ECONOMIC VALUE OF BIG GAME HUNTING: THE CASE OF MOOSE HUNTING IN ONTARIO

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ABSTRACT

Greater emphasis in recent years on sustainable resource management in forestry has generated higher demand for information on various nontimber values. Since most of the nontimber resources are not exchanged in conventional markets, their economic values are not readily available. This paper estimates the demand for and the economic value of a popular nontimber resource, recreational moose hunting in Ontario, using the travel cost method. In view of censored and truncated nature of moose hunting trips data and the bag limit, we used four alternative count data models, the Poisson, Geometric, the Negative Binomial type II and the Creel and Loomis models, to estimate the demand for recreational moose hunting. The results indicate that the demand for recreational moose hunting declines with higher travel cost and lower income and that the demand is both price and income inelastic. The results also indicate that truncation reduces the magnitude of both price and income elasticities. Finally, the estimated consumer surplus varies widely across model specifications. A direct implication of this result is that it is not only important to generate meaningful economic values of various nontimber resources, but it is also important to select the most appropriate set of values from a number of alternatives. Given the data and institutional characteristics, we recommend that the estimated benefits from the truncated Geometric and the Creel and Loomis models (C$175 to C$210 per moose hunting trip) should be used for policy purposes.

Keywords: Nontimber values, travel cost method, truncation, count data models, recreational moose hunting.

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INTRODUCTION

A typical forest in Canada provides not only timber but also a wide variety of nontimber goods and services. These include wildlife habitat, wilderness areas and recreation services such as canoeing, boating, hiking, wildlife-view-

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The authors are an Assistant Professor and a Senior Research Economist respectively. Financial support from the Ontario Ministry of Natural Resources, Sault Ste. Marie, Ontario is gratefully acknowledged. We would like to thank Clive Southey and two anonymous reviewers of the journal for their helpful comments. We would also like to thank Professor Ola Carlen, the Managing Editor of the journal for directing our attention to moose hunting studies in Sweden and for providing us two interesting articles. The usual caveat applies.

ing, fishing, hunting and skiing. Greater emphasis on integrated resource management in forestry since the late 1970s has generated higher demand for information on various nontimber values. However, most of the nontimber goods and services are not exchanged in conventional markets and hence, do not have market prices.

A number of methods have been used in recent years to measure the values of various nonmarket goods and services. These methods involve either asking directly the recreationists about their values for the resource being studied (the contingent valuation method), or relying on information about observed market choices related to recreational trips made by individuals (the travel cost methods). Travel-cost demand models have been used extensively in recreation demand studies for over 30 years. In a recent study, Smith & Kaoru (1990) synthesized empirical results from 77 travel cost recreation demand studies reported between 1970 and 1986 using meta analysis and found that travel cost demand studies derived consistent and policy relevant benefit estimates. Perhaps due to such consistency, the travel cost method has been accepted as a tool for measuring values (or benefits) of nonmarket goods and services in the United States since 1979 (Water Resource Council, 1979). Very recently, it has also been recommended by the Environmental Assessment Board of Ontario (EAB 1994) as a tool for measuring nontimber forest values in Ontario.

Hunting moose (*Alces alces*) is a popular outdoor recreational activity in Ontario. During the Fall in each year, northern Ontario attracts thousands of hunters from all over Ontario and from neighbouring provinces or states. For hunters residing in various northern Ontario communities, work and social life are coordinated with the moose hunting season. Due to recent fiscal constraints and declining budgets for managing forest resources in Ontario, considerable attention has been focused on the potential for higher user fees for hunting and other nontimber services. Implementation of any such changes to recreational moose hunting in Ontario requires a good understanding of price and income sensitivity of the demand for moose hunting.

There are only a few empirical studies on the demand for big game hunting in the literature. Adamowicz (1983) applied the contingent valuation method to evaluate the demand for bighorn sheep hunting in Alberta. Condon & Adamowicz (1995) also applied the contingent valuation method to evaluate the demand for moose hunting in Newfoundland. Boxall (1995) used a modified travel cost model to evaluate the demand for recreational hunting of Antelope in Alberta. Creel & Loomis (1990, 1992) and Offenbach and Goodwin (1994) used variations of the basic travel cost model to evaluate the demand for deer hunting in California and Kansas respectively. Boyle & Clark (1993) applied the contingent valuation method to determine the economic value of recreational moose hunting in Maine.

Since the mid 1980s, the economic value of big game hunting has also been investigated in Scandinavia. For example, Johansson *et al*. (1988) used the contingent valuation approach to estimate the economic value of moose hunting and to determine the effects of changes in moose population on hunters' willingness to pay for recreational moose hunting in the county of Västerbotten in Sweden. Mattsson (1990 a, b) has also applied the contingent valuation approach to determine the extent and economic values of moose hunting in Northern and Southern regions of Sweden. These studies not only provide the economic values of moose hunting in Sweden but also disaggregate total economic values of moose hunting into meat and recreational components.

No systematic attempt has been made in the past to determine the economic value of recreational moose hunting in Ontario. The major objective of this paper is to bridge this gap by providing estimates of the demand for moose hunting trips in Ontario. The second objective is to evaluate the adequacy of conventional count data models for modelling the demand for recreational moose hunting and explore the usefulness of three alternative count data models for this purpose.

Section two provides a brief overview of moose management and moose hunting in Ontario. A conceptual travel cost model for moose hunting is given in section three. Section four deals with four alternative count data models. Section five concentrates on data description, empirical specification and estimation of the demand for moose hunting trips. This section also includes discussions of results and estimated benefits of recreational moose hunting. Section six summarizes the major findings and offers some concluding remarks.

AN OVERVIEW OF MOOSE MANAGEMENT AND MOOSE HUNTING IN ONTARIO

Moose forms an essential component of the boreal forest ecosystem. By feeding on young deciduous trees and shrubs, moose protects young conifers from competing vegetation. Moose herds also add nutrient to the forest floor. For adequate food and shelter requirements, moose often prefers to live at the edge of a forest. Natural disturbances such as forest fire and insect outbreak and small and mid-sized logging operations are helpful for expanding moose population in the boreal forest.

Until the early 1960s, moose habitat management was not a major concern in Ontario and free and unlimited moose hunting was allowed. It is believed that the introduction of mechanical logging in the 1960 and subsequent large clear-cutting operations caused significant damage to the habitat requirements for moose and other wildlife in the boreal forest. Shrinking food and shelter requirements coupled with the provision of unlimited hunting contributed to a steady decline in moose population during the 1960s and 1970s. In the early 1980s, it was estimated that there were only 80,000 moose in this province and the population was declining. There was an immediate need to take some measures to stabilize and reverse that declining trend. Two major programs were introduced in 1983. The first one is called the *Featured Species Management Program*. This program attempts to manage the supply side of the problem by incorporating moose habitat requirements directly into the forest management plans and by prescribing the harvesting procedure, the time of harvest and the size of clear-cuts (OMNR 1988). The second program is called the *Selective Harvest System* which attempts to manage the demand side of the problem. Under the Selective Harvest system, the Ontario Ministry of Natural Resources (OMNR) area teams responsible for each Wildlife Management Unit (WMU) recommend, based on population estimates and population targets, how many adult moose especially cows can be harvested. The validation tags required for hunting adult moose are allocated based on such recommendations from each WMU. The key consideration in the selective harvest program is that there are enough adult moose left in the forest to sustain a healthy breeding population. Since the overall growth of the moose population is not affected significantly by the current level of harvest of calves, no validation tag is necessary for hunting calves in Ontario.

Licensing and Regulations for Moose Hunting in Ontario

Moose hunting season begins on September 17 and ends on December 15 each year in Ontario. The length of the hunting season varies somewhat depending on the location of a particular WMU, the type of licence and the equipment used to hunt. Ontario offers two different types of moose hunting licenses. One type for Ontario residents, and the other for non-residents. In general, the resident license fee is much lower than that of non-residents. A regular moose hunting licence purchased by a resident of Ontario allows him/her to hunt a calf anywhere in this province when the hunting season is open. However, a special validation tag is necessary to hunt an adult moose, bull or cow (OMNR 1994). The validation tag states the sex of the animal, the WMU for which the tag is valid, and the condition under which the animal may be taken. These tags are allocated through a lottery. No hunter should have more than one validation tag at the time of hunt.

The Selective Harvest System essentially imposes a quota on harvest. The quota represents the number of adult moose that can be harvested. In general, the number of validation tags issued is higher than the quota because not all hunters are successful on their hunt. The quota setting process takes this into account.

THE CONCEPTUAL MODEL

The demand for recreational moose hunting in the travel cost framework can be undertaken within the domain of neoclassical utility maximization. In this context, a representative consumer or household maximizes utility subject to budgetary and time constraints. Define x to be a vector of quantities of market goods with the corresponding price vector p_x and r to be the vector of quantities of recreational goods and services including recreational moose hunting, with the corresponding price vector p_r. The budget constraint of a representative consumer can be written as:

$$Y = wT_w = p_x'x + p_r'r. \tag{1}$$

Similarly, the time constraint can be written as:

$$T - T_w - T_r = 0, \tag{2}$$

where Y is full income, w is the market wage, T is total available time, T_w is time spent at work and T_r is the leisure time. Note that both sets of prices, p_x and p_r are likely to be affected by the value of consumer's time (i.e., the wage rate). Denoting the quality characteristics of the ith hunting site as q_i, the utility function for a recreationist can be written as:

$$U = U(x, r, q). \tag{3}$$

Maximization of equation (3) subject to full income and time constraints given in equations (1) and (2), yields a set of ordinary demand functions for the market goods and the recreational services. Thus, the ith consumer's demand function for moose hunting at the jth site is:

$$r_{ij} = f(p_x, p_r, Y, q). \tag{4}$$

Since it is difficult to measure the flow of recreational moose hunting services represented by r_{ij} in equation (4), the number of moose hunting trips are used as surrogates. Estimated coefficients of the ordinary demand function are often used to determine the value of recreational services. In particular, integration of the area under the demand function between any two prices yields a Marshallian consumer surplus measure:

$$CS = \int_{p^1}^{p^2} f(p_x, p_r, Y, q)\, dp. \tag{5}$$

Consumer surplus per trip or per hunter can be calculated and total economic value of moose hunting for a particular site can be derived. The effects of changes in site quality characteristics on the value of moose hunting can also be determined (Bockstael, McConnell & Strand, 1991).[1]

Econometric Models of Moose Hunting

The dependent variable in this study is the number of moose hunting trips taken by registered Ontario hunters during the hunting season of 1992. Hunting trips occur as nonnegative integers and no data is available for individual hunters taking zero trips. The sample is, therefore, censored and truncated. The truncation occurs at the zero trip level. So, the distribution of the dependent variable can be characterized by truncated count data models.

Since count data models explicitly recognize the nonnegative discrete nature of the dependent variable, they are particularly suitable for modelling moose hunting trips and similar recreational activities. Indeed, a number of recent studies such as Shaw (1988), Smith (1988), Creel & Loomis (1990, 1992), Grogger & Carson (1991), Hellerstein (1991), Offenbach & Goodwin (1994) and Englin & Shonkwiler (1995) have applied count data models in recreational demand analysis. In search for an appropriate specification of the demand for moose hunting in Ontario, we present four alternative count data models. One of these four models (i.e., the geometric distribution) has not been used in the valuation of big game hunting in the past.

The Poisson Distribution Model

The Poisson distribution forms the foundation for count data models. The basic Poisson model can be written as:

$$\text{Prob}\left(Y_i = k; k = 0,1,2,\ldots\right) = f(k) = \frac{\exp(-\lambda)\lambda^k}{k!} \qquad \forall\, \lambda > 0, \quad (6)$$

where Y_i is the ith observation on the number of moose hunting trip, $k = 0,1,2...$ are the set of possible nonnegative

[1] The analytical framework presented in this section takes into consideration the number of moose hunting trips but does not deal with the institutional constraint that the moose hunting season for an individual hunter ends as soon as he bags a moose. We address this issue in the following section.

integer values that Y_i can take and λ is the Poisson parameter to be estimated. This model can be extended to a regression framework and heterogeneity can be introduced by making λ a positive function of the explanatory variables such that:

$$\lambda_i = \exp(X_i'\beta), \tag{7}$$

where, X_i is a matrix of explanatory variables including a constant and β is a conformable matrix of unknown parameters to be estimated. The exponential form of (7) guarantees non-negativity of λ. Thus, the basic Poisson model captures the discrete and nonnegative nature of the dependent variable and allows one to draw inference on the probability of trip occurrence.

The structure of a truncated Poisson distribution is slightly different. Noting that $\text{Prob}(Y = 0) = f(Y = 0) = \exp(-\lambda)$, and that the probability of observing Y_i, given that it exceeds the truncation point, k, is $f_k(Y_i) = f(Y_i)/[1-F(k)]$, the Poisson probability distribution for counts with left truncation at $k = 0$ can be written as:

$$\text{Prob}(Y_i = k \mid k > 0) = \frac{\exp(-\lambda)\,\lambda^k}{k!}.\frac{1}{\left(1 - \exp(-\lambda)\right)}. \tag{8}$$

Since $\exp(-\lambda)$ is less than one, multiplication of the standard probabilities by the factor $[1 - \exp(-\lambda)]^{-1}$ inflates the probabilities. Allowing λ to vary as in (7), the zero-truncated Poisson log-likelihood function is:

$$\ln L = \sum_{i=1}^{n} \left\{ -\lambda_i + k X_i \beta - \ln(k!) - \ln\left[1 - \exp\left(-\lambda_i\right)\right]\right\}. \tag{9}$$

A distinctive feature of the Poisson model is that the conditional mean of the distribution is equal to its conditional variance (Larson, 1974). This equidispersion property is not always satisfied in reality. In some cases, the value of the conditional variance exceeds the value of conditional mean. This is called overdispersion. In the presence of overdispersion, the estimated regression parameters from an untruncated Poisson model are consistent but their standard errors are downwardly biased. However, the truncated Poisson estimators are both biased and inconsistent in the presence of overdispersion (Grogger & Carson, 1991). It is, therefore, important to test for the presence of overdispersion in the data set.

Cameron & Trivedi (1990) have developed two regression-based tests for overdispersion in the Poisson model. While both tests evaluate the null hypothesis of equidispersion, the alternative hypotheses are different. The alternative hypotheses in the first and second tests are: H_a: $Variance = 2 \times Mean$; and $Variance = [mean + (mean)^2]$ respectively. Very recently, Gurmu (1991) has developed score tests for overdispersion in the Poisson model truncated at zero. The null hypothesis of equidispersion is tested against untruncated or truncated at zero negative binomial models alternatives in these tests. Most of the tests for overdispersion in the untruncated Poisson regression models available in the literature can be obtained as special cases of the score tests. These features motivated us to employ Gurmu's score tests in this study.

Geometric Distribution Model

Geometric distribution is an alternative to the Poisson distribution if the data is overdispersed and displays a quick decay process. Note that the Poisson distribution also admits the discrete decay phenomenon but only when $\lambda < 1$. Following Mullahy (1986), the geometric distribution of the number of moose hunting trips, Y_i can be defined as:

$$\text{Prob}\left(Y_i = k; k = 0,1,2,\ldots\right) = \lambda^k (1+\lambda)^{-(k+1)}. \qquad (10)$$

The mean and variance of this distribution are, λ and $(1+\lambda)$ respectively. The model is parameterized such that $\lambda_i = \exp(X_i'\beta)$, where X is the matrix of explanatory variables including an intercept. The log-likelihood function of the geometric distribution can be written as:

$$\ln L = \sum_{i=1}^{n} \left\{ k \ln(\lambda_i) - (k+1)\ln(1+\lambda_i) \right\}. \qquad (11)$$

The log-likelihood function of the left truncated geometric distribution can be written as:

$$\ln L = \sum_{i=1}^{n} \left\{ (k-1)\ln(\lambda_i) - k\ln(1+\lambda_i) \right\}. \tag{12}$$

Negative Binomial Distribution Models

If a sample is both truncated and overdispersed, the negative binomial family of models offers another set of attractive alternatives to the Poisson count data model. Such alternatives can be justified on the grounds that measurement errors and/or omission of explanatory variables could introduce additional heterogeneity and hence, overdispersion in the data. Under such circumstances, it is assumed that the dependent variable is measured with a multiplicative error term μ_i which captures unobserved heterogeneity and that this error is uncorrelated with the explanatory variables. If the error term, μ_i, follows a Gamma distribution, a two parameter negative binomial model may be defined as follows (Hausman *et al.*, 1984):

$$\text{Prob}\left(Y_i = k; k = 0,1,2,\ldots\right) = \\ = \frac{\Gamma(k+\nu)}{\Gamma(k+1)\cdot\Gamma(\nu)} \cdot \left\{\frac{\nu}{\nu+\lambda}\right\}^{\nu} \cdot \left\{\frac{\lambda}{\nu+\lambda}\right\}^{k}. \tag{13}$$

The mean and variance of this distribution are λ and $[\lambda + \lambda^2/\nu]$ respectively. The parameter ν is called the precision parameter (Winkelmann & Zimmermann, 1995). To ensure non-negativity of λ, the model is parameterized by letting $\lambda_i = \exp(X_i'\beta)$ where X_i is a vector of explanatory variables. A wide range of model specifications con be obtained by setting the parameter ν as a function of explanatory variables such that:

$$\nu_i = (1/\alpha)\left(\exp(X_i'\beta)\right)^m; \quad \forall\ \alpha > 0, \tag{14}$$

where m is an arbitrary constant. When $m = 0$, the precision parameter ν_i is constant and equal to $1/\alpha$. The variance of the distribution becomes $\lambda\,(1 + \alpha\lambda)$. This specification is known as the Type II Negative Binomial model in the literature (Cameron & Trivedi, 1986; Gurmu, 1991). Such a model has been used by Creel & Loomis (1990) and Offenbach & Goodwin (1994), among others, to analyse the demand for big game hunting in the United States. An alternative specification of the Negative Binomial (NB) model can be obtained by setting $m = 1$. In this case, the variance of the distribution is, Var $(Y_i) = [E(Y_i)\times(1 + \alpha)]$. This specification is called the NB Type I model. By varying the value of m, one can obtain a wide variety of parametric specifications for the negative binomial model. By replacing ν with $1/\alpha$, the NB Type II probability distribution can be written as:

$$\text{Prob}\left(Y_i = k; k = 0,1,2,\ldots\right) = \\ = \frac{\Gamma\left(k + 1/\alpha\right)}{\Gamma(k+1)\cdot\Gamma\left(1/\alpha\right)}\cdot(\alpha\lambda)^k\cdot(1+\alpha\lambda)^{-(1/\alpha+k)}. \quad (15)$$

The geometric and Poisson count data models can be obtained as special cases of the negative binomial model given in equation (15). For example, one obtains geometric distribution as a special case of the NB distribution for α=1 while the Poisson distribution is obtained as a limiting case when α approaches 0. For a sample of n independent observations, the log likelihood functions of untruncated and left truncated NB Type II distributions respectively are as follows:

$$\ln L = \sum_{i=1}^{n}\left\{\ln\left(\Gamma\left(k+\frac{1}{\alpha}\right)\right) - \ln\left(\Gamma(k+1)\right)\right. \\ \left. - \ln\left(\Gamma\left(\frac{1}{\alpha}\right)\right) + k\ln\left(\alpha\lambda_i\right) - \left(k+\frac{1}{\alpha}\right)\log\left(1+\alpha\lambda_i\right)\right\}, \quad (16)$$

and,

$$\ln L = \sum_{i=1}^{n}\left\{\ln\left(\Gamma\left(k+\frac{1}{\alpha}\right)\right) - \ln\left(\Gamma(k+1)\right) - \ln\left(\Gamma\left(\frac{1}{\alpha}\right)\right)\right. \\ \left. + k\ln\left(\alpha\lambda_i\right) - \left(k+\frac{1}{\alpha}\right)\ln\left(1+\alpha\lambda_i\right) - \ln\left[1-\left(1+\alpha\lambda_i\right)^{-1/\alpha}\right]\right\}. \quad (17)$$

Creel and Loomis Model

Although the count data models discussed above take into account the discrete and nonnegative nature of the dependent variable, a key feature of moose hunting regulation in Ontario is not considered in these models. Since it is illegal for a hunter to shoot more than one adult moose during a particular hunting season, the hunting season for a hunter ends as soon as he bags a moose. Suppose at a given travel cost, a hunter was willing to make three moose hunting trips to a particular site. During the first visit he sees a moose and decides to bag it. As a result, his hunting season ends after the first trip. This raises the possibility that the estimated consumer surplus may not duly reflect the true willingness to pay for moose hunting trips if the institutional constraint is not incorporated in the model. The extent of departure, however, will depend on the number of fewer trips a hunter makes relative to the number of trips he would like to make. If a hunter bags a moose during the first visit although he was willing to make three trips, the actual demand curve for moose hunting trips will lie below the desired demand curve. Note that the desired demand curve is unobservable due to the institutional constraint. If the observed number of trips are used to approximate the desired demand for moose hunting, the estimated economic benefits could be downwardly biased.

Creel & Loomis (1992) developed a model which accounts for bag limits. If p is the probability of making a moose hunting trip (k) and q is the probability of bagging a moose (B) during a hunting season, then the joint density for k and B is given by:

$$\begin{aligned} f(k,B) &= p^k (1-q)^{k-B} q^B (1-p)^{1-B} \\ f(0,1) &= 0. \end{aligned} \tag{18}$$

This joint density implies an econometric model with two endogenous variables, the number of trips taken, k, and whether or not a moose is bagged, B. Note that k is a nonnegative integer while B is a discrete {0, 1} variable.

By conditioning the joint distribution on $k > 0$, we obtain the truncated distribution as,

$$f(k, B \mid k > 0) = p^{k-1}(1-q)^{k-B} q^{B}(1-p)^{1-B}. \tag{19}$$

The marginal density for k can be obtained by summing over B. Note that truncation only affects the terms of the joint distribution involving the probability p; the probability of bagging a moose is not affected by the truncation. Creel & Loomis (1992) use the following logistic parameterization for p and q:

$$p = \frac{1}{1+e^{-X\beta}}; \qquad q = \frac{1}{1+e^{-Z\Phi}}, \tag{20}$$

where X and Z are matrices of explanatory variables and β and Φ are conformable vectors of parameters. Creel & Loomis (1992) used a set of three explanatory variables, travel cost, income and hunting quality for both p and q. The last variable in this set, measured by the number of legal deers seen by a hunter on the last trip of the season at a particular site, is assumed to have a positive effect on the number of trips and on the probability of bagging an animal. Unlike the three previous count data models, the desired demand for moose hunting is not proxied by the expected number of hunting trips (E(k)). Instead, it is measured by the expected number of trips given that no moose has been bagged (i.e., E($k \mid B$=0)). This conditional expectation readily incorporates the influence of a bag limit on the desired number of hunting trips. Assuming that the probability of making k trips follows a logistic distribution, it can be shown that $E(k \mid B = 0) = p/(1-p) = \exp(X\beta)$ (see the Appendix for details).

The likelihood functions of Creel and Loomis model along with those of the Poisson, geometric and the NB type II count data models are implemented in TSP (Hall, 1995) to obtain the results of the demand for moose hunting trips in Ontario.

EMPIRICAL SPECIFICATION AND ESTIMATION OF COUNT DATA MODELS

This section describes data and explains the specification and estimation of empirical count data models. The results of the demand for moose hunting trips in Ontario obtained from alternative count data models are also discussed in this section.

Data Description

The data used in this study relate to the 1992 moose hunting season at Wildlife management Unit #21A (WMU21A) located in northern Ontario. It is one of the most popular WMUs for moose hunting because of its remoteness and moose population density. During the 1992 season some 1286 hunters received moose validation tags to hunt an adult moose at WMU21A and about 99% of these hunters were from Ontario.

Most of the data came from the Ontario Ministry of Natural Resources records.[2] The round trip distance for each hunter from his/her home-town to WMU21A was multiplied by cost per kilometre (35.3 cents for a mid-size car for the 1992-93 season) obtained from the Canadian Automobile Association (CAA) to calculate vehicle related costs (CAA 1994). A licence fee of $26.50 per resident hunter per season was added to the vehicle related costs (level one). A $10.00/hunter/season equipment cost and a $15.00/hunter/day food and lodging costs were also added to the travel costs (level two).

The treatment of time is an important but controversial issue in travel cost analysis. There is general agreement in the profession that time plays an important role in recreational decisions and that the opportunity cost of time spent travelling should be included in the costs of travel. However, there is no universally accepted method for incorporating the opportunity cost of time in recreational demand analysis (Bockstael *et al.*, 1987; Cesario, 1976; DeSerpa, 1971; Shaw, 1992; Smith *et al.*, 1983). The approach used by

[2] The Wildlife branch of the OMNR annually compiles data on moose validation tag applications and lottery results. The first database records the application serial number, the applicant's postal code and his or her first and second choices of the WMUs to which the application should be entered for the draw. The second database contains application serial numbers of the hunters who won the draw along with the type of moose (cow or bull) they can hunt and the designated WMU where they can hunt. After matching the application serial numbers from the two databases, the postal code from the first database and the designated WMU from the second database give the origin-destination combination for each hunter. The OMNR uses Conquest, a software package marketed by Compusearch Micromarketing Data and Systems of Toronto, to compute the distance a hunter travels to go moose hunting. Using the latitudes and longitudes of the WMU centroid and the postal code of a hunter, the program computes the "as the crow flies" distance between the hunter's origin and the designated WMU. The distance calculated by Conquest is scientific and reliable.

Cesario (1976) is simpler than other approaches and has been widely used in recreation demand analysis. Consequently, following Cesario (1976) we value both travel time and on-site time at one-third of the wage rate. The cost of time for each hunter was calculated assuming a 40 hour work week and a 52 week year. The cost of time thus obtained was added to "level-two" travel costs. The resulting travel cost figures were used in our analysis.[3] The income variable consists of 1991 average employment income and 1991 average other income at the Enumeration Area (EA) level. This information is based on 1991 census data and was adjusted to 1992 level using consumer price index (CPI).[4]

Available OMNR documents did not contain any information on the number of moose hunting trips taken by each individual hunter with a moose validation tag. Hunters with moose validation tags for WMU21A in 1992 were contacted over telephone for this and a number of related information during July-September 1994. Just over 200 hunters provided information on the number of hunting trips made to the WMU21A, duration of each trip, number of hunters in each group and the number of moose hunted. A number of inconsistent responses were discarded. The final sample consists of 194 hunters.[5]

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[3] One of the few problems that still plague the Travel Cost Method is the calculation of the opportunity cost of time travelling and spent on site (Randall, 1994). A reviewer of the journal correctly points out the tentativeness of the approach we followed in this paper. Ideally, one should include questions to reveal individual hunter's opportunity cost of time spent travelling and on site. Unfortunately, no data on the opportunity cost of time for individual moose hunters' in this specific sample were available.

[4] In a typical recreation demand analysis (travel cost or contingent valuation) the income variable is often subject to substantial measurement error. This is because income is measured at the mid-value of a range (say, $50,000–$60,000). Also, there are good reasons to believe that individual recreationists misquote their income figures. In light of these problems, we believe that the average income at the EA level provides a better approximation of an individual hunter's income (if the EA is fairly small) than the income figures obtained through surveys.

[5] Since in a telephone interview it is unlikely to contact more frequent visitors to the hunting site more often than the less frequent ones, there is no endogenous stratification discussed by Shaw (1988) in our sample. Note, however, some hunters had problem remembering the number of moose hunting trips about two years after the 1992 hunting season. Only those hunters were included in the sample who could remember the number of moose hunting trips in 1992 with certainty.

Empirical Specification

Before the beginning of moose hunting season each year, potential moose hunters must decide whether or not to hunt. If the decision is yes, a hunting license must be purchased. This license allows a hunter to shoot a calf only. To obtain a moose validation tag, a group of 3 to 5 hunters give their preferences for alternative hunting sites. The successful hunters receive moose validation tags which specify the sex of the animal (bull or cow), the WMU for which the tag is valid and the condition under which the animal can be taken. After this stage, regulation prohibits a hunter to hunt an adult moose at another WMU other than the designated one. So, the possibility of substitution is zero. In this paper, we focus on the trip frequency stage of the moose hunting decision process.

The general specification of the travel cost model was

$$Y_i = f\big(Prices\,(\text{i.e. Travel costs}), Income, \beta, \varepsilon_i\big), \tag{21}$$

where β is the vector of parameters and ε_i is a vector of random disturbance terms. The dependent variable, Y_i is the number of moose hunting trips taken to WMU21A and is truncated at zero as mentioned above.

During the 1992 hunting season, hunters in Ontario made on an average 2.35 moose hunting trips (Table 1). This low mean suggests that the normally distributed specification may not provide a good approximation to the underlying data generation process for moose hunting trips. Note also that the data exhibit a quick decay process; about 78% of the sample hunters made only one trip during this season and the number of trips higher than one falls rapidly. This suggests that the geometric distribution may be a reasonable alternative to the Poisson count data models for this particular data set. Finally, the variance of the dependent variable is quite high, 12.89. Clearly, the equidispersion property of the Poisson distribution is at stake. The NB Type II also appears to be an attractive alternative to the Poisson count model. Finally, the policy constraint embedded in the Selective Harvest System in Ontario implies that Creel & Loomis (1992) model is also an alternative to the basic count data model.

TABLE 1: THE FREQUENCY DISTRIBUTION OF THE NUMBER OF MOOSE HUNTING TRIPS.

NUMBER OF TRIPS	FREQUENCY
1	152
2	10
3	3
4	6
5	4
6	2
7	1
8	0
9	4
10	1
12	5
15	3
20	3
Total	194.00
Mean: 2.345	Mode: 1
St. deviation: 3.590	Median: 1

Estimation, Results and Discussion

Since the decision to hunt and site choice have already been made, the function we estimate for recreational moose hunting trips in Ontario may be called a participation equation. In the past, researchers used Ordinary Least Squares (OLS) to estimate such an equation. While the estimated coefficients are biased and inconsistent, we report OLS results for comparative purposes. We used an exponential (i.e., semi-log) form for the continuous distribution estimators and for all count data models, the Poisson, geometric, the negative binomial type II and the Creel and Loomis model.[6] The continuous distribution model with untruncated sample has been estimated by non linear least squares (NLS) while the maximum likelihood procedure is used to estimate its truncated counterpart.[7] The maximum likelihood procedure is also used to estimate all count data models including the Creel and Loomis model.

[6] Estimation programs were written in TSP to implement log likelihood functions of different discrete distributions. These programs are available from the authors on request.

[7] For the empirical specification of truncated continuous model we followed Creel and Loomis (1990) who suggest that the lower truncation be set at 0.5 and not at zero. This is to ensure convergence in estimation and also to allow for a better approximation by the normal distribution of an unknown count data-generating-process (DGP)(Larson, p. 295).

Table 2 presents parameters estimated from linear and semi-log functions along with those obtained from untruncated Poisson, geometric and negative binomial type II distributions. The results obtained from the Creel and Loomis model are also given in Table 2. The standard errors of the coefficients were computed using the Eicker-White procedure (Davidson and MacKinnon 1993, pp.552–556). The Eicker-White procedure generates a heteroskedasticity-consistent covariance estimate that is asymptotically valid when there is heteroscedasticity of unknown forms (White, 1980). Since we have a wide range of moose hunting trips in our sample and the data appear to be overdispersed, we decided to use the heteroscedasticity-consistent covariance matrix estimator to correct for the overdispersion problem originating from an unknown form of heteroscedasticity. Note that sample size 183 is a subset of the original sample of 194. We employed Chebyshev's Empirical rule to remove extreme values of the dependent variable from the sample.[8] While the estimated parameters from the OLS are not directly comparable to those from the count data models, the parameters from nonlinear least squares (NLS) model are. However, estimated price and income elasticities are comparable across all models.

We assume that the probability of bagging a moose (q) declines over the course of the hunting season for two reasons. First, due to the availability of fewer adult moose during the second and subsequent hunting trips. Second, as the hunting season matures the weather gets cooler in the study area. Cooler weather discourages mating calls and moose tends to retreat into deep forest in preparation for the winter. Such a pattern of moose behaviour could have

[8] The number of moose hunting trips over 10 during the 1992 hunting season are called "extreme values". These are the hunters who live close to the hunting site. Since this particular information was collected about two years after the 1992 hunting season, it is quite possible that some of these frequent visitors have overstated the number of visits to the hunting site. To reduce any potential bias which can be introduced to the estimated benefits by these unusually high numbers of trips, we used a statistical procedure, Chebyshev's Empirical rule, to remove them from the sample. According to Chebyshev's Empirical rule, there is a 95% probability that a random variable will have a mound-shaped probability distribution if it takes on a value within two standard deviations from the mean (Judge *et al*., 1988, p. 42). The use of this rule has generated a sample size of 183; the mean number of moose hunting trips declined by 33% while its standard deviation declined by 54%. Obviously, a policy maker should put more faith in the results obtained for the reduced sample.

Table 2: Estimates for Recreational Moose Hunting Trips in Ontario: Untruncated Data (Sample Size: 194 & 183) .

Variable	Linear	Nonlinear	Poisson	Geometric	NB-Type II	Creel & Loomis
Price	−0.0058	−0.00256	−0.00204	−0.00190	−0.00199	−0.00195
	(6.78)	(8.35)	(13.91)	(15.07)	(14.73)	(10.92)
Income	0.000043	−0.0000133	0.0000072	0.0000139	0.0000112	0.000015
	(4.13)	(0.94)	(1.41)	(5.39)	(3.20)	(3.65)
Constant	6.208	3.20	2.15	1.76	1.94	2.09
	(7.54)	(4.72)	(7.73)	(11.40)	(8.92)	(10.07)
Dummy q_1	–	–	–	–	–	0.296
						(7.99)
Dummy q_2	–	–	–	–	–	−0.186
						(3.96)
Dummy q_3	–	–	–	–	–	−0.274
						(7.25)
α	–	–	–	–	0.163	
					(3.800)	–
Log–L	−468.64	−447.35	−323.05	−346.20	−305.32	−420.83
R^2/R^2_{LRT}	0.427	0.544	0.864	0.400	0.734	0.522
Price Elasticity	−4.896	−2.539	−2.016	−1.884	−1.964	−1.927
	[79.222]	[1.099]	[0.873]	[0.816]	[0.793]	[0.834]
Income Elasticity	1.432	−0.583	0.314	0.603	0.304	0.663
	[19.719]	[0.204]	[0.763]	[0.211]	[0.082]	[0.232]
			Sample Size: 183			
Price	−0.00245	−0.00140	−0.00135	−0.00124	−0.00135	−0.00104
	(6.19)	(9.05)	(10.31)	(10.47)	(10.46)	(7.28)
Income	0.0000091	0.0000052	0.0000048	0.0000040	0.0000048	0.000005
	(1.19)	(0.96)	(1.21)	(1.32)	(1.22)	(1.01)
Constant	3.733	1.514	1.495	1.433	1.495	1.548
	(7.36)	(5.52)	(7.04)	(7.89)	(7.37)	(6.65)
Dummy q_1	–	–	–	–	–	0.329
						(8.63)
Dummy q_2	–	–	–	–	–	−0.260
						(5.44)
Dummy q_3	–	–	–	–	–	−0.314
						(7.71)
α	–	–	–	–	0.005	
					(0.147)	–
Log–L	−313.65	−304.33	−246.40	−299.49	−246.38	−366.64
R^2/R^2_{LRT}	0.340	0.404	0.412	0.162	0.409	0.295
Price Elasticity	−5.308	−1.451	−1.399	−1.292	−1.399	−1.779
	[49.380]	[0.547]	[0.527]	[0.487]	[0.527]	[0.646]
Income Elasticity	0.500	0.227	0.210	0.175	0.209	0.381
	[3.246]	[0.081]	[0.075]	[0.062]	[0.075]	[0.213]

The figures in parentheses are "t" values while those in square brackets are standard deviations. The critical value of "t" at 5% level of significance is 1.96. The reported values of income and price elasticities are sample means of price and income elasticities calculated at each data point.

been captured by a variable measuring hunting quality (defined as the number of legal moose seen during the last two weeks of the hunting season). However, such information is not available and we were not successful in linking the probability of bagging a moose to the set of explanatory variables.[9] Based on above considerations and a failed attempt to model q directly, we introduced two dummy variables to capture the declining likelihood of bagging a moose ($D_1 = 1$ when 2, 3, 4 and 5 hunting trips are taken and zero otherwise; and $D_2 = 1$ when the number of trips is 6 or higher and zero otherwise).[10] The estimated coefficients of these dummy variables are given in Table 2. Based on these estimates, the probability of bagging a moose during the first trip is 0.296 which declines to 0.11 during the second, third, fourth and fifth trips. The probability of bagging a moose declines to 0.022 for six or higher number of trips. A similar but more pronounced declining pattern occurs with the reduced data sample.[11]

Based on a general R-squared measure of goodness of fit for nonlinear regression models which is related to the likelihood ratio test statistic for the joint significance of the slope parameters, the Poisson distribution model gives the best specification followed by the NB type II, nonlinear, Creel and Loomis and the Geometric models. The comparative picture remains unchanged for the reduced sample.[12]

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[9] We made an attempt to estimate the probability of bagging a moose as a logistic function of the price (travel cost) and income variables. The coefficients were not statistically significant.

[10] This specification was selected after some preliminary statistical testing of a more general model which included a larger number of dummy variables. The dummies with insignificant parameters were excluded. The final specification also yields a more pronounced declining probability of bagging a moose which we expected.

[11] The parameters of the Creel and Loomis model have been estimated by maximizing the associated log likelihood function. The dummy variables were included directly into the likelihood expression. Therefore, the coefficients of the dummy variables are, indeed, the marginal probabilities of bagging a moose.

[12] The R^2_{LRT} measure of goodness-of-fit is proposed by Kent (1983), Maddala (1983) and Magee (1990). It is specified as follows:

$$R^2_{LRT} = 1 - \exp(-LRT/n),$$

where n is the number of observations and LRT is the likelihood ratio test statistic for the joint significance of the slope parameters. This measure lies between 0 and 1, is invariant to units of measurement and becomes larger as the model "fits better". It is also a more general goodness-of-fit measure in the sense that R^2_{LRT} is equal to R^2_{OLS} in a linear model (Cameron & Windmeijer, 1997).

The estimated parameters from the truncated models are presented in Table 3. In terms of the R^2_{LRT} criterion, truncation improves the specification of all count data models. However, the improvements are more dramatic for the geometric distribution and the Creel and Loomis models than for the other models. A comparison of the results in Table 3 with those in Table 2 clearly indicates the importance of the quick decay process inherent in moose hunting trips data. It is interesting to note that the maximized values of the log-likelihood functions of the geometric and negative binomial models are very close. Note also that the estimated probabilities of bagging a moose in the truncated model are the same as those obtained for the untruncated model. Such a result stems from the fact that truncation does not affect the probability of shooting a moose.

A "*t*" test indicates that the estimated value of the precision parameter in the negative binomial model is not statistically different from zero. To test the null hypothesis that α is equal to one, we computed the t-statistic as $t=(\alpha-1)/SE(\alpha)$. While the null hypothesis was rejected for the untruncated models, it could not be rejected for the truncated ones.[13] This confirms that when data truncation is taken into account, geometric and negative binomial specifications yield similar results for this sample. In terms of the R^2_{LRT} criterion, however, the Poisson model still offers a better goodness of fit than the other models.

Across all of the model specifications, the price variable has the expected negative sign. The income variable has the expected positive sign in all but three cases. The number of moose hunting trips goes down with higher costs of the trip and lower income. Also, the number of moose hunting trips is more responsive to price changes than to changes in hunters' income. The results also show that recreational moose hunting trip in Ontario is a "normal good" (income elasticity is positive and < 1 in most cases). It is interesting to note the effects of extreme values and truncation on the estimated values of price and income elasticities. Truncation reduces the absolute value of price and income elasticities and the reductions are more pronounced for

[13] The associated t-values are: −19.456 and −27.93 for untruncated models and 0.459 and 0.205 for truncated models.

TABLE 3: ESTIMATES FOR RECREATIONAL MOOSE HUNTING TRIPS IN ONTARIO: TRUNCATED DATA (SAMPLE SIZE: 194 & 183).

Variable	Nonlinear	Poisson	Geometric	NB-Type II	Creel & Loomis
Price	−0.00621	−0.00416	−0.00533	−0.00554	−0.00573
	(3.655)	(9.608)	(13.205)	(11.610)	(11.890)
Income	−0.0000421	−0.0000127	0.0000101	0.0000136	0.000016
	(1.112)	(0.905)	(0.630)	(0.657)	(0.840)
Constant	5.042	3.507	2.845	2.71	3.232
	(2.793)	(5.220)	(4.001)	(3.410)	(4.130)
Dummy q_1	–	–	–	–	0.296
					(7.99)
Dummy q_2	–	–	–	–	−0.186
					(3.96)
Dummy q_3	–	–	–	–	−0.274
					(7.25)
α	–	–	–	1.366	
				(1.715)	–
Log-L	−327.63	−191.52	−152.68	−152.51	−258.84
R^2/R^2_{LRT}	0.582	0.956	0.803	0.685	0.826
Price Elasticity	−0.541	−0.890	−0.569	−0.509	−0.523
	[1.462]	[0.551]	[0.456]	[0.433]	[0.451]
Income Elasticity	−0.524	−0.181	0.098	0.120	0.131
	[1.599]	[0.193]	[0.143]	[0.182]	[0.194]
			SAMPLE SIZE: 183		
Price	−0.00325	−0.00330	−0.00482	−0.00631	−0.00488
	(9.243)	(10.009)	(10.752)	(3.902)	(9.325)
Income	0.0000041	0.0000077	0.0000142	0.0000171	0.000017
	(0.477)	(0.865)	(1.400)	(1.661)	(1.331)
Constant	1.909	1.926	2.152	1.259	2.350
	(4.163)	(4.509)	(4.399)	(0.360)	(4.540)
Dummy q_1	–	–	–	–	0.329
					(8.63)
Dummy q_2	–	–	–	–	−0.260
					(5.44)
Dummy q_3	–	–	–	–	−0.314
					(7.71)
α	–	–	–	14.45	
				(0.220)	–
Log-L	−213.18	−129.07	−109.49	−107.58	−213.82
R^2/R^2_{LRT}	0.314	0.694	0.589	0.516	0.625
Price Elasticity	−0.427	−0.783	−0.504	−0.095	−0.430
	[0.391]	[0.350]	[0.389]	[0.107]	[0.361]
Income Elasticity	0.047	0.114	0.121	0.027	0.125
	[0.106]	[0.115]	[0.107]	[0.056]	[0.196]

The figures in parentheses are "*t*" values while those in square brackets are standard deviations. The critical value of "*t*" at 5% level of significance is 1.96. The reported values of income and price elasticities are sample means of price and income elasticities calculated at each data point.

TABLE 4: RESULTS OF GURMU'S SCORE TEST FOR OVERDISPERSION IN THE POISSON COUNT DATA MODELS.

ALTERNATIVE HYPOTHESIS	GURMU'S "TAU" STATISTIC (UNTRUNCATED DATA)	GURMU'S "TAU" STATISTIC (TRUNCATED DATA)
Negative Binomial - Type II	11.314 (11.49)	12.263 (12.49)
Negative Binomial - Type II	0.237 (0.45)	7.364 (7.73)

The numbers in parentheses are the values of "tau" statistic corrected for sample size. The "tau" statistic is distributed as a standard normal variate. The critical value of a one-sided normal distribution at 5% level of significance is 1.645.

count data models than for the OLS and NLS models. In general, removal of extreme values from the sample has a dampening effect on the estimated parameters. Finally, based on the R^2_{LRT} values, the truncated count data models seem to fit the data better than other models.

A closer look at the estimated parameters in Table 3 suggests that price and income coefficients obtained from truncated geometric and NB type II models are similar. However, these estimates are different than those obtained from the truncated Poisson model. As noted earlier, the Poisson model does not give the best coefficient estimates in the presence of truncation. This is perhaps due to the mean-variance equality constraint implicit in the Poisson model. Imposition of this equality constraint would be incorrect for the data used in this paper. We used Gurmu's score test to verify the legitimacy of the equidispersion constraint. These results are presented in Table 4. The null hypothesis of equidispersion is rejected in three out of four cases. The null hypothesis is not rejected only when the untruncated model is estimated with the reduced data sample (i.e., with 183 observation). These results along with the statistical tests performed earlier imply that the NB type II and the geometric model are the most appropriate count data specifications of the demand for moose hunting trips in Ontario.

Estimated Benefits

The consumer surplus per moose hunting trip has been estimated following Creel and Loomis (1990). Since we used an exponential (i.e., semi-log) specification for all count data and nonlinear models, the consumer surplus per trip is equal to minus one over the estimated price coefficient. Because of the functional specification, however, the standard errors of the estimated benefits do not exist and must be obtained differently (Smith, 1988). Most analysts in the past have used a linearization procedure based on a Taylor Series approximation to derive the standard errors (e.g., Creel & Loomis, 1991; Englin & Shonkwiler, 1995). While it is simple to implement, this procedure becomes less reliable in the presence of high non-linearities. In view of this weakness, Creel & Loomis (1990, 1991) and Yen & Adamowicz (1993) suggest the use of a Monte Carlo simulation developed by Krinsky & Robb (1986) to generate standard errors of the estimated consumer surplus. Such a procedure is data intensive and hence, is not pursued here. Instead, we use a third and simpler procedure which, to our knowledge, has not been used before in recreational demand analysis. This procedure is based on Fieller's technique which enables one to compute exact confidence intervals for ratios of normally distributed variables (Miller *et al*. 1984). Since this is an exact procedure, the estimated confidence intervals are useful for policy analysis.

The estimated benefits along with their standard errors and exact 95% confidence intervals are presented in Table 5. All estimated consumer surplus values are statistically different from zero. The estimated benefit per moose hunting trip varies widely across specifications. However, for truncated geometric and the Creel and Loomis models the values of consumer surplus are very close ($208 and $205 Canadian respectively). Since, the decay process, over-dispersion, truncated count characteristics of the dependent variable and the institutional constraint (i.e., bag limit) have been taken into account in the truncated geometric model and in the Creel and Loomis model, the range of benefits from $175 to $210 Canadian per moose hunting trip should be preferred to the other estimates.[14] These surplus measures indicate that hunters realize significant benefits from recreational moose hunting in Ontario.

[14] These benefit estimates are comparable to the net economic value of moose hunting in Newfoundland ($114 to $251 per trip) estimated by Condon & Adamowicz (1995) using the contingent valuation method.

TABLE 5: ESTIMATED CONSUMER SURPLUS ($ CDN) PER MOOSE HUNTING TRIP IN ONTARIO.

NATURE OF COUNT & SAMPLE SIZE	Linear*	Nonlinear	Poisson	Geometric	NB- Type II	Creel & Loomis
		SPECIFICATIONS				
Untruncated 194	202.28	389.90	490.79	525.27	501.80	513.65
	(29.83)	(46.67)	(35.27)	(81.74)	(33.37)	(63.17)
	[0-857.91]	[315.8-509.4]	[430.2-571.3]	[464.8-603.8]	[443.9-577.0]	[435.5-626.1]
Untruncated 183	323.04	715.26	741.62	803.40	742.10	957.53
	(52.16)	(78.99)	(71.92)	(76.77)	(74.76)	(232.24)
	[0-1066.63]	[588.0-912.9]	[676.6-988.5	[676.6-988.5]	[624.6-913.0]	[754.4-1310.3]
Truncated 194	--	160.91	240.39	187.60	180.50	174.46
		(26.76)	(15.52)	(15.76)	(20.39)	(15.76)
		[104.7-346.9]	[222.2-261.7]	[163.4-220.3]	[154.4-217.1]	[149.7-208.9]
Truncated 183	--	307.53	303.00	207.54	158.3	204.94
		(43.03)	(25.33)	(22.68)	(35.00)	(24.65)
		[253.7-390.3]	[250.0-384.5]	[175.5-253.8]	[105.3-318.0]	[169.3-259.5]

The figures in parentheses are the linearized standard errors of the estimated consumer surplus/trip while those in square brackets are the 95% confidence interval for the estimated consumer surplus per trip.
* For the linear model, we report only the nonnegative part of the confidence interval.

The estimated benefits presented in Table 5 have interesting policy implications for sustainable forest management in Ontario. Sustainable forest management involves the identification of various timber and nontimber values, their relative contributions to satisfy societal demand and proper allocation of resources to ensure adequate provision of all these values in the future. Recreational moose hunting is a nontimber value, the adequate provision of which requires a higher emphasis on protecting moose habitats in Ontario's forest. A decision to provide higher protection to moose habitats will impose additional constraint on timber production. Clearly, there is a trade-off in sustaining these values. One can ask an interesting question in this situation: Is the marginal benefit from recreational moose hunting greater than the marginal cost (in terms of forgone timber values)? The estimated benefits in Table 5 can be used to provide an answer to this question. But which one of the estimated benefits to be used? Since the estimated benefit per moose hunting trip varies widely across models, it is important to choose the most appropriate model under the circumstances. Otherwise, erroneous policy decisions will result. For example, if we ignore the effect of truncation and the quick decay process inherent in the sample and choose the benefit estimate from the Poisson model ($490.79 per moose hunting trip), the total value of this resource will be inflated. Consequently, the future provision of other competing values will suffer. Among other things, the results in Table 5 clearly show that data characteristics and institutional characteristics need to be taken into account in order to generate reliable benefit estimates for policy purposes.

CONCLUDING REMARKS

The application of travel cost model with micro data has brought considerable progress in econometric estimation. A number of important sample characteristics such as censoring, truncation and endogenous stratification are now properly incorporated in recreational demand analysis. Owing to these improvements, the travel cost method has been accepted as a standard tool for measuring various unpriced values by the Environmental Protection Agency of the United States and the Environmental Assessment Board of Ontario.

In this paper, we employed the travel cost method to evaluate the demand for moose hunting trips in Ontario. This is the first systematic attempt to estimate the value of recreational moose hunting in Ontario. In view of censored and truncated nature of moose hunting trips, we used four alternative count data models based on the Poisson, geometric and negative binomial distributions and the Creel and Loomis model in our analysis. The coefficients for each of these models were obtained through maximizing the associated likelihood function while the standard errors of the estimated coefficients were obtained through the Eicher-White procedure. The results obtained from econometric estimation can be summarized as follows:

(i) The demand for moose hunting trips decline with higher travel costs and lower income. While the recreational moose hunting trips in Ontario is a “normal good”, its demand is more responsive to changes in travel costs than to hunters’ income.

(ii) The probability of shooting an adult moose during the first trip is about 30% which declines to 11% during the second to fifth trips. This probability declines to 2% for six or higher number of trips.

(iii) Truncation and extreme values have significant effects on the estimated parameters and on price and income elasticities. Removal of extreme values from the sample reduces the estimated value of the parameter while truncation reduces the absolute value of price and income elasticities.

(iv) The null hypothesis of equidispersion is rejected in 3 out of four cases, implying that that the coefficient estimates from the Poisson model may not be reliable for this data set. The estimates from alternative count data models such as the geometric, the NB type II and the Creel and Loomis models should be preferred to those from the Poisson model.

(v) The estimated consumer surplus varies widely across model specifications. This raises an important question: which one of the alternative benefit estimates should be recommended to a policy maker? It depends on the underlying data characteristics and on the institutional constraints. A model which takes into account various data and institutional characteristics in the analysis is likely to produce the most reliable benefit estimate. Based on this criterion, we recommend that estimated benefits from the truncated geometric model and the truncated Creel and Loomis model ($175 to $210 per moose hunting trip) should be used by policy makers.[15]

These results indicate that hunters realize significant benefits from recreational moose hunting in Ontario. The wide variation of estimated benefits across models imply that it is not only important to obtain theoretically consistent benefit estimates but it is equally important to select the most appropriate set of results from a number of alternatives. Otherwise, erroneous policy choices will result. Such policy choices may have detrimental consequences for sustainable forest management.

Finally, timber management practices often generate changes in the natural environment which have notable temporal effects on forests. Once the effects of these changes

[15] Since these results are based on just one season's data from a specific hunting site, due caution should be exercised before applying the results to other moose hunting sites in Ontario.

on unpriced forest values such as moose hunting, wildlife-viewing etc. are known, the management practices could be redesigned to ensure the flow of maximum overall benefits from various forest resources. This is an important area for future unpriced valuation research.

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Appendix: Implementation of the Creel and Loomis Model

In order to implement the Creel and Loomis model, we derived the marginal density for k by summing the joint distribution, $f(k, B)$, over B which is given by,

$$f(k) = f(k,0) + f(k,1) = p^k (1-q)^{k-1} (1-p+pq), \quad \text{for} \quad k > 0,$$
$$f(k) = 1-p, \quad \text{for} \quad k = 0. \tag{A.1}$$

Using the above expression, the mean and variance of k are derived as,

$E(k) = p/(1 - p + pq)$, and $V(k) = (p - p^2 - p^2 q + p^3)/(1 - p + pq)^2$ respectively.

To derive $E(k \mid B = 0)$, however, we resorted to the following steps:

i) Derive the probability that $B = 0$, (i.e., $P(B=0)$).

$$P(B=0) = \sum_{i=0}^{\infty} P(k=i, B=0) = (1-p) \sum_{i=0}^{\infty} (p - pq)^i = \frac{1-p}{1-p+pq}. \tag{A.2}$$

ii) Since by Bayes' theorem, $f(k \mid B = 0) = f(k)/\{P(B = 0)\}$, we can derive,

$$f(k \mid B=0) = \frac{f(k)}{P(B=0)} = \frac{p^k (1-q)^{k-1} (1-p+pq)^2}{1-p} \quad \text{for} \quad k > 0,$$
$$f(k \mid B=0) = 1-p+pq, \quad \text{for} \quad k = 0. \tag{A.3}$$

iii) The expected value of this conditional distribution can be derived as,

$$E(k \mid B=0) = 0 \times (1-p+pq) + \frac{(1-p+pq)^2}{(1-p)} \sum_{i=0}^{\infty} i \left[p^i (1-q)^{i-1} \right] = \frac{p}{1-p}. \tag{A.4}$$

Finally, if p depends on the explanatory variables according to logistic distribution given in eq. (20), the expected value, $E(T \mid B=0)$ can be computed as,

$$E(k \mid B=0) = \frac{\left(1/\left(1+e^{-X\beta}\right)\right)}{1 - 1/\left(1+e^{-X\beta}\right)} = e^{X\beta}. \tag{A.5}$$

Further details of this model can be found in Creel & Loomis (1992).