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An examination of sources of sensitivity of consumer surplus estimates in travel cost models

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ABSTRACT

We examine sensitivity of estimates of recreation demand using the Travel Cost Method (TCM) to four factors. Three of the four have been routinely and widely discussed in the TCM literature: a) Poisson verses negative binomial regression; b) application of Englin correction to account for endogenous stratification; c) truncation of the data set to eliminate outliers. A fourth issue we address has not been widely modeled: the potential effect on recreation demand of the interaction between income and travel cost. We provide a straightforward comparison of all four factors, analyzing the impact of each on regression parameters and consumer surplus estimates. Truncation has a modest effect on estimates obtained from the Poisson models but a radical effect on the estimates obtained by way of the negative binomial. Inclusion of an income-travel cost interaction term generally produces a more conservative but not a statistically significantly different estimate of consumer surplus in both Poisson and negative binomial models. It also generates broader confidence intervals. Application of truncation, the Englin correction and the income-travel cost interaction produced the most conservative estimates of consumer surplus and eliminated the statistical difference between the Poisson and the negative binomial. Use of the income-travel cost interaction term reveals that for visitors who face relatively low travel costs, the relationship between income and travel demand is negative, while it is positive for those who face high travel costs. This provides an explanation of the ambiguities on the findings regarding the role of income widely observed in the TCM literature. Our results suggest that policies that reduce access to publicly owned resources inordinately impact local low income recreationists and are contrary to environmental justice.

1. Introduction

The travel cost method (TCM) has emerged as one of the most powerful techniques used by applied scholars to measure non-market values of environmental amenities. A form of revealed preference analysis, TCM has gained a great deal of visibility internationally. In the past five years alone, studies on TCM have been published in the *Journal of Environmental Management* to measure values of protected areas in Spain (Martín-López et al., 2009), an ice-climbing destination in the northwestern United States (Anderson, 2010), whitewater kayaking sites in Ireland (Hynes et al., 2009) and a World Heritage Area in Australia (Fleming and Bowden, 2009). These and other articles on TCM have not only focused on estimating the values of the resources at hand, but also numerous broader issues facing researchers, including the value of travel time, the importance of considering substitutes, and a host of sampling and statistical issues and problems potentially facing the TCM researcher. These investigations have contributed greatly to a

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better understanding of sources of variability in results, even if a number of issues remain unresolved.

In this paper we explore four issues in using TCM to estimate consumer surplus associated with the recreational use of an environmental amenity. We examine how endogenous stratification; data set truncation; count data regression; and income-travel cost interaction impact the estimates of regression parameters and consumer surplus in both Poisson and negative binomial TCM models.

1.1. Endogenous stratification

On-site surveys are more likely to include a higher response from avid resource users than from those who seldom visit a site. This is a form of sample bias called endogenous stratification. Shaw (1988) developed a model that corrected for problems associated with Poisson samples drawn from on-site recreational surveys, including endogenous stratification. Englin and Shonkwiler (1995a) extended the analysis to the negative binomial model. In order to account for this form of sample bias, researchers routinely now apply the "Englin correction" to data sets obtained from on-site interviews by subtracting one visit from the number of visits a respondent has made to the site.

1.2. Data set truncation

Truncation in TCM data sets is an issue at both ends of the continuum. At the lower end, visitation is automatically truncated at zero, since visits cannot be negative. This form of *de facto* truncation has been the focus of considerable literature, and is not the focus of this study. At the upper end, truncation of data sets to disallow for (a) visits that originate relatively far from the destination and (b) observations with "excessive" visits has become common as well. Researchers have adopted a number of *ad hoc* measures to eliminate observations with extremely large travel costs and/or very high reported visits, believing that inclusion of these observations will produce biased parameter estimates and inflated consumer surplus values (Bin et al., 2005; Heberling and Templeton, 2009; McKean et al., 2012). However there is little in the way of systematic analysis to measure the effects that exclusion of these observations has on parameter and consumer surplus estimates.

1.3. Count data regression and overdispersion

Since the dependent variable in travel cost models, number of visits to a site, includes only integers (count data), researchers have adopted integer only (count data) regression procedures to estimate travel demand (Cameron and Trivedi, 2013; Creel and Loomis, 1990; Hellerstein, 1991; Hellerstein and Mendelsohn, 1993). Foremost among these has been the Poisson regression procedure. One problem with the Poisson is with its assumed distribution, where the mean is set equal to the variance. In many data sets however, the variance exceeds the mean. This violation of the assumed distribution is called overdispersion. Its presence causes the standard errors on regression parameters to be reduced, increasing the likelihood of Type I error – finding that a variable is statistically associated with number of visits when it really is not (Dean and Lawless, 1989; Palmer et al., 2007). A more recent study by Nakatani and Sato (2010) found an association between overdispersion and inflated consumer surplus estimates. Correction procedures exist for taking overdispersion into account in order to re-calculate standard errors. A second option in the case of an overdispersed TCM data set is to choose another count data regression procedure, the negative binomial (Berk and MacDonald, 2008; Heberling and Templeton, 2009). Straightforward comparisons of parameter and consumer surplus estimates obtained via Poisson or negative binomial regressions are lacking.

1.4. The role of income in TCM

One enigma that has faced TCM researchers over the years has received little scrutiny. It centers on the role of income in travel demand. Recreation or travel demand models are based on the more general neoclassical theory of consumer demand, which is in turn based on constrained utility maximization. The "law of demand," the inverse relationship between the price of a good or service and the quantity demanded, is one of the most widely supported relationships in the social sciences. It eventually serves as the basis for estimating the value of a non-market good or service by allowing integration of the area under the demand curve (Fig. 1). However, if the price/quantity relationship is the most well attested item to emerge from neoclassical theory, a close second is a positive relationship between consumer income and quantity demanded (Mas-Colell et al., 1995; Nicholson and Snyder, 2012). While the theory technically allows for a relationship that is zero or even negative, an enormous body of empirical work shows that virtually all goods and services display a positive relationship – so much so that items that possess this characteristic are dubbed "normal." But the travel cost literature has produced a body of evidence on travel demand and income that is quite unlike the results seen in ordinary consumer demand studies. A large percentage of TCM studies shows zero or negative signs on the relationship (Brox and Kumar, 1997; Englin and Shonkwiler, 1995a; Larson et al., 1997; Loomis et al., 2000; McConnell and Strand, 1983; McKean et al., 2010, 2012; Ralston and Park, 1989; Taylor et al., 2010; Weiler, 2006), implying that income has no impact on travel demand or that higher income reduces the demand to the site, making the site what economists call an "inferior good." While economists report these results in their studies, they rarely comment on the implications, or the fact that these results, at least in the context of the larger body of consumer demand theory, are anomalous.

Rather than ignoring the anamolous role of income in TCM, we examine how income may influence visitation by way of an interaction with travel cost. We hope to better identify the way income influences visitation and thus improve the TCM methodology. This

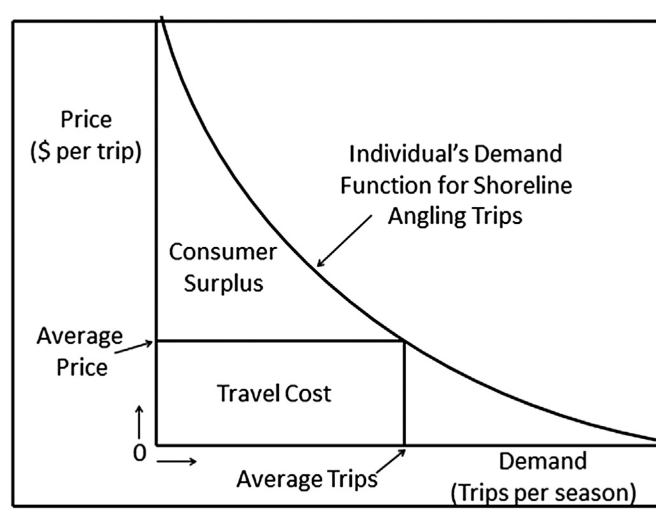

Fig. 1. Generalized demand function showing Consumer Surplus and Travel Costs (from Sohngen et al., 1999).

improvement has potential implications for policy and environmental equity as well. Low income visitors to recreation sites tend to have fewer options for recreation and enjoyment of environmental amenities than higher income individuals. Many are dependent on public lands and resources for environmental recreational opportunities where access is controlled largely by environmental management decision makers. Public recreation sites have increasingly come under threat in recent years as a result of trends in private development and policies that do not favor public access. Officials often have incentives to pursue these types of policies in order to increase local tax revenues. They may not be aware of the downside of their decisions in causing lost opportunities to those who are most vulnerable — low income local residents. As a result, revealing links between income and the use of publically provided environmental amenities should play a key role in making the case for improving and enhancing access to public recreation sites as opposed to reducing or eliminating them. Policies that achieve this objective form an important component of environmental justice (Rawls, 1999; Freeman, 2010; Smith, 2010).

2. Methods

2.1. The travel cost method (TCM)

When an individual makes a trip to engage in a form of recreation, that person is spending time and money to “produce” the trip. This creates an “implicit market” for the environmental amenity associated with the trip. The most obvious market purchase necessary for many individuals to make the trip includes out-of-pocket expenditures for transportation. Less obvious costs also accrue to the individual, such as depreciation on a vehicle used to get to the site. Another important cost is the value of the individual's time, as the person who takes a trip to a specific destination is forgoing an opportunity to work or spend time in another leisure activity.

The implicit market approach to valuation of an environmental amenity associated with a recreational trip begins with an assumption that is based on the law of demand: an inverse relationship between the travel cost and the number of trips the individual makes. Known as the travel cost method (TCM), this technique has emerged as the most commonly applied implicit market tool for valuing natural resource/environmental amenities (Hanley and Spash, 1995; Chizinski et al., 2005). More recently Loomis and Ng (2012) provided a thorough description of TCM and the myriad problems encountered when undertaking it.

The data requirements for implementing TCM are fairly significant and straightforward. TCM analysis lends itself well to an on-site intercept survey where the interviewer can ask the respondent the basic questions necessary to measure number of visits, and to construct a travel cost variable. An alternative to the on-site survey is to mail a survey to the general population. However, the weakness of a general population survey is that typically only a very small percentage of the sample utilizes the resource or visits the site being studied. As a result, on-site surveys have become the norm in TCM research (Haab and McConnell, 2002). A downside of an on-site survey is the inconvenience it poses to individuals trying to enjoy their recreational trip. One challenge to the TCM researcher is to obtain enough information from the respondent in order to construct a travel demand model in a very short period of time or with minimal contact with the respondent.

One practice that many TCM researchers have adopted to collect both travel distance and income is to ask for the respondents' zip code (Cameron, 1992; Heberling and Templeton, 2009). Using zip code median income as a proxy for household income has at least two advantages. It limits the length of the survey and reduces the intrusive nature of the interview which can lead to refusals by potential respondents. At many recreation sites some form of intercept survey may be occasionally conducted for a variety of reasons. Simply adding survey items such as number of trips, employment status, and home zip code may be sufficient to allow for TCM estimation. This was the case in the current study, where the Ohio Department of Natural Resources Division of Wildlife (ODNR, ODW) planned a creel survey of Ohio's (USA) Lake Erie shoreline anglers.

2.2. Data collection: the creel survey procedure

A creel survey is a face-to-face survey of anglers at or near the fishing location designed to gather biological, catch, and effort data on the fishery being studied. While conducting an isolated TCM study of shoreline anglers would be expensive, modifying the creel survey to obtain the data necessary for TCM analysis required little additional effort (Lupi et al., 2006; ODW, 2011). As the zip code was already included in the creel survey, only two additional TCM items: number of visits to the site and employment status were needed to provide the information necessary to conduct the TCM analysis.

The creel survey covered Ohio's Lake Erie shoreline of approximately 230 miles (370 km) at 39 of 164 publically accessible shoreline access sites (Bader et al., 2011). Survey sites were well defined, popular, and publicly accessible fishing sites at piers, breakwalls, tributary mouths and local and state parks located in urban, suburban and a few rural locations.

The Lake Erie shoreline creel survey was designed to efficiently collect fishing data (angler effort and catch) with a minimum of sampling bias (ODW, 2011). The survey days and work hours were carefully chosen to adhere to an efficient statistical design and variances from the schedule were minimized as much as possible (ODW, 2011). In 2006 the survey ran from May 10 to October 29. The 2007 survey ran from May 9 to October 31. Surveys were confined to daylight hours and were adjusted for shorter daylight hours in August, September and October. The survey schedules included morning and afternoon start times, and east and west starting points. The survey dates, start times and starting points were randomly selected within each weekday-weekend strata for each month (ODW, 2011). The ODNR ODW obtained 6072 usable responses, making this one of the larger data sets in the TCM literature.

2.3. Travel costs

The estimation of consumer surplus relies on the development of a function that expresses number of visits as a function of travel costs. In order to measure travel costs, TCM researchers have identified two separate components of costs that visitor bears in getting to and from the recreation destination: the cost of transportation and the value of travel time.

We were able to determine the estimated distances from the survey respondents' home zip code to the creel site where they were interviewed using the Google Maps Application Programming Interface (API). This resulted in a driving distance. For those anglers who fished in the same zip code in which they lived we used the straight line distance from the geographic center of the zip code to the creel site utilizing Google Earth™. The straight line distance was calculated from an Open Source online database of the latitudes and longitudes of the zip code centers (US Department of Commerce, 2012). The values were from “The Zip Code Database Project” (Colson, 2006). We used this as a proxy for the actual driving distance.

In order to obtain transportation costs per visit, we multiplied travel distance by two to get round trip distance and then multiplied by $.445 for business mileage per mile for 2006 (IRS, 2005) and $.485 for business mileage per mile for 2007 (IRS, 2006) to reflect the Internal Revenue Service (IRS) estimates for transportation costs for those years. To estimate travel time we used round trip distance and then and divided by 55 miles per hour and added 30 min. For both local and out-of town visitors, the 30 min component of the time value measures the amount of time moving about locally at or near the site. The 55 mile per hour component has a minimal influence on the calculation of travel time for those who live very close to the angling sites, but is an appropriate approximation for those who live even a few miles from the site.

Measuring the cost of travel time in recreation demand models has been subject to a great deal of discussion (Feather and Shaw, 1999; Hynes et al., 2009; McKean et al., 2012). Most economists agree that travel time has some value. The fact that a person is willing to expend time to get to and from a recreation site demonstrates that the person places value on the trip and resulting experience, but the value of the time the person sacrifices is not at all clear (Phaneuf and Smith, 2004). Imputing a person's hourly wage as a measure of the value of travel time seems to have a basis in economic analyses (Cesario, 1976). However, many people are not paid hourly, but instead are on salary. Even for those who are paid hourly, it is not clear if they are actually giving up an hourly wage for time at work in order to take a trip. Some may be giving up more, if overtime pay exists at time and a half wages, as it sometimes does. However, many do not have the opportunity to work more than a given number of hours per week. For both hourly and salaried workers, vacation time can accrue that allows them to take trips without losing time at work. Beyond the issues we can identify for salaried and wage earners, many visitors to recreation sites are unemployed or retired. While unemployment or retirement might mean that the value of a person's time is relatively small, it does not mean their time has no value at all.

Cesario (1976) initiated the seminal practice of valuing recreation travel time at one-third the wage rate. Adoption of his convention or a slight modification of it has been the norm in the TCM literature. Estimating a value of time endogenously has become an alternative, but is very data intensive (McConnell and Strand, 1983; McKean et al., 2012) and the results have varied widely. At one extreme Fezzi et al. (2013) found that travel time may be valued as much as 75% of the wage rate. At the other extreme McKean et al. (2012) found little to no relationship between the value of travel time and the wage rate. Englin and Shonkwiler (1995b) however, estimated a value of travel time of 39.7% of the wage rate for all workers. This is close to the Cesario convention. Earnhart (2004) developed the practice of valuing the time of employed workers at 9% to 18 % of the wage rate. He valued non-workers' travel time at half that of the hourly and salaried worker.

In order to obtain estimates of the value of travel time, we adopted a procedure based largely on conventions that have been adopted by economists over the years (Victoria Transport Policy Institute, 2012). First we measured an imputed wage rate by dividing annual income in dollars by 2080 h. For respondents who are currently employed we divided the wage by three. For those who were unemployed or retired we divided by six to place a lower value on the opportunity cost of their travel time while recognizing that their time still has value (Earnhart, 2004).

2.4. The dependent variable: number of trips taken

As stated above, the measurement of consumer surplus requires the estimation of an equation that specifies the number of visits (demand in Fig. 1) as a function of price (travel cost). Consumer surplus is calculated as the area under the curve identified in the figure. The most commonly used statistical procedure for estimating the demand equation is regression analysis. However, use of a standard regression procedure is not appropriate in TCM, because the dependent variable (number of trips) is not continuous. Instead, the variable only comes in integer values. These data are called "count" data because they are in the form of counting numbers (1, 2, 3…). We must choose an estimation procedure which not only disallows negative numbers, but also disallows fractions.

The most commonly used estimation technique for an equation where the dependent variable can only come in the form of positive integers is the Poisson regression (Cameron and Trivedi, 2013). The Poisson procedure however, is not without problems. A common pitfall with this form of regression is that the underlying Poisson distribution requires the mean of the dependent variable (in this case trips) to equal the variance. Often in data sets however, the variance is much greater than the mean. This problem is called overdispersion, and renders the standard errors smaller than they would be if the regression model were "efficient" (Cameron and Trivedi, 2013), potentially leading to Type I error.

An alternative to Poisson regression is a negative binomial regression, which is also appropriate for count data. It is generally used when values of the mean and variance of the dependent variable (in this case number of angler trips) diverge considerably (Haab and McConnell, 2002). Both of these regression procedures transform the number of trips into logarithms, which means that the consumer demand function in the graph in Fig. 1 is a curve that asymptotically approaches the axes. The area it sweeps out (consumer surplus) remains finite, and is fairly straightforward to calculate from regression results (Haab and McConnell, 2002). Regardless of which count regression procedure is used, two general problems associated with on-site TCM data have been identified: endogenous stratification and truncation (Englin and Shonkwiler, 1995a).

Endogenous stratification arises because interviewers are more likely to encounter respondents who use the resource more frequently than others. This can produce a biased sample, also known as avidity bias (Lupi et al., 2006; Loomis and Ng, 2012). This problem is potentially serious, particularly when the sample size is small. This is not the case in our study where interviewers made contact with over 8600 potential respondents and obtained over 6000 completed surveys. Moreover, the interviewers were instructed to contact all types of anglers at each location. If respondents had previously provided TCM data, the interviewers did not ask the TCM items again, which accounted for the drop of approximately 2600 responses. Despite the steps we took to obtain the most diverse on-site sample possible, it is still likely that the data set suffers from endogenous stratification. To measure the sensitivity of parameter and consumer surplus estimates, we calculated regressions with and without the Englin correction.

Truncation at the upper end of the data set is potentially an important issue in TCM research. This is because attributing the large travel cost associated with a distant visitor is not appropriate if the respondent also visited other sites on the trip, or initially made the trip to the area for another primary purpose (e.g. visiting family, conducting business). It is often difficult for a researcher to determine whether a visitor from a remote origin visited a site while near the area or whether the site was in fact the primary purpose of the trip. In the case of the former, including the observation along with the travel cost would produce biased parameter estimates and inflated consumer surplus estimates. On the other hand, obtaining the travel cost the respondents faced in making a "side trip" to the destination would be very data intensive and is beyond the resources available to many TCM researchers. While there is no consensus on a technique for truncation of outliers, some conventions have emerged (Bin et al., 2005; Heberling and Templeton, 2009; McKean et al., 2012). Our purpose is not to settle the issue of truncation, but rather to measure its effects on parameter and consumer surplus estimates and whether these effects vary by model specification and type of regression procedure.

One principal of truncation that has emerged is to exclude observations where distance exceeds what would be feasible for a day trip (Gentner, 2007). As we have no data to separate the value of angling from multipurpose trips, we focused on the single day trips in the dataset. Bader et al. (2011) report that 83% of the anglers interviewed in the 2006 and 2007 shoreline creel were from the eight Ohio, USA Lake Erie shoreline counties. Further, average Lake Erie shoreline angling time on-site in 2006 was 2.1 h and it was 2.0 h in 2007 (Bader et al., 2011). It seems reasonable to assume that trips over 200 miles (four hours travel time) one way would be for multiple purposes and trips of 200 miles or less would be specifically for angling. Moreover this distance for truncating TCM datasets is consistent with the norm as reflected in Bin et al., 2005; Gentner, 2007; Heberling and Templeton, 2009; and McKean et al., 2012. Additionally in the truncated data set we removed outliers where respondents reported visitations exceeding three standard deviations above the mean.

2.5. Independent variables: beyond travel cost

2.5.1. Income

Thus far we have established the basis for a regression equation specifying number of angler trips as a function of travel cost, with a negative relationship hypothesized between the two variables. The most important variable beyond these two that is normally included in travel cost modeling is income. Economic theory posits that income is an important shifter of the demand relationship between quantity and price for any kind of purchase or activity. In this analysis, income has entered into the calculation of travel cost already. Still, studies show that even with that inclusion, income as a separate variable potentially plays an important role in recreation demand (Phaneuf and Smith, 2004).

However, empirically over the years income has proved to be an enigma in TCM research. Numerous studies have shown negative relationships between income and travel to sites, while others just show a zero effect of income on travel demand. As a result of this enigma, recent TCM studies have even avoided using income in the analysis at all (Loomis and Ng, 2012). The failure of TCM to yield any kind of consistent relationship between income and travel demand is not trivial. We propose that it is very likely that the role income plays in travel demand is more complicated than models undertaken in the past have suggested. We also believe that rather than ignoring this or omitting income from the model we should explore various specifications in order to identify potential paths through which income can influence TCM results.

Economic theory suggests that income can interact with prices to make the relationship even more complicated (Nicholson and Snyder, 2012). Empirically some evidence has emerged in the tourism demand literature that this is in fact the case (Nicolau and Mas, 2008). Income must be considered because higher (lower) income means more (fewer) opportunities for the respondent. For example, those with higher incomes are more able to take a wider variety of angling trips (such as fishing from a boat, or traveling to more types of fishing destinations). As travel costs change, the influence income has on travel demand can change. In order to measure the full extent to which these changes take place it is necessary to include not only income and travel cost as stand-alone variables but also an interaction variable between the two.

2.5.2. Substitutes and other variables frequently used in TCM

It has become very common in the travel cost literature to include the cost of substitute sites (Gentner, 2007; Phaneuf and Smith, 2004). However, omission of substitute sites is appropriate in a variety of circumstances (Alberini and Longo, 2006; Common et al., 1999). The decision as to whether to include substitute sites in a travel demand model depends on the level of aggregation of the site destination as defined in the model. For a travel destination that is highly disaggregated, it is obvious that inclusion of substitutes is appropriate, since other disaggregated site destinations may be considered by the respondent. When the travel destination is an entire coastline consisting of dozens or even scores of specific sites, the selection of one versus others is incorporated into the travel cost to get to that site. One site's loss is another's gain, but total visits remain unaffected. The data set for this study included visits to 39 shoreline destinations along Ohio's Lake Erie coast, a very highly aggregated travel demand set.

Our models avoid explicit inclusion of substitutes because we maintain the hypothesis that the primary substitute for Lake Erie shoreline angling would be some kind of angling at another Lake Erie shoreline location or by Lake Erie boat angling – either a private boat or charter. The actual cost of both of these substitutes is either A) identical for all respondents or B) correlated with the existing travel cost variable in the equation. Therefore specification of an independent substitute variable in the regression is inappropriate in this case. We maintain that the Lake Erie shoreline fishing experience is the driver for these anglers and the most likely substitute would be other Lake Erie shoreline sites. Angling at inland lakes, streams or open Lake Erie boat fishing are not suitable substitutes due to time and fiscal issues. Even if inland lakes are substitutes, they are fairly uniformly distributed through the study area and thus their costs as substitutes does not vary enough among individuals to make a difference in the analysis.

Many travel demand equations also include a variety of other socio-demographic variables in the demand equation. These often include items such as age, gender, and experience with outdoor activities, to name a few. The survey utilized for this study did not obtain these items from respondents. The focus was to examine sensitivity of parameter and consumer surplus estimates to changes in model specifications vis-a-vis income-travel cost interactions. This enabled us to develop a TCM model and analyze the data using SPSS (Statistical Package for Social Sciences) and standard statistical methods. The TCM models we developed are described in Section 2.6 below.

2.6. Model specification

The equation excluding the income-travel cost interaction is:

$$Log_e \text{ angler trips}(y) = B_0 + B_1 \text{ Travel Cost } (\$) + B_2 \text{ Income } (\$ \text{ thousands}) \quad (1)$$

where B_0, B_1, and B_2, are parameters to be estimated by way of regression.

Consumer surplus per trip is calculated as the negative reciprocal of the rate of change in the angler trips with respect to travel cost (Haab and McConnell, 2002). The rate of change of the Log_e of angler trips with respect to travel cost is simply B_1.

Therefore without the income-travel cost interaction:

$$\text{Consumer surplus} = -1/B_1 \quad (2)$$

The equation including the income-travel cost interaction is:

$$Log_e \text{ angler trips}(y) = B_0 + B_1 \text{ Travel Cost } (\$) + B_2 \text{ Income } (\$ \text{ thousands}) + B_3 \text{ Income Travel Cost} \quad (3)$$

where B_0, B_1, B_2, and B_3 are parameters to be estimated by way of regression.

Under this specification the rate of change in angler trips with respect to travel cost is

$$\partial Log_e\, y/\partial TC = B_1 + B_3 \text{ Income} \quad (4)$$

producing a consumer surplus as follows:

$$\text{Consumer surplus} = -1/(B_1 + B_3 \text{ Income}) \quad (5)$$

In the first specification (without interaction) the association between income and angler trips is simply:

$$\partial Log_e y/\partial \text{ Income} = B_2 \quad (6)$$

In the equation with interaction, the association between income and angler trips is given by the expression:

$$\partial Log_e y/\partial \text{ Income} = B_2 + B_3 \text{ Travel Cost} \quad (7)$$

Setting the value of (7) to zero and solving yields:

$$\text{Travel Cost}_s = -B_2/B_3 \quad (8)$$

The solution to Equation (8) reveals the travel cost at which income effects switch from positive to negative or vice versa.

To examine the sensitivity of regression parameter estimates to changes in model specifications, we estimated Equations (1) and (3) by way of both Poisson and negative binomial regression procedures. We also wanted to examine the sensitivity of model estimates to Englin corrected and non-corrected specifications, to truncation to exclude outliers by number of trips and travel distance and to inclusion verses exclusion of the income-travel cost interaction term. Examining for all of these sensitivities gave us a total of 16 regression models.

3. Results and discussion

The mean values and standard deviations for the shoreline angler creel data sets are reported in Table 1. The mean one-way travel distance is 38.62 miles with a travel cost of $46.51 in the untruncated data set. Mean distance falls to 25.21 miles and mean travel cost falls to $30.90 in the truncated dataset. Mean number of angler trips is 21.21 and 18.68 in the untruncated and truncated data sets respectively. The variance in each case ($29.82^2 = 889$) and ($21.81^2 = 476$) greatly exceed the mean. This represents a case of classic overdispersion which is common in TCM data sets.

Table 1
Number of angler trips, one way travel distance, angler income and travel cost for the untruncated and truncated shoreline angler creel data. The dataset was truncated at 200 miles and 110 trips. Distance is in miles. Standard deviation is in parentheses (SD).

	Trips	Distance	Income	Travel cost
Untruncated Value	21.21	38.62	$39,125	$46.51
SD	(29.82)	(125.34)	($12,049)	($144.15)
Number of respondents	6072	5931	6072	5888
Truncated value	18.68	25.21	$39,087	$30.90
SD	(21.81)	(35.08)	($11,901)	($40.19)
Number of respondents	5767	5893	5893	5727

The first set of regression results is presented in Table 2. These are untruncated Poisson regressions. Note that the signs on travel cost and income are negative. However as expected, the two models that include income-travel cost interaction produce parameters which radically change the estimated effect of income on travel demand. Following Equation (8), the results from model 2 yields a switching point of $81.63:

$$\text{Travel Cost}_{S2} = -(-.008)/9.8\,E - 5 = 81.63$$

This indicates that the income elasticity of demand is negative for those who face travel costs below $81.63 (almost twice the mean of $46.51). At travel costs above $81.63, the income effect is positive. In model 4 the switching point is $77.67.

Presented in Table 2 are the likelihood Chi-Squares that indicate that all four models perform well ($P < .001$). We report the overdispersion parameter (α) which reveal that all four models are greatly overdispersed. Since the Poisson model suffers from overdispersion, the extremely low values on the standard errors we obtained in the regressions are not surprising. Overdispersion is well known to lead to deflated standard errors (Cameron and Trivedi, 2013), serving as the primary rationale for adopting the negative binomial.

The second set of regression results are presented in Table 3. These are untruncated negative binomial regressions. Note again that the signs on travel cost and income are negative. The notable finding here is that the Englin correction on the negative binomial produces a parameter estimate on income-travel cost interaction that is statistically significantly different from zero (model 8), while the Englin uncorrected model (model 6) does not. The switching point for income elasticity for model 8 is at -$205.88. Since travel cost cannot be negative, this result implies that the income effect on travel demand is strictly negative. Note that model performance continues to be excellent ($P < .001$) while overdispersion virtually disappears.

Next we turn to determine the impact of data set truncation on the models presented above. Table 4 presents the Poisson models truncated at 200 miles (four hour travel time) and 110 trips (three standard deviations above the mean). For the third time, the signs for the travel cost and income are negative. The switching points on income effect for model 10 and model 12 at $28.09 and $25.64 respectively are about one-third of those obtained from the untruncated Poisson models discussed previously. Although overdispersion fell by an average of six to eight orders of magnitude compared with the untruncated Poission, it is still severe as measured by α. These findings indicate the importance of truncating data sets to exclude outliers if researchers prefer to use the Poission model. Log likelihoods continue to produce results that are statistically significant at $P < .001$.

Our last set of regressions are the negative binomial models truncated at 200 miles and 110 trips. The results are presented in Table 5. The signs for travel cost and income are all negative except for model 15 where the parameter for income is zero. However, in the negative binomial regression models truncation trumps everything in that it has the most dramatic effect on the estimates of consumer surplus. Moreover, the truncated negative binomial model with the Englin correction and the income-travel cost interaction is not significantly different from any of the four truncated Poisson models. The switching points on the income effect for model 14 and model 16 are $33.78 and $30.30 respectively. These are both approximately at the mean of the travel cost for the truncated sample ($30.90). Combining data set truncation with the negative binomial effectively eliminates overdispersion. All likelihood Chi square values are statistically significant at $P < .001$.

Table 2
Results of Poisson Regression: dependent variable is the $\log_e$ of angler trips untruncated, Englin uncorrected and corrected, with and without income travel cost interaction.

	Uncorrected N = 5888				Corrected N = 5884			
	Model 1		Model 2		Model 3		Model 4	
Independent variable	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error
Intercept	3.533	.0096***	3.616	.0108***	3.516	.0098***	3.597	.0116***
Travel cost	−.009	9.7661E-5***	−.013	.0003***	−.011	.0001***	−.015	.0003***
Income per thousand	−.006	.0002***	−.008	.0003***	−.006	.0003***	−.008	.0003***
Income per thousand × travel cost	NA	NA	9.8 E-5	5.8 E-5***	NA	NA	1.03 E-4	7.8 E-7***
α	1.99 E+9		1.53 E+8		7.13 E+7		4.92 E+9	
Likelihood ratio Chi-square	1.6262 +E4***		1.6453 E+4***		1.8522 E+4***		1.8681 E+4***	

*** Denotes statistically significant at $P < .001$.

The consumer surplus estimates calculated from the 16 regression models are found in Table 6. Note that these estimates range from a low of \$69.62 to high of \$558.66, a factor of almost eight. Understanding the sources of this variation is important to environmental researchers and policy makers alike.

Consumer surplus estimates for untruncated Poisson models with and without the Englin correction vary by as much as \$20.20 (18%) while those with and without the income-travel cost interaction produce consumer surplus variation of only \$2.27 (2.0%). Although the income–travel cost interaction in these models is statistically significant, the consumer surplus does not appear to be greatly impacted. The Englin correction has more of an impact on consumer surplus then the income-travel cost interaction.

The consumer surplus estimates for the untruncated negative binomial models are roughly five times the corresponding results estimated by the untruncated Poisson. Here inclusion of the income-travel cost interaction is not significant in the model without Englin correction (model 6) but it is significant in the model that includes the Englin correction (model 8). The impact of the Englin correction lowers the consumer surplus about \$110 (20%) while the impact of the income-travel cost interaction, even when significant, lowers the consumer surplus only about \$18 (4%). While application of the Englin correction produces generally lower CS estimates, the difference is not statistically significant in the presence of the income-travel cost variable.

Consumer surplus estimates for the truncated Poisson models receiving the same Englin correction and interaction treatments are 21%–31% lower than for the untruncated Poisson models discussed previously. Application of the Englin correction lowers the CS estimate in the absence of the income/travel cost interaction by about 7.1%. However, when the income-travel cost interaction term is added, application of the Englin correction does not significantly change the CS estimate.

The consumer surplus estimates derived from the truncated negative binomial models are less than one-fifth those of the untruncated negative binomial models. Again, application of the Englin correction ceases to have a statistically significant effect on CS estimates when the income/travel cost interaction term is included in the equation. A comparison of models 15 and 16 reveals that the lower bound CS estimate in the model excluding the income-travel cost interaction is above the point estimate obtained from the regression that includes interaction. Model 15 produces confidence intervals that are very "tight" compared to model 16, but the fact that the interaction term is highly statistically significant indicates that this tightness is an illusion resulting from a misspecified model.

The results of this study suggest that simply moving to a negative binomial from an overdispersed Poisson regression is not necessarily a proper move because there are other sources of variation in the consumer surplus estimates. Moreover, the impact of each source varies depending on the model specification. It turns out that an overdispersed Poisson model is less sensitive to these changes than the negative binomial model. Given the more widespread use of the negative binomial when encountering overdispersion in count data sets, the results obtained here lead to the caveat that researchers need to explore specification alternatives when using the negative binomial. The income-travel cost interaction reveals that the relationship between income and travel demand is more complicated than what is generally indicated in the travel cost literature. However, its inclusion does not drastically change the consumer surplus estimates. On the other hand, the largest single factor affecting the negative binomial estimates is truncation of the data set to exclude outliers.

4. Conclusions

This study has explored four key issues which confront researchers using TCM to measure the value of environmental resources. Our analyses allowed us to examine sensitivity of parameter estimates and consumer surplus estimates to changes in model specification, type of count data regression model used, application of the Englin correction, and data set truncation. We

Table 3
Results of Negative Binomial Regression: dependent variable is the $\log_e$ of angler trips, untruncated, Englin uncorrected and corrected, with and without income travel cost interaction.

	Uncorrected N= 6028				Corrected N =5884			
	Model 5		Model 6		Model 7		Model 8	
Independent variable	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error
Intercept	3.423	.0424***	3.414	.0436***	3.398	.0424***	3.348	.0438***
Travel cost	−.002	.0001***	−.002	.0002***	−.002	.0001***	−.001	.0003***
Income per thousand	−.008	.0010***	−.008	.0011***	−.008	.0010***	−.007	.0011***
Income per thousand x travel cost	NA	NA	5.0 E-6	6.4 E-6	NA	NA	−3.4 E-5	7.7 E-6***
α	1.911		1.958		2.254		2.337	
Likelihood ratio chi-square	364.121***		364.882***		449.270***		467.380***	

*** Denotes statistically significant at $P < .001$.

Table 4
Results of the Poisson Regression: truncated at 200 miles and 110 trips, Englin uncorrected and corrected, with and without income travel cost interaction.

	Uncorrected N = 5724				Corrected (Englin) N = 5719			
	Model 9		Model 10		Model 11		Model 12	
Independent variable	Parameter	Standard error	Parameter	Standard error	Parameter	standard error	Parameter	Standard error
Intercept	3.292	.0104***	3.425	.0126***	3.261	.0107***	3.401	.0130***
Travel cost	−.013	.0001***	−.020	.0004***	−.014	.0001***	−.022	.0005***
Income Per Thousand	−.002	.0003***	−.005	.0003***	−.002	.0003***	−.005	.0003***
Income per Thousand x Travel Cost	NA	NA	1.78 E-4	9.4 E-5***	NA	NA	1.95 E-4	1.01 E-5***
α	23.702		23.320		25.594		25.098	
Likelihood ratio Chi-square	1.3716 E+4***		1.4041 E+4***		1.4874 E+4***		1.5212 E+4***	

*** Denotes statistically significant at $P < .001$.

Table 5
Results of Negative Binomial Regression: truncated at 200 miles and 110 trips, Englin uncorrected and corrected, with and without income travel cost interaction.

	Uncorrected N = 5724				Corrected (Englin) N = 5719			
	Model 13		Model 14		Model 15		Model 16	
Independent variable	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error
Intercept	3.206	.0442***	3.378	.0554***	3.165	.0442***	3.355	.0556***
Travel cost	−.011	.0003***	−.017	.0012***	−.012	.0004***	−.019	.0013***
Income per thousand	−.001	.0011	−.005	.0014***	.000	.0011	−.005	.0014***
Income per thousand x travel cost	NA	NA	1.48 E-4	2.85 E-5***	NA	NA	1.65 E-4	2.90 E-5***
α	1.416		1.374		1.712		1.653	
Likelihood ratio Chi-square	788.402***		816.542***		922.649***		956.442***	

*** Denotes statistically significant at $P < .001$.

used survey results obtained from on-site interviews of Lake Erie shoreline anglers resulting in a data set with over 6000 responses.

4.1. Endogenous stratification

The Englin correction has different kinds of impacts on different models. In the untruncated Poisson regression it has virtually the same influence (around 20%) on the model that includes the income–travel cost interaction with the one that does not. The impact is more moderate on the truncated Poisson models (around 5%). However, in the remaining regressions, while application of the Englin correction reduces the point CS estimates, these reductions become statistically insignificant in the presence of the income-travel cost variable.

4.2. Data set truncation

Truncating the data set to exclude outliers always leads to reduced consumer surplus estimates. Our results show that this reduction is far greater in the case of the negative binomial than in the case of the Poisson. By far the biggest factor in influencing the consumer surplus is truncation in the case of the negative binomial model. This is because the negative binomial appears to be far more sensitive than the Poisson to data set truncation.

The point at which to truncate TCM data sets remains unresolved and should be a focus of future research in TCM. One suggestion would be to follow the example we have included in our study which is to exclude observations where a) the travel distance exceeded what may be considered feasible for a one day visit and b)

Table 6
Consumer Surplus Results Poisson and Negative Binomial Regressions. Truncated and untruncated, Englin uncorrected and corrected, with and without income travel cost interaction.

Model Number	N	Consumer Surplus ($)	95% Confidence Interval ($)	Type	Truncation	Englin Correction	Interaction
1	5888	$111.11	(105.26, 117.65)	Poisson	No	No	No
2	5888	$108.84	(99.48, 120.15)	Poisson	No	No	Yes
3	5884	$90.91	(86.96, 95.24)	Poisson	No	Yes	No
4	5884	$90.97	(83.43, 99.99)	Poisson	No	Yes	Yes
5	5888	$558.66	(502.51, 625.00)	Negative Binomial	No	No	No
6	5888	$553.86	(393.08, 937.23)	Negative Binomial	No	No	Yes
7	5884	$448.43	(406.50, 500.00)	Negative Binomial	No	Yes	No
8	5884	$430.55	(302.22, 748.28)	Negative Binomial	No	Yes	Yes
9	5724	$76.92	(74.07, 80.00)	Poisson	Yes	No	No
10	5724	$76.75	(69.97, 85.00)	Poisson	Yes	No	Yes
11	5719	$71.43	(68.97, 74.07)	Poisson	Yes	Yes	No
12	5719	$69.62	(63.15, 77.58)	Poisson	Yes	Yes	Yes
13	5724	$90.91	(86.96, 95.24)	Negative Binomial	Yes	No	No
14	5724	$89.26	(66.61, 135.25)	Negative Binomial	Yes	No	Yes
15	5719	$83.33	(80.00, 86.96)	Negative Binomial	Yes	Yes	No
16	5719	$79.76	(60.44, 117.22)	Negative Binomial	Yes	Yes	Yes

where respondents reported number of trips exceeding three standard deviations above the mean.

One of the down sides of the Englin correction and truncation is that they reduce the number of observations. For those researchers who have relatively small data sets, this can potentially present a very serious problem. In our particular case we lose 2.9% of the observations from the uncorrected untruncated responses. The untruncated uncorrected model had a total of 5888 respondents. The truncated Englin corrected models had a total of 5719.

4.3. Count data regression and overdispersion

The data set met the needs of the study because like many data sets used in TCM it was overdispersed. As expected with an overdispersed data set, application of Poisson regression yielded parameter estimates that indicated a very high level of statistical significance. When the data set is overdispersed it is important to seek estimates obtained by an alternative to Poisson in order to examine whether or not the findings are the result of Type I error. As is common in TCM research we did this by turning to the negative binomial regression. A critical finding of our research is that naive application of the negative binomial when the data set is overdispersed can lead to highly inflated values of consumer surplus. The negative binomial models provide a wider range of consumer surplus values than do the Poisson models. These findings suggest that in turning to the negative binomial, issues of model specification and truncation become more important because the estimates obtained from the negative binomial models are more sensitive to these changes than those obtained from the Poisson.

4.4. The role of income in TCM

Initial regressions using only travel cost and income as independent variables implied a negative association between income and travel demand. This finding is a common result in the TCM literature, but is anomalous within the context of the broader literature on consumer demand. Inclusion of an income-travel cost variable radically changes the nature of this relationship, however. For those respondents who face relatively low travel costs the relationship is indeed negative. As travel cost increases, the impact of income on travel demand becomes positive. This kind of result has been hinted at in the TCM literature, but this study is the first to document the phenomenon. Compared to fishing from a boat, shoreline angling requires a minimal amount of equipment and is a relatively low cost fishery to enter. The results suggest that for low tech recreation experiences, in this case shoreline angling, income demand elasticities are negative for those who have low travel costs. These would be recreation participants who live close to the recreation site. Income elasticities however become positive for those who live further from the recreation site, thus facing higher travel costs. The travel cost at which the effects of income “switch” in the truncated corrected Poisson and negative binomial regressions are $25.64 and $30.30 respectively. These values are approximately at the mean of the truncated travel cost of $30.90.

Inclusion/exclusion of the interaction term has a greater impact on the negative binomial models compared to the Poisson models. Failure to include an interaction term between income and travel cost does not appear to greatly influence the estimated value of consumer surplus even when the interaction term is significant. Instead, the value to the researcher of including the interaction term lies within the realm of a better understanding of how people make decisions to visit a recreation site. This understanding, in turn has important implications for policy.

Access to the resource in this study, like access to resources in similar studies, is publically provided and therefore subject to the choices of public environmental management decision makers. The results of our study imply that policy decisions that limit public access to these kinds of sites will disproportionately harm local low income recreationists who have few recreation alternatives. In fact, our results make a very strong case for enhancing and improving public access to environmental amenities as a matter of fairness. High income locals engage in shoreline angling much less than their low income neighbors. Their access to the resource is not confined to the shoreline as they have opportunities for other forms of access such as boating trips, charter fishing, or trips to more distant recreation sites. Moreover, there is a good chance that these low income local anglers are using this activity to supplement their diets (Westphal et al., 2008), since fish provide an important source of low fat, high quality protein (Mozaffarian and Rimm, 2006). These considerations should play a role in the public debate in determining citizen access to environmental amenities. Our results suggest that policies that restrict public access for shoreline angling are contrary to environmental justice (Rawls, 1999).

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