A SEQUENTIAL CHOICE ALTERNATIVE TO THE TRAVEL COST MODEL

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ABSTRACT

The travel cost model is the standard model used in the recreation demand area. This model assumes that the decision on the number of trips in a given time period (a season for example) to a particular site is determined at the beginning of the time period. For certain types of recreation activity it may be better to model the decision to take a trip to a given site as a function of the outcome of previous trips and the realization of random variables on previous trips (as well as travel and time costs). The spatial choice behavior itself may be sequential in nature rather than continuous.

In this paper a model is developed which specifies the choice of a discrete number of sequentially chosen trips to a given site as a function of site specific variables and values realized on previous trips. This model improves upon the existing travel cost model by specifying discrete integer values for the number of trips, developing an explicit relationship between trips taken and the number of days spent on each trip, and allowing intraseasonal effects to determine the probability of taking an additional trip. A comparison is made between the traditional travel cost model estimates of consumer surplus and the estimates from this sequential discrete choice model

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INTRODUCTION

In estimating the demand for outdoor recreation the travel cost demand model, or some variant of it, has been the most popular empirical model. In its most basic form this model estimates the quantity of visits to a particular site as a function of the travel and time costs. The model can be derived from a utility maximization problem which chooses the optimal number of trips in a time period given travel and time costs and available income. The single site model has been modified to include multiple sites, a number of time constraints and a variety of other factors (see McConnell, 1985) but the basic form of the model remains. The travel cost model ignores intraseasonal effects and tends to assume away the problem of differing trip duration (with the notable exception of Wilman, 1987). It also requires modification in order to restrict the predicted number of trips to be positive (eg. Tobit models) and requires estimation of a Poisson regression (or some similar technique) to limit it to count data (Smith, 1988).

We examine an alternative model of recreation choice. In this model the number of trips is not chosen at the beginning of the season or year; rather trips are chosen sequentially, the choice of trip i+1 being conditional on the individual already consuming i trips. This model analyzes several aspects of recreation choice which have been ignored or obscured by the traditional travel cost model. This model allows intraseasonal effects to influence the number of trips chosen. The number of trips chosen is an integer beginning at zero. Also, the effects of days spent at the site and harvest success are evaluated.

We proceed by presenting the traditional travel cost model and estimation techniques. We then present the basis for the sequential choice model and its estimation. The third section contains an example of sequential choice and travel cost estimation of the demand for recreational hunting to a single site. The fourth section compares welfare estimates resulting from these models and the final section concludes the paper.

THE TRAVEL COST MODEL

The basic travel cost model can be written as the maximization of utility of trips and other goods subject to available income. The utility maximization problem can be solved to yield a demand function for visits to a particular site which takes the form

$$V_i = f(P, Y, w^*) \qquad (1)$$

where V_i is the number of visits by an individual to site i, P is a vector of relevant prices including travel costs to site i, Y is income and w^* is the value of time. Depending on the time constraints, the value of time is generally some function of the wage rate (see McConnell, 1985 and Bockstael, Strand and Hanemann, 1987). The demand function for a single site model is easily estimated from data on the number of visits and travel cost to the site (assuming no other variable costs are pertinent).

Estimation by ordinary least squares results in the problem of predictions of negative numbers of trips. Furthermore, estimation using only those individuals who actually visited the site corresponds to a censoring problem as the information of those choosing not to visit the site is ignored. As a result a truncated or censored regression approach is commonly used to estimate these demand functions (Smith 1988). The censored regression model takes the form

$$V_i^* = X_i\beta + u_i \qquad (2)$$

$$V_i = V_i^* \text{ if } V_i^* > 0 \qquad (3)$$

$$V_i = 0 \quad \text{if } V_i^* \le 0 \tag{4}$$

where V_i^* is the true dependent variable, V_i is the observed dependent variable, $X_i\beta$ is the set of explanatory variables and regression coefficients and u_i is the random error term (Amemiya, 1985). In the travel cost demand model, this censoring problem corresponds to a case in which no visits are observed for some of the relevant population. A model which ignores these individuals results in biased estimates of the demand parameters. There are several procedures for estimating the model set out in (2)-(4). One approach is to assume a normal distribution for the errors in equation (2) and use a Tobit model. If $F(\cdot)$ represents the normal CDF and $f(\cdot)$ represents a normal PDF, the parameters of the Tobit model are estimated by maximizing the following likelihood function.

$$\mathcal{L} = \prod_{V_i=0} [\, 1-F(X_i\beta/\sigma)] \prod_{V_i=1} \sigma^{-1} f[(V_i-X_i\beta)/\sigma] \tag{5}$$

The Tobit model requires data on the independent variables for those who visit the site and those who do not. An alternative is the Heckman two-step procedure which uses probit estimates of the probability of visiting the site to treat the bias introduced by censoring. A third approach to estimation is required when no information is available on those individuals who do not visit the site. This model is called a truncated model (Amemiya, 1985).

Several other controversial issues surround estimation of the travel cost demand model. The choice of functional form is critical in determining welfare estimates (Kling, 1988; Adamowicz, Graham-Tomasi and Fletcher, 1989) and parameter estimates. Inclusion of substitute prices and other independent variables in the demand function has been debated in this literature (Rosenthal, 1988 and McConnell, 1985). The traditional travel cost model assumes constant length trips while empirically we often observe variable length trips. Kealy and Bishop (1986) present a model in which they convert the visits model into one which estimates site demand as days per season. Wilman (1987) uses a repackaging model to incorporate differing trip lengths. Nevertheless, the issue of changing trip lengths remains unresolved in the literature.

While a variety of issues hamper formulation and estimation of the travel cost model, there appears to be consensus on the estimation of such models. A model which estimates the number of visits per season as a function of travel costs and is estimated using some form of censoring or truncation correction appears to satisfy most of the basic concerns addressed in the literature.

THE SEQUENTIAL CHOICE MODEL

The sequential choice model is a type of discrete choice model. The basic premise is that individuals choose to make a trip or not based on which decision yields higher utility. The choice of taking five trips, for example, suggests that the utility of the fifth trip (conditional on having taken four trips already) was greater than the utility of taking only four trips and the utility of taking six trips. More formally the model can be stated as

$$U_i = \beta X_i + \varepsilon_i \qquad (6)$$

where U_i is the utility obtained from alternative i, X_i is a vector of individual and site specific characteristics, β is a vector of parameters and ε_i represents an unobservable error term. Let P_i denote the probability that alternative (trip) i is chosen. This probability is written as

$$P_i = Pr(U_i \geq U_j;\ \forall\ j \in I);\ \forall\ i \in I \qquad (7)$$

where I is the index of the set of all alternatives. Two assumptions are made in order to estimate this model. First, no higher alternative can be chosen without having already chosen the lower ranked alternatives. Second, the marginal utilities of the alternatives in the choice set are independent random variables (Sheffi, 1979). The first assumption implies that trip i cannot be chosen without trips i-1, i-2, ... 1 having been chosen. The second assumption implies that choices of trips are made one at a time rather than at one point in the season (as in the travel cost model). This second assumption allows the decision to be framed in terms of utility differences, that is, if $U_i \geq U_{i+1}$ then alternative i will be chosen. These two assumptions will be used in the development below.

Define elements of the choice index I which are below choice i as I_1 and the elements of this index above choice i as I_2. The probability of choosing alternative i can now be written

$$P_i = Pr(U_i \geq U_j; \forall\ j \in I_1) \cdot Pr(U_i \geq U_j;\ \forall\ j \in I_2). \qquad (8)$$

Since alternatives are ranked in order and the marginal utilities are independent the first term in equation (8) can be expressed as

$$Pr(U_i \geq U_j; \forall\ j \in I_1) = \prod_{k=1}^{i} Pr(U_k \geq U_{k-1}) \qquad (9)$$

Only one alternative ranked higher than alternative i needs to be considered in estimating the probability of choice i, since the probability of choosing the remaining higher ranked alternatives is zero as their predecessors have not been chosen (Sheffi, 1979). The second half of equation (8) can be specified as

$$Pr(U_i \geq U_j; \forall\ j \in I_2) = Pr(U_i \geq U_{i+1}). \qquad (10).$$

The combination of I_1 and I_2 yields the probability of choosing alternative i as

$$P_i = Pr(U_i \geq U_{i+1}) \cdot \prod_{k=1}^{i} Pr(U_k \geq U_{k-1}) \qquad (11).$$

In order to make the notation simpler we define

$$P_{i+1|i} \equiv Pr(U_{i+1} \geq U_i) \qquad (12)$$

Equation 11 can now be expressed as

$$P_i = (1- P_{i+1|i}) \prod_{k=1}^{i} P_{k|k-1} \qquad (13)$$

This model is composed of a set of binary choices. All probabilities can be expressed as the choice between alternative i and alternative i+1 or i-1. Therefore, estimation of a simple logit or probit model of the choice to take trip i versus i+1 or i-1 would constitute an unrestricted estimator of this model(see Vickerman and Barmby, 1985). This unrestricted approach, however, loses the information in the previous trips. Simultaneous estimation of the binary choice models minimizes the number of parameters to be estimated and facilitates interpretation of the parameters.

The likelihood function for the restricted model, being the joint probability given a particular parameter vector, can be written as the product of the individual probabilities over all individuals of the sample. For the model in equation (13) this can be written as

$$\mathcal{L} = \prod_{s=1}^{S} [(1- P_{i+1|i}) \prod_{k=1}^{i} P_{k|k-1}] \qquad (14)$$

where S is the sample size and s indexes individuals. Given a specification of the utility function this likelihood function can be estimated with any nonlinear optimization routine.

The specification of the utility function is critical in this analysis. There are two forms of observations that enter the utility functions; those experienced at the same level on every alternative and those that are only experienced on some alternatives and/or at different levels for different alternatives. The first class of variables are called generic variables and the second class nongeneric[1]. The generic variables are experienced on every trip and would include such factors as travel cost and other socioeconomic predictors. In a linear form of utility function the generic variable X_i would be modeled as $U_i = i \cdot \beta \cdot X_i$, since it would be experienced on every trip, 1 through i. Nongeneric variables enter only on the trip they apply to and at the level experienced on that trip. An example of a nongeneric variable for a recreational hunting trip is harvest. In addition to the specification of generic and nongeneric variables, the form of the utility function must also be determined. In this paper, as in much of the literature in the discrete choice area, we use a linear form of utility.

DATA, MODELS AND ESTIMATION PROCEDURES

The data used for the estimation of the travel cost and sequential choice models were collected in a mail survey of recreational hunters in Alberta in 1982. The portion of the survey results used here is a set of Big Horn Sheep hunter data for travel to a single Wildlife Management Unit (WMU) in Alberta. The data include observations on travel distance, income, harvest on each trip, number of days spent on each trip and number of trips to that particular WMU.

Travel Cost Model Estimation

The travel cost model is estimated with the total number of visits to the site (V) as a function of travel costs (TC), income (Y), seasonal harvest (H), and the average number of days per trip (D) included as independent variables (equation 15). The latter two variables are included in order to facilitate comparison with the sequential choice model.

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1 There is some disagreement in the literature on the use of the term generic. Sheffi (1979) uses generic in the form above while Vickerman and Barmby (1985) and Barmby (1988) use generic for the opposite form.

$$V = \lambda_0 + \lambda_1 TC + \lambda_2 Y + \lambda_3 H + \lambda_4 D + \varepsilon \qquad (15)$$

Four methods for estimating the parameters of a linear travel cost demand function were used. These methods differ in their use of visitor and non-visitor information, and in the estimation procedure employed. It has been suggested that parameter estimates and computed welfare measures may vary substantially between alternative methods (Kealy and Bishop, 1986; Smith, 1988; Wilman and Pauls, 1987).

Two travel cost models were estimated using a simple OLS procedure. The first model included only the 110 individuals who reported having visited the site. This truncated model is the one most often encountered in the literature and the bias associated with OLS estimation is well documented (Maddala, 1986). A second model incorporated an additional 345 observations corresponding to individuals who, when surveyed, reported having hunted Big Horn Sheep in a WMU other than the one being investigated. Therefore, Model 2 incorporates additional data on individuals who did not visit the site (ie., it uses a censored sample), but fails to account for the limitations of the OLS estimation procedure.

A third model estimates the travel cost demand parameters for the censored sample using Heckman's two-stage procedure (Heckman, 1979). According to Heckman, the mean of the error term, ε, in equation (15) will be non-zero when observations on non-users are not included. Heckman shows that this bias can be corrected by including the inverse of the Mills Ratio (IMR) as an explanatory variable in the travel cost demand equation[2]. In stage one of Heckman's procedure, the IMR for each observation in the truncated sample

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[2] The IMR is equal to $f(-X\beta)/F(-X\beta)$, where $f(\cdot)$ represents the density and $F(\cdot)$ the cumulative distribution function of a standard normal variable.

is estimated. Consistent estimates of the IMR were found using results of a probit analysis in which the probability of a surveyed hunter visiting the particular WMU was a function of measured distance from the site, distance squared and income[3]. The second stage involves applying a least squares method to estimate the parameters of a travel cost equation which includes the IMR as an independent variable.

Finally, the censored travel cost model was estimated using the Tobit procedure (the likelihood function in (5)). The results of these four models are reported in Table 1.

The results are broadly consistent across models. As expected, the own price effect of traveling to the site is negative, though insignificant in the Heckman version of the censored model. This latter result is expected as the IMR and travel cost are both functions of distance; hence, high colinearity between these variables will make it difficult for the effects of each to be accurately separated. Income is an insignificant predictor of the number of visits in all models. In Models 1 and 3, the effect on the number of visits of the average number of days spent at the site is negative and significant. This implies that, among visitors to the WMU, those who take trips of longer average duration can be expected to take fewer trips. On the other hand, the sign of this coefficient in Models 2 and 4, which estimate demand parameters using the full censored sample, is positive and

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3 The results of the probit analysis were: $z = .882^{*} -.012 \cdot \text{Distance}^{*} + .010 \cdot \text{Distance}^{2*} + .007 \cdot \text{Income}$ Log likelihood = -177.5. Degrees of freedom = 451 . * denotes coefficients which are significant at the 5% level. This model seems fairly good in that it correctly predicts whether or not an individual will visit the site in 81% of cases. However, when we consider only individuals who actually visited the site, the model's predictive accuracy falls to 59%.

Table 1: Estimated Travel Cost Demand Models

	Model 1	Model 2	Model 3	Model 4
Sample: Estimator:	Truncated OLS	Censored OLS	Censored Heckman	Censored Maximum likelihood
Travel Cost	-.021[a] (.005)	-.008[a] (.001)	-.033 (.090)	-.063[a] (.007)
Income	.010 (.012)	.014 (.046)	.014 (.027)	.017 (.016)
Days	-.067[a] (.025)	.036[b] (.019)	-.068[a] (.025)	.103[a] (.047)
Harvest	.196 (.488)	.933[a] (.389)	.200 (.492)	1.56[b] (.930)
IMR	-	-	.756 (5.32)	-
Constant	3.457[a] (.477)	1.273[a] (.194)	3.193[b] (1.91)	1.436[a] (.682)
Number of Observations	110	455	110	455
R2	.184	.210	.184	-
L.L.	-	-	-	-370.8

a,b denote coefficients significant at the 5 and 10% levels respectively. Numbers in brackets are the standard errors.

significant. Inclusion of non-visitors (all of whom spent an average of zero days at the site) means that longer average trip duration is now associated with an expectation of visiting the site more frequently.

In all models the coefficient on total seasonal harvest is positive; it is, however, only in Models 2 and 4 (in which all non-visitors record a zero harvest level) that this effect is significant. Among those who did visit the site there is no evidence that hunting success (in terms of harvest) affects the visitation level[4].

Sequential Choice Estimation

In modeling the discrete choice decision we choose to specify utility as a function of travel cost, income (representing a socioeconomic shift variable) and the difference between the desired harvest and days, and harvest and number of days consumed on all previous trips. In this form harvest and the days are assumed to be exogenous variables. Harvest is often specified as exogenous as it is generally beyond the control of the individual. In this formulation we use the harvest on all previous trips (which is known to the individual) as a determinant of the choice of trip i. Days is not often modeled as exogenous but in this formulation we assume that days of hunting occur as a residual, perhaps after all other leisure and work time commitments have been met.The element which we wish to capture in this model is how the number of days spent in the season before trip i and the harvest before trip i affect the choice of trip i. We assume that the effect of increasing harvest or days early in the season will reduce the probability of taking an additional trip. Particularly in the case of big game hunting, it is hypothesized that once a hunter harvests an animal, the frequency of hunting is reduced dramatically.

The utility function for the discrete choice analysis is more formally specified as

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4 Our decision to use the average number of days per trip and seasonal harvest associated with visits to the study WMU, which non-visitors obviously did not use, rests with the fact that the primary purpose of this paper is to compare the results of the conventional travel cost model with those of the sequential decision model. If our primary interest lay in valuing the recreation site, a different model would likely have been estimated.

$$U_i = \alpha_i + i \cdot TC \cdot \beta_{tc} + i \cdot Y \cdot \beta_y + \gamma_d \left(D^* - \sum_{j=1}^{i-1} D_j\right) + \gamma_h \left(H^* - \sum_{j=1}^{i-1} H_j\right) \quad (16)$$

where TC is travel cost, D^* and H^* are the desired number of days per season and the desired harvest per season respectively, and D_j and H_j are the days and harvest on the jth trip respectively. The coefficients α_i, β_{tc}, β_y, γ_d and γ_h are parameters to be estimated. The choice of trip i versus trip i-1 depends on the utility difference or $U_{i+1} - U_i$. This difference can be expressed as

$$U_{i+1} - U_i = (\alpha_{i+1} - \alpha_i) + \beta_{tc}TC + \beta_y Y + \gamma_d D_i + \gamma_h H_i \quad (17)$$

Define U_{ij} as $U_{i+1} - U_i$. Given the utility difference U_{ij}, the probability of taking trip i conditional on already having taken trip j can be specified by the simple logit model as $P_{ij} = 1/(1+\exp(-U_{ij}))$. Using these simple probability statements the joint probability can be specified as in equation (14). The probability of taking any trips to the site must also be estimated (i=1, j=0). For this purpose the model is estimated using data on hunters who have not visited this site but have visited other sites. The utility function for the 0,1 choice uses only travel cost, income and a constant. The nongeneric variables are suppressed.

Results of the sequential choice model are presented in Table 2. The most notable feature is the strong significance level of the travel cost parameter. As expected, the higher the costs of travel the less likely is an additional trip. The coefficient on days is also significant indicating an inverse relationship between the number of days spent on site in the past and the probability of taking an additional trip. The coefficients on income and harvest have the expected sign. Income has a positive effect on the likelihood of an additional visit and harvest has a negative impact. However, both of these coefficients are insignificant. This suggests that

Table 2: Results of Sequential Choice Model Estimation

Parameter Name	Parameter Value	Standard Error	t-Statistic
C1	0.818409	0.325364	2.515368
C2	2.405368	0.401183	5.995682
C3	1.650489	0.389636	4.235980
C4	1.835375	0.445576	4.119104
C5	1.394243	0.476106	2.928430
C6	0.799048	0.580177	1.377250
C7	0.606437	0.767176	0.790479
TRAVEL COST	-33.967300	3.489304	9.734692
INCOME	0.977187	0.738936	1.322425
DAYS	-0.072606	0.030548	2.376752
HARVEST	-0.526452	0.380525	1.383489

ACTUAL SHARES VERSUS PREDICTED SHARES

VISITS	ACTUAL SHARE	PREDICTED SHARE (NAIVE APPROACH)	PREDICTED SHARE (FULL DATA APPROACH)
0.00000000	0.75824176	0.86648519	0.75824178
1.00000000	0.07912088	0.07716245	0.07374819
2.00000000	0.06153846	0.04195087	0.06394812
3.00000000	0.03296703	0.01019206	0.02999056
4.00000000	0.02857143	0.00332579	0.02490614
5.00000000	0.01978022	0.00077072	0.02048933
6.00000000	0.01098901	0.00010075	0.01182742
7.00000000	0.00879121	0.00001217	0.01684846

NUMBER OF ACTUAL VISITS	292.00
NUMBER OF VISITS PREDICTED BY NAIVE APPROACH	95.32
NUMBER OF VISITS PREDICTED FULL DATA APPROACH	310.58
VALUE OF LIKELIHOOD AT MAXIMUM	-356.77
VALUE OF LIKELIHOOD AT ZERO (EXCEPT CONSTANTS)	-683.75

harvest is not necessarily a primary determinant of trip choice. One interpretation of this finding is that hunters often spend time in surveying hunting areas for the next season. These would be considered hunting trips even after the harvest of an animal in a given season.

The predicted and actual shares are also presented in Table 2. Two methods of prediction were used; the naive prediction approach (which uses sample estimates at the mean to predict shares) and the full data aggregation approach (which uses the actual values of the independent variables). The full data approach provides a very close approximation to the actual distribution of trips. In summary, the sequential choice model seems to perform very well as a description of trip choice, with travel cost and previous time spent on site acting as significant explanatory variables.

WELFARE CALCULATION

One of the most common uses of the travel cost model in economics is to estimate the value of the site in terms of consumer surplus (see McConnell, 1985 or Walsh, 1986). In this section we compute and compare the average surplus per recorded visit for the travel cost and sequential choice models. The welfare estimates are given in Table 3.

Welfare in Models 1 and 2 is calculated simply as $V^2/-2\lambda_1$, where V is the actual number of visits and λ_1 is the estimated travel cost parameter in the relevant model[5]. When the estimation procedure used corrects for sample censoring, the estimate of consumer surplus must be adjusted to account for the fact that there is a probability that each individual will be in the

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[5] In cases in which the predominant source of error is believed to be due to measurement of the dependent variable (ie., number of visits), expected rather than actual visits should be used in welfare calculation (Bockstael and Strand, 1984). Welfare in Models 1 and 2 calculated using expected visits is $67/trip and $71/trip respectively.

Table 3: Consumer Surplus per Recorded Visit

Model	Consumer Surplus[a] ($/Visit)
Sequential Choice	30
Travel Cost	
Model 1 (OLS/Truncated)	89
Model 2 (OLS/Censored)	218
Model 3 (Heckman/Censored)	45
Model 4 (MaxLike/Censored)	10

[a] All estimates are in 1983 dollars.

sample (see Kealy and Bishop, 1986 or Wilman and Pauls, 1987). In the Heckman model, expected visits are calculated as $E(V) = F(z) \cdot PV$; where PV is the visit level predicted by the estimated demand curve and $F(z)$ is the probability of visiting the site as predicted by the earlier probit analysis. Aggregate consumer surplus is then calculated by increasing travel cost incrementally and calculating the expected number of visits to the site at each travel cost. Consumer surplus is the sum of the expected visits times the travel cost increment[6].

Where the censored Tobit model is estimated using a maximum likelihood procedure (Model 4), expected visits will be the same as predicted visits. Welfare, therefore, is calculated as for Models 1 and 2 but with expected visits replacing actual visits. Consumer surplus estimates for the linear travel cost models range between $10 and $218 per visit - an almost twenty-twofold difference. Clearly, in this data set at least, failure to use an estimation procedure which accounts for the use of a censored sample

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[6] According to our probit model the probability of visiting the site remains constant regardless of changes in travel cost. More realistically, an increase in travel cost would reduce the likelihood of visiting the site as well as decreasing the level of use, given a positive decision to visit (Smith, 1988).

can lead to substantial differences in measured welfare. The difference between welfare measures for the conventional truncated OLS estimator ($89) and the commonly used Heckman procedure for censored samples ($45) is less dramatic. Our results suggest that the error in benefit estimation associated with failing to use an appropriate procedure for a censored sample may be quantitatively more important than that associated with using OLS on a truncated (or on-site) sample.

Wilman and Pauls (1987), Smith (1988) and Kealy and Bishop (1986) have all compared consumer surplus estimates for a variety of travel cost models. For the most part their results are not easily compared to our own. Kealy and Bishop estimate demand equation parameters for a truncated sample using OLS and a maximum likelihood procedure; estimated welfare per recreation day is 3.5 times as large in the OLS model as it is in the ML model. Wilman and Pauls calculate aggregate welfare using the parameters of a truncated OLS model and a Heckman specification; they find little difference between the two measures[7]. Smith calculates welfare per trip for the same four model specifications and estimation procedures that we do; he too finds a large wedge between the surplus measured for a censored sample when parameters of the "naive" OLS and "correct" ML procedures are used. The difference between surplus in the truncated OLS and Heckman models is small[8].

The welfare estimate from the sequential choice model is computed as

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[7] Wilman and Pauls estimate consumer surplus slightly differently than we do. We have calculated aggregate surplus over the entire censored sample while Wilman and Pauls (having complete data on only a truncated sample) use only visitors to the site.

[8] Smith uses estimated trips to calculate consumer surplus in all of the linear models he examines. Although we have chosen to use actual trips to calculate welfare associated with Models 1 and 2, our ranking of surplus measures remains unchanged when expected trips is used (see footnote 5).

follows. The predicted number of visits, using a full data aggregation approach (see Sheffi, 1979) is computed. The travel cost is increased incrementally, computing the change in the predicted number of visits at each increment. The sum of the predicted number of visits times the increment corresponds to the area under a demand curve and thus is a measure of consumer surplus. The resulting estimate of surplus is $30 per trip. The welfare estimate from the sequential choice model falls into the range of the estimates from the censored models estimated with a correction procedure. However, the travel cost welfare estimates and the sequential choice welfare estimates are based upon decision models which are very different.

CONCLUSION

In this paper we have estimated five recreation demand models for Big Horn Sheep hunting at a single site. Four of the models are variants of the popular travel cost model in which the total number of trips is assumed to be chosen at the beginning of the season. These models are distinguished by the nature of sample bias and the estimation procedure used. The fifth represents an alternative model of recreation choice: trips are assumed to be chosen sequentially, thus enabling previous hunting success and cumulative days spent at the site to influence the probability of taking another trip.

The parameters of the travel cost and sequential choice models must be interpreted differently. However, travel cost and the average number of days spent at the site were the most significant determinants of the number of visits in the travel cost model, while travel cost and previous time spent at the site acted as important influences on the probability of taking an additional trip. We found that the sequential choice model performed well as a predictor of trip choice.

Welfare was measured for all models. An almost twenty-twofold difference between welfare measured for the various travel cost models highlights the need to apply appropriate estimation procedures to correct for sample bias. The value of the site in the sequential choice model did not differ substantially from that associated with the corrected travel cost models. Nevertheless, there are many cases where the sequential choice model will offer a more appropriate depiction of actual trip choice behaviour than does the rather naive model of choice which underpins the travel cost model.

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