DISCRETE CHOICE ANALYSIS OF OKLAHOMA FISHING LICENSE HOLDERS, FISHING TRIP DEMAND MODEL FOR EASTERN OKLAHOMA NATURAL STREAMS, AND FISHING TRIP DEMAND MODEL FOR FRESH WATER BODIES IN OKLAHOMA

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Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
May, 1999

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PREFACE

Most public outdoor recreational goods (provided through lakes, rivers, parks, etc) are not priced in the market place. This makes measurement of value a difficult task. They are frequently assigned an implicit value based on political or institutional considerations. However, the absence of market prices does not mean that these goods have no values. Economic values which are relevant to allocation decisions and directly comparable to the values imputed to other uses of resources are indeed produced. It is such measures of value which best express the intensity of desire for these services and amenities. The problem lies not in an absence of value but in the absence of a direct measure of value (Clawson and Knetsch, 1966). However, methods of valuation of nonmarket goods have been developed by researchers (for a review see Choi, 1993).

This dissertation consists of three separate but related essays. The first essay is titled "Discrete Choice Analysis of Oklahoma Fishing and Fishing and Hunting License Holders". It analyzes the factors that influence decisions to make fishing trips to different water bodies of Oklahoma.

Recent trends indicate increased use of discrete choice models based on McFadden's (1974) random utility framework to incorporate specific features of recreation decision-making as alternatives to the travel cost demand models. The random utility approach has been applied in three different situations: (a) share models designed to describe how a given level of recreation trips in a season is allocated among a specified set of sites (Morey (1981, 1984); (b) probability models describing the same decisions as choice probabilities for a given recreation trip linked with an independent framework for determining the number of trips in a season (Smith, 1996); and (c) single trip site selection models which model the decision as a product of the probability of taking a trip and the conditional probability of selecting a particular site, given a trip is to be taken (Smith, 1996). In this study the approach is closely related to the approach described in (c), i.e., the study focuses on estimating the parameters of probabilistic models for determining how likely a given license holder with certain social and geographical characteristics is to making a fishing trip to a given type of water body in Oklahoma.

The study is based on a 1992 sample survey of Oklahoma fishing and combination fishing and hunting licence holders conducted by the Department of Agricultural Economics, Oklahoma State University. The information obtained from the survey is analyzed using the logistic regression model to determine the socio-demographic factors influencing choice of water bodies in making fishing trips in Oklahoma.

The second essay is titled " Fishing Trip Demands to Small Streams in Eastern Oklahoma". There is little information on the economic importance of small natural stream fisheries in eastern Oklahoma. The study focuses on estimating a recreational fishing trip demand model for these fisheries. Recent literature indicates that the conventional travel cost method has theoretical drawbacks when used with fishing trip data. Recreational trip data are in integer form and assume nonnegative values. Modeling trip data using the travel cost or contingent valuation technique without considering the discrete and nonnegative nature of trip data results in biased estimates of model parameters (Hillerestein and Mendelsohn, 1993). More recent advances in this area provide alternative modeling techniques for discrete data such as fishing trips. These modeling techniques are generally known as count data models. In this study, the Poisson regression model is first used to estimate the parameters of the model, then a test on the appropriateness of the model is conducted. The test result indicates that the Poisson model is inappropriate for the fishing trip data because of over-dispersion in the data set. Other alternative models to the Poisson regression are considered. These include the negative binomial and the hurdle models. The negative binomial model is found appropriate for the fishing trip data. The data for this study is obtained from a follow up survey of Oklahoma annual fishing license holders who made fishing trips to eastern Oklahoma small streams in 1992. The results are used to estimate economic benefits of recreation fishing at these water bodies and to provide a basis for management and planning decisions.

The third essay titled " Fishing Trip Demands for Oklahoma Fresh Water Bodies" estimates a demand model for Oklahoma fresh water bodies in general. The essay is based on the 1996 national survey of fishing, hunting and wildlife-associated recreation data . In this essay no distinction is made between the types of water bodies visited by the license holder and no consideration is made about the type of license held by individuals in the survey.

ACKNOWLEDGMENTS

First of all I would like to express my deep sense of appreciation and gratefulness to my major advisor, Dr. Schreiner, for his skillful guidance, constant encouragement , patience and endless optimism through out five years of my graduate study. He exhibited tremendous support as I struggled to learn the true meaning of research. Special thanks also goes to other members of my advisory committee, Dr. Arthur Stoecker, Dr. Notie Lansford, and Dr. William Warde. I am also very grateful to Dr. Brian Adam for his kind support in providing me with the GAUSS software for my second essay. I would like also to thank Dr. Wade Brorsen for his invaluable advise and assistance. I would also like to express my gratitude for the benefit I have from financial assistance, and excellent technical and administrative support from the Department of Agricultural Economics at Oklahoma State University. I have also benefitted from financial support from the Food and Agriculture Organization of the United Nations. I am very much indebted to my parents and family for the love and warm support through out my study.

Finally, I would like to dedicate this research to the memoirs of my dear sister Mame Negash, who meant a lot in my life but was not lucky to live long enough and witness her brother's achievement.

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DISCRETE CHOICE ANALYSIS OF OKLAHOMA FISHING LICENSE HOLDERS

DISCRETE CHOICE ANALYSIS OF OKLAHOMA FISHING LICENSE HOLDERS

Abstract

A disaggregated logistic regression procedure for analysis of qualitative fishing trip data to different types of water bodies in Oklahoma and for different license type holders. The procedure uses the maximum likelihood method to estimate the parameters of the discrete choice model. Results of the study are useful in determining the degree of importance of the different water bodies for fishing by different license type holders. It is also useful in predicting what proportion of new license buyers will make fishing trips to the various water bodies.

DISCRETE CHOICE ANALYSIS OF OKLAHOMA FISHING LICENSE HOLDERS

1. Introduction

Previous studies on the value of recreation at the different types of water bodies in Oklahoma date back to the 1960s and earlier. These studies included impact analyses, demographic changes around water bodies, and analysis of expenditures associated with outdoor recreation (McNeely, 1969; Badger, Schreiner, and Presely,1977). Water and related land-based recreation benefits of the McClellan-Kerr Arkansas River Navigation System were estimated by Schreiner, et al (1985). Methods for planning optimum recreational facility development at a multiple purpose water resource project is shown by Schreiner, Chantaworn and Badger(1987).

Cannock and Choi estimated demand for recreational trips to water bodies in Oklahoma using discrete choice and travel cost methods, respectively (Cannock, 1988; Choi, 1993). Cannock's analysis gives information about the total visitor days by time period and their associated benefits and costs, information on the effects of changing entrance fee, substitution effect of optimum timing and level of recreational facility development and analysis of budget allocations across two competing lakes. Choi's research provides information about factors that explain anglers' expenditure behavior at the Mountain Fork

River trout fishery and estimates trip demands for the trout fishery.

The objective of this study is to extend probabilistic approaches to modeling the decision by Oklahoma fishing license holders to fish at different types of Oklahoma water bodies using survey data. Because individuals' decisions on whether or not to fish at a particular water body is a qualitative observation, the analysis is based on discrete choice methods.

The contribution of this study is to provide information on what types of license holders use the different water bodies in Oklahoma for fishing purposes. The results should be useful to wildlife policy makers in determining characteristic information about who utilizes the different water bodies in Oklahoma and how policy may be directed to influence this use.

2. Discrete Choice Model

Discrete choice problems are of interest to researchers in a variety of disciplines. Even though the origin of probabilistic choice models were in mathematical psychology (Ben-Akiva and Lerman, 1985), there has been a remarkable increase in the application of limited dependent and qualitative variable models in economics.

The economic analysis of the behavior of individual decision makers often leads to models that are of a limited dependent or qualitative variable nature. In recent years econometrics has embraced the use of limited dependent and qualitative variable models in applied work. This is largely due to the greater availability of survey data and an increasing awareness of aggregation bias in time-series regional and economy-wide modeling (Fry et al 1993).

Limited dependent variable models arise when data on the variable of interest is censored (when certain values of a dependent variable in a certain range assume a single value) or truncated (when dealing with the characteristics of a population from a sample drawn from a restricted part of the population; Green, 1993). Qualitative variable models should be used whenever the data of interest is discrete (the dependent variable we seek to model is a discrete outcome such as yes or no decision rather than continuous). Discrete variables may be either nominal (i.e. data classified into groups), ordinal (i.e. data classified into groups which have some ordering) or count (i.e. can only be a non-negative integer, Fry et al , 1993).

Many behavioral decisions involve choice among discrete alternatives. Examples are decisions on labor force participation, occupation, education, marriage, family size, residence, work location, travel mode, and brands of commodity purchases (McFadden, 1982; Green, 1993). A summary of economic decision making which is qualitative in nature is found in Hildenbrand, 1982.

Manski and McFadden (1981) and Domencich and McFadden (1975) argue that contemporary economic analysis of consumer behavior has focused on the objective market environment of economic decisions and has excluded whim and perceptions from any formal role in the utility maximization process. Assume consumers are rational in that they make choices that maximize their perceived utility subject to a set of constraints. If the utilities are fixed, then the choice among two or more mutually exclusive alternatives will be the one with the greatest utility. However, there are many errors in this maximization. This is due to an imperfect perception and optimization process by the economic agent, yielding stochastic choice behavior, and because of inability of the analyst to measure exactly all relevant variables (McFadden, 1982; Madala, 1983). From the standpoint of the observer, unmeasured psychological factors introduce a random element in economic decisions. Following Anderson, de Palma, and Thisse, 1992 (p. 33) the four different sources of uncertainty are:

1. Nonobservable characteristics. The vectors of characteristics affecting choice of the individual is only partially known by the modeler. Choices may also be affected by factors of which the consumer is not fully aware.

2. Nonobservable variations in individual utilities. Any population of consumers will have an associated variance in preferences and the random term will therefore have a variance that increases with increasing preference heterogeneity.

3. Measurement errors. The amount of the observable characteristics is not perfectly known.

4. Functional misspecification. The utility function is not known with certainty. The modeler must assume a particular functional relationship, and this may be a potential source of error.

Consequently, the errors will add a random component to the preferences. Then the choice behavior must be characterized in probabilistic terms, i.e. the result is a probabilistic theory of choice which has features in common with psychological models of judgement (Manski and McFadden, 1981).

Recent developments in the empirical analysis of recreation demand involves discrete/continuous choice models that explicitly incorporate both the relevant substitution and site quality effects that influence recreationists' choices regarding where and how often to recreate (Hellerstein and Mendelsohn, 1993; Rosenthal, 1987; Creel and Loomis, 1990; Kling, 1988; Morey, Rowe and Watson, 1993; Dobbs, 1993; Parsons and Kealy, 1995).

The derivation of probabilistic choice models is based on the concept of random utility. The approach is to impose assumptions about how recreation choices are made; in return, readily estimable models of recreation demands for several sites can be derived which are consistent with utility maximization behavior (Rosenthal, 1985).

Let the preferences of household *i* for nonmarket good j be represented through a utility function of the form:

$$U_j^i = U(X_j, W_i, \varepsilon_j^i) \tag{1}$$

where U^i (.) is the utility function for the individual or household; X_j is a vector of n=1,...,N attributes for the *j*th site; and W_i is a vector of m= 1,...,M socioeconomic characteristics of the *i*th individual or household. The term ϵ^i_j represents the random part of utility and varies from household to household. The random part of utility is an unknown function of the M socioeconomic and N site attributes as well as other unobserved attributes of the site and the individual or household. Thus U_j^i denotes the total utility household i derives from recreation at site j (Anas, 1982).

The assumption that the random and systematic parts of utility are separable allows equation (1) to be expressed as:

$$U_j^i = U(X_j, W_i) + \varepsilon_j^i \tag{2}$$

For i=0,1 the utilities U_0 and U_1 are random, and the ith individual or household will choose alternative one only if $U_0 > U_1$ or if the unobservable, or latent, random variable $Y^*_i = U_0 - U_1 \rangle 0$; (where Y_i is a binary response variable, in our case a decision to make a trip to a recreation site or not to make a trip). Consequently, the values of the observable random variable y_i are determined as:

$$y = \left[\begin{array}{ll} 1 & if\ y_i^* > 0 \\ 0 & if\ y_i^* \leq 0 \end{array} \right. \tag{3}$$

Rewriting as

$$\begin{aligned} y_i^* &= (W_{i1} - W_{i0})'\delta + X_i'(\gamma_1 - \gamma_0) + (e_{i1} - e_{i0}) \\ &= [(W_{i1} - W_{i0})', X_i'] \begin{bmatrix} \delta \\ \gamma_1 - \gamma_0 \end{bmatrix} + e_i^* \\ &= X_i'\beta + e_i^* \end{aligned} \tag{4}$$

where X_i', β, and e^*_i are, respectively, explanatory variables, unknown location parameters, and random errors in the linear statistical model for Y^*_i. It is clear that to make the model complete, a particular probability distribution for e^*_i must be chosen. The exact specification of the distributional form for the error term reflects different assumptions about behavior.

A variety of approaches have been employed by assuming different distributional forms for the error term. The most widely used approaches include the ordinary least squares

(OLS), the linear probability model, and the logistic or probit functions.

The OLS approach, though convenient in form, has a number of statistical problems. The first is that, while the dependent variable can only assume values of 1 and 0, the predictions generated from OLS model are unbounded. Second, the random terms are heteroskedastic since their value depends on the value of the explanatory variables.

The linear probability is conventionally modeled by assuming that all observations lie in the range where the probabilities are between zero and one, and then by employing OLS procedure. The problem with this model is that even when the specification is correct it is possible that a given sample of observations obtained from the true model will result in OLS parameter estimates which produce a fitted linear probability function. This will give rise to predicted values which lie outside the 0-1 interval for values of the explanatory variables at extremes of the observed range. This problem may be corrected by setting extreme predictions to 1 if the actual predicted value is greater than 1 and 0 if the actual prediction is negative. However, this may be unsatisfactory because, for some values of the explanatory variables, the predicted result may give a probability of 1 when, in fact, the observed value may be zero (or vice versa for a probability of zero, Wrigley, 1985).

The above limitations of OLS and the linear probability model suggest a more suitable model specification such as the logistic and normal probability functions. Recreation behavior is frequently couched in terms of discrete choices. The choices include recreation activity and recreation site. The logit model, including both binomial and multinomial versions, is used to model discrete choices (Stynes and Peterson, 1984).

Theoretically the logit model in its transformed mode relates a monotonic relationship between the dependent binomial (multinomial) outcome and the probability of its occurrence using an index which is a function of explanatory variables. Under these assumptions the "true" probability function has the characteristic shape of a cumulative distribution function (CDF). The two widely used CDF's are the normal and the logistic. The associated analysis is called probit and logit analysis, respectively (Judge et al, 1980).

One argument for using the normal CDF is that each individual makes choices between alternatives based on a certain value of a ranking index which reflects individual tastes. If there are many independent factors determining the critical level for each individual, the central limit theorem may be used to assume that the value of the ranking index is normally distributed random variable (Judge et al 1980).

Let $F(\epsilon)$ denote the cumulative distribution function of ϵ in (4). Then the choice probabilities can be computed as

$$P_j^i = \int_{-\infty}^{\infty} \frac{\partial F(\varepsilon)}{\partial \varepsilon_j^i} d\varepsilon_j^i \tag{5}$$

(where ϵ^i_j represents the random part of utility of non-market good j for household i) by integrating over the derivative of F with respect to its j arguments. This derivative is a distribution function such that

$$\frac{\partial F(\varepsilon)}{\partial \varepsilon_j^i} = F_j[U^i(X_j) + \varepsilon_j] \tag{6}$$

where $F_j[.]$ denotes a vector with its (j) components shown in the brackets. The integration of (6) yields

$$P_j = F_j[U(X_j), all\ j] \tag{7}$$

where F_j (.) is the choice probability function for alternative j. This condition states that the choice probability for alternative j is a function of the differences of the utility of that alternative and the utility of all other alternatives. This result stems from the assumption of additive random terms (Anas, 1982).

In principle, any proper, continuous probability distribution defined over the real line will suffice. The normal distribution has been used in several analyses, giving the probit model,

$$\begin{aligned} Prob(Y=1) &= \int_{-\infty}^{\beta' x} \phi(t)dt. \\ &= \phi(\beta' x) \end{aligned} \tag{8}$$

where ϕ(.) is a standard normal distribution (Green, 1993). However, the assumption that the error terms are normally distributed results in exceedingly complex calculations for the probability of selecting one alternative from three or more possibilities (Anas, 1982; Rosenthal, 1985; Amemiya, 1985; Green, 1993). There are two problems that have prevented wide use of the probit model (Pudney, 1989). The first is purely practical in that the evaluation of the mutivariate normal CDF in (6) requires an enormous amount of computer time when the choice set contains more than three possibilities.

The second problem concerns the use of the model for forecasting purposes. If a new alternative is added to the opportunity set, the matrix $\sum$ (variance-covariance matrix) has an added row and column requiring added parameters in the model. Predicting the response to an expansion of the opportunity set requires estimation of the values of these added parameters, but, because the sample data may not have been collected before the new alternative is introduced, the sample data may not contain the relevant information.

Numerical calculations become much simpler if the error terms in (1) are assumed to have a type 1 extreme value distribution, usually referred to as a Weibull distribution (Johnson and Kotz, 1970, p. 272).

If individual i faces j choices, the probability that the first alternative is chosen is

$$\begin{aligned} \mathbf{P_{i1}} &= Prob[U_{i1} > U_{i2} \text{ and } U_{i1} > U_{i3} \ldots \text{ and } U_{i1} > U_{ij}] \\ &= prob[e_{i2} < U_{i1} - U_{i2} + e_{i1} \\ &\quad \text{and } e_{i3} < U_{i1} - U_{i3} + e_{i1} \\ &\quad \ldots \text{ and } e_{ij} < U_{i1} - U_{ij} + e_{i1}] \end{aligned} \qquad \mathbf{(9)}$$

Following Judge et al (1980), it is convenient to look at (9) in differenced form as

$$\mathbf{P_{i1}} = prob[e_{i2} - e_{i1} < U_{i1} - U_{i2} \text{ and } \ldots e_{ij} - e_{i1} < U_{i1} - U_{ij}] \qquad \mathbf{(10)}$$

This transformation reduces the number of integrals that must be evaluated to determine the P_{ij}'s. It also explains why distributions that are closed under subtraction are good candidates for the joint density of the e_{ij}.

Thus, if Weibull distributions are assumed in the errors, the choice process should be modeled with a logit model. The difference of two Weibull distributions has a logistic distribution (Domencich and MacFadden,1975; Judge et al 1980).

The logit model has been used to capture important relationships in recreation forecasts. The logistic function is given analytically by the following:

$$p(y) = \frac{1}{1 + e^{-(a + \beta x)}} = \frac{e^{(a + \beta X)}}{1 + e^{(a + \beta X)}} \tag{11}$$

where, x is a set of independent variables and y is the dependent (binomial or multinomial) variable. This function is bounded and doubly asymptotic, approaching y=0 and y=1 as x approaches negative and positive infinity, respectively.

Two properties of the logistic function make it particularly well-suited to the modeling of recreational choices. First, the fact that its values are bounded by (0,1) interval permits it to be used as a probability function. Second, by means of the logit transformation the function may be easily converted to a convenient linear form.

3. Data

The data for the study were obtained from a survey conducted by Oklahoma State University, Department of Agricultural Economics, 1992. Data were gathered through telephone surveys of Oklahoma licensed anglers to assess their attitudes and opinions on, and effort and success at fishing in all water bodies in Oklahoma.

The procedure was to first complete a survey to identify the extent Oklahoma anglers fished the different water bodies from samples of the 1992 populations of fishing and combination fishing/hunting license holders (total population of all license holders was 627,000). The 1992 population of license holders was stratified by license type and a random sample was independently drawn from each. The original sample of 3,009 license holders was augmented by 600 randomly-selected eastern Oklahoma resident annual fishing license holders to increase the representation of eastern Oklahoma anglers (Appendix Table 1)[1]. The sample of lifetime license holders was from the population of those who were known to actively fish (i.e. not physically incapacitated or deceased).

An overview of the survey process is illustrated in the flow diagram in Figure 1. The right branch of the flow diagram describes the path for incomplete surveys, which occurred for 2,465 license holders. An incomplete survey occurred for many reasons. The three primary reasons were: wrong phone number, inability to contact person after five attempts, and outright refusal to answer questions. The left branch of the flow diagram shows the completed survey steps. Surveys were completed for 32% of the 3,609 license holders in the combined original and supplementary samples. Interviewers completed fewer surveys of license holders in the smaller supplementary sample, which contained only residents of eastern Oklahoma in 1992, than for the larger original sample, which contained license holders from Oklahoma and from outside the state (Figure 1).

Completed surveys from respondents who purchased a license in 1992 but did not fish in Oklahoma are designated by the encircled numeral 1 (Figure 1). Reasons for not fishing were because of purchasing a license too late in the season, illness, etc. The encircled numeral 2 (Figure 1) represents completed surveys from non-Oklahoma residents who purchased Oklahoma fishing licenses in 1992. There were 86 completed surveys from non-Oklahoma residents .

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[1]A follow-up survey of eastern Oklahoma natural stream anglers was administered in 1993. The additional sample of 600 eastern Oklahoma anglers was for purposes of increasing the number of participants in small stream fishing in the region.

4. Estimation

As with other choice models, logistic functions are estimated using econometric procedure . Estimation of the logit model is carried out using the maximum likelihood method (Madala, 1983)[2].

Logic of the maximum likelihood procedure is as follows. First, an expression for the likelihood of observing the pattern of response category choices in the data set are derived. Then, estimates of those values which maximize the likelihood of the observed pattern of responses are taken. Consider the likelihood of any sample of n observations. Because they are by assumption drawn at random from the whole population, and with a success probability of **F(β'X),** the likelihood of the entire sample is the product of the likelihoods of the individual observations. The likelihood of a particular sample of response category choices in a data set is

$$prob(Y_1=y_1,\ Y_2=y_2,\dots,\ Y_n=y_n) = \prod_{y_i=0}[1-F(\beta' X_i)]\prod_{y_i=1}F(\beta' X_i) \tag{12}$$

where F(β'X) is the logistic cumulative density function. The above likelihood equation for a sample of n observations can be conveniently written as

$$L = \prod_i [F(\beta' X_i)]^{y_i}[1-F(\beta' X_i)]^{1-y_i} \tag{13}$$

2

See the work of McFadden (1973) for proofs of the desirable properties of the maximum likelihood estimation in large samples.

Maximizing the likelihood function proceeds by transforming it to log form and then taking partial derivatives with respect to the parameters to be estimated. Log transformation is convenient for taking partial derivatives of the products in the likelihood function (Wrigley, 1985). The method of maximum likelihood argues that the calculated probability of observing the given sample should be the highest when the unknown β is near the true value, and hence a satisfactory estimate of the parameters is the maximand of the log likelihood function, or, in other words, a value $\hat{\beta}$ which maximizes L (Domencich and McFadden, 1975). The log likelihood in this case is

$$lnL = \sum_i [y_i \ln F(\beta' X_i) + (1-y_i)\ln(1-F(\beta' X_i))] \tag{14}$$

which is a simple sum of the logs of the arguments and is easily differentiable. The parametric values that maximize the log likelihood function are obtained through the usual procedure of taking partial derivatives of the log likelihood function with respect to the parameters and setting equal to zero;

$$\frac{\partial \ln L}{\partial \beta} = \sum_i \left\{ \frac{y_i f_i}{F_i} + (1-y_i)\frac{-f_i}{(1-F_i)} \right\} X_i = 0 \tag{15}$$

where $f_i = \partial F/\partial \beta$. Equation (15) is non-linear and is solved by iterative procedures (Agresti, 1990; Green, 1993). The iterative procedure operates until convergence and yields the following results:

(1) maximum likelihood estimator or the parameter vector. McFadden(1974) has shown that, under quite general conditions, maximum likelihood estimation of the

conditional logit model provides estimators that are asymptotically efficient and normally distributed. These results are used to construct approximate large-sample confidence bounds and tests of hypotheses for the parameters.

(2) corresponding estimates of functions of parameters such as derivatives and quasi-elasticities are also a maximum likelihood estimate of the function (Cramer, 1991).

(3) the (asymptotic) standard errors of the parameter estimates derived from the estimate of their (asymptotic) covariance matrix. We know that the maximum likelihood estimators are consistent, asymptotically efficient, and asymptotically normally distributed. Thus, a consistent estimate of the asymptotic covariance matrix that can be used as a basis for hypothesis tests or confidence intervals is

$$-\left[\frac{\partial^2 \ln L}{\partial\beta\partial\beta'}\right]^{-1} \tag{16}$$

evaluated at the final set of parameter estimates $\tilde{\beta}$ (Judge et al, 1980),i.e. the asymptotic covariance matrix for the maximum likelihood estimator is estimated using the inverse of the Hessian evaluated at the maximum likelihood estimates.

(4) the maximum value of the log likelihood function.

The value of the log likelihood function for particular sets of parameter estimates is useful when considering and testing simplifying assumptions (such as zero coefficients, or the absence of certain variables from the model), or restrictions on the parameter vector. Provided the restricted model is nested as a special case within a general or unrestricted model, this can be tested by the log likelihood ratio or LR test. The test statistic is

$$LR = 2(\log L(\hat{\theta}_u) - \log L(\hat{\theta}_r)) \tag{17}$$

with u and r denoting unrestricted and restricted models respectively. Under the null hypothesis that the restriction holds, this statistic is asymptotically distributed as chi square with r degrees of freedom, equal to the number of (independent) restrictions on the parameter vector.

A critical step in assessing the appropriateness of the model is to examine its fit, how well the model describes the observed data (Hosmer, Taber and Lemeshow; 1991). Assessing goodness of fit usually involves two stages: (1) computing a statistic that provides a summary measure of the errors, and (2) examining the individual error components that are large under the assumption of a good-fitting model.

In the conventional multiple regression context, the overall fit of a model is measured by the R^2 (coefficient of determination) statistic. There have been several attempts to derive goodness of fit measures for the qualitative response models. One measure of fit is the maximized value of the log likelihood function ln L.

The log likelihood function has a convenient statistical distribution in large samples and can be given an intuitive interpretation using information theory (Domencich and McFadden, 1975). Because the hypothesis that all of the slopes in the model are zero is the most frequent test, the log likelihood computed with only a constant term, ln L_0, should also be reported. Similar to the R^2 in a conventional regression model, the likelihood ratio index is expressed as:

$$LRI = 1 - \frac{\ln L}{\ln L_0} \tag{18}$$

One feature of this measure is that it is bounded by zero and one (Green, 1993).

The log $L(\hat{\theta})$, where $\hat{\theta}$ is maximum likelihood estimator, is a natural measure of fit, and it can be used intuitively for comparisons between different models fitted to the same data set, even if they are not nested, and also for comparisons between the same model fitted to different data sets (Cramer, 1991).

5. Variables

Separate discrete choice models were used to explain the probability of Oklahoma (resident) license holders fishing in six different water body types (Table 1). The six water body types are reservoirs, small impoundments, farm ponds, large rivers, small rivers not in eastern Oklahoma and small rivers in eastern Oklahoma[3].

The explanatory variables included in the model are gender, age, education, ethnicity, license type, location, and total number of fishing trips. Gender distinctions among the probabilities of trips to different water body types would imply that males would prefer one type of fishing experience and females a different type. For example males may have a higher probability of fishing more rugged or more inaccessible water types such as rivers and streams compared to females. Similarly, age may be a factor in explaining the probability of fishing the different water body types. For example, older license holders may prefer easier access or less strenuous fishing conditions compared to younger license holders. Education may be

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[3] Further description of the water body types is given as a footnote in Table 1.

correlated with income and hence the less expensive types of fishing may have higher probabilities among lower educated license holders. Similarly, ethnicity may be correlated with education and income and hence one type of water body fishing is preferred to another. License type, whether it is for fishing only or combination hunting and fishing, may influence the probability of fishing the different water body types. Those that hunt as well as fish may have higher probabilities of fishing the less accessible water body types compared to the license holders that only fish.

The screening survey did not collect information on the cost per trip for fishing the various water body types. Furthermore, the different water body types are not evenly distributed geographically across the state. Hence, variables on the geographic location of the license holder are included (Figure 2). Reservoirs, rivers, and streams are more prevalent in the eastern part of the state. Hence, license holders located in northwest (NW), southwest (SW), north central (NC) and south central (SC) are expected to have lower probabilities of fishing reservoirs, rivers, and streams as compared to license holders located in northeast (NE) and southeast (SE) Oklahoma. All geographic regions have small impoundments and farm ponds and hence license holders may have more equal probabilities in fishing these water body types.

Total trips is a measure of avidness in fishing. The more trips made in total, the greater the probability of fishing each water body type. Descriptive statistics of these variables are presented in Table 2.

Another important variable is income. Even though there was an effort to obtain information about income, the response rate was very low. Because of this, income as an explanatory variable would significantly reduce the sample size and was thus excluded from the set of regressors.

6. Results and Discussion

This section reports the results of maximum likelihood estimation for the discrete choice models for fishing the different water bodies in Oklahoma (Tables 3 to 8). The empirical results are presented in terms of parameter estimates, measure of the statistical reliability of the parameter estimates (i.e., t-statistics), likelihood values of the full model (the model with the set of explanatory variables), and the reduced model (intercept only) .

The likelihood ratio (LR) statistic is a test of the hypothesis that all slope parameters are zero. This hypothesis was rejected at one percent significance level for all six types of water bodies (Tables 3-8) which implies that the logistic function fits the data well. The likelihood ratio test statistic which indicates the presence of significance between the restricted log likelihood estimation and the unrestricted is the highest for small streams in eastern Oklahoma and the lowest for reservoirs. The number of significant parameters varies by water body type. Twelve parameter estimates are significant for small streams in eastern Oklahoma while reservoirs has only four significant parameters.

Individual tests for each explanatory variable indicates that not all have the same sign, magnitude and significance across all types of water bodies. Gender is significant only for small streams both within and outside of eastern Oklahoma. Both cases have the expected negative sign implying that females have a lower probability of fishing small streams as compared to males.

The variables on age groupings vary in sign and statistical significance from water body to water body. The reference group is 35 to 44 years of age. All age groups have comparable probabilities for fishing reservoirs. The oldest age group has a statistically significant lower probability of fishing small impoundments compared to the reference group. For farm ponds, younger age groups have higher probabilities and older age groups have lower probabilities compared to the reference group. Older age groups have lower probabilities of fishing large rivers compared to the reference group and younger age groups. Small streams, not in eastern Oklahoma, have limited number of observations (65) across all age groups and have few observations in the extreme young and old age groups. The reference group has the highest probability with the next youngest (25 - 34 years) and next oldest (45 - 54 years) both having statistically lower probabilities of fishing. Small streams in eastern Oklahoma have the highest probability of fishing for the reference group and all older groups have statistically significant lower probabilities.

Ethnic background is not significant for any of the water bodies except large rivers. Non-white license holders have a higher probability of fishing large rivers compared to the reference group of white license holders. Education level is significant for reservoirs and small rivers and streams located outside eastern Oklahoma. For reservoirs the likelihood of making a trip declines for license holders with high school or lower education levels as compared to those beyond a high school graduate. For small streams not in eastern Oklahoma the result is reverse. The probability of making a fishing trip increases for high school and lower education levels as compared to the reference group which is vocational and above including some college.

The type of license holder (fishing only and combination hunting and fishing) is a significant parameter for reservoirs, small impoundments, farm ponds, and large rivers. Except for reservoirs, the probability increases for small impoundments, farm ponds, and large rivers if the license type is combination hunting and fishing. Because reservoirs were the predominate water body fished, there is a higher probability that the avid fisherman who only will fish in reservoirs than will the combination license holder.

Geographical location of the license holder's residence gives important information about accessibility, distance, and cost of a trip to specific water bodies. The reference location is southeast (SE) Oklahoma. This region has an abundance of small streams and residents are close to a number of reservoirs. Reservoirs were the predominate water body fished by all license holders. Results of the discrete choice model indicates that there are no statistically significant differences in the probabilities of residents in the different locations fishing at reservoirs. Whereas for small streams in eastern Oklahoma, all of the geographical variables are significant with the expected negative sign. The probability of fishing small impoundments decreases if the residence of the license holder is in northeast or northwest Oklahoma compared to southeast Oklahoma residents. License holders whose residence is in southwest and southcentral have higher probability of fishing farm ponds than do southeast Oklahoma residents. This is probably associated with higher availability of farm ponds relative to other water body types. As expected, out-of-state license holders find farm ponds less attractive for fishing and thus have a lower probability. In the case of large rivers, license holders living in northwest, southwest, and southcentral have lower probability of fishing large rivers compared to the southeast residents. Again, out-of-state license holders are less likely to fish large rivers. The probability of fishing small streams not in eastern Oklahoma increases if the license holder is located in northwest or southwest Oklahoma and declines if they are located in northeast Oklahoma than are southeast resident license holders. All location variables are significant and have the expected negative sign for small streams in eastern Oklahoma. This indicates that license holders located elsewhere other than southeast Oklahoma are less likely to fish small streams in eastern Oklahoma as compared to southeast Oklahoma resident license holders. This is expected because of the predominate location of small streams in eastern Oklahoma. This implicitly implies the lower cost of trips to eastern Oklahoma natural streams for southeastern Oklahoma residents.

Total trips made per season (1992) represent how avid license holders are at fishing. The more trips license holders make, the higher the probability of fishing each water body type. The coefficient on total trips is positive and significant for each water body type.

Only three of the explanatory variables were statistically significant for reservoirs education, license type, and total trips). This is because a large number of all license holders fish reservoirs and hence the discrete choice model with the set of explanatory variables is not able to differentiate nonparticipants from participants.

In terms of overall fit of the model, expected sign of coefficients and number of significant parameters, the model is relatively better able to differentiate participants from nonparticipants for small rivers in eastern Oklahoma. A total of eleven variables are significant at the five or ten percent probability level (gender, age 45-54, age 55-64, age 65 and over, NW, SW, NC, SC, NE, Out-of-state, and total trips).

8. Conclusion

An empirical approach was used to determine which types of water bodies were most frequently fished by license holders. The estimation is relatively simple. A discrete choice model reveals the decision to make a fishing trip or not to make a fishing trip to different water bodies of Oklahoma.

Statistical results of the empirical analysis indicate a certain amount of differentiation with the set of explanatory variables. The identified set of explanatory variables discriminated better for small tivers in eastern Oklahoma than for reservoirs. Relatively good probabilistic models were obtained and these results identify directions for improvement of the models. The results of this research could be improved and made more useful to policy makers by acquiring more complete geographical data, site characteristics, trip costs and income. Results will also be improved if more socioeconomic characteristics of the license holders are available.

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Table 1. Description of Variables

Description	Value
Dependent variables	
Reservoirs	1 = if made a trip to reservoirs; 0 otherwise
Small impoundments	1 = if made a trip to small impoundments; 0 otherwise
Farm ponds	1 = if made a trip to farm ponds; 0 otherwise
Large rivers	1 = if made a trip to large rivers; 0 otherwise
Small rivers not in eastern Ok.	1 = if made a trip to small rivers not in eastern Oklahoma, 0 = otherwise
Small rivers in eastern OK.	1 = if made a trip to small rivers in eastern Oklahoma, 0 = otherwise
Independent variables	
Gender	0 = male; 1 = female.
Age1	1 if age between 16 and 24 yrs.; 0 otherwise
Age2	1 if age between 25 and 34 yrs.; 0 otherwise
Age (reference)	between 35 and 44 yrs
Age3	1 if age between 45 and 54 yrs; 0 otherwise
Age4	1 if age between 55 and 64 yrs. 0 otherwise
Age5	1 if age 65 and above; 0 otherwise
Education level	1 =up to and including high school graduate, 0 = more than high school graduate
Ethnic back ground	
Ethnic1	1 = if nonwhite
License type	0=license is fishing only; 1=combination hunting and fishing
Location	
NW	1 = residence is in northwest Oklahoma; 0 otherwise
SW	1 = residence is in southwest Oklahoma; 0 otherwise
NC	1 = residence is in northcentral Oklahoma;0 otherwise
SC	1 = residence is in southcentral Oklahoma;0 otherwise
SE (reference)	resident is southeast Oklahoma
NE	1 = residence is in northeast Oklahoma; 0 otherwise
Out-of-state	1= out of state resident; 0 otherwise
Total trips	total trips made to all water bodies

Reservoirs = over 400 acres; small impoundments(lakes) = 2 to 400 acres; farm ponds = privately owned; large rivers, eg. Arkansas, Red, Canadian, Cimarron; small rivers, creeks, and streams, eg. Baron Fork, Mountain Fork, Illinois, and Washita.

Table 2. Descriptive Statistics of Variables

Variable Name	N	Mean	Standard Deviation	Minimum	Maximum
Reservoir	1043	0.62033	0.48554	0	1
Small impoundments	1043	0.34899	0.47688	0	1
Farm ponds	1043	0.41035	0.49213	0	1
Large rivers	1043	0.18984	0.39236	0	1
Small rivers not in eastern Ok.	1043	0.06232	0.24185	0	1
Small rivers in eastern OK.	1043	0.16012	0.36689	0	1
Gender	1043	0.20326	0.40262	0	1
Age1	1043	0.08245	0.27519	0	1
Age2	1043	0.18600	0.38929	0	1
Age (reference)	1043	0.27133	0.4449	0	1
Age3	1043	0.21189	0.40884	0	1
Age4	1043	0.16683	0.37300	0	1
Age5	1043	0.07478	0.26317	0	1
Education	1043	0.7325	0.44287	0	1
Ethnic back ground					
Ethnic1	1043	0.11314	0.31691	0	1
License type	1043	0.37872	0.48530	0	1
Location					
NW	1043	0.09875	0.29847	0	1
SW	1043	0.09300	0.29057	0	1
NC	1043	0.16203	0.36866	0	1
SC	1043	0.10574	0.30730	0	1
SE (reference)	1043	0.15532	0.06238	0	1
NE	1043	0.30681	0.46139	0	1
Out-of-state	1043	0.06232	0.24185	0	1
Total trips	1043	34.834	63.464	0	930

Table 3. Maximum Likelihood Results for Oklahoma License Holders Fishing at Reservoirs, 1992.

Variable name	Coefficient	Standard error	t-Ratio
_Constant	0.52245	0.24123	2.1658*
Gender	-0.001	0.17432	-0.0056
Age			
Age1 (16-24 years)	-0.1659	0.26088	-0.636
Age2 (25-34 years)	-0.0878	0.19612	-0.4475
Age3 (45-54 years)	0.2306	0.19150	1.2041
Age4 (55-64 years)	-0.0403	0.20191	-0.1995
Age5 (65 years and above)	0.1699	0.27348	0.6213
Ethnic1 (Non whites)	-0.2678	0.20771	-1.2892
Educn1 (high school and under)	-0.2744	0.15232	-1.8015**
Geographical residence			
NW (north west OK)	-0.0868	0.25911	-0.3351
SW (south west OK)	-0.4037	0.2629	-1.5356
NC (north central OK)	0.14657	0.22849	0.64145
SC (south central OK)	0.37914	0.26262	1.4436
NE (northeast OK)	0.21917	0.19769	1.1086
Out-of-state (out of OK state)	0.50964	0.32231	1.5812
License types	-0.33966	0.14991	-2.2658*
Total trips (No.)	0.0064	0.0016	4.0425*
Log L (0)[a] = -692.45			
Log L[b] = -668.68			
LR test value = 47.5538			

* significant at =0.1
** significant at =0.05
a The log of likelihood value for intercept term only.
b The log of likelihood value for the model with set of regressors.

Table 4.Maximum Likelihood Results for Oklahoma License Holders Fishing at Small Impoundments, 1992.

Variable name	Coefficient	Standard error	t-Ratio
Constant	-0.5640	0.23908	-2.3592*
Gender	0.04825	0.17967	0.26855
Age			
Age1 (16-24 years)	-0.0836	0.26446	-0.31612
Age2 (25-34 years)	-0.0423	0.19747	-0.21441
Age3 (45-54 years)	-0.1515	0.19184	-0.78956
Age4 (55-64 years)	-0.2983	0.20973	-1.4224
Age5 (65 years and above)	-0.6010	0.29416	-2.0432*
Ethnic1 (Non whites)	0.33351	0.20731	1.6088
Educn1 (highschool and below)	-0.1054	0.15129	-0.6967
Geographical residence			
NW (northwest OK)	-0.6922	0.28168	-2.4573*
SW (southwest OK)	-0.0588	0.26578	-0.22136
NC (northcentral OK)	0.02782	0.22655	0.1228
SC (southcentral OK)	-0.3007	0.26017	-1.558
NE (northeast OK)	-0.3368	0.19854	-1.6965**
Out-of-state	-0.4912	0.34128	-1.4394
License type	0.54875	0.15206	3.6087*
Total trips (No.)	0.00319	0.00113	2.8191*
Log L (0)[a] = -674.63			
Log L[b] = -650.32			
LR test value = 48.6243			

* significant at =0.1

** significant at =0.05

a The log of likelihood value for intercept term only.

b The log of likelihood value for the model with set of regressors.

Table 5. Maximum Likelihood Results for Oklahoma License Holders Fishing at Farm Ponds, 1992.

Variable name	Coefficient	Standard error	t-Ratio
Constant	-082948	0.2511	-3.3034*
Gender	-0.01963	0.1887	-0.1051
Age			
Age1 (16-24 years)	0.20783	0.2689	0.77293
Age2 (25-34 years)	0.44654	0.2031	2.1988*
Age3 (45-54 years)	-0.2196	0.1946	-1.1282
Age4 (55-64 years)	-0.8875	0.2264	-3.6207*
Age5 (65 years and above)	-1.0401	0.3143	-3.3921*
Ethnic1 (Non whites)	0.13554	0.2183	0.62099
Educn1 (high school and under)	-0.0252	0.1579	-0.1051
Geographical residence			
NW (residence is north west OK)	0.43582	0.2688	1.6211
SW (residence is south west OK)	0.925	0.2767	3.3432*
NC (residence is north central OK)	0.38239	0.235	1.6273
SC (residence is south central OK)	0.84476	0.2632	3.21*
NE (residence is north east OK)	-0.2558	0.2080	-1.2298
Out-of-state	-2.1842	0.6025	-3.625*
License type	0.539	0.1551	3.4756*
Total trips (No.)	0.0079	0.0015	5.3831*
Log L (0)[a] = -706.10			
Log L[b] = -609.59			
LR test value = 193.024			

* significant at =0.1

** significant at =0.05

a The log of likelihood value for intercept term only.

b The log of likelihood value for the model with set of regressors.

Table 6. Maximum Likelihood Results for Oklahoma License Holders Fishing at Large Rivers, 1992.

Variable name	Coefficient	Standard error	t-Ratio
_Constant	-1.5102	0.2953	-5.1149*
Gender	-0.1606	0.2324	-0.691
Age			
Age1 (16-24 years)	0.0515	0.3068	0.1679
Age2 (25-34 years)	0.0683	0.2341	0.2918
Age3 (45-54 years)	-0.3099	0.2387	-1.2980
Age4 (55-64 years)	-1.1842	0.3106	-3.8122*
Age5 (65 years and above)	-1.1464	0.4304	-2.6637*
Ethnic1 (Non whites)	0.4051	0.2402	1.6867**
Educn1 (high school and under)	0.3042	0.2010	1.5133
Geographic residence			
NW (northwest OK)	-1.6337	0.4646	-3.5163*
SW (southwest OK)	-2.0352	0.5056	-4.0256*
NC (northcentral OK)	-0.0912	0.2682	-0.34
SC (southcentral OK)	-0.5408	0.3217	-1.681**
NE (northeast OK)	-0.0414	0.2286	-0.1811
Out-of-state	-1.0538	0.5114	-2.0607*
License type	0.3858	0.189	2.042*
Total trips (No.)	0.007	0.0013	5.2296*
Log L (0)[a] = -506.88			
Log L[b] = -444.76			
LR test value = 124.251			

* significant at =0.1

** significant at =0.05

a The log of likelihood value for intercept term only.

b The log of likelihood value for the model with set of regressors.

Table 7. Maximum Likelihood Results for Oklahoma License Holders Fishing at Small Rivers not in Eastern Oklahoma, 1992.

Variable name	Coefficient	Standard error	t-Ratio
Constant	-3.438	0.5409	-6.3565*
Gender	-0.9997	0.4976	-2.009*
Age			
Age1 (16-24 years)	-0.3857	0.4916	-0.7846
Age2 (25-34 years)	-1.2101	0.4862	-2.4888*
Age3 (45-54 years)	-1.1705	0.4765	-2.4565*
Age4 (55-64 years)	0.1382	0.3580	0.386
Age5 (65 years and above)	-0.0298	0.5063	-0.0588
Ethnic1 (Non whites)	0.20346	0.4131	0.4926
Educn1 (high school and under)	0.7367	0.3562	2.0681*
Geographical residence			
NW (northwest OK)	1.4252	0.4736	3.0095*
SW (southwest OK)	1.1612	0.5021	2.3125*
NC (northcentral OK)	0.4639	0.4876	0.9513
SC (southcentral OK)	0.7168	0.4999	1.434
NE (northeast OK)	-0.9661	0.5482	-1.7624**
Out-of-state	-0.2119	0.8236	-0.2573
License type	0.0964	0.2924	0.3296
Total trips (No.)	0.0049	0.0017	2.8879*
Log L (0)a = -243.34			
Log L^b = -208.92			
LR test value = 68.836			

* significant at =0.1

** significant at =0.05

a The log of likelihood value for intercept term only.

b The log of likelihood value for the model with set of regressors.

Table 8. Maximum Likelihood Results for Oklahoma License Holders Fishing at Small Rivers in Eastern Oklahoma, 1992.

Variable name	Coefficient	Standard error	t-Ratio
_Constant	-0.6485	0.3027	-2.1424*
Gender	-0.9434	0.2941	-3.2076*
Age			
Age1 (16-24 years)	-0.1631	0.3628	-0.4495
Age2 (25-34 years)	-0.0564	0.2652	-0.2126
Age3 (45-54 years)	-0.4721	0.2707	-1.7438**
Age4 (55-64 years)	-0.795	0.3127	-2.5421*
Age5 (65 years and above)	-1.6708	0.5559	-3.0057*
Ethnic1 (Non whites)	-0.1300	0.2943	-0.4419
Educn1 (high school and under)	-0.2441	0.2143	-1.1392
Geographical residence			
NW (northwest OK)	-6.2747	2.4976	-2.5123*
SW (southwest OK)	-4.1953	1.0463	-4.0098*
NC (northcentral OK)	-1.4364	0.3203	-4.484*
SC (southcentral OK)	-1.1386	0.3423	-3.3263*
NE (northeast OK)	-0.4023	0.229	-1.7568**
Out-of-state	-2.326	0.75	-3.1013*
License type	0.3183	0.2061	1.5447
Total trips (No.)	0.0100	0.0015	6.6441*
Log L (0)[a] = -458.77			
Log L[b] = -355.32			
LR test value = 206.916			

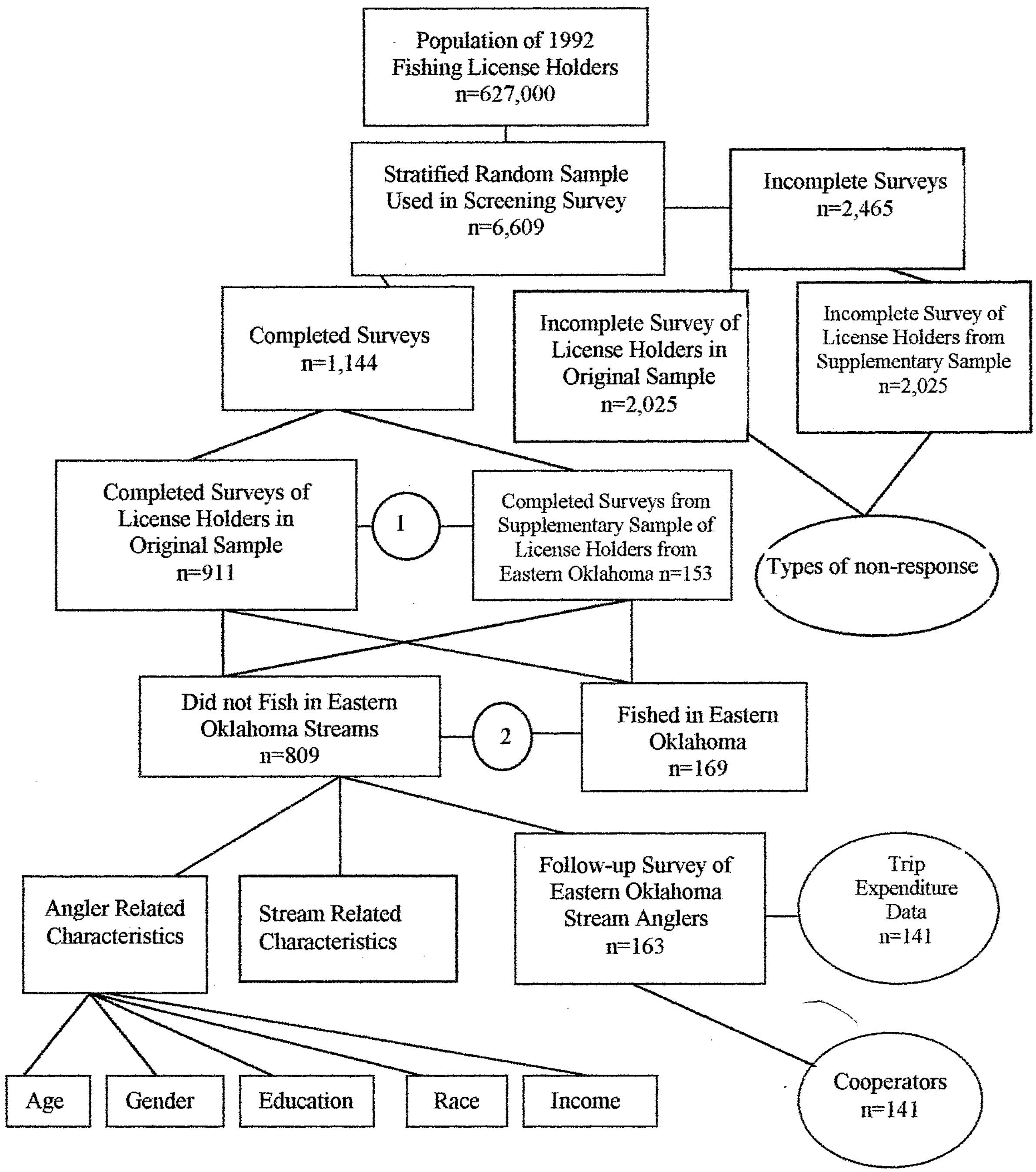
* significant at =0.1

** significant at =0.05

a The log of likelihood value for intercept term only.

b The log of likelihood value for the model with set of regressors.

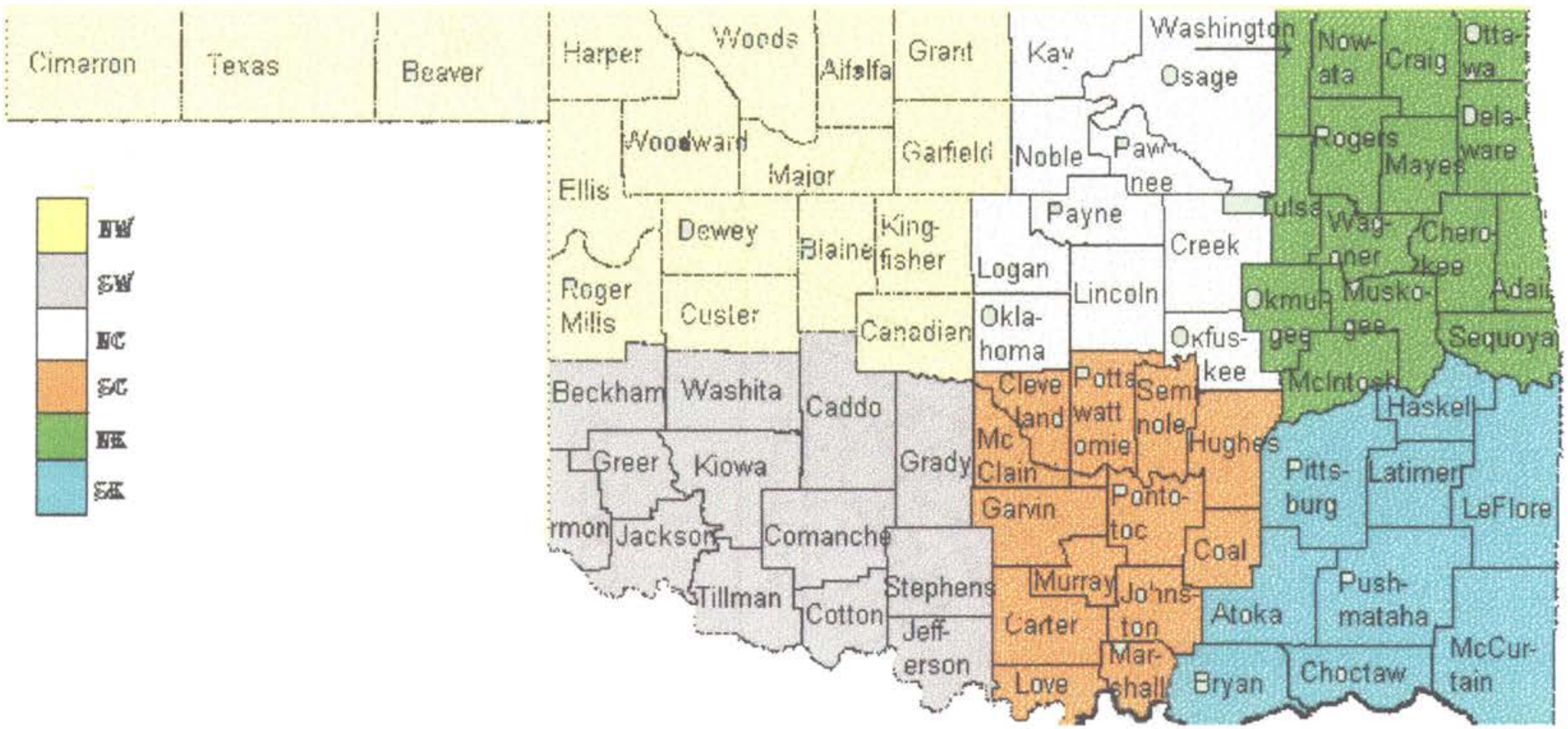
Figure 1. Flow Diagram of Screening Survey Process



1. These license holders (n=80) indicated that they did not fish in Oklahoma during 1992
2. There were 86 non-resident completed surveys.

Source: Oklahoma Department of Wildlife Conservation, Final Report for Project F-41-R-16.

Figure 2 . Geographical Subdivision of Oklahoma License Holders Residence



APPENDICES

Source: Oklahoma Department of Wildlife Conservation. 1994. Final Report for Project F-41-16.

Appendix Table 1. Oklahoma license holders (1992) by type of license, sample size and number of telephone surveys administered

License type	License holders (FY 1992)	Sample size	Survey administered: Completed interviews	Non-response
Resident, annual combination hunting-fishing	78,000	501	142 (10)	359
Resident, annual fishing	350,000	1,609	511(15)	1,098
Non-resident, annual fishing	37,000	123	44(0)	79
Non-resident, 10-day fishing	8,000	50	20(0)	30
Non-resident, 3-day fishing	62,000	126	22(0)	104
Lifetime[2]	51,000	900	291(25)	609
Senior, resident[2]	41,000	300	114(30)	186
Total	627,000	3,609	1,144(80)	2,465

[1] Number in parentheses is the number of completed interviews in which the license holder indicated they did not fish in Oklahoma during 1992. These are included as completed surveys.
[2] It includes fishing only and combination hunting and fishing license types. Data from the files of Active license holders.
Source: Fisher, W., D. Schreiner, C. Martin, Y. Negash, and E. Kessler. 1987. Evaluation of the Smallmouth bass recreational fishery in eastern Oklahoma streams. Oklahoma Department of Wildlife Conservation, Federal aid in Sportfish Restoration. F-41-R-18, Final Report, Oklahoma City.

Appendix Table 2. Gender distribution of Oklahoma resident anglers by license type with comparison to state population, 1992 (percent).

Gender group	State population 16 years and older 1991	License type				Weighted total
		Annual fishing	Annual Combination	Lifetime	Senior	
Male	47.0	71.2	96.4	94.4	81.0	78.0
Female	53.0	28.8	3.6	5.6	19.0	22.0
Total	100.0	100.0	100.0	100.0	100.0	100.0
Number in sample	NA	511	140	290	113	NA
Not reported	NA	0	2	1	1	NA
Sample size (all)	NA	511	142	291	114	NA
Population	2,411,100	350,000	78,000	51,000	41,000	520,000

Appendix 3. Age distribution of Oklahoma resident anglers by license type with comparison to state Population (1992, percent)

Age group	State Population 16 years old and older, 1991	Annual fishing	Annual Combination	Lifetime	Annual Senior	Weighted Total
16-17 years old	4.0	0.9	0.7	1.1	NA	0.8
18-24 years old	12.0	8.2	7.1	10.3	NA	7.6
25-34 years old	21.0	17.6	24.2	20.9	NA	17.5
35-44 years old	20.0	28.2	22.7	30.8	NA	25.4
45-54 years old	16.0	24.6	22.3	24.1	NA	22.2
55-64 years old	10.0	18.8	22.3	11.4	3.6	17.4
65 years old and older	17.0	1.7	0.7	1.4	96.4	9.1
Total	100.0	100.0	100.0	100.0	100.0	100.0
Number in Sample	NA	508	140	282	110	NA
Not reported	NA	3	2	9	4	NA
Sample size (all, whether fished or not)	NA	511	142	291	114	NA
Population	2,411,100	350,000	78,000	51,000	41,000	520,000

Appendix 4. Education distribution of Oklahoma resident anglers by license type with comparison to state population, 1992 (percent).

Education group	State Population 16 years old and older, 1991	Annual fishing	Annual Combination	Lifetime	Annual Senior	Weighted Total
11 years or less	19.0	10.5	7.9	10.8	28.3	11.5
12 years	42.0	61.5	58.6	58.4	48.7	59.8
Votech, Some College	21.0	7.0	7.9	4.6	1.8	6.5
4 years of college or more	17.0	21.0	25.6	26.2	21.2	22.2
Total	100.0	100.0	100.0	100.0	100.0	100.0
Number in Sample	NA	510	140	286	113	NA
Not reported	NA	1	2	5	1	NA
Sample size (all, whether fished or not)	NA	511	142	291	114	NA
Population	2,411,100	350,000	78,000	51,000	41,000	520,000

Appendix 5. Race distribution of Oklahoma resident anglers by license type with comparison to state population, 1992 (percent).

Race group	State Population 16 years old and older, 1991	Annual fishing	Annual Combination	Lifetime	Annual Senior	Weighted Total
White	87.0	86.6	90.6	89.6	90.2	87.8
Black	5.0	2.3	2.2	0.0	2.7	2.1
All others	8.0	11.1	7.2	10.4	7.1	10.1
Total	100.0	100.0	100.0	100.0	100.0	100.0
Number in Sample	NA	510	139	289	110	NA
Not reported	NA	1	3	2	4	NA
Sample size (all, whether fished or not)	NA	511	142	291	114	NA
Population	2,411,100	350,000	78,000	51,000	41,000	520,000

Appendix 6. Types of waters fished by samples of Oklahoma resident anglers by license holder type, 1992.

License Holder	Sample Size (Number)	Did Not Fish in 1992	Types of Waters Fished (Percent of Sample)					
			Reservoir	Small Impound-ment	Farm ponds	Large rivers	small rivers and creeks Streams outside Eastern Oklahoma	small rivers and Creeks Streams in Eastern Oklahoma
Original Sample[1]								
Annual	511	2.3	67.7	22.9	36.6	12.8	6.4	12.5
Combination	142	7.0	54.2	28.8	40.0	16.9	9.8	14.0
Lifetime	291	8.6	50.2	39.9	53.2	20.6	12.0	20.9
Senior	114	26.3	46.5	22.8	18.4	11.4	6.1	8.7
Supplementary Sample[2]								
Annual	167	4.2	49.1	37.7	30.5	26.9	3.5	22.2

Details do not add to 100% because of multiple responses.

[1] An independent random sample on the stratified (by license type) population of 1992 Oklahoma fishing license holders.

[2] A second sample of resident, annual fishing license holders residing in a stratum of Oklahoma's most eastern counties.

ESSAY II

Fishing Trip Demand Model For Eastern Oklahoma Natural Streams

Fishing Trip Demand Model For Eastern Oklahoma Natural Streams

Abstract

One of the methodological problems with recreation trip data is that the sample responses are nonnegative integer counts drawn from a heterogeneous population. Disaggregate count data models are presented and estimated for fishing trips to small natural streams in eastern Oklahoma. The Poisson regression model is presented first. However, the test for overdispersion indicates the Poisson model to be inappropriate. Alternatives to the Poisson model are considered, namely, the negative binomial and the hurdle count data models. The negative binomial model was found more appropriate for the fishing trip data. The estimated trip demand model was used to compute economic benefits per trip to small streams in eastern Oklahoma.

Fishing Trip Demand Model For Eastern Oklahoma Natural Streams Fishing

1. Introduction and Problem Statement

Recreation demand modeling has been used by economists since the early 1960s. Economists use travel costs to reveal recreationist's preferences and to estimate demand for trips for purposes of measuring the nonmarket value of recreation sites (Smith, 1996).

There is little information available on the economic value of eastern Oklahoma small natural streams for use as fisheries. In addition, it is known that Oklahomans make fishing trips to other fisheries in Oklahoma as well as to fisheries outside of the state. However, it is not known if there exists a substitution relationship between fishing trips to natural streams and to other fisheries within Oklahoma and out-of-state. Furthermore, exploration in the use of state policy in managing eastern Oklahoma's small natural streams and the effects of substitution of fishing trips between different fisheries is limited without information on the values of these nonmarket goods. It is the purpose of this research to estimate trip demands for eastern Oklahoma small natural streams and to assess the presence of substitution effects with other fisheries.

2. Approaches to the Valuation of Nonmarket Recreation Goods

There are two basic approaches to valuing nonmarket recreation goods: the indirect (extended revealed preference) approach and the direct (structured conversation) approach (Smith, 1996; Turner, Pearce and Bateman, 1993) .

The indirect approach is the travel cost method and examines individuals' purchases of market priced goods which are necessary to enjoy associated nonmarket goods such as fishing trips. This indirectly seeks to recover estimates of individuals' willingness-to-pay for nonmarket goods by observing their behavior in related markets.

The direct approach is the contingent valuation method and measures demand by examining individuals' stated preferences for nonmarket goods, i.e. direct solicitation of individuals' preferences for nonmarket goods.

2.1 Travel Cost Method

The travel cost recreation demand model is an indirect method, initially proposed by Harold Hotelling in 1947 and occupies a major place in the applied research programs of resource and environmental economics. It is indirect in the sense that it uses data on marketed inputs needed for the provision of a final flow of service.

Early application of travel cost demand models was motivated by the need to value recreation benefits provided by public investment projects. For example, constructing a dam for a hydroelectric generating plant, flood control, or both, creates a lake and opportunities for water based recreational activities. Estimating these benefits requires an aggregate demand function for a site considered to be a perfect substitute for the one created by the project being evaluated. More recent applications include evaluating regulatory or management options that change the features of existing recreation sites (Smith, 1989).

The travel cost method, with its different variants, estimates the relationship between trips to a site, recreation price, and other explanatory variables and then simulates the effect of an increase in the price of the recreational opportunity by an increase in trip costs.

The model recognizes that individuals making trips to a recreation site pay an implicit price which is out-of-pocket travel cost. By observing the number of trips to the site and the costs for individuals at different distances from the site (including fees and related charges), information is obtained comparable to that provided by market transactions. The presence of spatial variation allows different prices for different individuals and thus the model may be estimated using cross-section data (Fletcher et al, 1990).

In this method, each person is assumed to have choices, reflected by preference or utility (U), over the number of trips to a set of recreation sites as well as over the consumption of nonrecreation market goods. The utility function representing person i's preferences is given by equation (1) and restrictions on the choices that are feasible by the constraints are equations (2) to (4):

$$U_i(X_i, V_i, L_i; q_i) \tag{1}$$

$$PX_i + C_i V_i \leq Y_i(T_i^W) \tag{2}$$
money budget constraint

$$T_i^w + T_i^L + T(V_i) = T \tag{3}$$
time budget constraint,

$$T_i^W \in \Omega_i^W, T_i^L \in \omega_i^L; T_i^X \in \omega_i^X \tag{4}$$
other time restrictions

where X, V, and q are vectors, respectively, of quantity of market goods, number of trips to recreation sites , and qualities of recreation sites for individual i. P and C_i are prices of market goods, X_i, and the round-trip travel cost, respectively. L_i is the time spent by person i in leisure activities other than those represented in V. T represents the length of the time horizon: superscripts w, x, and L on T represent, respectively, vectors of time spent working at various wage jobs, time necessary to consume market goods, and time spent in various leisure activities not captured in V. The time spent recreating during trips is given by $T(V_i)$ and is determined by the number of trips of specific duration to all sites. Y represents income over the appropriate time period from all wage sources and depends on the time spent working. The Ωs are sets of (possibly individual-specific) constraints on the work, leisure, and goods consumption time vectors.

It is assumed that choices are generated by maximization of (1) subject to (2), (3), and

(4). This results in vectors of demand functions for market goods and for recreation trips:

$$X_i^*(P,\ C_i,\ Y_i,\ T,\ \Omega_i^W,\ \Omega_i^M,\ \Omega_i^x) \tag{5}$$

Despite its wide use there are criticisms of the model. The assumptions on how time

$$v_i^*(P,\ C_i,\ Y_i,\ T,\ \Omega_i^W,\ \Omega_i^M,\ \Omega_i^X) \tag{6}$$

is allocated or on the price available for added working time influences the opportunity cost of time and therefore the nature of the "implicit price" (Smith, Desvousges, and McGiveny, 1983). Sensitivity of the travel cost model relates to the basic unit of consumption. Most early studies treated trips to the site as the basic unit of consumption, implicitly assuming a fixed time on-site during each trip. When on-site time per trip is a choice variable, marginal rates of substitution (between number of trips during a season and the time on site during each trip) responds differently to different sets of relative prices (McConnell, 1990).

Evaluations of the travel cost method have been positive (Bockstael, McConnell, and Strand 1991; Ward and Loomis, 1986).

2.2. Contingent Valuation Method

Contingent valuation relies on responses to hypothetical situations (Riddick, DeSchriver, and Weissinger, 1984). It is an income compensation approach. Estimation involves construction of experimental situations to obtain information about individuals' indifference curves. Hypothetical markets and institutions are created and surveys are administered to assist consumers in revealing their preferences for nonmarket goods (Durden and Shogren, 1988). The critical assumption is that properly designed surveys can elicit responses comparable to those arising under actual situations.

Recreationists are confronted with different scenarios, such as recreation quality levels and level of service , and then asked how much they would be willing-to-pay to obtain the higher quality or service level rather than the current quality and level.

There are various methods for obtaining willingness-to-pay values. The most common technique is the "iterative bidding game" approach. It is conducted either through face-to-face interview or by telephone solicitation. In this method the respondent is asked if he or she would be willing to pay a specified dollar amount to obtain a given environmental improvement (or prevent a given environmental decline). If the response is "Yes", then the interviewer increases the bid by a specified increment and repeats the question. The process continues until a "No" response is obtained. The bid is then decreased by a specified amount until a "Yes" response is again obtained and this bid is recorded as the maximum willingness-to-pay (Foster, 1989).

Alternatives to the bidding game format are the direct question and payment card methods. These approaches use either an "open-ended" format in which the respondent is simply asked to reveal his maximum willingness-to-pay (dollar value) or a "closed-ended" format in which the respondent is asked if they would be prepared to pay a specified amount and respond YES or NO. For the latter model the amount is varied but each respondent has only a binary choice - YES or NO. Both formats may be used in mail surveys as well as by direct person-to-person interview (discussion about the different contingent valuation methods and their criticisms is presented by Hanley, Shogren and White, 1997).

The main problem with the CVM is biases. If individuals believe that they will have to pay their stated willingness-to-pay amounts, then they have an incentive to understate their true preferences. On the other hand, if they believe that they will not have to pay their stated willingness-to-pay, they may have an incentive to overstate their preferences in order to ensure that the proposed project is undertaken. The second major concern is the hypothetical nature of the CVM in that individuals will not behave the same in the hypothetical market as they would in an actual situation.

2.3. Household Production Function Model

Another class of indirect valuation methods is the household production function (HPF) model. The HPF framework argues that marketed (and nonmarketed) goods and services are demanded as intermediaries in a household's consumption process. They are inputs that, together with the time of household members, are used to produce service flows. It uses averting behavior or HPF models try to infer an individual's value for some aspect of environmental quality when private actions can influence how it is experienced (Smith, 1996). The HPF has been applied to valuing recreation services (Dayek and Smith, 1978; Cichetti, Fisher and Smith, 1976; Bocksteal and McConnell, 1981; McConnell, 1979; Desvousges, Smith, and McGivney, 1983). In Becker's (1965) formulation, households combine marketed goods with time inputs to produce unobservable final commodities. These unobservable commodities are the source of utility. In the HPF, households are both producers and consumers, i.e. the important premise of household production theory is that an "output" of a recreational experience is not solely determined by site operators, guides or other providers. Recreational experiences also involve the participants themselves as they invest their time, money, equipment, skills, and enthusiasm in creating satisfying trips. Thus recreationists are both the ones who demand recreational opportunities, as well as the ones who supply these goods using available sites, facilities, and services as inputs (Berstrom and Richard, 1991). In this dual role households accomplish two tasks. First, they find the least cost strategy to produce a final set of commodities. Second, they choose the final commodity bundle which maximizes utility. An advantage of using the HPF is that it provides a theoretical basis to include substitution effects among sites and the effect of changes in site characteristics on benefit estimates (Rosenthal, 1985). This feature is useful for considering the linkages between investment which changes site characteristics and the demand for outdoor recreation. Detailed discussion and different applications are found in Smith (1996).

The major criticism of the HPF is that without a priori assumptions about constant returns to scale in production and no joint production, it is impossible to estimate marginal willingness-to-pay for environmental products (Mäler, 1985; Pollack and Wachter, 1975).

These conditions are not met in HPF. Bocksteal and McConnell (1983) point out that it is necessary to assume either quality per trip is exogenous or, instead, to use factor demands. On the other hand, Smith, Desvousges and Fisher (1986) acknowledge the HPF does help understand the important assumptions that underlie the function which yields valuable qualitative insights.

3. Count Data Models

Recent literature identifies several theoretical problems associated with the travel cost method (Hellerstein and Mendelsohn, 1993; Dobbs, 1993). These problems deal with the nature of trip data and technique used to model. Trip demands are inherently discrete and take on only positive integer values. Thus modeling trip demands using the travel cost method may give a biased result. Recent developments in the literature deal with alternative specifications to accommodate discreteness and nonnegativity. These alternative specifications are broadly known as count data models and have been used in valuation of recreational resources as well as resources used in other fields of study (Cameron and Trivedi, 1986; Caudill and Mixon, 1995; Chapell, Ikmenyi and Mayer, 1990; Gilbert, 1979; Hausman, Hall and Griliches, 1984; King, 1989b; Lambert, 1992; Gurmu and Trivedi, 1992). These alternative specifications include the Poisson, negative binomial, and hurdle models.

Count (alternatively called event-count) data is the number of events occurring within a specific observation period. These data take the form of nonnegative integers. Examples include type and frequency of recreation trips to a site, number of labor strikes in a given time period, labor mobility, and number of visits to a medical practitioner in a specified time period (Fry, et al., 1993).

The most widely used regression model is the normal linear regression model (NLM) with systematic component $E(N/X)=X\beta$, where N is a number of measurements on individual counts and X is associated individual characteristics. An estimate for β may be obtained by the method of maximum likelihood which reduces to ordinary least squares for the case of uncorrelated and homoskedastic errors. The distributional assumption for the random component has to account for the nonnegativeity of the data, and their integer nature (Winkelmann,1997). Count data estimators fit recreation trip data better than a continuous distribution-based estimators. Count data estimators restrict positive probability assignment of possible events, while continuous distribution estimators give positive probability to fractional and possibly negative values of the independent variable (Creel and Loomis, 1990). Theoretical and practical applications of the count data models are discussed below.

Two features of fishing trip demand functions complicate the estimation process: nonnegativity and integer values. Nonnegative trip demand results in a censored data set. If estimation processes do not account for the censored nature of data and integer values, then results may be biased (Hellerstein and Mendelsohn, 1993).

Survey instruments are generally used to record individual trips to recreation sites. When the data include the total number of trips taken in a given period, and especially when these data are only available for one recreation site, then count data models are appropriate (Shonkwiler and Shaw, 1996).

Two frequently used count data models are the Poisson and the negative binomial regression models. The Poisson model has been used as a bench mark model for basic count data outcomes (Winkelmann, 1997). It arises for events occurring "randomly and independently" in time (Johnson and Kotz; 1992)

The univariate Poisson distribution is derived as the following (Parzen, 1960). Let the random variable Y=0, 1, 2, ... denote the number of events of interest (in our case the number of fishing trips to eastern Oklahoma small streams) in a given time interval and y(t, t + dt) denote the number of events actually observed in the short time interval (t, t + dt). The number of events in an interval of given length is Poisson distributed with probability density function:

$$pr(Y=y) = f(y;\lambda) = e^{-\lambda}\left[\frac{\lambda^y}{y!}\right], \quad y=0,1,2,\ldots, \; \lambda \in \mathbb{R}^{+} \tag{7}$$

It is a one-parameter probability distribution with expected value or mean:

$$E[Y] = \lambda, \tag{8}$$

and variance:

$$Var[Y] = \lambda \tag{9}$$

From (8) and (9) it shows that the Poisson distribution has identical mean and variance and is equal to λ. The parameter may be interpreted as the mean rate at which events occur per unit of time; consequently, it is referred to as the mean rate of occurrence of events (Parzen, 1960; Land, McCall, and Nagin, 1996). Parzen (1960) generalizes the Poisson process as follows: if X is the number of events occurring in a time interval of length t, then X obeys Poisson probability law with the mean λt. Consequently, λ is the mean rate of occurrence of events per unit of time in the sense that the number of events occurring in a time interval of length 1 follows a Poisson probability law with mean λ. The proof of this generalization is found in Parzen (1960; pp. 253).

The Poisson model is conveniently expressed in a regression framework by defining the most common specification for the conditional mean function,

$$E[y_i \mid x_i, t_i = 1] = \lambda_i = e^{\beta' x_i}, \tag{10}$$

where, x_i denotes a $(1 \times k)$ vector of regressor (alternatively called a covariate vector) variables for y_i (observations of a discrete response variable, i.e. the dependent count variable), and β is a vector of unknown parameters of certain dimension depending on the number of covariates.[4] Equation (10) also preserves the nonnegativity of λ.

Thus equation (7) can be written as, i.e. the density function for y_i,

$$f(y_i \mid X_i) = \frac{e^{-e^{\beta' x_i}} e^{\beta' x_i}}{y_i!} \tag{11}$$

and thus the density implies the moment restriction:

$$E[y_i \mid x_i] = var(y_i \mid x_i) = \lambda_i \tag{12}$$

The explanatory variables influence the dependent variable (the number of event

[4] See Cameron and Trivedi (1986), Gurmu and Trivedi (1996), Madala (1983).

occurrences in a specified time interval) not directly, but through the mean occurrence rate of the process (Winkelmann, 1997).

The advantages of this stochastic specification include (1) discrete and nonnegative nature of observations, (2) non-negligible probability for zero outcomes, and (3) inferences that can be drawn on the probability of event occurrences (Green, 1994; Gurmu and Trivedi, 1996; and Winkelmann, 1997).

A common practical problem when analyzing sets of data thought to be Poissonian is a breakdown in the variance-mean relationship because of overdispersion (rarely underdispersion: Johnson and Kotz; 1992). In other words, the equality of mean and variance assumption inherent to the Poisson distribution is restrictive for certain data generating processes. The effects of overdispersion are twofold: first, the summary statistics have larger variances than expected; and second, there may be a loss of efficiency if an inadequate model is adopted. This restriction and other limitations have led researchers to employ a variety of alternative specifications. Following Greene, modifications of the Poisson model have been suggested to accommodate the following:

(i) over- and underdispersion, which is a violation of the Poisson restriction that the variance of the observed random variable equals its mean,

(ii) unobserved individual heterogeneity, for example, in panel data which mandates the introduction of a disturbance term into the Poisson specification much like that which appears in conventional regression models, and which induces overdispersion, and

(iii) "non-Poissonness," (Johnson and Kotz (1969)) which is reflected in an overabundance or underabundance of certain specific values, usually zero value (Green, 1993).

Several approaches to detect the restrictive nature of the mean-variance equality of the Poisson model and to accommodate a more flexible model have been developed (e.g. Cameron and Trivedi, 1990; Hausman, Hall and Griliches, 1984; King 1989b, 1989c). With overdispersion, one way to remove the restriction of the Poisson model is to pick a less restrictive probability density function. This can be done by an additional overdispersion parameter with the interpretation that overdispersion results from the unobserved heterogeneity in the phenomenon being modeled, and justifies treating the Poisson parameter as a random variable (Gurmu and Trivedi, 1996).

Following Gurmu and Trivedi (1996) and King (1989b), a random disturbance term can be added to the intercept β_0, which is equivalent to introducing a multiplicative disturbance in the conditional mean function. Replace (12) by

$$\lambda_i^* = E(y_i|x_i, \nu_i) = e^{(x_i'\beta + \epsilon_i)} = e^{(x_i'\beta)}.\nu_i \tag{13}$$

or alternatively,

$$\ln \lambda_i^* = X_i\beta + \epsilon_i \tag{14}$$

where the unobserved heterogeneity term $\nu_i = e^{(\epsilon_i)}$ reflects a specification error such as unobserved or omitted exogenous variables. Let $g(\epsilon_i)$ denote the probability density function for ϵ_i. Then the marginal density of Y_i can be obtained by integrating with respect to ϵ_i

(Cameron and Trivedi, 1986; Land., McCall, and Nagin, 1996):

$$pr[Y_i = y_i] = \int Pr[y_i = y_i|X_i,\epsilon_i]g(\epsilon_i)d\epsilon_i$$
$$= \int \frac{e^{-e^{(X_i\beta+\epsilon_i)}} e^{(X_i\beta+\epsilon_i)^{y_i}}}{Y_i!} g(\epsilon_i)d\epsilon_i \tag{15}$$

We assume that the v_i's are identically and independently distributed (iid) and that they are independent of the x's.

Further assume that $E(v_i)=1$, $var(v_i) = \sigma_v^2$, and $E(y_i|x_i,v_i)= var(y_i|x_i,v_i)= exp(x_i'\beta)v_i$. Then the moments of y_i conditional on covariates, can be derived as (Gurmu and Trivedi, 1996)

$$E(y_i|x_i) = e^{(x_i'\beta)} \tag{16}$$

and

$$var(y_i|x_i) = e^{(x_i'\beta)}[1 + \sigma_v^2.e^{(x_i'\beta)}]>E(y_i|x_i) \tag{17}$$

The above formulation has the advantage of relaxing the mean-variance equality restriction of the Poisson model.

Expression (15) defines a compound Poisson distribution whose precise form depends upon the specific choice of $g(\epsilon_i)$. For certain parametric forms, such as the gamma, a closed form expression for (15) can be obtained; but for other choices, such as the standard normal density, the resultant Poisson might not have a closed form and hence be computationally cumbersome (Cameron and Trivedi, 1986).

An alternative to the Poisson specification is the negative binomial regression model (Green, 1994). This is a more flexible alternative to the Poisson distribution, especially when it is doubtful that the strict requirements, particularly independence, for a Poisson distribution are satisfied (Johnson and Kotz; 1992). The analytical form is given as follows (Green, 1994):

$$pr(y_i) = \frac{\Gamma(y_i+\psi)}{\Gamma(\psi)y_i!}\mu_i^{\psi}(1-\mu_i)^{y_i}, \quad \psi>0, \quad y_i = 0,1,\ldots \tag{18}$$

where

$$\mu_i = \frac{\psi}{\psi+\lambda_i}. \tag{19}$$

This has

$$E(y_i) = \lambda_i \tag{20}$$

and

$$Var[y_i] = \lambda_i[1 + (1/\psi)\lambda_i] = \lambda_i(1 + \alpha\lambda_i), \quad \alpha=1/\psi \tag{21}$$

Equation (21) has the property of the negative binomial distribution, namely, that its variance is greater than its mean. The negative binomial model has been formulated with overdispersion as an end in itself or it may be derived as a consequence of incorporating unobserved individual heterogeneity (Hausman, Hall, and Griliches, 1984).

Because it does not force equality of its mean and variance, the negative binomial has greater flexibility than the Poisson. However, Johnson and Kotz; (1992) point out that if the negative binomial is found empirically to give a good fit for a particular type of data, then the experimenter may still have to decide how to interpret the fit in terms of the many possible modes of genesis of the distribution. There are of course situations where a good fit is not obtainable with the negative binomial distribution, and in such cases it is usual to consider the possibility of a mixture of distributions (Johnson and Kotz, 1992).

One possible genesis of the negative binomial model is a mixture where the Poisson parameter λ_i is assumed to vary randomly according to a probability law. If $g(\epsilon_i)$ in (15) is assumed to be a gamma distribution, then the integration of (15) leads to negative binomial (Cameron and Trivedi, 1986; Johnson and Kotz, 1992; Winkelmann, 1997).

Winkelmann (1997) shows its derivation as follows. Let a random variable x be gamma distributed $\Gamma(\alpha,\beta)$ if the density takes the form

$$f(x;\alpha,\beta) = \frac{\beta^{\alpha}}{\Gamma(\alpha)} x^{\alpha-1} e^{\left(\frac{-x}{\beta}\right)}, \qquad x > 0,\ \alpha > 0,\ \beta > 0. \tag{22}$$

The mean and variance of x are $E(x) = \alpha/\beta$ and $Var(x) = \alpha/\beta^2$, respectively (Mendenhall, Wackerly and Scheaffer; 1990). Let ϵ_i in (15) be gamma distributed with $\Gamma(\alpha,\alpha)$. Then $E(\epsilon) = 1$ and $Var(\epsilon) = \sigma_{\epsilon}^2 = 1/\alpha$. Recalling $\lambda^* = \lambda\epsilon$, thus

$$f(\lambda^*;\lambda,\alpha) = \frac{\alpha^\alpha}{\Gamma(\alpha)}\left(\frac{\lambda^*}{\lambda}\right)^{\alpha-1} e^{-\frac{\lambda^*\alpha}{\lambda}}\frac{1}{\lambda}$$
$$= \frac{(\alpha/\lambda)^\alpha}{\Gamma(\alpha)}\lambda^{\alpha-1}e^{-\lambda^*\frac{\alpha}{\lambda}} \tag{23}$$

It should be noted that the mean is parameterized. Therefore, from equation (23) λ^* is gamma distributed $\Gamma(\alpha,\alpha/\lambda)$ with mean λ and variance $(1/\alpha)\lambda^2$. The integration of (23) then leads to the negative binomial distribution for y (Cameron and Trivedi, 1986; Green, 1994; Winkelmann, 1997):

$$f(y|\alpha,\lambda) = \frac{\Gamma(\alpha+y)}{\Gamma(\alpha)\Gamma(y+1)}\left(\frac{\alpha}{\lambda+\alpha}\right)^\alpha\left(\frac{\lambda}{\lambda+\alpha}\right)^y \tag{24}$$

$$E[Y|\alpha,\lambda] = \lambda, \quad Var(Y|\alpha,\lambda) = \lambda + \frac{1}{\alpha}\lambda^2 = \lambda + \sigma_\epsilon^2\lambda^2 \tag{25}$$

with $(1/\alpha)$ usually called the precision parameter (Lawless, 1987). The regression model is complete setting λ_i such that

$$\lambda_i = e^{(x_i\beta)} \tag{26}$$

Since $\lambda_i > 0$ and $\alpha_i > 0$ it is clear that the variance exceeds the mean. It is because of the additional parameter that makes negative binomial distribution more flexible than the Poisson distribution. Moreover, deriving the negative binomial distribution as a compound Poisson distribution allows the introduction of a stochastic error term, capturing unobserved heterogeneity and measurement errors similar to the error term in the linear regression model (Pohlmeier and Ulrich, 1994).

Another limitation of standard count models is that the zeros and nonzeros (positives) are assumed to come from the same data generation process. Mullahy (1986) suggestes that these two processes are not constrained to be the same.[5] His emphasis was to address whether the statistical model governing the binary outcome of the count being either zero or positive might differ from that determining the magnitude of the positive counts.

The basic idea is that a binomial probability governs the binary outcome of whether a count variate has a zero or a positive realization. If the realization is positive, the hurdle is crossed, and the conditional distribution is governed by a truncated-at-zero count data model. This is achieved by combining a dichotomous model for the count being zero or positive and a truncated-at-zero model for strictly positive outcomes.

4. Empirical Model and Estimation of Count Data Models

4.1. The Model

Each individual license holder is assumed to maximize utility subject to an income constraint. An additional constraint is that the choice for trips, X_1, must be a nonnegative integer. It is also assumed that at the beginning of the season each individual chooses X_1 and

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[5] Craig (1971) developed the basic idea of the hurdle model as a modification of the Tobit Model.

the quantity of other goods, $\mathbf{X}_2$.

Following Hellerstein and Mendelsohn (1993), utility maximization is expressed as a function of X_1 and $\mathbf{X}_2$, i.e.

$$\max_{x_1 \in I, x_2} [Y(X_1, \boldsymbol{X_2}, \epsilon; \beta | P * X = p_1 x_1 + \boldsymbol{p_2} x_2 = Y] \tag{27}$$

Where **P** (the vector of prices) is divided into P_1 (the price of the indivisible good) and $\mathbf{P}_2$ (a vector of prices of other goods). ϵ are unobservable factors specific to an individual, and Y is income. Because X_1 is restricted to $0,1,2,\ldots$, equation(27) can be rewritten as

$$\max_{x_1 \in I} \left(\max_{x_2} U[(X_1, \boldsymbol{X_2}, \epsilon; \beta) | \boldsymbol{P_2 X_2} = Y - P_1 X_1] \right) \tag{28}$$

The dual of (28) is the expenditure function and is expressed as;

$$\begin{aligned} E[P_1, \boldsymbol{P_2}, \epsilon; U_o] = Min(P_1 X_1^{*} + [\min(\boldsymbol{P_2 X_2})] \\ s.t.\ U(X_1^{*}, \boldsymbol{X_2}, \epsilon; \beta) = U_o, X_1^{*} = X_1) \end{aligned} \tag{29}$$

where U_o is a reference level of utility.

The compensated demand for X_1, $\mathbf{H}(P_1, \mathbf{P}_2, \epsilon, U_o) = \partial E/\partial P_1$, will be constant over discrete ranges of the expenditure function, with discrete jumps at prices that define the end points of these ranges (Hellerstein and Mendelson, 1993).

Price variation is observed across individuals, where each individual in the sample possesses a unique set of unobservable (ϵ) factors. At any price these factors determine the quantity each individual consumes.

Estimation of demand for this type of data proceeds by determining the probabilities of observing a level of demand , given prices, income and other observable variables. One approach to specifying these probabilities is through a probability density function. In this way, estimation of the demand curve is by computing the parameters of a probability density function. These parameters will vary as prices vary; and thus the probability of observing a particular level of demand.

4.2. Estimation

This section specifies the Poisson regression model, estimates parameters of the model, discusses properties of the estimator and proceeds to alternative estimators when certain of the assumptions of the Poisson process are violated.

The parameters of the Poisson regression model are estimated using the maximum likelihood procedure. Given an independent sample, the conditional (joint) probability distribution of the sample is given by the product of the individual (conditional) probabilities. Assuming that the random variable $(Y_i|, X_i)$ is independently and equally distributed and that the conditional model of Y_i , i=1,2,...,n given X_i, i=1,2,...,n is written in the form of a joint density,

$$L = \prod_{i=1}^{n} f(y_i|x_i;\beta_0) = \prod_{i=1}^{n} f_0(y_i|x_i) \tag{30}$$

where $f(y_i|x_i)$is given by (11), i.e.

$$pr(Y_i = y_i|x_i) = \frac{e^{-e^{(x_i\beta)}} e^{(x_i\beta)y_i}}{y!} \tag{31}$$

Equation (30) is the likelihood function. Maximization is simplified if equation (30) is transformed to logarithmic form. The maximizing parameter values of the log likelihood function also maximizes (30). Then, the log likelihood function for the Poisson regression model takes the form

$$\begin{aligned} \log L(\beta;y,x) &= \sum_{i=1}^{N} \log f(y_i) = \sum_{i=1}^{N} \left[-\lambda_i + y_i \log\lambda_i - \log(y_i!)\right] \\ &= \sum_{i=1}^{N} \left[-e^{(x_i\beta)} + y_i x_i \beta - \ln(y_i!)\right] \end{aligned} \tag{32}$$

The maximizing value of β, denoted as $\hat{\beta}$, has to fulfill the necessary first order conditions

$$\frac{\partial L(\beta;x,y)}{\partial \beta} = \sum_{i=1}^{N} \left[y_i - e^{(x_i\beta)}\right] x_i^{'} = 0 \tag{33}$$

and the Hessian matrix (matrix of second order conditions) is given by

$$H(\beta;x,y) = \frac{\partial^2 L(\beta;x,y)}{\partial\beta\partial\beta^{'}} = -\sum_{i=1}^{N} e^{(x_i\beta)} x_i^{'} x_i \tag{34}$$

The Hessian is always negative definite, the log likelihood is globally concave and the second order conditions for maximum at $\hat{\beta}$ are fulfilled (Green, 1994; Gurmu and Trivedi, 1996;

Winkelmann, 1997). Equation (33) is non-linear in β, therefore it should be solved through an iterative algorithm. But, given log-concavity of the likelihood function, the solution by standard methods such as Newton's method is straight forward and is a convenient way to compute the maximum likelihood estimator (MLE) of β. Winkelmann (1997) has shown that the MLE of β, i.e. $\hat{\beta}$, is a consistent and asymptotically efficient estimator.

However, the estimates from the Poisson model will not have the desired properties if the data display over or underdispersion. An alternative model should be used to handle these problems. As discussed in previous sections, the negative binomial and the hurdle models are alternatives to the Poisson model.

In its simplest form, the negative binomial model, as represented in (24), is specified with $\alpha = 1/\sigma^2$ and $\lambda_i = e^{(X_i\beta)}$ (Gurmu and Trivedi, 1996; Winkelmann, 1997). The outcome of this specification for the first two conditional moments, i.e. mean and variance, is shown in (17).

From (21) we see that the specification leads to a quadratic mean-variance relation. Cameron and Trivedi, (1986) show that different negative binomial regression models can be generated by linking the parameters λ_i and α_i of the underlying process to the explanatory variables X_i. By letting α_i vary across individuals such that $\alpha_i = \sigma^{-2}\lambda_i$ and $\lambda_i = e^{x_i\beta}$, α is no longer constant across individuals but is a function of the explanatory variables. $\alpha_i = (1/\theta)\lambda_i^k$, where $\theta > 0$ is a dispersion parameter and k is an arbitrary constant. The negative binomial model has $E(y_i|x_i) = \lambda_i$ and $var(y_i|x_i) = \lambda_i + \theta\, \lambda_i^{2-k}$. The most common models are Negbin I obtained by setting k=1 and Negbin II obtained by letting k=0. Negbin I implies a linear-in-λ_i

variance function, and Negbin II implies quadratic variance function (Gurmu and Trivedi, 1996).

The two parameterizations imply different assumptions about the variance function and will, in general, lead to different estimates of the parameter β.

Estimation of the negative binomial model is through the maximum likelihood procedure. The log-likelihood and the gradient function of the negative binomial model is given by :[6]

$$\log L = \sum_{i=1}^{N} \left\{ \left(1(y_i > 0) \sum_{j=0}^{y_i - 1} \log(\psi + j) \right) - \log y_i! \right. \\ \left. + \ \psi \log u_i y_i \log(1 - u_i) \right\} \tag{35}$$

$$\frac{\partial \log L}{\partial \beta} = \sum_{i=1}^{N} u_i e_i x_i \tag{36}$$

$$\frac{\partial \log L}{\partial \psi} = \sum_{i=1}^{N} \left\{ \left(1(y_i > 0) \sum_{j=1}^{y_i - 1} \frac{1}{\psi + j} \right) + \log u_i + (1 - u_i) \left(1 - \frac{y_i}{\lambda_i} \right) \right\} \tag{37}$$

6

This log likelihood is due to Green (1994). Green derives this form after manipulating the function to eliminate the gamma integrals. It is beyond the scope of this study to demonstrate the derivation of the likelihood and thus the reader is referred to Green(1991) pp. 560 for rigorous derivation.

where **1** is indicator function, **1**(condition) = 1 if the condition is true and 0 if not, at various points (Green, 1994). Lawless (1987) provides detailed analysis of maximum likelihood estimation of the negative binomial regression model.

Another class of count data models treat zeros and nonzero (positive) counts as originating from different data generating processes. This assumption is not present in standard count data models discussed so far. Mullahy (1986) suggested modified count models in which these two processes are not constrained to be the same. This modified count data model is termed a hurdle model and the idea underlying its formulation is that a binomial probability model governs the binary outcome of whether a count variate has a zero or a positive realization. If the realization is positive, the 'hurdle' is crossed, and the conditional distribution of the positives is governed by a truncated-at-zero count data model. This implies for an appropriate specification of a count data model (fishing trips to eastern Oklahoma natural streams in our case) the decision to make a trip and the frequency of trips need to be treated as different stochastic processes (Pohlmer and Ulrich, 1994).

The hurdle specification rests on the basic assumption that the process is driven by two sets of parameters and allows for a systematic difference in the statistical process governing individuals with zero counts and those with one or more counts.

Let $\theta_1 = (\beta_1^{'}, \sigma_1)^{'}$ and $\theta_2 = (\beta_2^{'}, \sigma_2)^{'}$ denote the parameter vectors of the two stage process. Then, the likelihood function for the hurdle specification is given by:

$$L = \prod_{i \in \Omega_0} pr\{y_i = 0 \mid x_i^{'}\beta_1, \sigma_1^2\}$$
$$\times \prod_{i \in \Omega_1} (1 - pr\{y_i = 0 \mid x_i^{'}, \sigma_1^2\}) \frac{pr\{y_i | x_i^{'}\beta_2, \sigma_2^2\}}{pr\{y_i \geq 1 | x_i^{'}\beta_2, \sigma_2^2\}} \tag{38}$$

The first product governs the hurdle part and indicates the probability of a zero count - in our model it indicates that there is no decision to make a trip to eastern Oklahoma natural streams. This outcome is a binomial probability model with parameter vector θ_1. The second product represents the process that the hurdle has been passed and it is given by a truncated-at-zero model with parameter vector θ_2. The first term in the second product is the probability of deciding to make a fishing trip, while the fraction represents the probability of a positive count conditional on the decision to make a fishing trip. The sets Ω_0 and Ω_1 represent the subsamples of individuals who made no trip and those who made at least one trip to eastern Oklahoma natural streams.

Following Pohlmeier and Ulrich (1994), let the binary variable d_i take on the value of one if trip has taken place and zero otherwise, then the likelihood function can be expressed as the product of two parametrically independent likelihood functions:

$$L = \prod_{i \in \Omega} pr\{y_i = 0 | x_i^{'}\beta_1, \sigma_i^2\}^{1-d_i} (1 - pr\{y_i = 0 | x_i^{'}\beta_1, \sigma_1^2\})^{d_i}$$
$$\times \prod_{i \in \Omega_1} \frac{pr\{y_i | x_i^{'}\beta_2, \sigma_2^2\}}{pr\{y_i \geq 1 | x_i^{'}\beta_2, \sigma_2^2\}} \tag{39}$$

where the first product is the likelihood for the binary process (trip versus no-trip) defined over the total sample Ω, and the second product is the likelihood of a truncated-at-zero count model (defined over the sample of individuals with positive counts). Taking the log of equation (39) we have:

$$\log L = \log\left\{ \left[\prod_{i \in \Omega} pr\{y_i = 0 | x_i' \beta_1, \sigma_i^2\}^{1-d_i} (1 - pr\{y_i = 0 | x_i' \beta_1, \sigma_1^2\})^{d_i} \right] \times \left[\prod_{i \in \Omega_1} \frac{pr\{y_i | x_i' \beta_2, \sigma_2^2\}}{pr\{y_i \geq 1 | x_i' \beta_2, \sigma_2^2\}} \right] \right\} \tag{40}$$

$$\log L = [\Lambda^{p1}(\beta_1)] + [\Lambda^{p2}(\beta_2)] \tag{41}$$

Λ^{p1} can be regarded as a log likelihood function for the binary (zero/positive) outcome and Λ^{p2} as a log likelihood function for a truncated-at-zero model. Thus, the maximum likelihood estimates of β_1, β_2 can be obtained by separate maximization of the two log likelihoods.

5. Data

The data for this study was obtained from a follow-up of a screening survey of Oklahoma license holders conducted by the Department of Agricultural Economics, Oklahoma State University (Oklahoma Department of Wildlife Conservation , 1994). The screening survey identified license holders who fished in eastern Oklahoma small rivers and streams in 1992. Completed surveys for 163 license holders making a trip in 1992 to eastern Oklahoma small rivers and stream became the sample for a second follow-up survey in 1993.

The second survey obtained information on socio-demographic attributes, number of fishing trips to all fisheries, travel distances, and trip-related expenditures to all Oklahoma fisheries (ODWC, 1994).The data set was reduced to 100 because of the presence of the following:

(i) seven senior citizen license holders were excluded from the study. This is because this license type is based on the age of the angler and poses a problem when using the age factor as a variable in the model.

(ii) nine observations had poor response and missing information.

(iii) 45 license holders have no response regarding purchasing of a license and making trips to different fisheries in 1993.

(iv) six anglers did not buy a license nor fished in Oklahoma in 1993.

(v) one out-of-state resident.

6. Empirical Results

The count data model was used to estimate fishing trip demand for eastern Oklahoma small natural streams. The dependent variable is the number of trips made by the sample of license holders in 1993. Independent variables include travel cost to eastern Oklahoma small natural streams, number of trips to other fisheries, and socio-demographic data for the sample of license holders. Description of the variables is in Table (1). Frequency distribution of the number of trips to eastern Oklahoma small streams is presented in Table (2). Descriptive statistics of the variables are in Table (3). The variables include gender, age, education level, ethnic background, trips to alternative fisheries, trip cost and number of fishing trips to small natural streams in eastern Oklahoma. The figures in Table (3) are based on 80 observations. Twenty observations reported no trip to small streams in eastern Oklahoma. One observation is excluded from estimation since the value for trip cost is comparatively very high and perceived as an outlier. Therefore, cost per trip is zero. Because implicitly the trip cost is assumed to measure price of a trip it seems implausible to consider zero price. There might be different reasons in the perception of the license holder to make no trips. For this reason the analysis is based on the truncated at zero data set.

Gender is represented as a dummy variable and is equal to 1 if gender is female , zero otherwise. Males on the average make more fishing trips than females and females choose more accessible fishing sites (Negash and Schreiner, 1999). Consequently, it is expected that females make fewer trips to natural streams as compared to males. Age and age square are used to test a nonlinear response among license holders. The expected result is that older license holders make fewer trips because natural streams fishing is more strenuous (Negash and Schreiner, 1999). Education level is subdivided into three groups (Table 1). The reference group is high school graduate with perhaps some post graduate training but less than a college degree. About 73 percent of the sample is classified in the reference group. Ethnic background enters the model as a dummy variable. The two groups are whites and nonwhites. Race will be equal to one if the license holder is nonwhite, zero otherwise. Because income data is not available for all license holders, the education and ethnic variables may act as a surrogate for income. Thus, less educated and nonwhite license holders may make fewer trips if trips are positively correlated with income.

Maximum likelihood estimates of parameters for the constrained and unconstrained Poisson model are presented in Table 4. The coefficients for the ten explanatory variables except AGE, AGESQ and RACE have t-ratios that exceed conventional criteria of statistical significance, i.e. all have a p-value of practically zero. The overall fit of the Poisson model, as indicated by the chi-square statistic, shows that improvement in goodness of fit is achieved by the addition of the ten regressors and is highly significant as compared to the model with intercept term only.

The Poisson model through its inherent moment restriction is likely to over- but rarely underestimate the variance (Winkelmann, 1997). Three of the most widely referenced tests for the presence of overdispersion are those of Cameron and Trivedi (1986, 1990) and Dean and Lawless (1989) tests.

Cameron and Trivedi's (1986) test for overdispersion utilizes the fact that a Poisson random variable has the first two moments equal. Based on this, the test analyzes the relationship:

$$E\left[(y_i - \mu_i)^2\right] - \mu_i = \alpha \, g(u_i) \tag{42}$$

where μ_i is the mean and $g(\mu_i)$ is some function of μ_i. The test on α is, therefore, a means of testing for Poisson variation. This procedure is used to test the appropriateness of the

Poisson mode for the fishing trip data.

Following Cameron and Trivedi (1990), the test on the mean specification indicates the presence of overdispersion in the data set. The result, with heteroskedastic t-ratio shown in parenthesis, is as follows:

$$
\begin{aligned}
E\,[(y_i - \mu_i)^2 - \mu_i] &= \underset{(1.649)}{515.95} \times g(\mu_i), \text{ where } g(\mu_i) = \mu_i \\
&= \underset{(.9735)}{0.548} \times g(\mu_i), \text{ where } g(\mu_i) = \mu_i^2
\end{aligned}
$$

The above test indicates evidence of overdispersion in the data. The first equation implies a linear-in-μ_i variance function and the second equation implies quadratic-in-variance relationship. One consequence of using the Poisson specification in the presence of overdispersion is that the standard errors of the coefficients are underestimated and as a result the t-ratios of the Poisson model are biased upward.

Because there is overdispersion in the data, the model was estimated using negative binomial specification. The results are presented in Table 5.

The parameter estimates of the negative binomial model, as opposed to the Poisson model, have standard errors of higher magnitude. In fact, this result corresponds to the expectation that there is overdispersion in the data. A significant dispersion parameter (α) also confirms the presence of overdispersion. Results in Table 5 show only the intercept, trips to reservoirs, trips to small lakes, trip cost to eastern Oklahoma natural streams and the dispersion parameter (α) to be significant at the 10 % p-value. The sign for the trip cost has expected direction. The estimated parameters for trips to reservoirs and small lakes are positive indicating a competetive relationship to small stream fishing in eastern Oklahoma.

The frequency distribution of the number of fishing trips to eastern Oklahoma natural streams (Table 2) shows the presence of a high proportion of zero trips (19.8 %). This produces overdispersion even in the absence of heterogeneity. As noted previously, although the count nature of the dependent variable implies the use of a poisson or negative binomial model, theory suggests that the count data should have been generated by a two stage process such as that of the hurdle model (Mullahy, 1986).

Therefore, to accommodate the presence of a relatively high proportion of zeros, the hurdle model was used to estimate the count data model. These results are presented in Table 6.

In the first stage the decision to make a trip to eastern Oklahoma natural streams is modeled using the logit model. It is found that none of the explanatory variables are significant.

In the second stage, we first used the truncated-at-zero Poisson model. All the explanatory variables with the exception of AGE, AGESQ and RACE are significant. The fact that no parameter in the first stage is significant implies that the assumption that the zeros and the positive counts may be the results of two different data generating processes is inappropriate. The second stage estimates are equivalent to the previous estimates of the Poisson and negative binomial models. This, in fact, should be the case because both models deal with the same truncated data. For this reason no overdispersion test is made to determine the appropriateness of the Poisson model in the second stage.

7. Benefit per Trip Estimate

Benefit per trip is often measured by computing consumer surplus and calculated by integrating the area under a demand curve and above the price line. With count data models, the estimated demand function is a probability distribution of number of trips. Taking the expected value of this distribution yields the expected number of trips at each price (trip cost). By integrating underneath this expected response, a measure of the expected value of consumer surplus is obtained (Hellerstein and Mendelsohn, 1993).

For a given price (trip cost) change from P_1 to P_2, the expected value of the consumer surplus (E[CS]) is

$$E[CS] = \int_{P_1}^{P_2}\int_{E} [f(\epsilon)Q(X,\epsilon;\beta)]d\epsilon dp \tag{43}$$

where $Q(X,\epsilon;\beta)$ is an individual's demand curve for the trips which will be a step function with the exact shape dependent on ϵ . $f(\epsilon)$ is the probability density function and captures the influence of unobservable factors on trip demand. Equation (60) can be rewritten as

$$\int_{P_1}^{P_2}\lambda(X;\beta)dp = E[CS] \tag{44}$$

where $\lambda(X;\beta)$ is the expected value of a trip (the mean) and is given by

$$\lambda(X;\beta) = \int_{E} [f(\epsilon)Q(X,\epsilon;\beta)]d\epsilon \tag{45}$$

Trip demand is assumed, ceterus paribus, negative binomial distributed, with mean equal to

$$\lambda(X;\beta) = e^{X\beta} \tag{46}$$

Integrating equation (46) over the relevant range of trip cost yields the expected value of consumer surplus per trip. The benefit estimate for each license type is calculated by evaluating (45) at the mean values of each explanatory variable and then integrating the expected trip from the average to the maximum trip cost for each license type. The estimated benefit per trip by license type is presented in Table 7. The benefit per trip ranges from \$ 1.38 for life time fishing license holders to \$ 30.30 for annual combination fishing and hunting license holders. The benefit per trip for annual fishing license holders is \$ 8.31. Annual benefits (benefit per trip by mean number of trip) ranges from \$ 1.38 for life time fishing license holders to \$ 1116.88 for life time combination fishing and hunting license holders.

8. Conclusion

The purpose of this study was to estimate the demand for eastern Oklahoma natural stream fishing trips. Because of the nature of trip data, the traditional travel cost method was replaced by the count data model approach. Discussion on the different nonmarket valuation approaches was presented. Basic count data models and their empirical issues as applied in recreation demand analysis was also discussed.

Using sample telephone follow-up survey data, the demand for fishing trips to small natural streams in eastern Oklahoma was estimated. The Poisson model is the most widely used approach for count data. However, because of its mean-variance equality restriction, application is limited when data manifest overdispersion. Overdispersion was observed in the current survey data and thus the model was reestimated using the less restrictive negative binomial model. Except for the Poisson model, all the demographic variables in the negative binomial model are insignificant. The sign for trip cost is as expected (negative) and it is highly significant. Reservoir and small lakes trips are significant at the 1% and 10% significance level, respectively, and indicate a competetive relationship with trips to small streams in eastern Oklahoma. The fishing data displays a higher proportion of zero trips to small natural streams in eastern Oklahoma. This could be a source for overdispersion. However, the result indicates that there is no evidence for the presence of two data generating processes for zero and the positive observations. Therefore, the negative binomial model fits best as compared to the Poisson and hurdle model.

A limitation of this study is that the sample is based on the response of a screening survey which identified those license holders who fished in small natural streams in eastern Oklahoma in 1992. However, it is possible that license holders made fishing trips to these fisheries even though they did not make a trip in 1993. Small sample size is also another limitation.

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Table 1 . Description of Variables

Dependent	
Eoktrp	number of trips made in 1993 to eastern Oklahoma small streams
Independent	
Gender	0 = male; 1 = female.
Age	age in years
Agesq	age square
Education0	reference group; high school graduate and/or votech or some college
Education1	dummy variable for education level; 1=if less than high school, 0 otherwise
Education2	dummy variable for education level; 1=if college graduate and above, 0 otherwise
Race	0 = white; 1= nonwhite
Tripres	number of trips to reservoirs
Tripslak	number of trips to small lakes
Triplriv	number of trips to large rivers
Trip cost	cost per trip to eastern Oklahoma small streams ($)

Table 2 . Sample Frequency Distribution of Dependent Variable

No. of Trips	Frequency	Percent	Cumulative Frequency	Percent
0	20	20.0	20	20.0
1	4	4.0	24	24.0
2	3	3.0	27	27.0
3	4	4.0	31	31.0
4	3	3.0	34	34.0
5	9	9.0	43	43.0
6	4	4.0	47	47.0
7	3	3.0	50	50.0
8	4	4.0	54	54.0
9	3	3.0	57	57.0
10	7	6.9	64	64.0
14	1	1.0	65	65.0
15	5	5.0	70	70.0
16	2	2.0	72	72.0
17	1	1.0	73	73.0
19	1	1.0	74	74.0
20	4	4.0	78	78.0
22	1	1.0	79	79.0
25	1	1.0	80	80.0
26	1	1.0	81	81.0
30	2	2.0	83	83.0
32	1	1.0	84	84.0
33	1	1.0	85	85.0
36	1	1.0	86	86.0
40	2	2.0	88	88.0
43	1	1.0	89	89.0
50	2	2.0	90	90.0
52	1	1.0	91	91.0
60	1	1.0	92	92.0
63	1	1.0	93	93.0
70	1	1.0	94	94.0
75	1	1.0	95	95.0
85	2	2.0	97	97.0
100	2	2.0	99	99.0
235	1	1.0	100	100.0

Table 3. Descriptive statistics for the truncated data with 80 observations.

Variable	Mean	Std Dev	Minimum	Maximum
Eoktrp	23.11	33.640	1.0	235
GENDER	0.11	0.318	0	1
AGE	39.9	12.110	18	64
AGESQ	1756.42	988.600	324	4096
EDUCN0	0.725	0.449	0	1
EDUCN1	0.086	0.284	0	1
EDUCN2	0.185	0.393	0	1
RACE	0.123	0.333	0	1
TRIPRES	16.36	30.220	0	200
TRIPSLAK	4.440	11.640	0	90
TRIPLRIV	4.15	8.985	0	50
TRIPCOST	6.49	11.160	0	80

Table 4. Maximum Likelihood Estimates of Parameters for the Poisson Count Model

Variable	Coefficient	Standard Error	t-value	P-value
Constant	2.84	0.273	10.48	0.0000
GENDER	0.3395	0.0646	4.949	0.0000
AGE	0.011	0.0138	0.716	0.4337
AGESQ	-0.00002	0.0002	0.011	0.9911
EDUCN1	-0.484	0.115	-4.219	0.0000
EDUCN2	0.691	0.0637	10.848	0.0000
RACE	-0.009	-0.0827	-0.112	0.9105
TRIPRES	0.0067	0.0005	12.909	0.0000
TRIPSLAK	0.0163	0.0018	9.014	0.0000
TRIPLRIV	-0.009	0.0033	-2.884	0.0039
TRIPCOST	-0.150	0.0082	-17.999	0.0000
Log likelihood function		-757.393		
Restricted log likelihood		-1364.604		
Chi-squared		1214.422		
Degrees of freedom		10		
Significance level		0.0000		

Table 5. Maximum Likelih0od Estimates of Parameters for the Negative Binomial Model

Variable	Coefficient	Standard Error	t-value	P-value
Constant	3.006	1.159	2.600	0.0093
GENDER	0.199	0.3811	0.521	0.6024
AGE	-0.0191	0.0600	-0.32	0.7493
AGESQ	0.0004	0.0007	0.529	0.5969
EDUCN1	-0.541	0.9217	-0.587	0.5574
EDUCN2	0.084	0.3448	0.244	0.8076
RACE	0.077	0.3158	0.242	0.8086
TRIPRES	0.0086	0.0051	1.695	0.0902
TRIPSLAK	0.0446	0.0122	3.668	0.0002
TRIPLRIV	-0.0068	0.0122	-0.645	0.5186
TRIPCOST	-0.0545	0.0069	-7.857	0.0000
alpha (α)	0.6943	0.1588	4.373	0.0000
Log likelihood function		-309.97		
Restricted log likelihood		-757.39		
Chi-squared		894.85		
Significance level		0.0000		

Table 6. Maximum Likelihood Estimates of Parameters for the Poisson Hurdle Model

	Stage 1 (Logit)		Stage 2 (Poisson)	
Variable	Coefficient	t-value	Coefficient	t-value
Constant	3.5839	1.161	2.84	10.345
GENDER	-0.2195	-0.298	0.339	5.209
AGE	-0.1015	-0.655	0.0011	0.783
AGESQ	0.00104	0.559	- 0.000002	-0.011
EDUCN1	0.0170	0.019	-0.4841	-4.219
EDUCN2	0.7785	0.954	0.6906	10.848
RACE	0.1283	0.154	0.0093	0.112
TRIPRES	-	-	0.0069	12.909
TRIPSLAK	-	-	0.0163	9.014
TRIPLRIV	-	-	-0.0096	-2.884
TRIPCOST	-	-	-0.15	-17.999
Log likelihood function		-49.26	-757.393	
Restricted log likelihood		-50.262	-1364.604	
Chi-squared		2.0005	1214.666	
Degrees of freedom		6	10	
Significance level		0.919	0	

Table 7. Estimated Benefit Per Trip and Total Benefit for Small Streams in Eastern Oklahoma by License Type.

License Type (No)	Mean Cost ($)	Max. Cost ($)	Benefit per Trip($)	Mean Trip[a]	Estimated[a] Total Trips	Estimated Total benefit ($ 1000)
Annual, combination fishing and hunting	12.10	80.0	30.30	22.3	245500	7423.50
Annual, fishing	4.08	20.0	8.31	26.9	1177400	9784.19
Lifetime, fishing	4.97	16.0	1.38	20.7	58000	80.04
Lifetime, fishing and hunting	7.96	33.3	42.95	12.9	157900	6781.81

a The ODWC survey, 1992.

ESSAY III

FRESHWATER FISHING TRIP DEMAND IN OKLAHOMA

FRESHWATER FISHING TRIP DEMAND IN OKLAHOMA

1. Introduction

The different types of freshwater fisheries available in Oklahoma provide diverse recreational fishing experiences for both state and out-of-state anglers. Individuals devote considerable resources (monetary and time) to freshwater fishing in Oklahoma. Results of the 1992 and 1996 National Survey of Fishing, Hunting, and Wildlife Associated Recreation, show an increased economic impact of sport fishing in the state of Oklahoma over the 1992 - 1996 period (Table 1).

Freshwater sport fishing is an important recreation activity for Oklahoma residents and non-residents and generates employment opportunities and tax income. Therefore, it plays an important role in the welfare of individuals and society as a whole. However, the data of Table 1 does not convey the importance of sport fishing to the anglers. Willingness -to-pay for the fishing experience is the basis for determining its importance to anglers.

In the first essay the factors that influence the decision and choice of Oklahoma license holders to make fishing trips were analyzed. Distinctions between types of fisheries, types of license holders and residential location of license holders were made. In the second essay, a trip demand model for small streams in eastern Oklahoma was estimated and benefits per trip calculated. Other explanatory variables, including trips to water bodies other than small streams in eastern Oklahoma, were considered.

The main focus of this study is to estimate a demand model for sport fishing trips to all types of fisheries in Oklahoma using the 1996 National Survey of Fishing, Hunting, and Wildlife Associated Recreation. Economic value of fishing trips to all fisheries by all anglers in the state are estimated.

Because the national survey does not distinguish the different types of freshwater bodies (lakes, streams, reservoirs, etc) the model estimated is more general than the model estimated in the second paper.

2. Theory of Recreation Demand and Benefit Analysis

One common nonmarket valuation technique is the travel cost method (TCM). It is extensively used to estimate economic benefits received by participants in outdoor recreation (Carson et al., 1996). The TCM is a revealed preference model; it uses actual trip expenditures by the respondents to derive a demand curve from which to estimate recreation benefits. It can be applied to recreation sites in which visitors vary in their trip distance, cost and time. The basic premise of the TCM is that the number of trips to the recreation site will decrease with increases in distance traveled. The TCM estimates the demand curve for a recreation site by recognizing that the price of consuming recreation at the site in question varies directly with the distance the consumer is from the site. With careful surveying of the out-of-pocket costs, time costs and trips taken during the past year, a demand curve can be estimated and consequently used to calculate consumer surplus (Fix and Loomis, 1998). In this study, because the data are actual freshwater fishing experiences of anglers, the TCM approach is used.

An alternative method of nonmarket valuation is the contingent valuation method (CVM). As opposed to TCM, the CVM is a stated preference model, where revealed preferences (surveys of willingness-to-pay) are used to estimate demand functions and economic benefits for nonmarket goods.

An important feature of fishing trip data sets is the joint integer and nonnegative nature of the dependent variable, i.e. the number of trips to a fishing site. The travel cost method which does not consider the integer and nonnegative nature of data, yields biased estimates (Hellerestein and Mendelsohn, 1993).

A recent innovation in travel cost modeling of recreation site demand is the use of discrete count distributions (Creel and Loomis, 1991; Grogger and Carson, 1991; Haab and McConnell, 1996; Hellerstein and Mendelsohn, 1993; and Terza and Wilson, 1990). The attractiveness of count distributions is that they focus on nonnegative integer values which match directly with the data that characterizes individual recreation demand.

3. Methodological Approach

Count data models have two different uses. In some cases, the interest is modeling the conditional mean function and in making inferences about the statistical significance of key parameters - for example, the price sensitivity of the average number of trips. In other cases, the entire frequency distribution of events (trips) may be of interest (Gurmu and Trivedi, 1996). In this study we emphasize the use of count data models for modeling the conditional mean of fishing trips to freshwater fisheries in Oklahoma and then make inferences about the relevant explanatory variables.

The Poisson count data model is the basis for several empirical studies dealing with discrete and/or count data. It arises in situations as the probability distribution for the discrete, nonnegative count of the frequency of an event. Areas of application include the number of individuals arriving at a service station, the number of homicides per year (Grogger and Carson, 1991), and the number of patents applied for and received (Hausman and Griliches, 1984; Green, 1994).

Trip data are assumed to be generated by the following Poisson distribution:

$$Prob[Y=y_i|t_i] = \frac{e^{(t_i\lambda)}(t_i\lambda)^{y_i}}{y_i!} \quad ,y_i = 0,1,... \tag{1}$$

where λ is the first moment of the Poisson distribution , and thus is the expected value of the number of fishing trips to freshwater fisheries in Oklahoma. Explanatory variables , X_i, enter the model by specifying the Poisson parameter, λ, as a function of X_i and an unknown parameter vector, β, to be estimated. Consequently, the Poisson model is analogous to the familiar regression specification in that the expected value of the number of fishing trips is $E(Y_i \mid X_i) = g(X_i,\beta_i)$, where $g(X_i,\beta_i) = \lambda$. Following Hausman and Griliches (1984) the mean rate of occurrence per unit of time is specified as:

$$\lambda_i = e^{X_i\beta} \tag{2}$$

In several empirical studies the Poisson count data model is found to be limiting which has led to alternative count data models. The most frequent problem encountered is the assumption of equal mean and variance of the data. The Poisson model is also restrictive when unobserved individual heterogeneity is present in the data set (Hausman and Griliches, 1984). The latter contributes to overdispersion (conditional variance of the dependent variable exceeds its conditional mean). Overdispersion is thus a form of heteroskedasticity (Creel and Loomis, 1990). Therefore, in the presence of overdispersion, the Poisson model is not appropriate.

In the presence of overdispersion the negative binomial model is more suitable than the Poisson model. The negative binomial model has its conditional variance greater than its conditional mean. The negative binomial probability also arises by assuming the mean value or λ varies among the sample observations according to the gamma distribution. It can be specified as (Gurmu and Trivedi, 1996):

$$f(Y=y = \frac{\Gamma(y_i+\psi_i)}{\Gamma(\psi_i)\Gamma(y_i+1)}\left(\frac{\psi_i}{\lambda_i+\psi_i}\right)^{\psi_i}\left(\frac{\lambda_i}{\lambda_i+\psi_i}\right)^{y_i}, \quad y=0,1,... \tag{3}$$

where the parameter λ_i is the mean and $1/\psi_i$ is the precision parameter. In the context of regression,

$$\lambda_i = e^{x_i'\beta}$$
$$\psi_i = (\frac{1}{\alpha})\lambda_i^k \tag{4}$$
$$where\ \alpha>0\ .$$

ψ is a dispersion parameter and k is an arbitrary constant. The negative binomial has

$$E(y_i|x_i) = \lambda_i \quad and$$
$$var(y_i|x_i) = \lambda_i + \alpha\lambda_i^{2-k}\ . \tag{5}$$

Commonly, k=1 and gives a linear-in λ variance function. The negative binomial model is an alternative to the basic Poisson model in accommodating overdispersed data.

4. Data

The data were obtained from the National Survey of Fishing, Hunting, and Wildlife-Associated Recreation. The survey reports results from interviews with residents about their fishing, hunting, and other fish- and wildlife-related recreation.

The 1996 freshwater survey was designed to provide state level estimates of the number of people who participated in recreational hunting and fishing, and other forms of wildlife-related activities (e.g. wildlife observation). The survey was conducted in two stages: an initial screening of households to identify likely sportsmen and wildlife watching participants, and a series of follow-up interviews of selected persons to collect detailed data about their wildlife-related recreation during 1996. Information was collected on the number of people engaged in the activities, where and how often they pursued the activities, and money spent pursuing these activities (U.S. Department of Interior, Fish and Wildlife Services, 1996).

Three types of fishing are reported: (1) freshwater, excluding the Great Lakes, (2) Great Lakes, and (3) salt water fishing. The survey includes not only licensed anglers but also those who have no license.

The total sample for the state of Oklahoma consists of 348 individuals. Of this number, 184 observations were considered for the estimation of the freshwater trip demand model. The reduced number of observations accounted for missing information, incomplete data, or they did not make fishing trips in 1996.

The national survey provides additional information on gender, age, education, ethnic background, occupation, number of trips to different freshwater fisheries, trip related and unrelated expenditures. Tables 2 and 3 display the dependent and independent variables of the model and descriptive statistics of the data, respectively.

5. Estimation

Estimation of both the Poisson and negative binomial regression models proceeds using maximum likelihood. The likelihood for the Poisson model is given by:

$$L = \prod_{i=n}^{N} f(Y_i|X_i;\beta_0) = \prod_{i=n}^{N} \frac{e^{-e^{(x_i\beta)}} e^{(x_i\beta)y_i}}{Y_i!} \tag{7}$$

Taking the log of equation (7) we form the log likelihood function, i.e.

$$\begin{aligned} \log L(\beta;y,x) &= \sum_{i=1}^{N} \log f(y_i) = \sum_{i=1}^{N} \left(-\lambda_i + y_i \log\lambda_i - \log(y_i!)\right) \\ &= \sum_{i=1}^{N} \left(-e^{(x_i\beta)} + y_i x_i \beta - \ln(y_i!)\right) \end{aligned} \tag{8}$$

Maximization of equation (8) yields the value of β which satisfies the first and second order conditions given by:

$$\frac{\partial L(\beta;x,y)}{\partial \beta} = \sum_{i=1}^{N} \left[y_i - e^{(x_i\beta)}\right] x_i' \tag{9}$$

and

$$H(\beta;x,y) = \frac{\partial^2 L(\beta;x,y)}{\partial\beta\partial\beta'} = -\sum_{i=1}^{N} e^{(x_i\beta)} x_i' x_i \tag{10}$$

Equation (9) is nonlinear in β, so a solution for the system is obtained iteratively. Newton's method is most frequently used in this setting (Green, 1993).

The Poisson model may not be appropriate in the presence of overdispersion. This is due to the restriction that the mean and variance of the data are assumed equal. Under this condition the estimates of the Poisson regression model do not have the desired properties. Various testing procedures have been developed to check the assumption of equal mean and variance of a given data set (Cameron and Trivedi, 1986, 1990a; Dean and Lawless, 1989).

The negative binomial is a more flexible alternative to the Poisson model in the presence of overdispersion. The negative binomial model also results by assuming the Poisson parameter λ_i to vary randomly according to gamma distribution. Winkelmann (1997) has shown the derivation of the negative binomial model through this assumption. The negative binomial density function is given by:

$$f(y|\alpha,\lambda) = \frac{\Gamma(\alpha+y)}{\Gamma(\alpha)\Gamma(y+1)}\left(\frac{\alpha}{\lambda+\alpha}\right)^{\alpha}\left(\frac{\lambda}{\lambda+\alpha}\right)^{y} \tag{11}$$

with

$$\begin{aligned} E[Y|\alpha,\lambda] &= \lambda, \\ Var(Y|\alpha,\lambda) &= \lambda + \frac{1}{\alpha}\lambda^2 \end{aligned} \tag{12}$$

and

$$\lambda_i = e^{(x_i\beta)} \tag{13}$$

since $\lambda_i > 0$ and $\alpha_i > 0$ and the variance is greater than the mean.

Estimation of the negative binomial model is also by maximum likelihood. The log likelihood function is given by:

$$\log L = \sum_{i=1}^{N} \left\{ \left(\mathbf{1}(y_i>0) \sum_{j=0}^{y_i=1} \log(\psi+j) \right) - \log y_i! + \psi \log u_i y_i \log(1-u_i) \right\} \tag{14}$$

where **1** is indicator function, **1**(condition)=1 if the condition is true and 0 if not, at various points (Green, 1994).

$$\frac{\partial \log\text{-}L}{\partial \beta} = \sum_{i=1}^{N} u_i e_i x_i \tag{15}$$

$$\frac{\partial \log\text{-}L}{\partial \theta} = \sum_{i=1}^{N} \left\{ \left(1(y_i>0) \sum_{j=1}^{y_i-1} \frac{1}{\psi+j} \right) + \log u_i + (1-u_i)\left(1 - \frac{y_i}{\lambda_i} \right) \right\} \tag{16}$$

The hurdle model assumes that a large proportion of zero trips in the sample might have been the result of different data generating processes as compared to a positive number of trips. However, the proportion of zero trips in our data set is only 2.2 % (Table 4). Therefore, the hurdle model was not considered in this study.

6. Empirical Results

The results of the maximum likelihood estimates of the parameters of the Poisson and the negative binomial regression models are presented in Tables 5 and 6, respectively. The dependent variable is the number of fishing trips made to freshwater fisheries in Oklahoma during 1996. Independent variables include gender, age, ethnic background, academic level, and trip cost.

Gender enters the model as a dummy variable and takes the value one if the person is female and zero otherwise. On average, we expect males to make more fishing trips as compared to females. Age is a continuous variable and the quadratic form is used to test for the presence of nonlinearity in the relationship between number of fishing trips and age. We expect the probability of making fishing trips to freshwater bodies to increase as age increases from younger to older but then to decrease as age increases beyond a certain age level. Ethnic background and academic levels also enter the model as dummy variables.

Maximum likelihood estimates of the parameters for the Poisson regression model are presented in Table 5. The t statistics for all coefficients except education1 (kindergarten or never attended school) are significant. This may be the result of overdispersion in the data set. Overdispersion affects the significance of parameter estimates by inflating the t-statistic from the Poisson model (Gurmu and Trivedi, 1996).

Testing for overdispersion using Cameron and Trivedi's procedure indicates the presence of overdispersion. This procedure makes use of the fact that Poisson variates have identical first and second moments: i.e. the mean and variance of Poisson distributed data are equal. The test for the equality of mean and variance is completed by regressing the squared residuals from the Poisson regression on the predicted values for that same regression:

$$var(Y_i) = \mu_i + \alpha g(\mu_i) \tag{17}$$

Under the condition of mean-variance equality, we expect the estimated coefficient, α, to be equal to one. The test for $\alpha=0$ is therefore a test for overdispersion (Cameron and Trivedi, 1990). The results for the data of this study indicate overdispersion, i.e. the coefficient, α = 6.591 with very small p-value .

Consequently, the model is reestimated using the negative binomial regression. The results of this estimation are presented in Table 6. The results are significantly different from that of the Poisson estimates in terms of significance. Six variables are found significant at the 10 percent probability level as opposed to eight for the Poisson.

7. Benefit Estimates

Benefit estimates per trip are calculated by integrating the expected number of trips from the mean trip cost to the maximum value, other factors held at their mean values, i.e.

$$E[CS] = \int_{P_1}^{P_2} \lambda(X;\beta)dp = E[CS] \tag{18}$$

where $\lambda(x;\beta)$ is the expected value of a trip and is given by

$$\lambda(X;\beta) = \int_E [f(\epsilon)Q(X,\epsilon;\beta)]d\epsilon dp \tag{19}$$

and

$$\lambda(X;\beta) = e^{x\beta} \tag{20}$$

Substituting parameter estimates (Table 6) in the above equation and evaluating equation (18) gives us the benefit estimate for the mean number of fishing trips to freshwater bodies in Oklahoma. The value of the estimated total benefit is \$ 457.59 and the per trip benefit is \$ 30.51. Comparatively, the estimated benefit per trip for this study and that of trips to small streams in eastern Oklahoma are very close.

8. Conclusion

This study presented the Poisson regression model along with its alternative, the negative binomial model, to estimate parameters of the demands for fishing trips to freshwater bodies of Oklahoma. It is also shown that, in the presence of overdispersion, the Poisson regression model inflates the t-statistic, thus allowing more parameters to be significant. The alternative negative binomial model, which does not restrict the mean-variance equality, resulted in fewer significant parameters.

In both models gender is found to be significant and has the expected negative sign, which implies that keeping other factors constant males are likely to make more fishing trips to freshwater bodies as compared to females. The age factor for both the Poisson and the negative binomial models are significant and of the expected sign. Age squared is also significant. The negative sign of the estimated coefficient of age square implies that as age increases, keeping other factors constant, individuals are likely to make more fishing trips but after a certain age level it declines. Ethnic background is significant and has a positive sign. None of the education variables are significant for the negative binomial model. Cost of trip is significant in both models and has the expected negative sign.

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Table 1. The Economic Impact of Sport Fishing in Oklahoma, 1992 and 1996.

Item	1992	1996
Angler Expenditure ($)	387,326,000	490,767,292
Economic Output ($)	793,506,000	1,012,537,832
Earnings ($)	208,209,000	258,906,659
State Sales Tax ($)	17,403,000	22,084,528
State Income Tax ($)	5,946,000	5,472,069
Federal Income Tax ($)	21,541,000	24,252,897
Jobs (number)	11,610	14,797

Source: The 1996 National Survey of Fishing, Hunting and Wildlife Associated Recreation.

Table 2 . Description of Variables

Dependent variable	
TRIPS (no.)	number of trips made in 1996 to fresh waters in Oklahoma
Independent variables	
AGE	age in years
AGESQ	age square
GENDER	0 = male; 1 = female.
EDUCATION1	1=never attended school or kindergarten; 0 otherwise
EDUCATION2	1=elementary school graduate; 0 otherwise
EDUCATION3	1=highschool graduate ; 0 otherwise
EDUCATION4	1= college graduate; 0 otherwise
NONWHITE	1= ethnic background is nonwhite; 0 otherwise
TRIPCOST ($)	average trip cost per trip to freshwater bodies in Oklahoma

Table 3. Descriptive Statistics of the Variables for the 1996 Data Set for Oklahoma

Variable	N	Mean	Std Dev	Minimum	Maximum
Dependent variable					
TRIPS (No.)	184	14.64	20.268	0	130
Independent variables					
AGE	184	42	15.12	16	79
AGESQ	184	11764	1353.8	256	6241
GENDER	184	0.326	0.475	0	1
EDUCN1	184	0.011	0.104	0	1
EDUCN2	184	0.027	0.163	0	1
EDUCN3	184	0.500	0.501	0	1
EDUCN4	184	0.462	0.499	0	1
NONWHITE	184	0.147	0.355	0	1
TRIPCOST ($)	184	51.27	154.08	0	1457

Table 4. Frequency Distribution of Number of Fishing Trips to Oklahoma Freshwater Fisheries, 1996.

No. of trips	Frequency	Percent	Cumulative Frequency	Percent
0	4	2.2	4	2.2
1	29	15.8	33	18.0
2	18	9.8	51	27.8
3	18	9.8	69	37.6
4	15	8.2	84	45.8
5	6	3.3	90	49.1
6	9	4.9	99	54.0
7	1	0.5	100	54.5
8	5	2.7	105	57.2
9	5	2.7	110	59.9
10	10	5.4	120	65.3
11	2	1.1	122	66.4
12	1	0.5	123	66.9
13	2	1.1	125	68.0
14	2	1.1	127	69.1
15	5	2.7	132	71.8
16	3	1.6	135	73.4
17	3	1.6	138	75.0
19	1	0.5	139	75.5
20	5	2.7	144	78.2
21	1	0.5	145	78.7
22	1	0.5	146	79.2
23	1	0.5	147	79.7
25	2	1.1	149	80.8
26	1	0.5	150	81.3
30	3	1.6	153	82.9
32	2	1.1	155	84.0
33	1	1.1	156	85.1
35	3	1.6	159	86.7
36	1	0.5	160	87.2
37	1	0.5	161	87.7
38	1	0.5	162	88.2
39	1	0.5	163	88.7
40	2	1.1	165	89.8
43	1	0.5	166	90.3
44	1	0.5	167	90.8

Continued...
Table 4. Frequency Distribution of Number of Fishing Trips to Oklahoma Freshwater bodies, 1996.

No. of trips	Frequency	Percent	Cumulative Frequency	Percent
45	1	0.5	168	91.3
50	6	3.3	174	94.6
52	1	0.5	175	95.1
55	1	0.5	176	95.6
60	2	1.1	178	96.7
65	1	0.5	179	97.2
75	1	0.5	180	97.7
85	1	0.5	181	98.2
90	2	1.1	183	99.3
130	1	0.5	184	100

Table 5. Maximum Likelihood Estimates of Parameters for the Poisson Count Model

Variable	Coefficient	Standard Error	t-value	P-value
Constant	1.816	0.141	12.877	0.000
GENDER	-0.452	0.045	-9.992	0.000
AGE	5.231	0.659	7.935	0.000
AGESQ	-4.641	0.714	-6.52	0.000
EDUCN1	-0.142	0.142	-1.002	0.3165
EDUCN2	-0.988	0.182	-5.442	0.000
EDUCN4	-0.172	0.042	-4.128	0.000
RACE	0.419	0.053	7.858	0.000
TRIPCOST	-0.009	0.0006	-13.389	0.000
Log likelihood function		-1863.439		
Restricted log likelihood		-2139.142		
Chi-squared		531.4064		
Degrees of freedom		8		
Significance level		0		

Table 6. Maximum Likelihood Estimates of Parameters for the Negative Binomial Model

Variable	Coefficient	Standard Error	t-value	P-value
Constant	1.772	0.554	3.319	0.0014
GENDER	-0.481	0.198	-2.428	0.0152
AGE	5.269	2.624	2.201	0.0447
AGESQ	-4.687	2.698	-1.737	0.0823
EDUCN1	-0.121	0.905	-0.133	0.8940
EDUCN2	-0.831	0.872	-0.953	0.3404
EDUCN4	-0.225	0.171	-1.313	0.1892
RACE	0.404	0.232	1.741	0.0816
TRIPCOST	-0.006	0.0012	-4.705	0.0000
alpha (α)	1.129	0.1712	6.591	0.0000
Log likelihood function		-648.731		
Restricted log likelihood		-1863.439		
Chi-squared		2429.414		
Significance level		0.0000		

Summary

This dissertation is composed of three separate but related essays dealing with the economic analysis of recreational fishing in Oklahoma. The first estimates a probabilistic model to determine factors affecting decision to make a fishing trip and which types of water bodies in Oklahoma are visited. The discrete choice model is used to estimate the parameters of the probabilistic model. Seven separate choice models were estimated for different types of water bodies found in Oklahoma. These are reservoirs, small impoundments, small lakes, farm ponds, large rivers, small rivers located in noneastern parts of Oklahoma and small rivers in eastern Oklahoma.

The maximum likelihood results for the different water bodies indicate that the number of significant parameters and the sign and magnitude of the parameters are not the same for each water body type. Reservoirs have the fewest number of significant parameters. On the other hand, small natural streams in eastern Oklahoma has comparatively more significant parameter estimates. Geographical location of license holders, and the frequency of trip to a given water body type are found to be important variables in the model. This is a plausible result because comparatively higher frequency of trip by a license holder to a given site indicates his strength of preference to that specific water body and also the farthest the residence of a license holder is from a given water body the higher is the cost associated with making fishing trip and vice versa. Other explanatory variables such as gender, age, ethnic background, and type of license holders have different statistical results depending on the type of water body.

The second essay focuses on estimation of a demand model for fishing trips to small natural streams in eastern Oklahoma. These streams provide recreational fishing opportunities for both Oklahoma residents and out-of-state anglers. Previous to this study, there was no estimate of the economic benefit of these water bodies for fishing. The Poisson, negative binomial and hurdle models were used to estimate the parameters of the fishing trips demand model.

The Poisson model resulted in statistically significant parameter estimates. However, because of its inherent equal mean-variance restriction it is likely to underestimate the variance. The regression based test for equal mean-variance of the fishing trips data indicates the presence of overdispersion. The negative binomial regression is used to accommodate overdispersion and is more appropriate for the data set. The hurdle model determines whether the zero observations and the positive trips come from different data generation processes. It was also found to be inappropriate for the fishing trip data. All of the parameter estimates for the binary logit model were statistically insignificant implying that there is no evidence that the zero and positive trip data came from two different data generating processes. The benefit estimate is based on the negative binomial result.

Limitations of this essay include small sample size and the fact that license holders who responded in 1992 may not have fished the small natural streams in Oklahoma in 1993, the year of the follow-up-survey. The latter problem implies that other license holders who did not make fishing trips in 1992 may have visited the streams in 1993.

The third essay is methodologically similar to the second essay and estimates a demand model for fresh water fishing in Oklahoma in general. The data used in this study was obtained from the 1996 National Survey of Fishing, Hunting, and Wildlife Associated Recreation. The survey does not identify anglers by type of water body fished or by type of license. Oklahoma residents who made fishing trips in Oklahoma were used in the analysis. The negative binomial regression was found to be a better fit than the Poisson model, again because of the presence of overdispersion. Average benefit per trip to all fresh water bodies in Oklahoma was estimated at $ 30.51.

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Education: Graduated from Misrak Comprehensive Secondary High School, Addis Ababa, Ethiopia in 1982; received Bachelor of Science Degree in Agricultural Economics from Addis Ababa University, Alemaya College of Agriculture in November, 1986; received Masters of Science Degree in Agricultural Economics from Oklahoma State University in August, 1995; Completed requirements for the Doctor of Philosophy degree at Oklahoma State University in May, 1999.

Professional Experience: Graduate Research Assistant, Department of Agricultural Economics, Oklahoma State University, September, 1995 to December, 1998; Planner, National Office for Central Planning, Addis Ababa, Ethiopia, 1986-1992.

Name: Yohannes Negash   Date of Degree: May, 1999

Institution: Oklahoma State University   Location: Stillwater, Oklahoma

Title of Study: DISCRETE CHOICE ANALYSIS OF OKLAHOMA FISHING LICENSE HOLDERS, FISHING TRIP DEMAND MODEL FOR EASTERN OKLAHOMA NATURAL STREAMS, AND FISHING TRIP DEMAND MODEL FOR FRESH WATER BODIES IN OKLAHOMA

Pages in Study: 139   Candidate for the Degree of Doctor of Philosophy

Major Field: Agricultural Economics

Scope and Method of Study: This study comprises three essays. The first essay focuses on determining the socio-economic factors influencing the likelihood of making a fishing trip to a specific type of water body of Oklahoma license holders. The logistic regression model is used in the analysis and data for the study was collected by the Department of Agricultural Economics, Oklahoma State University. The second essay deals with estimation of trip demand function and the economic benefit per trip to small streams in eastern Oklahoma. Count data modeling using the Poisson and negative binomial distributions was used in the analysis. The data for this study was based on a follow up survey of 163 Oklahoma fishing license holders identified from the previous survey. The third study focuses on the estimation of fishing trip demand for fresh water bodies in Oklahoma. In this study no distinction between types of water bodies fished and whether the angler was a license holder was made. A similar approach to the second study was used. However, the data for this study comes from the 1996 National Survey of Fishing, Hunting and Wildlife-Associated Recreation conducted by the U.S. Department of Interior, Fish and Wildlife Service.

Findings and Conclusion: The result of the first essay indicates that the factors influencing the probability of making a fishing trip by a license holder varies depending on the type of water body under consideration. Among other factors, geographical location of license holder, avidity of the license holder to fish was found to strongly influence the probability of a fishing trip to a particular water body in Oklahoma. The study is useful in planning and management of the different water bodies. In the second study the estimated benefit per fishing trip to small streams in eastern Oklahoma was found to vary by license holder type and it ranges between $ 1.40 to $ 24.68. The benefit estimate per fishing trip to fresh water bodies in Oklahoma was about $ 31 using the 1996 national survey data.

ADVISOR'S APPROVAL: Dean F. Schreiner