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Alternative Approaches to Incorporating the Opportunity Cost of Time in Recreation Demand Models

Christopher D. Azevedo*
Department of Economics and Finance
University of Central Missouri
Warrensburg, MO 64093-5074
(660) 543-4219
cazevedo@ucmo.edu

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Economists have long recognized the important role played by the opportunity cost of time in recreation demand models. This importance derives primarily from the time-intensive nature of goods such as outdoor recreation. The time spent in travel is an important component of the travel cost or site “price,” the correct specification of which is instrumental in calculating accurate welfare measures. The sensitivity of welfare measures to the opportunity cost of time was highlighted by Bishop and Heberlein, who found that valuing travel time at half the wage rate, as opposed to not including it at all, resulted in a fourfold difference in consumer surplus estimates for their application.

One of the first authors to examine the opportunity cost of time was Cesario, who used a fixed ratio of the wage rate to value time. He wrote, “[I]t may be tentatively concluded that the value of time with respect to non-work travel is between one fourth and one half of the wage rate” (Cesario, p. 37). McConnell and Strand generalized this approach by estimating the implicit value of time directly from the data rather than assuming a fixed proportion. Bockstael *et al.* went further by recognizing that the wage rate might not provide information about the respondent’s opportunity cost of time in cases where the respondent faces a fixed work week. Other research has included the development of hedonic wage models (Smith *et al.*; Feather and Shaw) and examining the conditions under which the full wage rate is the appropriate value of time (Larson (1993)).

Despite recognizing its importance, no consensus has been reached as to the appropriate method of dealing with travel time. Most researchers take a pragmatic approach to the issue by using a fixed fraction of the wage rate, usually one third (Feather and Hellerstein (1991) and Desvousges and Waters (1995)).

Coinciding with the developments in the opportunity cost of time research have been developments in the literature concerning the relationship between revealed preference (RP) data and stated preference (SP) data.[1] These two forms of data initially enjoyed a rather adversarial relationship. Researchers would often focus on how SP data performed by treating the RP data as the "correct" basis of comparison. If the SP data performed comparably then it was said to have validated the RP data.

This began to change in the early 1990's. Rather than treating RP and SP as competing valuation techniques, analysts began to view them as complementary, where the strengths of each methodology could be used to provide more precise, and possibly more accurate, benefit estimates. The impetus for this change was a paper by Cameron (1992) in which she combined information on the number of fishing trips in Southern Texas with responses to an SP question regarding the angler's willingness-to-pay for annual angling. She noted that the same set of preferences that generate the RP data ought also to generate the SP data. Thus, both sources of data yield information on a common set of parameters. There are now numerous examples of authors using both RP and SP data to jointly estimate the parameters of a preference function (McConnell, *et al.*; Adamowicz *et al.;* Larson (1990); Dickie, Fisher, and Gerking).

An interesting aspect of models that link RP and SP data is that they can be used to test various hypotheses concerning consistency between the two types of data. The most common approach to testing consistency is a hypothesis test of whether or not the revealed and stated preference data sets generate identical estimates of the parameters of the preference function. For a more complete discussion of these types of hypothesis tests see Azevedo, Herriges, and Kling (2003).

In this paper, I examine four options for parametrically specifying the opportunity cost of travel time. Further, each option will be examined using the three methodologies for valuation discussed above: revealed preference data, stated preference data, and a model that links the two sources of data. These methodologies can be thought of as three different "laboratories" in which I can investigate the consequences of alternative treatments of time costs. These two dimensions (modeling choice vs. laboratory) provide a total of 12 variations.

There are two objectives of this paper. The first is to empirically investigate the sensitivity of the welfare estimate to both the modeling choice and the data generating process. The important question is whether the more rigorous methods yield welfare estimates that differ greatly from the welfare estimates obtained through the simpler methods. The second objective is to empirically investigate the effect of the parametric modeling decision on the results of hypothesis tests of consistency between RP and SP data.

It is important to note that this paper is not intended to be a survey of the various methods of accounting for time in the recreation demand context. It is intended to be an examination of the effect of a particular modeling decision using a handful of similar models.

The remainder of the paper is structured as follows. I will begin by describing both the laboratories and the parametric options for specifying the opportunity cost of time. An application using Iowa wetland data will then be discussed. Finally, the results and their implications will be explored.

Laboratories and Modeling Options

It will be instructive to first examine the three laboratories that will be used: revealed preference data alone, stated preference data alone, and both revealed and stated preference data in a linked model. The RP data will take the form of standard travel cost data, while the SP data will take the form of the respondent's answer to a hypothetical question. Numerous authors have discussed the various limitations of RP data (Randall) and SP data (Loomis; Diamond and Hausman). Though this discussion is beyond the scope of this paper, it has been a motivating factor in the development of hypothesis test of consistency between the two types of data. The hypothesis test proposed in this paper is one example.

Suppose that the ordinary (Marshallian) demand associated with a single recreation good can be written simply as:

$$q_i^j = f^j\left(p_i^j, y_i; \beta^j\right) + \varepsilon_i^j \qquad (1)$$

where $j = R, S$ depending on whether revealed or stated preference data is being used, q_i^j is the quantity consumed by individual i, p_i^j denotes the associated price, y_i is the individual's income, and β^j is a vector of unknown parameters. The additive stochastic term is used to capture heterogeneity in individual preferences within the population, and is assumed to follow a normal distribution, with $\varepsilon_i^j \sim N\left(0, \sigma_j^2\right)$.

Laboratory 1: Revealed Preference Data

Revealed preference data is often gathered through survey methods and includes information on the number of trips taken to the site in questions, as well as constructed proxies for the price of traveling to the site. As described above, the ordinary demand

(Marshallian) associated with the recreation good can be written simply as

$q_i^R = f^R(p_i^R, y_i; \beta^R) + \varepsilon_i^R$. Since LHS censoring is present in the data (as in many recreation demand applications), the standard Tobit model is used to obtain consistent estimates of the parameters of this function accounting for censoring.[2] Specifically, the likelihood function for the Tobit model is written

$$LL^R = \sum_{i=1}^{n} \left\{ D_i^R \ln\left[\sigma_R^{-1} \phi\left(\frac{q_i^R - f^R(p_i^R, y_i; \beta^R)}{\sigma_R} \right) \right] + \left(1 - D_i^R\right) \ln\left[\Phi\left(\frac{-f^R(p_i^R, y_i; \beta^R)}{\sigma_R} \right) \right] \right\} \quad (2)$$

where Φ and ϕ are the standard normal cdf and pdf, respectively, and $D_i^R = 1$ if $q_i^R > 0$; $= 0$ otherwise.

Laboratory 2: Stated Preference Data

Stated preference data can take a variety of forms, from direct value elicitations (contingent valuations) to behavior elicitations (contingent behavior). Suppose that in the process of gathering RP data, the survey respondents are asked: "How many recreation trips would you have taken to this site if the cost per trip increased by $*B*?" The response to this question represents a form of SP data. The respondent is providing the quantity of trips they would have taken, q_i^S, at the new, higher price, p_i^S. If, as in the case of the RP data, it is assumed that the survey responses are driven by an underlying set of preferences, the stated demands flow from demand equations of the form $q_i^S = f^S(p_i^S, y_i; \beta^S) + \varepsilon_i^S$, where $p_i^S = p_i^R + B_i$.

Having constructed the log-likelihood function for the RP data, it is quite straightforward to construct it for the SP data since they are of identical form. Thus, the log-likelihood function in Equation (2) will also describe the SP data, requiring only that R be replaced with S everywhere.

Laboratory 3: Linking Revealed and Stated Preference Data

In this case, the RP and SP data both come from the same respondent and both relate to the same recreation season. It is therefore possible to use these two points on the respondent’s recreation demand curve in conjunction. If the RP and SP data are to be linked in joint estimation of preferences, efficiency would dictate that the likely correlation between the RP and SP responses be accounted for. The log likelihood function for the linked model is given by

$$
\begin{aligned}
LL = \sum_{i=1}^{n} \Bigg\{ & D_i^R \left[\ln \phi\left(\frac{q_i^R - f_i^R}{\sigma_R} \right) - \ln\left(\sigma_R\right) \right] + D_i^R D_i^S \left[\ln \phi\left(\frac{q_i^S - f_i^S - \theta^S\left(q_i^R - f_i^R\right)}{\sigma_S\sqrt{1-\rho^2}} \right) - \ln\left(\sigma_S\sqrt{1-\rho^2}\right) \right] \\
& + D_i^R\left(1 - D_i^S\right) \left[\ln \Phi\left(\frac{f_i^S - \theta^S\left(q_i^R - f_i^R\right)}{\sigma_S\sqrt{1-\rho^2}} \right) \right] + \left(1 - D_i^R\right)\left(1 - D_i^S\right) \ln\left(\int_{-\infty}^{\frac{-f_i^R}{\sigma_R}} \int_{-\infty}^{\frac{-f_i^S}{\sigma_S}} \phi_2\left(\eta_1, \eta_2; \rho\right) d\eta_1 d\eta_2 \right) \Bigg\}
\end{aligned} \tag{3}
$$

where, $\rho \equiv Corr\left(\varepsilon_i^R, \varepsilon_i^S\right)$, $\theta \equiv \rho\sigma_S / \sigma_R$, $f_i^k = f^k\left(p_i^k, y_i^k; \beta^k\right)\ (k = R, S)$, and $\phi_2(\cdot,\cdot;\rho)$ denotes the standard normal bivariate pdf. [3]

This model can be used to test a variety of hypotheses concerning the consistency of the RP and SP data. All of the coefficients entering the SP portion of the likelihood can be constrained to be the same as those in the RP portion, in which case both forms of data are being used to estimate a single set of demand parameters. Likewise, all parameters can be allowed to differ, in which case the SP data is being used to estimate the parameters of the SP model, the RP data is being used to estimate the parameters of the RP model, and the model specifically accounts for correlation between the SP and RP errors. It is also true that any subset of parameters can be constrained to be equal between the two data sources.

A common finding in the literature is that evidence in favor of consistency between RP and SP parameters is often observed if the hypothesis test allows for differences in the variance of the two models. Add Henshar quote? "..accounting for differences in variance often accounts for most of the differences in taste parameters in a number of new and published empirical preference and choice results."

The parameter estimates reported in this paper will be for a linking model that allows σ_R and σ_S to differ, but restricts all other RP and SP parameters to be equal. This hypothesis takes the form $H_O : \beta^R = \beta^S$. A likelihood ratio statistic is used, with $\psi = 2\log\left(L^0/L\right)$, where L^0 is the restricted model's likelihood function value and L is the unrestricted model's likelihood value.

Within each of these three laboratories, four methods of incorporating time into the recreation demand model will be utilized. Each of the models differs according to the parametric specification of the variables related to the time cost in the demand function, and in general progress from ad hoc to more rigorous treatments of the opportunity cost of time.

Model 1: Fixed Marginal Opportunity Cost of Time

The first method to be examined is the use of a fixed fraction of the full wage rate to represent the respondent's opportunity cost of time. The idea being that by traveling, the respondent is forgoing the opportunity to work additional hours to increase their income. The same fixed fraction is used for all respondents. Although clearly ad hoc, this method has the advantage of simplicity, and a majority of past authors have chosen to model the opportunity cost of time in this manner.

Choosing a linear specification for equation (1), the trip demand function for respondent i takes the form

$$q_i^j = \alpha^j + \beta_p^j p_i^j + \beta_y^j y_i + \varepsilon_i^j, \;\; j = R, S \qquad (4)$$

The price term takes the form $p_i^j = C_i + \lambda w_i T_i$, where C_i denotes out-of-pocket travel expense, λ denotes the fraction of the respondent's wage at which travel time will be valued, w_i denotes the wage rate, and T_i is round-trip travel time.[4] For this application, λ will be set at one third $(1/3)$, implying that the marginal opportunity cost of time is one-third the full wage rate for all recreators, regardless of their employment status or ability to work additional hours.[5]

Model 2: Estimating a Single Marginal Opportunity Cost of Time

A generalization of the previous model is to allow the data to determine the marginal opportunity cost of time. Rather than arbitrarily choosing λ, McConnell and Strand develop a model that explicitly estimates the fraction of the full wage rate at which time is valued by adding that fraction as a parameter to be estimated. They note, "This method permits the proportion to vary from one study to another, rather than imposing either an arbitrary estimate or one from a sample different from the study's sample" (McConnell and Strand, p. 153).

In this case, the price specification takes the form

$$p_i^j = C_i + \lambda^j w_i T_i, \;\; j = R, S \qquad (5)$$

where λ^j is the proportion of the wage at which travel time is valued, and is a parameter to be estimated. This approach is more appealing than the assertion of an arbitrary fixed fraction of the wage rate, but has not enjoyed common usage due to difficulties with collinearity, a problem not present in this application.[6]

Model 3: Accounting for Employment Status, First Approach

Neither of the models discussed above make any distinction between respondents within the sample with regard to the opportunity cost of time. However, it seems intuitively reasonable to expect respondents who can trade time for money at the margin to have a different opportunity cost of time than respondents who cannot. To reflect this idea, Model 3 differentiates between respondents who can optimally adjust their work hours at the margin and those who must work at a job with a fixed number of hours.

In this case the price specification takes the form

$$p_i^j = C_i + I_i \lambda_a^j w_i T_i + (1 - I_i)\lambda_f^j w_i T_i\,, \quad j = R, S \tag{6}$$

where I_i is an indicator variable that takes a value of unity if respondent i can optimally adjust their work hours at the margin and a value of zero if they must work a fixed number of hours, λ_a^j is the marginal opportunity cost of time for respondents who can adjust their work hours, while λ_f^j is the marginal opportunity cost of time for respondents who must work a fixed number of hours. This approach allows for some flexibility but is still a rather ad hoc method of accounting for the employment status of the respondent.

Model 4: Accounting for Employment Status, Bockstael et al. Model

The final method was developed in Bockstael, Strand, and Hanemann, who approached the problem by examining the structure of the time constraint. They emphasized that the nature of an individual's labor supply decision determines whether their wage rate yields information about the marginal value of their time. It may not be possible for a respondent to optimally adjust the number of hours worked. If this is the case, they will be found at a corner solution where they choose either to not work, or to work a job with a fixed number of hours. The respondent may choose to work a part-time job with a flexible number of hours in addition to their job with fixed hours, or they may choose not to work at all.

The important point of their paper is that it is only appropriate to use the wage rate to estimate the opportunity cost of time for respondents who can optimally adjust their work hours. For respondents who cannot trade time for money, the wage provides no information about the opportunity cost of time. It is also important to note that the Bockstael *et al.* model is derived from a utility theoretic basis, whereas the previous three models represent ad hoc attempts to account for the opportunity cost of time.

Bockstael *et al.* specify a utility function, the maximization of which results in a linear trip demand function. The trip demand function for respondents who can optimally adjust their work hours takes the form

$$q_i^j = \alpha^j + \gamma_1^j \left(y_i + w_i \overline{T}_i \right) + \beta'^j \gamma_1^j \left(C_i + w_i T_i \right) + \varepsilon_i^j , \tag{7}$$

where $\overline{T}_i$ represents discretionary time (time spent not working) and $\beta'^j = \beta^j \big/ \left(\gamma_1^j + \gamma_2^j \right)$.

Notice that if the respondent can optimally adjust their work hours at the margin, the marginal impacts of income and discretionary time, valued at the full wage rate, are identical and are represented by γ_1^j. Additionally, the marginal impacts of out-of-pocket travel expense and travel time, valued at the full wage rate, are identical and are represented by $\beta'^j \gamma_1^j$.

The trip demand function for respondents who can not optimally adjust their work hours takes the form

$$q_i^j = \alpha^j + \gamma_1^j y_i + \gamma_2^j \overline{T}_i + \beta_i'^j \gamma_1^j C_i + \beta_i'^j \gamma_2^j T_i + \varepsilon_i^j \,. \tag{8}$$

It is important to note that the wage does not enter the demand function of respondents who cannot optimally adjust their work hours. Also, notice that the marginal impact of discretionary time is now represented by the parameter γ_2^j (as opposed to γ_1^j), while the marginal impact of travel time is represented by $\beta'^j \gamma_2^j$ (as opposed to $\beta'^j \gamma_1^j$). None of the previously discussed models exhibit these attributes.

The model is applied by simultaneously estimating equations (9) and (10) while imposing the restriction of parameter equality between the two equations. For a thorough explanation see Bockstael *et al.*

In general, these models progress from ad hoc to more rigorous treatments of the opportunity cost of travel time.[7] The effect of the various treatments on welfare estimates, as well as the hypothesis tests of consistency between SP and RP data will be examined with an application described in the next section.

Application to Wetlands in Iowa

These models will be estimated using data drawn from a 1997 survey of 6000 Iowa residents concerning their use of Iowa wetlands. The goal of the survey was to elicit information from respondents about their visits to, knowledge about, and attitudes toward the existing wetlands in Iowa, as well as efforts to preserve and expand those resources. Of the deliverable surveys, 59 percent were returned. The survey instrument elicited travel cost information, contingent behavior information, contingent valuation information, as well as socioeconomic information (e.g., gender, age, and income). The survey also gathered employment information such as the respondent’s hourly wage and whether they were able to adjust the number of hours they work in order to increase their income. A complete discussion of the Iowa Wetland data set can be found in Azevedo (1999).

This analysis draws on the first section of the survey. This section focused on the respondent's visits to Iowa wetlands during the past year. After carefully defining what was meant by a "wetland," respondents were asked the number of recreation trips they had taken during the past year to wetlands in each of fifteen possible zones (see Figure 1). These zones, defined along county lines for convenience of the survey respondent, were designed to reflect major types of wetlands within the state.[8] Responses to this first question provide the basis for the revealed preference variable, q_i^R. In particular, q_i^R represents the number of wetland recreation trips individuals took to wetlands located in their own zone.

Individuals were then asked how their pattern of usage would have changed if the cost of visiting wetland zones near their residence, zones X, Y, and Z for example, were higher.[9] In particular, they were asked to "…[c]onsider all of the recreation trips you made to wetlands in zones X, Y, and Z in 1997. Suppose that the **total cost per trip of each of your trips** to these areas had been $*B* more (for example, suppose that landowners charged a fee of this amount to use their land or that public areas charged this amount as an access fee)."

The value of $*B* varied across the individuals surveyed, with bid values of $5, $10, and $15 each randomly assigned to 60% of the sample and bid values of $20, $30, $40, and $50 each assigned to 40% of the sample. The initial bid distribution was based on previous travel cost studies performed a Storm Lake, Iowa, and was discussed with focus groups conducted with Iowa residents. Analysis of the results of a pre-test of 600 surveys using this bid design indicated that it was adequate.

Respondents were then asked to detail how their behavior would have changed with the increased cost, both in terms of the reduction in visits to areas X, Y, and Z, as well as changes in visits to other zones within the state. These questions provide the basis for constructing the SP quantity variable, q_i^S.

While the surveys provide direct information on the trip quantities, the travel costs themselves must be constructed. The first step in the process was to establish travel time, t_i^z, and travel distance , d_i^z, for visits to the wetland zones (*z* = 1,…,15). One survey question asked the respondent to place an X on a map, similar to Figure 1, indicating the location of their most recent wetland visit. The longitude/latitude coordinates for the visitation points in each of the 99 counties were then averaged to find the mean visitation point in that county. For each respondent, the travel time and travel distance from their residence to each of the 99 mean visitation points was calculated using PC Miler, a software package designed for use in the transportation and logistics industry. This resulted in a data set with 99 travel times and distances for each respondent in the database. Finally, zonal travel times (t_i^z) and distances (d_i^z) were calculated as a weighted average of their respective county-level values.[10]

It is important to note that the use of centroids, as described above, can introduce error into the estimation process. Bateman *et al.,* (1999) examines the use of centroids in travel cost estimation can result in inflated welfare estimates. The size of the bias is related to the size of area used in the centroid calculation. However, one must bear in mind that the purpose of this paper is not to generate the most reliable consumer surplus estimates possible, but rather to compare various approaches of modeling the opportunity cost of time using a group of similar models. To the extent that the use of centriods introduces error into one model, it also introduces the same error into the other models considered in the paper.

I have chosen to focus on a subset of the survey sample; those households in the Prairie Pothole Region of north central Iowa (zones 4, 5, and 8). This region of Iowa is characterized by a fairly homogenous form of wetland defined in the survey as consisting of "…natural depressions in the landscape that are filled with water for at least part of the year and may range in size from a fraction of an acre to over 500 acres."

Table 1 contains summary statistics for the data. I consider the aggregate number of trips to the region, defined as $q_i^k \equiv q_i^{k4} + q_i^{k5} + q_i^{k8}$ ($k = R, S$). Travel times and distances were formed as weighted averages of the zone 4, 5, and 8 values, where the weights used for individual *i* were the average percentage of trips to each zone among individuals in *i*'s zone of residence. On average, for the 269 households with completed surveys in the Prairie Pothole region, 8.2 trips (q_i^R) were actually taken, with an average out-of-pocket travel cost of \$23. With the average hypothetical price increase (\$*B*) of about \$25 per trip, respondents indicated that they would average only about 2.7 trips (q_i^S).

Figure 2 illustrates the quantity of trips taken at the original set of prices (Demand – RP) as well as at the higher set of prices (Demand – SP). The figure illustrates that there is considerable overlap between the RP and SP quantities in this data set. The complete range of quantities is represented for both forms of data, which indicates that they both provide information on the same region of the demand curve. Naturally, more information will be provided on the lower quantity region by SP data set due to the fact that it includes higher prices than the RP data set.

Parameter Estimates

Models 1 through 4 were each estimated with the three data laboratories. Table 2 shows parameter estimates, with t-statistics in parenthesis, for each of the four models.[11] Results are grouped by model as well as by laboratory. Average consumer surplus (CS) estimates are provided, along with the results of the hypothesis test of consistency between RP and SP data.

In general, the parameter estimates have the expected signs and most of them are statistically significant. The most striking aspect of these results is the difference in the estimates of λ between the RP and SP laboratories. Model 2 estimates a revealed preference λ of –0.06 (not significantly different from zero), while the stated preference λ is 0.43. Model 3 also estimates revealed preference λ's very near zero with stated preference λ's significantly larger. This implies that the practice of using a fixed λ, often chosen at or near one-third, would likely be more problematic with the RP data.

Another interesting result is that the estimates of λ_f and λ_a within Model 3 are very similar. This indicates that with respect to the magnitude of marginal opportunity cost of time, for this demand specification, there does not appear to be much difference between respondents who can adjust their work hours and those who cannot. In the RP laboratory, the estimate for λ_f is 0.002 while the estimate for λ_a is 0.00. Though they are very similar in magnitude, the hypothesis of equality between the two is rejected. In both the SP and RP-SP laboratories the estimates for λ_f and λ_a are slightly different (0.48 vs. 0.41 in the SP case and 1.48 vs. 0.50 in the RP-SP case) but still very close. Of course, this result is likely a consequence of the ad hoc nature of the model and the inability of the wage data to provide information about the opportunity cost of time for respondents who cannot optimally adjust their work hours, rather than evidence that the opportunity cost of time is the same for the two.

All models exhibit a high degree of correlation between the RP and SP data sets, as shown by the estimates of ρ in Laboratory 3. Estimates of ρ are 0.70 for Model 1, 0.73 for Model 2, 0.72 for Model 3, and 0.66 for Model 4.

Implications: Welfare Measures and RP-SP Consistency

As noted previously, the use of centroids in the travel cost calculations likely introduced bias into the welfare estimates, so they are probably not the most useful from a policy perspective. However, they can still be used for model comparison purposes. The results show that the modeling choice can have a significant effect on the consumer surplus measure. Within the RP Laboratory, consumer surplus ranges from a low of 82.80 (Model 2) to 429.88 (Model 4, flexible hours). The consumer surplus estimates for Model 4 are not very precise compared to the other three models.

Within Laboratory 2, consumer surplus ranges from a low of 216.53 (Model 1) to 429.88 (Model 4, flexible hours). Within Laboratory 3, consumer surplus ranges from a low of 147.89 (Model 4, fixed hours) to 235.35 (Model 4, flexible hours).

For a given model, the choice of data used can have a dramatic effect on the consumer surplus estimates. Laboratory 1 (RP data alone) consistently produces lower consumer surplus estimates than Laboratory 2 (SP data alone), with Laboratory 3 (RP-SP) falling between the two, as expected.

The modeling choice can also have a significant effect on the hypothesis test of consistency between RP and SP data, even when differences in the variance of the two sources of data are accounted for. Laboratory 3 is used to test the hypothesis of parameter equality between the RP and SP data sets. Hypothesis test results are shown in Table 2. Models 1 and 4 both show evidence in favor of consistency between the SP and RP data (failure to reject the null hypothesis of consistency), while Models 2 and 3 both show evidence contrary to the hypothesis of consistency.

The evidence in favor of consistency exhibited by Model 1 is directly dependent on the value of λ chosen by the researcher. To illustrate this, a search procedure was conducted that varied the value of λ, each time estimating the model and conducting the hypothesis test of consistency. Figure 3 shows the result of this search procedure.

There exists a range of λ values that will result in a failure to reject the null hypothesis of consistency between the revealed and stated preference data. The "fail to reject" region includes values of λ between 0.08 and 1.36.

This is an important finding. Testing for consistency between revealed and stated preference data is often a goal of papers that link both forms of data. As these results show, the choice of model can have a significant impact on the outcome of hypothesis tests of consistency between revealed and stated preference data. Further, when estimating the model with a fixed λ, the consistency results depend on whether the value of λ chosen falls into the range of "consistent λ's" for that data set. However, if the opportunity cost of travel time is added as a parameter to be estimated as in Models 2 and 3, all tests result in a rejection of the null hypothesis of consistency. Consistency tests for Model 4 resulted in a failure to reject the hypothesis of consistency.

Conclusions

In this paper I have examined a few of the choices that are available for modeling the opportunity cost of time. By choosing some representative methods of modeling the opportunity cost of time, it has been shown that this modeling choice can have important impacts on welfare estimates. Along the same lines, the choice of which type of data to use (RP, SP, RP and SP) can impact the welfare estimates.

It has also been shown that the parametric modeling choice can impact the results of the hypothesis test of consistency between RP and SP data. Using the same data, hypothesis tests for models 2 and 3 show evidence against consistency, while the same tests for models 1 and 4 show evidence in favor of consistency.

It was further shown that the choice of model one (the pragmatic approach of picking a fixed fraction), along with a fixed rate of one third, results in a failure to reject the hypothesis of consistency for this application. Changing either the modeling choice or the fraction of the full wage at which time is valued can reverse the results of the hypothesis test.

These results illustrate that the researcher should carefully consider the choice of how to model the opportunity cost of time in the recreation demand model. The method used can impact not only the magnitude of the welfare estimates, but also the outcome of hypothesis tests of consistency between stated and revealed data.

References

Adamowicz, W., J. Louviere, and M. Williams. “Combining Revealed and Stated Preference Methods for Valuing Environmental Amenities,” *Journal of Environmental Economics and Management*, 10(1994): 271-292.

Azevedo, C. D. “Linking Revealed and Stated Preference Data in Recreation Demand Modeling,” Ph.D. Dissertation, Iowa State University (1999).

Azevedo, C. D., J. A. Herriges, and C. L. Kling. “Combining Revealed and Stated Preferences: Consistency Tests and Their Interpretations,” *American Journal of Agricultural Economics*, 85(2003): 525-537.

Bateman, I. J., J. S. Brainard, A. A. Lovett, and G. D. Garrod. “The Impact of Measurement Assumptions Upon Individual Travel Cost Estimates of Consumer Surplus: a GIS Analysis,” *Regional Environmental Change*, 1(1999): 24-30.

Bishop, R. and T. Heberlein. “Travel Cost and Hypothetical Valuation of Outdoor Recreation: Comparisons with an Artificial Market,” Department of Agriculture Working Paper, University of Wisconsin (1979).

Bockstael, N. E., I. Strand, and W. M. Hanemann. “Time and the Recreation Demand Model,” *American Journal of Agricultural Economics,* 69(1987): 293-302.

Cameron, T. “Combining Contingent Valuation and Travel cost Data for the Valuation of Nonmarket Goods,” *Land Economics* 68(1992): 302-317.

Cameron, T., G. Poe, R. Ethier, and W. Schulze. “Alternative Nonmarket Value-Elicitation Methods: Are The Underlying Preferences the Same?” *Journal of Environmental Economics and Management*, 44(2002): 391-425.

Cesario, F. J. "Value of Time in Recreation Benefit Studies," *Land Economics,* 52(1976): 32-41.

Desvousges, W. H. and S. M. Waters. *Report on Potential Economic Losses Associated with Recreation Services in the Upper Clark Fork River Basin*. Durham, N.C.: Triangle Economic Research.

Diamond, P. A. and J. A. Hausman. "Contingent Valuation: Is Some Number Better Than No Number?" *Journal of Economic Perspectives,* Fall 1994, 45-64.

Dickie, M., A. Fisher, and S. Gerking. "Market Transactions and Hypothetical Demand Data: A Comparative Study," *Journal of the American Statistical Association,* 82(1987), 69-75.

Feather, P., and D. Hellerstein. "Calibrating Benefit Function Transfer to Assess the Conservation Reserve Program," *American Journal of Agricultural Economics,* 79(1997): 151-162.

Feather, P. and Shaw W. D. "Estimating the Cost of Leisure Time for Recreation Demand Models," *Journal of Environmental Economics and Management,* 38(1999): 49-65.

Larson, D. "Testing Consistency of Direct and Indirect Methods for Valuing Nonmarket Goods," University of California, Davis, draft manuscript, December 1990.

Larson, D. "Separability and the Shadow Value of Leisure Time," *American Journal of Agricultural Economics*, 75(1993): 572-577.

Loomis, J., A. Gonzalez-Caban, and R. Gregory. "Do Reminders of Substitutes and Budget Constraints Influence Contingent Valuation Estimates?" *Land Economics,* 70(1994): 499-506.

McConnell, K., and I. Strand. “Measuring the Cost of Time in Recreation Demand Analysis: An Application to Sport fishing,” *American Journal of Agricultural Economics*, 63(1981): 153-156.

McConnell, K., Q. Weninger, and I. Strand. “Joint Estimation of Contingent Valuation and Truncated Recreational Demands,” Chapter 7 in *Valuing Recreation and the Environment: Revealed Preference Methods in Theory and Practice*, edited by J. A. Herriges and C. L. Kling, Edward Elgar Press, Aldershot, 1999: 199-216.

Randall, A. “A Difficulty with the Travel Cost Method,” *Land Economics*, 70(1994): 88-96.

Smith, V. K., W. H. Desvousges, and M. P. McGivney. “The opportunity cost of travel time in recreational demand models,” *Land Economics*, 59(1983): 259-277.

Endnotes

[1] The terms revealed preference data and stated preference data are used to differentiate between data that is revealed by actual respondent behavior (for example, the number of trips actually taken), versus data that is hypothetical in nature (for example, the number of trips you would take at a price of $X).

[2] Censored data arise when values of the dependent variable in a certain range are reported as a single value. In this case, quantity of trips taken by the respondent must be greater than or equal to zero, even though the respondent may desire to take a negative number of trips at the price proposed.

[3] The derivation of this log-likelihood function is available from the author upon request.

[4] Recall that the SP price takes the form $p_i^S = p_i^R + B$.

[5] Notice the similarity between Model 1 and the hedonic wage approach. In Model 1, the respondent's time is being valued at one third of their reported wage rate. In a hedonic approach such as the Feather and Shaw (1999) model, the respondent's time is valued at their shadow wage, which is estimated separately and enters into the recreation demand model as data. Though the hedonic approach is operationally similar to Model 1, it is based on a much sounder theoretical basis.

[6] Collinearity is often a problem with this approach since out-of-pocket travel expense, C_i, and travel time, T_i, are closely related. In this application, the wage data, w_i, introduced enough variation between travel expense and travel time that collinearity was not a problem.

[7] All of these models ignore the issue of substitute sites, which is often an important aspect of recreation demand models. However, the data that is used to estimate these models was drawn from a geographical area characterized by very homogenous wetland areas.

[8] For example, zones 4, 5, and 8 represent the prairie pothole region of north central Iowa. Pothole wetlands are the result of glacial activity and characterized by depressions in the land, most of

which are less than two feet deep and filled with water for at least part of the year. In contrast, riverine wetlands dominate regions 1 through 3 and 13 through 15, and are associated with marshy land near rivers and streams.

[9] The wetland zones (X, Y, and Z) were assigned to individuals based upon the region of the state in which they lived. Specifically, the fifteen zones in Figure 1 were grouped into five "megazones," reflecting regional wetland areas. These megazones were defined as the Missouri River Region (1,2,3), the Prairie Pothole Region (4,5,8), the Iowa River Corridor Region (9,10,11), the Mississippi Region (13,14,15), and the remainder of the state (6, 7, 12). The zonal number (X, Y, Z) for a given survey respondent consisted of those zones defining the megazone in which the respondent lived.

[10] Each county's weight was determined by the percentage of trips within that county's zone taken to that county. For example, zone three is made up of Pottawattamie, Mills, and Fremont counties. There were 92 trips taken to zone three. 41 trips were taken to Pottawattamie County, 24 trips were taken to Mills County, and 27 trips were taken to Fremont County. Therefore, the weight for Pottawattamie County was 0.45, the weight for Mills County was 0.26, and the weight for Fremont County was 0.29.

[11] A test for heteroskedasticity in the residuals of the form $\sigma^2 = \sigma^2 \exp(\alpha P)$ was conducted. The hypothesis of homoskedasticity (i.e. $\alpha = 0$) could not be rejected at standard significance levels. The results from the heteroskedasticity test are available from the author upon request.

Table 1. Data Summary for 4,5,8 Megazone (Standard Errors in Parenthesis)

Number of respondents	269
Average out-of-pocket travel cost	\$22.62 (10.26)
Average round trip travel time (hours)	1.31 (0.55)
Average out-of-pocket travel cost with $\$B$ increase	\$47.91 (16.84)
Average Income	\$35,000 (\$26,000)
Percent of respondents taking zero trips prior to price increase	34
Percent of respondents taking zero trips after the price increase	74
Average number of trips (RP)	8.22 (11.04)
Average number of trips (SP)	2.61 (6.32)

Table 2. Parameter Estimates (t-statistic in parenthesis, standard error in brackets)

		Laboratory 1: RP	Laboratory 2: SP	Laboratory 3: RP-SP
Model 1: Fixed $\lambda = 1/3$	α	15.69 (7.20)**	10.57 (2.66)**	14.92 (7.38)**
	β	-0.52 (-7.68)**	-0.45 (-5.99)**	-0.50 (-12.79)**
	γ	0.18 (4.81)**	0.18 (3.20)**	0.18 (4.99)**
	σ_R	13.79 (18.09)**	--	14.05 (19.17)**
	k_S	--	15.26 (10.97)**	1.01 {0.25}
	ρ	--	--	0.70 (17.54)**
	CS	185.12 [26.66]	216.53 [39.94]	189.61 [15.94]
	RP-SP consistency			Fail to reject
Model 2 Estimating λ	α	27.11 (8.77)**	9.77 (2.31)*	14.22 (6.84)**
	β	-1.15 (-8.37)**	-0.42 (-4.64)**	-0.46 (-8.02)**
	λ	-0.06 (-1.59)	0.43 (2.39)*	0.47 (3.30)**
	γ	-0.02 (-0.32)	0.20 (2.92)**	0.22 (4.58)**
	σ_R	13.26 (18.30)**	--	14.48 (18.10)**
	k_S	--	15.31 (11.25)**	0.98 {-0.24}
	ρ	--	--	0.73 (16.92)**
	CS	82.80 [10.00]	239.85 [60.92]	206.38 [26.38]
	RP-SP consistency			Reject
Model 3 Different λ's	α	25.04 (8.90)**	9.77 (2.41)*	14.00 (6.65)**
	β	-1.03 (-8.61)**	-0.41 (-4.70)**	-0.45 (-8.34)**
	λ_f	0.002 {8.34}**[1]	0.48 {0.90}[1]	1.14 {0.86}[1]
	λ_a	0.000 (0.08)	0.41 (2.36)	0.44 (3.57)**
	γ	0.04 (1.10)	0.20 (3.10)	0.22 (4.24)**
	σ_R	13.33 (18.30)	--	14.40 (16.20)**
	k_S	--	15.27 (10.46)	0.97 {-0.42}
	ρ	--	--	0.72 (14.62)**
	CS	93.11 [11.11]	242.68 [66.19]	213.33 [26.50]
	RP-SP consistency			Reject
Model 4 Bockstael *et al.*	α	13.56 (7.41)**	12.82 (2.88)**	11.98 (7.10)**
	γ_1	0.10 (6.18)**	0.05 (1.20)	0.09 (7.45)**
	γ_2	0.21 (0.47)	1.26 (2.43)**	0.33 (0.82)
	β'	-5.89(-9.22)**	-8.20 (-2.51)*	-5.65 (-8.42)**
	σ_R	13.41 (18.37)**	--	13.56 (20.31)**
	k_S	--	14.75 (11.03)**	1.04 {0.48}
	ρ	--	--	0.66 (15.50)**
	CS: flexible hours	201.82 [416.30]	429.88 [886.72]	235.35 [485.47]
	CS: fixed hours	126.82 [308.28]	270.13 [656.63]	147.89 [359.50]
	RP-SP consistency			Fail to reject

** Denotes significance at the 99% confidence level

* Denotes significance at the 95% confidence level

[1] t-statistic for a hypothesis test of significant difference between λ_f and λ_a

Figure 1. Iowa wetland zones

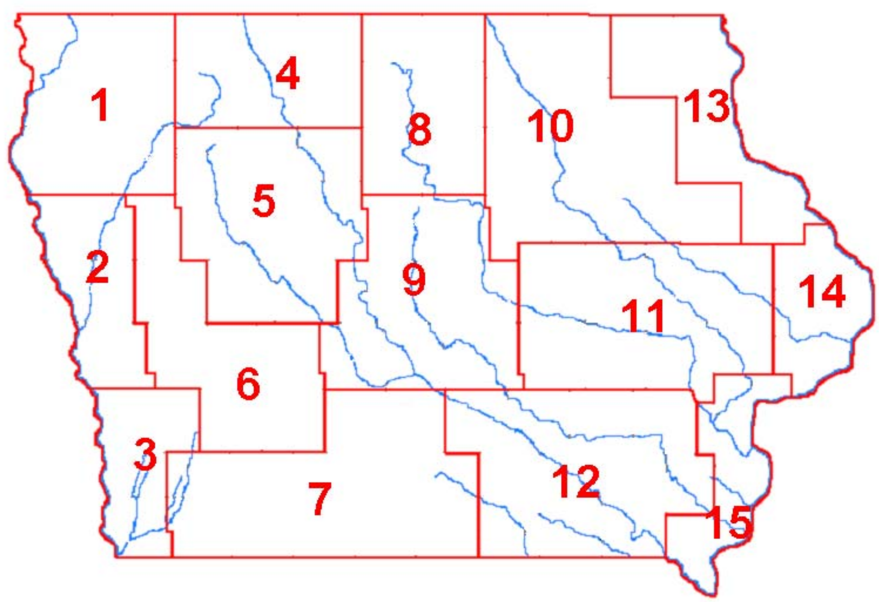

Figure 2. Data Plot

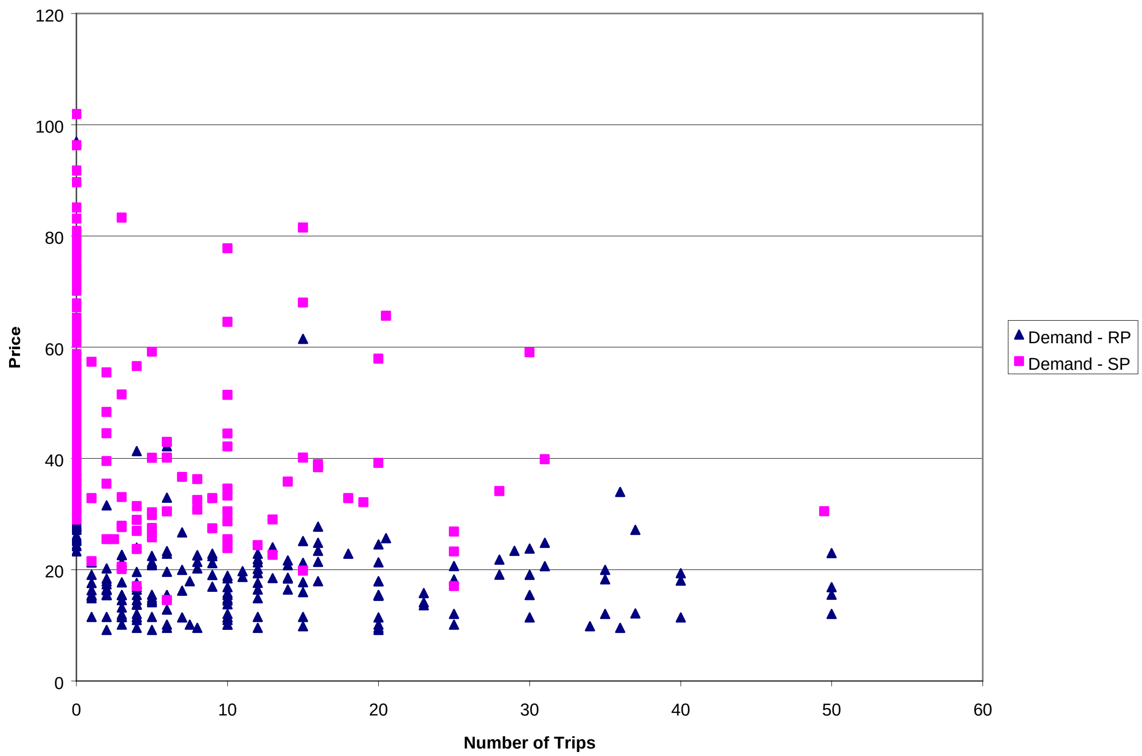

Figure 3. Testing general consistency with fixed lambda