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The Determinants of Value for a Marine Estuarine Sportfishery: The Effects of Water Quality in Texas Bays

by

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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 $\kappa = b\sqrt{3}/\pi$, 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 $b = \pi/\sqrt{3}$. 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":

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

so that

[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

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[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:

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

The augmented vectors of variables, x* and coefficients, $\gamma*$, may be treated as one would treat the explanatory variables and coefficients in an ordinary logit estimation. From $\gamma*$, it is possible to compute point estimates of the desired parameters β and κ. If we distinguish the elements of $\gamma*$ 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. Data

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. Specifications

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:

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

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

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

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 α_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 α^* 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 α_2^* and the other α_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:

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

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

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

Since the individual parameters α_1*, α_2*, and α_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, α_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.

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

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

The gradient vector for this model is then given by:

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

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

The elements of the Hessian matrix are:

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

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

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

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

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

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

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

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]

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[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. Texas Department of Water Resources Water Quality Data

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. <u>Texas Water Development Board Water Quality Data</u>

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. Health Department Data

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. Census Data (1980) for Texas, by 5-Digit Zip Code

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 H0: 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 H0: 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