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A Structural Equations Approach to Modeling Consumptive Recreation Demand

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In this analysis we develop a two equation structural model of a count travel cost model of recreational angling demand and angling success. By modeling the two equations jointly we avoid the difficulties associated with the usual approach which estimates the demand for recreational fishing sites *assuming* the existence of an exogenous measure of fishing quality. Our analysis explicitly develops the joint log likelihood function that combines the two processes. We estimate our model using full information maximum likelihood methods.

1. INTRODUCTION

The demand for recreational trips has been estimated in a variety of ways, with many approaches being variations on the basic cost model used by economists since the 1960s. Ever since Stevens [29] recreation demand models have incorporated site characteristics. Studies of hunting typically include harvest, and other measures of site quality (see Creel and Loomis [8]). In the fishing literature commonly used fishing site characteristics include some measure of catch, the fishing site's size, water depth, or various measures of water quality which can influence the fishing experience [9, 25]. Though our approach could be used to model demand for a variety of consumptive recreational activities, we focus on recreational fishing demand and the role of catch.

An ideal measure would be an individual specific, exogenous catch measure that ranks sites by fishing quality. What is important is a measure of fishing quality that is relevant to each individual angler. Following the previous literature [6, 10, 9, 25, among others] anglers are assumed to prefer to catch more fish rather than less fish. Consequently, some estimate of expected catch enters the consumer's demand function as an explanatory variable. The estimate is usually based on the angler's self-reported catch and calculated as the average catch or catch per unit effort (CPUE) for all the anglers who visited a fishing site. Averaging over all anglers at a site is presumed to produce an exogenous estimate of catch per unit effort. In a second approach Carson *et al*. [6] used the individual's catch rate from the previous

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year. There are, however, at least two problems associated with using these catch measures in the demand function for fishing.

First, using average catch as an explanatory variable misses the important role that biological site characteristics play in determining fishing success. By using the usual catch measure, efforts to link changes in catch and the alteration of biological conditions to environmental deterioration or improvement are problematic. Simulating changes in the value of the fishing experience without well specified biological linkages will be ad hoc. For example, some policy analyses are focused on a ‘‘doubling of catch rate’’ (e.g., [26]). A legitimate question is what sort of biological improvement, if any, would double catch rates? These issues are especially important in policy and legal contexts. Natural resource damage assessments (NRDA), for example, generally require that the physical effects models be linked closely to economic models. See Morey *et al*. (1995).

A second issue associated with the traditional approach is the role of CPUE as an independent variable in the demand function. The maintained assumption that CPUE is exogenous to an individual angler may be implausible unless many independent observations of catch and effort are observed for each lake. If these conditions are not met, catch and trip demand are determined jointly, resulting in a system of equations. Parameters estimated using observed or reported catch as an independent variable in the demand function will be biased if the CPUE measure is endogenous.

Our approach to addressing these issues is to develop a structural model of recreational fishing demand. Our model consists of two equations: a traditional pooled site demand model and a production function for the number of fish caught by the individual. The two equations are linked because the predicted catch from the latter is a determinant of recreational fishing demand. We model total trips demanded during the fishing season using the Poisson distribution.

In the following section we develop a count travel cost and a total catch function relating the number of fish caught to biological conditions, angler skill, and angling capital. These two functions are then integrated into a single structural system that includes a joint total catch function and count data recreation demand model. The structural model is applied to anglers who visit lakes in the northeastern United States. In the fourth section we present the results of our jointly estimated two equation structural model. Our method results in consistent coefficient estimates and allows the influence of changes in factors affecting total catch to be linked to fishing demand.

2. A JOINT STRUCTURAL MODEL OF TRIP DEMAND AND FISH CATCH

2.1. *A Model of Recreational Angling Trip Demand*

As Hellerstein and Mendelsohn [17] have shown, count models can be thought of as the aggregated result of repeated discrete choice random utility models. In this analysis we focus on the short run model of seasonal trip demand for fishing at a site. Because this is a short run analysis, we do not deal with long run equilibrium in such areas as angling skill, changing information about site qualities or congestion.[1] To begin, the individual's seasonal trip demand for fishing at site j is modeled as

$$Q_j = f(P_j), \tag{1}$$

where Q_j is the number of angling trips per season taken by the individual to site j and P_j is the travel cost to and from site j. The number of trips (Q_j) taken by anglers in our sample are all nonnegative integers, and all of the individuals in our sample take at least one trip. We apply the truncated Poisson to account for the positive integers and truncated attributes of our data [14, 7, 8, 16, 11]. We pool the data across sites and individuals, so that the actual trip demand equation is estimated using a truncated Poisson model with a log likelihood given in

$$\text{Log likelihood} = -\lambda_i + Q_i \mathbf{X}_i \beta - \ln(Q_i!) - \ln(1 - e^{-\lambda_i}), \tag{2}$$

where the $\mathbf{X}$ vector contains characteristics of the individuals and sites in the sample and $\lambda_i = e^{\mathbf{X}_i \beta}$. One of the site characteristics indicates fishing quality, measured by the expected number of fish caught be an individual angler at the site.

Several measures of fishing quality have been used in demand studies, including the angler's self-reported catch, the angler's CPUE, the average catch (AC) for some sample of anglers, or similarly, the average CPUE. Nearly all existing models of fishing demand assume that the site-specific total catch is exogenous to the angler in the trip demand function. Exogeniety is thought to be preserved by some averaging process. The AC and the CPUE for the sample of anglers who visit one or more fishing sites can be calculated for specific "target" species of fish (e.g., salmon is the focus in Shaw [26]), for anglers of differing abilities [26], or for anglers doing specific types of fishing. The finer the degree of disaggregation, however, the more likely it becomes that AC will end up being determined by only a very small number of anglers, making AC a suspect measure. If the catch measure used as an explanatory variable in the trip demand function is not exogenous to the individual, the estimated coefficients will be inconsistent. These issues also arise in one guise or another when the demand for any consumptive recreational activity is modeled. For example, Creel and Loomis [7] model deer hunting demand using hunters' actual harvest. In this paper we proceed quite differently from previous efforts by modeling total catch as an output that is a function of inputs.

2.2. *The Total Catch Function*

Total catch is produced by an individual using a combination of resources, capital, and labor. To produce a fish an angler must have access to a stock of fish and other site resources. Anglers can use boats, different types of fishing gear, and human capital (skill and experience), as well as effort. This general approach is not new. As part of the research conducted for the National Acid Precipitation Assessment Program (NAPAP), investigators attempted to link acidification and the demand for freshwater recreational fishing via a stock/harvest model which

[1] Nevertheless, in out econometric application variables such as skill, trip length, and boat ownership are potentially important because we will pool individuals. Which variables to include is a specification issue that must be determined in each study.

first calculates the CPUE for many different lakes for the analysis [10]. Karou *et al.* [19] model the *activity* of fishing, usually measured by an hour or a "day" of fishing, as the output the angler produces. In contrast to their approach, we let catch be the output.

Our catch function generally follows the commercial fisheries literature (for example, see Campbell [5]). We include physical and human capital, effort, and biological measures of the health of fishery stocks. Physical capital includes the services of a boat, the access to the site, and the gear used to catch a certain species of fish. Angling skill is a form of human capital. Finally, total catch will be affected by the hours of effort spent fishing. It is assumed that the longer one fishes, the larger the catch. An empirical question is whether diminishing marginal productivity holds as hours spent fishing increase.

In the commercial fisheries' literature, stock is typically included as an explanatory variable. No matter how productive the angler, he will not catch a fish at a site that does not have any fish. Unfortunately, measures of the stocks of recreational fish are rarely available. Given the sheer number of lakes visited by recreational anglers it is simply too costly to estimate the stocks in individual lakes except in unusual situations such as well-funded NRDAs that involve fish injuries. As a result, a reduced form that describes the biological productivity of the lake, such as lake chemistry and other water quality indicators can be used to describe the biological productivity of a lake.

This approach is appealing for two reasons. One is that environmental regulations normally prescribe a certain minimum water quality standard. By including the specific water quality indicators that are being regulated it is simple to simulate the effect of improving specific lakes on total catch. The second attraction is that these data are relatively inexpensive to collect. As a result, water quality data in controversial areas are relatively abundant.

A functional form must be proposed for the production function, including the probability distribution underlying the number of fish caught. Given that fish caught will, like recreation trips, be nonnegative integers, we again adopt the Poisson model. McConnell *et al.* [22] applied a Poisson distribution of fish catch as part of a two-step process that incorporates fish catch into a random utility model. Kaoru *et al.* [19] also model catch using a Poisson, but recognize the potential for problems in the endogeneity between time spent fishing and total catch and thus replace the effort (hours spent fishing with an instrumental variable.

An important phenomenon that remains to be modeled is the common observation that many anglers do not catch fish. We model this observation using a double hurdle version of the Poisson distribution (see Johnson *et al.* [18] and Shonkwiler and Shaw [27]). The double hurdle approach captures the possibility that some of the zeros, no fish caught, are not generated by the Poisson process but rather by an unrelated process. Some authors refer to this as the zero inflated Poisson (ZIP) or zero altered Poisson (ZAP) (see Green [13]). Following this literature the log likelihood for our catch function may be written

$$\begin{aligned}\text{Log likelihood} = {} & \delta\left[\ln\left(\omega + (1-\omega)e^{-\theta_i}\right)\right] \\ & + (1-\delta)\left[\ln(1-\omega) - \theta_i + \mathrm{TC}_i(\mathbf{Z}_i\alpha) - \ln(\mathrm{TC}!)\right], \quad (3)\end{aligned}$$

where $\Theta_i = e^{\mathbf{Z}_i\alpha}$, TC is the total annual catch, ω is the probability that the angler does not get over the hurdle (i.e., does not catch a fish), the vector $\mathbf{Z}$ includes characteristics of the individual and the fishing sites, and $\delta = 0$ if the angler caught at least one fish, otherwise $\delta = 1$.

2.3. *A Joint Empirical Model of Fish Catch and Fishing Demand*

Consistent estimators require joint estimation of the two Poisson functions because we model the angler's demand for a trip as a function of the individual angler's expected catch at the site. Assuming independence of the two Poisson processes, the combined two-part log likelihood function includes the log likelihood function for the catch function and the log likelihood for the trip demand function, where the latter stems from the probability mass function for the truncated Poisson and uses the parameterized model for expected catch in the demand specification. This can be written as

$$\begin{aligned}\text{Log likelihood} = {} & \delta_i\left[\ln\left(\omega + (1-\omega)e^{-\theta_i}\right]\right. \\ & +(1-\delta_i)\left[\left(\ln(1-\omega) - \theta_i + \mathrm{TC}_i(Z_i\alpha) - \ln(\mathrm{TC}_i!)\right]\right. \\ & - \lambda_i + Q_i\left[(X_i \mid E[\mathrm{TC}_i])\beta\right] \\ & - \ln(Q_i!) - \ln(1-e^{-\lambda_i}), \end{aligned} \tag{4}$$

where $(X_i \mid E[\mathrm{TC}_i])$ explicitly shows that the vector of variables in the trip demand function includes the predicted total catch as one of the variables, β is the vector of parameters, and $\lambda_i = e^{X_i \mid E[\mathrm{TC}_i]}$. The standard Poisson log likelihood is found by setting ω to zero. We estimate these combined log likelihood functions using full information maximum likelihood (FIML).

FIML methods provide the most efficient method of estimating this joint model. Unlike two stage or sequential estimation methods all the information inherent in the data is used in the estimation process. FIML is especially important in our context because the linkage between the catch and trips functions is highly nonlinear. An additional benefit is that by estimating our model using FIML methods the corrections to the variance−covariance matrix suggested by Murphy and Topol [24] are not needed. This correction is necessary if a two-step estimator such as the one applied by McConnell *et al.* [22] is used.[2]

3. DATA

The data we use in the application come from items in two overlapping data sets. The first is from the NAPAP Freshwater Recreational User survey of anglers. This was a stratified general population random digit telephone survey of residents of New York (excluding New York City proper), New Hampshire, Vermont, and Maine during 1989. A total of 5724 households were contacted, from whom 1144 anglers were recruited into the study. Information on all angling trips by these

[2] An issue we do not explore is whether the two processes have correlated error structures. Unfortunately, addressing the possibility of correlated Poisson distributions requires the use of the Holgate bivariate Poisson distribution which assumes positive correlation between the two Poisson processes. If the two processes are positively correlated the estimates provided by the Holgate bivariate Poisson will be more efficient than those provided by our procedure [20]. If, however, the two processes are negatively correlated the resulting model will be misspecified. We use the uncorrelated version of the model to avoid the possibility of misspecification.

anglers was obtained through mid-summer and early fall telephone interviews. The survey gathered information on trips to lakes as well as angler specific information including distance, income, skill levels, and reported catch. We calculated travel costs using one-third the angler's implied wage rate (income divided by 2080) to value the travel time and valued distance at $0.25 per mile.

The other data set comes from the Eastern Lake Survey (ELS) and provides information on water chemistry for a random sample of lakes. The portion of the ELS used in this analysis was the random sample of 763 lakes larger than 4 hectares in the upper northeastern United States. We match these data with lakes visited by the anglers who responded to the NAPAP survey (see Englin *et al.* [10] or Englin and Lambert [9] for further details) on a lake by lake basis. Our final sample includes 120 anglers who visited 61 lakes. The anglers in the sample report their catch by trout species and our measure of total catch (TC) is an aggregation of the individual trout species.

Parsons and Needleman [25] suggest that dissolved oxygen concentrations influence freshwater fish stocks. Several field studies show that freshwater fish occur in greater abundance in waters with dissolved oxygen concentrations of 5 mg/liter or more (see citations in Spoor [28]). Controlled experiments show that higher, nontoxic levels of dissolved oxygen provide lower stresses to fish populations, depending on acclimation [4], and support the thresholds developed in field studies [28]. In our sample of lakes, dissolved oxygen ranges from 0.88 to 11.94 mg/liter, with a mean of about 3.4 mg/liter. It appears that many lakes in our sample are at the low end (38 lakes have dissolved oxygen less than 5.0 and 7 lakes have dissolved oxygen less than 2.0). Variability in dissolved oxygen may thus be an important factor in determining expected catch and, consequently, trip demand.

Similarly, changes in water clarity, or turbidity, might indicate changes in trout species' habitat. While the direction of influence of turbidity varies across different fish species, trout are predators and depend on their eyesight to locate prey. Clearer water is an advantage for trout. Alabaster and Lloyd [1] suggest that waters containing 25–80 g/m^3 suspended solids, or turbidity of 30–40 NTU, should maintain good or moderate fishing quality, which, ceteris paribus, is expected to yield a lower quality than clearer waters. Reduced water clarity, perhaps due to elevated suspended solids, can be associated with a reduction in submerged macrophytes (which provide food and cover), but can also reduce the risk of avian predation [15]. Our sample of lakes have turbidity (suspended solids) ranging from 0.1 to a maximum of 5.5 NTU (the mean is only about 0.6), which indicates quite clear water across the sample. Turbidity is used in our model below and is expected to influence total fish catch in the catch production model.

4. EMPIRICAL RESULTS

4.1. *Econometric Results*

Table I provides estimates of the parameters of two models. These include the double hurdle Poisson catch and standard Poisson catch with the associated Poisson travel cost function. The parameters in both models are relatively precisely estimated. The travel cost parameter in both is significantly different from zero at the 1% level. Younger anglers tend to make more fishing trips than older anglers

TABLE I
FIML Catch and Trip Demand Function Parameter Estimates[a]

Variables	Joint estimates of standard Poisson equations: Demand function	Joint estimates of standard Poisson equations: Catch function	Joint estimates of double hurdle Poisson equations: Demand function	Joint estimates of double hurdle Poisson equations: Catch function
Demand Intercept	1.723*** (0.161)		1.669*** (0.161)	
Travel cost (dollars)	−0.021*** (0.003)		−0.021*** (0.003)	
Whether a boat ramp is present	0.487*** (0.114)		0.490*** (0.116)	
Angler's age (years)	−0.009*** (0.003)		−0.009*** (0.003)	
Predicted catch (TC) (No. of fish)	0.081*** (0.023)		0.138 (0.094)	
Catch Intercept		−1.431*** (0.309)		−0.087 (0.436)
Effort (hours spent angling)		−0.058*** (0.016)		−0.036 (0.025)
Effort squared (hours spent angling squared)		0.0009*** (0.0001)		0.0006*** (0.0002)
Whether the angler uses a boat		1.195*** (0.217)		1.052*** (0.291)
Whether the angler has advanced skills		0.787*** (0.168)		0.147 (0.200)
Turbidity (NTU)		−1.733*** (0.264)		−1.382*** (0.338)
Dissolved oxygen (mg/liter)		0.421*** (0.036)		0.341*** (0.056
Hurdle				0.648*** (0.054)
Log likelihood	−663.376		−599.944	

[a]Standard errors are in parentheses.
*Significant at the 10% level or beyond.
**Significant at the 5% level or beyond.
***Significant at the 1% level or beyond.

in the sample investigated here. Anglers take more trips to lakes with boat ramps. This likely reflects the positive influence of fishing from a boat on the success of the fishing trip. The magnitudes of the coefficients of the trip demand functions are not greatly different between the standard and double hurdle specifications of the total catch function. The demand models exhibit a positive relationship between predicted total catch and the number of trips taken for both the double hurdle and standard Poisson specifications.

The lake water quality variables selected have a significant effect on fishing catch. For trout lakes, high turbidity decreases the predicted quantity of fish caught by our sample of anglers. This is consistent with our focus on trout which are visual predators. Less clear water makes it more difficult for them to feed. As expected, higher concentrations of dissolved oxygen increase the number of trout caught. Our finding is consistent with biologists' predictions for trout as well. It should be noted that there may be intraseasonal angling success variables that are not captured with our annual catch data. This may be an important issue in other studies.

4.2. *Welfare Estimates*

The semilogarithmic specification of the functional form leads to a rather simple form for the consumer's surplus (CS) measure. The usual integral under the demand function leads to a formula for Marshallian CS per trip of $-1/\beta_{\mathrm{TC}}$, or 1 divided by the parameter on the travel cost variable in the model. In either of our model specifications, the travel cost parameter is -0.021, yielding a consumer surplus estimate of about $47 per trip. This is somewhat lower than the reported estimates of Englin and Lambert [9], who use similar data but with a single equation demand model as a function of various "exogenous" measures of fishing quality. The difference is likely to be the result of the different modeling approaches used in the two papers. While our welfare estimate compares favorably with other estimates of the value of a fishing trip in the literature on the value of recreational fishing [30], Kling [21] has shown that these estimates may be biased upward since the model does not explicitly account for cross-site substitution. Following Englin and Shonkwiler [12] we can calculate the standard error of our welfare estimate using a second order Taylor series approximation. We find that the standard error of our per trip welfare estimate is $6.94.[3]

Consumer's surplus for the entire season (TCS over all trips) is given by

$$\mathrm{TCS} = \frac{\hat{Q}\,(\text{catch}, \text{boat}, \cdots)}{B_{\mathrm{tc}}}. \tag{5}$$

For our sample, the TCS for the average angler is approximately $210. This estimate reflects both the per-trip CS and the small average number of trips taken by the sample to a given lake. It is important to note two things. One is that since the model is estimated using pooled data the consumer surplus estimates are for a representative site. Second, the TCS *does* depend on predicted Q, which in turn depends on the catch variable in the model. It is through the change in predicted catch to change in total trips feedback loop that annual consumer surplus is affected in our model. Therefore, while per trip CS does not change when catch changes, we derive the TCS measure for a change in two of the environmental variables which determine catch, turbidity and dissolved oxygen.

We note that TCS is not very responsive to changes in turbidity because the latter has a small influence on the total number of trips. This is not surprising for the lakes in our sample, as it would take turbidity levels 6 to 8 times higher in NTU than our lakes exhibit before fishing quality might begin to be affected. Even a 50% increase in turbidity only reduces TCS by about $8 per season for the average angler in the sampler.

[3] As a basis for comparison we estimated the models sequentially. When we do this we find that the standard Poisson model provides a per trip welfare estimate of $48 per trip while the double hurdle model provides an estimate of $50 per trip. The catch parameter in the sequentially estimated Poisson model is 0.049 and is significant at conventional levels. This is smaller than the FIML estimates but of the same order of magnitude. In the sequential double hurdle model the catch parameter is insignificantly different from zero.

We also simulate an increase in dissolved oxygen for the lakes with dissolved oxygen at less than 5.0 mg/liter. We increase each lake's dissolved oxygen to a minimum dissolved oxygen level of 5.0 mg/liter. Increasing the poorest lakes to a minimum dissolved oxygen level of 5.0 mg/liter increases average catch from 1.04 fish to 1.79 fish. As a result anglers increase their total trips per angler from 4.44 to 5.06 trips on average. This in turn leads to an increase of about $29 per season in consumer's surplus averaging across all anglers.

Of course a variety of regulations could be simulated. In the context of a cost−benefit analysis of a new regulation it would be desirable to tighten the regulation until the benefits equaled the costs. We show the results of simulating ever increasing dissolved oxygen requirements in Fig. 1. The vertical axis shows consumer surplus per season. The horizontal axis shows the minimum acceptable level of dissolved oxygen. Increasing the minimum level of dissolved oxygen increases the annual consumer surplus from the existing conditions, $210 per season to nearly $275 per season if the worst lake in the sample had a dissolved oxygen content of 6 mg/liter.

The increase in welfare is driven by two factors. First, increasing the dissolved oxygen increases fish catch, which increases total trips thereby increasing annual consumer surplus. Second, increasing the minimum level of dissolved oxygen increases the quality in more and more lakes as the minimum approaches 6 mg/liter. Of course, one could simulate other water quality regulations as well.

5. SUMMARY AND CONCLUSIONS

An angler's utility is typically derived from catching fish, and is not generally assumed to derive from water chemistry characteristics. The usual approach to incorporating a catch measure in the demand function for recreational fishing just uses an arithmetic average catch and does not allow examination of the linkage between environmental or biological characteristics and fishing demand. In this paper a joint structural model has been used to allow consideration of environmen-

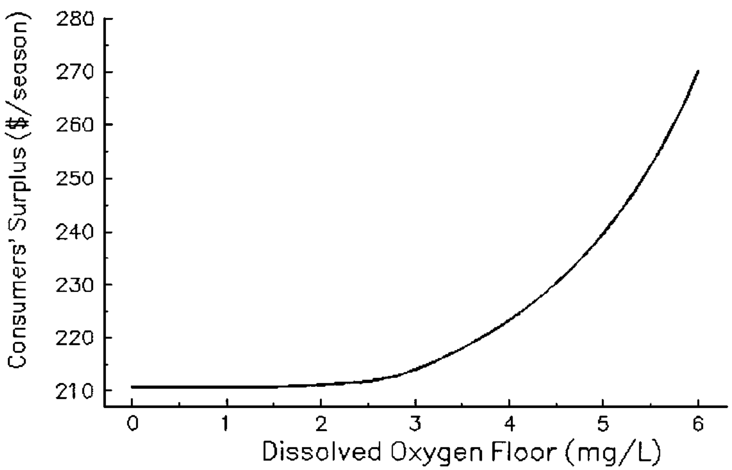

FIG. 1. Annual consumer surplus resulting from increasing minimum levels of dissolved oxygen.

tal and biological factors in an angler's demand for a fishing trip. Two measures of water quality serving as proxies for fish stocks were found to be important determinants of fish catch/fishing demand.

Welfare measures for a sample of anglers who fish at selected lakes in the northeastern United States are calculated for changes in our two measures. Increases in dissolved oxygen lead to a significant increase in total seasonal consumer's surplus (TCS), while increases in turbidity lead to only a slight decrease in TCS. These changes can be highly dependent on other water characteristics and we caution against inferring a general relationship between the two characteristics and fish catch. Given the form of our demand model, the effects of the environmental changes might be more pronounced for a sample of more avid anglers than we consider here.

Our method of analysis can be used for any recreational activity where a measure of harvest is a determinant of trip demand. While we have carefully examined recreational angling, hunting is another natural application. For waterfowl and small game hunting the analysis we have provided here could be applied directly. If one is considering big game hunting where the bag limit is one animal, a probit equation predicting success would be used instead of our Poisson catch equation. Another application would be to bird watchers. Bird watchers count birds by species, a form of consumption. In this case an equation that predicted numbers of species of birds seen by the birder could be employed. There are, no doubt, many other applications that would prove fruitful as well.

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