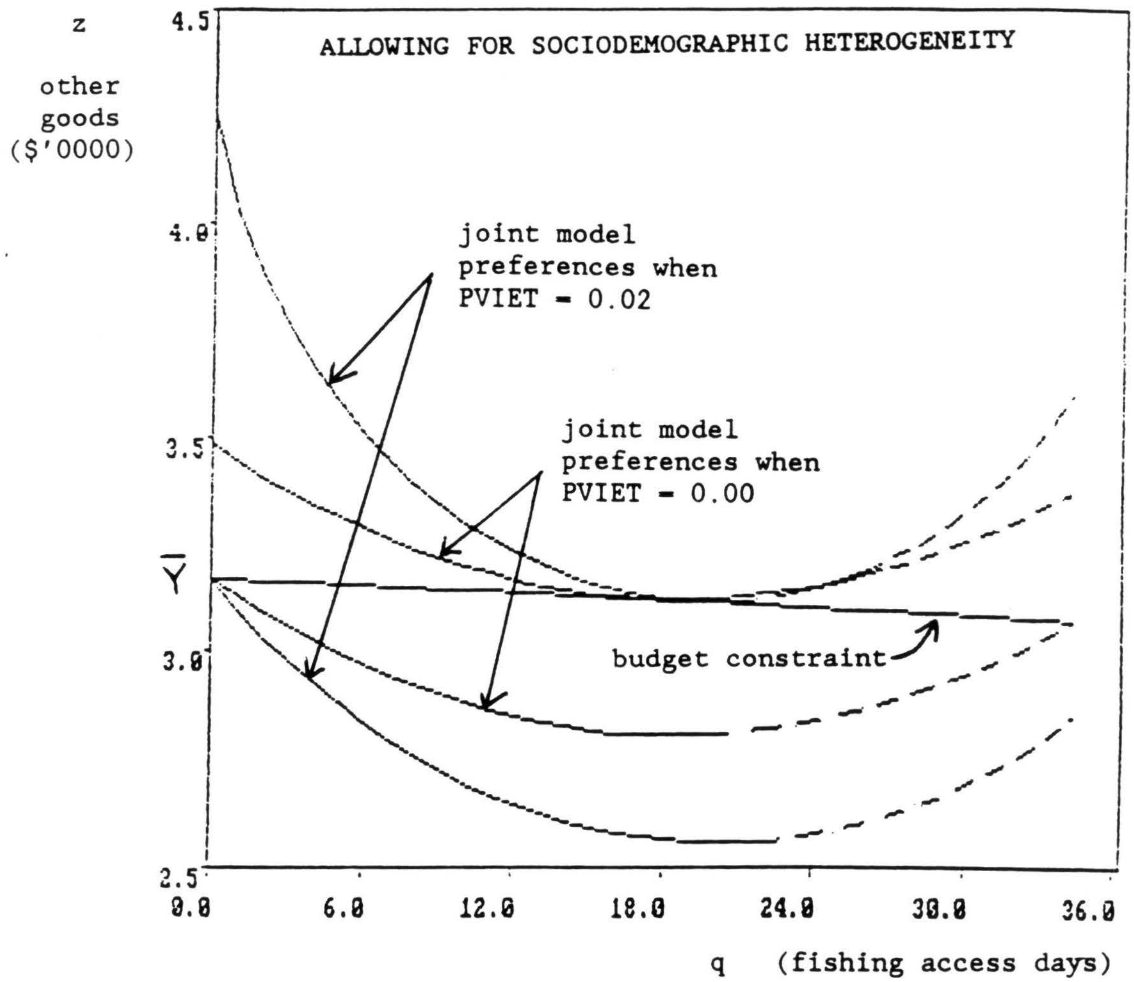

Figure 4 - Systematic variation in preferences when utility parameters are allowed to vary linearly with the zip code proportion of census respondents of Vietnamese origin. Plotted for respondent with mean income and travel costs.

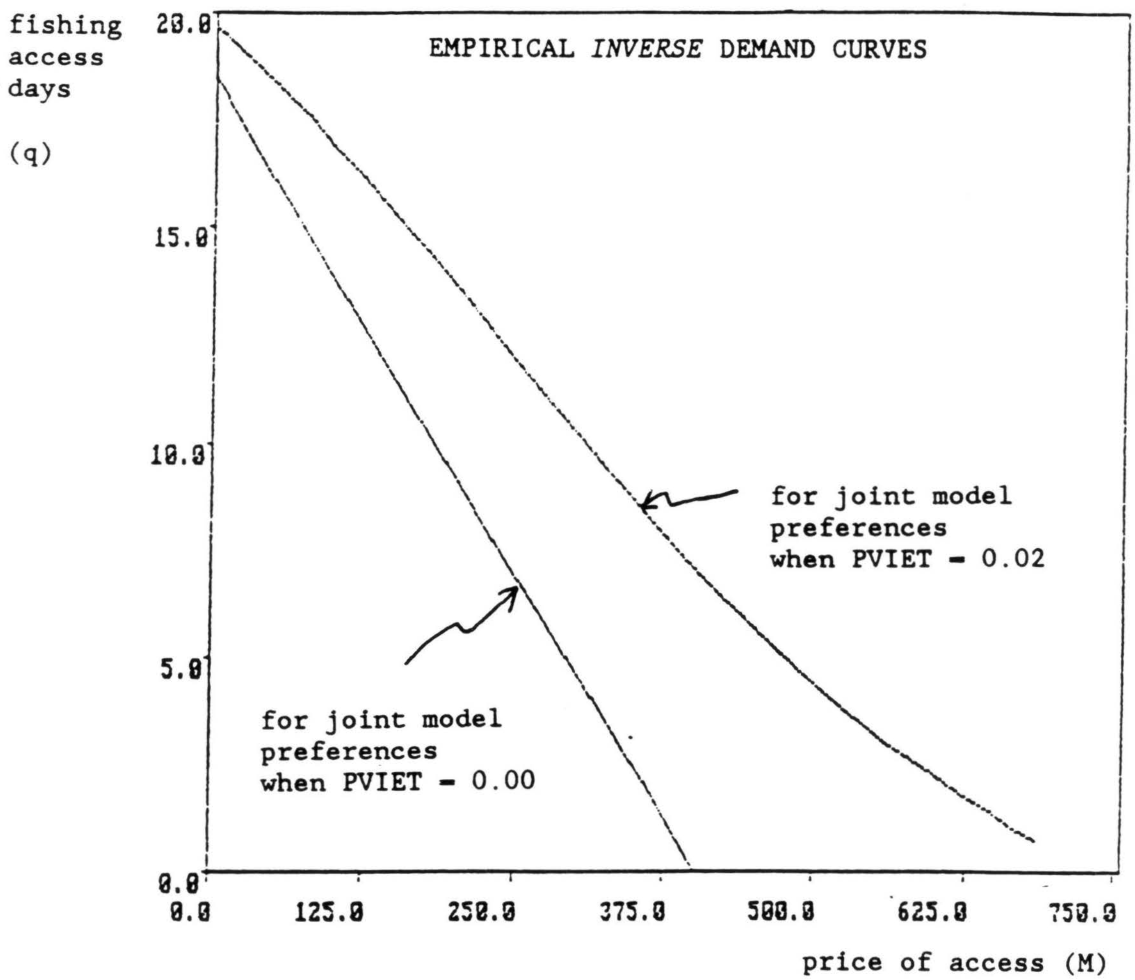

Figure 5 - Differences in empirical demand curves according to proportion Vietnamese for two respondents with otherwise identical income and travel costs.

systematically differently to the hypothetical CVM question. Respondents from zip codes with higher proportions of population with Vietnamese ancestry are more inclined to claim that they would continue to fish despite substantial annual access fees. Figure 5 shows how these different preferences translate into systematically different inverse demand curves. The demand curve for the PVIET = 0.02 group is situated considerably further out than that for the PVIET = 0 group.

What is the policy significance of the finding that preferences for fishing access can vary across sociodemographic groups? Different preferences imply that any policy measure the government might contemplate will have *distributional* consequences. This will be true whether the policy affects real incomes or the relative price of access or if it consists of access restrictions. Distributional effects can be of critical importance in policy-making.

Ethnic differences are just one of a variety of sources of heterogeneity which could be recognized explicitly in resource valuation models of this type. For models intended to allow simulation of specific policy measures, it will also be important to incorporate dimensions of heterogeneity which can be affected by these policy actions. For example, individual values for access to a recreational fishery are affected not only by angler characteristics, but also by attributes of the resource in question. In one illustration, for a subsample of this dataset, we have addressed the effects on social value of respondent's perceptions about pollution levels (Cameron, 1988b). Not surprisingly, deteriorating environmental quality reduces the demand for access and diminishes the social value of the resource. Likewise, improvements increase social value. This type of model can be used to simulate anticipated social benefits accruing to recreational anglers if government or private expenditures are devoted to cleanup efforts.

We have also supplemented a subset of the survey data used here with independently gathered data on the abundance of the primary gamefishing target species (Cameron, 1988c). The experiment reveals that gamefish abundance makes intuitively plausible and statistically significant differences in preferences and therefore in the social value of the resource. This type of model can be used to simulate the social benefits to recreational anglers as a consequence of fish stock depletions or enhancement programs.[21]

VI. CONCLUSIONS AND CAVEATS

A *fully utility-theoretic specification* distinguishes this analysis from much earlier empirical work on the valuation of non-market resources. By concentrating on identifying the underlying *preference structure* for access days versus all other goods and services, theoretically sound measures of access values (equivalent and compensating variations) can readily be produced.

Several features of the "basic" model should be emphasized. First, it starts from an assumption of quadratic direct utility, presumed to explain the hypothetical contingent valuation responses. Second, the associated non-linear Marshallian demand functions are employed to explain the observed demand decisions by the respondents (a "travel cost" type of model). Third, the corresponding parameters in the utility and the demand functions are

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[21] For our three examples of how respondent and resource heterogeneity can be accommodated in this prototype model, we have assumed that these sources of heterogeneity are mutually orthogonal, so that they may be entered individually and separately. For sufficiently large surveys, the complexity of these heterogeneous models is limited only by the variables upon which data have been collected and by computing capacity. Very elaborate models can potentially be accommodated.

constrained to be identical. Fourth, the quantity demanded under the CVM scenario is fully endogenized. And finally, unobservable attributes of respondents are allowed to affect both types of responses simultaneously through a non-zero (estimated) error correlation.

The "basic model" forms a minimal prototype for models in a wide range of applications in resource valuation. However, this paper has also described a variety of important extensions--potentially very relevant to subsequent researchers. "Prior" assumptions about the relative qualities of the hypothetical CVM questions and the "real" travel cost data can be used to modify the influence of each of these responses during joint estimation the utility parameters. Examples have also demonstrated that it is straightforward to allow the parameters of the quadratic preference structure to vary systematically with the levels of (exogenous) respondent or resource attributes.

To review the central empirical findings (for *these* data, in combination with the assumption of quadratic preferences), the "basic model" yields a sample average fitted equivalent variation of $3451 for a complete loss of access to the fishery. In contrast, if access days for each individual were restricted by only 10%, the average equivalent variation would be only $35. The implications of the model for small local variations are probably more reliable, although in this case, the complete loss *is* explicitly "within the range of the data" because of the information extracted from the CVM responses.

Some caveats should be emphasized. The sample for this application was consciously trimmed along a number of dimensions. Most notably, anyone who reported fishing more than 60 days per year was dropped from the sample. When attempting to fit a single utility function to an entire sample, the assumption of identical preferences must be at least roughly tenable. People who fish more than 60 days per year probably have fundamentally different preferences. With enough detailed information about the exogenous sociodemographic attributes of these individuals that might account for these differences, one could accommodate broad heterogeneity. This survey, however, provides little such information. In order to highlight the capabilities of the model (without obscuring the relationships due to unrecognized heterogeneity), it is necessary to disenfranchise some extremely avid anglers. Consequently, if these average values are scaled up to the population of anglers, the total will *underestimate* the true value of the fishery. Fortunately, with more detailed surveys (and future generations of computing hardware and software), more comprehensive models will certainly be practicable.

From a policy standpoint, it is also critical to emphasize that in many applications, the benefits computed for the group of resource users represented by the survey sample will comprise only a portion of the total social benefits generated by the resource. Non-consumptive use of the resource will often be substantial; option and existence value can sometimes be larger by orders of magnitude than the user values implied by surveys such as the one analyzed in this study. The dollar measures of benefits produced here, for example, are only a lower bound on the total social benefits enjoyed by residents of Texas, the rest of the United States, the continent, or the entire world.

Methodologically, this research has demonstrated that it is indeed *feasible*, and probably highly desirable, to employ referendum contingent valuation data in the context of a fully utility-theoretic model whenever the quality of the data justify such an effort. These results also demonstrate that forcing contingent valuation utility parameter estimates to be consistent with observed demand behavior can have a substantial effect on the estimated preference structure, the implied demand functions, and ultimately on the apparent social value of the resource or public good.

It has also been demonstrated that jointly estimating the discrete/continuous choices of respondents *without* parameter constraints allows a rigorous statistical check of the consistency of the hypothetical CVM responses with demonstrated real market decisions (conditional on the functional form chosen for utility). The implications of this dimension of the problem are being explored in greater depth in some follow-up research. Previous validation studies have typically relied on entirely separate models for CVM data and other types of data, such as travel cost information or market experiments. This earlier strategy allows comparisons of *point* estimates of value, but precludes any statistical assessments of the degree of similarity between the results. In contrast, the joint models presented here permit standard likelihood ratio tests. For this sample, the hypothetical CVM data and the observed TCM data appear to imply sharply different sets of preferences if completely independent sets of utility parameters are estimated. In other applications, however, *consistent* responses under the real and hypothetical scenarios may be readily accepted. Such a finding would reinforce the credibility of contingent valuation procedures in those contexts.

When CVM and TCM data are combined in the estimation process, in order to exploit all of the information available, it has been demonstrated that the researcher can systematically accommodate into the estimation process any prior opinion regarding the relative reliability of the two types of data. It is possible to like the two source of preference information without forcing the implied utility function to be exactly identical.

In sum, this research demonstrates the value of combining both contingent valuation and travel data whenever possible. Pooling of these two types of valuation information allows the advantages of each technique to temper the disadvantages of the other. Making the underlying preference structure of consumers the core of the analysis facilitates joint modeling of the two decisions. It also allows a rigorous assessment of the probable responses of individual consumers under a wide range of simulated counterfactual scenarios, and permits welfare estimates which are consistent with neoclassical microeconomic theory.

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APPENDIX I

An Alternative Interpretation of the Contingent Valuation Question

In this study, an alternative interpretation of the CVM question is conceivably possible. Perhaps respondents think of the access fee T as implicitly reflecting a *price* change at their current consumption level, q(Y,M), rather than a lump sum tax. They may interpret the question as asking whether or not they would choose non-zero access days if the price per day went from M to M+(T/q(Y,M)). In this case, the the CVM question would seem to be asking respondents whether their post-price change optimal consumption of access days would be positive. (I.e. if their optimal number of access days was negative, their highest utility would correspond to zero access days, providing that preferences are well-behaved.) The results reported in this paper have emphasized the "lump sum tax" interpretation, but some results for the alternative "price change" interpretation are provided here for comparison, since the interpretation *does* affect the resulting estimates of resource value.

Rather than the *utility-difference* underlying the discrete response in equation (5), this *projected optimal consumption level* would "drive" the discrete choice portion of the model. A "yes" response implies that the respondent's optimal consumption of access days under the hypothesized scenario is positive. A "no" would mean that optimal consumption would actually be negative, but zero days are the fewest which can be consumed. The "yes/no" response thus provides censored information regarding the magnitude of optimal quantity demanded. Unlike conventional probit models, where the location of the distribution is unknown (and therefore set arbitrarily to zero), the "threshold" in this case is exactly zero days. As above, $g(x_i,\beta)$ will be adopted as the generic representation for the Marshallian demand function corresponding to the quadratic utility model, where the variables x_i include income and the "price" of a day of access. As in Section III, υ can be used as the same (constant) standard error of the conditional distribution of quantities demanded. The magnitude of υ can be inferred from observed consumption under current prices, so the conditional dispersion of the unobservable dependent variable in the CVM model is "known" (in contrast to the conventional probit situation).

Providing, then, that it is reasonable to assume that real and hypothetical behavior are derived from the identical set of underlying preferences, the discrete responses to the CVM question can be used to supplement the estimation of the underlying demand parameters. Specifically, the expression $(f(x_i,\beta)/\sigma)$ in equations (5) and (7) will be replaced by $g(x_i{*},\beta)/\upsilon$, where $x_i{*}$ includes current actual income, but price M is replaced by the hypothesized $(M+T/q(Y,M))$.

One difference under this interpretation of the CVM question is that this specification no longer allows identification of the individual utility parameters (β_1 through β_5, up to the scale factor, σ, of the unobservable dispersion in the latent variable driving the CVM response). Only the demand parameters, $\beta_1{*}$, $\beta_3{*}$, $\beta_4{*}$, and $\beta_5{*}$ and υ can be identified. Fortunately, the utility function is invariant to the scale of the parameters and arbitrarily setting $\beta_2 = 1$ will result in exactly the same implications in terms of optimizing behavior.

The demand parameter estimates for the utility function under this fundamentally different interpretation of the CVM question appear in Table I.1. It is not surprising that the point estimates differ systematically from their counterparts in the body of the paper.

For this version of the joint model, the marginal utilities at the means of the data are positive; the price elasticity of demand for access days is about -0.035; the income elasticity is 0.11. The implied global optimum is 20.2 access days and $78212 in median household income.

While the fitted utility function under this interpretation is completely plausible from a theoretical standpoint, the implications of this model are quite a bit different from the "lump-sum tax" interpretation. The sample mean of the fitted equivalent variations for a complete loss of resource access, according to these preferences, is markedly higher, at $7386 (with standard deviation $2244). Clearly, subsequent surveys will have to be very careful in conveying to respondents exactly what type of scenario is intended, since the interpretation of the question can make almost an order of magnitude difference in the results.

Table I.1

Model with CVM Question Interpreted as Price Change

Parameter	Point Estimate (asymp. t-ratio)
β_1* (z)	19.80 (5.366)
β_2* (q)	1.000 -
β_3* ($z^2/2$)	-2.613 (-2.573)
β_4* (zq)	0.03155 (1.726)
β_5* ($q^2/2$)	-0.06163 (-18.23)
υ	16.18 (86.75)
ρ	0.08754 (3.080)
Max. LogL	-15708.12

APPENDIX II

Alternative Direct and Indirect Utility Specifications

Other linear-in-parameters functions that have been widely used empirically include the translog and the generalized Leontief specifications. The translog is quadratic in the logarithms of the arguments, but it is critical for the basic model in this paper that *direct* utility levels be defined and non-zero when consumption of one commodity (namely, recreation days) goes to zero. This disqualifies the ordinary translog model, since this function is only defined over strictly positive quantities of each good.[22]

The generalized Leontief specification satisfies the boundary requirements, and is generally considered to be a more "flexible" functional form than the quadratic. However, while a generalized Leontief *indirect* utility function can readily be differentiated to yield Marshallian demands, this similar functional form for the *direct* utility function yields Marshallian demands which are prohibitively complex.

Empirical research on consumer decisions has sometimes employed the Stone-Geary utility function and its corresponding "linear expenditure system" demand equations. This specification may at first seem attractive, but it too is only appropriate when one is considering *interior* consumer optima. In this case, the utility function would be:

$$U(z,q) = (z - \beta_1)^{\beta_2} (q - \beta_3)^{\beta_4} \qquad \text{(II.1)}$$

The corresponding demand for fishing days will be given by:

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[22] One could, of course, shift the utility surface one unit towards the origin along the dimension of each good by adding one to each quantity within the functional form for the translog direct utility. However, when the direct utility function, rather than the indirect utility function, takes on a translog functional form, the associated Marshallian demand functions are awkward to derive; they are even more awkward if the function is additively shifted.

$$q = \beta_3 + (\beta_4/p)\ [Y - \beta_1 - \beta_3\ p] \tag{II.2}$$

where the price of the composite good, z, has again been normalized to unity.

This utility function is not linear in parameters, so initial estimates cannot be obtained via a conventional maximum likelihood probit package. But there is a bigger problem, stemming from the necessity of considering utility levels for zero days of access. In particular, the systematic portion of the utility difference function, which would form the non-linear "index" function for the discrete choice portion of the model, would take the following form:

$$\Delta U = [(Y\text{-}M\text{-}T) - \beta_1]^{\beta_2}\ [q - \beta_3]^{\beta_4} - [\ Y - \beta_1\ ]^{\beta_2}\ [\ - \beta_3\ ]^{\beta_4} \tag{II.3}$$

The problem for estimation stems from the last term. The coefficient β_4 is often fractional. Attempting to take the β_4-root of a negative number can be expected to create difficulties. Furthermore, the usual interpretation of β_3 is that is represents "subsistence" consumption levels of commodity q, so negative values of the parameter itself are unlikely to result, or to be defensible intuitively, if they do. As expected, in attempts to estimate this model using the data employed in the rest of this study, the algorithm persistently failed.

The quadratic form is a useful local approximation to any arbitrary surface. Why not then expand to third-order terms? Several of the quantities of interest which are derived from the calibrated model necessitate solving the fitted utility function for the value of one of its arguments. The standard formula for computing quadratic roots is straightforward to use. The formulas for the roots of cubic equations are considerably less easy. (See CRC, 1981, p.9.) However, continuing empirical research explores such forms, since the results for quadratic utility specifications suggest that a higher degree of parameterization might be supported.[23]

Contemporaneous work by Huppert (1988) employs an alternative strategy in the context of a standard simultaneous equations model. He begins with a simple functional form (log-linear) for the Marshallian demand specification and accepts the corresponding (unnamed) functional form for the underlying utility function. Huppert's payment card contingent valuation responses are treated as a continuous variable, so that the joint estimation of the utility and demand parameters can be accomplished via standard packaged simultaneous non-linear least squares algorithms.

It is interesting to compare the results derived using a quadratic direct utility function (and implicitly its associated indirect utility function) with those derived for a model that *begins* with an *indirect* utility function which is quadratic in prices and income. This will imply a very different function form for the direct utility function.

If indirect utility, V, is quadratic in the price of z, the price of q (i.e. M), and income Y, the terms in the unitary price of z will be absorbed into a constant and into the coefficients on M and Y. The effective functional form will be:

(II.4) $$V(M,Y) = \alpha_1 M + \alpha_2 Y + \alpha_3 M^2/2 + \alpha_4 MY + \alpha_5 Y^2/2.$$

The corresponding Marshallian demand for q is given by application of Roy's Identity:

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[23] The data appear to support cubed terms in z and q, but the optimization algorithm cannot seem to settle upon coefficients for the second-order interaction terms, z^2q and zq^2. The two cubed terms do make a statistically significant improvement in the log-likelihood function for the model.

$$(\text{II.5}) \qquad q(Y,M) = -(\partial V/\partial M)/(\partial V/\partial Y)$$
$$= (-\alpha_1 - \alpha_3 M - \alpha_4 Y)/(\alpha_2 + \alpha_4 M + \alpha_5 Y),$$

or, normalizing α_2 to unity:

$$(\text{II.6}) \qquad q(Y,M) = (-\alpha_1{*} - \alpha_3{*}M - \alpha_4{*}Y)/(1 + \alpha_4{*}M + \alpha_5{*}Y).$$

The respondent will decide to pay lump sum tax T and continue fishing if $V(M,Y-T) > V(Y)$, i.e., if

$$(\text{II.7}) \qquad \Delta V(Y,M,T) = f(x_i,\beta) = \alpha_1\, M + \alpha_2\, (-T)$$
$$+ \alpha_3\, M^2/2 + \alpha_4\, M(Y - T) + \alpha_5\, [(Y-T)^2 - Y^2]/2 > 0.$$

The equivalent variation, E, which would leave the respondent indifferent between fishing and not fishing is given by the quadratic root E of:

$$(\text{II.8}) \qquad \alpha_5/2\, E^2 - [\, \alpha_2 + \alpha_4 M + \alpha_5 Y\,]\, E + [\alpha_1 M + \alpha_3 M^2/2 + \alpha_4 MY\,] = 0.$$

The joint model can be set up as in the text of the paper, except now we have $f(x_i,\beta) = \Delta V(Y,M,T)$ and $g(x_i,\beta)$ is replaced by the Marshallian demand formula derived in this section.

The indirect utility approach has the distinct advantage that it does not require endogenous determination of post-tax quantity demanded, $q(Y-T,M)$. However, the direct utility specification corresponding to this representation of preferences is prohibitively awkward to derive, so the intuitive advantages of standard indifference curve diagrams are beyond our reach.

Nevertheless, it is straightforward to estimate the joint model of indirect utility differences and the corresponding Marshallian demands. We have done so. The parameter estimates appear in Table II.1.

Unfortunately, while the direct utility approach used in the body of the paper easily satisfies the regularity conditions for a valid utility function, this is not the case for the quadratic indirect utility specification used here. $V(M,Y)$ should be nonincreasing in M and nondecreasing in Y. At the means of the data, however, the parameters given in Table II.1 produce a value oς 97.87 for $\partial V/\partial M$ and a value of -5.653 for $\partial V/\partial Y$. As a consequence of these irregularities, the values we compute for the equivalent variation associated with a loss of access are nonsensical. In other applications, however, the indirect utility approach (possibly using alternative functional forms) may prove to be satisfactory, or even preferable, to the direct utility model, especially if it is deemed unnecessary to provide empirical indifference curves as a visual aid.

Table II.1

Quadatic Indirect Utility Specification

Parameter	Point Estimate (asymp. t-ratio)
β_1* (M)	75.50 (6.642)
β_2* (Y)	-4.123 (-6.667)
β_3* ($M^2/2$)	-4936.81 (-8.237)
β_4* (MY)	11.59 (3.374)
β_5* ($Y^2/2$)	-0.4929 (-2.624)
υ	15.97 (82.04)
ρ	0.2043 (8.506)
Max. LogL	-15957.66

APPENDIX III

Estimates in the absence of travel cost data

In some applications, M may be measured accurately and may be relatively constant across fishing days, but in other cases, it may not. Sometimes, the researcher may be better off ignoring the questionable information on M, and using a simpler "Engel curve" model as opposed to a "demand function" (where equation numbers indicate revisions of the original specification):

$$(1') \qquad \Delta U = U(Y - T, q^1) - U(Y, 0) > 0.$$

If the data on M are excluded, z will be identically Y.

$$(10') \qquad \Delta U(Y,T) = \beta_1 \{[Y-T] - Y\} + \beta_2 q^1 + \beta_3 \{[Y-T]^2 - Y^2\}/2 + \beta_4 [Y-T]q^1 + \beta_5 (q^1)^2/2.$$

$$(11') \qquad q(Y) = [1 + (\beta_4 *) Y] / [- \beta_5 *].$$

$$(17') \qquad \partial q/\partial p = [\beta_5(\beta_1 - \beta_3 Y) - 2\beta_4(\beta_2 + \beta_4 Y)] / [\beta_5]^2$$

$$\partial q/\partial Y = -\beta_4/\beta_5.$$

In order to appreciate the benefits of joint estimation with income data and numbers of trips but in the absence of travel costs as proxy data for prices, one can consider the estimates of the utility function parameters when the data on M in this sample are ignored. Table III.1 displays these results. At the means of the data, these fitted parameters imply a utility function with positive marginal utility from other goods, but *very* slightly negative marginal utility from access days. This implies that the utility function in this case is not globally concave. The saddle point of the utility function is located at 12.25 access days and \$-47348. Nevertheless, the level curves are still convex to the origin. At the means of the data, the price elasticity of demand for access days is -0.125 and the income elasticity is 0.0682.

Figure III.1 shows the effects on the fitted preference function of ignoring travel costs in the estimation phase. As benchmarks, this figure includes the "basic" indifference curve for a typical respondent (curve E) as well as the indifference curve based on the CVM portion (curve A) and the *demand* portion (curve D) of the unrestricted model. Here, however, attention should be focused on the indifference curve for a model similar to the basic model except that the available data on travel costs are ignored (curve A). Even this very "thin" information about market demand pulls the parameter estimates a long way away from the unrestricted CVM estimates depicted by curve A. Still, it is not clear in this application that the resulting (much smaller) equivalent variation estimates will be superior to those generated by the CVM portion of the unrestricted model.

Table III.1

Jointly Estimated Model Ignoring Travel Costs (i.e. M = 0; Only Engel Curves from Observed Demand Employed)

β_1 (z)	3.586 (1.342)
β_2 (q)	0.1259 (13.19)
β_3 ($z^2/2$)	0.7711 (0.9538)
β_4 (zq)	0.005329 (2.058)
β_5 ($q^2/2$)	-0.008213 (-22.46)
υ	16.12 (81.85)
ρ	0.2343 (9.076)
log L	-15679.17

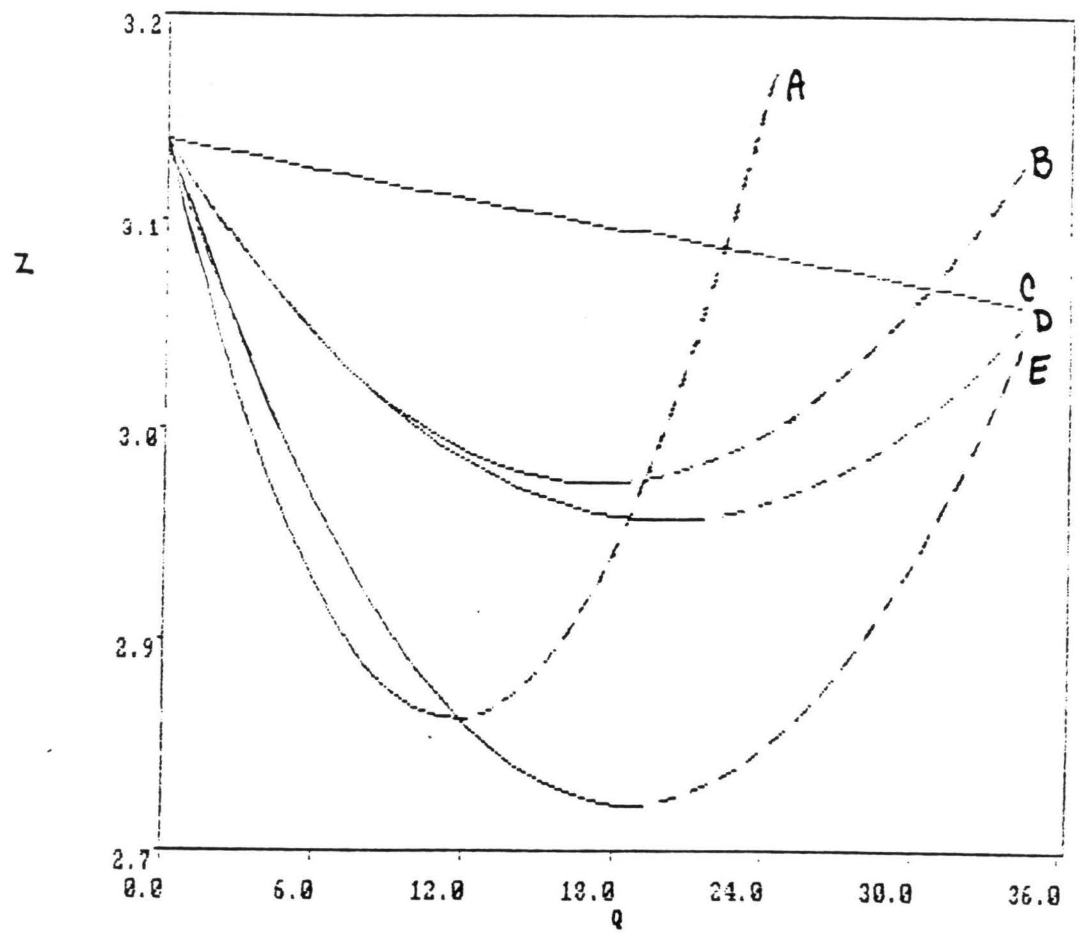

Figure III.1 - For respondent with mean income and travel costs, effects of ignoring travel costs during estimation of utility parameters by modified basic model: actual budget constraint (C), indifference curve from basic model (E), indifference curve from the CV portion of the unrestricted model (A), indifference curve from demand portion of unrestricted model (D), and indifference curve from model estimated without travel cost (using only Engel curve information) (B).

APPENDIX IV

An Ad Hoc Reweighting Scheme

Researchers who work with maximum likelihood estimation of models using sample data are by now very familiar with reweighting procedures for scaling the influence of different observations to allow the sample to more nearly reflect the proportions of each types of person in the entire population. Each observation in the sample is represented by one additive term in the log-likelihood function, each bearing an implicit unit weight. Non-unit weights, based on cross-tabulations performed on the population and on the sample, are computed by calculating the ration of population proportions to sample proportions in each cell of the cross-tabulation. Respondents who represent undersampled groups in the population then have their contribution to parameter estimation scaled up; oversampled respondents are given weights of less than unity to decrease their influence on the final parameter estimates.

If CVM and TCM responses are treated as equally credible, the two terms in the log-likelihood function in (7) corresponding to each type of information each receive an implicit *unit* weight. Fortunately, the dismantling of the joint normal error distribution into a conditional times a marginal error distribution leaves the error correlation, ρ, determined entirely within the discrete choice CVM portion of the likelihood function. It seems feasible, therefore, to "undo" the CVM and TCM terms in the likelihood function and to scale the influence of each type of information in determining the final parameter estimates.

If, for example, intuition suggests that the available CVM information is only half as reliable as the "real" travel cost information, one might change the weights on the CVM terms in the log-likelihood function to 2/3 and those on the TCM demand terms to 4/3 (so that the weights still sum to two).

This ratio of the weights will be designated as a "reliability" factor of .5 for the CVM information.

Given the maintained hypothesis of a quadratic utility function, one can ask just how small the weight on the CVM information would have to become before LR tests could just fail to reject the null hypothesis of parameter equivalence for the two models. For equal unit weights (relative weight = 1.0) the results for the constrained and unconstrained models from Table II are reproduced in Table IV.1. The second pair of columns in that table show the consequences of decreasing the relative weight on the CVM information. The relative reliability of the CVM information has been decreased to 0.1 and it is still possible to reject the hypothesis of common utility parameters. It would therefore be quite a "stretch" to bring the utility implications of the hypothetical CVM responses into line with observed demand behavior in this particular application.

Still, the observed demand behavior might itself be misleading if the true opportunity costs of access are poorly proxied by travel costs. It may be inappropriate to expect the preferences implied by the two types of value information to be identical. Likewise, the simple quadratic utility function and homogeneous preferences may be too restrictive. Therefore, this finding does not *necessarily* refute the equivalence of the *true* preferences underlying these two types of responses.[24]

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[24] We have extended the specification of the direct utility function to include cubic terms in z and q. The data are not rich enough to support separate parameters for the terms z^2q or zq^2. For the new "basic" model with seven utility parameters, the maximized value of the log-likelihood function is -15699.41. For the corresponding "unrestricted" model with separate CVM and TCM parameters, convergence has not been attained after several hundred iterations, but the log-likelihood function has been driven as high as -15631.95, which is more than adequate to reject the restrictions.

Table IV.1

Joint Models with Separate CVM and TCM Parameters
(CVM and TCM equally credible; CVM discounted by weighting;
CVM discounted by disproportionate variances)

Parameter	Rel.wt. = 1.0.[a]		Rel.wt. = 0.1	
	Basic Model	Unconstr. Model	Basic Model	Unconstr. Model
β_1 (z)	3.909 (8.237)	1.276 (0.7457)	7.840 (6.385)	1.290 (0.2952)
β_2 (q)	0.1192 (19.55)	28.17 (2.573)	0.1399 (12.64)	39.43 (0.9207)
β_3 $(z^2/2)$	-0.1167 (-1.836)	1.498 (2.834)	-1.036 (-2.986)	1.494 (1.111)
β_4 (zq)	0.002579 (2.006)	2.263 (2.147)	-0.001093 (-0.6008)	3.157 (0.8039)
β_5 $(q^2/2)$	-0.006837 (-22.80)	-502.3 (-1.311)	-0.007060 (-13.47)	-983.3 (-0.4689)
$\beta_1{*}=\beta_1/\beta_2$	-	75.89 (5.756)	-	76.03 (7.703)
$\beta_2{*}=\beta_2/\beta_2$		1.0 -		1.0 -
$\beta_3{*}=\beta_3/\beta_2$	-	-10.89 (-2.428)	-	-11.88 (-3.567)
$\beta_4{*}=\beta_4/\beta_2$	-	-0.01749 (-0.9029)	-	-0.02129 (-1.495)
$\beta_5{*}=\beta_5/\beta_2$	-	-0.04739 (-14.97)	-	-0.04721 (-20.09)
υ	16.01 (81.98)	15.97 (82.04)	15.98 (110.5)	15.97 (110.6)
ρ	0.2315 (9.086)	0.2505 (9.749)	0.2324 (4.030)	0.2495 (4.166)
max Log L	-15708.17	-15640.61[b]	-25938.13	-25920.04[c]

[a] "Rel. wt." is the size of the weight on the hypothetical CVM information relative to the weight on the observed demand behavior.

[b] LR test for hypothesis of same β parameters for CVM and TCM utility functions is 115.12 (when the 5% critical value of the χ^2 test statistic is 9.49 and the 1% critical value is 13.28).

[c] LR test for same β parameters is 36.1; still rejects hypothesis.

APPENDIX V

Implementing These Prototype Models in Other Applications

The illustration in this paper pertains to the valuation of a particular recreational fishery. However, the joint model developed here is potentially applicable to the valuation of *any* non-market good where consumers would have to incur varying travel costs in order to engage in the process of consumption. Individually, the travel cost method and the contingent valuation methods each have shortcomings. Implications drawn from their combined evidence are likely to be much more robust.

While relatively good, the data used in this paper are still less than ideal. The *specific* implications of the fitted models described here must be judged accordingly. But this research has provided vital groundwork for future studies.

First, the sampling procedures used in the gathering of the data employed in this study were not ideal. In particular, rotating sites for the survey were chosen, and virtually everyone who passed during the 10 a.m. to 5 p.m. period was interviewed. This precludes "outgoing" surveys for avid anglers who may be out well before 10 a.m., although many of these anglers would be intercepted upon their return. A more serious problem is that we cannot identify respondents who have been interviewed more than once. At best, we have a reasonable sample of fishing trips, not anglers, so the estimated preferences may be biased towards those of frequent anglers. This problem cannot be remedied with this data set.

It would be highly desirable to have individual-specific measures of income (and other sociodemographic variables). Census zip code means are helpful, but much information is lost in using group averages as proxies for the true variables. If at all possible, the survey instrument should elicit these data for each respondent.

The contingent valuation question should be phrased so as to make it clear whether the hypothesized change is intended to be a lump-sum change in income (as modeled in the body of this paper), or a change in relative prices (as explored in Appendix I). This information is vital to the utility-theoretic formulation of the estimating model, and great care must be taken to ensure that the CVM question is completely unambiguous.

The present survey asks about travel costs for the *current* fishing day. What the model requires is *typical* costs for a *typical* fishing trip, or better yet, enough information to construct the actual schedule of opportunity costs as they increase with number of access days. This would make the travel cost portion of the model more reliable. The current model also must presume that individuals fish most of the time at the same location. Much more sophisticated analyses will be required in order to introduce site choice modeling into this framework.[25]

Respondents could be asked specifically about how *sure* they are concerning their hypothetical responses to the CVM and travel cost questions. This information could be incorporated into the weighting scheme for the auto-validation of the CVM data.

Option and existence values cannot be captured with the current data set. Selection problems in the assessment of recreation demand have received considerable attention recently (e.g. Smith, 1988). A random sample of households in the target population could be contacted by telephone. If they do not currently consume access days, quantity demanded will simply be zero.

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[25] At present, site choice modeling has been pursued in a largely atheoretic multiple discrete choice framework. Blending the two approaches might have to wait for further computer software and hardware innovations.

Travel costs to relevant sites could still be elicited and appropriate CVM questions could be formulated to allow extension of this modeling framework to non-use demands.

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The Effects of Variations in Gamefish Abundance on Texas Recreational Fishing Demand: Welfare Estimates

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ABSTRACT

In an extensive earlier paper (Cameron, 1988a) we developed a fully utility-theoretic model for the demand for recreational fishing access days, applied to a sample of 3366 Texas Gulf Coast anglers. The model employs "contingent valuation" and "travel cost" data, jointly, in the process of calibrating a single utility function defined over fishing days versus all other goods and services. The theoretical specification (quadratic direct utility) and the econometric implementation will not be reproduced here. In this application, we supplement the original data set with information from the ongoing Resource Monitoring Program of the Texas Department of Parks and Wildlife. The RMP concerns all species, but we focus on the abundance of the primary game fish (red drum) across the eight major bay systems and over time. This improves upon earlier studies which utilize endogenous actual catch information. We allow the parameters of the underlying utility function to vary systematically with exogenously measured abundance to assess the impact of this important resource attribute upon the demand for access days. We use empirical estimates (and counterfactual simulations) of equivalent variation as measures of the social value of the fishery under current conditions and under alternative fish stock scenarios.

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The Effects of Variations in Gamefish Abundance on Texas Recreational Fishing Demand: Welfare Estimates

1. Introduction

In Cameron (1988a), we derived and estimated the parameters of a quadratic utility function for a trimmed sample of Texas Gulf Coast recreational fishermen. The utility function, in its simplest form, is defined over fishing access days and all other goods and services (income). The novelty of that paper is primarily its utilization of a fully utility-theoretic framework for analyzing *both* "contingent valuation" (CV) data (respondents anticipated behavior under hypothetical scenarios) *and* "travel cost" data (respondents' actual behavior in the consumption of access days). The latter form of data gives us a feel for the consequences of small local variations in access prices; the former provides additional information, however hypothetical, regarding more drastic changes in the consumption environment.

The earlier paper develops the basic specification and goes on to consider several extensions to that basic model: discounting the influence of the CV data in the estimation process; estimation without travel cost data (only income and consumption); and the accommodation of heterogeneous preferences. In the last category, we demonstrated that it is straightforward to adapt these models to allow for systematic variation in the preference function according to geographical or sociodemographic factors.

In this paper, we will again employ heterogeneous utility functions, but we will only be able to exploit a subset of the data. We wish to concentrate upon the potential effects of respondents' perceptions about resource quality on their demand (valuation) of access to the recreational fishery.

Readers are referred to Cameron (1988a) for a vital preface to this research. We avoid extensive duplication in this paper by presuming readers are familiar with the findings of the earlier paper.

2. Outline of the Specification

As before, we will adopt the quadratic family of utility functions, for the same variety of reasons explained in the earlier paper. We will let U denote direct utility, Y will be income, and M will be current fishing day expenditures ("travel costs", roughly). Also, q will be the number of fishing days consumed and z (= Y - Mq) will denote consumption of other goods and services. We will let A denote the abundance of red drum, the primary gamefish species. The quadratic direct utility function will thus take the form:

$$U = \beta_1 z + \beta_2 q + \beta_3 z^2/2 + \beta_4 zq + \beta_5 q^2/2, \tag{1}$$

where the β_j are no longer constants, but will be allowed to vary linearly with the level of A: $\beta_j{*} = \beta_j + \gamma_j A$, $j=1,\ldots,5$.

3. Data

The data used for this model consist of a 3318 observation subset of the 3366 observations used in the earlier paper. The data come from an in-person survey conducted by the Texas Department of Parks and Wildlife primarily between May and November of 1987 (although there are a few observations for the first days of December). The primary purpose of the survey is to count numbers and species of fish making up the recreational catch, but during this particular period, additional economic valuation questions were posed to respondents.

In particular, the contingent valuation question took the form: "If the total cost of all your saltwater fishing last year was ____ more, would you have quit fishing completely?" At the start of each day, interviewers randomly chose a starting value from the list $50, $100, $200, $400, $600, $800, $1000, $1500, $5000, and $20,000. In addition, respondents were queried regarding actual market expenditures during the current trip: "How much will you spend on this fishing trip from when you left home until you get home?" This is as close as we can get to a measure of "travel cost."

The same basic criteria for deleting particular observations are applied in this paper as are described in Cameron (1988a). The same caveats regarding the sample also apply in this case. The sample employed in this study is slightly smaller only because our gamefish abundance data are drawn from a separate source: the Resource Monitoring Program of Texas' Department of Parks and Wildlife. We have their data only for April through the end of November, so the few December interviews in the survey sample were simply dropped.

The Resource Monitoring Program uses several types of fishing gear: gill nets, bag seines, beach seines, trawls, and oyster dredges. The Program involves vast numbers of samples being drawn across the entire Gulf Coast. For 1983-1986, we had over 23,000 samples, with complete records of the numbers of individuals of each species collected in the sample. Since low temperatures in 1984 resulted in a substantial fish kill along the Texas Gulf Coast, we utilize only those samples drawn in 1985 and 1986 to construct our abundance measures. Also, only gill nets capture the types of fish that recreational anglers would be seeking, so we use only the catch using this gear type. Still, we have roughly 5400 samples to work with.

One problem, however, is that gill nets were apparently not used during the months of July and August. So we must fill in for missing data for these two months. Fortunately, for each month and each of the eight major bay systems along the coast, we typically have between 40 and 80 samples in each of the two years. Once we have computed *mean* "catch per unit effort" for each month and each bay, the time series for the April-November data is fairly smooth for the seven most usual species of game fish (red drum, black drum, spotted seatrout, croakers, sand seatrout, sheepshead, and founder). We have used quadratic approximations for the May-October range of the data to fill in abundance estimates for the two missing months.

Preliminary atheoretic logit models based upon the contingent valuation data suggest that among the top three recreational target species--red drum, spotted seatrout, and flounder--only variations in the number of red drum have a statistically significant effect upon the implied value of a recreational fishing day. Consequently, we elect to employ only the abundance of red drum as a control for resource quality in this study.

The means and standard deviations for both the full sample of 3366 and the subset of 3318 responses are given in Table 1. As can be seen, the subset is still representative of the larger sample.

4. Utility Parameter Estimates

To assess whether or not the preference function differs systematically with the level of gamefish abundance, we estimate two models. First, we re-estimate the "basic" joint model from the earlier paper using *just* the subset of 3318 observations. This specification constrains the β coefficients to be identical across all levels of gamefish abundance. Then we generalize the model by allowing each β to be a linear function of A, which involves the introduction of five new α parameters. Since the "basic" specification is a special case of the model incorporating heterogeneity, a likelihood ratio test is the appropriate measure of whether A "matters." Results for the two models are presented in Table 2. The LR test statistic is 8.18. The 5% critical value for a $\chi^2(5)$ distribution is 11.07, and 10% critical value is 9.24. Thus the LR test just fails to reject independence of the utility function from the abundance of gamefish. (However, if one were to generalize the utility function to include only the interaction term zA and its coefficient γ_1, and

Table 1

Descriptive Statistics for Full Sample and "Gamefish Abundance" Subset

Variable	Description	Full Sample (n = 3366)	Subset (n = 3318)
Y	median household income for respondent's 5-digit zip code (in $10,000) (1980 Census scaled to reflect 1987 income; factor=1.699)	3.1725 (0.6712)	3.2772 (0.6705)
M	current trip market expenditures, assumed to be average for all trips (in $10,000)	0.002915 (0.002573)	0.002927 (0.002576)
T	annual lump sum "tax" proposed in CV scenario (in $10,000)	0.05602 (0.04579)	0.05608 (0.04576)
q	reported total number of salt water fishing trips to sites in Texas over the last year	17.40 (16.12)	17.37 (16.14)
I	indicator variable indicating that respondent would choose to keep fishing, despite tax T	0.8066 (0.3950)	0.8071 (0.3946)
A	Resource Monitoring Program, catch per unit effort of red drum (gill nets) by month and by major bay system	-	0.1487 (0.06161)

Table 2

Parameter Estimates for "Basic"
and "Gamefish Abundance" (A) Models

Parameter	Basic Model (n = 3318)	Abundance Model (n = 3318)
β_1 (z)	3.192	5.039
	(7.968)	(6.266)
β_2 (q)	0.1191	0.1133
	(19.18)	(10.87)
β_3 ($z^2/2$)	-0.08953	-0.2622
	(-1.056)	(-1.322)
β_4 (zq)	0.002661	0.004570
	(1.967)	(1.164)
β_5 ($q^2/2$)	-0.006862	-0.006920
	(-22.16)	(10.31)
γ_1 (zA)	-	-12.85
		(-2.390)
γ_2 (qA)	-	0.03166
		(0.5281)
γ_3 ($z^2A/2$)	-	1.191
		(0.6256)
γ_4 (zqA)	-	-0.01112
		(-0.4287)
γ_5 ($q^2A/2$)	-	0.0004552
		(0.1137)
υ[a]	16.03	16.03
	(81.46)	(81.38)
ρ	0.2354	0.2343
	(9.187)	(9.033)
Log L	-15485.96	-15481.87[b]

[a] See Cameron (1988a) for discussion of the υ and ρ parameters.
[b] χ^2 test statistic is 8.18; at 10% level, $\chi^2(5) = 9.24$.

none of the other variables or γ coefficients, the incremental improvement in the fit of the model would be statistically significant. The 0.5 percent critical value of a $\chi^2(1)$ distribution is only 3.84.)

5. Implications of Fitted Parameter Estimates

In the earlier paper, several properties of the estimated models were recommended for attention. Here, the properties of the fitted utility function vary across levels of gamefish abundance, A. Consequently, we will examine the fitted utility function at the subsample mean of A (______) as well as at several other benchmark levels. It is entirely possible to compute values for several interesting quantities for each individual in the sample. Here, however, we will focus initially on the "mean" consumer.

Table 3 summarizes several properties of the fitted utility function for the several levels of gamefish abundance. As expected, changes in gamefish abundance substantially affect the value respondents place on access to this fishery. Value in this case is measured several ways. Compensating variation (CV) is the amount of additional income a respondent would require, if denied access to the resource, to make their utility level the same as that which could be achieved with the optimal level of access. Equivalent variation (EV) is the loss of income which would leave the respondent just as much worse off as would a denial of access. We also compute the equivalent variation for partial reductions in the level of access.

A visual depiction of the effect of gamefish abundance on the preferences of anglers (defined over fishing days and all other goods) is provided in Figure 1 for A = 0.1 and for A = 0.2. As anticipated, indifference curves for A = 0.2 have considerably greater curvature, implying that anglers are less willing to trade off fishing days for other goods when gamefish abundance is higher. In contrast, with lower abundance, the curvature is considerably less, implying that under these circumstances,

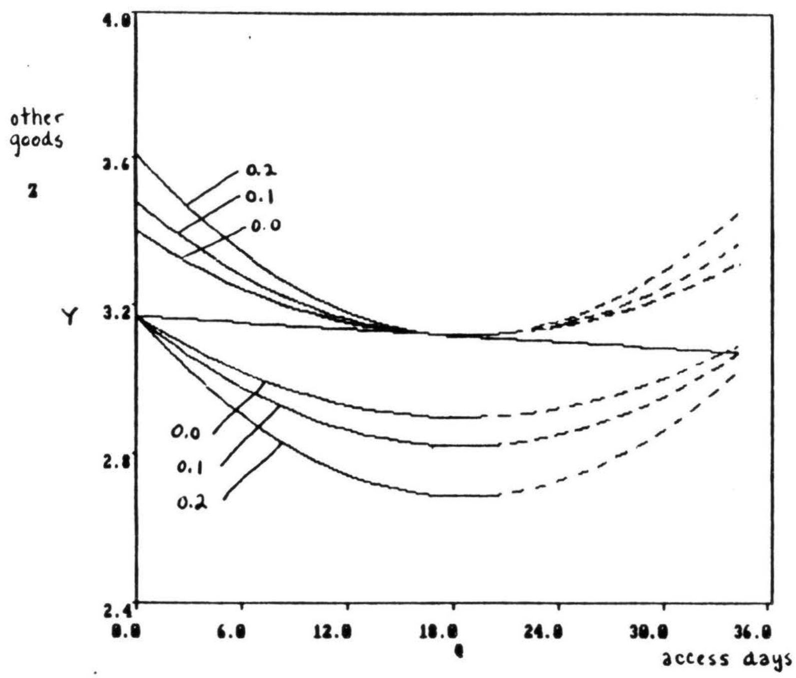

Figure 1 - Effects of changes in the abundance of the primary gamefish on preferences for fishing access days. Empirical indifference curves for mean consumer with abundance at 0.2, 0.1, and 0.0. (Actual mean - 0.149, standard deviation - 0.062, usable sample size n - 3318.)

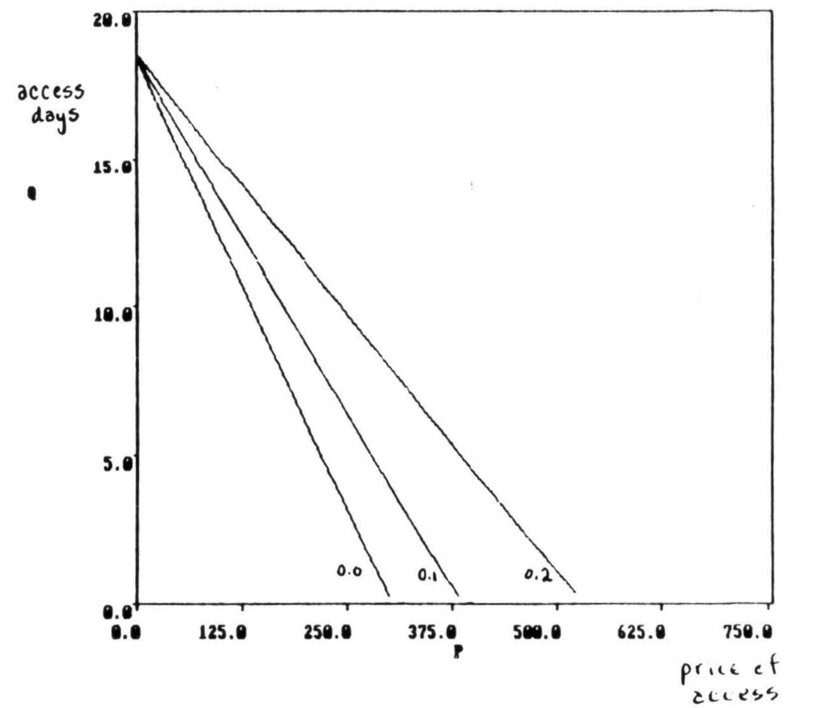

Figure 2 - Empirical inverse demand curves for fishing access days for mean consumer at primary gamefish abundance levels of 0.2, 0.1 and 0.0. (Actual mean - 0.149, standard deviation - 0.062, usable sample size n - 3318.)

anglers consider other goods to be relatively better substitutes for fishing days. For example, when A = 0.1, the same change in the relative price of a fishing day will lead to a larger decrease in the optimal number of days consumed than when A = 0.2.

In addition to the properties of the utility function and its corresponding Marshallian demand functions, we might be interested in calculating the derivatives of these Marshallian demand functions with respect to the level of the A variable. The Marshallian demand function for the model with heterogeneity is:

$$(2) \qquad q = [\ (\beta_2+\gamma_2 A) + (\beta_4+\gamma_4 A)Y - (\beta_1+\gamma_1 A)M - (\beta_3+\gamma_3 A)MY\ ] \ / \ [\ 2(\beta_4+\gamma_4 A)M - (\beta_3+\gamma_3 A)\ M^2 - (\beta_5+\gamma_5 A)\ ]$$

Figure 2 plots the inverses of these fitted Marshallian demand functions (with access days q on the vertical axis, and the price of access on the horizontal axis). These demand curves are drawn for an individual with mean income Y and mean travel costs M.

As A varies from 0.0 to 0.1 to 0.2 (compared to the actual mean value of 0.1487), these demand curves shift out further and further. Observe that, although the demand function can be highly non-linear in M, the fitted values of the parameters (for these data and in combination with the sample mean angler characteristics) happen to yield demand functions which are almost linear.

Notice that variations in A, in the fitted model, have rather dramatic effects upon the implied "choke price" (reservation price) for access to the resource: the greater the gamefish abundance, the higher the choke price. This can be interpreted as implying that with greater levels of preferred gamefish abundance, higher and higher prices for access would be willingly paid before individuals will cease entirely to go fishing.

Table 3 also gives the utility maximizing number of fishing days demanded, q, at the sample mean values of M and Y, as a function of the changing levels of gamefish abundance, A. Note that this optimal number of days is not very sensitive to A. This is a consequence of the fact that changes in A seem to have a substantial effect upon the curvature of indifference curves; they have less of an effect on their location.

The variation in the configuration of preferences, and the obvious shifts in the demand curves as a function of A imply that the social value of access to the fishery will depend upon the level of gamefish abundance at fishing sites. To illustrate this sensitivity, we can concentrate upon the equivalent variation for a complete loss of access to the resource, as a function of A, for a representative consumer with sample mean levels of Y and M. These variations can be detected by scanning across the columns in Table 3. Table 3 suggests that for a typical angler, improving gamefish abundance (red drum only) by a factor of 1.5 times its current level of A = .1487 would increase the annual value of access to the fishery by about 36% and improving abundance by 1.2 would increase access values by about 12%. In contrast, decreasing abundance to 0.8 of its current level would decrease the annual value of access by about 10%; decreasing abundance to 0.5 of its current level would decrease access values by 22%. If it is safe to extrapolate these estimates (based on functionally "local" variations in actual abundance levels) to a scenario where red drum are completely eliminated, the loss in access values would be about 37%. (Remaining value would derive from the catch of other species, and from the non-catch utility derived from fishing days.)

6. Discussion and Conclusions

As mentioned above, a full explanation of the empirical innovations embodied in the use of a joint contingent valuation/travel cost model for

Table 3

Properties of the Fitted Utility Function (for "Mean" Consumer)
(n = 3318; valid sample with available abundance data)

Property	at 1.5(mean A)	at 1.2(mean A)	at mean A	at 0.8(mean A)	at 0.5(mean A)	at A = 0
Utility Function Parameters:						
β_1*	2.173	2.746	3.129	3.511	4.084	5.039
β_2*	0.1204	0.1190	0.1180	0.1171	0.1157	0.1133
β_3*	0.03545	-0.04961	-0.08504	-0.1205	-0.1736	-0.2622
β_4*	0.002089	0.002586	0.002916	0.003247	0.003743	0.004570
β_5*	-0.006818	-0.006838	-0.006852	-0.006865	-0.006886	-0.006920
Function Maximum:						
z*	-528.08	57.40	37.93	29.98	24.16	19.73
q*	-144.18	39.10	33.37	31.23	29.93	29.40
Demand Elasticity wrt						
price	-0.05569	-0.06598	-0.07278	-0.07915	-0.08919	-0.1063
income	0.05568	0.07288	0.08428	0.09529	0.1121	0.1405
Optimal number of Access days (q)	17.65	17.45	17.31	17.17	16.97	16.62
Compensating Variation for Complete Loss of Access	$4873	$4046	$3620	$3266	$2835	$2299
Equivalent Variation for Complete Loss of Access	$4796	$3943	$3515	$3164	$2741	$2221
EV for Access Restricted to α of Current Fitted Level, for α =						
0.1	$3885	$3196	$2850	$2566	$2223	$1801
0.2	3069	2527	2254	2029	1758	1425
0.3	2350	1936	1727	1555	1348	1092
0.4	1726	1423	1270	1143	991	803
0.5	1199	988	882	795	689	558
0.6	767	633	565	509	441	357
0.7	431	356	318	286	248	201
0.8	192	158	141	127	110	89
0.9	48	40	35	32	28	22

valuing a recreational fishery is given in Cameron (1989). This paper represents a specific generalization of the model which allows the parameters of the direct quadratic utility function to vary systematically with the level of just one species of gamefish. We have selected the most popular gamefish species (red drum). A more elaborate model, of course, could let the utility parameters vary systematically with any number of characteristics of the resource, not just the abundance of a single species of gamefish.

Since we concentrate only upon red drum abundance, even the reduction to zero of red drum stocks (in the most extreme simulation described in the last section) will not lead everyone to cease fishing entirely. Other species of gamefish will remain. In this specification, variations across location and month in red drum abundance may be correlated with the abundance of other species. If this is the case, our red drum abundance measure will be capturing variations in the abundance of more than one species. Nevertheless, we do not capture the distinct effects of any seasonal or location variation in species abundance that is uncorrelated with red drum abundance.

The simulated variations in red drum abundance used as illustrations in this paper are by far the coarsest simulations that could be generated by a model such as this. We have concentrated solely on variations in abundance as they would affect a representative consumer with mean income and travel costs. However, since each individual's estimated preference function depends on the abundance of red drum during the month and in the bay system in which they are fishing, the model is perfectly able to simulate the impact upon the value of fishery access to individuals of forecasted changes in red drum abundance either by month or by geographical area. As the configurations of individuals' indifference curves change, so will their optimal number of fishing days and the equivalent variation associated with partial or complete loss of access.

The intent of this paper, therefore, is to illustrate the versatility of the constrained, jointly estimated contingent valuation/travel cost model for recreational fisheries valuation. It is satisfying to find thoroughly plausible changes in economic quantities as a consequence of exogenous variations in resource characteristics. This generalization of the "common utility function" model to a "systematically varying utility function" model should serve as a very useful prototype for subsequent research.

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Using the Basic "Auto-validation" Model to Assess the Effect of Environmental Quality on Texas Recreational Fishing Demand: Welfare Estimates

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ABSTRACT

In an extensive earlier paper (Cameron, 1988a) we developed a fully utility-theoretic model for the demand for recreational fishing access days, applied to a sample of 3366 Texas Gulf coast anglers. The model employs "contingent valuation" and "travel cost" data, jointly, in the process of calibrating a single utility function defined over fishing days versus all other goods and services. The theoretical specification (quadratic direct utility) and the econometric implementation will not be reproduced here. Instead, we focus specifically on the implications of an extension to this model. We employ a subset of 506 observations from the same survey for which respondents were asked to indicate their *ex post subjective* assessment of the environmental quality at the fishing site. We allow the parameters of the underlying utility function to vary systematically with the perceived level of environmental quality to assess the impact of environmental factors on the demand for access days. Treating the 10-point response scale for environmental quality (E) as a continuous variable, we find (among other results) that for the average angler improving E from one standard deviation below the mean to one standard deviation above increases the value of the fishery (measured by equivalent variation) by about $1400 (about 50%).

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Using the Basic "Auto-validation" Model to Assess the Effect of Environmental Quality on Texas Recreational Fishing Demand

1. Introduction

In Cameron (1988a), we derived and estimated the parameters of a quadratic utility function for a trimmed sample of Texas Gulf Coast recreational fishermen. The utility function, in its simplest form, is defined over fishing access days and all other goods and services (income). The novelty of that paper is primarily its utilization of a fully utility-theoretic framework for analyzing *both* "contingent valuation" (CV) data (respondents anticipated behavior under hypothetical scenarios) *and* "travel cost" data (respondents' actual behavior in the consumption of access days). The latter form of data gives us a feel for the consequences of small local variations in access prices; the former provides additional information, however hypothetical, regarding more drastic changes in the consumption environment.

The earlier paper develops the basic specification and goes on to consider several extensions to that basic model: discounting the influence of the CV data in the estimation process; estimation without travel cost data (only income and consumption); and the accommodation of heterogeneous preferences. In the last category, we demonstrated that it is straightforward to adapt these models to allow for systematic variation in the preference function according to geographical or sociodemographic factors.

In this paper, we will again employ heterogeneous utility functions, but we will only be able to exploit a subset of the data. We wish to concentrate upon the potential effects of respondents' perceptions about environmental quality on their demand (valuation) of access to the recreational fishery.

Readers are referred to Cameron (1988a) for a vital preface to this research. We avoid extensive duplication in this paper by presuming readers are familiar with the findings of the earlier paper.

2. Outline of the Specification

As before, we will adopt the quadratic family of utility functions, for the same variety of reasons explained in the earlier paper. We will let U denote direct utility, Y will be income, and F will be current fishing day expenditures ("travel costs", roughly). Also, q will be the number of fishing days consumed and z (= Y - Fq) will denote consumption of other goods and services. We will let E denote subjective environmental quality. The quadratic direct utility function will thus take the form:

$$U = \beta_1 z + \beta_2 q + \beta_3 z^2/2 + \beta_4 zq + \beta_5 q^2/2, \tag{1}$$

where the β_j are no longer constants, but will be allowed to vary linearly with the level of E: $\beta_j{*} = \beta_j + \gamma_j E$, $j=1,\ldots,5$.

3. Data

The data used for this model consist of a 506 observation subset of the 3366 observations used in the earlier paper. The data come from an in-person survey conducted by the Texas Department of Parks and Wildlife between May and November of 1987. The primary purpose of the survey is to count numbers and species of fish making up the recreational catch, but during this particular period, additional economic valuation questions were posed to respondents.

In particular, the contingent valuation question took the form: "If the total cost of all your saltwater fishing last year was ____ more, would you have quit fishing completely?" At the start of each day, interviewers randomly chose a starting value from the list $50, $100, $200, $400, $600,

\$800, \$1000, \$1500, \$5000, and \$20,000. In addition, respondents were queried regarding actual market expenditures during the current trip: "How much will you spend on this fishing trip from when you left home until you get home?" This is as close as we can get to a measure of "travel cost."

The same basic criteria for deleting particular observations are applied in this paper as are described in Cameron (1988a). The same caveats regarding the sample also apply in this case. The sample employed in this study is smaller only because the *ex post* subjective environmental quality questions were asked of only approximately one-eighth of the full sample. This question was just one of eight rotating questions on special issues.

The precise wording of the environmental quality question was "To what extent were you able to enjoy unpolluted natural surroundings [during this fishing trip]?" Responses were given on a Likert-type scale of 1 to 10, with 10 being highest. The means and standard deviations for both the full sample of 3366 and the subset of 506 responses are given in Table 1. As can be seen, the subset is fairly representative of the larger sample.

4. <u>Utility Parameter Estimates</u>

To assess whether or not the preference function differs systematically with the level of environmental quality, we estimate two models. First, we re-estimate the "basic" joint model from the earlier paper using *just* the subset of 506 observations. This specification constrains the β coefficients to be identical across all levels of environmental quality. Then we generalize the model by allowing each β to be a linear function of E, which involves the introduction of five new α parameters. Since the "basic" specification is a special case of the model incorporating heterogeneity, a likelihood ratio test is the appropriate measure of whether E "matters." Results for the two models are presented in Table 2. The LR test statistic is

Table 1

Descriptive Statistics for Full Sample and "Environmental" Subset

Variable	Description	Full Sample (n = 3366)	Subset (n = 506)
Y	median household income for respondent's 5-digit zip code (in $10,000) (1980 Census scaled to reflect 1987 income; factor=1.699)	3.1725 (0.9995)	3.1681 (1.0134)
F	current trip market expenditures, assumed to be average for all trips (in $10,000)	0.002915 (0.002573)	0.003255 (0.002767)
T	annual lump sum "tax" proposed in CV scenario (in $10,000)	0.05602 (0.04579)	0.05661 (0.04770)
q	reported total number of salt water fishing trips to sites in Texas over the last year	17.40 (16.12)	15.78 (15.32)
I	indicator variable indicating that respondent would choose to keep fishing, despite tax T	0.8066 (0.3950)	0.7905 (0.4073)
E	Likert-scale subjective ex post assessment of current environmental quality at site	-	8.073 (2.177)

Table 2

Parameter Estimates for "Basic" and "Environmental" Models

Parameter	Basic Model	Environmental Model
β_1 (z)	1.381 (1.080)	1.218 (0.6385)
β_2 (q)	0.1109 (6.635)	0.04825 (1.051)
β_3 ($z^2/2$)	0.6173 (1.526)	1.081 (1.106)
β_4 (zq)	0.008387 (1.990)	0.006219 (0.4773)
β_5 ($q^2/2$)	-0.008041 (-8.611)	-0.003755 (-1.383)
γ_1 (zE)	-	0.07805 (0.4148)
γ_2 (qE)	-	0.007991 (1.389)
γ_3 ($z^2E/2$)	-	-0.07346 (-0.6631)
γ_4 (zqE)	-	0.0003104 (0.1882)
γ_5 ($q^2E/2$)	-	-0.0005533 (-1.664)
υ[a]	15.13 (31.79)	15.15 (31.76)
ρ	0.2929 (4.631)	0.2975 (4.637)
Log L	**-2339.80**	**-2334.69**

[a] **See Cameron (1988a) for discussion of additional parameters.**

10.22. The 5% critical value for a $\chi^2(5)$ distribution is 11.07 and the 10% critical value is 9.24. Thus, the improvement in the log-likelihood just misses being statistically significant at the 5% level for this small sample. Nevertheless, this difference seems large enough to warrant pursuing the implications of the fitted model. In any case, we can be confident that the statistical significance would improve with larger samples.

5. Implications of Fitted Parameter Estimates

In the earlier paper, several properties of the estimated models were recommended for attention. Here, the properties of the fitted utility function vary across levels of environmental quality, E. Consequently, we will evaluate the function at the subsample mean of E (8.0731) as well as at the maximum value of E (10) and at a lower benchmark value (6), which represents approximately one standard deviation below the mean. It is entirely possible to compute values for several interesting quantities for each individual in the sample. Here, however, we will focus on the "mean" consumer. Note that we have elected to use the mean values for income and fishing day expenses computed for the entire sample of 3366, on the presumption that the means in this sample are more typical of the mean for the population as a whole. (This is arbitrary; the results will be similar for the "mean" consume in the smaller subset.)

Table 3 summarizes several properties of the fitted utility function for the three benchmark levels of environmental quality. As expected, decreases in environmental quality substantially affect the value respondents place on access to this fishery. Value in this case is measured several ways. Compensating variation is the amount of additional income a respondent would require, if denied access to the resource, to make their utility level the same as that which could be achieved with the optimal level of access.

Table 3

Properties of the Fitted Utility Function

Property	E = 10	E = 8.0731	E = 6
Utility Function Parameters:			
β_1*	1.998	1.848	1.686
β_2*	0.1282	0.1128	0.09619
β_3*	0.3467	0.4883	0.6406
β_4*	0.009324	0.008726	0.008082
β_5*	-0.009288	-0.008222	-0.007075
Function Saddle Point:			
z*	-5.973	-3.954	-2.764
q*	7.802	9.518	10.44
Demand Elasticity wrt			
price	-0.06034	-0.07351	-0.09211
income	0.1623	0.1610	0.1593
Compensating Variation for Complete Loss of Access	$3742	$2970	$2283
Equivalent Variation for Complete Loss of Access	$3741	$2997	$2314
EV for Access Restricted to α of Current Fitted Level, for α =			
0.1	$3018	$2418	$1867
0.2	2376	1903	1470
0.3	1814	1453	1122
0.4	1329	1064	823
0.5	921	737	570
0.6	588	471	364
0.7	330	265	205
0.8	147	117	91
0.9	37	29	23

Equivalent variation is the loss of income which would leave the respondent just as much worse off as would a denial of access. We also compute the equivalent variation for incomplete reductions in the level of access.

A visual depiction of the effect of environmental quality on the preferences of anglers (defined over fishing days and all other goods) is provided in Figure 1 for E = 10 (which can be considered "good" environmental quality) and for E = 6 ("relatively poor" environmental quality). As anticipated, indifference curves for E = 10 have considerably greater curvature, implying that anglers are less willing to trade off fishing days for other goods when the environmental quality is high. In contrast, with poorer environmental quality, the curvature is considerably less, implying that under these circumstances, anglers consider other goods to be relatively better substitutes for fishing days. For example, when E = 6, the same change in the relative price of a fishing day will lead to a larger decrease in the optimal number of days consumed than when E = 10.

In addition to the properties of the utility function and its corresponding Marshallian demand functions, we might be interested in calculating the derivatives of these Marshallian demand functions with respect to the level of the E variable. The Marshallian demand function for the model with heterogeneity is:

$$(2) \qquad q = \frac{[\, (\beta_2+\gamma_2 E) + (\beta_4+\gamma_4 E)Y - (\beta_1+\gamma_1 E)F - (\beta_3+\gamma_3 E)FY \,]}{[\, 2(\beta_4+\gamma_4 E)F - (\beta_3+\gamma_3 E)\, F^2 - (\beta_5+\gamma_5 E) \,]}$$

Table 4 gives the utility maximizing number of fishing days demanded at the sample mean values of F and Y, as a function of the subjective level of environmental quality, E. Locally, there are only very slight differences in these fitted demands as a consequence of environmental changes.

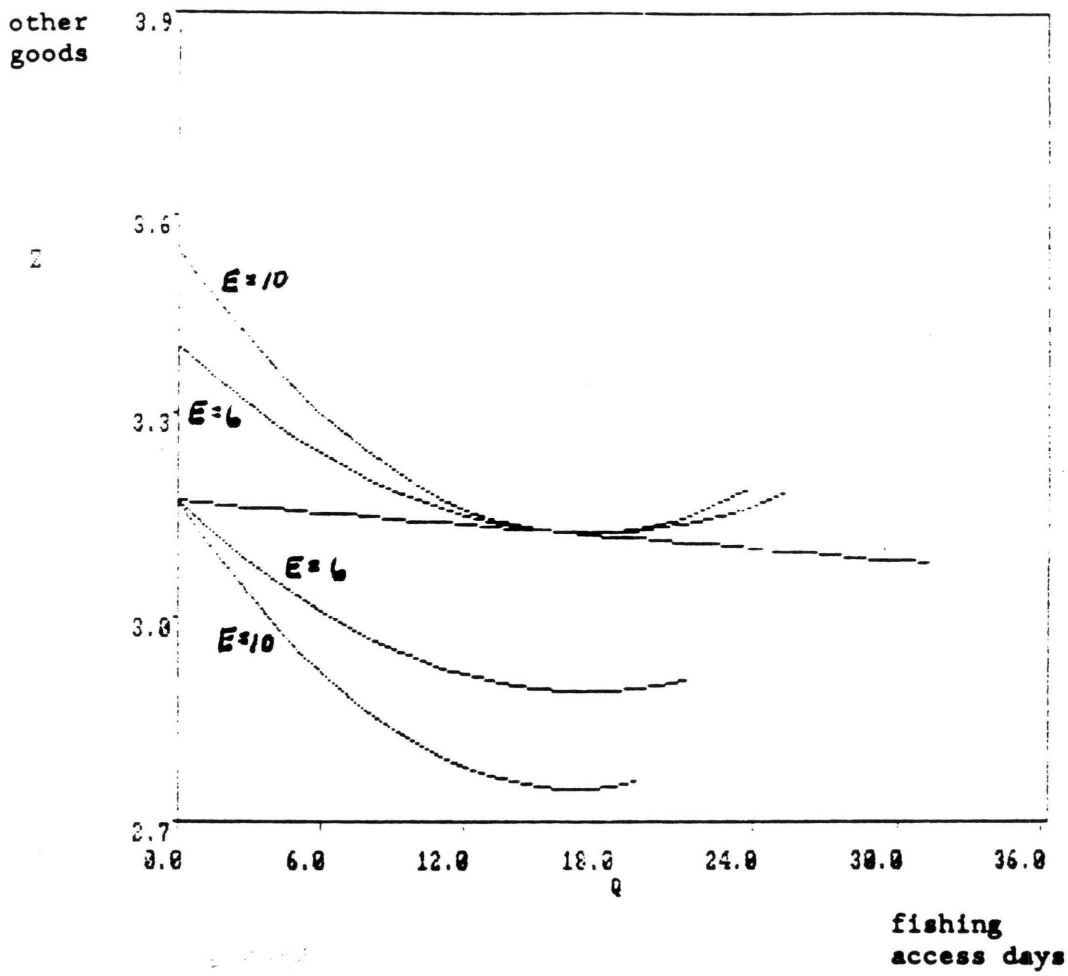

Figure 1. Fitted indifference curves for consumer with mean characteristics and E = 10; same for E = 6

Table 4

Optimal Demand, Derivatives and Elasticities
wrt Environmental Quality
(evaluated at mean Y and F, n = 3366)

E	q*	$\partial q/\partial E$	$(\partial q/\partial E)(E/q^*)$	EV for complete loss of access
1	14.72	0.2876	0.01953	$ 1046
2	14.97	0.2260	0.03018	1264
3	15.18	0.1822	0.03601	1499
4	15.34	0.1501	0.03912	1751
5	15.48	0.1257	0.04060	2022
6	15.60	0.1068	0.04110	2314
7	15.70	0.09193	0.04100	2630
8	15.78	0.07993	0.04052	2971
9	15.86	0.07014	0.03981	3340
10	15.92	0.06204	0.03896	3741

We may be especially interested in the derivative of this fitted demand function with respect to E. It will depend not only on F and Y, but also on the level of E itself:

$$(3)\ \partial q/\partial E = \{[2(\beta_4+\gamma_4E)F - (\beta_3+\gamma_3E)\ F^2 - (\beta_5+\gamma_5E)]\ [\gamma_2 + \gamma_4Y - \gamma_1F - \gamma_3FY] - [(\beta_2+\gamma_2E) + (\beta_4+\gamma_4E)Y - (\beta_1+\gamma_1E)F - (\beta_3+\gamma_3E)FY]\ [2\ \gamma_4F - \gamma_3F^2 - \gamma_5]\}\ /\ [\ 2(\beta_4+\gamma_4E)F - (\beta_3+\gamma_3E)\ F^2 - (\beta_5+\gamma_5E)\ ]^2.$$

This formula is untidy, but can be readily computed. Table 4 gives the values of this derivative as well as the corresponding elasticity, $(\partial q/\partial E)(E/q)$, for the full range of integer values of E which are possible in the data.

A visual display of the effects of changes in E upon the configuration of the fitted inverse demand curve for an individual with mean Y and F is presented in Figure 2. Observe that, although the demand function can be highly non-linear in F, the fitted values of the parameters (for these data and in combination with the sample mean angler characteristics) yield demand functions which are almost linear. Each fitted demand curve passes through the value of F and the corresponding particular fitted value of q* (for each E) for this representative consumer. Notice that variations in E, in the fitted model, have rather dramatic effects upon the implied choke price for access to the resource: the better the environmental quality, the higher the choke price.

The variation in the configuration of preferences, and the obvious shifts in the demand curves as a function of E imply that the social value of access to the fishery will depend upon the subjective level of environmental quality at fishing sites. To illustrate this sensitivity, we have computed the equivalent variation for a complete loss of access to the resource, as a function of E, for a representative consumer with sample mean levels of Y and

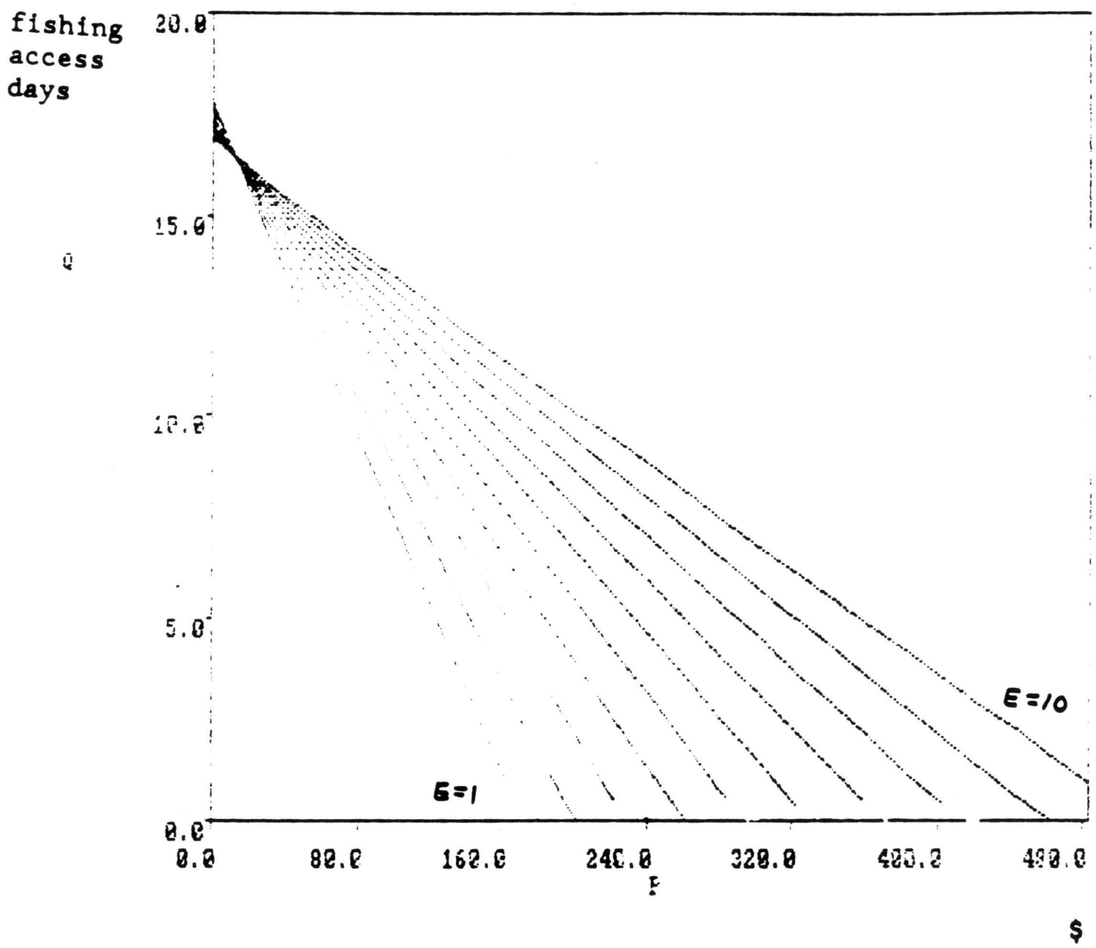

Figure 2. Effects of increasing subjective environmental quality on inverse demand curve for an angler with sample mean characteristics.

F. These equivalent variations are also given in Table 4. Bear in mind that the range of E from 6 to 10 accounts for approximately one standard deviation on either side of the mean value reported in the sample. The EV estimates in Table 4 suggest that for a typical angler, improving environmental quality from the "6" level to the "10" level would add approximately $1400 to the annual value of access to the fishery (an increase of over 50%).

This value must be considered in relation to the actual distribution of E values in the sample. Tables 5 and 6 give the details of these responses. Almost 40% of the sample is completely satisfied with current environmental quality. This suggests an alternative "simulation" based on the fitted model. Instead of simply considering the mean angler, it is also possible to simulate changes in E for each individual angler in the sample. Under current conditions, the equivalent variation for a complete loss of access varies over the sample from $648 to $4235, with a mean of $3037 and a standard deviation of $778. If we take every respondent who reported a subjective environmental quality level of *less* than 10 and increase their value of E by one unit, the distribution of these fitted equivalent variation values can be expected to change. In fact, the new fitted values vary from $839 to $4238, with a mean of $3253 and a standard deviation of $715. Thus the increase in the mean of the equivalent variations, when we improve by one unit the experiences of those who were less than completely satisfied experience currently, is approximately $216. If we could scale this up to the entire population, this represents an increase in the social value of the fishery of approximately 6.6%.

6. Subjective Environmental Qualities as a Function of Physical Measures

The subjective environmental quality question on the Texas Parks and Wildlife Survey elicits information about overall environmental quality. We

Table 5

Descriptive Statistics for E Variable

MOMENTS

N	506		
MEAN	8.07312	SUM	4085
STD DEV	2.17742	VARIANCE	4.74118
SKEWNESS	-1.216	KURTOSIS	0.897612

QUANTILES(DEF=4)

100% MAX	10	99%	10
75% Q3	10	95%	10
50% MED	9	90%	10
25% Q1	7	10%	5
0% MIN	1	5%	4
		1%	1

RANGE	9
Q3-Q1	3
MODE	10

Table 6

Frequency Distribution of E Values

```
                                                         FREQ  CUM.  PERCENT   CUM.
                                                               FREQ            PERCENT

1    ]*                                                     7     7     1.38     1.38
2    ]*                                                     7    14     1.38     2.77
3    ]**                                                   10    24     1.98     4.74
4    ]**                                                   11    35     2.17     6.92
5    ]*********                                            46    81     9.09    16.01
6    ]*****                                                25   106     4.94    20.95
7    ]********                                             41   147     8.10    29.05
8    ]*******************                                  93   240    18.38    47.43
9    ]****************                                     81   321    16.01    63.44
10   ]*************************************               185   506    36.56   100.00
     ----+---+---+---+---+---+---+---+---+-
        20  40  60  80  100 120 140 160 180

                FREQUENCY
```

do not presently have access to typical or specific air quality measurements for different areas along the Texas Gulf Coast, but in the course of related research (Cameron, 1988b), we have attempted to determine how a variety of water quality measures are related to respondents' subjective assessments of environmental quality.

From a variety of auxiliary sources reported in Cameron (1988b), including the Texas Department of Water Resources, and the Resource Monitoring division of Texas Parks and Wildlife, we have obtained data on the characteristics of tens of thousands of water samples over the few years up to and including the time period of the valuation survey. Most of the water quality "parameters" have been averaged by month and by each of the eight major bay systems along the Texas Gulf Coast. A few are available only by bay system. (See the original document for details.)

Table 7 reproduces the results for E regressed on a variety of water quality parameters in an *ad hoc* specification. Not surprisingly, the relationship between the subjective environmental quality measure and "typical" water quality is quite weak. For this reason, we do not devote space in this paper to a discussion of the explanatory variables. The reader is referred to Cameron (1988b) for this information. Certainly, many more physical factors will affect perceptions than simply the few for which we have measurements. Attributes of the respondent can also be expected to have some impact upon the subjective assessments of environmental quality. Other regressions reported in the appendices of Cameron (1988b) examine the influence of socioeconomic variables on these responses. They also establish the presence of some seasonal and geographical variation.

Table 7

OLS Regression of "Ability to Enjoy Unpolluted Natural Surroundings: on Measured Water Quality Variables

F-TEST	4.247
OBS	695

VARIABLE	PARAMETER ESTIMATE	STANDARD ERROR	T FOR H0: PARAMETER=0
INTERCEP	8.334	1.860	4.481
MTURB	0.001600	0.01016	0.158
MSAL	0.01851	0.01795	1.031
MDO	-0.2415	0.1387	-1.742
TRANSP	0.02034	0.01311	1.551
DISO	0.2204	0.1077	2.047
RESU	0.005304	0.006889	0.770
NH4	6.053	3.659	1.654
NITR	-2.236	1.155	-1.936
PHOS	2.357	1.700	1.386
CHLORA	-0.002728	0.02576	-0.106
LOSSIGN	-0.009637	0.02440	-0.395
OILGRS	-0.003734	0.001145	-3.261
CHROMB	0.02663	0.02361	1.128

8. Conclusions

Clearly, there is good evidence that angler's value of the fishing experience is affected by their subjective assessment of environmental quality. For this *small* sample from the Texas survey, allowing for heterogeneous preferences which vary with environmental quality makes a statistically significant improvement in the econometric model at almost the 5% level. Despite the fact that we have lumped all other goods in the consumption bundle into a single composite, the fundamental regularity conditions for a utility-theoretic model are satisfied. Of course, all of the caveats mentioned in Cameron (1988a) and Cameron (1988b) also apply to this analysis, so the results must be interpreted with some caution.

Unambiguously, if anglers' *perceptions* of environmental quality can be improved, our model indicates that the social value of the resource will be increased (and vice versa, of course). What is clear, however, is that a better link must be forged between perceptions and actual physical quantities of pollutants (both air and water). We need to know just what it takes to raise someone's response from an 8 to a 9 on this type of Likert-scale question. This will require cooperation between physical and social scientists.

REFERENCES

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