Ask a Hypothetical Question, Get a Valuable Answer?

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Abstract

This paper models the recreation demand for Iowa wetlands, combining survey data on both actual usage patterns (i.e., revealed preferences) and anticipated changes to those patterns under hypothetical increases in trip costs (i.e., stated preferences). We formulate and test specific hypotheses concerning potential sources of bias in each data type. We consistently reject consistency between the two data sources, both in terms of implied wetland values and underlying preference parameters. Careful attention is paid to the interpretations of the test results, noting particularly how the interpretation of the same results can vary with the "school of thought" of the reader.

Key Words: Revealed preference, stated preference, recreation, wetlands.

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*"Economists have inherited from the physical sciences the myth that
scientific inference is objective, and free of personal prejudice.
This is utter nonsense."*—Leamer (1983, p. 36)

I. Introduction

Economists began investigating the use of surveys to elicit consumers' willingness-to-pay for public goods over three decades ago. The vast majority of the early applications concerned environmental goods, although numerous other public goods have been the subjects of valuation surveys. In the last decade, the use of surveys to elicit welfare values has come under debate by the profession at large. The now famous National Oceanic and Atmospheric Administration (NOAA) blue ribbon panel (Arrow et al. 1993) was assembled to consider the validity of these survey methods (also called contingent valuation or stated preference methods) and the *Journal of Economic Perspectives* ran a symposium with competing views on the topic (Diamond and Hausman 1994; Hanemann 1994; Portney 1984).

The fundamental question in this debate might be stated: can carefully designed survey methods provide informative data on consumers' willingness to pay for public goods, or does the hypothetical nature of these instruments render them irrelevant, regardless of how much attention is given to truth-revealing mechanisms in their construction? The initial reaction of most economists to this question is that hypothetical questions will generate hypothetical answers that likely bear little relation to the "true" answers. Critics of stated preference (SP) methods point to numerous potential sources of bias. For example, it has been argued that survey respondents may ignore or downplay their budget constraint in answering hypothetical questions (e.g., Arrow et al. 1993; Loomis, Gonzalez-Caban, and Gregory 1994; Kemp and Maxwell 1993). Additional criticisms include concerns that SP-based willingness-to-pay estimates fail to vary sufficiently

with the scope of the resource being valued, the so-called "embedding effect" (e.g., Desvousges et al. 1993; Kahneman and Knetsch 1992), and that they are inordinately sensitive to the elicitation format used (e.g., McFadden 1994; Diamond and Hausman 1994).

Yet, there also is substantial evidence that answers to carefully designed surveys contain at least some information content. At the most basic level, Mitchell and Carson (1989, pp. 206-207) note that valuation estimates based upon SP methods are typically correlated in the expected direction with those independent variables that theory predicts should influence consumer preferences. Thus, the demand for an environmental improvement is usually found to decrease with the cost of its provision and increase with the income level of the respondent. Of course, internal validity checks are not sufficient to justify a reliance on SP-based valuations. To further investigate their validity, researchers have turned to comparisons to valuation estimates based upon revealed preference (RP) data, including actual market transactions for related goods (e.g., Cameron 1992a; Adamowicz, Louviere, and Williams 1994) or simulated market transactions obtained in a laboratory setting (e.g., Cummings et al. 1997; Cummings and Taylor 1999). The shear number of such comparisons has grown dramatically over the past two decades. In summarizing 83 studies with 616 such comparisons, Carson et al. (1996) find that the ratio SP to RP valuations for essentially to same good ranges from 0.005 to 10.269. However, the ratio generally lies near 1.00 and the RP and SP estimates are highly correlated (with a rank correlation between 0.78 and 0.92). For many, including the now infamous NOAA panel, these results hold out the hope that useful information can be gleaned from properly designed SP surveys. The question remains as to how best to use that information: in isolation, calibrated to similar RP results, or combined with RP data.

In this paper, we address this issue in the context of valuing recreational wetland usage in Iowa. The empirical analysis draws on a 1997 survey of 6,000 Iowa residents, which elicited both revealed and stated preferences regarding the use of wetland regions in the state. Like previous efforts to combine RP and SP data (e.g., Cameron et al. 1999; McConnell, Weninger, and Strand 1999; Huang, Haab, and Whitehead 1997), we develop a joint model of individual responses to both the RP and SP questions and use the resulting framework to test for consistency between the two sources of information. In doing so, however, we also emphasize testing specific hypotheses concerning sources of bias in *both* revealed and stated preference

data. In carrying out these sets of hypothesis tests, we carefully investigate alternative interpretations of the results, noting particularly how the interpretation of the same results can vary with the "school of thought" of the reader. These arguments are in the vein of Leamer's (1983) famous discussion of alternative interpretations of the same data by those with different initial views of capital punishment.

The remainder of the paper is divided into six sections. Section II begins by reviewing the various schools of thought that have emerged in the literature in interpreting RP and SP data. The underlying behavioral and econometric models are detailed in Section III, along with hypothesis tests designed to test for specific sources of bias in each data source. The Wetlands database is then described in Section IV. Model specifications are presented in Section V with the results of the model estimation and hypothesis testing provided in Section VI. Section VII offers a summary and conclusions.

II. Schools of Thought

Nearly two decades ago, Leamer warned of the potential fragility of econometric analysis to hidden "whimsical assumptions" and the delusion of the "...goal of objective inference" (1983, p. 37), arguing that the initial beliefs of a researcher too often drive the conclusions gleaned from a database. These concerns are no less relevant today and nowhere more apparent than in the debate over the relative merits of stated and revealed preference methods in valuing of nonmarket amenities. With literally hundreds of comparisons between RP and SP valuations appearing in the literature, the prior beliefs of the analyst often color the hypotheses tested and inferences made from conflicts between the two sources of data. In this section, we describe three basic schools of thought that seem to have emerged.

The first school of thought, which we will refer to as the "RP-lovers" sect, views SP data with skepticism. In its extreme form, the group denounces SP methods, characterizing its use in the policy arena as misguided. Proponents of this view argue that "...contingent valuation surveys do not measure the preferences they attempt to measure..." and that "...changes in survey methods are not likely to change this conclusion" (Diamond and Hausman 1994, p. 46). The less extreme portion of this sect holds out some hope for SPs to inform policymakers, while holding

onto the sanctity of RP data. McConnell, Weninger, and Strand (1999, p. 201) echo this sentiment when they consider a joint model of RP and SP data:

> In other words, the preference structure that governs the RP decision may be completely independent from the preference structure that governs the SP decision. If so, the information gleaned from SP methods is arbitrary and can lead to unreliable estimates of trip value. On the other hand, when the underlying preference structure is identical, both the RP and SP decisions provide useful information for valuing environmental amenities.

Thus, SP methods are only of value if they are consistent with their RP counterparts. Indeed, the notion of "calibrating" welfare estimates obtained from SP data is essentially a tenet derived from this school of thought, as it implies a calibration to RP estimates.

A smaller, though no less devoted, sect is the "SP-lovers" school of thought. Much like their counterparts, "SP-lovers" view with skepticism results based on commonly used RP techniques, such as hedonic pricing and travel cost methods, noting their many sources of bias and limited applicability to the valuation of environmental amenities. Travel cost methods suffer, among other things, from "...value-allocation assumptions related to multipurpose 'visits'; dependence of costs on assumptions concerning fixed/variable direct travel costs, costs (benefit?) of time in travel and on-site; and problems in obtaining values which are appropriately 'marginal' vis-à-vis the site/activity in questions" (Cummings, Brookshire, and Schulze 1986, p. 95). As Randall (1994, p. 88) argues, the trip quantities employed in a travel cost model may be "revealed," but the prices necessary to derive trip demand functions, and hence welfare estimates, are not. Consequently, the travel cost method "...yields only ordinally measurable welfare estimates..." and "...cannot serve as a stand-alone technique for estimating recreation benefits." Similarly, the hedonic pricing methods are plagued by "…persistent collinearity between 'important' variables and extraordinarily low explanatory power in regression equations" (Cummings, Brookshire, and Schulze 1986, p. 96). At the very least, this school of thought would argue that SP methods deserve equal footing in the pantheon of valuation techniques. At its extreme, this school of thought would hold that RP preference methods are not only fraught with limitations, but simply not capable of capturing the range of use and nonuse values associated with environmental changes, leaving SP methods as the only game in town.

In recent years, a third school of thought has emerged, arguing for a reliance on both revealed and stated preferences (e.g., Cameron 1992a; Adamowicz, Louviere, and Williams

1994; Kling 1997). These "agnostics" suggest a shift in focus away from viewing RP and SP as competing sources of values and towards seeing them as complementary sources of information. In this view, both data sources illuminate, though imperfectly, consumer preferences for environmental amenities of interest. Revealed preference methods bring the "discipline of the market" to stated preference valuations, whereas SP methods can shed light on the consumer of preferences for price and quality attribute levels that are not currently observed in the market (Cameron 1992b). Discrepancies between the individual parameter estimates obtained using RP and SP estimates are not necessarily indicative of a failure of either method, but instead suggest that the two sources are working in correcting the limitations inherent in each method. This ecumenical view would not fall back on either data source as "correct," but would rely instead on their combination as providing the best source of welfare estimates.

III. Behavioral and Econometric Models of Preferences

In developing behavioral models underlying revealed and stated preference data sources, we focus our attention on a single recreation good (q), though obvious extensions exist to the multiple good situations. Individual *i*'s "true" preferences are assumed to result in an ordinary (Marshallian) demand equation given by:

$$q_i = f\left(p_i, y_i; \beta\right) + \varepsilon_i \tag{1}$$

where q_i denotes the quantity consumed by individual *i*, p_i denotes the associated price, y_i is the individual's income, and β is a vector of unknown parameters. The additive stochastic term is used to capture heterogeneity in individual preferences within the population. Ideally, the analyst would have available data on the actual price and quantity for environmental good in question, along with quality attributes for that good and individual socio-demographic characteristics. Unfortunately, for both revealed and stated preference models, environmental valuation efforts often rely upon imperfect and indirect measures for these variables.

Revealed Preferences

Revealed preference models, such as travel cost models, rely upon surveys to elicit information on the number of trips taken to the site in question (q_i^R) and to construct proxies for

the price of traveling to the site (p_i^R), including the cost of expended time in traveling to the site. The demand relationship modeled using this data is assumed to take the form:

$$q_i^R = f^R \left(p_i^R, y_i^R; \beta^R \right) + \varepsilon_i^R . \qquad (2)$$

As is often the case in the literature, the error term is assumed to be drawn from a normal distribution, with $\varepsilon_i^R \sim N \left(0, \sigma_R^2 \right)$. Standard econometric procedures can then be employed to obtain consistent estimates of the parameters of the function accounting for the truncation from the left at zero. Specifically, maximum likelihood estimation would rely upon the log-likelihood function

$$LL^R = \sum_{i=1}^{n} \left(D_i^R \ln \left\{ \sigma_R^{-1} \phi \left[\frac{q_i^R - f^R \left(p_i^R, y_i^R; \beta^R \right)}{\sigma_R} \right] \right\} + \left(1 - D_i^R \right) \ln \left\{ \Phi \left[\frac{-f^R \left(p_i^R, y_i^R; \beta^R \right)}{\sigma_R} \right] \right\} \right) \qquad (3)$$

where $\Phi(\cdot)$ and $\phi(\cdot)$ are the standard normal cdf and pdf, respectively, and $D_i^R = 1$ if $q_i^R > 0; = 0$ otherwise.

There are, of course, numerous reasons for discrepancies between the demand relationships in equations (1) and (2). First of all, trip data are typically quantities based upon survey questions asking the individual to recall their number of trips over the past year. Recall errors and rounding by survey respondents contribute to differences between both the quantities and the error distributions in the two equations. Second, and perhaps of greater concern, are the discrepancies between the actual visitation costs (p_i) and those constructed by the analyst (p_i^R). It is standard practice to compute travel costs as the sum of the out-of-pocket cost of visiting the site in question (typically using a fixed cost per mile times the round-trip distance to the site) and a proxy for the value of the time used in getting to the site. Time is most often valued as a fixed fraction of the individual's wage rate (Cesario 1976).[1] The reliance on this, or similar, conventions drives a wedge between the individual's true demand equation in (1) and the estimated relationship in (2). In turn, this has led a number of critics to argue that because "…visitation costs are inherently subjective…any particular welfare estimate is in part an artifact of the particular conventions selected for imposition" and hence suspect (Randall 1994, pp. 88-89).

Stated Preferences

Stated preference data can take a variety of forms, including direct value elicitations (i.e., contingent valuations) or contingent behavior data (e.g., providing information on how individual trip quantities might change as the price per trip or site attributes changed). We will focus on the latter type of SP data. In particular, suppose that in the process of gathering RP data, the survey respondents are asked: "How many recreation trips would you have taken to the site if the cost per trip increased by \$B?" In this case, the resulting database looks identical to the RP data set, providing both price (p_i^S) and quantity (q_i^S) data for each individual. The preferences revealed through these questions can be represented by the demand equation

$$q_i^S = f^S\left(p_i^S, y_i^S; \beta^S\right) + \varepsilon_i^S \tag{4}$$

where $p_i^S = p_i^R + B$ and $\varepsilon_i^S \sim N\left(0, \sigma_S^2\right)$. Estimation of the demand relationship in (4) alone would proceed much like in the RP setting, with a log-likelihood function identical to that in equation (3), except that *R* would be replaced with *S* in all of the superscripts and subscripts. Efficiency gains can be achieved by recognizing the likely correlation between RP and SP responses (i.e., between ε_i^R and ε_i^S). The appropriate log-likelihood function for the joint estimation is given by:[2, 3]

$$
\begin{aligned}
LL = \sum_{i=1}^{n} \Bigg\{ & D_i^R \Bigg[\ln \phi\left(\frac{q_i^R - f_i^R}{\sigma_R}\right) - \ln\left(\sigma_R\right) \Bigg] + D_i^R D_i^S \Bigg[\ln \phi\left(\frac{\left(q_i^S - f_i^S\right) - \theta^S\left(q_i^R - f_i^R\right)}{\sigma_S\sqrt{1-\rho^2}}\right) - \ln\left(\sigma_S\sqrt{1-\rho^2}\right) \Bigg] \\
& + D_i^R\left(1 - D_i^S\right) \Bigg[\ln \Phi\left(\frac{-f_i^S - \theta^S\left(q_i^R - f_i^R\right)}{\sigma_S\sqrt{1-\rho^2}}\right) \Bigg] + \left(1 - D_i^R\right)\left(1 - D_i^S\right) \Bigg[\ln \int_{-\infty}^{\frac{-f_i^R}{\sigma_R}} \int_{-\infty}^{\frac{-f_i^S}{\sigma_S}} \phi_2\left(\eta_1, \eta_2; \rho\right) d\eta_1 d\eta_2 \Bigg] \Bigg\}
\end{aligned}
\tag{5}
$$

where $Corr\left(\varepsilon_i^R, \varepsilon_i^S\right) = \rho$, $\theta \equiv \rho\sigma_S/\sigma_R$, $f_i^k = f^k\left(p_i^k, y_i^k; \beta^k\right)$ (*k* = *R*, *S*), and $\phi_2\left(\cdot, \cdot; \rho\right)$ denotes the standard bivariate normal pdf. This model can be used to test a variety of hypotheses concerning the consistency of the RP and SP data.

As with the RP data, there are numerous reasons one might expect preferences revealed by SP questioning, and modeled in equation (4), to differ from the individual's true preferences. As noted above, one of the most common concerns is that individuals fail to adequately account for their budget constraint and the availability of substitute commodities in responding to

hypothetical scenarios presented to them in a survey. Thus, the income they perceive as being available for allocation towards the commodity in question may be inflated (i.e., $y_i^s > y_i$). In addition, individuals may have greater uncertainty regarding their preferences under unfamiliar price and quality settings; i.e., one might expect that $\varepsilon_i^s = \varepsilon_i + \eta_i^s$, where η_i^s captures the additional uncertainty or variability in preferences under the hypothetical conditions.

Hypothesis Testing

There are three primary reasons for jointly estimating the RP and SP demand equations. The first and least ambitious is to garner improved efficiency in the parameter estimates by recognizing the likely correlation between the two data sets. It is hard to argue with this objective regardless of the school of thought from which one starts.

The second reason for combining the two models is to allow for hypothesis testing. Unfortunately, both the tests conducted and the interpretation of the results often depend upon the perspective brought to the exercise. For example, the most common hypothesis tested is one that imposes complete consistency between the two models; i.e.,

$$H_0^1 : \beta^R = \beta^S \text{ and } \sigma_R = \sigma_S . \tag{6}$$

Traditionally, rejection of this hypothesis has been widely viewed as a repudiation of the SP data and methodology, though this is clearly an "RP-lovers" perspective. An equally valid viewpoint is that the discrepancies arise due to problems with the RP data; i.e., the "SP-lovers" perspective. These viewpoints also influence which model one falls back on for welfare analysis in the event that H_0^1 is rejected. Obviously, "RP-lovers" and "SP-lovers" would fall back on their respective preferred models. The "agnostics," on the other hand, might argue that discrepancies between the two models should in fact be expected. The RP data are bringing the discipline of the market to bear on the SP data and the SP data are examining regions of consumer preferences outside of the range of consumers' experiences in the marketplace. From this perspective, welfare analysis is best served by relying upon the combined model using both sources of information.[4]

A modification to the overall consistency test allows for differences in the underlying variation in the two models, while constraining the demand parameters themselves to be equal; i.e.,

$$H_0^2 : \beta^R = \beta^S . \tag{7}$$

Allowing for differences in the distribution of preferences in the revealed and stated preferences models has been suggested by a number of authors, including Haab, Huang, and Whitehead (2000) and Cameron et al. (1999).

In addition to testing for overall consistency between the two models, one can, as suggested by Cameron (1992b), focus on the specific weakness of each model. For example, one might generalize the SP demand equation as follows:

$$q_i^S = f^S \left(p_i^S, \tau_y y_i^R; \beta^S \right) + \varepsilon_i^S . \tag{8}$$

This replaces y_i^S in equation (4) with $\tau_y y_i^R$, where τ is a parameter to be estimated. The argument that respondents to SP questions tend to downplay their budget constraints is then reflected by the expectation that $\tau_y > 1$. The hypothesis test in this case would correspond to restricting (2) and (8) such that

$$H_0^3 : \beta^R = \beta^S \text{ and } \sigma_R = \sigma_S, \text{ while } \tau_y \text{ remains unrestricted} . \tag{9}$$

This hypothesis test essentially treats the RP data as the base against which the SP data are tested.

An alternative approach is to reverse the roles of the RP and SP data. If the analyst believes the SP data are correct, but the RP data are subject to error, then the SP data can be used as the basis for a validity test of the RP data. As noted previously, Randall (1994) has argued forcibly that the price term in RP data is poorly measured and is likely the cause of significant bias. An external validity test of the RP data can then be performed by substituting p_i^R in the RP models with $\tau_p p_i^R$, where $\tau_p > 0$, and generalizing equation (2) by using

$$q_i^R = f^R \left(\tau_p p_i^R, y_i^R; \beta^R \right) + \varepsilon_i^R . \tag{10}$$

Again, if τ_p is not estimated to be significantly different from one, external validity for the RP data would not be rejected. The corresponding hypothesis test would test the following restriction on equations (4) and (10):

$$H_0^4 : \beta^R = \beta^S \text{ and } \sigma_R = \sigma_S, \text{ while } \tau_p \text{ remains unrestricted} . \tag{11}$$

All four of the hypothesis tests identified above can be viewed as restrictions on the generalized system of demand equations in (8) and (10), with:

- $\tilde{H}_0^1 : \beta^R = \beta^S$, $\tau_y=1$, $\tau_p=1$, and $\sigma_R = \sigma_S$; i.e., complete consistency.

- $\tilde{H}_0^2 : \beta^R = \beta^S$, $\tau_y=1$, and $\tau_p=1$; i.e., consistency in demand parameters but not in terms of error variances.

- $\tilde{H}_0^3 : \beta^R = \beta^S$ and $\tau_p=1$; i.e., when respondents answer the SP questions, in addition to having a different error variance, they also ignore their budget constraint. Consistency holds in all other respects.

- $\tilde{H}_0^4 : \beta^R = \beta^S$ and $\tau_y=1$; when respondents answer the RP question, in addition to having a different error variance, they also do not treat the computed travel cost term (p) as the cost of accessing the recreation site (analysts have calculated the incorrect price). Consistency holds in all other respects.

IV. Data

The data used to illustrate the above pooling model are drawn from a 1997 survey of 6,000 Iowa residents concerning their use of the state's wetland resources. The goal of the survey was to elicit information from respondents about their visits to, knowledge about, and attitude towards both the existing wetlands in Iowa as well as efforts to preserve and expand these resources. Of the deliverable surveys, there was a 59 percent response rate (with 3,143 surveys returned).[5]

Our analysis draws on the first section of the survey, which focused on visits to wetlands during the past year. After carefully defining what was meant by a "wetland," the survey asked respondents to recall the number of 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.[6] Responses to this first question provide the basis for the RP variable q_i^R. Individuals were then asked how their pattern of usage would change if the cost of visiting wetland zones near their residence (X, Y, and Z) increased.[7] 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)."[8] They were then asked to detail how their behavior would have changed with the increased cost, both in terms of reductions in visitations to areas X, Y, and Z,
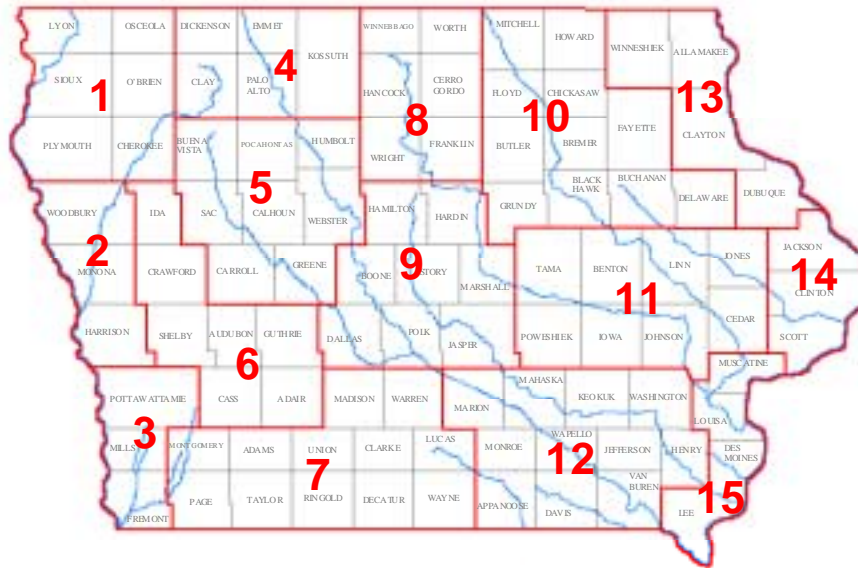
FIGURE 1. Wetland Zones

and 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 ($z = 1,\ldots,15$). One of the survey questions asked the respondent to place an X on a map, similar to Figure 1, locating their most recent wetland visit. The longitude/latitude coordinates for the visitation points in each of the 99 counties were averaged to find the mean visitation point in that county. Travel time and distance for each respondent from their residence to each of the 99 mean visitation points was then constructed using PC Miler, a software package designed for use in the transportation and logistics industry. This gave us a data set with 99 travel times and distances for each respondent in the database. Finally, the zonal travel times (t_i^z) and distances (d_i^z) were calculated as a weighted average of their respective county travel county level values.[9]

For the purposes of this paper, we have focused our attention on a subset of the survey sample; i.e., those households in the Prairie Pothole Region of north central Iowa (zones 4, 5, and 8). We consider the aggregate number of trips to this region, with $q_i^k = q_i^4 + q_i^5 + q_i^8$ $(k = R, S)$. Travel times and distances were formed as weighted averages of the zone specific 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 278 households with completed surveys in the Prairie Pothole region, 8.2 trips (q_i^R) were actually taken. Respondents indicated that they would average only 2.7 trips (q_i^S) with the average hypothetical price increase ($B) of $27 per trip.

V. Model Specification

The parametric specifications for the demand functions in (8) and (10) were chosen to be of a simple linear form, with

$$q_i^R = \beta_0^R + \beta_p^R \tau_p p_i^R + \beta_y^R y_i^R + \varepsilon_i^R \tag{12}$$

and

$$q_i^S = \beta_0^S + \beta_p^S p_i^S + \beta_y^S \tau_y y_i^S + \varepsilon_i^S . \tag{13}$$

Clearly, given the linear form in equation (12), the parameters β_p^R and τ_p are not separately identified. β_y^S and τ_y likewise are not separately identified in equation (13). To deal with the issue, and to simplify the exposition below, we reparameterize the model as follows:

$$q_i^R = \tilde{\beta}_0^R + \tilde{\beta}_p^R p_i^R + \tilde{\beta}_y^R y_i^R + \varepsilon_i^R \tag{14}$$

and

$$q_i^S = k_0 \tilde{\beta}_0^R + k_p \tilde{\beta}_p^R p_i^S + k_y \tilde{\beta}_y^R y_i^S + \varepsilon_i^S . \tag{15}$$

In this case, the k_j 's measure the discrepancies between the RP and SP demand equation parameters, with $k_j = 1 \,\forall j$ and $\sigma_R = \sigma_S$ corresponding to complete consistency between the two models.

Finally, the trip prices p_i^R and p_i^S must be specified. As suggested by McConnell and Strand (1981), we parameterize these prices as:

$$p_i^k = c_i + \lambda^k L_i \quad k = R, S \tag{16}$$

where λ^k is a parameter to be estimated, $c_i \equiv 0.22 d_i$ denotes the travel cost (computed as round-trip travel distance times 22¢ per mile), and $L_i = w_i t_i$ denotes full time costs (computed as the individual's wage rate times the round-trip travel time). As noted above, it is standard practice in the recreation demand literature to fix λ^k at some value, typically between 0.25 and 0.5, rather than estimating its value.

Substituting (16) into equations (14) and (15) results in the following system of demand equations:

$$q_i^R = \tilde{\beta}_0^R + \tilde{\beta}_p^R \left(c_i + \lambda^R L_i \right) + \tilde{\beta}_y^R y_i^R + \varepsilon_i^R \tag{17}$$

and

$$q_i^S = k_0 \tilde{\beta}_0^R + k_p \tilde{\beta}_p^R \left(c_i + k_\lambda \lambda^R L_i \right) + k_y \tilde{\beta}_y^R y_i^S + \varepsilon_i^S \tag{18}$$

where $k_\lambda \equiv \lambda^S / \lambda^R$. The hypothesis tests corresponding to those outlined above become:

- <u>Complete Consistency</u>. $\tilde{H}_0^1 : k_j = 1 \ \forall j$ and $\sigma_R = \sigma_S$.

- <u>Heteroskedasticity Hypothesis</u>. $\tilde{H}_0^2 : k_j = 1 \ \forall j$.

- <u>Price Hypothesis</u>. $\tilde{H}_0^3 : k_0 = 1, \ k_\lambda = 1,$ and $k_y = 1$.

- <u>Income Hypothesis</u>. $\tilde{H}_0^4 : k_0 = 1, \ k_p = 1$ and $k_\lambda = 1$.

VI. Results

The system of demand equations in (17) and (18) was estimated using standard maximum likelihood procedures, with the likelihood function in (5) correcting for the potential truncation at zero for either or both RP and SP trip data and accounting for possible correlation between the two error terms. The resulting parameter estimates are provided in Table 1 for the unconstrained model and for each of the constrained specifications outlined above. For the SP parameters, we provide both the estimated values for the k_j's and the implied levels for the SP parameters $\tilde{\beta}_j^S \equiv k_j \tilde{\beta}_j^R$ in square brackets.

Focusing first on the unconstrained model, we note that all of the parameters have the expected signs. The price coefficient for the RP data is just above negative one and statistically

TABLE 1. Parameter estimates (standard errors in parentheses)

Parameter	Unconstrained	Complete Consistency $\tilde{H}_0^1$	Hetero-skedasticity Hypothesis $\tilde{H}_0^2$	Price Hypothesis $\tilde{H}_0^3$	Income Hypothesis $\tilde{H}_0^4$
β_0^R	23.38** (2.91)	14.52** (1.94)	14.22** (2.08)	13.47** (2.40)	13.77** (2.26)
β_p^R	-0.94** (-0.13)	-0.47** (-0.04)	-0.46** (-0.06)	-0.42** (-0.09)	-0.44** (-0.06)
λ^R	0.06 (0.06)	0.44** (0.11)	0.47** (0.14)	0.53** (0.19)	0.50** (0.15)
β_y^R	0.08 (0.05)	0.21** (0.05)	0.22** (0.05)	0.22** (0.05)	0.22** (0.05)
σ_R	13.84** (0.73)	14.34** (0.78)	14.48** (0.80)	14.47** (0.84)	14.47** (0.85)
k_0	0.48^a [11.22] (0.14)	1.00	1.00	1.00	1.00
k_p	0.38^a [-0.36] (0.07)	1.00	1.00	1.04 [-0.44] (0.08)	1.00
k_λ	14.69 [0.88] (15.55)	1.00	1.00	1.00	1.00
k_y	3.33 [0.27] (2.18)	1.00	1.00	1.00	0.93 [0.21] (0.12)
k_σ	1.04 [14.39] (0.09)	1.00	0.98 [14.21] (0.08)	0.99 [14.40] (0.08)	0.98 [14.24] (0.07)
ρ	0.72** (0.04)	0.72** (0.04)	0.72** (0.04)	0.73** (0.04)	0.73** (0.04)
-log L	1114.37	1127.56	1127.50	1127.32	1127.35
P-values		<.001	<.001	<.001	<.001
CS_R	99.61	197.39	203.50	222.95	212.25
CS_S	264.65	197.39	203.50	213.52	212.25

** and * denote significance at 99 and 95 percent confidence levels, respectively, a and b denote significant departures from 1.00 at 99 and 95 percent confidence levels.

significant. While the income coefficient is small and statistically insignificant, it is positive and with a small standard error. Interestingly, the coefficient on the wage rate, which is traditionally fixed at a level between 0.25 and 0.50, is also close to zero. Given these parameter estimates, the probability that λ^R exceeds 0.25 is less than 0.1 percent. Indeed, our estimate of λ^R is not statistically different from zero at any reasonable confidence level.

The SP parameters differ from their RP counterparts in a number of areas. In particular, both the intercept and price terms are significantly different, with both k_0 and k_p significantly less

than one. This indicates, for example, that the price response in the SP data set is much smaller than in the RP counterpart. The remaining k_j 's are all greater than one, though not significantly so. The estimate of k_λ suggests that greater weight is placed on the wage rate in the SP choices than in their RP counterpart, with the point estimate for $\lambda^S = 0.88$. The underlying variability of preferences revealed by the two data sets is similar, with $k_\sigma \equiv \sigma_S/\sigma_R$ estimated to be close to one and precisely measured. This result is in contrast to other efforts integrating RP and SP data sets that found the source of inconsistency between the two data sets to be in the degree of preference dispersion (e.g., Cameron et al. 1999; Haab, Huang, and Whitehead 2000). Finally, we note that there is substantial correlation between the two data sources, with $\rho = 0.72$ and significantly different from zero.

Although parameters of the demand equations are important, they are typically used in the policy arena as an intermediate step to computation of welfare impacts. As one might expect, the substantial differences in price coefficients between the RP and SP models lead to substantial differences in the associated welfare measures. In Table 1, we provide estimates of the average consumer surplus associated with wetland visitations. The surplus derived from the SP model (CS_S) is over two and half times that obtained using the RP model (CS_R).

Turning to the constrained models, we find that each of the model restrictions is rejected at any reasonable significance level. Consistency between RP and SP data is not borne out by the data, either in its strict form or when we allow for different levels of variances for two data sources. Indeed, even in its unconstrained form, the demand systems suggest $\sigma_R = \sigma_S$ (with $k_\sigma = 1.04$). Less restrictive forms of consistency are no more successful. The price hypothesis, which an SP-lover might argue for, suggests that the source of the inconsistency between the two demand systems lies in the formation of the trip price. Yet this hypothesis is soundly rejected. Similarly, the income hypothesis, which our RP-lover might suggest, argues that the source of the inconsistency lies in the lack of attention paid to income by SP survey respondents, but this hypothesis also is rejected.

The problem, of course, is where do we go from here? We have two sources of data with conflicting conclusions regarding the value of wetland use. One can always hope that the two valuations lead to the same policy conclusions. If they do not, one's "school of thought"

regarding the RP and SP controversy will play a key role. Moderate RP- and SP-lovers are likely to stop at the unconstrained model, taking solace in the improved efficiency achieved by jointly estimating the two demand systems and relying on their respective valuations (CS_R and CS_S). Indeed, they may never even estimate the various constrained models. The zealots within each group, however, will rely on tests as a source of vindication for their respective positions. For the RP-lovers, the various consistency tests only serve to solidify their suspicion of the stated preference approach. However, these same results can be employed by the SP-lover to argue against RP models by simply reversing the presumption as to which is the correct model!

In contrast, the agnostic's approach to the results in Table 1 is likely to be substantively different. Rather than falling back on the unconstrained model in the face of the various rejections of consistency, they are more like to embrace the specification under $\tilde{H}_0^1$ or $\tilde{H}_0^2$. According to the agnostic, the rejection is expected. Indeed, the agnostic would likely be disappointed if the constrained parameter estimates were not significantly different from the unconstrained ones, as that would indicate that the gains sought by combining data sources did not occur! That is, the SP data was not carefully enough designed to "fill in" missing pieces from the RP data and/or the RP data had sufficient measurement error or other problems such that it could not impose market discipline on the SP data. The agnostic's preferred strategy would be to estimate the models jointly, imposing consistency across all parameters, or possibly allowing for difference variances (the complete consistency or heteroskedasticity hypothesis in Table 1). By so doing, all information available on consumers' preferences is best utilized.

VII. Summary and Conclusions

This paper has investigated the combining of revealed and stated preference data to jointly estimate the parameters of consumer preferences for a public good. We have presented a simple model for combining two different data sources and demonstrated how several hypotheses concerning these data sources can be formalized and tested in such a model. In the wetlands application discussed here, consistency between the RP and SP data was consistently rejected.

In interpreting the lack of consistency found between the estimated parameters, we identified and discussed several "schools of thought." Analysts who identify with RP-lovers will be inclined to take parameter and welfare estimates from RP data as the most accurate

representation of the underlying true parameters, interpreting consistency tests with SP data as evidence for or against the validity of SP as a method. In contrast, SP-lovers will view welfare and parameter estimates from SP data as the best available estimates and interpret consistency tests with RP data as referendums on RP's validity. In contrast, those identifying with an "agnostic" approach will be inclined to see consistency tests as relatively unimportant, but instead prefer to combine data sources to estimate a single set of parameters and welfare estimates, thus enjoying the strengths of each method. Clearly in each of these three approaches, the role and interpretation of consistency tests in nonmarket valuation is closely related to the prior point of view of the analyst.

The fundamental debate concerning the legitimacy of SP methods relative to RP discussed in the introduction will continue to be much discussed. However, we are not optimistic that consistency tests between RP and SP data such as those described here will play a key role in settling the disagreement between those who see SP data as inherently flawed and those who see it as the last, best hope for nonmarket valuation. It is simply too easy to interpret the results of these tests to be consistent with one's prior views.

On the other hand, combining data sources holds considerable promise for those who are willing to credit each method with strengths and weaknesses. By designing questionnaires to elicit RP and SP data to take advantage of their respective strengths and then combining the data sources in estimation, analysts may be able to provide policymakers with more efficient and accurate estimates of the value of public goods. This research agenda has only begun and will require significant effort on the part of environmental economists to identify the parameters under which improved welfare estimates can be obtained through such methods.

VIII. Endnotes

1. There have been a number of efforts to better capture the value of travel time by estimating the appropriate fraction of the individual's wage rate (McConnell and Strand 1981; Bockstael, Strand, and Hanemann 1987) or the monetary value of leisure time (Feather and Shaw 1999). However, the use of a fixed wage fraction (between 25 and 50 percent) continues to dominate the applied literature.

2. The derivation of this log-likelihood function is available from the authors upon request.

3. Louviere (1996) refers to this integration of RP and SP data sets having the same form as *pooling* models. A second category of models, *combining* models, integrates information from RP and SP data sets with different underlying forms. For example, Cameron (1992a) combines RP fishing trip demand data with discrete choice SP data on whether individuals would take any fishing trips if a lump-sum access fee were imposed. Similar efforts have been undertaken by Larson (1990) and Huang, Haab, and Whitehead (1997).

4. A weaker form of "agnosticism" might argue for presenting the welfare estimates obtained from the unconstrained RP and SP models as bounding the true values. An Alternative ("atheistic") perspective is, of course, to view the rejection of H_o^1 as a rejection of both data sources, suggesting that neither model be used for welfare analysis.

5. The post office returned 594 surveys as undeliverable. Details of the survey design and administration can be found in Azevedo (1999).

6. 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 are 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, rivering wetlands dominate regions 1 through 3 and 13 through 15, and are associated with marshy land near rivers and streams.

7. The wetland zones (X, Y, and Z) were assigned to each individual based upon the region of the state in which they lived. Specifically, the 15 zones in Figure 1 were grouped into five "megazones," reflecting regional wetland areas. Specifically, the 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 zones (X, Y, Z) for a

given survey respondent consisted of those zones defining the megazone in which the respondent resided.

8. The value of $B varied across the individuals surveyed, with bid values of $5, $10, and $15 each randomly assigned to 20 percent of the sample and bid values of $30, $30, $40, and $50 each assigned to 10 percent of the sample.

9. Each county's weight was determined by the percentage of trips within that county's zone taken to that country. For example, zone three is made up of Pottawattamie, Mills, and Fremont counties. There were 92 trips taken to zone three: 41 trips to Pottawattamie County; 24 trips to Mills County; and 27 trips 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.

IX. References

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