AN ABSTRACT OF THE THESIS OF

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Title: A Monte Carlo Study of Several Methods for Estimating Linear Demand for Outdoor Recreation from Censored and Truncated Data.

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Objective of this study was to compare accuracy of several travel cost methods, by employing Monte Carlo simulations in the single site framework. Estimates from five methods were compared to the "true" travel cost coefficient and "true" consumer surplus. Each method was ranked, using the root mean squared error (RMSE) criterion.

Each method was applied to one of two kinds of travel cost data: censored data that includes both users and non-users of recreation, and truncated data from on-site surveys consisting of only users. For censored data, the Tobit (TOBIT) method and OLS (OLSALL) were used, and for truncated data, the zone average travel cost (ZATC) method, the truncated normal (TRUNCN) estimator, and OLS (OLSUSR) were employed.

Two types of consumer surplus were compared: (1) Predicted (traditional) consumer surplus (TRCS) that uses predicted values of the dependent variable, and

(2) "actual" or Gum-Martin consumer surplus (GMCS) that uses observed values.

Hellerstein's (1992) method for computing TOBIT TRCS was used in this study, which supposedly gives better estimates of TOBIT TRCS. This improvement, however, did not always give a better RMSE ranking than ZATC or OLSALL TRCS.

The smaller the proportion of non-users in the data, the better were the TOBIT estimates. When the non-users portion was larger, ZATC and OLSALL sometimes gave better estimates of consumer surplus than TOBIT.

An unexpected identity of linear demand estimated by OLSALL and the classic ZATC model was discovered. An original proof of this identity is given in Appendix 1. Because of this identity, both OLSALL and ZATC gave identical TRCS estimates. However, GMCS estimates differed because of averaging involved with ZATC.

For censored data, TOBIT gave the best linear demand and GMCS estimates, but for truncated (user-only) data, best estimates of consumer surplus were from the supposedly obsolete ZATC model, fitted by Bowes-Loomis weighted least squares.

Another new finding was that for data suitable for ZATC, missing zero observations can be synthesized, thus permitting use of TOBIT. However, thorough testing of such a scheme was beyond the scope of this thesis.

A MONTE CARLO STUDY OF SEVERAL METHODS FOR ESTIMATING LINEAR DEMAND FOR OUTDOOR RECREATION FROM CENSORED AND TRUNCATED DATA

by

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TABLE OF CONTENTS

TABLE OF CONTENTS

Chapter **Page**

LIST OF TABLES

LIST OF TABLES

LIST OF APPENDICES TABLES

A MONTE CARLO STUDY OF SEVERAL METHODS FOR ESTIMATING LINEAR DEMAND FOR OUTDOOR RECREATION FROM CENSORED AND TRUNCATED DATA

CHAPTER I
INTRODUCTION

The use of amenity resources for recreation is a very important part of the ever growing recreation industry in the United States. This growth is mostly attributable to the growth in income and increasing interest in back-to-nature recreational types of leisure time activities. The growing awareness and concern on the use and non-use values of environmental amenity resources was and is the driving force for the preservation, conservation, and development of those resources by government and the general public. These increasing interests cause a more complex and sometime lengthy process of allocation of publicly owned natural resources.

The economic problem facing the decision makers in natural resources management is how to allocate resources among competing uses and to allocate optimally scarce public funds to preserve, conserve, and develop natural resources under consideration. The use of prices as a guide in the allocation process may not be possible in many cases. Information on prices is simply not available for non-marketed goods and services. In theory, optimal allocation of resources can be determined once information on benefits and costs can be collected. Economists have long attempted to estimate the benefits of recreational use of amenity resources. The improvement of such estimation methods is the main subject in this area of resource allocation.

Economic Valuation of Recreation

Fishery resources along Oregon coasts and rivers and game resources all over the state provide recreation for people of Oregon and from other places. Those renewable resources and natural scenic beauty in many parts of the state are important sources of income for many people in recreation industry.

The existence and quality of those resources are critical for many businesses which depend on and are related to recreation. To justify government expenditures for managing natural resources in recreational use, benefits have to be estimated. The problem arises because recreational use of resources is not transacted in the market from which the demand equations can be derived and equilibrium prices can be detected. In the early days of economists' concern about economic valuation of outdoor recreation, the benefits from recreation were estimated using the commercial value of related commodities which are the subjects of the recreational activities. However, when the value of sport-fishing is evaluated in terms of the commercial value of the fish caught, the value of sport-fishing tends to be underestimated. The same underestimation is also true with hunting recreation. The economic value to the recreationists may well be much higher than the total amount of out-of-pocket money that they spend for their leisure activities. A monetary value has to be assigned to fishing instead of to the fish in sport-fishing valuation. In hunting recreation, a monetary value has to be assigned to the hunting experience rather than to some similar market value of the hunted game animal. A hunting experience that does not result in bagging any game does not imply a zero economic value. The quality of hunting, however, will have an effect on the demand for hunting. Among other things, it is for that reason that travel cost demand was of interest to many economists. Since quality has a potentially big impact for a change in demand, any expenditure to enhance quality might have a substantial welfare effect. In terms of benefit and cost analysis the estimate of welfare change is very crucial for the planning process of resource management.

Given the large expenditures by all recreationists, the monetary value per fish caught or per game animal bagged can be much higher than their commercial monetary value. Recreationists' "willingness-to-pay" over and above costs associated with his or her recreation activity is used as a measure of the net benefits from that recreation.

Recreation expenditures of all consumers were $250 billion in 1982, exceeding the total spending on national defense and home construction (Walsh, 1986). Freeman (1982) estimates that approximately $5.0 to $6.7 billion worth of benefits from improving water and air quality accrue to recreationists annually. Other estimates can be presented to show a high value of benefit estimates from recreational use of environment (Kling, 1986; Walsh, 1986). However, regardless of these estimates of benefits, there is strong agreement that recreational use of environmental amenity resources is a substantial part of natural resource value. The benefits from quality improvement were also credited to the increase in the demand for recreation.

Economists interested in evaluating the benefits associated with non-market goods, such as recreation, have proposed a variety of recreation demand estimation models. Such models are addressed to estimate the benefits from recreational use of resources and to estimate the net benefits from the improvement of resource quality. These estimates provide the basis for policy analysis and decision making and will have implications on economic efficiency. Welfare estimates based on those estimation models should therefore be as reliable as possible. Travel cost models are commonly used to estimate the demand for and benefits of recreation.

Statement of the Problem

Over the years many interested economists have done much work to improve on the travel cost model and its extensions in search of its generalization over a large possible area of application. The correct theoretical setting and statistical accuracy of estimation have been key aspects of this later research.

Several models have been introduced with good statistical performances, but these models predict a wide variety of benefit estimates, especially when different econometric methods have been applied. Should the model with the best statistical performance be chosen or recommended? The difficulty that arises in comparing the estimates is that although many econometric models exhibit good statistical performances, a wide variety of benefit estimates does not indicate which model should be recommended for policy analysis and decision making. This difficulty is because the "true" value as a basis for comparison and choice of the models is not known. The least risky action for the researcher might be to recommend the smallest estimate of benefit. That recommendation, however, might heavily underestimate the real value of benefits. If the decision on a project for quality enhancement is not made because of too low a ratio of benefits to cost, the decision will result in the loss of the opportunity of welfare gains for the society.

A wide variety of models can, so far, only be judged by their underlying assumptions from which the models are constructed. Because of the above difficulties found in empirical work, Kling (1986) introduced a procedure where a model comparison can be made between several alternatives. She proposed that such comparison be implemented using a Monte Carlo simulation approach. The "true" value of benefits is known and the resulting estimates from simulation experiments using various models are then compared to the "true" value. The performance of different models in estimating the true value of benefits is the basis to evaluate them and to decide the best model. She developed the true model from her empirical data, and her simulated experimental data for fitting various models under investigation were also constructed from the same empirical data.

Kling's work was in the multiple site model framework of travel cost demand. While the multiple site model is popular for several theoretical and empirical reasons, the simple single site model did not disappear from the relevant agenda of research in the area. A wide possible area of applications are still open to the use and development of the single site model. In many cases substitute recreation sites are either not available or inappropriate to be considered as meaningful substitutes. (The difficulty of using substitute recreation sites has been shown by Kling's Monte Carlo experiments where more accurate benefit estimates were obtained by deleting substitute sites, even though substitute sites were part of the "true" underlying demand models.)

Travel cost demand models are typically estimated from survey data. In these recreational surveys, respondents can be randomly drawn from the population under consideration or from an on-site survey. The first mode of sampling is theoretically correct for estimating the benefits of recreation for the whole population. This sampling method will draw users and non-users of the recreational resource under investigation. This method of sampling is sometimes difficult or expensive in practice; consequently, on-site surveys often have to be conducted instead of all-population surveys. While on-site surveys often have some advantages in practicality and ease of conducting the survey, there are some disadvantages in using it to estimate benefits. The difference in estimates of benefits from using on-site survey data, without correction for the non-user portion, can be substantial, as will be shown later from our experimental results.

Monte Carlo experiments for the single-site travel cost demand model have been conducted by Hellerstein (1992), where he studied and compared the Tobit estimation method. He proposed that some correction be made for Tobit predicted consumer surplus estimation since earlier predicted consumer surplus calculations systematically underestimated the "true" consumer surplus. Several studies (Ribaudo and Epp, 1984; Kealy and Bishop, 1986; Smith, 1988; Bockstael et al., 1990; Creel and Loomis, 1990; and Smith and Kaoru, 1990) noted problems of using "user-only" data from on-site surveys for estimating the benefits. Benefit overestimates resulting from using coefficient estimates derived from user only data can be very significant.

Objective of the Study

The objective of this dissertation is to compare the performances of several estimation methods that are commonly used or have been proposed in travel cost demand studies. These methods will be used to estimate the travel cost demand in the single site modeling framework. The "true" value as a basis for evaluating performance of alternative models will be based on a known, pre-determined model and hypothetical travel cost conditions that the author considers to be a reasonable approximation of Oregon's sport-fishing and game-hunting activities. The approach in this study will be to use Monte Carlo experiments with 100 sets of data generated for each of several variances of normally distributed random errors. Two types of data will be analyzed: user-only data and data from the whole population so as to include non-users of recreation.

A more specific objective of this study is to evaluate the potential accuracy of Tobit estimation, given the possibility of obtaining data on the users. However, in cases where such data are not available, it is hypothesized that one should use the truncated normal estimation method. The use of ordinary least squares for either the complete data set or the user only data is well known to give biased estimates of the "true" demand coefficients. If the complete data set is available, this bias will depend on the proportion of non-users in the sample set (Greene, 1990, p.730). The smaller the proportion of non-users in the sample from the whole population, the smaller the difference will be between estimated and the "true" demand equation parameters. Since the non-user proportion of the samples is not known in an on-site survey, the use of truncated normal estimation is seen as a theoretically valid method for on-site data.

CHAPTER II
VALUATION METHODS OF NON-MARKET COMMODITY: REVIEW OF RELATED LITERATURE

In the neoclassical theory of demand an individual derives the demand for commodities from utility maximization. Given her utility function, an individual will supposedly maximize her utility subject to a budget constraint. Facing different prices, ceteris paribus, she will demand different quantity of the commodity under consideration. In other words, given her budget she will choose a bundle of commodities that will maximize her utility. Given the market price for that commodity she will demand a quantity where the price line intersects her demand schedule. Provided that there is a perfect market in terms of market supply and demand schedules, the price at which those two schedules intersect gives an equilibrium point. At that point, and only at that point, the welfare of those who transact in the market is maximized. The consumer surplus, a welfare measure, is defined as the area over and above the equilibrium price line under the demand curve.

Economic valuation of a commodity that is not produced and exchanged in a market is difficult because no demand curve can be derived from market data. There is no information on quantity and price in market transactions. Even when the price to use a recreation facility has been set up by its owner or manager, without a defensible demand curve, no net economic value or benefit can be derived. The

National Park Service in 1950, as quoted by Brown et al. (1964), suggested that the "cost" method be employed to evaluate benefits of recreation. A reasonable estimate of benefits arising from a reservoir was contended to equal the amount of the specific costs of developing, operating, and maintaining the facilities. Another early approach proposed to value net economic benefits of recreation was to use gross national product (GNP) per capita per day as the value of each day spent on recreation. The value of time for a day is therefore assumed to be the same, regardless of what activity an individual has chosen that day.

Later, economists developed two main methods to estimate economic values of non-market commodities: direct valuation, better known as the contingent valuation method (CVM), and indirect valuation via the travel cost model (TCM) approach. These two methods take account of the unavailability of a market for the commodity under study. Either a proxy for market or a hypothetical market has to be developed from which the demand for the commodity can be derived or deduced. This study deals specifically with the travel cost model; however, both methods will be reviewed. Contingent valuation will be reviewed briefly while the travel cost model approach will be reviewed in more detail.

The review in this chapter is not intended to cover all the voluminous literature in non-market valuation, and it is not intended to comment on all relevant publications dealing with travel cost models. This review is meant to present enough background to place this study in some perspective in the area of use and development of travel cost models. This chapter and the following chapter will review travel cost demand studies in the historical perspective and will provide some background information on important aspects that the studies, including this dissertation, try to solve. Some specific aspects concerning data and related estimation methods will be discussed in chapter III.

The Direct or Contingent Valuation Method

Contingent valuation method is the leading form of non-market valuation using the direct approach. In this method the researcher constructs a simulated market and conducts a survey to investigate how the consumer would react to different prices and qualities of recreation in the simulated market. The researcher strives to elicit the respondents' willingness to pay for the recreational experience or the willingness to accept payment for not participating. It is assumed that the consumers will react to different simulated market situations in a way similar to their reactions in the real market. From these reactions to the simulated market the price and quantity combinations can be used to construct a demand function.

The quality of estimation using CVM depends on how the simulated market was constructed, how it is understood by the respondents (consumers), and how they react to the changing situations of the hypothetical market they are facing. The truthfulness of the respondent's answer is obviously crucial in getting high quality benefit estimates. Several biases might arise in a study using CVM. These biases are known as (1) strategic bias, regarding whether consumers may strategically give a biased answer, for example with respect to the "free-ride" problem, (2) information bias, which is a bias caused by the hypothetical nature of the market facing the respondents such that respondents might be significantly influenced by information provided by the researcher, (3) instrument bias which includes vehicle and starting point bias, (4) hypothetical bias that might occur because respondents are predicting what their behavior would be given a hypothetical and unfamiliar situation, and (5) other biases related to sampling and survey, and these may include sampling bias, non-respondent bias, and interviewer bias (Schulze, d'Arge, and Brookshire, 1981; Rowe and Chestnut, 1983; Walsh, 1986; Forster, 1989). Schulze et al. (1981) in their study on previous results from CVM valuation, reported that there was no empirical evidence to support the existence of strategic bias. However, Rowe and Chestnut (1983) disagree with Schulze et al.'s conclusion on strategic bias. In their article Rowe and Chestnut also discussed the study by Schulze et al., and recommended several improvements in conducting CVM studies to minimize the bias. The interviewer elicits respondents' willingness to pay through a bidding scheme. The result of this bidding depends very much on how well the hypothetical market is presented, how the starting point in bidding is set, what kind of vehicle for payment is used, how simple and easily understood are the changing situation of the market for the respondents, and how big or small is the possibility for the truthfulness to be revealed by respondents. Recent research on CVM has addressed the above problems. Boyle and Bishop (1988), for example, studied the alternative to iterative bidding technique to avoid the problem of starting point bias. Initial bids can influence respondents' final bids. The alternatives to iterative bidding are payment card and dichotomous choice. Payment cards were set in the range of dollar values beginning from zero and increasing in a fixed interval. This alternative technique, however, requires respondents to state their valuation by choice of cards. Information on the cards and the range of dollar values might influence the responses to CV questions. Bishop and Heberlein (1979) proposed that another alternative to iterative bidding be used. In the technique that they called dichotomous choice, respondents are asked to state whether they accept (say yes) or reject (say no) to the take-it-or-leave-it offer for the item being valued. This technique is superior in its simplicity; however, the qualitative answer that respondents give provides less information about respondents' actual values or preferences than when the other techniques were used.

In their study, using both CVM and TCM, Smith, Desvousges, and Fisher (1986) support some researchers' conclusion that CVM estimates have substantial variability and are subject to design limitations. Smith et al. found that difference in question format yields different results, and this can be traced to the sources of biases mentioned earlier. This "framing effect", a problem related to how the interview is formulated, would induce the respondents' answer to the interviewer's questions in eliciting willingness-to-pay. This issue was one of the biggest hindrants to the extensive use of CVM (Slovic, 1990; Slovic and Lichtenstein, 1983; Tversky, Slovic, and Kahneman, 1990).

Brookshire et al. (1976), however, concluded that their comparative analysis provided evidence on the validity of the use of survey methods in the CVM framework as a means of determining the value of public goods. Aside from its potential comparability to indirect valuation using the travel cost model, CVM has the ability in its application to deal with some cases where TCM cannot or cannot correctly be implemented. These circumstances where CVM is applicable and TCM is not are in valuing non-use value of resources, in valuing resource-based sites, and in valuing local recreation sites where travel distance is not a significant determinant, such as city park recreation (Walsh, 1986). For this reason, and some limitations facing TCM, the use of CVM is popular, especially in the area of environmental economics. Even though theoretically possible to elicit either willingness to pay or willingness to accept from the consumers, researchers found that CVM was more appropriate to elicit willingness to pay.

The Indirect Valuation Method

Valuation using indirect methods is based on the use of observed data. Indirect methods of valuation rely on the behavior of households in related markets to reveal valuation of non-marketed goods. Since valuation is based on observed behavior, indirect methods are preferred by most economists to deal with the valuation problem for which it is appropriate (Smith et al., 1986). This method is generally known as the travel cost approach.

One group of models developed to predict future use or participation rate of recreation was based on the gravity model. O'Rourke (1974) presented a good review of the traditional gravity models with respect to their use in recreation studies. He noted that in many cases, for example in recreation, the attractiveness of recreation site generated the flow of traffic toward the site and not the reverse.

In its original formulation, the gravity model could not be used to estimate the economic value of recreation. Cesario (1969, 1973, and 1974) discussed variants of the gravity model that he referred to as the trip distribution model. Cesario and Knetsch (1976) used a variant of gravity model to estimate the benefits of recreation and referred to it as a demand function, from which the Marshallian consumer surplus estimate was derived.

Sutherland (1982) presented a general and complex gravity model for estimating benefits. His model was used as a preliminary step to a travel cost model where the quantity variables were provided by the result of the gravity model.

Because of the lack of an underlying economic theoretical basis in its application and development, the gravity model is not considered an appropriate method for economic valuation. Economists, for this reason, used and developed travel cost models.

Hotelling's letter to the National Park Service is attributed as the beginning of travel cost demand model development. Hotelling, in his letter to the Director of National Park Service in 1947, quoted in Brown, Singh, and Castle (1964, pp.6-7), suggested using a procedure to estimate future park visits. Hotelling basically suggested a method for estimating a demand function from which one could obtain a good estimate of consumer surplus. His method was to define concentric zones around the park such that the cost of travel to the park from any point in a zone was approximately equal. An estimate of the number of visitors to the park in a year could be listed for each zone, and this number relative to the zone's population could be plotted against the cost of travel.

In the travel cost model, travel cost is used as a proxy for price in the demand for recreation. The rationale behind travel cost model is that individuals travel to a recreation site because they value its services. The travel is undertaken if the site's services are sufficiently highly valued. If the non-market good (the recreation site) is not provided, travel will not be undertaken (Adamowicz and Graham-Tomassi, 1992).

Clawson (1959) was the first to successfully implement the procedure suggested by Hotelling to estimate the demand for and the value of outdoor recreation. The estimated travel costs per visit to the park were paired with the number of visits per 100,000 people in a zone. The zone is defined as a distance range from the park. He measured net economic benefits in terms of maximum revenue that could be raised by an owner of the park who charged a single price for visiting the park, rather than estimating consumer surplus as suggested by Hotelling. Clawson developed the model based on the following assumptions: (1) people in all zones have the same average preference function for the recreational activity, (2) the marginal preference for travel in all zones equal zero, (3) the only factor that matters is travel cost, i.e., travel time and other nonmonetary costs are not a factor, and (4) the price and availability of substitutes are equal for all zones. (Substitutes were not included in Clawson's model.)

Knetsch (1963) pointed out some limitations of the assumptions in Clawson's simple travel cost model. Clawson's model did not include travel time incurred, the availability of substitutes, and congestion in the recreation area. Since travel time is not included in the model, the estimated demand curve will be biased to the left of the true demand curve. Because the bias is not accounted for in the estimated value of benefits, the value of recreation will be underestimated.

Brown, Singh, and Castle (1964) were the first to statistically estimate the travel cost demand equation. In their economic valuation of the Oregon salmon and steelhead sport fishery they included distance and income as explanatory variables in their model, in addition to travel cost. The basic zonal average travel cost model was used to estimate demand for salmon and steelhead sport fishing. From the resulting demand they estimate estimated consumer surplus as a measure of benefits. Their model was an extension of the basic model introduced by Clawson.

The traditional travel cost model, based on the original formulation introduced by Clawson (1959), used zone average values for estimating the demand equation. All observations from a given distance zone are averaged into a single value. The number of observations in statistical demand estimation depends on the zoning made by the researcher. The delineation of the zones is very crucial in the estimation since averaging of the observations implies the averaging of the observed behavior in each and every zone. As hypothesized, there will be a larger number of observations for distance zones that are closer to the recreation site than for zones that are further away. A problem also arises with respect to population in the zones. Without weighting, the use of average data will be inefficient since zones with few observations will be given the same weight as zones with a large number of observations, for example from the zone which is very close to the recreation site and relatively heavily populated (Raja Abdullah, 1988). Bowes and Loomis (1980), Christensen and Price (1982), and Vaughan, Russell, and Hazilla (1982) discussed some of the estimation problems involved in such situation. One recommended solution would be to divide each distance zone into sub-zones to have approximately the same number of observations in each sub-zone. The number of observations, and the efficiency, in the estimation would therefore increase. However, Bowes and Loomis recommended a weighted least squares approach which is optimal for zone average data.

Although problems of different number of observations might be solved by dividing zones into sub-zones with nearly the same number of observations, the zone average travel cost model was criticized for being inefficient because some information can be lost in the averaging process. Brown and Nawas (1973) argued that estimates of travel cost coefficient based on zone averages are often statistically inefficient, which would then reduce precision in estimating the crucial price (travel cost) variable.

So far the issue of time that was raised by Knetsch was not addressed in the estimated models. Cesario and Knetsch (1970) proposed combining all time and travel costs into one cost variable. Others suggested including time as an explanatory variable in the demand equation. However, this inclusion of time will cause multicollinearity between the travel time and travel cost variables. Brown and Nawas (1973) suggested that improvement be made by using individual observations instead of averaging individual observations within distance zones. With efficient use of individual observations, distance traveled (instead of its surrogate, travel time) can be included as an explanatory variable in the estimated demand equation without introducing as much multicollinearity with travel costs. In this approach the dependent variable was the number of trips taken in a season by each sampled individual or household, and the explanatory variables are travel cost, distance, income, and socioeconomic characteristics.

Gum and Martin (1975) used this travel cost model with a large number of individual observations in their study of rural outdoor recreation in Arizona. They included travel distance, as Brown and Nawas did, and they showed that no multicollinearity problem arose. They argued that the data on total days of outdoor recreation of individual recreationists can be used as a shifter variable representing tastes and preferences; therefore, no assumption of constant taste among consumers of a recreation good was imposed. The issue of substitution was also raised; however, they only dealt with substitution between recreational activities. The problem of whether hunting is a close, or appropriate, substitute for fishing was questionable.

One difficulty that may arise in using individual observations was shown by Ward and Loomis (1986). For certain types of recreation, an individual or household may only take one trip per year or per season. If typical recreationists only take one trip per year, then there will be many observations with dependent variable equal to one. This will cause a problem of estimation.

Costs that accrue to recreationists include travel costs which are mainly a function of vehicle variable cost, food, lodging, and opportunity cost of time. The opportunity cost of time has been one of the main subjects of discussion in travel cost literature. Many researchers argued that opportunity cost of time should be related to income and hence, the wage. Keith and Workman (1975) constructed a model that included cost of time. In their model, trips are a function of travel cost, on-site expenditures, and foregone income, as a proxy for opportunity cost of time. The coefficient for foregone income was empirically tested, and their study indicated that opportunity cost of time was significant and an important part of total costs. Cesario (1976) used opportunity cost of time as one third of the wage rate for an adult, and for children the value was 25% of the value for adults. He modeled travel cost as a function of distance and opportunity cost of time, and he used his regression result to construct the value of the total costs variable. This approach was an improvement of the ad hoc model proposed by Cesario and Knetsch (1970) where they used travel cost as a function of travel distance and time (multiplicative variable), and then used the travel cost as an explanatory variable in the demand function. McConnell and Strand (1981, 1983) hypothesized that opportunity cost of time was some ratio, k, of average family income per hour times the travel time. They regressed recreation days against cash costs and opportunity cost of time as separate variables. The ratio of regression coefficients was an estimate of the ratio, k, and it has a range between zero and one. Some research estimated the value of k equal an average of 0.122 to 0.146 from using McConnell and Strand's model on aggregated data (Hof and Rosenthal, 1986). If k equals one, then opportunity cost of time is exactly equal to the wage rate (Smith, Desvousges, and McGivney, 1983). Johnson (1983) argued that k underestimates the real ratio, k^*. However, the alternative that Johnson proposed may result in a negative value of k as it was applied to McConnell and Strand's data. This result can be used to explain that travel itself might be either utility or disutility to recreationists.

Bockstael, Strand, and Hanemann (1987) developed a theoretically consistent approach for including opportunity cost of time in recreation demand, conditional on the recreationist's labor market situation. In the demand function for individuals at a corner solution in a labor market, travel cost and travel time are independent variables. With interior solutions in the labor market, time is valued at the wage rate, and it was combined with travel cost to produce one cost variable.

In considering how travel time should be treated in the utility maximization framework, Shaw (1992) suggested that one should consider carefully the type of recreation being modeled. Time used or needed might or might not enter into the utility function or constraint considered by the recreationist. A detailed preliminary study of the recreation activity in particular may even result in a recommendation as to which valuation method would be appropriate to use. Despite the difference in the resulting estimate of k value, almost all are in agreement that k should be derived from an empirical estimation.

Another issue that was raised on the deficiency of Clawson's travel cost model was that it did not include substitutes. It is important to include substitutes in the demand equation since the demand for the substitute is related to the demand for the substitutable goods. The price of the substitute and its cross elasticity with respect to the goods under consideration will affect the demand for those studied goods. The single site model considers only a single good with no substitute. Since it is very likely that more than one similar recreation destination exist in the same area or region then some economists developed a model to account for the availability of substitute sites that compete for the visitors. The more substitute sites available in the area, the shorter the distance limit for the visitor to go to a given recreation destination. The exclusion of substitutes with similar characteristics will overestimate the benefits (Burt and Brewer, 1971; Gum and Martin, 1975). However, Caulkins, Bishop, and Bouwes (1985), by using hypothetical situations and a Monte Carlo experiment approach, showed that overestimation was not necessarily the case. The exclusion of alternative sites from the model may cause either an overestimate or underestimate of the true value of benefits.

The reason for the choice of a site are twofold: distance and site quality characteristics. Consideration of substitute inclusion into the model will therefore be related to the inclusion of site quality as well. In the original single site travel cost model, no site quality variable can be included since quality variation cannot usually be identified with only one given site. However, sometimes quality, such as fishing success, can change at one site during the year. Benefits of quality improvement can only be estimated by estimating the change in demand for recreation caused by changes in quality. (See, for example, Stevens, 1966 for this type of approach.) With no changes in quality, no change in benefits can be estimated by using the regression coefficient for the quality variable for which the improvement is planned.

The first simulation model that included substitutes was the pooled model where a single demand equation was estimated from pooled data for several sites (Kling, 1986). In this model, pooled observations across all sites were used to estimate the effect of available substitutes on the visits to a particular site. All sites can be treated as the same commodity, and they differ only in quality levels and price.

Caulkins, Bishop, and Bouwes (1982) applied the typical trip model where a demand equation was estimated using either the sum of all visits to all sites or the number of trips to the "typical" site as the dependent variable and its quality characteristics and travel cost to that site were included as explanatory variables. The typical site was defined as one of the most often visited or the one that was indicated by recreationist as the most preferred site. The model was formulated as

$$X_i = \beta_0 + \beta_1 q_i + \beta_2 P_i + \beta_3 y_i + e_i \quad i=1,....,M \qquad (2.1)$$

where β_j is the jth parameter to be estimated, X_i is the ith individual total trips to the typical site or to all sites, q_i is the quality measure of typical site, P_i is the travel cost, y_i is the ith individual's income, and e_i is a random error term. When X_i denotes the total trips to all sites then $X_i = \Sigma_{ij}\, x_{ij}$, where x_{ij} is the number of trips taken by individual i to site j. The total number of sampled individuals is M. They also included socio economic variables and quality characteristics of the second most often visited site. Reiling, Gibbs, and Stoevener (1973) and Freeman (1979) consider visits to each site as separate observations in the estimation of the demand functions. The model that they estimated is

$$X_{ij} = \beta_0 + \beta_1 P_{ij} + \beta_2 q_j + \beta_3 y_i + e_{ij} \qquad (2.2)$$
$$i=1,...,M;\ j=1,...,N$$

where i indicates ith individual and j indicates jth site. X_{ij} is the number of ith individual trips to site j, P_{ij} is travel cost for individual i to site j, q_j is a quality measure of the jth site, y_i is ith individual income, and e_{ij} is the random error term. In this model trips to various sites are pooled into one model for estimation. Some difficulty might arise from using the above model. Regarding the substitution, it is questionable that price of substitute site n+1 affects the number of visits to site n in the same way as the price of substitute site n affect the number of visits to site n+1. Although it is reasonable to think that own price and income affect the number of visits to different sites in the same way, it is difficult to decide on how to include substitute sites in the analysis. Kling (1986), following Kling, Bockstael, and Strand (1985), suggested that substitution prices be included in the estimation in the form of a stacked regression.

Caulkins et al. included prices and qualities of the most and second most often visited sites in the estimated demand function. They consider the effect of substitute sites on demand, although in a limited way. The inclusion of more than one substitute in this model form is not known.

Bias resulting from the exclusion of substitute site prices can have a substantial impact on benefit estimates. Caulkins, Bishop, and Bouwes (1985) addressed this problem by showing that the assumed substitutes may, in fact, result in either decreased or increased benefits. In some cases, they pointed out through their hypothetical cases, it is possible that the two sites are complements instead of substitutes.

The coefficient bias resulting from the omission of a cross quality term is difficult to determine. Quality can be measured either in objective measure or subjective measure, i.e., in terms of the perceptions of individuals on quality. The most commonly used measure of quality variable is the objective measure. Using this measure in Caulkins et al. (1985) framework, it would be possible to consider substitute quality as the quality of the second most often visited site, and bias can be determined straightforwardly. If own-quality and cross quality are substitutes and positively correlated, the coefficient of own-quality will be too low when the cross quality term is omitted. The change in consumer surplus estimate with respect to a small change in own-quality will also be too small. The quality may not vary among individuals if the quality variable is measured in term of quality perceptions. It would possibly be positively correlated (Kling, 1986).

The difficulties in dealing with substitutes in the single equation framework gave rise to the use of a system of demand equations. Burt and Brewer (1971) proposed a system of linear demand equations based on travel cost and income. Since travel costs, the proxy for prices, to all sites are included in each demand equation, the system of demand equations will capture the substitution possibility between sites. They did not include quality variables explicitly in their model since these variables would not vary across observations. They imposed symmetry on cross price coefficients. The model was estimated using generalized least squares. Somewhat similar to Burt and Brewer's, using Zellner's seemingly unrelated regression Raja Abdullah (1988) estimated the benefits associated with sportfishing in Oregon coasts in the regional travel cost model framework. Raja Abdullah suggested that some type of flexible functional form consistent with individual theory of demand be used.

The above model assumes that the sites are perfect substitutes for each other, and the reduction of the price of a site will draw recreationists from other sites. This is one limitation that the model imposes.

In dealing with incorporating quality into the model Vaughan and Russell (1982) introduced a varying parameter model. In addition to estimating the travel cost demand equation, they regressed the coefficients in the demand equation to the various measures of site characteristics which are invariant across zones at a given site.

Smith, Desvousges, and McGivney (1983) used the varying parameter model to estimate water quality benefits of 43 U.S. Corps of Engineer's water recreation facilities. They provided a theoretical basis for the varying parameter model introduced by Vaughan and Russell. They applied OLS estimation on their data and, later, Smith and Desvousges (1985) presented a revised model with respect to econometric estimation methods applied to the data sets used in Smith et al.'s (1983) research.

The problem of including substitute prices remains in the varying parameter model for the same reason as with the other pooled models. Considering the two step procedure, if own price and two substitute prices are used in the first stage estimation of a system of demand equations, there is no reason to group the coefficients of P_1 together to use in the estimation of the second stage since P_1 is own price for X_1 but a substitute price for X_2 and X_3. One would expect the change in quality to affect parameters differently.

A model that considers multiple sites and the structure of choice problem facing individuals is the random utility model. This model is based on the recognition of the discrete nature of choice that an individual faces when she has to decide where to go for her recreation. Instead of having continuous choice as commonly treated in neoclassical theory of demand, an individual has to choose from a discrete choice set. The decision of a recreationist is recognized as a two-step decision making process. First, an individual has to choose whether she will or will not go to recreate and, second, when she does she has to decide as to where and for how long or with how much intensity. Kling (1986) pointed out that recreation is a commodity that often deals with corner solutions. This has something to do with the first step of the above decision making process. The model is estimated using a multinomial logit estimation method and, therefore, this model is generally called the multinomial logit (MNL) model.

Another method known in indirect valuation is the hedonic travel cost method (Brown and Mendelsohn, 1984). This model seeks to reveal how much recreationists are willing to pay for individual characteristics of recreation sites. Quality variable is the main focus of this method. It is this quality characteristic that the individual demands in her recreation while the other models focus on the sites with whole quality characteristics.

In the hedonic travel cost method an individual recreationist has a utility function that includes characteristics of recreation sites, number of recreation trips, and a bundle of other goods. The total cost per trip was defined as

$$V_1(Z) = a_1+f(Z)+T(Z)+C(Z) = a_1+\beta_0 T(Z)+\beta_1 \phi C(Z) \qquad (2.3)$$

where f(Z) is the sum of user fees, T(Z) is travel costs, C(Z) is travel time costs, a is the fixed cost of trip, and Z denotes the vector of site characteristics. In Brown and Mendelsohn's empirical work on steelhead sportfishing in Washington, Z has three components: scenery, congestion, and fish density. The prices of recreation attributes were estimated by regressing travel costs on bundles of characteristics associated with recreation destinations. The demand for site characteristics was then revealed by comparing the site selection of recreationists facing different attribute prices.

Smith and Kaoru (1987) presented some problems in using the hedonic travel cost method from Brown and Mendelsohn. They argued that definition of relevant zones for the price functions as well as their estimation are not clearcut. The definition of zone was arbitrary as shown by Brown and Mendelsohn's use of town as residential zone. Plausible decisions in implementing the model can lead to large variations in the performance and benefit estimates. Another problem presented was that the set of sites for individuals to consider in planning was imposed by researcher. This set determines the hedonic travel cost function. The method did not allow the possibility for a change in the choice set due to changes in the sites' characteristics.

A wide variety of models and their applications have been discussed in this chapter. There is no single, simple formula or guidance that can be proposed for choosing the most appropriate model to solve a problem at hand. The problems of model comparisons and choice and its possible solutions will be discussed in chapters III and IV.

CHAPTER III
SOME METHODOLOGICAL ISSUES PERTAINING TO TRAVEL COST MODELS

Although travel cost model studies have had a history of more than three decades, some problems have not been solved. Improvement of the models remains possible and worthwhile. Several problems will be discussed in this chapter. The problems to be discussed here are not the only ones that can be found in the use and development of travel cost (TC) models. The improvement of TC models is a continuous task, and therefore some research in the future will always be necessary. The attempts to find new findings as well as replications, confirmations, or duplications of previous research will probably be required for the benefits that can be produced from the development of knowledge through theoretical and empirical work (Tomek, 1992). Some efforts to find solutions to certain TC problems will be addressed in this thesis in the following chapters.

The Problem of User-only Data from On-site Samples

Many studies in the TC area addressed the decision tree that has to be used as a basis for modeling. A two-step decision making process has to be taken by an individual with respect to recreation. First, an individual decides whether she will participate in a recreation activity. If she participates, she must decide where to go, and she also must choose (this may be considered as another step) the intensity of her recreation activity (Bockstael et al., 1990).

Most travel cost model studies use on-site surveys to collect data for estimating parameters of the demand function. The use of this type of data, without considering the role of individuals who do not participate in recreation, will lead to the overestimation of the demand for, and therefore the benefits of, recreation in a particular site. In many cases, however, this is the only data source available or, perhaps, the only data that it will be possible to collect reliably.

Failing to recognize the effect of not including the non-participant in the demand estimation will result in a biased estimate. If this estimate is used for the management of the recreation site, a loss of potential welfare gain for society could result.

Several studies suggested the improvement of estimation by using some new estimating alternatives. As many studies indicated, the use of user only data without adjustment for non-participants may result in very high overestimates of benefits. Smith and Desvousges (1985) found that using unadjusted individual observations or user only data would result in benefit estimates of three to thirty times as much as estimates from the data set that recognizes the users and non-users of recreation. That finding was a revised version of findings in the earlier work of Smith, Desvousges, and

McGivney (1983) that did not recognize truncation and censoring in the estimation.

Shaw (1988) indicated three intrinsic data problems associated with on-site sampling:

(1) the observations will only be non-negative integers;

(2) there will be a problem with truncation; and

(3) endogenous stratification: people who go to the site frequently are more likely to be sampled than ones who go occasionally.

Problems (2) and (3) above can be overcome by implementing a more carefully designed survey that allows unlimited visit data and the random pick of sample to be as even as possible such that people with different frequencies of visits will have equal probability to be in the sample set. Problem (1) may not be accurately stated since on-site surveys must result in positive observations. Vardi (1988) also argued that demand equations estimates would be biased if these estimates were derived from on-site, intercept surveys. Ribaudo and Epp (1984) also noted that failing to account for non-users in the estimation would result in overestimating benefits. Neglecting the effect of non-participants by applying ordinary least squares (OLS) on user-only data can overestimate benefits by three and a half times (Kealy and Bishop, 1986), almost eight times (Bockstael et al., 1990), up to thirty times (Smith and

Desvousges, 1985) as much as benefits adjusted for the existence of non-participants.

Conducting a survey that will include non-users as well as users might be costly, if applicable, in practice. Although the on-site, intercept survey data will have some limitations, on-site surveys are often less expensive, less time consuming, easier to conduct and, possibly, more reliable than surveying the whole population. To correct for biases caused by analysis of incomplete on-site data, one may have to use the data but recognize its truncated nature due to excluded non-users. Some researchers (for example Kealy and Bishop, 1986; Smith, 1988; Bockstael et al., 1990) implemented a truncated normal maximum likelihood estimation approach to their user-only data sets. These researchers and others, based on the issue of individual choice and decision making behavior, argued that the truncated normal model should be used to replace OLS. However, the use of user-only data loses information on participation choice.

To look at the truncated normal model, consider a problem of travel cost data where no non-user data is available. All observations in the data will have only positive values. Here we have a case of data truncated at zero. For a continuous random variable, x, that has a probability density function f(x) and a is a constant, the limit of truncation, then

$$f(x \mid x>a) = f(x) \,/\, Prob(x>a). \qquad (3.1)$$

In the truncated normal case, for a variable x that is distributed normally with mean μ and has a standard deviation σ,

$$\mathrm{Prob}(x>a) = 1 - \Phi((a-\mu)/\sigma) \qquad (3.2)$$
$$= 1 - \Phi(\alpha)$$

where $\alpha = ((a-\mu)/\sigma)$ and $\Phi(.)$ is the standard normal cumulative distribution function. The truncated normal distribution function is

$$f(x|x>a) = f(x)/(1-\Phi(\alpha)) \qquad (3.3)$$

$$=[(2\pi\sigma^2)^{-1/2}e^{-(x-\mu)/2\sigma^2}]/(1-\Phi(\alpha))$$

$$=[(1/\sigma)\phi((x-\mu)/\sigma)]/(1-\Phi(\alpha))$$

where $\phi(.)$ is the standard normal probability distribution function. Variable x, when its distribution is truncated, is called a truncated normal random variable.

The truncated regression model is derived as follows (Greene, 1990).

Assume that $\mu = \mathbf{B}'\mathbf{x}_i$, then

$y_i = \mathbf{B}'\mathbf{x}_i + \epsilon_i$ $\qquad$ ϵ_i distributed $N(0,\sigma^2)$

$y_i|\mathbf{x}_i \approx N(\mathbf{B}'\mathbf{x}_i,\sigma^2)$

$E(y_i|y_i>a) = \mathbf{B}'\mathbf{x}_i+\sigma[\phi((a-\mathbf{B}'\mathbf{x}_i)/\sigma)/(1-\Phi((a-\mathbf{B}'\mathbf{x}_i)/\sigma)]$ (3.4)

and from

$f(y_i) = 1/\sigma[\phi((y_i-\mathbf{B}'\mathbf{x}_i)/\sigma)/(1-\Phi((a-\mathbf{B}'\mathbf{x}_i)/\sigma)]$

is derived the log-likelihood function, which is

$$\ln L = -n/2(\ln(2\pi)+\ln\sigma^2) - 1/2\sigma^2\ \Sigma_i(y_i-\boldsymbol{\beta}'\mathbf{x}_i)^2$$
$$- \Sigma_i \ln[1-\Phi((a-\boldsymbol{\beta}'\mathbf{x}_i)/\sigma)], \qquad (3.5)$$

where a is the truncation point.

With advances in computing technology, estimation using the maximization of the above log-likelihood function can be done with relative ease. Some approximation can be applied to truncated data as Olsen (1980) suggested, by first applying OLS on the truncated data and using the correction table that he developed. Amemiya (1973) proposed an estimation method that is consistent and asymptotic normal by using the maximum likelihood estimator. The maximization of the above log likelihood function as presented by Amemiya (1973) and Greene (1990) is to be followed in this study to get the truncated normal estimates of demand coefficients.

Estimation Methods for Complete Data Sets

The easiest, and traditionally standard way of estimating a regression equation is by using ordinary least squares estimation. This was the method first used by Brown, Singh, and Castle (1964) for statistical estimation of travel cost demand, five years after Clawson (1959) introduced his historical travel cost method, based upon a tabular, two-stage analysis. Some improvements were later proposed, for example, weighted least squares with weights based on population (Bowes and Loomis, 1980), semilog specification (Ziemer, Musser, and Hill, 1971), to mention only a few.

By looking at the decision making process that every person uses when they are facing a set of choices, including recreation, the complete data on individual observations would include non-users of recreation. That means the complete data set in the sample would include observations with zero trips. We need to use the estimation methods that recognize the sample selection effect, such as the Heckit model from Heckman (1979), or censored regression (Tobit) model proposed for the first time by Tobin (1958). The application of such models in travel cost demand estimation has been reported by several researchers. Smith (1988) compared the performances of Heckit, Tobit, OLS, truncated normal maximum likelihood, and Poisson estimations. Bockstael et al. (1990) compared the Tobit, Heckit, and Cragg's (truncated normal) models on sport-fishing. Bockstael et al., based on statistical performances, found that Tobit performed best provided that zero observations were available. If no zero observations were available, based on theory, the truncated normal (Cragg, 1970) ought to be used. Smith (1988) and Bockstael et al. (1990) concluded that because of variation among the models that they analyzed, the effect of the participation decision was negligible. One should therefore focus on the frequency decision and various sample selection adjustments.

The relative performances of several estimation methods applied to two types of data, user-only versus complete data, will be the focus of this study. For the complete data set, OLS and Tobit will be used. OLS is to be implemented because of its traditional use, and Tobit for theoretical and empirical reasons. Theoretically, Tobit is applicable to the travel cost demand model framework, considering selection effects. Participation can only be either zero or positive because negative demand cannot be observed. Despite the possibility that some individuals might have a negative intention on recreation, one can only observe that those individuals do not participate in recreation. Therefore, non-participants will demand zero trips to the recreation site. However, the estimate of benefits from recreation should account for those who do not participate. The use of OLS on the data set that has a structure of zeros and positive observations on the dependent variable will be inconsistent (Greene, 1990). The observations should be regarded as censored, given that some individuals will demand zero trips. Zero is the limit observations that conventional regression methods fail to account for.

In the Tobit estimation framework, consider a random variable y, a transformed variable from the original variable y^*, by

$$y = 0 \qquad \text{if} \quad y^* \leq 0$$

$$y = y^* \qquad \text{if} \quad y^* > 0.$$

If y^* distributed $N(\mu,\sigma^2)$ then

$$\begin{aligned} \text{Prob}(y=0) &= \text{Prob}(y^* \leq 0) \\ &= \Phi(-\mu/\sigma) \\ &= 1 - \Phi(\mu/\sigma); \end{aligned}$$

and if $y^*>0$, y has the density of y^*.

The general formulation of Tobit regression is

$$\begin{aligned} y^* &= \boldsymbol{\beta}'\mathbf{x}_i + \epsilon_i && (3.6) \\ y &= 0 && \text{if } y^* \leq 0 \\ y &= y^* && \text{if } y^* > 0. \end{aligned}$$

The log-likelihood function for the censored regression model is

$$\begin{aligned} \ln L = -n_1/2(\ln(2\pi)+\ln\sigma^2) - 1/2\sigma^2\ \Sigma_1(y_i-\boldsymbol{\beta}'\mathbf{x}_i)^2 \\ - \Sigma_0 \ln[1-\Phi((\boldsymbol{\beta}'\mathbf{x}_i)/\sigma)]. \qquad (3.7) \end{aligned}$$

where n_1 is the number of non-limit observations, Σ_0 denotes limit observations, and Σ_1 denotes non-limit observations. Amemiya (1973) in his paper showed that maximization of the above log-likelihood function would produce an estimator with all desirable properties.

If OLS is applied to censored data the estimate would be biased. The bias depends on the amount of censoring and, therefore, in the travel cost model, the proportion of users to the total number of observations in the complete data set. Greene (1990, p.730) mentioned the empirical regularity of the bias resulted from using OLS. By scaling the least squares estimates by the reciprocal of the proportion of users in the sample, one can obtain an approximation to the maximum likelihood estimates.

As will be shown by the results of this study, the larger the proportion of users to the total observations of the complete data, the closer the OLS estimates tend to the Tobit estimates.

The difficulty that arises in interpreting results of comparisons from empirical data, as made by Smith (1988) and Bockstael et al. (1990) is that the "true" value to which the estimates should be compared was not known. Recommendations therefore had to be based on statistical performances of the model studied rather than being compared to the "true" value of estimates. However, several recent studies by Kling (1988a, 1988b) and Hellerstein (1992), have used a Monte Carlo simulation approach to enable the researcher to use the "true" value as a basis for comparing the competing alternative models. This approach, to be discussed later, will be used in this study.

The Choice of Appropriate Model

In the history of travel cost model development, many formulations, model specifications, and estimation methods have been proposed. Many of these models have been presented and discussed in previous chapters. Some models are appropriate to use in dealing with certain situations while others are not, but these others might be appropriate to implement in different problem settings. As some researchers have noted, theory has little guidance as to which functional form is appropriate in general (Zarembka, 1974; Kealy and Bishop, 1986).

The problem of choosing the most appropriate model and estimation method basically depends on the situation that one faces. The underlying assumptions behind model formulation, the consistency of the model with the economic theory of demand, the feasibility of data collection and processing, and econometric theoretical and practical considerations are among the most important factors for one to consider in the model choice process. Mendelsohn (1987) concluded that none of the models or approaches clearly dominate in all circumstances where some travel cost analysis is needed. When there are multiple sites for individuals to choose from and the relevant characteristics are the distinguishing feature between the two sites, he suggested that the multiple-site travel cost model be used; but when there are multiple sites and independence of irrelevant alternatives is satisfied, the multinomial logit (MNL) model might be best used. However, when there is a single site to choose from, or a single site is dominant, then the single site travel cost model should be used.

Although all economic models of recreation begin from the same postulate of the individual facing a choice problem and maximizing utility subject to budget, time, and other constraints, the models produced are numerous. Model formulations, decision structure on participation, site selection, measures of visits or uses of sites are all based on strategies adopted or to define the problem in dealing with the above mentioned postulate. Each strategy represented the analyst's judgment, and it is very important to test and to evaluate the relevance of this description of behavior (Brookshire and Smith, 1987). Comparative studies of various models or estimation methods have been done by many researchers. Most of the decisions on model choice relied on their statistical performances. The first step of decision making has to rely on the researcher's judgment about the underlying theoretical basis for the model to explain the behavior of the recreationists. Smith, Desvousges, and Fisher (1986) pointed out that judgment is an inevitable part of any empirical model of an economic process. In the area of valuation of non-market commodities, some economists felt more comfortable with the judgments needed for indirect valuation instead of the direct method of valuation since the indirect method relied on observable behavior. However, they emphasized that understanding the validity as well as the limitations of a proposed model is a crucial part in implementing it for given circumstances. The choice of model ought not to be a mechanical process. Given alternative models, the relative comparative performance of the model or method and its robustness to apply to as many situations as possible are the two most important criteria of choice.

In the matter of judgment, Adamowicz and Graham-Tomassi (1990) proposed a method of revealed preference test for non-market goods valuation methods. The underlying motivation behind their procedure was that since the demand for non-market goods was derived from utility maximization, it has to be consistent with the axiom of rational choice. They argued that their method might be applicable to the zone average travel cost model. The zone average travel cost model (ZATC) has been widely employed, but it was criticized as not based on the foundation of the theory of individual choice. If the test as proposed by Adamowicz and Graham-Tomassi could be devised on the ZATC data and the result showed that the data were consistent with the rationality axiom, then benefit measures derived from it could be given some sort of choice-based interpretation.

Kling (1986, 1988a, 1988b) argued that the reliability of the welfare estimate should be the criterion of model choice. The reliance on the statistical performance of the compared models that have been the basis of model choice (see for example: Ziemer, Musser, and Hill, 1980; Strong, 1983; Kealy and Bishop, 1986; Smith, Desvousges, and Fisher, 1986) had some problem in that there was no known "true" value as a basis for comparison to conclude which model was truly "the best". Again the researcher needs to study first the underlying concept of the model, investigating the consistency of the model with its theoretical basis. The analyst can then empirically test the model and check its performance. Should one choose a model with the relatively best statistical performance without any regard to the difference in the resulting estimates derived from the competing models? Smith et al. (1986) in their study found that the ratio of benefit estimates derived from their model using different estimation methods, one that ignored and one that accounted for the effect of non-users, can vary in the range of 29.20 to 374.99. The decision of model choice is, as Smith et al. pointed out, not a mechanical process.

Using a procedure that will be presented later in the next chapter, Kling (1986) proposed and used a Monte Carlo simulation approach to compare alternative models. In her proposed procedure the estimates of alternative, competing models can be compared to the "true" value. This simulation experiment approach is commonly used in econometrics (Johnston, 1972; Judge et al., 1985). In a similar way as Kling's, simulation has also been recently used in travel cost demand by Hellerstein (1992). This study will also make use of the same approach.

CHAPTER IV
THE MONTE CARLO EXPERIMENT AND ITS USE IN THE TRAVEL COST MODEL STUDIES

In chapter III, the problems with data from on-site, intercept surveys and data censoring in the complete data set were discussed. Use of ordinary least squares on such data results in biased and inconsistent estimates. Possible solutions to these problems were also discussed. In the first part of this chapter the Monte Carlo experiment, as a way to study the small sample properties of various proposed estimators and their relative performances in estimating the true benefits, will be discussed. The past use of Monte Carlo simulation in travel cost model studies will also be discussed. In the remainder of this chapter we will discuss the experiments to be conducted in this study.

The Monte Carlo Experiment

As noted earlier in the previous chapter, the researcher in travel cost model studies often has to use on-site, intercept survey data. Users of such data sets have often ignored the fact that non-users of the recreation site may supply additional, needed information. Recreational benefit estimates from using on-site, intercept survey data will be biased because of the truncated nature of the data. Truncated normal regression (TRUNCN) estimation has been proposed for such data because it gives an adjustment or correction for the truncated nature of the data.

If it is possible to sample the total population, including the non-users of the recreation facility, the data set will likely have many zero trips in it. The data are therefore censored at zero. The use of OLS on censored data is biased and inconsistent (Judge et al., 1988), but less so than if the data are truncated, as will be illustrated in our experiments. The censored regression (TOBIT) estimation method is commonly used to deal with such problems.

Amemiya (1973) and Greene (1990), among others, presented the maximum likelihood estimation procedures for TRUNCN and TOBIT. Amemiya stated that use of maximum likelihood would result in estimators with desirable properties. However, these estimators only have desirable large sample properties. To see how these estimators perform in small samples, one usually has to resort to use of Monte Carlo experiments.

Monte Carlo experimentation is a technique for evaluating the properties of estimators, particularly for small samples. In the Monte Carlo or sampling study, the researcher first specifies a theoretical "true" model that reflects the underlying data generation process. From that specification the samples are generated. The parameters are then estimated and the results analyzed to determine the sampling characteristics of the estimators (Judge et al., 1988, p.214). The true parameters are pre-determined and, therefore, known. These known, true, parameters will be used as a basis for comparing the estimates derived from the various estimators studied. The difference between the usual econometric Monte Carlo experiments and this study is that, in addition to the usual parameter estimate comparisons, the analysis in this study will also compare the consumer surplus estimates obtained. The "best" method is ordinarily the one with the closest average and/ or smallest variation as compared to the "true" regression parameter(s). However, in recreational benefit estimation, such a "best" method of travel cost coefficient estimation may or may not be the best for estimating the true consumer surplus.

Previous Monte Carlo Experiments with Travel Cost Models

One of the first published studies in the travel cost model literature that made use of Monte Carlo experiments was reported by Caulkins, Bishop, and Bouwes (1985). They used a simulation technique to examine the bias from omitting the cross price terms in their travel cost model. Many researchers argued that the exclusion of appropriate substitutes in the model (Burt and Brewer, 1971; Gum and Martin, 1975) would result in an overestimate of the consumer surplus associated with a particular recreation site. Caulkins et al. (1985) hypothesized the possibility of a complementary relationship between two recreation sites instead of being substitutes. The signs of cross price terms will be different for these two different types of relationship. They constructed the model and used a Monte Carlo simulation approach to generate the sample and to derive the consumer surplus estimate. They assessed the bias resulting from the "incorrect" specification of the model based on their hypothesis that complementarity might have existed between two assumed "substitute" sites. A limitation of their simulation from the usual Monte Carlo study was that it did not involve replications of the experiment.

Realizing the problem of comparing performances of alternative, competing models, Kling (1986) proposed an ingenious procedure for making model comparisons by using Monte Carlo simulation. Some comparative studies (see for example Caulkins et al., 1986; Smith et al., 1986; and Smith, 1988) relied only on the statistical performances of empirical models as the basis for model choice. A difficulty that arises in these empirical comparisons results from not knowing the "true" welfare estimate to which the estimates should be compared. Kling (1988a, 1988b) emphasized the accuracy of the welfare estimates as the most important criterion in the model choice.

In her research Kling (1986, 1988a, and 1988b) employed travel cost models in the multiple site framework. She generated the simulated data from an individual utility maximization process combined with site characteristics. In Kling (1986, 1988a) she generated the data following the linear expenditure utility function. On these data sets she estimated the coefficients and derived welfare estimates using pooled and logit travel cost models. She used weighted least squares and Tobit estimations on the pooled model and logit on the multinomial logit (MNL) model. Resulting coefficient and welfare estimates were compared to their corresponding known, true values. In Kling (1988b), in addition to the linear expenditure system, she employed Cobb-Douglas and translog utility functions to generate data, and she used the typical trip model in addition to the pooled and logit models. She discovered a surprising result: a fairly simplistic typical trip model performed well in estimating average welfare. In the Cobb-Douglas and translog simulations the typical trip model generated the closest estimates of the benefits and in the linear expenditure system it provided the second closest estimate. She pointed out that none of other models were as consistent as typical trip model in their performances across simulations.

Kling's studies using the Monte Carlo simulation approach showed a promising procedure through which a model choice can be made. One difficulty may arise, however, in implementing her proposed procedure. The alternative models in her studies generally underestimated the willingness-to-pay. This tendency, she reasoned, might be traceable to the way the data were generated from a utility maximization framework and the models used in the estimations. In Kling (1988a) she wrote that the underestimation of willingness-to-pay, in general, may be due to "the mismatch between the functional form used to generate the simulated data and the form used to estimate the econometric models" (p.339). It is partly for this reason and for the good performance of simplistic typical trip model that the model used in this study is the single site travel cost model, for both data generation and the parameter and benefit estimation.

Hellerstein (1992) investigated the application of the Tobit model to the individual observation data that he generated in a Monte Carlo simulation framework. He generated the simulation data following a simple linear model. In his research it is postulated that

$$\begin{aligned} y_i &= \beta_0 + \beta_1 P_i + \epsilon_i \qquad && \text{if } \epsilon_i \geq \beta_0 + \beta_1 P_i \qquad (4.1) \\ y_i &= 0 && \text{otherwise.} \end{aligned}$$

with $\beta_0 = 5.0$ and $\beta_1 = -0.25$. P_i is the price, or travel cost, variable which is uniformly distributed between zero and 25 and ϵ_i is an independently and identically distributed $N(0,\sigma^2)$ random variable. Fifty samples, each containing 400 observations, were generated. The **P** vector remain unchanged across samples while the ϵ vector was allowed to vary. For each sample set in his study, he estimated the model using ordinary least squares (OLS) and Tobit (TOBIT). From the resulting estimated coefficients eight measures of consumer surplus estimates were computed.

Bockstael et al. (1990) argued that when error is due to omitted variable, using observed values of the dependent variable in calculating consumer surplus yields a correct measure of consumer surplus. Such calculation implied that other variables, for example income, and their associated coefficients have no direct effect on consumer surplus. Hellerstein calculated actual consumer surplus estimate using the observed values of the dependent variable and called it TOB_Y CS.

Hellerstein (1992) however, argued that given stochastic nature of ϵ, instead of TOB_Y CS, it was often more useful to use expected value of CS, E(CS) or predicted CS, even when omitted variable reasoning was adopted. He gave an example that when making out-of-sample prediction, E(CS) is a preferred measure. To calculate E(CS) he used two types of calculations: linear CS, the way traditional CS from OLS is computed, and integrating under TOBIT mean. TOBIT mean is defined as

$$E(Y) = \Phi \cdot \mathbf{X\beta} + \sigma \cdot \phi \tag{4.2}$$

where Φ is normal distribution function, ϕ is normal probability density function, both evaluated at $(\mathbf{X\beta}/\sigma)$, $\boldsymbol{\beta}$ is vector of TOBIT estimates and σ is TOBIT standard error estimate. In (4.2) E(Y) was, therefore, recognized censoring of data. Hellerstein set up the ranking of the consumer surplus measures based on their average percent deviation from the true aggregate consumer surplus, which will later simply be called average percent deviation. He recommended that for the convergence of actual CS (TOB_Y CS) and predicted CS, the consumer surplus should be computed by integrating under the TOBIT mean with a choke price $P_c = -(\beta_0 + 2\sigma)/\beta_1$. Let us call this predicted CS TOB_$\int\mu2$ CS. Empirically, the convergence of these two measures of consumer surplus using TOBIT estimated coefficients was shown by the same low average percent deviation of TOB_Y and TOB_$\int\mu2$ for the same sample data (ranging from 10 to 21), but TOB_Y CS gave slightly lower average percent deviation than TOB_$\int\mu2$ CS for out-of-sample data. TOB_$\int\mu2$, despite its slightly lower performance than TOB_Y, performed better than the commonly used predicted CS calculation from TOBIT. Linear predicted CS computation (TOB_Xβ) and traditional CS computed from TOBIT predicted values (TOB_μ) performed worse than TOB_$\int\mu2$ and TOB_Y. While TOB_$\int\mu2$ gave the average percent deviation of 10 to 22, TOB_Xβ resulted in a range of 70 to 88, and TOB_μ gave an average percent deviation between 50 and 59. Predicted CS computed from OLS coefficient estimates resulted in a better range of average percent deviation than TOB_Xβ and TOB_μ, even thought it was known to be computed from biased coefficient estimates. Hellerstein noted that the average percent deviation increased as σ^2 increased.

Based upon his Monte Carlo simulation results, Hellerstein (1992) recommended that the TOBIT using "actual" or Gum-Martin consumer surplus (TOB_Y) be used to estimate individual CS. However, when one needs to use traditional

CS, as for making out-of-sample prediction, he suggested using predicted CS by integrating under the TOBIT mean with a choke price $P_c = -(\beta_0 + 2\sigma)/\beta_1$, i.e., using TOB_$\int\mu$2 CS. Other TOBIT predicted consumer surplus computations (TOB_Xβ, TOB_μ) would result in larger average percent deviation and, therefore, using TOBIT would not improve CS estimation as expected.

Design of Experiments for This Study

This study will make use of the results and information contained in Kling's (1986, 1988a, 1988b) and Hellerstein's (1992) work. Kling's proposed procedure was a way out of the difficulty that arises in empirical model comparisons. In her proposed procedure the true value of welfare was known since the simulated data were generated by maximization of a utility function. The resulting data, however, were estimated via models with different functional forms from the one that was used to generate the data. This "mismatch" may have been a factor causing, usually, welfare underestimates from the methods used. Such a mismatch did not occur in the framework used in Hellerstein's (1992) work. His work can also be supported by Kling's (1988b) findings of the relatively good performance of the typical trip model to estimate the true welfare estimate of the multiple site models. The appropriateness of the use of Marshallian consumer surplus can also be attributed to, among others, Kling's findings that the use of Hicksian compensating variation measure did not appear to improve the accuracy of her welfare estimates.

The following simple experiments are undertaken to avoid some of the problem encountered by Kling in her more sophisticated simulations. To avoid a possible mismatch between the assumed "true" utility function and the estimated demand function, this study is developed by postulating a "true" demand function, following the form and the procedure used by Hellerstein (1992). The "true" travel cost demand function in this study is defined as

$$y_i = 5 - 0.25\ TC_i + u_i \tag{4.3}$$

where y_i denotes the ith individual's number of trips, TC_i denotes the ith individual's travel costs, and u_i is the random error term. Given the demand model of (4.2), the simulation is conducted by first computing $E(y_i) = 5 - 0.25\ TC_i$ since the expected value of the normally distributed disturbance term, u_i, is assumed to be zero. Then, the observed $y_i = E(y_i) + u_i$ was computed using the PC's built-in random number generator to obtain u_i. It needs to be noted that observed y_i was rounded to its nearest positive integer value or to zero, if $y_i < 0.5$. All observed y_i less than zero were assigned values of zero.

In this first set of experiments it was assumed that there were three zones of origins of the recreationists. The population in each zone was assumed equal to 1,600. From each zone four percent of the population was assumed to be taken as a sample, and hence a blow-up factor of 25 was used to expand the sample estimate to be representative of the whole population.

Five sets of travel cost (TC) combinations, later called TC designs, are used in this experiment. These sets were developed to represent the range of travel costs of the three origins to the recreational destination. It is believed that this formulation was more appropriate for Oregon outdoor recreation rather than the uniformly distributed price (travel cost) variable in Hellerstein's research. The TC combinations, or designs, in the experiment were

Design #	Travel Costs/ Distances
1	4,12,20
2	4,12,16
3	2,10,18
4	2,10,14
5	4, 8,12

The preceding travel cost spacings were used after reviewing the average miles traveled per trip by Oregon salmon and steelhead anglers (Brown, Singh, and Castle, 1964, p.43). By main distance zones, these anglers averaged 38 miles in the zones nearest the angler's destinations=, 121 miles in the medium range zones, and 221 miles in the most in the most distant zones. Given Hellerstein's (1992) demand function, a travel cost (TC) of 20 gave an expected number of trips of zero. Therefore, the highest TC in Design #1 was set equal to 20, relatively close to one tenth of the 221 miles traveled by angler from the most distant zones, reported by Brown, et al. (1964). Lowest TC was set equal to 4, also about one tenth the average trip miles in 1964 for the zones closest to the recreational fishery. An intermediate zone TC equals 12 was also approximately one tenth of average trip distance observed in 1964. Thus, for Design #1, TC was set equal to 4, 12, and 20. The other designs were set up to test for the effect of smaller TC dispersion. E.g., the sum of mean-corrected squares of TC for Design #5, TC=4, 8, 12, is only one-fourth that of Design #1 where TC=4, 12, 20. Although other configurations were also tried, along with various assumed populations, the five designs reported here were thought to be adequate for at least some western U.S. conditions. These remarks are not intended to be critical of Hellerstein's (1992) design, which appears to be reasobnable for east cost conditions.

The generation of y_i was conducted following the procedure indicated earlier where u_i distributed $N(0,\sigma^2)$. Two values of σ^2 were used, 6.25 and 25. These values of σ^2 were based on Nawas' (1972, p.55) study on Oregon big-game hunting which had an estimated error variance of about 6.25, and Sorhus' (1980) sport-fishing study which had an error variance of 20 or more. In these experiments y_i was generated using a SHAZAM 5.13 package program with the random seed set at 54321. One hundred sets of data were generated for each design. Thus, there was a total of 500 sets of data generated for all five experiments.

The generated data sets were then used to estimate the linear demand models to be compared. The linear demand model was estimated by ordinary least squares (OLS) applied to all users and non-users of recreation resource (OLSALL), OLS applied to the data with recreation users only (OLSUSR), Tobit (TOBIT) fitted to both users and non-users, OLS applied in the zonal average TC (ZATC) model framework, and the truncated normal maximum likelihood (TRUNCN) estimation applied to user-only data. These five estimation methods utilize one or the other of two different types of data collected in travel cost studies: data sampled from the whole population versus data from on-site, intercept surveys that obtain user-only information.[1]

Consumer surplus values were computed for both expected or traditional consumer surplus (TRCS) that uses predicted visits in its computation, and "actual" or Gum-Martin consumer surplus (GMCS) where consumer surplus is computed using the observed number of visits.

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[1] ZATC, OLSALL and OLSUSR estimates were computed using programs in SHAZAM 5.13. TOBIT estimates were calculated using Tobit estimator in SHAZAM 5.13 and Hellerstein's (1991) GAUSS/GRBL package. TRUNCN maximum likelihood estimates were computed using MLE program in TSP 4.02 package.

Consumer surplus is defined as

$$CS=\int_{TC_{obs}}^{TC_c} Q(TC|\epsilon)\,dTC \tag{4.4}$$

where TC_{obs} is observed TC and TC_c is the choke price.

From that formulation for the single-site travel cost model, consumer surplus will be computed from the following simplified formula:

$$CS_i=\hat{y}_i^2/-2*\beta_1 \tag{4.5}$$

for the expected or traditional consumer surplus (TRCS), while the GMCS is computed using the above formula and replacing $\hat{y}_i$ with y_i, i.e., using the observed rather than the predicted value of the dependent variable.

Kling (1988a) used three criteria to analyze the relative performances of the models under consideration. The average error was measured by the mean simulation error (ME), defined as

$$ME = (1/N)\ \Sigma_i\ (C_i^p - C_i^a), \tag{4.6}$$

where C_i^p is the welfare estimate and C_i^a is the actual (true) simulated welfare change for individual i. This ME statistic can be normalized by using the mean of the simulated true willingness-to-pay, C^*, as the denominator such that

$$MEC = ME\ /\ C^*. \tag{4.7}$$

Another statistic was used to analyze the variability of the estimates in the experiment: square root of mean square error (Pindyck and Rubinfeld, 1981; Johnston, 1984). This commonly used statistic is also used in this study. Root of mean square error for Y is defined as

$$RMSE=\sqrt{\frac{1}{N}(Y_1-Y^a)^2} \tag{4.8}$$

where Y denotes the variable for which RMSE is calculated, N denotes the number of samples (i = 1, 2, ..., N), Y_i indicates the value of ith sample of Y, and Y^a indicates the actual or the "true" value of Y.

If the calculated consumer surplus was negative or zero the set was dropped and excluded from the computation of the average consumer surplus and root mean square error (RMSE) of consumer surplus for the corresponding method. The RMSE calculation uses the "true" consumer surplus for each experiment as a basis for its calculations. The RMSE values for the estimates are used as indicators of their relative performances. A method or model with a smaller RMSE indicates a better performance in estimating the benefits of outdoor recreation than a model with a larger RMSE.

CHAPTER V
RESULTS OF THE MONTE CARLO EXPERIMENTS

Following Hellerstein (1992), the "true" expected relationship between individual trips and travel costs for the linear model in this study was formulated as

$$E(y_i) = 5 - 0.25\ TC_i. \tag{5.1}$$

The estimated coefficients vary by the estimation methods used, as well as between replications for each method. In this set of Monte Carlo experiments, five estimation methods for the linear demand model were used. The resulting estimated coefficients gave some indication of the accuracy of the five estimation methods. Accuracy can be defined as the closeness between the estimates and the "true" coefficients. One general conclusion on the closeness between the estimates and the "true" coefficients is based on the average value of the estimates. However, a "good" average value can be the result of averaging from a wide range as compared to a biased average estimate with a smaller range of estimates.

As noted earlier, square root of mean square error, one of the most commonly used criteria, will be used to rank the goodness of the methods. The use of RMSE as a ranking criterion takes variation in the sample values into consideration. A biased average estimate can sometimes have a smaller root mean square error (RMSE) than an unbiased estimate with a higher variance.

As noted in the previous chapter, current emphasis of travel cost model studies is on the accuracy of the models for the estimation of benefits from recreation, or from any other economic resource or activity for which the study was conducted. It is therefore worthwhile to see if the accuracy of the regression coefficient estimation coincides with the goodness of the model for estimating the benefits in terms of consumer surplus.

The benefit estimates in this study were calculated in term of consumer surplus. The analyses to follow are based on the use of traditional (TRCS) and Gum-Martin (GMCS) consumer surpluses.

One way to assess the accuracy of consumer surplus estimates of the various methods studied is to look at their average estimated benefits. Relative performance of each method of estimation in this regard was indicated by the ratio of the value of estimated consumer surplus to the "true" known consumer surplus. The closer this ratio is to a value of one, the better is the performance of the model in terms of average accuracy of estimate. Just as for the estimated travel cost (TC) coefficients discussed earlier in this chapter, an average estimated value close to the "true" value may or may not coincide with the smallest interval of the estimates making up the average value. For this reason, RMSE value was again proposed as a basis for ranking the goodness of the models for estimating the "true" consumer surplus.

The "actual" or Gum-Martin consumer surplus differs from the traditional or expected consumer surplus in that the traditional consumer surplus is based on the predicted values of the dependent variable while the GMCS is based on the actually observed values. The GMCS and TRCS estimates for the linear demand model were calculated following the formula explained in previous chapter.

The Monte Carlo simulation was conducted for two values of error variances. One value was derived from Nawas' (1972, p.55) data set for Oregon big game hunting. The error variance in Nawas' study was about 6.25. However, for the salmon sport fishing, a variance of 20 or more was computed (Sorhus, 1980). In this study variances of 6.25 and 25 were assumed to be plausible for recreation activities in Oregon. The main body of this chapter will be on the results of simulation with variance equal 6.25. The estimation results of the data sets generated with random error variance of 25 will be reported in Appendix 2. The sensitivity of the results with respect to two levels of random error variances will be discussed when appropriate in this chapter.

Experiments with Variance = 6.25

TC Design #1

The results for Design #1, TC_k=[4,12,20] where k

Table 1. Regression Coefficient Estimates of Linear Demand Models, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #1, TC_k = [4,12,20]. RMSE in parentheses.

Estimation Method	Range of estimates of β_1 from:	to:	Average estimates of β_0	β_1	Rank by RMSE of β_1
OLSALL	-0.249023	-0.127930	4.755286 (0.448493)	-0.190957 (0.063871)	2
TOBIT	-0.354337	-0.154053	5.050798 (0.436227)	-0.266305 (0.037944)	1
ZATC	-0.249023	-0.127930	4.755286 (0.448493)	-0.190957 (0.063871)	2
OLSUSR	-0.200736	-0.050385	4.883498 (0.411505)	-0.130957 (0.122526)	4
TRUNCN	-0.346670	-0.049265	4.914660 (0.505759)	-0.176762 (0.089267)	3

Table 2. Accuracy of Consumer Surplus Estimates from Monte Carlo Experiments, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #1, TC_k = [4,12,20].

Parameter Estimates	Complete Data OLSALL	Complete Data TOBIT	User Only Data ZATC	User Only Data OLSUSR	User Only Data TRUNCN
True CS					
Ave. True CS = 112,550.50					
Traditional CS (TRCS)					
Ave. TRCS	96,855	92,570	96,855	176,568	114,962
TRCS/True CS	0.86	0.82	0.86	1.57	1.02
RMSE	19,340	28,350	19,340	75,283	42,629
Rank on CS:					
a. TRCS	1	2	1	4	3
b. Overall	3	4	3	7	6
Gum-Martin CS (GMCS)					
Ave. GMCS	148,645	106,845	97,155	223,973	172,776
GMCS/True CS	1.32	0.95	0.86	1.99	1.54
RMSE	40,090	15,905	19,071	122,616	82,468
Rank on CS:					
a. G-M CS	3	1	2	5	4
b. Overall	5	2	3	9	8

indicates the kth zone and k=1, 2, 3, is shown in Tables 1 and 2. The range of estimates of the regression coefficient of β_1 and the means of estimates of both β_0 and β_1 are reported in Table 1. In Table 2 the resulting average consumer surplus calculation using the estimated coefficients from Monte Carlo data were reported for both the traditional and Gum-Martin consumer surpluses.

Note that for Design #1, as well as for any of the other designs, a surprising and unexpected identity was discovered between zone average travel cost (ZATC) and ordinary least squares applied to both users and non-users (OLSALL). The zone average travel cost (ZATC) method, except for rounding, always gave the same results as OLSALL. This identity holds for any case, even with unequal population zones if the Bowes-Loomis weighted least squares procedure is followed. Bowes and Loomis (1980) recommended that when zones have unequal populations, zonal average observations should be weighted by one over the square-root of zonal population. A proof of the unexpected equivalence between OLSALL and ZATC is given in Appendix 1.

An intuitive verbal explanation can be given for the OLSALL-ZATC identity. First, bear in mind that a constant sampling rate is assumed for all the distance zones of origin, i.e., the same percentage of each zone's population makes up the sample. However, a larger percent of the sample from nearby zones will be users of the recreation, and a smaller percent of the sample from more distant zones will be users, with a correspondingly larger percent of non-users. Thus, if we knew only the users, as from an on-site survey, the use of ZATC would automatically account for the number of non-users since the ZATC model uses visits per capita as the dependent variable. Non-users are automatically included by dividing estimated total visits per zone by that zone's total population. (This relationship is illustrated by an example in Chapter VI.)

In terms of closeness of the estimates to the known "true" travel cost regression coefficient, β_1, using RMSE as the ranking criterion, TOBIT was the best for Design #1 followed by OLSALL and/ or ZATC, followed by TRUNCN, and OLSUSR was the worst of the five.

For TC Design #1, where travel costs from three zones of origin to the destination were [4,12,20], ZATC gave the best TRCS estimate of the "true" consumer surplus since ZATC TRCS had the smallest RMSE. However, ZATC and OLSALL TRCSs did underestimate the "true" consumer surplus, while OLSUSR and TRUNCN overestimated it. Recalling the performance of all methods in estimating the demand function, it can be seen that for the first design in this experiment the most accurately estimated travel cost coefficient does not necessarily imply the best estimate of consumer surplus. If one uses TRCS as an estimate of consumer surplus, while TOBIT was superior to ZATC and OLSALL for estimating the travel cost coefficient, it performed poorer than ZATC and OLSALL, in estimating the "true" consumer surplus. The recent improved method by Hellerstein (1992) for computing TOBIT TRCS (TOB_Jμ2) was used in Table 2 and later tables and provided a better estimate of TRCS than the commonly used TOBIT predicted consumer surplus, based on expected values of TOBIT and linear CS computation (TOB_μ). However, for TC Design #1 the improvement was not as good as expected.

If GMCS were used to estimate the CS value, TOBIT was clearly superior in estimating both the travel cost coefficient and the true consumer surplus. The use of OLS on user-only data (OLSUSR) to estimate the demand function and consumer surplus gave a very poor result. The application of regression based on the truncated normal distribution (TRUNCN) improved the estimation as compared to OLSUSR. In fact, in terms of average TRCS it gave an average value closest to the "true" value of consumer surplus. (This performance is shown in Table 2 in the line TRCS/True CS.) Although the average TRCS from TRUNCN was closer to the true CS than ZATC and OLSALL, it showed more variation in its individual CS estimates; therefore, ZATC and OLSALL gave a smaller RMSE than TRUNCN.

TC Design #2

The second design had travel costs from origins to destination of [4,12,16]. Coefficient estimates are presented in Table 3, and consumer surplus estimates are in Table 4.

Estimated coefficients for all methods in Design #2 were somewhat closer, on average, to the "true" value as compared to the first design. Results for Design #2 can be read from Tables 3 and 4 in the same way as for Design #1 in Tables 1 and 2. The RMSE ranking of the β_1 estimates is the same as the ranking for Design #1. TOBIT again performed the best, followed by ZATC and/ or OLSALL, TRUNCN, and OLSUSR. Although TRUNCN did not give as good a result as ZATC/ OLSALL, it did improve over OLSUSR. Hence, given only user data, using TRUNCN will improve estimation of both the travel cost coefficient and consumer surplus, compared to OLSUSR. TRUNCN was the best of all in one respect. When estimating TRCS, i.e., the average estimate of TRUNCN TRCS was the closest to the average true consumer surplus. However, since the TRUNCN estimates of TRCS had a large variance, the RMSE of TRUNCN consumer surplus fell behind ZATC/ OLSALL for estimating traditional consumer surplus. When the observed visits were used to calculate consumer surplus, and therefore GMCSs were calculated, TOBIT was the "best" of all because it had an average GMCS very close to the "true" consumer surplus, and it also had the smallest RMSE.

Table 3. Regression Coefficient Estimates of Linear Demand Models, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #2, TC_k = [4,12,16]. RMSE in parentheses.

Estimation Method	Range of estimates of β_1 from:	to:	Average estimates of β_0	β_1	Rank by RMSE of β_1
OLSALL	-0.279576	-0.115513	4.890737 (0.416867)	-0.210435 (0.050924)	2
TOBIT	-0.365362	-0.148024	5.029991 (0.459037)	-0.264141 (0.043332)	1
ZATC	-0.279576	-0.115513	4.890737 (0.416867)	-0.210435 (0.050924)	2
OLSUSR	-0.215444	-0.079004	5.015667 (0.379455)	-0.149220 (0.105187)	4
TRUNCN	-0.841640	-0.093806	5.049517 (0.451349)	-0.192511 (0.099515)	3

Table 4. Accuracy of Consumer Surplus Estimates from Monte Carlo Experiments, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #2, TC_k = [4,12,16].

Parameter Estimates	Complete Data OLSALL	TOBIT	User Only Data ZATC	OLSUSR	TRUNCN
True CS					
Ave. True CS = 120,060.50					
Traditional CS (TRCS)					
Ave. TRCS	94,617	112,861	94,617	165,453	118,374
TRCS/True CS	0.79	0.94	0.79	1.38	0.99
RMSE	30,057	28,262	30,057	58,983	40,601
Rank on CS:					
a. TRCS	2	1	2	4	3
b. Overall	4	2	4	7	6
Gum-Martin CS (GMCS)					
Ave. GMCS	145,681	116,260	94,901	209,648	171,394
GMCS/True CS	1.21	0.97	0.79	1.75	1.43
RMSE	36,011	21,238	29,816	101,726	72,126
Rank on CS:					
a. G-M CS	3	1	2	5	4
b. Overall	5	1	3	9	8

While the other estimation methods for Designs #1 and #2 consistently underestimated or overestimated the "true" consumer surplus, TRUNCN showed a different pattern. For Design #1 TRUNCN TRCS average estimate overestimated true consumer surplus by two percent, while for Design #2 TRUNCN underestimated it by one percent. The average estimate in both designs are very close to the true value. However, one problem with using TRUNCN based on the results of these two designs, as well as of the later designs, was that TRUNCN on average gave a biased estimate of β_1. Furthermore, the TRUNCN estimate of β_1 had several times as much variance as compared to ZATC or OLSALL. This high variance of the TRUNCN estimate of β_1 led to a correspondingly high variance (and RMSE) of the TRUNCN estimates of TRCS and GMCS.

While TRCS for ZATC and OLSALL will always be the same, ZATC estimated GMCS more accurately than OLSALL for these first two designs, and also for the later designs. For all designs, relative performance of ZATC was about the same for both TRCS and GMCS. However, the use of observed visits to estimate ZATC GMCS showed slightly less bias from underestimation than when using predicted visits. For Design #2, the slightly smaller RMSE of GMCS put ZATC in the third place overall after TOBIT GMCS and TOBIT TRCS. TOBIT GMCS was the "best" for Design #1 and Design #2. TOBIT TRCS with "correction" as proposed by Hellerstein performed better than ZATC both in terms of its ratio of average TRCS to the true CS and its RMSE. The use of TOB_Jμ2 from Hellerstein (1992) improved on TOBIT linearly computed TRCS (TOB_μ). Such an improvement put TOBIT TRCS in the second place overall after TOBIT GMCS. The ratio of TOBIT TRCS to the true consumer surplus was 0.94 while the same ratio for TOBIT GMCS was 0.97. OLSUSR estimates of consumer surplus using either TRCS or GMCS were always the worst among all five methods. The OLS method with user only data (OLSUSR) should, again, not be recommended for general use, at least for TC patterns and σ^2 values similar to those of this study.

TC Design #3

The results of the third design, TC_k = [2,10,18], as shown in Tables 5 and 6 indicated similar performances of all methods to performances in Design #1 and Design #2. The TOBIT estimated travel cost coefficient for the demand function was very close to the true value, -0.261687 versus -0.25, with RMSE of β_1 equal 0.033488. ZATC and OLSALL had an average estimate of β_1 equal -0.202695 with RMSE of β_1 equal 0.052297. When predicted visits were used to estimate the consumer surplus, the TOBIT's and TRUNCN's TRCS average estimates were closer to the true value than ZATC's and OLSALL's. However, ZATC's and OLSALL's RMSE were smaller than TOBIT's and TRUNCN's. The smaller value of RMSE

Table 5. Regression Coefficient Estimates of Linear Demand Models, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #3, TC_k = [2,10,18]. RMSE in parentheses.

Estimation Method	Range of estimates of β_1 from:	to:	Average estimates of β_0	β_1	Rank by RMSE of β_1
OLSALL	-0.250000	-0.155273	4.840182 (0.355996)	-0.202695 (0.052297)	2
TOBIT	-0.356628	-0.193722	4.968600 (0.350922)	-0.261867 (0.033488)	1
ZATC	-0.250000	-0.155273	4.840182 (0.355996)	-0.202695 (0.052297)	2
OLSUSR	-0.199783	-0.066433	5.018983 (0.320326)	-0.145400 (0.107011)	4
TRUNCN	-0.297467	-0.095543	5.049339 (0.378220)	-0.194445 (0.069269)	3

Table 6. Accuracy of Consumer Surplus Estimates from Monte Carlo Experiments, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #3, TC_k = [2,10,18].

Parameter Estimates	Complete Data OLSALL	TOBIT	User Only Data ZATC	OLSUSR	TRUNCN
True CS					
Ave. True CS = 135,466					
Traditional CS (TRCS)					
Ave. TRCS	115,575	127,523	115,575	191,045	126,824
TRCS/True CS	0.85	0.94	0.85	1.41	0.94
RMSE	23,339	25,950	23,339	66,972	32,291
Rank on CS:					
a. TRCS	1	2	1	4	3
b. Overall	3	4	3	8	5
Gum-Martin CS (GMCS)					
Ave. GMCS	168,281	130,696	115,979	238,759	181,609
GMCS/True CS	1.24	0.96	0.86	1.76	1.34
RMSE	37,369	17,068	22,994	114,084	61,594
Rank on CS:					
a. G-M CS	3	1	2	5	4
b. Overall	6	1	2	9	7

placed ZATC and OLSALL ahead of TOBIT and TRUNCN in the accuracy of estimating the true consumer surplus. TOBIT TRCS computed following Hellerstein's correction procedure improved on the estimate based on the commonly used computation of predicted CS (TOB_μ). RMSE for TOB_μ was calculated at 48,603 and the ratio of TOB_μ TRCS to the true CS was 0.65. When the Hellerstein's correction was used the ratio of TOBIT TRCS to the true CS was 0.94 and its RMSE was 25,590 as shown in Table 6. TOBIT TRCS after correction performed better than TRUNCN TRCS although the ratio of TRUNCN TRCS to the true consumer surplus on average was 0.99. However, the improvement from using TOB_Jμ2 instead of TOB_μ did not put TOBIT TRCS ahead of ZATC or OLSALL for Design #3.

For TC Design #3 TOBIT performed the best in estimating both the travel cost coefficient and GMCS. For TC Designs #1 and #2 the average estimates of traditional consumer surplus (TRCS) calculated from the TRUNCN coefficients were the least biased estimate of true consumer surplus. For all three TC designs, however, the TOBIT estimated GMCS had lower RMSE than TRUNCN TRCS. TRUNCN in Design #3 again showed a relatively large dispersion of individual sample TRCS estimates. Therefore, although TRUNCN TRCS estimate of true consumer surplus was less biased than ZATC or OLSALL, its RMSE was larger than ZATC and OLSALL.

TC Design #4

The fourth TC design was the same as the third except that the last zone of origin was $4 less, giving TC_k = [2,10,14]. Results from this design are presented in Tables 7 and 8. The same ranking of travel cost coefficient estimation methods as for earlier Tables 1, 3, and 5 is shown in Table 7. Similarity of the rankings in Table 5 and Table 7 might be expected because of the similarity in their designs.

The use of GMCS as compared to TRCS for ZATC made the estimation of consumer surplus better. The Gum-Martin method of consumer surplus computation decreased the bias by ZATC by almost one percent, compared to the traditional method of computation. Although this improvement was not substantial, it usually put ZATC in a better ranking than OLSALL, considering the use of either method for computing consumer surplus. However, in Table 8 OLSALL gave a better estimate of GMCS than did ZATC.

For Design #4, there still was no consistency between TRUNCN's average TRCS estimation and ranking based on RMSE of TRCS as compared to ZATC or OLSALL. The TRUNCN's average TRCS estimate was the second closest to the true consumer surplus, and TOBIT was the closest. The average estimate of TRUNCN TRCS was closer to the true consumer surplus than ZATC or OLSALL. However, its RMSE showed a larger dispersion among the individual TRUNCN TRCS estimates than the

Table 7. Regression Coefficient Estimates of Linear Demand Models, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #4, TC_k = [2,10,14]. RMSE in parentheses.

Estimation Method	Range of estimates of β_1 from:	to:	Average estimates of β_0	β_1	Rank by RMSE of β_1
OLSALL	-0.317243	-0.161830	4.969085 (0.372802)	-0.223013 (0.043955)	2
TOBIT	-0.378243	-0.197462	5.020679 (0.402535)	-0.266407 (0.043244)	1
ZATC	-0.317243	-0.161830	4.969085 (0.372802)	-0.223013 (0.043955)	2
OLSUSR	-0.250148	-0.092762	5.091778 (0.353312)	-0.160158 (0.096112)	4
TRUNCN	-0.317991	-0.112678	5.076408 (0.400206)	-0.198695 (0.068537)	3

Table 8. Accuracy of Consumer Surplus Estimates from Monte Carlo Experiments, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #4, TC_k = [2,10,14].

Parameter Estimates	Complete Data OLSALL	TOBIT	User Only Data ZATC	OLSUSR	TRUNCN
True CS					
Ave. True CS = 146,648.50					
Traditional CS (TRCS)					
Ave. TRCS	114,810	145,977	114,810	189,609	135,540
TRCS/True CS	0.78	0.99	0.78	1.29	0.92
RMSE	35,772	26,843	35,772	58,711	39,862
Rank on CS:					
a. TRCS	2	1	2	4	3
b. Overall	5	2	5	7	6
Gum-Martin CS (GMCS)					
Ave. GMCS	167,482	140,178	115,139	238,213	193,215
GMCS/True CS	1.14	0.96	0.79	1.62	1.32
RMSE	32,609	22,110	35,466	104,929	63,862
Rank on CS:					
a. G-M CS	2	1	3	5	4
b. Overall	3	1	4	9	8

individual TRCS estimates from ZATC. Therefore, the smaller variance of ZATC estimates gave it a higher rank than TRUNCN, based on RMSE. For user only data, one should probably use either the ZATC or TRUNCN estimation method. Considering the theoretical reasons for not relying on aggregate data, one might prefer to use TRUNCN. However, RMSE was lower for ZATC. OLSUSR would probably perform poorly. Either TRCS or GMCS from OLSUSR substantially overestimated the true consumer surplus, on average. This findings supports the warning presented in the research reported by, among others, Kealy and Bishop (1986), Smith (1988), and Bockstael et al. (1990). Hellerstein's (1992) correction procedure to calculate the predicted or traditional consumer surplus estimate showed an improvement that made TOBIT TRCS place second overall on the RMSE ranking. Despite TOBIT TRCS's closer average estimate to true consumer surplus than TOBIT GMCS, TOBIT TRCS showed a larger variation of individual estimates than TOBIT GMCS.

TC Design #5

The fifth TC design had the smallest variation in travel costs of the five TC designs with $TC_k = [4,8,12]$. In Table 10 the TOBIT estimate of GMCS again had the lowest RMSE. The ratio of ZATC estimated consumer surplus to the known true value was 0.82 for both TRCS and GMCS, and its

Table 9. Regression Coefficient Estimates of Linear Demand Models, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #5, TC_k = [4,8,12]. RMSE in parentheses.

Estimation Method	Range of estimates of β_1 from:	to:	Average estimates of β_0	β_1	Rank by RMSE of β_1
OLSALL	-0.361328	-0.101563	4.899427 (0.453375)	-0.215762 (0.057262)	2
TOBIT	-0.425634	-0.127353	4.966330 (0.494616)	-0.253636 (0.053927)	1
ZATC	-0.361328	-0.101563	4.899427 (0.453375)	-0.215762 (0.057263)	2
OLSUSR	-0.292999	-0.051710	5.046316 (0.427182)	-0.160177 (0.101283)	4
TRUNCN	-0.390996	-0.072921	5.052533 (0.523742)	-0.200659 (0.078927)	3

Table 10. Accuracy of Consumer Surplus Estimates from Monte Carlo Experiments, $\mathbf{y_i = 5 - 0.25\ TC_i + u_i}$, $\mathbf{u_i}$ distributed N(0,6.25), Design #5, TC_k = [4,8,12].

Parameter Estimates	Complete Data OLSALL	TOBIT	User Only Data ZATC	OLSUSR	TRUNCN
True CS					
Ave. True CS = 150,443					
Traditional CS (TRCS)					
Ave. TRCS	122,777	183,745	122,777	204,908	141,047
TRCS/True CS	0.82	1.22	0.82	1.36	0.94
RMSE	39,004	54,489	39,004	96,063	53,651
Rank on CS:					
a. TRCS	1	3	1	4	2
b. Overall	3	6	3	7	5
Gum-Martin CS (GMCS)					
Ave. GMCS	181,944	154,732	123,102	260,724	208,467
GMCS/True CS	1.21	1.03	0.82	1.73	1.39
RMSE	52,687	35,796	38,800	151,607	99,514
Rank on CS:					
a. G-M CS	3	1	2	5	4
b. Overall	4	1	2	9	8

RMSE for GMCS was only slightly worse than for TOBIT. Again, a lower RMSE for ZATC GMCS gave a higher ZATC ranking than OLSALL. TOBIT had the lowest RMSE for both the travel cost coefficient and GMCS. The use of Hellerstein's proposed TRCS computation did not do much to improve TOBIT TRCS performance. It showed a worse performance than ZATC and OLSALL, although it was better than OLSUSR. TRUNCN TRCS performed better than TOBIT TRCS for Design #5 both in terms of average TRCS estimate and RMSE.

Conclusions from the Monte Carlo Experiments

For all five TC designs TOBIT gave the best estimates of β_1, both in terms of closeness of the average estimate to the "true" value of β_1 and the smallest RMSE values. It was followed by OLSALL and/ or ZATC. As proven in Appendix 1, OLSALL and ZATC will give identical coefficient estimates. ZATC, however, in terms of application, has one advantage over OLSALL. It can be used with the user-only data. As will be shown in the next section, we can also utilize the ZATC results to find an approximation to the TOBIT framework by computing an approximate number of non-users, those that will demand zero trips. With the additional zero trip observations one can then apply the TOBIT estimation method which, theoretically, is then the most appropriate method. Ordinary least squares estimation on user-only data was found to result in seriously biased TC coefficient estimates. OLSUSR consistently underestimated the TC coefficient and, therefore, often greatly overestimated consumer surplus for both the traditional and Gum-Martin method of computation. This is not unexpected since the absolute value of the TC coefficient will be in the denominator of consumer surplus calculation. The greater the underestimation of the TC coefficient estimate, the greater was the overestimation of the consumer surplus.

Results of these five experiments showed a consistency of performance of all five estimation methods. This consistency was illustrated by the ranking of the methods based on RMSE of the travel cost (TC) coefficient estimates. When both user and nonuser observations are available, TOBIT was the best to use; however, if the observations were user-only, ZATC performed the best.

Since ZATC provided lower RMSE for both the travel cost coefficient and consumer surplus, it can be recommended for the case of user-only data. On average, the OLSUSR method greatly underestimated the TC coefficient and overestimated consumer surplus. The regression based on the truncated normal distribution (TRUNCN) gave a TC coefficient estimate with lower RMSE than OLSUSR but higher than ZATC. The RMSE for TRUNCN consumer surplus was also higher than for ZATC. Thus, based upon the linear model and distance zones used in these experiments, TRUNCN could not be recommended over ZATC, even though more accurate than OLSUSR.

The earlier results of experiments did not change for the first four designs when a larger variance was used. In the experiments with error variance of 25 the ranking of the estimating methods based upon travel cost coefficient and consumer surplus showed that TOBIT performed the best, indicated by its smallest RMSE. For TC Design #5 with TC_k = [4,8,12], however, travel cost coefficient from ZATC/ OLSALL gave a smaller RMSE than TOBIT, even though average TOBIT estimate was closer to the true value than ZATC's or OLSALL's.

If one has only individual user (positive) observations, two different approaches might be considered. (1) Assuming that the proper sample blow-up factor(s) is (are) known, along with the populations of the various distance zones, then the ZATC approach could be used to give fairly accurate estimates of the TC coefficient and consumer surplus. (Of course, for an on-site survey, it would be necessary to obtain the home addresses of the visitors so as to be able to construct the distance zones.) (2) Having the information needed for ZATC would also permit one to approximate the number of zeroes for each distance zone. However, rather than using OLSALL to obtain the same TC coefficient and consumer surplus from ZATC, one might use the more accurate TOBIT estimator with the new data set where the zero observations have been synthesized. This second approach will be explored in the next chapter.

CHAPTER VI
POSSIBLE USE OF TOBIT ON USER-ONLY DATA SUITABLE FOR ZONAL AVERAGE TRAVEL COST MODELS

In Chapters IV and V the superiority of TOBIT both theoretically and empirically for estimation with censored (complete) data has been discussed. However, many travel cost demand estimates must use data from on-site surveys. In such cases the truncated nature of the data would prevent the use of TOBIT to estimate the travel cost demand models. For the zonal average travel cost (ZATC) model, one step in the analysis is to compute the blow-up factor (which is the reciprocal of the sampling rate). In this chapter, we discuss how to use data and information collected for a ZATC model to deduce the number of non-users of recreation in the individual observation framework. From this approximation one can construct a data set with both users and non-users and from this synthesized data, the demand equation can be estimated using TOBIT.

From ZATC to TOBIT

Suppose we have a set of individual observations where the "true" function is

$$q_i = 5 - 0.25\ TC_i + \alpha_i \qquad (6.1)$$

where α_i denotes intensity instead of the ordinary random error, where $E(\alpha_i) = 1/64[1(-6)+6(-4)+15(-2)+20(0)+15(2)+6(4)+1(6)] = 0$. The scenario of this example is presented in Table 11.

Table 11. Experimental Design with Three Distance Zones and Observations Generated from the Individual Demand Function $q_i = 5 - 0.25\ TC_i + \alpha_i$, $TC_k = [4,12,20]$, where $E(\alpha_i) = 1/64[1(-6)+6(-4)+15(-2)+20(0)+15(2)+6(4)+1(6)] = 0$.

Dist Zone	Zone Population	TC per Zone	Intensity of Demand	Expected Observed Visits per Part	Number Respondents in Sample	Expected Total Number Visits	ZATC Observation
1	1600	4	-6	0	1	0	
		4	-4	0	6	0	
		4	-2	2	15	750	
		4	0	4	20	2,000	4.03125
		4	2	6	15	2,250	
		4	4	8	6	1,200	
		4	6	10	1	250	
					57[a]	6,450	
2	1600	12	-6	0	1	0	
		12	-4	0	6	0	
		12	-2	0	15	0	
		12	0	2	20	1,000	2.25
		12	2	4	15	1,500	
		12	4	6	6	900	
		12	6	8	1	200	
					42[a]	3,600	
3	1600	20	-6	0	1	0	
		20	-4	0	6	0	
		20	-2	0	15	0	
		20	0	0	20	0	0.9375
		20	2	2	15	750	
		20	4	4	6	600	
		20	6	6	1	150	
					22[a]	1,500	

[a] Number of positive (individual) observations in the sample from each zone. Individuals with zero visits will not be observed.

Now suppose we use the scenario in Table 11 in the ZATC framework. We would have information on the number of positive observations, number of individuals from each zone, and, after some computations, zone average visit per capita as shown in the last column of Table 11. The ZATC estimation with three observations results in the estimated demand function

$$q_j = (Y_j/pop_j) = 4.7266 - 0.19336\ TC_j \qquad (6.2)$$

where q_j indicates per capita visit from the jth zone and Y_j is the total number of visits from the jth zone, pop_j is the population of the jth zone, and TC_j is the travel cost of the jth zone of origin to the recreational site.

The blow-up factor in this ZATC estimation equals 25 (from a sampling rate of 4 percent). Based on information about the blow-up factor and zonal populations we can infer that in this case of equal zonal populations we would have 64 observations in each zone. From Table 11 we know that we have 57 positive observations from zone 1, 42 from zone 2, and 22 from zone 3. Since we should have 64 individual observations from each zone we can synthesize the number of non-users (individuals that demand zero visits) for each zone. There will be 64-57=7 observations with zero visits from zone 1, 22 from zone 2, and 42 from zone 3. In the OLSALL individual observation setting the number of zeros for each zone would be added to the positive observations from the on-site survey. From Table 11 we have a total number of observations of 192 with 121 positive observations.

Having synthesized the new data set, OLS (OLSALL) can be applied to the new data. The individual travel cost demand equation estimated using OLS on all 192 individual observations is

$$q_i = 4.7266 - 0.19336\ TC_i. \tag{6.3}$$

Note that the travel cost coefficient of the demand equation estimated in (6.3) by using OLS on the individual observations that include users and non-users (OLSALL) is identical to that obtained by ZATC in (6.2). (This identity follows from the theorem proven in Appendix 1.) However, the R value for OLSALL is, as expected, lower than R for ZATC (0.532 for OLSALL and 0.996 for ZATC). If the three zones have unequal populations, (6.2) and (6.3) will also have identical coefficients if the Bowes-Loomis weighted least squares procedure were used in fitting the ZATC model.

Using the same new, synthesized data set, one can estimate the demand equation using TOBIT instead of OLSALL. Applying OLSALL to the new data in an individual observation setting did not change or improve the estimates from ZATC. However, using TOBIT, as shown in Chapter V, will usually improve the estimates of both the travel cost coefficient and consumer surplus. Applying TOBIT to the new data set gives

$$q_i = 5.0698 - 0.29045\ TC_i. \tag{6.4}$$

Thus, TOBIT improved the travel cost coefficient estimation. How does the resulting TOBIT consumer surplus estimate compare to the estimates derived from OLSALL and ZATC? The comparison of the three methods to the "true" consumer surplus is presented in Table 12.

From the results reported in the equations (6.2) through (6.4) and Table 12 one can argue that TOBIT performed the best in estimating both the travel cost coefficient and the "true" consumer surplus. The results reported in Table 12 are parallel to the results in Tables 1 through 10 in Chapter V. If the proposed method for calculating the predicted consumer surplus from Hellerstein (1992) were followed the TOBIT estimates of TRCS would also likely be the best. Of course, the use of OLSALL on the synthesized data would give exactly the same estimates as ZATC.

The (deliberately) oversimplified example of this chapter is presented only to illustrate the possible use of TOBIT when there is sufficient information about the user-only data to fit the ZATC model. Results from this example in Table 12 should not be used to imply that TOBIT would necessarily give more accurate consumer surplus estimates in such cases. Although it would be possible to design realistic Monte Carlo experiments to test the use of TOBIT on suitable user-only data, such research is beyond the time and financial constraints of this thesis.

Table 12. Consumer Surplus Estimates from OLSALL, ZATC and TOBIT for the Example Case, $y_i = 5 - 0.25\ TC_i + \alpha_i$, $TC_k = [4,12,20]$, $E(\alpha_i) = 1/64[1(-6)+6(-4)+15(-2)+20(0)+15(2)+6(4)+1(6)] = 0$.

Estimation Method	Traditional CS (TRCS)		Gum-Martin CS (GMCS)	
	TRCS	TRCS/ True CS	GMCS	GMCS/ True CS
True CS	109,800	1.00	109,800	1.00
ZATC	91,666.39	0.83	91,817.90	0.84
OLSALL	91,666.39	0.83	141,963.18	1.29
TOBIT	92,550.01	0.84	94,508.52	0.86

If the procedure presented in this chapter can be adopted, one could use an on-site survey to derive estimates that commonly have to be obtained from samples drawn from the entire population. While samples that include both users and non-users are ideal for deriving TOBIT estimates, such a survey usually would require a higher budget than an on-site survey. A survey of non-users cannot, of course, be conducted on-site; therefore, surveying the non-users will require higher costs, as well as more time. Information collected from users and non-users away from the recreational site will usually not be as reliable due to recall bias. These cost and reliability issues make the on-site survey a better choice than a survey of the general population, especially if a procedure to synthesize samples from entire population can be implemented, as the one presented in this chapter.

In 1977, a survey of Oregon anadromous anglers by the Department of Agricultural and Resource Economics, Oregon State University, cost an estimated $27,000.00. Despite extensive planning, the data collected (by mail and telephone follow-up) suffered from problems of memory error and recall bias. On the other hand, more accurate data were collected by the Oregon Department of Fish and Wildlife (ODFW) at ten major fishing ports along the Oregon coast. ODFW was able to collect information needed for travel cost model with little extra expense since they needed to interview the anglers anyway with regard to their catch (Raja Abdullah, 1988).

CHAPTER VII
SUMMARY AND CONCLUSIONS

After Clawson (1959) presented his two-stage travel cost method for estimating the demand for and value of outdoor recreation for several national parks, there have been many suggested changes and refinements of the travel cost (TC) model, both in terms of its specification and its estimation. As discussed in more detail earlier, most studies that have compared different specifications and estimating procedures have had to rely upon statistical performances of the various models fitted to empirical data sets. Although these empirical studies have been helpful, such studies have also at times been hampered from drawing definitive conclusions because the "true" coefficients and benefits were usually unknown. Exceptions to this limitation are rare but can occasionally be found, e.g., Bishop and Heberlein (1979). More recently, Monte Carlo experiments have been used to evaluate various demand specifications and/ or estimating procedures (Kling, 1988a, 1988b; Hellerstein, 1992). These Monte Carlo simulations had the advantage of definitely determining, within reasonable error limits, which model or method best estimates the "true" demand function and corresponding "true" consumer surplus.

Comparison of various methods of estimating linear travel cost demand and benefits in this study is based upon two types of data: (1) censored data from samples that include both the users and non-users of recreation, and (2) truncated data from samples drawn from users only. The main objective of this dissertation was to compare the performance of estimating methods commonly used for the preceding two types of data.

Three methods were compared for the truncated (user-only) data: (1) the classic zone average travel cost (ZATC) model, (2) the application of OLS to fit the individual user observations (OLSUSR), and (3) the truncated normal estimate of TC demand from the individual user observations (TRUNCN). Two estimating methods were used and compared for the censored (both user and non-user) data: (1) Estimates from OLS fitted to the censored data (OLSALL) and (2) estimates from the TOBIT method. Several interesting and important conclusions that can be drawn from the experiments are as follows:

1. The TOBIT estimator best estimated the travel cost coefficient across all experiments in terms of observed root mean square error (RMSE). TOBIT estimates of observed consumer surplus (GMCS) were also best in eight sets of experiments out of nine in estimating consumer surplus when the "true" underlying demand was, following Hellerstein (1992),

$$y_i = 5 - 0.25\ X_i + u_i, \tag{7.1}$$

where y_i denotes zero or integer number of trips for the ith observation, X denotes travel cost of the ith observation,

$\mathbf{u}_i$ is a normally distributed variable with mean zero and specified variance. However, when the constant term in (7.1) was reduced to 3, a more accurate estimate of observed consumer surplus was given by ZATC in two sets of experimentas out of five. Although more research is needed, TOBIT seemed to do less well when there were a larger proportion of zeros in the censored data.

2. The travel cost (TC) coefficient was too small in absolute value when linear demand was estimated by OLSALL. The greater the proportion of zeros in the censored data, the greater was the bias in the OLSALL estimated TC coefficient, as noted by Greene (1990), and the greater was the overestimation of consumer surplus based upon the actual observations (GMCS). However, the traditional consumer surplus estimate (TRCS), based upon OLSALL predicted visits, was more stable and accurate, even though usually biased downward by 10 to 20 percent. Therefore, based upon the experiments of this study, the OLSALL estimate of TRCS were usually more accurate than GMCS, the consumer surplus computed from the actual visits, even though the experimental design would imply that GMCS would be closer to the true CS (Bockstael and Strand, 1987).

3. An unexpected identity of linear demand estimated by OLSALL and the old zone average travel cost (ZATC) model was discovered. (That this identity was no statistical accident is shown by the proof of the theorem, given in Appendix 1.)

The identity is even more surprising since OLSALL requires (censored) data on both users and nonusers whereas the ZATC estimate can be obtained from user-only (truncated) data. Because of the identity of the linear travel cost demand coefficients, both OLSALL and ZATC give identical TRCS estimates. However, the GMCS estimates differ because of the averaging involved in the ZATC fitting.

4. Just as for OLSALL, the ZATC model increasingly underestimates the true travel cost coefficient as the percentage of nonusers in the population increases. However, just as for OLSALL, ZATC estimates of traditional (predicted) consumer surplus (TRCS) were stable and fairly accurate, despite a consistent downward bias of around 10 to 20 percent in most cases. The ZATC estimate of consumer surplus based upon actual visits (GMCS) were slightly higher and, therefore, slightly more accurate than the estimated TRCS. However, these ZATC estimates of GMCS and TRCS were usually within one percent or less of each other.

5. For the truncated (user-only) data, the truncated normal (TRUNCN) estimate of the travel cost (TC) coefficient was unbiased, but TRUNCN had much higher variance than ZATC, thereby often resulting in higher RMSE of the TC coefficient estimate by TRUNCN than for ZATC. Similarly, more accurate estimates of consumer surplus were obtained from ZATC than from TRUNCN.

6. For the truncated (user-only) data, application of OLS

the individual user-only observations (OLSUSR) always gave the worst average performance, cause by underestimating the TC coefficient and greatly overestimating consumer surplus. Therefore, a distinction needs to be made on the performance of OLS. OLS provided fairly good traditional consumer surplus (TRCS) estimates when the linear demand function was fitted to censored data but rather poor estimates when truncated (user-only) data were used.

In summary, for censored data, the best linear demand and consumer estimates were obtained from TOBIT, but for truncated (user-only) data, most accurate estimates of consumer surplus were obtained from the supposedly long discredited zone average travel cost (ZATC) model, fitted by Bowes-Loomis weighted least squares. However, when the data are suitable for the ZATC model, it is possible to synthesize the missing zero observations and to use TOBIT to estimate the linear demand function. Testing such a scheme would require a different experimental design with additional experiments and was beyond the scope of this thesis. If this synthesizing procedure can be shown to be accurate, an unbiased estimate from TOBIT could be obtained with less cost. Given limited management budgets, such a cost effective proposed procedure would benefit public resource managers in their recreational resource valuations.

Several important limitations of the research of this thesis should be noted. First, all experiments were based upon a linear demand function for a single recreational site. Use of other functional forms could result in quite different conclusions. Also, multisite models could give different results, although Kling's research (1988a, 1988b) indicates that full multiple site models do not always improve accuracy of benefit estimation. Another limitation pertains to the normal random variable u term added to the expected values of y to generate the observed y values in the experiments. Except for the rounding to zero or nearest positive integer value for y, the generated y (dependent variable) values were ideal for TOBIT and TRUNCN. Additional research with more typical nonnormal u terms would be interesting and worthwhile. Finally, given the integer nature of the dependent variable used in the Monte Carlo experiments, the use of count models, such as the Poisson or negative binomial, would be expected to give good estimates of linear demand and consumer surplus. Unfortunately, lack of access to suitable count model computer programs prevented use of these methods of estimation, but these methods should be tested in future research.

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APPENDICES

APPENDIX 1
EQUALITY OF PREDICTED CONSUMER SURPLUS FROM OLSALL AND ZONE AVERAGE TRAVEL COST MODELS FOR LINEAR DEMAND

For the usual case of unequal distance zone populations, the zone average travel cost (ZATC) linear demand function should be fitted by weighted least squares, as shown in earlier important research by Bowes and Loomis (1980). They showed that optimal weighting of the zonal observations is achieved by fitting the transformed equation,

$$y_t^* \,/\, \sqrt{POP_t} = a^* \sqrt{POP_t} + b^*(X_t \sqrt{POP_t}). \tag{1}$$

In (1), y_t^* denotes the sum of sample visits from distance zone t times the sample blow-up factor, and POP_t is the population of distance zone t. If the Bowes-Loomis procedure in (1) is used for fitting the ZATC model, as should be done to preserve the BLUE property, we can prove the following theorem:

Theorem

Predicted consumer surplus computed from linear demand and the ZATC model fitted by Bowes-Loomis weighted least squares is identical to predicted consumer surplus from linear demand fitted by OLS to all the individual observations (OLSALL), if travel costs within a distance zone are equal and the sampling rate is the same for all zones.

Proof

Starting with the "all observations case" and focusing on the two normal equations in a and b, we have

$$a\ \Sigma^T{}_{t=1}\ n_t + b\ \Sigma^T{}_{t=1}\ n_t \cdot X_t = \Sigma^T{}_{t=1}\ Y_t \tag{2}$$

$$a\ \Sigma^T{}_{t=1}\ n_t \cdot X_t + b\ \Sigma^T{}_{t=1}\ n_t \cdot X_t{}^2 = \Sigma^T{}_{t=1}\ X_t \cdot Y_t$$

where n_t denotes the total number of observations, both users and nonusers, in distance zone t with $n_i \neq n_j$ if $i \neq j$; X_t denotes the (constant) travel cost in zone t; and Y_t denotes the sum of sample visits originating from zone t.

The corresponding normal equations for the Bowes-Loomis weighted least squares model in (1) is easily seen to be

$$a^*\ \Sigma^T{}_{t=1}\ POP_t + b^*\ \Sigma^T{}_{t=1}\ POP_t \cdot X_t = \Sigma^T{}_{t=1} BF_t \cdot Y_t \tag{3}$$

$$a^*\ \Sigma^T{}_{t=1}\ POP_t \cdot X_t + b^*\ \Sigma^T{}_{t=1}\ POP_t \cdot X_t{}^2 = \Sigma^T{}_{t=1} X_t (BF_t \cdot Y_t)$$

where X_t and Y_t are defined as in (2); POP_t denotes the population of zone t; and BF_t is the sample blow-up factor. Note that assuming the sample rate is the same for all zones implies that the blow-up factor, BF_t is also a constant, k, for all zones. That is,

$$BF_t = k = POP_t\ /\ n_t \Rightarrow POP_t = k\ n_t. \tag{4}$$

Substituting k n_t for POP_t and $BF_t = k$ in (3), we can rewrite (3) as

$$ka^*\ \Sigma^T{}_{t=1}\ n_t + k\ b^*\ \Sigma^T{}_{t=1}\ n_t \cdot X_t = k\ \Sigma^T{}_{t=1}\ Y_t \tag{3a}$$

$$ka^*\ \Sigma^T{}_{t=1}\ n_t \cdot X_t + k\ b^*\ \Sigma^T{}_{t=1}\ n_t \cdot X_t{}^2 = k\ \Sigma^T{}_{t=1}\ X_t \cdot Y_t.$$

Dividing both equations of (3a) by $k \neq 0$ gives exactly (2), except for a^* and b^*, which implies $a^* \equiv a$ and $b^* \equiv b$.

Note that the predicted consumer surplus (CS_t) for zone t from the linear demand fitted by OLS to all the individual observations is

$$CS_t(\text{OLSALL}) = BF_t \, \hat{y}_t^{\,2} \,/\, -2b = (POP_t/n_t)(n_t \cdot \hat{y}_t^{\,2}/-2b) \tag{5}$$

$$= POP_t(\hat{y}_t^{\,2}/-2b,$$

and predicted CS_t^* from the ZATC model in (1) is

$$CS_t(\text{ZATC}) = [\sqrt{POP_t}(\hat{y}_t^{\,*})]^2/-2b^* = POP_t(\hat{y}_t^{\,*2}/-2b^*) \tag{6}$$

which implies that $CS_t(\text{OLSALL}) \equiv CS_t(\text{ZATC})$ since $a^* \equiv a$ and $b^* \equiv b$ implies $\hat{y}_t^{\,*} \equiv \hat{y}_t$. Q.E.D.

APPENDIX 2
RESULTS OF MONTE CARLO EXPERIMENTS FOR VARIANCE EQUALS 25

Results of the experiments for the first four of five TC designs with variance = 25 are reported in Tables A.1 through A.4. In these tables the RMSE ranking of estimation methods for the travel cost coefficient and consumer surplus is presented. The ranking of the travel cost coefficient estimators for these experiments is the same as for the first four designs where the variance equaled 6.25.

For Design #5, results of the experiments gave seven non-negative and three very small (in absolute value) TC coefficient estimates for OLSUSR, one small absolute value of TC coefficient for TOBIT, and several estimates with small absolute value of TC coefficients for OLSALL/ ZATC and TRUNCN. These small (in absolute value) and non-negative TC coefficients gave large and unstable consumer surplus estimates for both TRCS and GMCS. Since these occasional very large estimates of CS were so unstable, the average results were unreliable and not presented. The unstable estimates of CS were caused by the small variance in travel costs for Design #5 in combination with the high variance of 25 for the random u term. E.g., TC_k = [4,8,12] for Design #5 gives a variance of the OLSALL estimated TC coefficient of about four times that for Design #1 with TC_k = [4,12,20].

Results of experiments with a larger variance showed consistently larger true consumer surplus than one with a smaller variance. This finding is similar to the results reported by Hellerstein (1992).

Table A.1. Accuracy of Travel Cost Coefficient and Consumer Surplus Estimates from Monte Carlo Experiments, $y_i = 5 - 0.25\ TC_i + u_i$, u_i distributed N(0,25), Design #1, TC_k = [4,12,20].

Parameter Estimates	Complete Data		User Only Data		
	OLSALL	TOBIT	ZATC	OLSUSR	TRUNCN
True CS					
Ave. True CS = 236,649.5					
B1	-0.166768	-0.270222	-0.166768	-0.110391	-0.196611
RMSE	0.090361	0.062581	0.090361	0.145678	0.097010
Rank	2	1	2	4	3
B0	5.279232	5.019224	5.279232	6.530984	5.714310
RMSE	0.607889	0.778922	0.607889	1.634752	1.235687
Traditional CS (TRCS)					
Ave. TRCS	180200	174038	180200	454715	140471
TRCS/True CS	0.76	0.74	0.76	1.92	0.59
RMSE	75029	133667	75029	307573	141015
Rank on CS:					
a. TRCS	1	2	1	4	3
b. Overall	3	4	3	8	5
Gum-Martin CS (GMCS)					
Ave. GMCS	375596	232559	181075	637206	341676
GMCS/True CS	1.59	0.98	0.77	2.69	1.44
RMSE	169398	61644	74498	500535	227896
Rank on CS:					
a. G-M CS	3	1	2	5	4
b. Overall	6	1	2	9	7

Table A.2. Accuracy of Travel Cost Coefficient and Consumer Surplus Estimates from Monte Carlo Experiments, $y_i = 5 - 0.25\ TC_i + u_i$, u_i distributed N(0,25), Design #2, TC_k = [4,12,16].

Parameter Estimates	Complete Data OLSALL	TOBIT	User Only Data ZATC	OLSUSR	TRUNCN
True CS					
Ave. True CS = 249,109					
B1	-0.181460	-0.268741	-0.181460	-0.132950	-0.216746
RMSE	0.085201	0.074119	0.085201	0.130908	0.109464
Rank	2	1	2	4	3
B0	5.365553	4.973229	5.365553	6.705996	6.034685
RMSE	0.738796	0.857578	0.738796	1.845507	1.511084
Traditional CS					
Ave. TRCS	159948	220408	159948	442381	173829
TRCS/True CS	0.64	0.88	0.64	1.78	0.70
RMSE	92350	135514	92350	389836	183137
Rank on CS:					
a. TRCS	1	2	1	4	3
b. Overall	3	4	3	7	5
Gum-Martin CS					
Ave. GMCS	375176	250507	160895	622139	417386
GMCS/True CS	1.51	1.01	0.65	2.50	1.68
RMSE	184285	83650	91754	595384	416060
Rank on CS:					
a. G-M CS	3	1	2	5	4
b. Overall	6	1	2	9	8

Table A.3. Accuracy of Travel Cost Coefficient and Consumer Surplus Estimates from Monte Carlo Experiments, $y_i = 5 - 0.25\ TC_i + u_i$, u_i distributed N(0,25), Design #3, TC_k = [2,10,18].

Parameter Estimates	Complete Data: OLSALL	Complete Data: TOBIT	User Only Data: ZATC	User Only Data: OLSUSR	User Only Data: TRUNCN
True CS					
Ave. True CS = 263,036					
B1	-0.177051	-0.272103	-0.177051	-0.122090	-0.212329
RMSE	0.083449	0.064719	0.083449	0.137907	0.103631
Rank	2	1	2	4	3
B0	5.327747	4.929503	5.327747	6.612693	5.703709
RMSE	0.622479	0.699394	0.622479	1.715670	1.297506
Traditional CS					
Ave. TRCS	199024	226625	199024	498160	162163
TRCS/True CS	0.76	0.86	0.76	1.89	0.62
RMSE	85194	83629	85194	410083	171542
Rank on CS:					
a. TRCS	2	1	2	4	3
b. Overall	4	2	4	8	6
Gum-Martin CS					
Ave. GMCS	397624	257995	200269	694551	404777
GMCS/True CS	1.51	0.98	0.76	2.64	1.54
RMSE	162777	64973	84509	633117	326170
Rank on CS:					
a. G-M CS	3	1	2	5	4
b. Overall	5	1	3	9	7

Table A.4. Accuracy of Travel Cost Coefficient and Consumer Surplus Estimates from Monte Carlo Experiments, $y_i = 5 - 0.25\ TC_i + u_i$, u_i distributed N(0,25), Design #4, TC_k = [2,10,14].

Parameter Estimates	Complete Data OLSALL	TOBIT	User Only Data ZATC	OLSUSR	TRUNCN
True CS					
Ave. True CS = 281,435					
B1	-0.196822	-0.278197	-0.196822	-0.138977	-0.222370
RMSE	0.078414	0.077539	0.078414	0.123985	0.090853
Rank	2	1	2	4	3
B0	5.488186	5.082328	5.488186	6.703901	5.918589
RMSE	0.795076	0.812726	0.795076	1.799988	1.330077
Traditional CS					
Ave. TRCS	210413	259991	210413	468825	166520
TRCS/True CS	0.75	0.92	0.75	1.67	0.59
RMSE	98608	96443	98608	388640	171646
Rank on CS:					
a. TRCS	2	1	2	4	3
b. Overall	2	1	2	8	5
Gum-Martin CS					
Ave. GMCS	398982	288047	211643	649130	397700
GMCS/True CS	1.42	1.02	0.75	2.31	1.41
RMSE	196694	100718	99498	601319	309513
Rank on CS:					
a. G-M CS	3	2	1	4	3
b. Overall	6	4	3	9	7

APPENDIX 3
RESULTS OF MONTE CARLO EXPERIMENTS FOR CONSTANT EQUALS THREE

For variance = 6.25 and constant in the TC demand equation equals 3, the summary of 100 experiments per design are presented in Tables A.5 - A.9. In Table A.5 results for two types of data, censored versus truncated, were presented. For censored data we can compare the TOBIT estimator and the biased OLS estimator fitted to all (zero and positive) trip data. In the first line of numbers in Table A.5 the estimated travel cost (TC) coefficients are presented with average root mean squared errors in the second line.

As might be expected, the TOBIT estimate of the TC coefficient is much more accurate than the OLSALL estimate with RMSE of only 0.0642 compared to 0.1208 for OLSALL. The higher RMSE from OLSALL results from its much larger bias, -0.1305-(-0.25) =0.1195 versus only 0.0485 for the TOBIT. However, the variance for the TOBIT estimate is about five times as high, 0.00177 versus 0.00031 for OLSALL. The higher variance of TOBIT is the cause of its somewhat less impressive performance when used to compute consumer surplus, based upon the actual y_{ij} observations (GMCS).

The OLSALL estimate of GMCS is almost twice too large in Table A.5, as would be expected since its TC coefficient is almost twice too small. However, for the traditional estimate of consumer surplus (TRCS) ZATC and OLSALL give a much more accurate estimate of the true consumer surplus. Why does OLSALL do so much better when TRCS is used as compared to GMCS? The reason follows from what we know about OLS regression. The total sum of squares for observed y is $\Sigma y_i^2 = \Sigma\hat{y}_i^2 + \Sigma\hat{e}_i^2$ and $R^2 = \Sigma\hat{y}_i^2 / \Sigma y_i^2$, as shown in most elementary textbooks. Thus, with OLSALL, both the numerator and denominator of TRCS are underestimated as compared to the true consumer surplus (CS), thereby partially offsetting the error in the estimated traditional CS.

Although the preceding explains why OLSALL does better than expected in estimating the true CS from TRCS, one may still wonder how the accuracy of TOBIT CS estimation from GMCS could be worse (greater RMSE) than OLSALL when the true TC coefficient of -0.25 is estimated most accurately by TOBIT in terms of RMSE. This paradoxical result occurs because the TC coefficient appears in the denominator, as in GMCS and TRCS. Even though most of the CS values computed from the unbiased estimator will be closer to the true CS, a few coefficients that are too small can cause unusually large CS values that greatly inflate the MSE and RMSE of the estimated CS.

In Table A.5 the TOBIT estimate of β_{TC} is much more accurate than for the other estimates with RMSE about one-half or less. However, this superior estimate of β_{TC} did not always result in the most accurate estimate of consumer surplus since OLSALL (fitted to both user and zero visits) had smaller RMSE of 5,363. (A note of caution is needed here because Hellerstein (1992) has recently shown a much better way to estimate the traditional CS from the TOBIT model. It is quite possible that Hellerstein's estimate of traditional CS would outperform OLSALL, at least in some of the tables, and as shown in other parts of experiments reported in Chapter V and Appendix 2.)

A rather remarkable result in Tables A.5 to A.9 is that the much maligned and long discredited zone average travel cost (ZATC) model gave exactly the same TC coefficient and traditional CS estimate as OLSALL, which is especially remarkable since the ZATC model is fitted to truncated (user only) positive visit data.

From a theoretical viewpoint one would expect the best unbiased estimates of β_{TC}, based upon the truncated data, to be obtained from the truncated normal (TRUNCN) estimator. In fact, in the Tables A.5 - A.9 the average TRUNCN estimate of β_{TC} is fairly close to the true value of $\beta_{TC} = -0.25$. Also, the TRUNCN estimate of β_{TC} has the smallest RMSE of all the estimates based on the truncated data in Tables A.5 - A.9. However, the superior TRUNCN estimates of β_{TC} do not result in the most accurate CS estimates. In all TC scenarios tried thus far, the long obsolete ZATC model gave the most accurate (lowest RMSE) CS estimates from the truncated data.

Unexpectedly poor estimates of CS were obtained from OLS fitted to the truncated or user only data (OLSUSR).

Average estimated CS was overestimated by two to three hundred percent! One might expect OLS fitted to user only data to do more poorly than OLSALL since information provided by the zero observations was not available to OLS user only.

Table A.5. Estimates of Travel Cost Coefficient and Consumer Surplus by Five Methods with 'TRUE' Model, $y_i = 3 - 0.25\ TC_i + u_i$, and u_i distributed N(0,6.25), TC_k = [4,12,20].

Statistic	Type of Estimator and Data				
	Censored Data		Truncated Data		
	TOBIT	OLS ALL	ZATC	TRUNCN	OLS USR
Ave. Est. β_{TC}	-0.2799	-0.1443	-0.1443	-0.2886	-0.0968
RMSE (Est. β_{TC})	0.0467	0.1083	0.1083	0.1094	0.1611
Ave. Est. GMCS	37,861	86,057	41,432	52,599	138,374
RMSE (GMCS)	8,984	43,017	4,849	12,340	112,224
Ave. Est. TRCS	17,618	40,781	40,781	45,307	104,255
RMSE (TRCS)	27,435	5,363	5,363	6,907	74,496
Ave. True CS	44,118	44,118	44,118	44,118	44,118

Table A.6. Estimates of Travel Cost Coefficient and Consumer Surplus by Five Methods with 'TRUE' Model, $y_i = 3 - 0.25\ TC_i + u_i$, and u_i distributed N(0,6.25), TC_k = [4,12,16].

Statistic	Type of Estimator and Data				
	Censored Data		Truncated Data		
	TOBIT	OLS ALL	ZATC	TRUNCN	OLS USR
Ave. Est. β_{TC}	-0.2857	-0.1480	-0.1480	-0.2584	-0.0938
RMSE (Est. β_{TC})	0.0574	0.1051	0.1051	0.0900	0.1596
Ave. Est. GMCS	40,794	78,773	36,449	50,299	144,658
RMSE (GMCS)	8,934	35,952	10,185	26,445	133,836
Ave. Est. TRCS	17,884	36,242	36,242	44,227	109,035
RMSE (TRCS)	28,044	10,354	10,354	17,165	90,287
Ave. True CS	45,433	45,433	45,433	45,433	45,433

Table A.7. Estimates of Travel Cost Coefficient and Consumer Surplus by Five Methods with 'TRUE' Model, $y_i = 3 - 0.25\ TC_i + u_i$, and u_i distributed N(0,6.25), TC_k = [2,10,18].

Statistic	Type of Estimator and Data				
	Censored Data		Truncated Data		
	TOBIT	OLS ALL	ZATC	TRUNCN	OLS USR
Ave. Est. β_{TC}	-0.2743	-0.1403	-0.1403	-0.2833	-0.0962
RMSE (Est. β_{TC})	0.0414	0.1111	0.1111	0.0830	0.1562
Ave.Est. GMCS	50,741	98,761	51,085	52,372	154,488
RMSE (GMCS)	8,476	44,644	6,662	16,332	109,614
Ave. Est. TRCS	25,423	50,551	50,551	49,753	117,357
RMSE (TRCS)	30,157	6,944	6,944	11,251	70,934
Ave. True CS	55,285	55,285	55,285	55,285	55,285

Table A.8. Estimates of Travel Cost Coefficient and Consumer Surplus by Five Methods with 'TRUE' Model, $y_i = 3 - 0.25\ TC_i + u_i$, and u_i distributed $N(0,6.25)$, $TC_k = [2,10,14]$.

Statistic	Type of Estimator and Data				
	Censored Data		Truncated Data		
	TOBIT	OLS ALL	ZATC	TRUNCN	OLS USR
Ave. Est. β_{TC}	-0.2902	-0.1729	-0.1729	-0.3025	-0.0968
RMSE (Est. β_{TC})	0.0595	0.1083	0.1083	0.1029	0.1560
Ave.Est. GMCS	53,581	89,581	46,392	55,752	179,830
RMSE (GMCS)	11,856	31,583	15,833	23,360	135,678
Ave.Est. TRCS	26,785	46,147	46,147	50,559	146,538
RMSE (TRCS)	34,521	16,079	16,079	15,696	100,314
Ave. True CS	60,994	60,994	60,994	60,994	60,994

Table A.9. Estimates of Travel Cost Coefficient and Consumer Surplus by Five Methods with 'TRUE' Model, $y_i = 3 - 0.25\ TC_i + u_i$, and u_i distributed N(0,6.25), $TC_k = [4,8,12]$.

Statistic	Type of Estimator and Data				
	Censored Data		Truncated Data		
	TOBIT	OLS ALL	ZATC	TRUNCN	OLS USR
Ave. Est. β_{TC}	-0.2824	-0.1663	-0.1663	-0.3110	-0.1133
RMSE (Est. β_{TC})	0.0759	0.0937	0.0937	0.1599	0.1450
Ave.Est. GMCS	55,275	94,191	44,732	55,752	198,339
RMSE (GMCS)	15,078	42,518	18,449	23,360	160,806
Ave.Est. TRCS	24,911	43,081	43,081	50,559	143,089
RMSE (TRCS)	35,335	18,640	18,640	15,696	136,971
Ave. True CS	59,253	59,253	59,253	59,253	59,253

APPENDIX 4
HOW TO DUPLICATE THE EXPERIMENTS CONDUCTED IN THIS STUDY

The "true" travel cost demand function is

$$y_i = 5 - 0.25\ TC_i + u_i. \tag{1}$$

Using equation (A.4.1) as a basis for experiments, the simulation was conducted as follows:

1. $E(y_i) = 5 - 0.25\ TC_i$ was computed. For each design there were three zones of origin. These three zones of origin were transformed into three TC zones. TC zones for the five designs in these experiments were:

Design #	TC
1	4, 12, 20
2	4, 12, 16
3	2, 10, 18
4	2, 10, 14
5	4, 8, 12.

From each zone, for each design, a total sample of 64 people were assumed to be drawn from a zonal population of 1,600, i.e., we have a blow-up factor of 25. Therefore, one experiment required 64 times 3 equal 192 observations. For each design, 100 experiments were conducted.

2. The observed $y_i = E(y_i) + u_i$ was computed. As indicated in Chapter IV, u_i was a random variable distributed normally with mean zero and a given variance. For these experiments,

based upon Nawas' (1972) and Sorhus' (1980) study results, the variances were set equal to 6.25 and 25.

The values of the random u variable were generated using a SHAZAM 5.13 program where the seed was set at 54321.

3. The generated observation was rounded to the nearest integer, if it was positive and greater than 0.5. If the generated observed y_i had a positive value less than 0.5, or if it had a negative value, it was rounded to zero. The reason for the rounding to a positive integer or zero was that visits can only be observed as positive integer values or zero. Value of zero denoted a non-user, i.e., a person who does not participate in the recreation activity.

4. Since we have users and non-users in the data sets, we have two types of data available for the experiments. Five estimating methods can be fitted into available generated data:

a. Censored (users and non-users) data:

a.1 OLS (**OLSALL**),

a.2 Tobit (**TOBIT**).

b. Truncated (user-only) data:

b.1 Zonal average TC (**ZATC**) model framework,

b.2 Truncated normal maximum likelihood (**TRUNCN**),

b.3 OLS data with recreation users only (**OLSUSR**).

In this study OLSALL, ZATC, TOBIT, and OLSUSR TC coefficient estimates were obtained from the use of SHAZAM 5.13 programs. For TOBIT, the TC coefficient estimates were also checked by using Gauss/ GRBL program from Hellerstein (1991). The TRUNCN maximum likelihood estimations were conducted using TSP mainframe version 4.02.

5. Consumer Surplus.

The ultimate objective of travel cost demand estimation is to derive a reliable estimate of value with regard to non-market goods. In outdoor recreation valuation the estimated value usually is presented in terms of consumer surplus, despite some objections on the relative inaccuracy of that welfare measure in general. For this study two measures of consumer surplus were used: (1) Predicted or traditional consumer surplus (TRCS), and (2) observed, actual, or Gum-Martin consumer surplus (GMCS). Consumer surplus is defined as

$$CS=\int_{TC_{obs}}^{TC_c} Q(TC \mid \epsilon)\, dTC. \tag{2}$$

A simplified CS formula is

$$CS_i=\hat{y}_i^2/-2*\beta_1 \tag{3}$$

for the expected or traditional consumer surplus (TRCS). The actual, observed or Gum-Martin CS (GMCS) is computed using the above formula, but replacing $\hat{y}_i$ with y_i, i.e., using the observed rather than the predicted value of the dependent variable.

6. Criterion for Ranking the Estimating Methods.

Square root of mean square error (Pindyck and

Rubinfeld, 1981; Johnston, 1984) or RMSE. Root of mean square error for Y is defined as

$$RMSE=\sqrt{\frac{1}{N}(Y_i-Y^a)^2} \tag{4}$$

where Y denotes the variable for which RMSE is calculated, N denotes the number of samples (i = 1, 2, ..., N), Y_i indicates the value of ith sample of Y, and Y^a indicates the actual or the "true" value of Y.

If the calculated TRCS was negative, the estimated TRCS was set equal zero. The RMSE calculation used the "true" consumer surplus for each experiment as a basis for its calculations. The RMSE values for the estimates were used as indicators of their relative performances. A model with a smaller RMSE indicates a better performance in estimating the benefits of outdoor recreation than a model with a larger RMSE.

It should be noted that the predicted value for TRUNCN TRCS was computed as a simple linear function, just as for OLSUSR. Although more complex expressions for the expected values of y could be used, the simple linear function seemed to work fairly well, giving lower RMSE for TRUNCN TRCS than for TRUNCN GMCS.