Valuation for Environmental Policy: Ecological Benefits

A Workshop sponsored by U.S. Environmental Protection Agency's National Center for Environmental Economics (NCEE) and National Center for Environmental Research (NCER)

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U.S. Environmental Protection Agency (EPA)
National Center for Environmental Economics (NCEE) and
National Center for Environmental Research (NCER)
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Agenda

April 23, 2007: Valuation for Environmental Policy

8:00 a.m. – 8:30 a.m. **Registration**

8:30 a.m. – 8:45 a.m. **Introductory Remarks**
Rick Linthurst, National Program Director for Ecology, EPA, Office of Research and Development

8:45 a.m. – 11:30 a.m. **Session I: Benefits Transfer**
Session Moderator: Steve Newbold, EPA, NCEE

8:45 a.m. – 9:15 a.m.	Benefits Transfer of a Third Kind: An Examination of Structural Benefits Transfer George Van Houtven, Subhrendu Pattanayak, Sumeet Patil, and Brooks Depro, Research Triangle Institute
9:15 a.m. – 9:45 a.m.	The Stability of Values for Ecosystem Services: Tools for Evaluating the Potential for Benefits Transfers John Hoehn, Michael Kaplowitz, and Frank Lupi, Michigan State University

9:45 a.m. – 10:00 a.m. **Break**

10:00 a.m. – 10:30 a.m.	Meta-Regression and Benefit Transfer: Data Space, Model Space and the Quest for 'Optimal Scope' Klaus Moeltner, University of Nevada, Reno, and Randall Rosenberger, Oregon State University
10:30 a.m. – 10:45 a.m.	Discussant: Matt Massey, EPA, NCEE
10:45 a.m. – 11:00 a.m.	Discussant: Kevin Boyle, Virginia Tech University
11:00 a.m. – 11:30 a.m.	Questions and Discussion

11:30 a.m. – 12:45 p.m. **Lunch**

April 23, 2007 (continued)

12:45 p.m. – 3:30 p.m. **Session II: Wetlands and Coastal Resources**
Session Moderator: Cynthia Morgan, EPA, NCEE

12:45 p.m. – 1:15 p.m. A Combined Conjoint-Travel Cost Demand Model for Measuring the Impact of Erosion and Erosion Control Programs on Beach Recreation
Ju-Chin Huang, University of New Hampshire; George Parsons, University of Delaware; Min Qiang Zhao, The Ohio State University; and P. Joan Poor, St. Mary's College of Maryland

1:15 p.m. – 1:45 p.m. A Consistent Framework for Valuation of Wetland Ecosystem Services Using Discrete Choice Methods
David Scrogin, Walter Milon, and John Weishampel, University of Central Florida

1:45 p.m. – 2:00 p.m. **Break**

2:00 p.m. – 2:30 p.m. Linking Recreation Demand and Willingness To Pay With the Inclusive Value: Valuation of Saginaw Bay Coastal Marsh
John Whitehead and Pete Groothuis, Appalachian State University

2:30 p.m. – 2:45 p.m. Discussant: Jamal Kadri, EPA, Office of Wetlands, Oceans, and Watersheds

2:45 p.m. – 3:00 p.m. Discussant: John Horowitz, University of Maryland

3:00 p.m. – 3:30 p.m. Questions and Discussion

3:30 p.m. – 3:45 p.m. **Break**

3:45 p.m. – 5:45 p.m. **Session III: Invasive Species**
Session Moderator: Maggie Miller, EPA, NCEE

3:45 p.m. – 4:15 p.m. Models of Spatial and Intertemporal Invasive Species Management
Brooks Kaiser, Gettysburg College, and Kimberly Burnett, University of Hawaii at Manoa

4:15 p.m. – 4:45 p.m. Policies for the Game of Global Marine Invasive Species Pollution
Linda Fernandez, University of California at Riverside

4:45 p.m. – 5:00 p.m. Discussant: Marilyn Katz, EPA, Office of Wetlands, Oceans, and Watersheds

5:00 p.m. – 5:15 p.m. Discussant: Lars Olsen, University of Maryland

5:15 p.m. – 5:45 p.m. Questions and Discussion

5:45 p.m. **Adjournment**

April 24, 2007: Valuation for Environmental Policy

8:30 a.m. – 9:00 a.m.	**Registration**	
9:00 a.m. – 11:45 a.m.	**Session IV: Valuation of Ecological Effects** Session Moderator: William Wheeler, EPA, NCER	
	9:00 a.m. – 9:30 a.m.	Integrated Modeling and Ecological Valuation: Applications in the Semi Arid Southwest David Brookshire, University of New Mexico, Arriana Brand, Jennifer Thacher, Mark Dixon,Julie Stromberg, Kevin Lansey, David Goodrich, Molly McIntosh, Jake Gradny, Steve Stewart, Craig Broadbent and German Izon
	9:30 a.m. – 10:00 a.m.	Contingent Valuation Surveys to Monetize the Benefits of Risk Reductions Across Ecological and Developmental Endpoints Katherine von Stackelberg and James Hammitt, Harvard School of Public Health
10:00 a.m. – 10:15 a.m.	**Break**	
	10:15 a.m. – 10:45 a.m.	Valuing the Ecological Effects of Acidification: Mapping the Extent of Market and Extent of Resource in the Southern Appalachians Shalini Vajjhala, Anne Mische John, and David Evans, Resources for the Future
	10:45 a.m. – 11:00 a.m.	Discussant: Joel Corona, EPA, Office of Water
	11:00 a.m. – 11:15 a.m.	Discussant: David Simpson, Johns Hopkins University
	11:15 a.m. – 11:45 a.m.	Questions and Discussion
11:45 a.m. – 1:00 p.m.	**Lunch**	
1:00 p.m. – 4:15 p.m.	**Session V: Water Resources** Session Moderator: Adam Daigneault, EPA, NCEE	
	1:00 p.m. – 1:30 p.m.	Valuing Water Quality as a Function of Physical Measures Kevin Egan, Joe Herriges, John Downing, and Katherine Cling, Iowa State University
	1:30 p.m. – 2:00 p.m.	Cost-Effective Provision of Ecosystem Services from Riparian Buffer Zones Jo Albers, Oregon State University; David Simpson, Johns Hopkins University; and Steve Newbold, NCEE
2:00 p.m. – 2:15 p.m.	**Break**	
	2:15 p.m. – 2:45 p.m.	Development of Bioindicator-Based Stated Preference Valuation for Aquatic Resources Robert Johnston, Eric Shultz, Kathleen Segerson, Jessica Kukielka, Deepak Joglekar, University of Connecticut; and Elena Y. Besedin, Abt Associates

April 24, 2007 (continued)

	2:45 p.m. – 3:05 p.m.	Comparing Management Options and Valuing Environmental Improvements in a Recreational Fishery Steve Newbold and Matt Massey, NCEE
	3:05 p.m. – 3:20 p.m.	Discussant: Julie Hewitt, EPA, Office of Water
	3:20 p.m. – 3:35 p.m.	Discussant: George Parsons, University of Delaware
	3:35 p.m. – 4:05 p.m.	Questions and Discussions
4:05 p.m. – 4:15 p.m.	**Final Remarks**	
4:15 p.m.	**Adjournment**	

Benefits Transfer of a Third Kind: An Examination of Structural Benefits Transfer

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Abstract: Most benefit transfer applications use unit value or benefit function transfer approaches, which do not directly impose consistency with an underlying economic structure. This paper examines a third kind of approach – structural benefits transfer (SBT) -- in which the transfer is directly tied to utility theory via the preference structure. It extends previous SBT applications by (1) exploring five different utility function specifications and comparing their implications for predicting benefits, and (2) including nonuse values in each specification. The approach is demonstrated by combining results from a travel cost study and a contingent valuation study for improvements in river water quality. The results show that SBT estimates for selected water quality improvements and conditions are sensitive to preference specification; however, they also highlight the strengths and limitations of different specifications, by providing plausibility checks on the range of predicted outcomes. For example, in this application, SBT functions based on a linear trip demand specification produce more plausible benefit predictions than a log-linear demand or a Stone-Geary framework.

Key Words: Benefit transfer, Structural benefit transfer, Preference calibration

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1. Introduction

The policy community frequently uses benefit transfer methods because they offer a practical and low cost way to provide benefit estimates for benefit-cost analyses, natural resource damage assessments, and other natural resource policy and management analyses. These methods take and adapt results from existing primary valuation studies and apply them to assess the benefits of selected policy changes.

For the most par, benefit transfer approaches fall into two categories-- “unit value” transfers or “value function” transfers—where the key distinction between the two approaches is the degree to which differences between the study and policy contexts are formally accounted for in the transfer. In unit value transfers, a single value or range of values, such as the value per recreation day or per unit change in water quality, is usually transferred with little or no adjustment for differences between the two settings. With benefit, or value, function transfers, information from existing studies is used to identify a functional relationship between the value of interest and the factors that may influence the magnitude of the value (e.g., using meta-regression analysis). This functional relationship allows the analyst to account for differences between the two settings and adapt the transfer estimates accordingly.

Although commonly used for policy analysis, these traditional approaches to benefit transfer do not explicitly impose consistency with the economic theory that is assumed to underlie the value estimates. Moreover, to the extent that they use existing value estimates based on different nonmarket valuation methods, they typically combine them in an ad-hoc manner.

To address these limitations, a third kind of benefits transfer – ”structural benefits transfer” (or“preference calibration”)– has been proposed in which the transfer methodology is directly tied to utility theory via the preference structure (Smith et al. 2002; Bergstrom and Taylor, 2006). Structural benefits transfer is in essence a form of benefit function transfer; where the functional form is specifically derived from an assumed utility function. Although this third approach has the potential to improve and strengthen benefit transfers, it has thus far only been applied and evaluated in a limited number of examples.

This paper further examines and evaluates structural benefits transfer as an alternative transfer method by extending existing applications in two main directions. First, we apply preference calibration using several different utility function specifications and compare their implications for predicting benefits. Second, whereas existing applications have focused on use-related values for environmental improvements, we explicitly include nonuse values in the preference specifications. Through these applications, we examine the generalizability and the robustness of the basic logic of structural benefits transfer.

The paper begins in the next section by providing a background discussion of the structural benefits transfer approach. Section 3 then introduces and describes the preference specifications that will be applied, and Section 4 discusses how estimates from different nonmarket valuation methods can be directly linked to these preference specifications. Section 5 presents a case study application focusing on water quality changes using the five preference specifications. The results and implications of these applications are then discussed in Section 6, along with suggested directions for future research.

2. Background

The main concept underlying preference calibration is that, if one is willing to make explicit assumptions about the functional form of utility with respect to a nonmarket commodity (e.g., environmental quality or health), then information from existing empirical valuation studies can in principle be used to estimate the parameters of the function. When both the utility function parameters and available benefit estimates are few in number, it is possible to calibrate the parameter values such that they produce benefit measures that match the observed empirical estimates. This is the approach used in this paper. As the number of available benefit estimates increases, structural meta-analysis techniques can instead be used to statistically estimate the parameter values (Smith and Pattanayak, 2002; Bergstrom and Boyle, 2006).

Structural benefit transfer recognizes that the selected preference specification has direct implications for both the functional form and the parameters of the corresponding welfare functions (i.e., willingness to pay (WTP), quasi-expenditure, or variation functions, as described for example by McConnell [1990]) and Whitehead [1995]). Therefore, it defines a benefit transfer function with (1) a functional form that is directly derived from the preference specification and (2) parameters that are calibrated from existing empirical estimates.

The preference calibration logic was initially presented and illustrated in studies focusing on water quality changes using a utility specification with a modified constant elasticity of substitution (CES) form (described in more detail below). Using this simple form, which did not, not specifically include nonuse values, Smith et al. (2000) combined travel cost estimates from Englin et al. (1997) and contingent valuation (CV) estimates from Carson and Mitchell (1993) to calibrate preferences. Smith et al. (2002) expanded this approach by including hedonic property value estimates from Boyle et al. (1999), recalibrating the preference parameters, and generating illustrative benefit estimates with the calibrated function. More recently, the general approach has been extended to the area of health valuation related to both morbidity and mortality (Van Houtven et al., 2004; Smith et al., 2006) and visibility benefits (Smith and Pattanayak, 2002).

In all of these cases, the process for developing a structural benefit transfer function generally involves the following steps:

1) Specify a "representative" individual's preference function.
2) Define explicitly the relationships between the available benefits measures and the specified preference function.
3) Derive the structural benefit function that is implied by the assumed preference structure.
4) Adapt the available information from existing benefit studies to assure cross-study compatibility.
5) Calibrate or estimate preference function parameters that are as consistent as possible with the observed benefit measures.
6) Insert the calibrated or estimated parameters into the structural benefit function.

Based on this same general process, in the following sections we apply the preference calibration logic using five different preference specifications to a case study application of water quality changes.

3. Specifying Preferences

To characterize the preferences of a representative individual with respect to changes in water quality, we specify five alternative indirect utility (V) functions, which we refer to as (1) modified constant elasticity of substitution (CES); (2) linear trip demand; (3) semi-log demand ; (4) log-linear demand; and (5) Stone-Geary specifications. Using these alternative specifications allows us to explore the sensitivity of benefit transfer predictions (for changes in water quality) with respect to the assumed functional form of utility.

As shown below, each indirect utility function is specified in terms of income (Y), round-trip travel cost (P), and water quality level (Q).

Modified CES:

$$V_A = \left(\varphi_A Q^{\psi_A}\right) + \left((P - Q^{\gamma_A})^{-\alpha_A} Y^{\delta_A}\right)^{\beta_A} \tag{1}$$

Linear Demand:

$$V_B = \varphi_B Q^{\psi_B} + \left[Y + \frac{1}{\delta_B}\left(\alpha_B - \beta_B P + \gamma_B Q - \frac{\beta_B}{\delta_B} \right) \right] \cdot \exp\left[\frac{\delta_B}{\beta_B}\left(\gamma_B Q - \beta_B P\right) \right] \tag{2}$$

Semi-log Demand:

$$V_C = \varphi_C Q^{\psi_C} + \frac{Y^{(1-\delta_C)}}{(1-\delta_C)} + \left(\frac{1}{\beta_C}\right) \cdot \exp\left(-\beta_C P + \alpha_C + \gamma_C Q\right) \tag{3}$$

Log-linear Demand:

$$V_D = \varphi_D Q^{\psi_D} + \frac{Y^{(1-\delta_D)}}{(1-\delta_D)} - \left(1-\beta_D\right)^{-1} e^{\alpha_D} Q^{\gamma_D} P^{(1-\beta_D)} \tag{4}$$

Stone-Geary:

$$V_E = \varphi_E Q^{\psi_E} + Q^{\gamma_E} \cdot \ln\left(\frac{Q^{\gamma_E}}{-\beta_E P} \right) + \left(1 + Q^{\gamma_E}\right) \cdot \ln\left(\frac{Y^{\delta_E} - \alpha_E - \beta_E P}{1 + Q^{\gamma_E}} \right) \tag{5}$$

Equation 1 is similar to the modified CES indirect utility function used in previous preference calibration analyses (Smith et al ,2002; Smith et al., 2000). Equations 2, 3, and 4 are derived respectively from linear, semi-log, and log-linear trip demand specifications, and Equation 5 is based on a Stone-Geary utility function (see for example, Larson [1991] and Herriges et al. [2004]).[1] To capture nonuse values, each specification includes an additively

[1] To match the number of parameters used in the other functional forms, an additional parameter, δ, is added to the income term in the Stone-Geary model.

separable subcomponent (of the form φQ^{ψ}), which is independent of P and Y. These nonuse values will not be manifested in value estimates based on revealed preference methods, but they are likely to be included in estimates from stated preference studies.

All five preference specifications include six parameters. For each specification, we represent the vector of parameters as $\boldsymbol{\theta}_{\mathbf{j}}$, such that, for example, $\boldsymbol{\theta}_{\mathbf{A}} = (\alpha_A, \beta_A, \gamma_A, \delta_A, \varphi_A, \psi_A)$ is the parameter vector for the modified CES preferences. These are the parameters to be calibrated.

4. Linking Benefit Measures to the Preference Function

In this paper, we calibrate these preference parameters for each specification by combining results from a travel cost and a contingent valuation analysis. The travel cost analysis provide estimates of recreation demand (i.e., number of water based recreation trips per year [X]) and changes in Marshallian consumer surplus (ΔMCS) resulting from changes in water quality. The CV method provides estimates of Hicksian compensating surplus (WTP) for changes in water quality.

Tables 1 and 2 report algebraic expressions for X, ΔMCS , and WTP, which are directly derived from the preference functions listed in Equations 1 to 5. The demand functions are derived by applying Roy's Identity to the indirect utility functions, and the ΔMCS functions are derived by changing the level of water quality (from Q_0 to Q_1) in these demand equations. The WTP functions are derived by solving for the compensating surplus that equalizes indirect utility for different levels of Q. Each expression is a function of the exogenous variables Y, P, and Q, and each one also includes parameters from its corresponding preference specification.

5. Preference Calibration Application

The first objective of this preference calibration application is therefore to identify values for the preference parameters that replicate as closely as possible the observed empirical estimates of X, WTP, ΔMCS (based on conditions defined by Y, P, and Q). We can then insert these calibrated parameter values in the WTP equations shown in Table 2 and use these equations as structural benefit transfer functions.

The two empirical studies used in this application were conducted in the early 1980's as part of a larger research project for EPA.[2] Both studies focused on measuring water quality benefits for households living in the vicinity of the Monongahela River in Southwestern Pennsylvania. The two studies also used data from the same 1981 survey of residents living within the Monogahela River Valley. This survey was based on a stratified sample of 393 households from the five-county area surrounding the Pennsylvania portion of the Monongahela River, including the Pittsburgh metropolitan area. Administration of the survey resulted in 301 completed interviews.

The first study used data from the survey to estimate a recreation demand travel cost model (Smith et al., 1983). This study identified 13 recreation sites along the Pennsylvania portion of the river and 69 respondents who had visited at least one of these sites. The total

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[2] For both an overview and detailed summary of this larger research project, see Smith and Desvousges (1986).

number of user-site combinations, each of which represented a single observation, was 94. Smith et al. applied a generalized travel cost model to estimate trip demand functions for each site. They then used these demand functions to estimate the increase in consumer surplus per household per season that would result from increasing water quality levels from boatable conditions to fishable conditions and from boatable to swimmable conditions.

The second study was based on responses to a contingent valuation scenario that was presented as part of the survey (Desvousges et al., 1987). At the time of the survey, the overall water quality levels in the Pennsylvania section of the Monongahela were assumed to be characterized by boatable conditions. Respondents were asked to value three water quality changes:. (1) raising levels from boatable to fishable conditions, (2) raising levels from fishable to swimmable condition, and (3) avoiding a decrease from boatable to nonboatable conditions. The survey used different elicitation methods (iterative bidding, open-ended, and payment card) for different subsamples. For this analysis, we use the open-ended responses, which were collected from 51 respondents, including both users and nonusers of the Monongahela river sites.

5.1.2 Defining Consistent Measures Across the Studies

To define a continuous unit of measure for Q that is consistent across the two studies, we use the same Resources for the Future (RFF) water quality ladder/scale (Vaughan, 1986) that was presented to respondents in the contingent valuation survey to describe water quality changes. According to this 1-to-10 point scale, nonboatable, boatable, fishable, and swimmable water quality levels are assigned values of 0.5, 2.5, 5.1, and 7, respectively.

The summary statistics and benefit estimates used in the calibration applications are summarized in Table 3. The travel cost study provides estimates of the average baseline number of trips (X = 7.22), average income, and average travel cost for the sample of 94 recreators. All dollar values from these studies have been converted to 2005 dollars using the consumer price index (CPI). The baseline demand for trips is assumed to be evaluated at a water quality level that is "consistent with supporting boating (the current [1977] recreational use of the river)" (Smith et al., 1983) (Q_0 = 2.5). The travel cost study also provides ΔMCS estimates for two water quality improvements -- one to fishable quality (Q_1 = 5.1) and the other to swimmable quality (Q_1 = 7).

The contingent valuation study also provides estimates of average income and baseline trips for its sample of respondents. Average income is 10 percent lower than for travel cost study sample, and average baseline trips is 67 percent lower, primarily because two thirds of the CV sample are nonusers. Average travel costs (P) are not reported for the CV sample; however, they can be derived by inverting the trip demand functions in Table 3 and expressing P as a function of Y, X, Q and the preference parameters. The WTP estimates for the three water quality changes range from $26.64 (improving water quality from Q_0=5.1 to Q_1=7) to $52.64 (avoiding a decrease from Q_1=2.5 to Q_0=0.5).

5.1.3 Calibrating Parameters.

To calibrate parameters for each specification, we define six conditions representing the difference between observed values for X, ΔMCS, and WTP (numbers in bold italics in Table 3) and their predicted values using the equations in Table 1 and 2. From the first column of travel cost results in Table 3 we define:

$$7.22 - X(18, 2.5, 46{,}398 ; \boldsymbol{\theta}) = \varepsilon_1 * 7.22 \qquad (6.1)$$

$$14.56 - M(18, 2.5, 5.1, 46{,}398 ; \boldsymbol{\theta}) = \varepsilon_2 * 14.56 \qquad (6.2)$$

From the second column of travel cost results we define:

$$30.58 - M(18, 2.5, 7.0, 46{,}398 ; \boldsymbol{\theta}) = \varepsilon_3 * 30.58 \qquad (6.3)$$

From the three columns of CV results we define:

$$37.81 - M(P, 2.5, 5.1, 46{,}398 ; \boldsymbol{\theta}) = \varepsilon_4 * 37.81 \qquad (6.4)$$

$$26.64 - M(P, 5.1, 7.0, 46{,}398 ; \boldsymbol{\theta}) = \varepsilon_5 * 26.64 \qquad (6.5)$$

$$52.64 - M(P, 0.5, 2.5, 46{,}398 ; \boldsymbol{\theta}) = \varepsilon_6 * 52.64 \qquad (6.6)$$

where P is derived from the inverse demand function $X^{-1}(2.4\ \ 2.5, 46{,}398 ; \theta)$ (see footnote to Table 1) at baseline conditions for the CV sample..

Ideally, we would identify solutions for the parameter vector **θ** that would make each of the six equations exactly equal to zero. However, due to the nonlinearities in this system, no exact solution could be found for any of the five preference specifications. As an alternative, we solved for values of the parameter vector **θ** that minimize the sum of squared differences (SSD, with differences expressed in percentage terms) between observed and predicted values in Equations (6.1) to (6.6) -- i.e., minimize $\Sigma_i(\varepsilon_i)^2$.

The calibrated parameter results are reported in Table 4 for each specification. Overall, the linear demand specification provides the closest fit, with an SSD=0.000143, followed by the semi-log demand specification (SSD=0.008). The interpretation of the parameters is often different across preference specifications; however, all indirect utility specifications include an additively separable subcomponent of the form φQ^{ψ} representing nonuse values. As expected, these parameters are always found to have positive values, implying that water quality has a positive effect on nonuse related utility. In all but one specification (log-linear), the calibrated value for ψ is less than one, implying a declining marginal effect of water quality on nonuse values. Also, in all specifications the γ parameter determines the marginal effect of water quality on the use-related component of indirect utility. Its calibrated value is consistently positive across specifications. Similarly, the δ parameter determines the marginal effect of income on utility, and its calibrated value is also consistently positive.

In the linear, semi-log, and log-linear demand models, the β, δ, and γ parameters can also be interpreted as representing the marginal effects of travel cost, income, and water quality on trip demand. When the calibrated value for β has a positive sign, as it does in the three specifications, it implies a negative effect of P on trip demand, which is consistent with expectations. The log-linear demand model implies an almost unit elastic trip demand with respect to P, and the linear demand implies that each dollar decrease in round trip costs increase the annual number of by almost 5. Similarly, the positive calibrated values for the δ parameter imply that trips are a normal good, with an income elasticity between 0.45 and 0.68 in the semi-log and log-linear models.

5.1.4 Predicting Values with the Calibrated Parameters.

To further evaluate the calibrated parameters, we insert them back into the equations in Tables 1 and 2, and we predict X, ΔMCS, and WTP for selected combinations of individual characteristics (Y and P) and changes in water quality (Q_0 and Q_1). The predictions, which are shown in Table 4, provide important additional internal validity checks on the calibrated parameters. For each preference specification, the six numbers in shown in bold italics are the predicted values associated with Equations 6.1 to 6.6. Since these are the equations that were used to calibrate the parameters, the predicted values all match closely with the corresponding values in Table 3. The other values reported in Table 4 include (1) predicted average travel cost for the CV sample, (2) predicted trips for the two samples under different water quality conditions, (3) predicted ΔMCS values for the CV sample, and (4) predicted WTP values for the travel cost sample.

In the linear and log-linear demand models, the predicted average travel cost for the CV sample is respectively 1 percent and 15 percent higher than for the travel cost sample, and in the Stone-Geary model it is 9 percent lower. In contrast, the modified CES and log-linear models predict average travels costs for the CV sample that are more than double. Two opposing effects make it difficult to form strong priors about the expected sign and magnitude of these differences. On the one hand, the predicted average travel cost for the CV sample should be higher than for the travel cost sample because the former includes nonusers who are expected on average to live farther from the water resource. On the other hand, the CV sample's average income is 10 percent lower, which implies a lower opportunity cost for travel. Nevertheless, the Stone-Geary results, with 9 percent lower travel costs for the CV sample, do not seem plausible.

Compared to the linear, semi-log, and Stone-Geary models, the modified CES and log-linear models also predict that trip demand is much less sensitive to water quality changes. The log-linear model shows virtually no changes in trips even for large changes in water quality, whereas the linear and semi-log models predict that trips for the travel cost (user) sample would more than double (from 7.22 to almost 19 trips per year) if water quality increased from boatable to swimmable. On the other end of the spectrum, the Stone-Geary specification predicts an almost tenfold increase in trips. The lack of sensitivity of the log-linear model to water quality changes and oversensitivity of the Stone-Geary model cast doubt on the validity of these calibrated preferences for benefits transfer.

For similar water quality changes, all models predict lower ΔMCS for the CV sample, and higher WTP for the travel cost sample. These differences occur because the average income for the CV sample is lower and because all of the models predict higher travel costs and fewer trips for the CV sample. Again, the smallest differences come from log-linear model.

The values reported in Table 4 are fundamentally "in-sample" predictions, because they are based on observed conditions in the two source studies. In Figures 1 through 3, we use a broader set of conditions to evaluate the calibrated models as transfer functions for predicting WTP. For these figures, we selectively vary water quality changes, income, and travel cost, and we compare WTP predictions across the preference specifications.

Figure 1 shows how predicted WTP for a 1 unit change in water quality (on a 10 point scale) varies with respect to baseline water quality (Q_0). Income is held constant at $45,000 and travel cost at $18 for all predictions. In each case, WTP is highest when starting from the lowest baseline level (Q_0=1), and it decreases as long as Q_0 is less than 5 (below fishable). Above the fishable level, however, predicted WTP for a unit change is U-shaped for all specifications, except the log-linear and Stone-Geary models which predict monotonically declining WTP. None of these WTP predictions are implausible, but the semi-log model is distinctly more convex than the other models.

Figure 2 shows predicted WTP for a change in water quality from fishable (Q_0=5.1) to swimmable (Q_1=7) conditions when average annual household income is varied between

$30,000 and $70,000 and average travel cost is held constant at $18 per round trip. Figure 3 shows predicted WTP when average travel cost is varied between $16 and $20 and average household income is held constant at $45,000. As expected, all specifications predict increasing WTP with respect to income and decreasing WTP with respect to travel costs. The log-linear demand model is least sensitive to both types of variation. In particular, it shows almost no sensitivity to changes in travel cost, which again casts doubt on the validity of this specification for representing preferences for water quality changes. Again, on the other end of the spectrum, the Stone-Geary model exhibits extreme sensitivity to both income and travel cost changes.[2] In contrast, the linear demand model predicts roughly unit elasticity of WTP with respect to income variation and declining WTP (from $56 to $30) when travel cost increases by 25 percent from $16 to $20. The WTP predictions from the semi-log demand are only slightly less sensitive to income and travel cost changes than the linear demand model. The modified CES shows similar sensitivity to income, but is relatively insensitive to travel cost changes.

5. Discussion and Conclusions

This paper demonstrates how the preference calibration method for developing structural benefit transfer functions can be generalized to several alternative preference specifications and can be expanded to include nonuse values. In addition to using a modified CES utility specification, similar to the one used in previous applications, we calibrated preference parameters using four other specifications. In each case, we combined summary data and estimates from a travel cost study with estimates from a contingent valuation study. Both of these source studies estimate nonmarket values for specific improvements in river water quality,

[2] Below $45,000 income and above $18 travel cost, which are close to the values where the model was calibrated, the Stone-Geary model predicts 0 trips. As a result, the Stone-Geary curves “flatten out” in these regions and only reflect nonuse values.

and they also provide information on average use levels (trips), travel costs, and incomes for their respective samples.

For each preference specification, we calibrated six preference parameters. These parameters have somewhat different interpretations and roles in the respective specifications; however, their calibrated values all have plausible signs. For example, the parameters φ, ψ, and γ are all directly related to the marginal utility of water quality improvements, and as expected they are all calibrated with positive signs.

To more thoroughly evaluate the parameter estimates and their implications for benefits transfer, we apply them to the Hicksian WTP functions derived from each specification. In effect, this gives us a calibrated benefit transfer function for each specification, which we use to predict average WTP for selected combinations of water quality levels and changes, income, and travel costs. This process mimics how the functions would be used to estimate benefits for selected policy conditions and changes.

The results show that the structural benefit transfer estimates can be very sensitive to the selection of preference specification. However, they also highlight the strengths and limitations of different specifications, by providing plausibility checks on the range of predicted outcomes.

The linear demand model provides the most consistently plausible results, with (1) positive WTP between \$15 and \$25 for each unit increment in water quality, (2) close to unit elasticity of WTP with respect to income variation, and (3) declining WTP with respect to travel cost. The semi-log demand and modified CES specifications also produce sensible estimates of WTP; however, the semi-log demand model produces WTP estimates that are notably more convex with respect to baseline water quality than other specifications, and the modified CES estimates are relatively insensitive to differences in travel cost. In contrast, the Stone-Geary model produces the least reliable results. In particular, the WTP estimates are implausibly sensitive to both income and travel cost differences. The results from the log-linear model are also somewhat suspect for opposite reasons -- they show virtually no sensitivity to travel cost differences and very low sensitivity to income changes.

In addition to providing structural WTP functions, the preference calibration results can also be used to specify functions for predicting trip demand (or travel costs) and Marshallian consumer surplus. These predictions are not only relevant for policy analysis (as measures of behavioral changes and use values), but they also provide secondary checks on the plausibility of the calibrated results. These secondary predictions (reported in Table 4) confirm the findings from the WTP functions – that the linear demand, semi-log demand, and modified CES specifications generate more plausible estimates than the log-linear and , in particular, the Stone-Geary specifications.

A main advantage of structural benefits transfer is that it imposes a degree of internal validity on the benefit transfer process, by requiring consistency with preferences and economic theory. This paper demonstrates how benefit transfer functions that are internally consistent with different preference specifications can be developed. However, more research is required to determine whether these advantages extent to convergent validity. The existing empirical research evaluating the convergent validity of traditional benefit transfer approaches, where "out of sample" benefit transfer estimates are compared to benefit estimates using original valuation results, has yielded at best mixed results (Shrestha and Loomis, 2003; Downing and Ozuna 1996; Kirchhoff et al., 1997). It remains to be seen whether structural benefits transfer can improve on these results.

An inherent feature of the preference calibration approach described in this paper is that it is most applicable when there are a limited number of available benefit estimates from different nonmarket valuation studies. In this case we use two ΔMCS estimates from a travel cost study and three WTP estimates from a CV study. However, when a large number of such estimates are available (e.g., values related to mortality risks) the logic of preference calibration can in principle be extended to statistical estimation and meta-regression analysis. This concept of "structural meta-analysis," as introduced by Smith and Pattanayak (2002) and discussed in more detail in Smith et al. (2006) and Bergstrom and Taylor (2006), presents a number of empirical challenges, but it continues to be a potentially fruitful area for future research.

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Table 1. Algebraic Expressions for Trip Demand and Change in Marshallian Consumer Surplus

Preference Specification	Trip Demand $X = X(P, Q, Y; \theta)$ [a]	Change in Marshallian Consumer Surplus (ΔMCS) $\Delta MCS = M(P, Q_o, Q_1, Y; \theta)$
Modified CES:	$X_i = \frac{\alpha_A}{\delta_A} \cdot \frac{Y}{\left(P - Q_i^{\gamma_A}\right)}$	$\Delta MCS = \frac{\alpha_A}{\delta_A} \cdot Y \cdot \left[\ln\left(P - Q_0^{\gamma_A}\right) - \ln\left(P - Q_1^{\gamma_A}\right)\right]$
Linear Demand:	$X_i = \alpha_B - \beta_B P + \delta_B Y + \gamma_B Q_i$	$\Delta MCS = \frac{\left(X_1^2 - X_0^2\right)}{2\beta_B}$
Semi-log Demand:	$X_i = \exp\left(\alpha_C - \beta_C P + \delta_C \ln(Y) + \gamma_C Q_i\right)$	$\Delta MCS = \frac{\left(X_1 - X_0\right)}{\beta_C}$
Log-linear Demand:	$X_i = e^{\alpha_D} Q_i^{\gamma_D} P^{-\beta_D} Y^{\delta_D}$	$\Delta MCS = \frac{\left(X_1 - X_0\right) \cdot P}{\left(\beta_D - 1\right)}$
Stone-Geary:	$X_i = \left(\frac{Q_i^{\gamma_E}}{1 + Q_i^{\gamma_E}}\right) \cdot \left(\frac{Y^{\delta_E} - \alpha_E}{P \cdot \left(\delta_E Y^{\delta_E - 1}\right)}\right) + \frac{\beta_E}{\left(1 + Q_i^{\gamma_E}\right) \cdot \left(\delta Y^{\delta_E - 1}\right)}$	$MCS_i = \left(\frac{Q_i^{\gamma_E}}{1 + Q_i^{\gamma_E}}\right) \cdot \left(\frac{Y^{\delta_E} - \alpha_E}{\delta_E Y^{\delta_E - 1}}\right) \bullet \left\{ \ln\left[Q_i^{\gamma_E} \left(\frac{Y^{\delta_E} - \alpha_E}{-\beta_E}\right)\right] - \ln(P) - 1 \right\} - \frac{\beta_E P}{\left(1 + Q_i^{\gamma_E}\right) \cdot \left(\delta_E Y^{\delta_E - 1}\right)}$ $\Delta MCS = MCS_1 - MCS_0$

[a] The corresponding inverse demand functions can be specified by solving for P:

$$P = X^{-1}(X, Q, Y; \theta)$$

Table 2. Algebraic Expressions for Hicksian WTP

Preference Specification	**Hicksian WTP** $WTP = W(P, Q_0, Q_1, Y; \theta)$
Modified CES:	$\mathrm{WTP} = \mathrm{Y} - \dfrac{\left[(\varphi Q_0^{\psi}) - (\varphi Q_1^{\psi}) + ((P - Q_0^{\gamma})^{-\alpha} y^{\delta})^{\beta}\right]^{\frac{1}{\beta \cdot \delta}}}{(P - Q_1^{\gamma})^{\frac{-\alpha}{\delta}}}$
Linear Demand:	$WTP = \dfrac{1}{\delta}\left[\left(X_1 - \dfrac{\beta}{\delta}\right) - \left(X_0 - \dfrac{\beta}{\delta}\right) \cdot \exp\left(\dfrac{\delta\gamma}{\beta}(Q_0 - Q_1)\right) + \varphi(Q_1^{\psi} - Q_0^{\psi}) \cdot \exp\left(\dfrac{\delta}{\beta}(\beta P - \gamma Q_1\right)\right]$
Semi-log Demand:	$\mathrm{WTP} = \mathrm{Y} - \left\{\mathrm{Y}^{-\delta} \cdot \left[\mathrm{Y} - \dfrac{(X_1 - X_0)}{\beta/(1-\delta)}\right] - \varphi(Q_1^{\psi} - Q_0^{\psi}) \cdot (1-\delta)\right\}^{\frac{1}{(1-\delta)}}$
Log-linear Demand:	$\mathrm{WTP} = \mathrm{Y} - \left\{\mathrm{Y}^{-\delta} \cdot \left[\mathrm{Y} - \dfrac{(X_1 - X_0) \cdot P}{(\beta - 1)/(1-\delta)}\right] - \varphi(Q_1^{\psi} - Q_0^{\psi}) \cdot (1-\delta)\right\}^{\frac{1}{(1-\delta)}}$
Stone-Geary:	$\mathrm{WTP} = \mathrm{Y} - \alpha - \beta P - (1 + Q^{\gamma}) \bullet$ $exp\left(\dfrac{\varphi(Q_0^{\psi} - Q_1^{\psi})}{1 + Q_1^{\gamma}} + \left(\dfrac{Q_0^{\gamma}}{1 + Q_1^{\gamma}}\right) \cdot \ln\left(\dfrac{Q_0^{\gamma}}{-\beta P}\right) - \left(\dfrac{Q_1^{\gamma}}{1 + Q_1^{\gamma}}\right) \cdot \ln\left(\dfrac{Q_1^{\gamma}}{-\beta P}\right) + \left(\dfrac{1 + Q_0^{\gamma}}{1 + Q_1^{\gamma}}\right) \cdot \ln\left(\dfrac{Y - \alpha - \beta P}{1 + Q_0^{\gamma}}\right)\right)$

Table 3. Summary Estimates and Data from Water Quality Valuation Studies[a]

	Travel Cost Study (Smith et al., 1983)		Contingent Valuation Study (Desvousges et al., 1987)		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Mean Household Income[b] (Y)	\$46,400	\$46,400	\$41,977	\$41,977	\$41,977
Mean Travel Cost[b] (P)	\$18	\$18	n.r	n.r	n.r
Mean Number of Trips (X_0)	***7.22***	7.22	2.41	n.r	n.r
Initial WQ (Q_0)	2.5	2.5	2.5	5.1	0.5
Improved WQ (Q_1)	5.1	7.0	5.1	7.0	2.5
Mean Change in MCS[b] (ΔMCS)	***\$14.57***	***\$30.58***			
Mean Willingness to Pay[b] (WTP)			***\$37.81***	***\$26.64***	***\$52.64***

n.r. = not reported

[a] The values in italics define the six conditions used to calibrate the six preference parameters

[b] In 2005 dollars

Table 4. Calibrated Parameters and Predicted Values for Six Preference Specifications

Calibrated Preference Parameters			Travel Cost Study (1)	Travel Cost Study (2)	CV Study (3)	CV Study (4)	CV Study (5)
			Predicted Values				
MODIFIED CES		**P**			\$44.35	\$44.35	\$44.35
α_A= 0.001640	δ_A=0.680081	**X_0**	***7.12***	7.12	2.41	2.53	2.31
β_A=0.105856	φ_A=0.000197	**X_1**	8.20	9.16	2.53	2.62	2.41
γ_A=0.901721	ψ_A=0.501745	**ΔMCS**	***\$15.73***	***\$28.16***	\$5.09	\$3.70	\$4.13
SSE = 0.029351		**WTP**	\$55.58	\$90.80	***\$41.41***	***\$24.51***	***\$50.92***
LINEAR DEMAND		**P**			\$18.22	\$18.22	\$18.22
α_B= 50.06902	δ_B= 0.000842	**X_0**	***7.22***	7.22	2.41	9.12	-
β_B= 4.910293	φ_B= 134.65826	**X_1**	13.93	18.84	9.12	14.03	2.41
γ_B= 2.582500	ψ_B= 0.229865	**ΔMCS**	***\$14.46***	***\$30.84***	\$7.88	\$11.57	\$0.59
SSE = 0.000143		**WTP**	\$44.44	\$75.74	***\$37.87***	***\$26.53***	***\$52.73***
SEMI-LOG DEMAND		**P**			\$20.76	\$20.76	\$20.76
α_C= 0.759377	δ_C= 0.686323	**X_0**	***7.19***	7.19	2.41	4.19	1.57
β_C= 0.371970	φ_C= 0.044946	**X_1**	12.52	18.79	4.19	6.29	2.41
γ_C= 0.213500	ψ_C= 0.428440	**ΔMCS**	***\$14.34***	***\$31.18***	\$4.80	\$5.64	\$2.25
SSE = 0.008004		**WTP**	\$52.24	\$89.98	***\$40.19***	***\$25.18***	***\$51.60***
LOG-LINEAR DEMAND		**P**			\$51.54	\$51.54	\$51.54
α_D= 0.000103	δ_D= 0.453201	**X_0**	***7.219***	7.219	2.407	2.407	2.406
β_D= 1.000979	φ_D= 0.0465354	**X_1**	7.220	7.220	2.407	2.407	2.407
γ_D= 0.000177	ψ_D= 1.1985167	**ΔMCS**	***\$16.78***	***\$24.23***	\$16.02	\$7.11	\$36.15
SSE = 0.069741		**WTP**	\$41.31	\$68.47	***\$39.46***	***\$25.96***	***\$50.98***
STONE-GEARY		**P**			\$16.43	\$16.43	\$16.43
α_E= 0.000414	δ_D= 0.94819	**X_0**	***7.18***	7.18	2.41	43.73	-
β_E= -1,527.578	φ_E= 0.003731	**X_1**	48.79	67.25	43.73	62.07	2.41
γ_E= 0.042245	ψ_E= 0.19086	**ΔMCS**	***\$15.26***	***\$29.37***	\$11.47	\$11.73	\$0.03
SSE = 0.008398		**WTP**	\$46.29	\$75.20	***\$39.61***	***\$25.41***	***\$52.00***

Figure 1. Predicted WTP for a Unit Change in Water Quality: Sensitivity to Baseline Water Quality

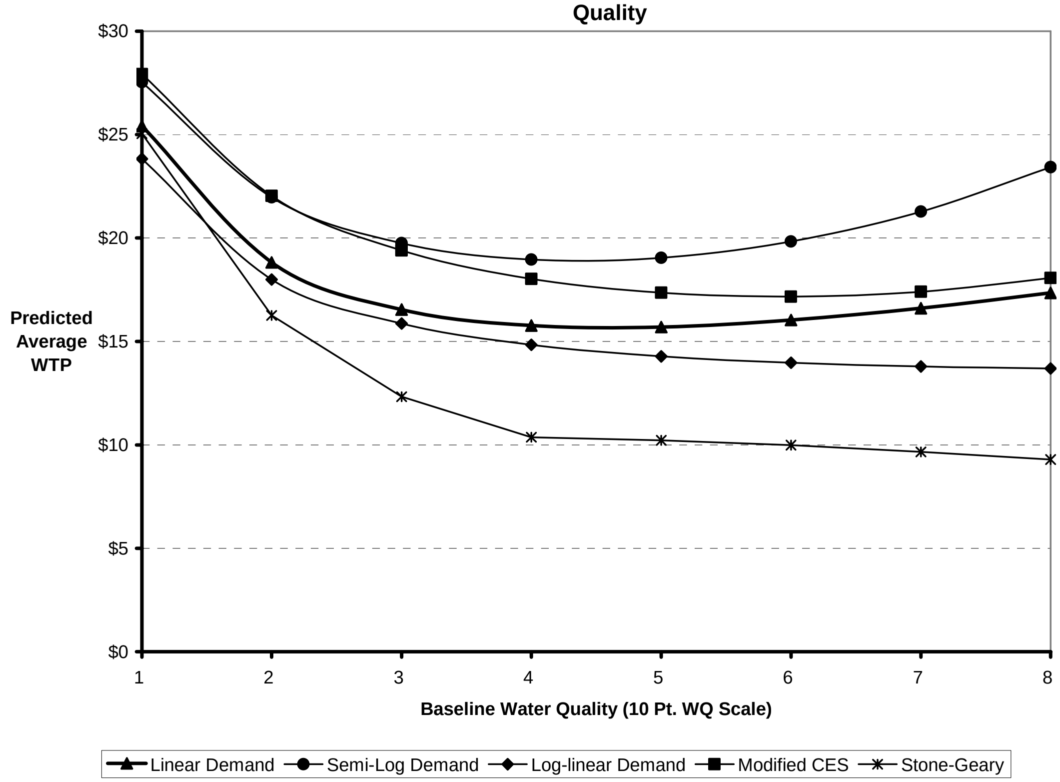


Figure 2. Predicted WTP for a Boatable-to-Fishable Water Quality Change: Sensitivity to Income

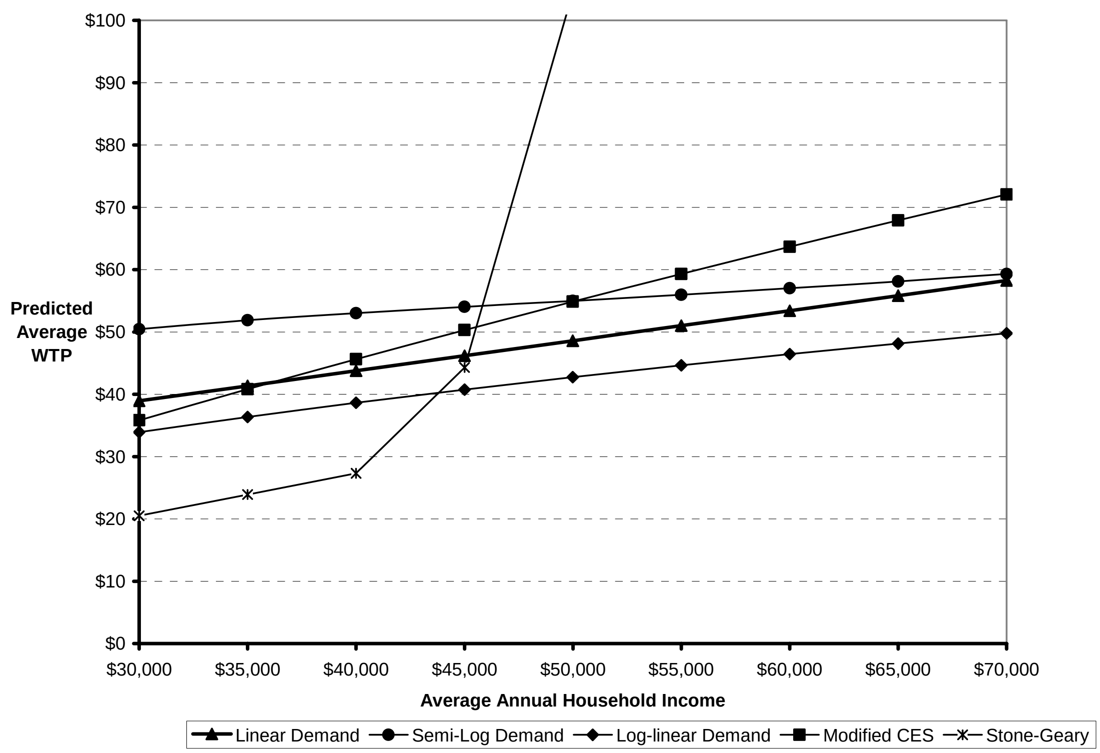
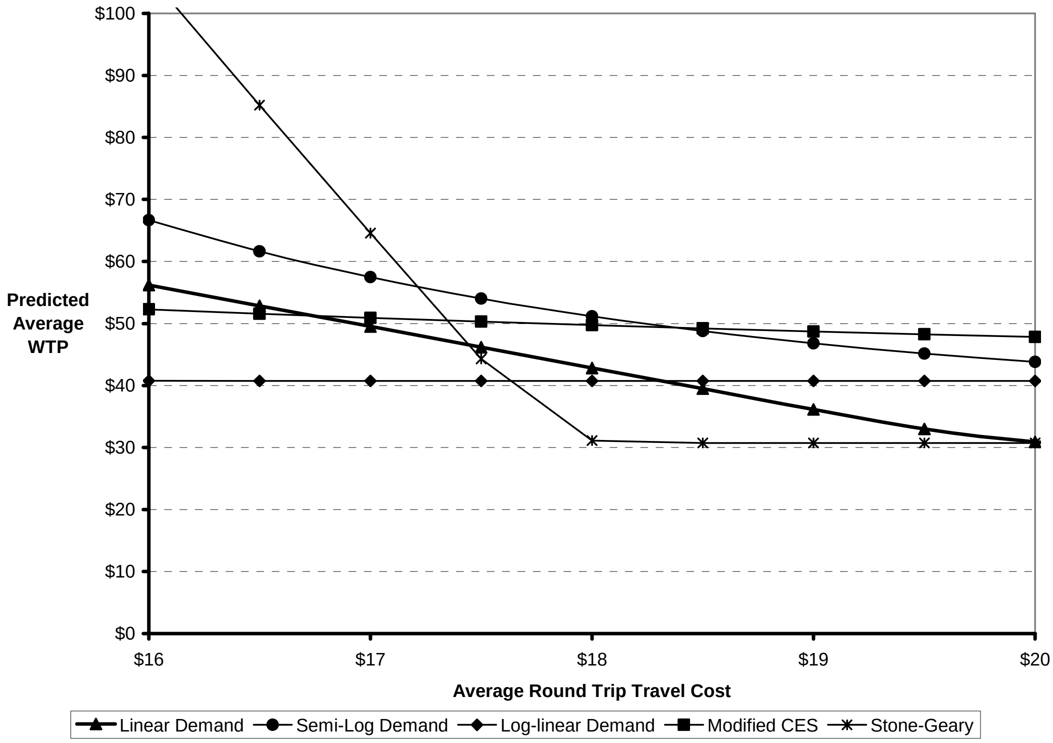


Figure 3. Predicted WTP for a Boatable-to-Fishable Water Quality Change: Sensitivity to Travel Cost



SPLIT-SAMPLE TESTS OF "NO OPINION" RESPONSES IN AN ATTRIBUTE BASED CHOICE MODEL

By

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ABSTRACT

Researchers conducting surveys that elicit preferences must decide whether to formally include response options that allow respondents to express “no opinion.” Using a split-sample design, we explore the implications of alternative formats for including, or not including, “no opinion” response options in an attribute based choice experiment. We provide evidence that using multiple “no opinion” responses may help researchers differentiate between respondents who choice a “no opinion” option due to satisficing and respondents that are indifferent between alternatives. Although there is literature suggesting that “no opinion” responses can be recoded as “no” responses in the case of referendum-based contingent valuation, in our case recoding “no opinion” responses as if they were “no” responses yielded substantially disparate results.

I. INTRODUCTION

In surveys eliciting stated preferences, some respondents do not state a preference, opting instead to answer a choice question with a response such as “don’t know”, “not sure”, or “would not vote.” These responses are variants of the “no opinion” responses discussed in more general survey research (Krosnick 2002). Treatment of “no opinion” responses in stated preference studies has largely focused on studies that use the contingent valuation method (CVM). The attribute-based method (ABM), also called choice experiments or stated choice, is a comparatively new technique that is related to, and has grown out of, CVM (Holmes and Adamowicz 2003; Foster and Mourato 2003, Louviere et al, 2000). The ABM presents respondents with a set of attributes of a good, where typically one attribute is price. The attributes and prices are varied across respondents. This differs from CVM where typically only price is varied across respondents. Thus ABM allows the researcher to value the implicit price for each attribute, much like a hedonic price study (Holmes and Adamowicz 2003). Both CVM and ABM often involve discrete choice responses, and as a result random utility models can be used in the estimation of both methods. Indeed, CVM is often considered a special case of ABM (Boxall et al. 1996).

In many ABM-based studies, respondents have been asked to choose between two or more attribute-price sets. This is similar to the referendum style questions commonly used in CVM, especially in the case where one attribute-price set is treated as a *status quo*. The National Oceanic and Atmospheric Administration (NOAA) panel recommended including a “no vote” option for binary choice CVM studies (Arrow et al. 1993). While, this recommendation has spawned a growing body of research on how to treat “would not vote” and other types of “no opinion” responses in the CVM literature, the issue has received less attention in ABM studies.

The literature on ABM does contain a related, but logically distinct, strain of research. In some ABM studies, respondents are presented with a choice set that includes several alternatives composed of varied attributes and a "none" alternative (Louviere et al, 2000) or an "opt-out" alternative (Boxall et al. 1996). In the setting of a product choice, the "none" option might be treated as a "don't buy" decision. In a recreational site choice context, the "none" option might represent a no-trip decision or it might represent a trip to a site not included in the choice set (Banzhaf et al. 2001). In other settings, the "none" option may be considered a choice to maintain the status quo. Typically, researchers explicitly model this type of alternative as one of the elements in a multinomial choice model. In contrast, here we consider a distinct issue in the ABM, in which a failure of respondents to choose an alternative is not a choice for the status quo. Instead, we examine the instance in which respondents' failure to choose one of the ABM alternatives is akin to a "no opinion" response.

There is growing evidence in the CVM binary choice literature that "no opinion" responses should not be treated as "for" votes (Groothuis and Whitehead 2002; Caudill and Groothuis 2005; Carson et al. 1998). However, there is not yet agreement as to whether "no opinon" responses should be treated conservatively as "against" votes (Carson et al. 1998; Kronsick 2002), or whether no opinion responses may represent cognitive difficulties, potentially resulting from an indifference in utility, and therefore should be treated as a truly unique response (Krosnick et al. 2002; Evans et al. 2003; Alberini et al. 2003; Caudill and Groothuis 2005; Champ et al. 2005). Furthermore, even those who believe that no opinion responses should be treated as unique responses largely base their argument on improving econometric efficiency with few arguing that the conservative approach yields inconsistent estimates. Groothuis and Whitehead (2003) observe that the appropriateness of treating no opinion responses as unique or "against" votes may depend on whether the study is attempting to measure willingness-to-pay (WTP) or willingness-to-accept (WTA).

Arguments for treating no opinion responses as unique are typically based on Wang's (1997) hypotheses on why a respondent may choose a no opinion response. Wang (1997) posits that there are four general categories of respondents who choose no opinion responses: 1) those who reject the CVM scenario, 2) those who know their preference and decline to answer, 3) those who make an effort and are truly unsure, and 4) those who do not make an effort and are therefore unsure.

Kronsnick et al. (2002) also present an analysis of why a respondent may choose a no opinion response. They present evidence that often no opinion responses are the result of satisficing, or simply that the "work" involved with answering the question is too great and a no opinion response involves the least work or the lowest risk.[1] Kronsnick et al. (2002) also discuss an alternative hypothesis regarding no opinion responses; the respondent's optimizing process may result in true indifference making the respondent truly unsure when the choices are "close" in terms of the associated net benefits or welfare yields. Therefore, a respondent may reply with a no opinion response because they are indifferent in a utility sense. However, it is unlikely that there is a clear line between a no opinion response resulting from optimizing and from satisficing since a respondent may begin optimizing, but may "give-up" before reaching true indifference.

More recent investigations by Alberini et al. (2003), Caudill and Groothuis (2005) and Evans et al. (2003) have aimed to improve estimation efficiency through "sorting" no opinion responses, especially focusing on identifying and making use of responses that would fall into Wang's (1997) latter two categories or that may be considered to be cases of optimizing as asserted by Krosnick et al. (2002). However, there has been little effort to sort no opinion responses that result from other phenomena; for example, no opinion responses that result from respondents being unsure due to utility indifference, and no opinion responses that result from respondents that are satisficing. Moreover, all the work to date has been based on ordinal polychotomous-choice and multi-bounded questions, which introduce other types of difficulties (Vossler and Poe 2005).

There also remains some question about the comparability of ABM studies to CVM studies (Stevens et al. 2000; Foster and Mourato 2003). ABM studies may be cognitively more difficult than CVM studies and ask respondents to explore their preferences in more detail (Stevens et al. 2000). This may result from the explicit substitutes in the ABM format. Furthermore, the multidimensional trade-offs implicit in ABM may result in a larger number of respondents who honestly “don’t know” or are closer to indifference relative to CVM. To date, there have been no studies examining whether reclassifying no opinion responses in ABM as “against” responses, considered a conservative classification in CVM, yields estimates that are consistent with similar surveys where a “no opinion” option is not offered.

This paper presents an examination of two research questions on no opinion responses in ABM studies. First, does recoding no opinion responses as “against” provide estimates consistent with those derived from surveys where there is no option of expressing no opinion? Secondly, does offering respondents with two qualitatively different no opinion responses allow expressions of welfare indifference to be sorted from those who express no opinion for other reasons? This latter issue may be generalizable to CVM because it attempts to distinguish Wang's (1997) third type of response (indifferent or too close to call) from Kronsnick et al.’s (2002) satisficing or other variants of “no opinion.”

II. SURVEY INFORMATION

A binary choice ABM survey was implemented using a web-based method with a split-sample design. In addition to the usual experimental design of the attributes, there were four unique versions of the ABM survey that differed in the response options respondents faced for their choice questions. The four sets of response formats were:

(i) "yes", "no", "too close to call" (TCC), and "not sure" (NS) (all options treatment),

(ii) "yes" and "no" (yes/no treatment),

(iii) "yes", "no", and NS (NS treatment), and

(iv) "yes", "no", and TCC (TCC treatment),

where the last expression in parentheses is what the four treatments will be called.

The TCC response is intended to reflect situations close to indifference. Collectively the NS and TCC responses are referred to as "no-opinion" responses as a shorthand to refer to respondents that did not explicitly choose yes or no in the choice scenario. The surveys that were distributed across the four groups of response categories all utilized the same experimental design for the ABM attributes.

The web-based ABM survey elicited preferences for inland, freshwater wetland mitigation. The questionnaire was developed using a series of focus groups and pretest interviews (Kaplowitz et al. 2004), and the policy setting and choice questions follow that of the paper instrument discussed in Lupi et al. (2002). Each respondent was presented with the characteristics of a common wetland that had already been approved for drainage ("drained wetland") and the characteristics of a wetland being proposed as compensation ("restored wetland") for the wetland to be drained. The attributes of the wetlands presented to respondents were wetland *type* (wooded, marsh, mixed), *size* (acres), public *access* attributes, and *habitat* attributes (see Appendix for sample choice question). The respondents were then asked, "In your opinion, is the restored wetland good enough to offset the loss of the drained wetland?" Each respondent was asked to make up to five comparisons, but each respondent was only exposed to one response option format. Details of web survey design, administration, and general results are reported in Hoehn et al. (2004).

III. RESPONSE FREQUENCY ANALYSIS

As mentioned above, the survey design incorporated four different sets of response options. Response category statistics for the completed choice questions are presented in Table 1.[2] As expected, the response treatment including all options ("all options") resulted in the highest proportion of "no opinion" responses (25%). Chi-square tests where used to compare the probability of a "no opinion" response across the four different survey response treatments and results are presented in Table 2.[3] Table 2, section A, shows that the proportion of "no opinion" responses is significantly different when all four response options are presented to respondents as compared to instances in which one type of "no opinion" response is available to respondents. This is true at all common significance levels. It seems clear from these results that respondents are more likely to choose a "no opinion" response option when both the TCC and NS options are available to them as part of their response choice set. A chi-square test comparing the TCC survey treatment and the NS survey treatment yielded a low p-value (< 0.016). This result suggests that the TCC and NS response options are not viewed as equivalent response options by respondents, and indicates that the wording of the "no opinion" options may matter.

Carson et al. (1997) used chi-square tests to determine the effect of no opinion responses on the proportion of “yes” and “no” responses in a CVM study. A similar analysis was conducted for the ABM data, and the results are displayed in Table 2 section B. The proportion of “yes” to “no” responses was significantly different, at the 95% confidence level, between surveys that did not allow respondents to express “no opinion” and surveys that offered either TCC or NS as response options. The chi-square analysis of the proportion of responses when both “no opinion” responses were offered (the all options version) against the instances when only “yes” and “no” responses were offered yielded a p-value of 0.07. This p-value implies that the null hypothesis of no significant difference between these two proportions should not be rejected at the 95% confidence level, but may be rejected at the 90% confidence-level. This difference may not be significant at the traditional 95% confidence level but may yield different economic results. That is, the yes’s and no’s from these two groups may produce different estimates of WTA.

Further examining the response categories, “no opinion” responses were pooled with “no” responses, and retested against the yes-no ratio from the survey treatment that only allowed “yes” or “no” responses (Table 2 section C). All chi-square tests for all of these comparisons yielded p-values < 0.05. This result implies that pooling “no opinion” responses with “no” responses, as suggested by Carson et al. (1998), results in significantly different yes-no ratios, in contrast to the findings of Carson et al. (1998) for CVM. It remains unclear in the “all options” case, where both TCC and NS were presented as response options, whether both TCC and NS pulled equally from “yes” and “no” responses.

The distribution of yes-no ratios across response formats that allowed for a “no opinion” response was also tested (Table 2 section D). The ratio of “yes” to “no” responses did not change significantly when TCC or NS was offered as the “no opinion” response option. The distribution of yes and no responses when both NS and TCC response options where available as response choices was compared to the distribution of yes and no responses when only one “no opinion” response option was presented and were found to be significantly different at the 95% confidence level. That is, when more than one “no opinion” option was presented to respondents, the proportion of yes and no responses differed significantly.

These results indicate that survey participants may respond to the phrasing, language, or number of “no opinion” response items lending evidence to the hypothesis that various no opinion responses may represent unique types of responses. Further, these results suggest that “no opinion” responses do not pull evenly from “yes” and “no” responses and that, unlike Carson et al.’s (1998) CVM study, these responses do not consistently pull from “no” responses. It appears in this instance that no opinion responses pull more heavily from “no” responses– see Table 1. Moreover, “no opinion” responses seem to pull more evenly from “yes” and “no” responses when both TCC and NS are presented as options as opposed to when only one type of no opinion response is available (Tables 1 and 2). It appears that the marginal impact of adding a second “no opinion” response option is to pull more from “yes” than “no”, even when the first “no opinion” response option pulled more from “no” than “yes”.

There are three potential explanations for the apparent divergence in results between this ABM study and previous CVM studies. First, the underlying ABM study focuses on respondents’ WTA compensation (Groothuis and Whitehead 2003) as measured by in-kind trade-offs. Second, there may be something unique to the ABM response format that is different from CVM studies. Thirdly, it is possible that the additional “no opinion” response option causes responses to pull more evenly from both “yes” and “no.” Based on response ratios, TCC and NS responses seem to be good substitute responses when only one of the response options is available to respondents. When both TCC and NS are present, it may be presumed that a TCC response may involve, perhaps, an attempt by respondents to optimize, especially if it is assumed that this response is indeed qualitatively different from a more general NS response.[4] Next, we explore possible response category effects of welfare estimates.

IV. EFFECTS ON WELFARE

The wetlands mitigation survey used in this study asked respondents to make an in-kind tradeoff between acres of drained and restored wetlands. In essence, respondents were asked if restoration of a larger wetland would compensate for the loss of an existing wetland. This makes acres of wetlands the unit of currency for this study. Various quality attributes for the wetlands were also included in choice sets, and these act to shift demand for wetland acres. Responses were coded into 11 response variables. These variables included change in wetland acreage (effectively price), dummy variables for capturing changes in wetlands' general vegetative structure, public access, and habitat conditions for amphibians, songbirds, wading birds, and wildlife flowers (changes could be poor to good or good to excellent). Changes in wetland acres where recorded as the change in the total number of acres. Dummy variables where coded as one for a positive change, zero for no change, and -1 for a negative change. Changes from poor to excellent where indicated by both the poor to good and good to excellent dummy variables being coded as one (other coding followed this pattern). A change from no access to access was coded as one (-1 for the other direction), while changes in wetland type where coded as one if there was a change.

In-kind welfare measures can be estimated using random utility theory (Holmes and Adamowicz 2003). A random effects logit model that addresses the panel data was estimated for each of the four survey response format versions, and parameter ratios were used to calculate the minimum WTA in acres of restored wetland per acre of drained wetland (Table 3, first row). Specifically, WTA *ceteris paribus* was found by dividing the constant parameter by the negative of the marginal utility of acres. All models fit the data, with log-likelihood ratio tests against a model with a single choice dummy being significant at all common significance levels.

Each model included all variables, though not all coefficients estimated where significant at the 90% or 95% confidence level. In all models, estimates for the parameter associated with improving wild flower habitat from poor to good where not significant at that 95% confidence level (Table 3). The parameters associated with other variables that were not significant are indicated in Table 3. The parameter associated with wetland acres was significant at the 95% confidence level for all models.

Estimation results can be interpreted as the marginal implicit prices, in kind, associated with the change defined by the variable. For the constant term, the marginal implicit price is the change in acres required to maintain the same level of utility. That is, if the WTA estimate were zero then one acre restored wetland would be adequate compensation for one acre of drained wetland. In cases in which only "yes" and "no" options were presented to respondents, a restored wetland could have up to eight fewer acres for each acre of the drained wetland, *ceteris paribus*, before respondents would prefer the drained wetland (Table 3, first row). This may reflect a preference toward getting something out of a restoration project as opposed to not getting any restoration. In cases in which there were "no opinion" responses, dropping the "no opinion" responses from the analysis yielded WTA estimates that were closest to those derived from the yes/no format. The WTA estimates, *ceteris paribus,* varied greatly across response treatments. The WTA estimates showed that more than three times less compensation was demanded by respondents when “no opinion” responses were dropped as opposed to pooled with no’s. Recoding the “no opinion” responses as “no” responses in the all response options format makes the ratio of “yes” to “no” less than one (Table 1) and causes the WTA to be positive, i.e., one acre drained required more than one acre to offset the loss.[5]

An important aspect of the ABM is that allows the relative importance of the attributes to be ranked. From above we saw that recoding the data changed the yes to no ratio, and therefore, we affected the constants, as expected. However, recoding the data to address the alternative approaches for treating the no opinion responses should not affect the ranking of attributes if “no opinion” responses represent satisficing. To investigate if recoding affected the relative importance of attributes, the marginal implicit prices associated with each attribute variable (Table 3) where ranked from the largest marginal impact to lowest marginal impact (Table 4). Changing wildflower habitat from poor to good had the lowest maximum difference in rank (excluding a change in wetland type which has a negative value), though these marginal implicit prices where calculated based on parameters that were not significant at that 95% confidence level. Improving wading bird habitat from poor to good consistently ranked as having a high marginal implicit price ranging (median rank of 2 a maximum difference in ranks of 3). Changes in song bird habitat from poor to good also had a high median rank, 2, but had a maximum difference in ranks of 5. This difference is driven by the ranks associated with the TCC and all options format when the “no opinion” response are pooled with “no.” This provides some evidence that TCC response may not represent satisficing. The attribute ranks for the NS format are identical for all attributes regardless of whether the NS was pooled with “no” or dropped.

This provides some evidence that NS by itself acts more like a "no" response due to satificing than an expression of indifference.

Rank correlations between treatments provide further evidence that TCC and NS responses are not used interchangeably (Table 5). The ordering of marginal implicit prices between TCC treatments (TCC responses pooled with no and dropped) showed a correlation with the ranking of the marginal implicit prices across all treatments. However, there is a decline in the strength of the correlation across formats in the order of NS, all options, and TCC. Moreover, all formats and treatments, except *TCC pooled with no* demonstrated a rank correlation with the yes/no format. The attribute ranks from the TCC format with TCC pooled with "no" did not correlate well with either NS treatment (this approach had the three lowest correlations in the table). That said, some of the approaches gave marginal implicit prices that ranked the attributes in a manner that was highly correlated across the modeling strategies, which would be reassuring for benefits transfer of the attribute valuations.[6] The strong correlations among the yes/no format and the NS format (either treatment) indicate that NS response may represent satisficing. However, the impact of recoding TCC as "no" on the ranks of the attributes indicates that TCC responses may not simply be satisficing.

V. UNDERSTANDING NO OPINION RESPONSES

The evidence presented in the preceding sections of this paper indicates that whether or not to treat "no opinion" responses as "no" responses is not straight forward. Treating "no opinions" as "no" lead to non-positive WTA estimates because of the effect of the recoding on the constant term, and in the case of TCC greatly affect the ranks of the wetland attributes. Therefore, we do not advocate simply treating "no opinion" response as "no" in the attribute-based choice models. It is also unlikely that "no opinion" responses should be treated as "yes" responses. However, "no opinion" responses can make up a substantial portion of survey responses when a no opinion response category is present. In this studies' survey treatment where all response options were available, 25% of the responses were either TCC or NS, and this leads to two important questions. First, is there evidence that some preference information may be recovered from "no opinion" responses? Second, is there a discernable difference between the responses with a change in wording of "no opinion" responses (i.e., "too close to call" versus "not sure"), aside from the previously discussed effect on attribute ranks?

To address these questions, we used parameter estimates derived from the simple yes/no model to predict "yes" responses for the data that was held aside or reserved for model assessments (see footnote 2). The 1,865 unused (reserved) responses served as a set of "true" responses for testing purposes and were all from the treatment containing all four response options (all options treatment). The model parameters were used to predict the probability of a yes response for the reserved data. If the model has the ability to discern yes from no votes, then for respondents that actually answered yes, we would expect the mean predicted probability of a yes to be larger than the mean predicted probability of a yes for those respondents that actually chose no. Further, if respondents chose either TCC or NS as a result of an attempt to optimize but found the welfare yield to be "close" to their level of indifference, then we would expect the mean predicted value associated with TCC and NS responses to be between the mean predicted value associated with "yes" and "no" responses.[7] This is indeed the case as shown in Table 6.

To test if these means are significantly different from one another, a single factor ANOVA was used. The group mean square is 7.94 and the error mean square is 0.03 yielding an F-statistic = 90.36 with 3 and 1,823 degrees of freedom, which yields a p-value that is essentially zero. This implies that the mean associated with at least one response type is significantly different from the mean associated with at least one other response type. If the model has predictive power, then it should be expected, that at least “no” and “yes” responses were significantly different.

The Tukey test, also known as “the honestly significant difference test” and “wholly significant difference test,” was used to identify the response options that had significantly different means in a set of *post hoc*, pair-wise comparisons (Zar 1996). Tukey tests allow one to determine if there are pairs of means such that the null hypothesis of no difference would not be rejected if just those two means where tested alone. Results are presented in Table 7. The critical value for the Tukey test with error degrees of freedom of 1,823, and four categories at the 95% confidence level is 3.633. All comparisons yielded a Tukey q-statistic greater than the critical value except the NS-TCC comparison (q = 2.954). This result supports the hypothesized expectation that the predicted mean associated with “yes” and “no” responses are indeed different. It is also interesting to note, that these results indicate that both “no opinion” responses are significantly different from both “yes” and “no” responses – implying the model has predictive power. This indicates that “no opinion” responses may indeed reflect that “no-opinion” respondents are near their utility indifference.

An alternative explanation for the means associated with “no opinion” responses lying between the means of “yes” and “no” responses is that the predicted variance associated with “no opinion” responses is significantly large. However, the ANOVA results show that the means are indeed significantly different. In light of these results, in future analyses it may be possible to gleam extra information by treating the “no opinion” responses as a unique answer. It is also possible that by including multiple “no opinion” responses, respondents that would otherwise satisfice are forced to examine their preferences, at least enough to choose between TCC and NS.

VI. CONCLUSION

To our knowledge, this is the first paper to explore the treatment of “no opinion” responses in an ABM setting that tries to differentiate between alternative types of no opinion responses. The differences and similarities between ABM and CVM are well documented (Boxall et al. 1996; Holmes and Adamowicz 2003). Research on how to treat no opinion responses in the CVM literature has been advancing since the NOAA commission made its recommendation to include a "no-vote" option. The work presented in this paper provides contrary evidence regarding conventional wisdom that “no opinion” responses should be treated as “no” responses as in the CVM literature (Carson et al. 1998).

There are two alternative hypotheses that may be used to explain the results presented here. First, the ABM response format may be different enough so that no opinion responses represent optimizing and not satisficing. This may be because the tabular form lessens the cognitive work asked of the respondent (Viscusi and Magat 1987) and facilitates making tradeoffs (Hoehn et al, 2004). However, it may be that the results presented here have more to do with the WTA framing of our choice question, supporting Groothuis' and Whitehead's (2002) findings.

Dropping “no opinion” responses appears to yield results most consistent with surveys that do not offer no opinion response options. As the number of no opinion options increased so too did respondents’ use of those responses. It does seem likely that the inclusion of two no opinion responses eliminate many respondents that may be leaning in a given direction, and potentially would have answered "yes" or "no." It is also likely that by adding a second no opinion response option a disproportionate number of would-be "yes" voters switch to one of the no opinion responses (this may be true even if a disproportionate number of would-be "no" voters would choose “no opinion” when only one no opinion option is available). This result seems to present a tradeoff for researchers. If there is a way to recover information from some no opinion responses, then adding an additional response option may be beneficial. However, if no such tool exists then sample size may be greatly reduced.

In this paper, we present evidence that when two no opinion response options are offered respondents may have used these options differently, to express indifference that may have resulted from optimizing (“too close to call”) as opposed to uncertainty that may have resulted from satisficing (“not sure”). The effect that TCC had on attribute ranks indicates that this option is affecting the decision making process in ways consistent with indifference.

Understanding how to treat response options that allow respondents to express “no opinion” is important to the future development and refinement of attribute-based stated preference techniques. These techniques are increasingly contributing to our ability to measure preferences for goods and services that have non-use values or potential attributes that extend beyond current conditions. This paper provides a first step in understanding how to treat “no opinion” responses in the ABM format, but more work in this area is still needed. Specific areas of future study include investigating if estimating the probability of a “too close to call” response can be used to estimate indifference and improve the ability to predict choices. However more than anything else, more case studies need to be examined, especially cases involving WTP.

VII. APPENDIX I. SAMPLE SURVEY.

Wetlands Scorecard #3:
How do the Drained and Restored Wetlands Compare?

Wetland Features	Drained Wetland	Restored Wetland
Is it marsh, wooded, or a *mix* of marsh and woods?	Wooded	Mixed
How large is it?	12 acres	24 acres
Is it open to public?	Yes	Yes
Are there trails and nature signs?	No	Yes
How good is the habitat for different species?		
Amphibians and reptiles like frogs and turtles	good	excellent
Small animals like raccoon, opossum, and fox	good	good
Songbirds like warblers, waxwing, and vireo	good	--
Wading birds like sandpiper, heron, or crane	--	excellent
Wild flowers?	good	good

What do the habitat ratings mean?

excellent:	The wetland habitat supports these species in better than average numbers and variety; a casual observer is very *likely to see a variety* of these species.
good:	The wetland habitat supports these species in average numbers and variety; a casual observer is *likely to see a few* of these species.
--	The wetland habitat supports these species in very small numbers or not at all; a trained observer is *unlikely to find any* of these species.

Wetland Case #3

The scorecard on the left page compares the natural features of the drained and restored wetlands.

In your opinion, is the restored wetland good enough to offset the loss of the drained wetland in Case #3? (Circle the letter next to your decision)

a. Yes, the restored wetland offsets the loss of the drained wetland

b. No, the restored wetland does not offset the loss of the drained wetland

c. Too close to call

d. Not sure

The Fine Print:

The drained and filled wetlands...

...are *common* wetland types.

...do *not* contain any rare species or rare habitat.

...are the *same* in terms of features not mentioned in the scorecard.

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Endnotes

[1] The work requirements may range from physically reading the survey to understanding the question to actually evaluating preferences.

[2] A total of 4,865 responses where received for the "all options" treatment, (i). However 1,865 of these observations where randomly selected and reserved for later use in assessing the model predictions.

[3] All chi-square tests use the Yates correction for variables coming from a binomial distribution (Zar 1996).

[4] It could be argued that one effect of including no opinion options would be to lower item non-response rates. The item non-response rates were as follows: all options (0.8%), Yes/No (0.7%), NS (0.4%), and TCC (1.5%). These differences are statistically significant (p-value < 0.0001). Interestingly, the TCC rate stands out as being higher than the NS rate which provides some further evidence that TCC is being used by respondents differently than NS. Overall though, none of the treatments had substantial levels of item non-response.

[5] Recall under MLE in the logit model, the estimated constant parameter will ensure that the average of the predicted probabilities of yes answers will match the sample share of yes answers. To the extent that the "no opinion" answers are not being explained by the other parameters of the models, then under the recoding of responses the new estimated constant must adjust to match the new sample shares. Thus, recoding of "no opinion" responses as "no" responses has the clear effect of lowering the constant and hence lowering the marginal implicit prices.

[6] Clearly the latter did not apply to the valuations for the constant term where use in benefits transfer would be warrant caution.

[7] Indeed, in a model that had perfect ability to discriminate the choices in accord with the theory, we would expect the predicted yes probabilities to be > 0.5 (<0.5) for the yes answers (for the no answers). For those that selected TCC, we'd expect predicted yes probabilities to be about equal to 0.5 – they point of indifference implied by RUM theory. Hypotheses for the NS option expectations are less clear. Suppose the NS represent saticficing, then really easy choices would get answered and the easiest to answer are the choices where they are clearly yes or clearly no. In this case, we'd expect that NS tends to act like TCC but does so with larger variance.

Table 1. Responses data, TCC = too close to call, NS = not sure .

Survey version/ Response treatment		**Total responses**	**Proportion of**						
			of Yes	**of No**	**of TCC**	**of NS**	**Proportion “no opinion” (NS + TCC)**	**Ratio of "yes" to "no"**	**Ratio of "yes" to "no pooled with no opinion”**
All options	i	3000	0.467	0.287	0.164	0.082	0.25	1.63	0.88
Yes/No	ii	1586	0.590	0.410	-	-	0.00	1.44	-
NS	iii	1619	0.553	0.288	-	0.159	0.16	1.92	1.24
TCC	iv	1683	0.537	0.272	0.191	-	0.19	1.97	1.16

Table 2. Chi-square test results.

A. Probability of an "no opinion" response

comparison	NS v. TCC	All options v. NS	All options v. TCC
χ^2 statistic	5.8360	47.1749	18.3050
p-value	0.0157	0.0000	0.0000

B. The ratio of Yes to No for "no opinion" formats compared to Yes/No treatement

comparison	YES/NO and All options	YES/NO and NS	YES/NO and TCC
χ^2 statistic	3.2734	13.6764	16.4712
p-value	0.0704	0.0002	0.0000

C. The ratio of Yes to No when "no opinion" are pooled with "no"

comparison	YES/NO and All options	YES/NO and NS	YES/NO and TCC
χ^2 statistic	62.4845	4.4130	9.3238
p-value	0.0000	0.0357	0.0023

D. The ratio of Yes to No with "no opinion" responses compared among "no opinion" formats

comparison	TCC and NS	NS and All options	TCC and All options
χ^2 statistic	0.0961	4.9850	6.8678
p-value	0.7566	0.0256	0.0088

Table 3. Marginal implicit prices of attributes associated with the WTA in-kind acres compensation for drained wetlands.*

Survey type	Yes/ No	TCC pooled with No	TCC discarded	NS pooled with No	NS discarded	All options pooled with No	All options discarded
WTA ,ceteris paribus	-8.42	-2.54[b]	-11.96	-3.55[b]	-11.56	4.81	-5.16
change of wetland type	5.86	5.79	7.76	4.80	4.45	2.75	2.66[a]
access	-6.65	-4.89	-5.53	-7.48	-7.03	-5.64	-7.37
amphibian p → g	-7.40	-3.25[a]	-4.02	-8.78	-9.44	-7.32	-6.74
song bird p → g	-10.70	-3.36	-4.84	-10.24	-11.02	-4.97	-6.96
wading bird p → g	-7.69	-7.68	-7.56	-9.50	-10.20	-5.99	-6.72
wild flower p → g	-3.79[b]	-3.16[a]	-2.44[b]	-3.66[a]	-3.44[b]	-2.23[a]	-1.55[b]
amphibian g → e	-5.49	-4.39	-3.95	-6.92	-6.79	-5.24	-5.37
song bird g → e	-5.47	-3.41	-2.19[a]	-1.89[b]	-2.90	-5.24	-5.30
wading bird g → e	-5.49	-2.75	-3.57	-4.53	-4.98	-3.37	-3.50
wild flower g → e	-2.27[b]	-4.12	-4.52	-4.26	-3.81	-1.53[a]	-1.59[a]

* Values in this table represent the parameter estimate associated with the listed variable divided by the parameter on percent changes in areas. p → g = poor to good, and g → e = good to excellent. [a] and [b] indicate ratios using parameter estimates that were NOT significant at the 95 and 90%confidence levels respectively.

Table 4. Ranking of the absolute value of the marginal implicit prices and the maximum difference in ranking across models. Rankings of one had the largest marginal effect and 10 had the lowest marginal effect.

Answer coding	YES/ NO	TCC pooled with No	TCC dropped	NS pooled with No	NS dropped	No opinions pooled with No	No opinions dropped	Median rank	Maximum difference
change of wetland type	10	10	10	10	10	10	10	10	0
access	4	2	2	4	4	3	1	3	3
amphibian $p \rightarrow g$	3	7	5	3	3	1	3	3	6
song bird $p \rightarrow g$	1	6	3	1	1	6	2	2	5
wading bird $p \rightarrow g$	2	1	1	2	2	2	4	2	3
wild flower $p \rightarrow g$	8	8	8	8	8	8	9	8	1
Amphibian $g \rightarrow e$	6	3	6	5	5	4	5	5	3
song bird $g \rightarrow e$	7	5	9	9	9	5	6	7	4
wading bird $g \rightarrow e$	5	9	7	6	6	7	7	7	4
wild flower $g \rightarrow e$	9	4	4	7	7	9	8	7	5

Table 5. Rank correlation results between treatments (TCC = too close to call, NS = not sure).

	YES/ NO	TCC pooled with No	TCC discarded	NS pooled with No	NS discarded	No opinions pooled with No	No opinions discarded
YES/NO	**1.00**	0.39	0.72	0.94	0.94	0.75	0.87
TCC pooled with No	0.39	**1.00**	0.75	0.49	0.49	0.59	0.59
TCC discarded	0.72	0.75	**1.00**	0.85	0.85	0.56	0.75
NS pooled with No	0.94	0.49	0.85	**1.00**	1.00	0.68	0.84
NS discarded	0.94	0.49	0.85	1.00	**1.00**	0.68	0.84
no opinions pooled with No	0.75	0.59	0.56	0.68	0.68	**1.00**	0.81
no opinions discarded	0.87	0.59	0.75	0.84	0.84	0.81	**1.00**

Table 6. Summary statistics for predicted probability of yes by actual response in the reserved data.

	Actual Response			
	YES	NO	TCC	NS
Mean	0.669	0.514	0.585	0.602
Standard deviation	0.162	0.187	0.165	0.185
Total responses	916	490	303	118

Table 7. Tukey test results. The critical value at the 95% confidence level is 3.633.

Comparison	NO - YES	NO - NS	NO - TCC	YES - TCC	YES - NS	NS - TCC
Difference of means	0.155	0.088	0.070	0.085	0.068	0.017
Standard Error	0.003	0.005	0.004	0.003	0.004	0.006
Tukey q-statistic	48.107	17.872	16.356	24.515	17.948	2.954

Meta-Regression and Benefit Transfer: Data Space, Model Space, and the Quest for 'Optimal Scope'

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Meta-Regression and Benefit Transfer: Data Space, Model Space, and the Quest for 'Optimal Scope'

Abstract:

Meta-functional Benefit Transfer, while conceptually attractive, is often plagued by the paucity of available source studies and related small sample problems. A broadening of scope of the Meta-Regression Model by adding data from "related, yet different" contexts or activities may circumvent these issues, but may not necessarily enhance the efficiency of transfer functions if the different contexts do not share policy-relevant parameters. We illustrate how different combinations of contexts can be interpreted as 'data spaces' which can then be explored for the most promising transfer function using Bayesian Model Search techniques. Our results indicate that for some scope-augmented data spaces model-averaged benefit predictions can be more efficient than those flowing from the baseline context and data.

Key words: Bayesian Model Averaging, Stochastic Search Variable Selection, Meta-Analysis, Benefit Transfer, Resource Valuation

JEL codes: C11, C15, Q51

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I) Introduction

Benefit Transfer, i.e. the synthesis of existing resource valuation results and the transfer of these findings to a new policy site or context continues to grow in popularity with policy makers and resource managing agencies. For example, in a recent insiders' assessment of the role of Benefit Transfer (BT) at the U.S. Environmental Protection Agency (EPA), Iovanna and Griffiths [1] illustrate how BT has been employed in recent years on numerous occasions in the agency's enforcement of the Clean Water Act. The authors further predict that due to the triple constraints of expediency, financial strains, and administrative hurdles "original assessment studies will remain a rare exception" in future EPA valuation efforts.

It is not surprising, therefore, that the concept of BT has stirred increasing interest amongst resource economists in the U.S. and abroad, and spurred research efforts on both the theoretical underpinnings of BT (e.g. [2, 3]) and its econometric and computational implementation (e.g. [4-6]). This study focuses on the latter aspect of BT. Specifically, we examine the issue of 'optimal scope', i.e. the optimal size and composition of a meta-dataset when BT estimates are to be produced via a meta-regression approach.

In most situations that call for BT some information on the policy context, such as basic site characteristics or aggregate demographics for the underlying population of interest, will be available to the analyst. In that case, empirical findings generally support the use of functional BT over point ("value") transfers or simple aggregation of existing estimates (e.g. [7, 8]). If there exists a study for which the physical and temporal context and the composition of underlying stakeholders are very similar to those for the targeted policy application, parameter estimates from this single source can in theory be combined with policy site attributes to form the transfer function. In practice, however, a close correspondence across multiple dimensions for a study site and policy site is unlikely. Therefore, researchers have increasingly resorted to meta-analytical approaches to derive parameter estimates for function transfer.

The primary rationale for combining information from multiple existing sources in a meta-dataset and using a Meta-Regression Model (MRM) to derive parameter estimates for BT is that each source context will likely overlap with the policy scenario in one or several dimensions of site or population characteristics. In essence, the MRM produces parameters that apply to the "prototypical" context or site, and this prototypical context can be expected to more closely correspond to the policy setting than any single context alone. In addition, MRMs allow disentangling the effects of site attributes, user characteristics, and study-methodological factors on welfare estimates from underlying source studies.

As can be expected, this approach is not without flaws or pitfalls. Common shortcomings of the MRM-BT approach range from weak links with underlying economic theory ([2, 9]), difficulties in identifying appropriate source studies and collecting sufficient and adequate data ([10]), and econometric challenges related to data gaps and small sample issues ([6]).

Perhaps one of the most important, yet least analyzed challenges in meta-analytical BT is the question of 'optimal scope' of the MRM, given a specific target policy application. For example, if welfare measures associated with the reduction in sulfur dioxide are sought, could or should the MRM also include values corresponding to a reduction in, say, nitrogen oxides or carbon monoxide? If the value of a day of trout fishing is of primary interest, should the meta-model also include data on bass or salmon fishing? In econometric terms, the question of optimal scope can be interpreted as the exact definition of the dependent variable in the MRM, which, in turn, defines the set of source studies to be considered for inclusion in the meta-dataset. This issue has been briefly raised at various points in time in the literature (e.g. [9, 11, 12])[1], but has not yet been examined in depth in existing contributions.

This study aims to fill this gap. We discuss the exact nature of the optimal scope problem and illustrate the associated econometric dilemmas (next Section), develop an econometric framework that can aid in the determination of optimal scope (Section III), and apply this framework to simulated and actual meta-data (Section IV). Section V summarizes our findings and offers concluding remarks.

II) Optimal Scope: Conceptual and Econometric Considerations

Optimal Scope, Data Space, and Model Space

The question of optimal scope is best illustrated with a brief example: Imagine a resource planner that is considering improving habitat and access along a specific river segment and managing it as a recreational coldwater fishery[2]. The costs of the project are relatively clear, but, as usual, expected economic benefits to potential users are more difficult to assess. Time and funding considerations call for a BT approach. For simplicity, assume that the only relevant and well-predictable characteristic of the new fishery, other than the basic identifiers "coldwater fishery" and "running water", is the expected daily catch rate, x_p ("*p*" stands for "policy site"). A thorough literature search reveals a set of S_0 studies comprising n_0 observations that report welfare results for coldwater fishing at running water[3]. This suggests the following simple MRM:

$$y_{js} = \beta_0 + \beta_1 x_{js} + \varepsilon_{js} \tag{1}$$

where y_{js} *is a* welfare measure for a day of coldwater / river fishing at site *j* reported in study *s*, x_{js} is the catch rate for that site, ε_{js} is an i.i.d. distributed normal error term with zero mean, and the β -terms are meta-regression coefficients to be estimated by the MRM. For simplicity, we will abstract for the moment from econometric considerations such as study-specific unobservables and heteroskedasticity, as well as from the potential effect of study-methodological characteristics on reported welfare estimates. A Benefit Transfer measure for the policy site could then be computed as

$$\hat{y}_p = \hat{\beta}_0 + \hat{\beta}_1 x_p , \tag{2}$$

i.e. by combining MRM parameter estimates with known attributes of the policy site, in this case simply the expected catch rate x_p.

However, the analyst may have reservations taking this approach due to the following possible (and, in practice, commonly observed) reasons: (i) The sample size n_0 may be too small to estimate the parameters in (1) with any degree of precision, and / or (ii) the studies included in set S_0 have a narrow geographic distribution, a narrow definition of underlying visitor populations, or are in other ways too context specific to allow for the construction of a robust BT function. To attenuate these problems the analyst may want to combine the original set of studies with another available set S_1, comprising n_1 observations, that report welfare results and catch rates associated with *warmwater* / running water fisheries[4]. A natural rationale for combining the two data sets would be the hopeful anticipation that the regression intercept and the marginal effect of catch rates may be similar for both fishery types (reflecting similarity in underlying angler preferences), and that in that case a pooled MRM of the form (1), but with sample size $n = n_0 + n_1$ can be expected to generate more efficient parameter estimates, and thus a more efficient BT function.

The added studies deviate in one identifying dimension ("type of fishery") from the policy context. In other words, the *scope* of the MRM has been broadened to include both coldwater and warmwater fisheries, and the definition of the dependent variable has changed from, say, "WTP for a day of coldwater fishing at a river" to "WTP for a day of fishing (cold- or warmwater) at a river". In our terminology, this constitutes a re-definition (and augmentation) of the *data space* underlying the MRM. For notational convenience we will label the original ("baseline") dataset as d_0 , the added dataset as d_1 , the original *data space* as D_0 , and the augmented data space as D_1. Thus, we have $D_0 = \{d_0\}$ and $D_1 = \{d_0, d_1\}$.

Naturally, imposing any pooling constraints on the augmented MRM a priori would be risky. If the two activity types do not pool on the intercept, catch rate, or both, using (1) would amount to a model mis-specification, producing biased parameter estimates and misleading BT predictions for the policy context. A more prudent approach would be to start with the most general specification, i.e.

$$y_{js} = \beta_{0,c} + \beta_{1,c} x_{js} + \beta_{0,w} W_{js} + \beta_{1,w} W_{js} x_{js} + \varepsilon_{js} \tag{3}$$

where W_{js} is a 0/1 indicator for observations associated with the warmwater sub-set, $\beta_{0,w}$ captures the deviation in intercept for warmwater observations, and $\beta_{1,w}$ measures the differentiated marginal effect of catch rate on WTP for warmwater cases compared to the baseline effect for coldwater observations (now indexed by subscript *c*).

In the terminology of this study, equation (3) implicitly defines the *model space* for data space D_1. Specifically, the augmentation of scope of the MRM has ex ante added two additional regressors to the MRM – W_{js} and $W_{js}x_{js}$. This implies $2^2 = 4$ possible models, since each new regressor can either emerge as significant (and should thus be included in the augmented model) or not (and could thus be dropped from the augmented model). Indexing inclusion by "1", and exclusion by "0", the model space corresponding to data space D_1 can then be described as

$$\mathrm{M}_1 = \begin{bmatrix} M_{1,1} \\ M_{1,2} \\ M_{1,3} \\ M_{1,4} \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix} \tag{4}$$

In a classical framework, statistical *in*significance of estimates for both $\beta_{0,w}$ and $\beta_{1,w}$ would lend support for the $M_{1,1} = \begin{bmatrix} 0 & 0 \end{bmatrix}$ case, leading to the pooled model (1), with augmented sample size *n*. This model would then be a logical candidate to generate the BT function. Decision rules for cases $\mathrm{M}_{1,2} - \mathrm{M}_{1,4}$ are less clear-cut. Since the BT function will *always be solely based on estimates of the baseline parameters* (here $\beta_{0,c}$ and $\beta_{1,c}$), the added model coefficients constitute de facto nuisance terms which will add noise to the estimation of the parameters that are actually needed to construct the Benefit Transfer. In this case, broadening the scope of the MRM will only improve the efficiency of the BT function if the gain in sample size offsets the loss in degrees of freedom and estimation noise associated with the introduction of the nuisance terms.

Econometric theory provides only limited guidance as to these countervailing effects. In most cases the analyst will have to take an empirical approach to identify the optimal scope of the MRM. For example, a reasonable strategy would be to estimate both model (1) with original data space D_0 and the applicable version of model (3) for data space D_1, and to compute BT predictions and confidence intervals for both cases. The prediction with the tighter confidence interval could then be chosen to guide policy decisions for the new context.

Finally, assume another dataset d_2 exists for a second related activity that deviates in a different single dimension from the baseline context, say "coldwater fishing at stillwaters" (lakes, ponds, etc). This enables the analyst to define two additional data spaces, $D_2 = \{d_0, d_2\}$ and $D_3 = \{d_0, d_1, d_2\}$. The model selection procedure outlined above has to be repeated for each new space, as the trade-off between increase in sample size and efficiency loss due to nuisance parameters will be different in each case. Note that D_3 yields the MRM with the broadest scope, i.e. "WTP for a day of coldwater or warmwater fishing at rivers or stillwaters".

Classical Challenges and Bayesian Approaches

As conveyed in the above example, the classical strategy to determine the optimal scope of the MRM is conceptually straightforward: (i) Compile a baseline meta-dataset D_0 that corresponds exactly to the policy context, (ii) specify a baseline MRM that includes explanatory variables with known values for the policy site, (iii) identify "related, but different" activities or resource amenities and collect corresponding meta-data, (iv) specify the most general MRM for the resulting augmented data space, (v) through a series of specification tests, determine which activities share common parameters with the baseline context and impose the corresponding equality constraints on the augmented model, (vi) compute BT predictions for the baseline model and the augmented model, (vii) repeat steps (iii) – (vi) for other related activities and resulting data spaces, and (viii) choose the data space and MRM that produces the most efficient BT predictions.

However, there are several problematic issues with this approach. As can be imagined, the number of additional indicators and interaction terms (which become nuisance parameters if found significant in the augmented model) proliferates rapidly with both the number of initial regressors for which policy site information is available, and the related activities or amenities considered. To illustrate, given the availability of $d_a, a = 1 \cdots A$, additional data sets corresponding to "related" activities or amenities, the number of possible additional data spaces $D_t, t = 1 \cdots T$, amounts to $T = A + \binom{A}{2} + \binom{A}{3} + \cdots + \binom{A}{A-1} + 1 = \sum_{j=1}^{A-1} \binom{A}{j}$, i.e. the number of all single data sets that can be combined with the baseline data, all possible combinations of pairs of data sets that can be combined with d_0, all possible combinations of triplets, etc., until the final space that combines all available data. The last column in Table 1 shows the number of data spaces resulting from adding up to five activities to the baseline model.

Each data space requires the specification of a separate MRM and a corresponding series of specification tests to identify pooling restrictions. For each added activity, the MRM must ex ante include a deviation term for the intercept and interaction terms with all other baseline regressors, as shown in (3). For example, for k_1 original regressors, and a added activities, the resulting augmented MRM will include $k_1 \cdot a$ additional covariates[5]. The upper half of Table 1 depicts this product for up to five added activities and baseline regressors. While these figures appear manageable, the associated *model spaces* will comprise $2^{(k_1 \cdot a)}$ elements, i.e. all possible combination of included and excluded terms. Thus, model spaces and therefore the number of possible pooling restrictions can quickly take on formidable dimensions, even for a modest number of baseline regressors and added activities, as shown in the lower half of Table 1.

In a classical estimation framework, this poses the dilemma of either (i) embarking on a time-consuming battery of specification tests with the usual risks of propagating decision errors and other problems related to 'pretest estimators' (e.g. [13]), (ii) ex ante imposing pooling constraints, thus risking model mis-specification, or (iii) facing small sample problems by falling back on the baseline model or an MRM with reduced data space. Furthermore, with increasing data fragmentation, some cell counts for specific interaction terms may become too small for specification test to provide any meaningful guidance.

A related problem in a classical estimation framework arises through its reliance on asymptotic theory. Regardless of scope, a realistically specified MRM will at the very least have to control for intra-study error correlation and heteroskedastic error variances (e.g. [4], [6], [14]) This departure from the basic linear regression model and thus from well understood small sample properties requires invoking asymptotic theory in the interpretation of model and test results. However, for augmented MRMs with lower dimensional scope sample sizes may still be too small to have much confidence in asymptotic test results. This further complicates the model selection process within a given data space and thus the search for optimal scope.

We therefore propose a Bayesian approach to model search in this study. The general rationale of Bayesian Model Search (BMS) techniques is to assign a posterior model probability to each possible specification as part of the overall estimation process. Rather than assessing the superiority of one model over another through pair-wise hypothesis tests, the Bayesian approach either selects the model with the highest posterior probability, or, more frequently, creates a weighted average of model results for inference purposes. The latter strategy is labeled Bayesian Model Averaging (BMA). Hoeting et al [15], Chipman et al. [16], and Koop [17], Ch. 11, provide a good overview of these concepts and techniques.

The BMA approach controls for *model uncertainty*, i.e. the notion that even with extensive theoretical guidance the researcher can never be completely certain which of a set of competing model specifications best describes the underlying data. Rather than selecting a potentially inferior model, the researcher may then prefer to base any econometric inference on a weighted average over all models. This will naturally give more weight to "more likely" models, and low weight to models with low posterior probabilities. Not surprisingly, a common application of BMS and BMA is within the context of identifying the best set of explanatory variables in large regression models (e.g. ,[18, 19], [20, 21]) which, in essence, is also the problem at hand for this study.

Based on the exact computational strategy to generate posterior model probabilities BMS techniques can be grouped into two broad categories: (i) Strategies that require the computation of the marginal likelihood for each model to generate model weights (e.g. [22],[19]), and (ii) Strategies that assign mixture priors to each coefficients, and base model selection and weights on the posterior probabilities that a given coefficient should be included in the model (e.g. [23, 24]).

Since the derivation of the marginal likelihood is computationally burdensome for specifications other than the basic linear regression model[6], we will follow the second strategy to examine the model space for each MRM within a given data space, and, ultimately, to identify the MRM that generates the most efficient BT predictions. Specifically, we will employ George and McCulloch's [23] Stochastic Search Variable Selection (SSVS) algorithm to examine the plausibility of pooling restrictions in a given augmented MRM. We use the search results to assign posterior weights to each model in the MRM's model space, and illustrate how these results can be used to either select a single specification to generate the BT function, or to produce model-averaged BT predictions in cases where no single model receives overwhelming posterior support. The details of this approach are described in the next Section.

III) Econometric Framework

The baseline MRM

As point of departure we specify a baseline MRM that relates welfare measures for the activity or amenity of primary interest reported in study s for site j, y_{is}, to site and population characteristics for which information is also available for the policy context, $\mathbf{x_{js}}$, and study-methodological indicators $\mathbf{m_s}$. The importance of including these methodological indicators to avoid omitted variables problems has been acknowledged numerous times in meta-analytical research related to resource valuation. For a recent discussion see Johnston et al. [26] and Moeltner et al. [6].[7] The baseline model is thus given as

$$\begin{aligned} & y_{js} = \mathbf{x}'_{\mathbf{js}}\boldsymbol{\beta}_{\mathbf{x}} + \mathbf{m}'_{\mathbf{s}}\boldsymbol{\beta}_{\mathbf{m}} + \alpha_s + \varepsilon_{js} \qquad \text{with} \\ & \alpha_s \sim n\left(0, V_\alpha\right) \qquad \varepsilon_{js} \sim n\left(0, \sigma^2\omega_{js}\right), \quad \text{where} \quad \omega_{js} \sim ig\left(\tfrac{v}{2}, \tfrac{v}{2}\right). \end{aligned} \tag{5}$$

As indicated in (5) the baseline model also includes a normally distributed study-specific random effect term α_s with a mean of zero and variance V_α, and an observation-specific stochastic error term ε_{js}. Since most source studies report multiple welfare measures reflecting several sites or applications, the random effect term will capture study-specific unobservables and intra-study correlation. To control for heteroskedasticity, we specify ε_{js} to have observation-specific variance $\sigma^2\omega_{js}$, with ω_{js} drawn from an inverse-gamma distribution with shape and scale equal to $v/2$.[8] In essence, this stochastic structure corresponds to Geweke's [27] Student-t linear model with the added feature of a random effects term. As shown in that study the hierarchical specification of the variance of ε_{js} is exactly equivalent to drawing ε_{js} from a t-distribution with mean zero, scale σ^2 and v degrees of freedom. This allows for higher probabilities of large error variances than would be expected for a basic normal model, a likely occurrence in a meta-regression context. To be specific, for any given σ^2 a small value of v (say 5 to 10) implies a heavy-tailed distribution, while, as is well known, the t-distribution approaches normality for larger values of v. As discussed in Koop [17], Ch. 6, for v>100 the t-distribution becomes virtually indistinguishable from the normal (0, σ^2) density.

Allowing for heteroskedasticity and the possibility of large differences in error variances across observations and studies is of integral importance for our application. Specifically, it may well be possible that a given activity shares common marginal effects of regressors with the baseline context, yet differs substantially in the mix and magnitude of unobservables that enter the reported welfare measures. This may further improve the efficiency of data-augmented BT functions if variance terms for the added activity are generally smaller than those for the baseline model, but could also introduce additional noise into the MRM and thus the transfer function if error variances are larger than those for the baseline case. These effects and trade-offs become clearly visible in our empirical application. At the same time, our specification of heteroskedasticity follows the paradigm of parameter sparseness – it only requires the estimation of a single additional parameter, v. This is important given our objective of searching model space rapidly and efficiently, and the corresponding requirement to keep run-times for individual models as short as possible.

At the panel (= study) level, the baseline model can be written as

$$\mathbf{y_s} = \mathbf{x_s}\boldsymbol{\beta}_\mathbf{x} + \mathbf{m_s}\boldsymbol{\beta}_\mathbf{m} + \mathbf{i}_{\mathbf{n_s}}\alpha_s + \boldsymbol{\varepsilon}_\mathbf{s} \quad \text{with}$$
$$\boldsymbol{\varepsilon}_\mathbf{s} \sim mvn\left(\mathbf{0}, \sigma^2\boldsymbol{\Omega}_\mathbf{s}\right) \quad \text{and} \quad \boldsymbol{\Omega}_\mathbf{s} = diag\left[\omega_{1s} \quad \omega_{2s} \quad \cdots \quad \omega_{n_s,s}\right], \tag{6}$$

where $\mathbf{i}_{\mathbf{n_s}}$ is a vector of ones with length n_s, i.e. the total number of observations furnished by study *s*. It should be noted that conditional on α_s and $\boldsymbol{\Omega}_\mathbf{s}$, $\mathbf{y_s}$ remains multivariate-normally distributed with expectation $\left(\mathbf{x_s}\boldsymbol{\beta}_\mathbf{x} + \mathbf{m_s}\boldsymbol{\beta}_\mathbf{m} + \mathbf{i}_{\mathbf{n_s}}\alpha_s\right)$ and variance-covariance matrix $\left(\sigma^2\boldsymbol{\Omega}_\mathbf{s}\right)$.

Scope augmentation and the SSVS algorithm

Let us now combine the baseline data d_0 with meta-data for a related activity, d_1, as discussed in the previous Section. This adds a deviation indicator and a set of interaction terms to the original model, yielding

$$y_{js} = \mathbf{x}'_\mathbf{js}\boldsymbol{\beta}_\mathbf{x} + \mathbf{m}'_\mathbf{s}\boldsymbol{\beta}_\mathbf{m} + \mathbf{z}'_\mathbf{js}\boldsymbol{\delta} + \alpha_s + \varepsilon_{js} \quad \textit{with}$$
$$\mathbf{z_{js}} = \left[I\left(js \in d_1\right) \quad I\left(js \in d_1\right)x_{1,js} \quad I\left(js \in d_1\right)x_{2,js} \quad \cdots \quad I\left(js \in d_1\right)x_{k_1,js}\right]', \tag{7}$$

where *I(.)* is an indicator function taking a value of one if observation *js* belongs to the added data set.[9] The objective at hand is now to examine which of the elements in $\mathbf{z_{js}}$ are "close enough" to zero to call for a pooling restriction.

This is precisely the intuition behind the SSVS algorithm ([23, 24]). The basic idea of this approach is to assign a mixture prior to model parameters with uncertain explanatory importance, i.e. the elements of vector $\boldsymbol{\delta}$ in our case. Specifically, we model each coefficient in $\boldsymbol{\delta}$ to have a prior probability *p* of coming from a "well behaved" normal distribution with mean zero and "large" variance, and probability *(1-p)* of following a close-to-degenerate normal distribution with mean zero and a "very small" variance. The resulting mixture prior for, say, element δ_k can then be expressed as

$$pr\left(\delta_k\right) = \gamma_k \cdot n\left(0, c_k^2\tau_k^2\right) + \left(1-\gamma_k\right)\cdot n\left(0,\tau_k^2\right) \quad \text{with}$$
$$pr\left(\gamma_k\right) = bern\left(p\right), \tag{8}$$

where γ_k is a Bernoulli-distributed indicator term taking a value of one with probability *p*, and a value of zero with probability *(1-p)*. We follow standard SSVS notation by labeling the "small" variance as τ_k^2 and the "large" variance as $c_k^2\tau_k^2$ [10].

As indicated in (8) and discussed in [24], each element of $\boldsymbol{\delta}$ could in theory be assigned its own variance priors, perhaps based on "thresholds of practical significance". In other words, c_k^2 and τ_k^2 could be chosen such that δ_k is assigned to the degenerate distribution with high probability whenever its absolute value falls below a threshold beyond which it no longer affects the dependent variable for all practical purposes. While such coefficient-specific thresholds are meaningful in the medical field and related sciences, they are ex ante difficult to assess in our application. We thus follow a common alternative strategy by setting $c_k = c, \tau_k = \tau, \forall k,$ and standardizing *all* regressors in (7) to allow model coefficients to have the common interpretation of "marginal effect on y_{js} due to a 1-standard deviation movement away from the mean" for a given regressor (e.g. [17], Ch. 11). We will discuss the exact choice of c and τ in the empirical Section below.

The likelihood function for our full Bayesian specification for a scope-augmented MRM thus emerges as

$$
\begin{gathered}
pr\left(\mathbf{y} \mid \mathbf{X}, \mathbf{Z}, \boldsymbol{\theta}, \boldsymbol{\delta}, V_\alpha, \boldsymbol{\omega}\right) = \\
\prod_{s=1}^{S}\left\{(2\pi)^{-n_s/2}\left|\left(\mathbf{i}_{\mathbf{n_s}} V_\alpha \mathbf{i}_{\mathbf{n_s}}' + \sigma^2\boldsymbol{\Omega}_{\mathbf{s}}\right)\right|^{-1/2} \exp\left(-\tfrac{1}{2}\left(\mathbf{y_s} - \mathbf{X_s}\boldsymbol{\theta} - \mathbf{z_s}\boldsymbol{\delta}\right)'\left(\mathbf{i}_{\mathbf{n_s}} V_\alpha \mathbf{i}_{\mathbf{n_s}}' + \sigma^2\boldsymbol{\Omega}_{\mathbf{s}}\right)^{-1}\left(\mathbf{y_s} - \mathbf{X_s}\boldsymbol{\theta} - \mathbf{z_s}\boldsymbol{\delta}\right)\right)\cdot\right\} \\
\text{with} \quad \mathbf{X_s} = \begin{bmatrix}\mathbf{x_s} & \mathbf{m_s}\end{bmatrix}, \quad \boldsymbol{\theta} = \begin{bmatrix}\boldsymbol{\beta}_{\mathbf{x}}' & \boldsymbol{\beta}_{\mathbf{m}}'\end{bmatrix}', \quad \mathbf{X} = \begin{bmatrix}\mathbf{X}_1' & \mathbf{X}_2' & \cdots & \mathbf{X}_{\mathbf{S}}'\end{bmatrix}', \quad \mathbf{Z} = \begin{bmatrix}\mathbf{z}_1' & \mathbf{z}_2' & \cdots & \mathbf{z}_{\mathbf{S}}'\end{bmatrix}' \quad \text{and} \\
\boldsymbol{\omega} = diag\begin{bmatrix}\omega_{1s} & \omega_{2s} & \cdots & \omega_{n_s S}\end{bmatrix}
\end{gathered}
\tag{9}
$$

where S is the total number of studies included in the MRM. For notational convenience we have collected original regressors $\mathbf{x_s}$ and study-methodological indicators $\mathbf{m_s}$ into a common panel matrix $\mathbf{X_s}$, with corresponding combined coefficient vector $\boldsymbol{\theta}$. It should be noted that SSVS vector $\boldsymbol{\gamma}$ does not enter the likelihood function. This will facilitate the posterior updating for this vector as shown in Appendix A. The full set of priors for the augmented Bayesian MRM is given as

$$
\begin{aligned}
&(\mathrm{a}) \quad pr(\boldsymbol{\theta}) = mvn(\mathbf{0}, \mathbf{V_0}) \\
&(\mathrm{b}) \quad pr(\alpha_s \mid V_\alpha) = mvn(0, V_\alpha), \forall s \qquad pr(V_\alpha) = ig(\varphi_0, \gamma_0) \\
&(\mathrm{c}) \quad pr(\sigma^2) = ig(\eta_0, \kappa_0) \\
&(\mathrm{d}) \quad pr(\omega_{js} \mid v) = ig\left(\tfrac{v}{2}, \tfrac{v}{2}\right), \forall js \qquad p(v) = g\left(1, \tfrac{1}{v_0}\right) \\
&(\mathrm{f}) \quad pr(\delta_k \mid \gamma_k) = \gamma_k \cdot n\left(0, c^2\tau^2\right) + (1-\gamma_k) \cdot n\left(0, \tau^2\right), k = 1 \cdots k_z \\
&\qquad\;\; pr(\gamma_k) = bern(p), \forall k,
\end{aligned}
\tag{10}
$$

where k_z indicates the total number of regressors in $\mathbf{z_s}$. Equation (a) indicates that the prior for all coefficients not subjected to SSVS scrutiny is multivariate normal with mean vector **0** and variance-covariance matrix $\mathbf{V_0}$. Equation (b) re-states the hierarchical distribution of random effect α_s shown above, with the common variance V_α following an inverse gamma distribution with shape φ_0 and scale γ_0. The same prior distribution, albeit with potentially different shape and scale parameters, holds for σ^2, the common variance component of ε_{js}, as shown in equation (c). As discussed above, the heteroskedastic variance component of ε_{js} follows an inverse-gamma distribution with identical shape and scale parameter $v/2$, with the hyper-prior distribution of v given as gamma with shape 1 and inverse scale $1/v_0$. In our parameterization, this corresponds directly to the exponential distribution with inverse scale $1/v_0$. As discussed in Koop [17], Ch. 6, this choice of hyper-prior distribution for v is computationally convenient and assures the required condition of $v > 0$. Finally, equation (f) reiterates the hierarchical prior distribution for γ_k as discussed above. The likelihood in (9) and the priors in (10) also apply to variants of our model that do not call for the SSVS algorithm (see below). Naturally, a standardization of regressors and use of prior (f) are no longer needed in that case.

The Bayesian framework then combines likelihood function and priors to derive marginal posterior distributions for all parameters. We use a Gibbs Sampler (GS) along the lines suggested in Koop [17], Ch. 6, to simulate these distributions. The details of this algorithm are given in Appendix A.

Model weights and BT predictions

For each element of $\boldsymbol{\delta}$ and for each draw $r = 1 \ldots R$ of the GS, the posterior simulator produces a binary draw of γ_k based on its posterior probability, $pr(\gamma_k \mid \mathbf{y}, \mathbf{X}, \mathbf{Z})$, as outlined in detail in Appendix A. This draw will take the value of one if there is posterior support that δ_k belongs to the large-variance distribution and should thus be included in the augmented model, and a value of zero otherwise. For example, if $\boldsymbol{\delta}$ and thus $\boldsymbol{\gamma}$ have three elements, a GS sequence of 20 consecutive posterior draws of γ_k, k=1…3, could look like this:

$$\begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \end{bmatrix} = \begin{bmatrix} 0 & 1 & 1 & 1 & 0 & 1 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 1 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 & 1 & 0 & 0 & 0 & 0 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{11}$$

In the first round of this hypothetical GS sequence none of the coefficients in $\boldsymbol{\delta}$, and thus none of the variables in $\mathbf{z_{js}}$ were chosen for inclusion in the model, in the second and third round only the first element of $\mathbf{z_{js}}$ was selected, in the fourth round the first two elements were selected, and so forth.

This information can then be used to examine how often, out of *R* repetitions, *a given element of* $\boldsymbol{\gamma}$ is set to "1", i.e. how often the underlying explanatory variable is selected for inclusion in the model. In our simple example above, these empirical shares are $11/20 = 0.55$ for γ_1, $8/20 = 0.4$ for γ_2, and 5/20 = 0.25 for γ_3. This provides a quick first look at the *relative importance* of each ex ante questionable regressor. However, as shown e.g. in George and McCulloch [23] and Chipman [18] a more thorough examination of this sequence is needed to draw conclusions on model weights and model selection. As illustrated in the previous Section (equ. (4)), the number of elements in $\boldsymbol{\gamma}$ de facto determine the model space M_t for the added regressors in data space D_t. Thus, sequence (11) also contains information on the empirical probabilities for each possible model in M_t. In our simple example above there are 2^3 = 8 possible models. For example, model [0,0,0] was selected 4/20 times and would thus receive model weight 0.2. Model [0 0 1] was selected only once, yielding a model weight of 1/20 = 0.05, and so on.

The researcher can then select a single model as the "most promising specification" if model weights are distributed such that a specific model receives overwhelming support. Alternatively, if these posterior weights are more uniformly distributed and thus less discriminating, the analyst may want to use these weights to form model-averaged posterior inferences. Since the latter scenario is more likely in the context of MRM and BT, and since the selection of a single model is a trivial special case of forming model-averaged predictions, we will focus on the model-averaging approach in this analysis.

Thus, our generation of BT predictions associated with a given data space D_t proceeds in two steps: First, we standardize all regressors and implement the SSVS algorithm to derive individual model weights as described above. Second, after recording these weights, we re-run all models in model space M_t with non-standardized regressors, using the modified Geweke [27] model *without* the SSVS component. For each model, we then derive a posterior distribution of BT predictions, and then average these predictions over models using the model weights collected from Step 1. Analytically, this posterior distribution of BT prediction y_p given policy site descriptors $\mathbf{x_p}$ is given as

$$pr\left(y_p \mid \mathbf{x_p}\right) = \sum_{m=1}^{M} \left\{ \int_{\mathbf{\Gamma}} \left[\sum_{h=1}^{H} pr\left(y_p \mid \mathbf{x_p}, M_m, \mathbf{\Gamma}, m_h\right) pr\left(m_h\right) \right] pr\left(\mathbf{\Gamma} \mid \mathbf{y}, \mathbf{X}, \mathbf{Z}, M_m\right) d\left(\mathbf{\Gamma}\right) \right\} pr\left(M_m \mid \mathbf{y}\right) \tag{12}$$

where subscript m indexes a specific model in M_t, M denotes the total number of models in M_t, m_h labels a specific combination of methodological indicators, H is the total number of such combinations, and $\mathbf{\Gamma}$ comprises all model parameters as introduced in (10), with the exception of $\boldsymbol{\gamma}$, which is no longer needed for Step 2.

Equation (12) indicates that the posterior predictive distribution of y_p, conditional only on policy descriptors $\mathbf{x_p}$ is derived by marginalizing conditional draws of y_p over (i) methodological indicators, (ii) model parameters, and (iii) all models in M_t. The practical implementation of (12) is described in Appendix B. The statistical properties of the model-averaged posterior distribution of $\mathbf{y_p} \mid \mathbf{x_p}$ can then be examined for each available data space and compared to analogous predictions for the baseline model. We will illustrate this final step in selecting a transfer function within the context of our empirical applications in the next Section.

IV) Empirical Implementation

Simulated application

We first illustrate our approach using simulated data. To examine the performance of the SSVS algorithm under different sample sizes and error distributions we generate eight simulated data sets with degrees-of-freedom parameter v set to either 40 or 10 for each of four sample sizes, 2000, 1000, 600, and 300. These scenarios are captured in the first column of Table 2. We ex ante hypothesize that the ability of the SSVS algorithm to discern "true" models will diminish with smaller sample size and heavier tails of the error distribution (i.e. a smaller value of v). The $n = 300$, $v = 10$ scenario is designed to mimic some key aspects of typical meta-data traditionally employed for BT purposes, i.e. small to moderate sample size and considerable error noise.

For each simulation scenario we first create a baseline data set d_0 composed of S_0 "studies" with n_{s0} observations on "WTP" and three explanatory variables, yielding an initial baseline sample size n_0. For ease of communication and close correspondence with the empirical application below we label these variables "catch rate", "income" and "travel cost". Catch rate is computed as the log of a uniform (0.8, 20) variate, income is generated as $\log\left(\frac{1}{1000}\text{uniform}\left(30000, 200000\right)\right)$, and travel cost is derived as $\log\left(\frac{1}{10}\text{uniform}\left(10, 200\right)\right)$. We then add a constant term and combine these regressors with the coefficients given in the first row of Table 2. We further add a random effects term drawn from the standard normal distribution, and an error term drawn from a t-distribution with mean 0, scale 1, and v degrees of freedom. A dependent variable $\mathbf{y_0}$ is then computed following equation (5) (without methodological indicators).

Next, we create a second data set d_1 of same panel structure and sample size as the baseline, with regressors, random effects, and error terms drawn from the exact same distributions as hold for the baseline data. However, we specify regression coefficients that deviate from those stipulated for the baseline model in the slope coefficients for "catch rate" and "travel cost", as shown in the second row of

Table 2. This yields dependent variable $\mathbf{y_1}$. We then combine the two data sets in an augmented model with sample size *n* by stacking vectors $\mathbf{y_a}$, a = 1,2, and the two sets of explanatory variables, adding an indicator for the d_1- set, and its interactions with the three explanatory variables. This yields the specification given in equation (7) (without methodological indicators).

For each *n* / *v* scenario, we standardize these regressors and apply the SSVS algorithm to derive model weights for the $2^4 = 16$ individual models contained in the augmented model space M_1. We use the following prior values: $\tau = 0.03, c = 100, \mathbf{V_0} = c^2\tau^2, \mathbf{I_{k_1}} = 9\mathbf{I_{k_1}}, \varphi_0 = \gamma_0 = \eta_0 = \kappa_0 = \frac{1}{2}, v_0 = 10,$ and $p = \frac{1}{2}$. As discussed in George and McCulloch ([23], [24]), a larger value of *c* and a lower value of τ implies a sharper distinction between the two normal densities in the mixture prior for $\boldsymbol{\delta}$. However, the authors recommend keeping the ratio of the two variances, i.e. c^2, at or below 10,000 to avoid convergence problems. Such problems will also arise if τ is located "too close to zero". Our choice of τ and *c* reflects these conflicting concerns. The variance terms for the prior distribution of the baseline coefficients $\boldsymbol{\beta_x}$, i.e. the diagonal elements of $\mathbf{V_0}$, are chosen to correspond to the variance of the non-degenerate distribution of $\boldsymbol{\delta}$. The shape and scale parameters for the inverse-gamma priors imply diffuse distributions for σ^2, and V_α. Given our parameterization of the gamma prior for *v* in (10), the inverse scale v_0 also constitutes the expectation for this distribution, and v_0^2 denotes the variance. A value of 10 for v_0 implies that *v* is a priori expected to take this value, leading to a moderately heavy-tailed *t*-prior for the regression errors. At the same time, a variance of v_0^2 =100 keeps the prior distribution for *v* sufficiently diffuse to assign adequate weight to the data in posterior updating. Finally, the choice of 0.5 for the Bernoulli parameter *p* implies an equal prior weight of $\left(\frac{1}{2}\right)^{k_z}$ for each possible model contained in a given data space. For each scenario, the standard deviation of the proposal density for *v* in the Metropolis Hastings algorithm contained in the GS (denoted as s_v in Appendix A) is set to achieve an optimal acceptance rate of 44-50% (see e.g. [28] Ch. 11). All models are estimated using 15000 burn-in draws and 10000 retained draws in the Gibbs Sampler. The decision on the appropriate amount of burn-ins was guided by Geweke's [29] convergence diagnostic (CD).

The lower half of Table 2 shows the SSVS acceptance shares for each coefficient associated with the added regressors. A perfectly discriminating GS run would *always* select the interacted coefficients for "catch rate" and "travel cost", and never select the deviation from the constant term and the interacted coefficient for "income". As can be seen from Table 2, our simulated models with large sample sizes come close to this ideal notion of "perfect discrimination". For both the n = 2000 and n = 1000 cases acceptance shares are at 100% for "catch rate", and close to 90% for "travel cost", while the coefficients of deviation for the constant term and "income" are only selected in 5-8% of draws. The lower share of "hits" for "travel cost" compared to "catch rate" may be a result of the somewhat more subtle absolute difference between baseline and added data with respect to the travel cost coefficient, or it may simply be a manifestation of the relative lower information content for this variable in the generated data. It is also clear from the Table that a lower value for v, i.e. a more diffuse distribution of the regression error, results in a subtle but systematic further reduction in acceptance shares for "travel cost" for the two large-sample scenarios.

As is evident from the last four rows of the Table, the SSVS routine essentially loses its ability to identify the difference in coefficients between baseline and added data for "travel cost", while acceptance shares for "catch rate" remain fairly high even for the n = 300, v =10 scenario. Overall, this first examination of simulation results suggests that the ability of the SSVS algorithm to correctly identify regressors that should be included in a given model (i) generally diminishes with sample size, (ii) slightly diminishes with lower values of v, and (iii) can be variable-specific, depending on how informative the underlying data are for each individual regressor.

Data space, model combinations, and empirical model weights flowing from the SSVS analysis for the n = 300, v = 10 case are given in Table 3. The first row simply lists the baseline model, which, by definition, does not include any added regression terms. The last column depicts the empirical model weights assigned by the SSVS routine to each of the 16 possible models in data space D_1. Clearly, no single model receives overwhelming posterior support. The highest weight (0.48) is assigned to the partially correct model M_5, which stipulates a difference in coefficients for "catch rate", but a shared coefficient for "travel cost". The second largest share (0.267) is allocated to the null model M_1 while the correct model M_{11} only receives a very small posterior weight of 0.007. In our simulated context high weights for the null model and low weights for the correct augmented model simply imply that the underlying data lack sufficient information to identify structural parameter differences.

Overall, given our empirical context these results convey two important messages regarding the interpretation of model weights flowing from the SSVS algorithm: (i) A high weight for the null model, which a hopeful analyst may interpret as "perfect poolability" of two activities or contexts, may simply be indicative of noise in the underlying data, and (ii) the most appropriate model may not receive considerable posterior weight. This suggests a model averaging approach to generate BT predictions.

The results for the second step of our analysis are provided in Table 4. For ease of interpretation the first three columns reiterate data space, model labels, and model weights, respectively. The next four columns show the posterior means for the BT-relevant coefficients, i.e. the elements of $\boldsymbol{\beta}_{\mathbf{x}}$ in equation (7). The last six columns depict key statistical features of the posterior predictive distribution of BT prediction y_p. We follow the steps outlined in Appendix B to generate these predictions. For each of the R = 10,000 parameter draws from the original GS, we draw a set of r_p = 100 predicted values for policy outcome y_p. We then keep every 20th of these draws to reduce autocorrelation in our sequence. Thus, we retain 50,000 posterior predictive draws for our analysis[11]. To mimic our sport fishing application below and derive "realistic" WTP figures the statistics in Table 4 refer to the exponentiated version of this predictive distribution.

The first row in Table 4 gives the results for the baseline model. For our purposes the key features of these results are a mean predicted benefit of 32.5, with a numerical standard error (nse) of 0.5.[12] The last three columns show the lower bound, upper bound, and width of the corresponding 95% numerical confidence interval. As can be seen from the Table, the posterior means for BT-relevant coefficients generated by models in the D_1 space differ from those for the baseline model primarily in the estimated intercept. Given our random effects specification, this intercept is somewhat more difficult to estimate under small sample sizes. The baseline model grossly under-predicts the true value of -2.5 (see Table 2). The D_1 models, while still considerably off-target, are closer to the true values. Also, the added data reduces posterior noise in the BT predictions, as evidenced by the substantially smaller posterior standard deviation for all D_1 models compared to the baseline specification. Given the *known* shortcomings of the baseline model and the noticeably reduced posterior variability in the scope augmented models, the model averaged predictive distribution, given in the bottom row of the Table, would clearly be a more robust choice to form BT predictions than the baseline model. It also generates more efficient predictions than the baseline specification, as evident from the smaller *nse* and corresponding interval width.

Sport fishing application

To illustrate our methodology with actual meta-data, we selected a baseline set of studies that report aggregate estimates of consumer surplus for a day of *coldwater* fishing in a *running water* environment. All welfare observations are associated with all-or-nothing site values to allow for a clear association of WTP estimates with status quo site characteristics. The studies are drawn from two sources: an updated outdoor recreation meta-data set described in Rosenberger and Loomis [30], and the sport fishing meta-data collected by Boyle et al. [31]. These two sources combined constitute arguably the largest collection of recreational meta-information currently available. Yet, as shown in Table 5, we could only identify 15 studies comprising a total of 73 observations that satisfy our “policy context” criteria. This creates a realistic setting for the desire to augment the data with related activities.

We consider a scope augmentation along the dimensions used in our introductory example: *warmwater* fisheries, and *stillwater* environments. This yields four possible data spaces, as summarized in Table 5. As can be seen from the table, augmenting the scope of the data produces a marked increase in sample size, especially for the saturated data space D_4, which comprises 37 studies and 229 observations.

Our methodological indicators are "journal" (1 = journal article), "report" (1 = government report), "dc" (1 = dichotomous choice framework), "oe" (1 = open ended, iterative bidding, or payment card framework), "substitute" (1 = study addressed or incorporates substitute sites), and "sample 200" (1 = underlying sample size $\geq$ 200). The implicit baseline categories for publication source and elicitation format are "technical report, thesis, or dissertation", and "travel cost method", respectively. All data spaces have reasonable cell counts for these methodological categories, as shown in the second half of Table 5. To assure a positive value for WTP we model the dependent variable in log form.

For an illustrative implementation of our approach we require continuous baseline variables that – ideally - are reported for all observations. Given the data gaps traditionally encountered in meta-sets (see [6]) this proved to be a major challenge. We ultimately chose daily catch rate and annual household income (both in log form) to represent site attributes and population characteristics, respectively. We replaced missing observations for income (approximately 70% of cases) with State-level census information, and missing observations on catch rates (approximately 50% of cases) with predicted values flowing from an auxiliary regression model relating available catch rates to regional indicators, water types, and fish species. The derivation of daily catch rates was further complicated by the fact that many studies reported this attribute in units other than "per-day", which required additional conversion steps reliant on aggregate information. Despite these shortcomings our meta-dataset is still suitable to illustrate our conceptual and estimation framework.

The priors and number of GS draws for the standardized model with the SSVS components are the same as for the simulated case, except for the value of τ, which is increased to 0.3 to improve the convergence properties of the Gibbs Sampler . The standard deviation for the proposal density in the MH component varies from $10\sqrt{\frac{1}{n}}$ to $45\sqrt{\frac{1}{n}}$ to yield a uniform acceptance rate of 45-50% for all data spaces. Table 6 shows the composition of individual models for each data space. The one-dimensionally augmented data spaces D_1 and D_2 each include eight models, while this number increases sharply to 64 for the saturated space D_3. For the latter, only models with empirical weights $\geq$ 1% are listed in the Table

6 for ease of exposition. For each augmented data space, the first model (M_1) denotes the "null" model, i.e. the fully pooled specification.

The last column of Table 6 shows the posterior weights for each model produced by the first-stage SSVS analysis. For each data space, the null model carries by far the largest weight, with all other specifications receiving relatively minor weight shares. At this stage it might be tempting to embrace the null model and ignore all other specifications for BT purposes. However, this would be risky for two reasons: (i) The weight shares for the fully pooled version, while substantial, are far from overwhelming, and (ii) as seen from the simulated example, a large weight for the null model may simply indicate a lack of explanatory power in the underlying data. Overall, thus, there still exists a considerable degree of model uncertainty for all augmented data spaces, which again suggests a model-averaging approach.

Therefore, we subject all data spaces and models to the second step of our analysis. For D_3, we only estimate the models with probability weight of 1% or higher to conserve on computing time[13]. As for the simulated data we set $\mathbf{V_0} = 100 \cdot \mathbf{I_{k_1}}$ for this step. The results from this second stage analysis are captured in Table 7. The layout for Table 7 is the same as for Table 4. As can be seen from the first row the baseline model generates a posterior distribution of WTP with a mean \$67.13, a standard deviation of 94.14, and numerical standard error of 0.42. Augmenting the baseline scope of the MRM with observations on warmwater fishing reduces posterior noise as evidenced by a significantly smaller posterior standard deviation for all models in D_1. In contrast, posterior noise increases compared to the baseline model for models in D_2 and D_3.

Clearly, thus, WTP estimates associated with stillwater environments carry more error noise than estimates corresponding to warmwater fishing, ceteris paribus. Also, the point estimates for the posterior mean of y_p are systematically higher than the baseline result for all models in D_2 and most models in D_3. Therefore, the overall picture that emerges is that the context of *warmwater fishing in a running water environment* is more compatible with the baseline scenario than the context of *coldwater fishing in a stillwater environment*. Even the substantial gain in sample size for the fully saturated space D_3 cannot compensate for this lack of affinity with the baseline context and the added noise through larger regression errors. This is also evidenced by the larger standard deviation and *nse* for the model-averaged distribution for D_2 and D_3 compared to the baseline result.

In contrast, and this is perhaps the most important finding flowing from this analysis, the model-averaged predictive distribution for data space D_1 has slightly more efficient properties than the baseline posterior, as indicated by a smaller posterior standard deviation (79.9 vs. 94.1) and nse (0.36 vs. 0.42). We can thus conclude that a more efficient BT function is derived if the scope of the baseline data is augmented along the dimension "*warmwater fishing*", but not along the dimension of "*stillwater"*.

V) Conclusion

We illustrate in this study how Bayesian Model Search and Model Averaging techniques can be used to better utilize existing information on resource values for BT predictions. Specifically, we employ George and McCulloch's [23] SSVS algorithm to assign posterior probability weights to different model versions in a scope-augmented Meta-Regression. We show how these weights can then be used to derive model-averaged BT predictions for the augmented data space. Our approach circumvents typical classical challenges that arise when combining different data sets, such as the reliance on asymptotic theory for the interpretation of test results in a small-sample environment, the risk of compounding Type I or Type II decision errors in series of specification tests, and small cell counts for different context combinations. Our empirical findings indicate that for some augmented MRMs resulting model-averaged BT functions can be more efficient than those flowing from a baseline model with a narrower scope and smaller sample size.

While our meta-data are based on aggregate estimates of welfare and aggregate values for site and user characteristics, it should be noted that our methodology is also applicable to individual-level source data. In that case small sample problems may be less pressing. However, the general question of 'optimal scope' remains, and with it the classical challenges associated with rapidly proliferating model spaces in augmented data. The application of our approach to such refined and richer meta-data will be subject to future research.

APPENDIX A

This Appendix outlines the detailed steps of the Gibbs Sampler (GS) for the random effects regression model with t-distributed errors and an embedded SSVS routine for a subset of coefficients. It is convenient to apply Tanner and Wong's [32] concept of data augmentation and treat draws of $\boldsymbol{\alpha} = \begin{bmatrix} \alpha_1 & \alpha_2 & \cdots & \alpha_S \end{bmatrix}$ and $\boldsymbol{\omega} = \begin{bmatrix} \omega_{11} & \omega_{21} & \cdots & \omega_{n_S S} \end{bmatrix}$ as additional data. As in the main text, we label the regression coefficients subjected to SSVS scrutiny as $\boldsymbol{\delta}$ and the remaining coefficients as $\boldsymbol{\theta}$. This yields the augmented joint posterior $pr\left(\boldsymbol{\theta}, \boldsymbol{\delta}, \sigma^2, V_{\boldsymbol{\alpha}}, v, \boldsymbol{\gamma}, \boldsymbol{\alpha}, \boldsymbol{\omega} \mid \mathbf{y}, \mathbf{X}, \mathbf{Z}\right)$, which the GS breaks down into consecutive draws of conditional components.

Step 1: Draw $\boldsymbol{\theta}$, $\boldsymbol{\delta}$

It is convenient to stack $\boldsymbol{\theta}$ and $\boldsymbol{\delta}$ into a single coefficient vector $\boldsymbol{\xi}$ and to conformably combine data **X** and **Z** into common matrix **XZ**, with panel (= study) specific component $\mathbf{Xz_s}$. The prior variance of $\boldsymbol{\xi}$ can then be compactly written as $\mathbf{V}_{\boldsymbol{\xi}} = diag\left[\mathbf{V_0}, \mathbf{V}_{\boldsymbol{\delta}}\right]$, where $\mathbf{V}_{\boldsymbol{\delta}} = diag\left[\gamma_k \cdot n\left(0, c^2\tau^2\right) + \left(1-\gamma_k\right) \cdot n\left(0, \tau^2\right), k = 1 \cdots k_z\right]$. To avoid highly correlated draws and to expedite convergence we will draw $\boldsymbol{\xi}$ unconditional on the random effects $\boldsymbol{\alpha}$, along the lines suggested in Chib and Carlin [33]. This leads to the following conditional posterior:

$pr\left(\boldsymbol{\xi} \mid \mathbf{y}, \mathbf{X}, \mathbf{Z}, \sigma^2, V_\alpha, \boldsymbol{\omega}\right) = mvn\left(\boldsymbol{\mu_1}, \mathbf{V_1}\right)$ where

$$\mathbf{V_1} = \left(\mathbf{V}_{\boldsymbol{\xi}}^{\mathbf{-1}} + \sum_{s=1}^{S} \mathbf{Xz}_\mathbf{s}' \left(\mathbf{i_{n_s}} V_\alpha \mathbf{i}_{\mathbf{n_s}}' + \sigma^2 \boldsymbol{\Omega}_\mathbf{s}\right)^{-1} \mathbf{Xz_s}\right)^{-1} \text{ and } \quad \boldsymbol{\mu_1} = \mathbf{V_1}\left(\sum_{s=1}^{S} \mathbf{Xz}_\mathbf{s}' \left(\mathbf{i_{n_s}} V_\alpha \mathbf{i}_{\mathbf{n_s}}' + \sigma^2 \boldsymbol{\Omega}_\mathbf{s}\right)^{-1} \mathbf{y_s}\right).$$

Step 2: Draw $\boldsymbol{\alpha}$

Defining the conceptual regression model $\tilde{\mathbf{y}}_\mathbf{s} = \mathbf{y_s} - \mathbf{Xz_s}\boldsymbol{\xi} = \mathbf{i_{n_s}}\alpha_s + \boldsymbol{\varepsilon}_\mathbf{s}$ and applying standard results for posterior moments for Gaussian regressions (e.g. [34]), we obtain

$$pr\left(\alpha_s \mid \mathbf{y_s}, \mathbf{Xz_s}, \boldsymbol{\xi}, \sigma^2, \boldsymbol{\omega}\right) = mvn\left(\boldsymbol{\mu_1}, \mathbf{V_1}\right) \quad \text{where} \quad \mathbf{V_1} = \left(\mathbf{V}_{\boldsymbol{\alpha}}^{\mathbf{-1}} + \mathbf{i}_{\mathbf{n_s}}' \left(\sigma^2 \boldsymbol{\Omega}_\mathbf{s}\right)^{-1} \mathbf{i_{n_s}}\right)^{-1} \text{ and } \quad \boldsymbol{\mu_1} = \mathbf{V_1}\left(\mathbf{i}_{\mathbf{n_s}}' \left(\sigma^2 \boldsymbol{\Omega}_\mathbf{s}\right)^{-1} \tilde{\mathbf{y}}_\mathbf{s}\right).$$

Step 3: Draw V_α

Given the vector of random effects, the conditional posterior distribution for V_α can be derived in straightforward fashion as $pr\left(V_\alpha \mid \boldsymbol{\alpha}\right) = ig\left(\varphi_1, \gamma_1\right)$ with $\varphi_1 = \left(S + 2\varphi_0\right)/2$ and $\gamma_1 = \left(\boldsymbol{\alpha}'\boldsymbol{\alpha} + 2\gamma_0\right)/2$.

Step 4: Draw σ^2

Expressing the vector of random effects for the full sample as $\tilde{\boldsymbol{\alpha}}$ and applying standard results for generalized regression models, we obtain

$pr\left(\sigma^2 \mid \mathbf{y}, \mathbf{X}, \mathbf{Z}, \boldsymbol{\xi}, \boldsymbol{\omega}\right) = ig\left(\eta_1, \kappa_1\right)$ with $\eta_1 = \left(n + 2\eta_0\right)/2$ and
$\kappa_1 = \frac{1}{2}\left(\left(\mathbf{y} - \mathbf{XZ}\boldsymbol{\xi} - \tilde{\boldsymbol{\alpha}}\right)' \boldsymbol{\Omega}^{-1}\left(\mathbf{y} - \mathbf{XZ}\boldsymbol{\xi} - \tilde{\boldsymbol{\alpha}}\right) + 2\kappa_0\right)$.

Step 5: Draw v

The relevant kernel for draws of v is its prior times the segment of the likelihood in (9) that includes this parameter, i.e. $pr\left(v \mid \boldsymbol{\omega}\right) = \frac{1}{v_0}\exp\left(-\frac{v}{v_0}\right) \cdot \prod_{s=1}^{S}\prod_{js=1}^{n_s} \frac{\left(\frac{v}{2}\right)^{\frac{v}{2}}}{\Gamma\left(\frac{v}{2}\right)} \omega_{js}^{-\left(\frac{v}{2}+1\right)} \exp\left(-\frac{v}{2\omega_{js}}\right)$. This is a non-standard density, and we use a random walk Metropolis-Hastings algorithm (MH, [35], [36]) to take draws from this kernel. Specifically, we draw a candidate value of v_c in the r$^{\text{th}}$ round of the GS from a truncated-at-zero normal proposal density with mean v_{r-1}, i.e. the current value of v, and standard deviation s_v, and accept the draw as the new current value with probability $\alpha_v = \min\left(\frac{pr\left(v_c \mid \boldsymbol{\omega}\right)}{pr\left(v_{r-1} \mid \boldsymbol{\omega}\right)}, 1\right)$.
The standard deviation of s_v is chosen (after some trial and error in preliminary runs) to yield an acceptance probability in the 45-50% range, as suggested by Gelman et al. [28], Ch. 11.

Step 6: Draw $\boldsymbol{\omega}$

For this step we note that $\frac{\varepsilon_{js}}{\sigma} \sim n\left(0, \omega_{js}\right)$. We can then use again standard results for the Gaussian regression model to obtain $pr\left(\omega_{js} \mid y_{js}, \mathbf{xz_{js}}, \boldsymbol{\xi}, \sigma^2, v, \alpha_s\right) = ig\left(\psi, \zeta\right)$ with $\psi = \left(v+1\right)/2$ and

$\zeta = \frac{1}{2}\left(\left(y_{js} - \mathbf{xz'_{js}\xi} - \alpha_s\right)^2 / \sigma^2 + v\right).$

<u>Step 7:</u> Draw $\boldsymbol{\gamma}$

As shown in Koop et al [37], Ch. 16, conditional on δ_k, the conditional posterior of γ_k remains Bernoulli with an updated success probability (i.e. $pr\left(\gamma_k = 1 | \delta_k\right)$) of $\frac{p\phi\left(\delta_j;0,c^2\tau^2\right)}{p\phi\left(\delta_j;0,c^2\tau^2\right) + (1-p)\phi\left(\delta_j;0,\tau^2\right)}$, where ϕ denotes the normal density. In practice, draws from this updated Bernoulli are obtained by comparing this expression to a random draw u form the uniform [0,1] distribution. If $pr\left(\gamma_k = 1 | \delta_k\right) > u$, γ_k is set to one, and it is set to zero otherwise.

APENDIX B:

To derive the posterior predictive distribution of $y_p \mid \mathbf{x_p}$ we proceed as follows:

Step 1: The methodological indicators comprised in $\mathbf{m_s}$ delineate a set of H possible methodological combinations. We follow [6] and assign equal probabilities $\pi_h = \pi = 1/H$ to each combination.

Step 2: For a given draw of parameters within model M_m in the r^{th} round of the original GS we first draw a random effect $\alpha_{p,r}$ from $n\left(0, V_{\alpha,r}\right)$, then an error term $\varepsilon_{p,r}$ from $t\left(0, \sigma_r^2, v_r\right)$, and compute $y_{p,r,h} = \mathbf{x'_p}\boldsymbol{\beta}_{\mathbf{x,r}} + \mathbf{m'_h}\boldsymbol{\beta}_{\mathbf{m,r}} + \alpha_{p,r} + \varepsilon_{p,r}, h = 1 \ldots H$, where $\mathbf{m_h}$ represents a specific mix of methodological indicators. We then compute the weighted average over methodologies to obtain $y_{p,r} = \sum_{h=1}^{H}\left(\mathbf{x'_p}\boldsymbol{\beta}_{\mathbf{x,r}} + \mathbf{m'_l}\boldsymbol{\beta}_{\mathbf{m,r}} + \alpha_{p,r} + \varepsilon_{p,r}\right)\pi = \mathbf{x'_p}\boldsymbol{\beta}_{\mathbf{x,r}} + \pi\sum_{h=1}^{H}\mathbf{m'_l}\boldsymbol{\beta}_{\mathbf{m,r}} + \alpha_{p,r} + \varepsilon_{p,r}$.

Step 3: We repeat Step 2 r_p times to obtain multiple draws of $y_{p,r}$ for each set of parameters. While this is optional, it is computationally inexpensive and improves the efficiency of the predictive distribution.

Step 4: Repeat Steps 2 and 3 for each set of original parameter draws, i.e. for each $\Gamma_r, r = 1 \ldots R$. The resulting sequence of $r_p \cdot R$ draws of $y_{p,r}$ can then be examined to assess the properties of BT predictions associated with model M_m.

Step 5: To generate a model-averaged posterior predictive distribution of $y_p \mid \mathbf{x_p}$, we repeat Steps 2- 4 for each model M_m in the model space M_t of data space D_t, multiply each model-specific sequence by the model-specific weight flowing from the SSVS analysis as shown in Section III, and sum over sequences.

Notes:

[1] Bergstrom and Taylor [9] deem this issue alternatively "commodity consistency" across source studies.

[2] Coldwater fisheries traditionally include species such as trout, steelhead, salmon, mountain whitefish, and grayling.

[3] For simplicity and ease of exposition we will abstract in this example and in the remainder of this study from data gap issues and resulting "N vs. K" dilemmas as discussed in Moeltner et al. [6]. In other words, we assume that all source studies include information on all policy-relevant explanatory variables. It would be straightforward to incorporate "N vs. K" corrections into the econometric framework outlined in this analysis.

[4] In the U.S., common warmwater fish are crappies, small and largemouth bass, sunfish, yellow perch, and catfish.

[5] For simplicity and without loss in generality, we abstract from any higher order interactions in this study. Naturally, the proliferation of regressors and required specification tests would further accelerate with the consideration of such terms.

[6] As described in Raftery [25] there exist a variety of mathematical approximations for the marginal likelihood that can be used to ease computational requirements in posterior simulators. However, these approximations all rely on asymptotic theory for consistency. As mentioned in Chipman et al. [16], such approximations can become unreliable in small sample-cases. Since small-sample issues are important in this study, we refrain from using BMS methods based on approximated marginal likelihoods.

[7] Naturally, the baseline model could also include other regressors than methodological indicators for which no information is available for the policy context, but which may be important for model stability. Just like the elements of $\mathbf{x}_{js}$ these additional covariates would then have to be interacted with activity indicators as new data sets are added to avoid mis-specification errors. Furthermore, since there are no known values for the policy site to insert for these covariates when generating BT predictions, BT

predictions would have to be marginalized over these regressors, in analogy of our treatment of methodological indicators (see also [6]). To avoid these straightforward but tedious computational additions we will abstract from such variables in this analysis.

[8] In our parameterization, this implies an expectation of $\frac{v}{2}\left(\left(\frac{v}{2}\right)-1\right)^{-1}=\frac{v}{v-2}$, and $2\left(\frac{v}{2}\right)+1=v+1$ degrees of freedom.

[9] To avoid a proliferation of interaction terms and added computational complexity in generating BT predictions we assume that the effect of methodological covariates does not change significantly across activities. For most "related activities" that one would traditionally consider in a data-augmented model this is likely a relatively robust assumption.

[10] While seemingly adding notational clutter, the introduction of the γ_k-term and the resulting hierarchical setup for the mixture distribution of δ_k corresponds well to the Bayesian notion of "hierarchical priors", i.e. the prior of δ_k depends on another *model* parameter γ_k, which, in turn has a hyper-prior distribution with parameter *p*. It is also a natural and logical setup to allow for the derivation of a *posterior* probability for the event $\gamma_k = 1$, which is of crucial importance in our case.

[11] To guard against dramatic outliers, we further truncate this distribution at the 99.9th percentile, i.e. we discard the 50 largest observations. This final adjustment is implemented in identical fashion for all models. Intuitively, this correction could be interpreted as "imposing income constraints" on the predicted WTP values.

[12] The nse is computed as $std/\sqrt{\left(R_p\right)}$ where *std* is the standard deviation of the predicted distribution and R_p is the length of the series. A numerical 95% confidence interval is obtained as (posterior mean $\pm 1.96 \cdot nse$).

[13] The 13 models in D_3 listed in Tables 6 and 7 have a combined model weight of 0.85. For model-averaging purposes we calibrate each individual model weight by this total to preserve the adding-up condition for the posterior probability mass function of these weights.

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Table 1: Proliferation of Data Space and Model Space

		number of baseline regressors					
		1	2	3	4	5	number of data spaces
		number of additional terms in the MRM					
number of added activities ("data sets")	1	1	2	3	4	5	1
	2	2	4	6	8	10	3
	3	3	6	9	12	15	7
	4	4	8	12	16	20	15
	5	5	10	15	20	25	31
		number of possible models					
number of added activities ("data sets")	1	2	4	8	16	32	
	2	4	16	64	256	1,024	
	3	8	64	512	4,096	32,768	
	4	16	256	4,096	65,536	1,048,576	
	5	32	1,024	32,768	1,048,576	33,554,432	

Table 2: Coefficients and SSVS Acceptance Shares for Simulated Data

	constant	catch	income	travel cost
true coefficients for baseline data	-2.500	1.000	0.600	-0.400
true coefficients for added data	-2.500	1.400	0.600	-0.200
simulation scenario	acceptance shares			
n = 2000, v = 40	0.052	1.000	0.047	0.889
n = 2000, v = 10	0.065	1.000	0.047	0.850
n = 1000, v = 40	0.079	1.000	0.072	0.857
n = 1000, v = 10	0.073	1.000	0.076	0.693
n = 600, v = 40	0.143	0.998	0.087	0.058
n = 600, v = 10	0.182	0.993	0.098	0.069
n = 300, v = 40	0.105	0.620	0.092	0.074
n = 300, v = 10	0.106	0.597	0.100	0.079

Table 3: Data Space, Model Space and Empirical Model Weights for Simulated Data

		interaction terms (1 = included)					
data space	model	d1	d1*catch	d1*inc	d1*tc	n	model weight
D_0	M1	-	-	-	-	150	N/A
D_1	M1	0	0	0	0	300	0.267
	M2	0	0	0	1	300	0.036
	M3	0	0	1	0	300	0.045
	M4	0	0	1	1	300	0.005
	M5	0	1	0	0	300	0.479
	M6	0	1	0	1	300	0.028
	M7	0	1	1	0	300	0.033
	M8	0	1	1	1	300	0.002
	M9	1	0	0	0	300	0.039
	M10	1	0	0	1	300	0.004
	M11	**1**	**0**	**1**	**0**	**300**	**0.007**
	M12	1	0	1	1	300	0.000
	M13	1	1	0	0	300	0.045
	M14	1	1	0	1	300	0.004
	M15	1	1	1	0	300	0.007
	M16	1	1	1	1	300	0.001

d1 = indicator for added data
catch = catch rate
inc = income
tc = travel cost
“correct model” shown in boldface

Table 4: Estimated Coefficients and Predictions for Simulated Data

			relevant coeff's for prediction				exponentiated distribution of predictions					
Data Space	Model	weight	const.	catch	inc	tc	mean	std	nse	low	up	width
D_0 (n=150)	M1	-	-0.593	0.979	0.314	-0.395	32.500	110.803	0.496	31.528	33.472	1.944
	M1	0.267	-1.055	1.150	0.380	-0.355	29.469	67.062	0.300	28.881	30.057	1.176
	M2	0.036	-1.050	1.149	0.379	-0.432	25.096	56.402	0.252	24.602	25.591	0.989
	M3	0.045	-1.061	1.148	0.321	-0.356	21.941	50.697	0.227	21.496	22.385	0.889
	M4	0.005	-1.068	1.152	0.328	-0.374	21.916	49.394	0.221	21.483	22.349	0.866
	M5	0.479	-1.157	1.007	0.392	-0.360	19.786	42.485	0.190	19.414	20.159	0.745
	M6	0.028	-1.164	1.007	0.393	-0.361	20.327	47.280	0.212	19.912	20.742	0.830
	M7	0.033	-1.148	0.997	0.401	-0.361	21.183	48.234	0.216	20.760	21.606	0.846
D_1 (n=300)	M8	0.002	-1.184	1.003	0.410	-0.371	20.819	46.345	0.207	20.413	21.226	0.813
	M9	0.039	-1.341	1.147	0.384	-0.356	22.589	52.436	0.235	22.129	23.049	0.920
	M10	0.004	-1.298	1.147	0.383	-0.376	22.745	53.107	0.238	22.279	23.210	0.931
	M11	0.007	-0.982	1.152	0.305	-0.360	22.021	49.699	0.222	21.585	22.457	0.872
	M12	0.000	-	-	-	-	-	-	-	-	-	
	M13	0.045	-1.063	0.989	0.394	-0.360	22.572	52.329	0.234	22.114	23.031	0.917
	M14	0.004	-0.968	0.986	0.391	-0.393	22.078	49.731	0.223	21.642	22.514	0.872
	M15	0.007	-0.724	0.992	0.321	-0.362	22.267	50.384	0.225	21.825	22.709	0.884
	M16	0.001	-0.626	0.989	0.318	-0.397	22.161	51.172	0.229	21.712	22.610	0.898
D_1, weighted average	-	-	-	-	-	-	23.017	51.239	0.229	22.569	23.466	0.897

catch = catch rate
inc = income
tc = travel cost
mean = posterior mean / std = standard deviation / nse = numerical standard error / low (up) = lower (upper) bound of numerical 95% confidence interval for the mean / width = (up – low)

Table 5: Data Space Composition and Methodological Indicators for Sport Fishing Data

	data space composition					
	fishery		water type			
data space	cold	warm	river	still	studies	obs.
D_0	x		x		15	73
D_1	x	x	x		21	94
D_2	x		x	x	28	112
D_3	x	x	x	x	37	229

	cell counts for methodological indicators					
	journal	report	dc	oe	subst	samp200
D_0	13	23	38	5	22	35
D_1	16	41	40	10	23	35
D_2	37	27	39	8	47	41
D_3	51	105	52	21	49	53

dc = dichotomous choice method
oe = open ended, iterative bidding, payment cards
subst = substitute sites are addressed or included
samp200 = sample size ≥ 200

Table 6: Data Space, Model Space and Empirical Model Weights for Sport Fishing Data

		interaction terms (0 = excluded, 1 = included)							
data space	model	warm	warm*catch	warm*inc	still	still*catch	still*inc	n	model weight
D_0	M1	-	-	-	-	-	-	73	N/A
D_1	M1	0	0	0	-	-	-	94	0.589
	M2	0	0	1	-	-	-	94	0.116
	M3	0	1	0	-	-	-	94	0.066
	M4	0	1	1	-	-	-	94	0.013
	M5	1	0	0	-	-	-	94	0.109
	M6	1	0	1	-	-	-	94	0.085
	M7	1	1	0	-	-	-	94	0.013
	M8	1	1	1	-	-	-	94	0.009
D_2	M1	-	-	-	0	0	0	112	0.519
	M2	-	-	-	0	0	1	112	0.116
	M3	-	-	-	0	1	0	112	0.098
	M4	-	-	-	0	1	1	112	0.034
	M5	-	-	-	1	0	0	112	0.104
	M6	-	-	-	1	0	1	112	0.082
	M7	-	-	-	1	1	0	112	0.027
	M8	-	-	-	1	1	1	112	0.021
D_3 (all models with weight >=0.01)	M1	0	0	0	0	0	0	229	0.373
	M2	0	0	0	0	0	1	229	0.051
	M3	0	0	0	0	1	0	229	0.041
	M5	0	0	0	1	0	0	229	0.053
	M6	0	0	0	1	0	1	229	0.037
	M9	0	0	1	0	0	0	229	0.075
	M10	0	0	1	0	0	1	229	0.010
	M13	0	0	1	1	0	0	229	0.013
	M17	0	1	0	0	0	0	229	0.045
	M33	1	0	0	0	0	0	229	0.073
	M34	1	0	0	0	0	1	229	0.010
	M35	1	0	0	0	1	0	229	0.011
	M41	1	0	1	0	0	0	229	0.060

warm = indicator for warmwater fishery
still = indicator for stillwater environment
catch = catch rate
inc = income

Table 7: Estimated Coefficients and Predictions for Sport Fishing Data

Data Space	Model	n	model weight	relevant coeff's for prediction: const	ln(catch)	ln(inc)	exponentiated distribution of predictions: mean	std	nse	low	up	width
D_0	M1	73	-	2.101	-0.091	0.116	67.127	94.143	0.421	66.302	67.953	1.651
D_1	M1	94	0.589	1.278	-0.070	0.198	75.260	89.731	0.401	74.473	76.047	1.574
	M2	94	0.116	1.814	-0.036	0.133	58.446	64.415	0.288	57.881	59.011	1.130
	M3	94	0.066	0.301	-0.189	0.302	67.063	74.234	0.332	66.412	67.714	1.302
	M4	94	0.013	1.016	-0.095	0.214	58.540	65.788	0.294	57.963	59.117	1.154
	M5	94	0.109	1.503	-0.031	0.160	58.437	64.237	0.287	57.873	59.000	1.127
	M6	94	0.085	2.117	-0.034	0.104	58.431	63.823	0.286	57.872	58.991	1.119
	M7	94	0.013	0.886	-0.095	0.226	58.816	65.485	0.293	58.242	59.390	1.148
	M8	94	0.009	1.444	-0.097	0.175	57.883	64.508	0.289	57.317	58.448	1.131
D_1, weighted average	-	112	-	-	-	-	68.925	79.923	0.358	68.224	69.626	1.402
D_2	M1	112	0.519	3.711	0.066	-0.050	76.073	141.499	0.633	74.832	77.314	2.482
	M2	112	0.116	3.982	0.060	-0.070	79.788	141.514	0.633	78.547	81.030	2.483
	M3	112	0.098	3.738	0.061	-0.057	75.880	139.043	0.622	74.661	77.100	2.439
	M4	112	0.034	4.331	-0.106	-0.085	86.487	140.202	0.627	85.257	87.716	2.459
	M5	112	0.104	4.113	0.060	-0.081	81.361	148.390	0.664	80.060	82.662	2.602
	M6	112	0.082	3.552	0.056	-0.028	81.897	139.779	0.625	80.671	83.122	2.451
	M7	112	0.027	4.218	-0.103	-0.074	87.100	148.214	0.663	85.800	88.400	2.600
	M8	112	0.021	4.044	-0.099	-0.058	89.162	153.572	0.687	87.815	90.509	2.694
D_2, weighted average	-	112	-	-	-	-	78.440	142.073	0.636	77.194	79.687	2.493
D_3 (all models with weight >=0.01)	M1	229	0.373	0.827	-0.072	0.231	80.799	120.148	0.538	79.746	81.853	2.107
	M2	229	0.052	0.98	-0.057	0.219	83.936	127.849	0.572	82.815	85.057	2.242
	M3	229	0.041	1.305	-0.021	0.186	85.828	130.985	0.586	84.679	86.977	2.298
	M5	229	0.054	1.131	-0.059	0.205	83.622	124.39	0.557	82.532	84.713	2.181
	M6	229	0.037	0.757	-0.054	0.239	82.748	122.661	0.549	81.672	83.824	2.152
	M9	229	0.075	-0.154	-0.082	0.307	66.299	93.872	0.42	65.476	67.122	1.646
	M10	229	0.010	-0.022	-0.07	0.296	68.065	96.538	0.432	67.218	68.912	1.694
	M13	229	0.013	0.001	-0.069	0.294	68.135	98.28	0.44	67.273	68.997	1.724
	M17	229	0.045	1.132	-0.046	0.201	83.019	127.803	0.572	81.898	84.14	2.242
	M33	229	0.074	-0.47	-0.08	0.335	65.914	91.694	0.41	65.11	66.718	1.608
	M34	229	0.010	-0.275	-0.067	0.319	68.08	97.649	0.437	67.224	68.936	1.712
	M35	229	0.011	0.142	-0.018	0.277	70.804	104.73	0.469	69.886	71.723	1.837
	M41	229	0.060	0.903	-0.08	0.21	66.723	93.643	0.419	65.902	67.544	1.642
D_3, weighted average*	-	229	-	-	-	-	77.448	114.190	0.511	76.446	78.450	2.004

mean = posterior mean / std = standard deviation / nse = numerical standard error / low (up) = lower (upper) bound of numerical 95% confidence interval for the mean / width = (up – low)

Session I: Benefits Transfer

Comments by Matt Massey on:

Benefits Transfer of a Third Kind: An Examination of Structural Benefit Transfer, George Van Houtven, Subhrendu Pattanayak, Sumeet Patil, and Brooks Depro

Meta-Regression and Benefit Transfer: Data Space, Model Space, and the Quest for 'Optimal Scope', Klaus Moeltner and Randall Rosenberger

Split-Sample Tests of "No Opinion" Responses in an Attribute Based Choice Model, Eli Fenichel, Frank Lupi, John Hoehn, and Michael Kaplowitz

Benefit Transfer

- Both VHPPD and MR investigate ways to conduct benefit transfers in situations where there are only a small number of “appropriate” studies (and a potentially larger number of “related” studies”)

- In some ways, the strength of each study is the weakness of the other

Benefit Transfer

- Both Studies start by:

1. Choosing a specific form for the utility or welfare function
2. Then collect all appropriate studies

- Then the methods start to diverge

Structural BT

3. Starting from the utility function specified in Step 1, expressions for the results reported in the studies from Step 2 are derived (i.e. WTP, number of trips, …)

4. The reported results from the studies in Step 2 are then plugged into the expression from Step 3 and the expressions are then solved for the coefficient values that return the reported results

5. The coefficient values from step 4 are then used in the utility function specified in Step 1 and used to solve for the desired welfare effects

Structural BT

- Strengths
  - Utility theoretic
  - Can deal with small (and large) sample sizes
  - Relatively quick and easy to do
- Weaknesses
  - No specific guidance on how to select the appropriate model

Bayesian Model Search

3. Add “related activity” studies to the dataset and re-specify the model to include the necessary new variables
4. Use SSVS algorithm to assign prior probabilities to all model parameters with uncertain explanatory importance
5. The priors from Step 4 are then combined with the likelihood function to derive posterior distributions for all parameters
6. For each element in the model, the posterior distributions from Step 5 are used to predict whether or not a variable belongs in the model
7. Step 6 is repeated for multiple draws and the percentage of times a variable is predicted to be included in the model can then be used to either identify a dominant model or to create a weights for each model specification

Bayesian Model Search

8. Next all model specifications are then rerun without the SSVS component.
9. For each model then derive posterior distributions of BT predictions
10. Average the predictions from Step 10 using the model weights collected in Step 7

Bayesian Model Search

- Strengths
  - Provides specific guidance on how to select the appropriate model
  - Can help to augment small sample sizes by determining what “related” information can help improve estimation
- Weaknesses
  - Relatively complicated and hard to do

Valuation for Environmental Policy: Ecological Benefits

A Workshop sponsored by U.S. Environmental Protection Agency's National Center for Environmental Economics (NCEE) and National Center for Environmental Research (NCER)

Crowne Plaza Washington National Airport Hotel
1480 Crystal Drive
Arlington, VA 22202

April 23-24, 2007

Disclaimer

U.S. Environmental Protection Agency (EPA)
National Center for Environmental Economics (NCEE) and
National Center for Environmental Research (NCER)
Valuation for Environmental Policy: Ecological Benefits

Crowne Plaza Washington National Airport Hotel
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(703) 416-1600

April 23-24, 2007

Agenda

April 23, 2007: Valuation for Environmental Policy

8:00 a.m. – 8:30 a.m.	**Registration**	
8:30 a.m. – 8:45 a.m.	**Introductory Remarks** Rick Linthurst, National Program Director for Ecology, EPA, Office of Research and Development	
8:45 a.m. – 11:30 a.m.	**Session I: Benefits Transfer** Session Moderator: Steve Newbold, EPA, NCEE	
	8:45 a.m. – 9:15 a.m.	Benefits Transfer of a Third Kind: An Examination of Structural Benefits Transfer George Van Houtven, Subhrendu Pattanayak, Sumeet Patil, and Brooks Depro, Research Triangle Institute
	9:15 a.m. – 9:45 a.m.	The Stability of Values for Ecosystem Services: Tools for Evaluating the Potential for Benefits Transfers John Hoehn, Michael Kaplowitz, and Frank Lupi, Michigan State University
9:45 a.m. – 10:00 a.m.	**Break**	
	10:00 a.m. – 10:30 a.m.	Meta-Regression and Benefit Transfer: Data Space, Model Space and the Quest for 'Optimal Scope' Klaus Moeltner, University of Nevada, Reno, and Randall Rosenberger, Oregon State University
	10:30 a.m. – 10:45 a.m.	Discussant: Matt Massey, EPA, NCEE
	10:45 a.m. – 11:00 a.m.	Discussant: Kevin Boyle, Virginia Tech University
	11:00 a.m. – 11:30 a.m.	Questions and Discussion
11:30 a.m. – 12:45 p.m.	**Lunch**	

April 23, 2007 (continued)

12:45 p.m. – 3:30 p.m.	**Session II: Wetlands and Coastal Resources** Session Moderator: Cynthia Morgan, EPA, NCEE	
	12:45 p.m. – 1:15 p.m.	A Combined Conjoint-Travel Cost Demand Model for Measuring the Impact of Erosion and Erosion Control Programs on Beach Recreation Ju-Chin Huang, University of New Hampshire; George Parsons, University of Delaware; Min Qiang Zhao, The Ohio State University; and P. Joan Poor, St. Mary's College of Maryland
	1:15 p.m. – 1:45 p.m.	A Consistent Framework for Valuation of Wetland Ecosystem Services Using Discrete Choice Methods David Scrogin, Walter Milon, and John Weishampel, University of Central Florida
1:45 p.m. – 2:00 p.m.	**Break**	
	2:00 p.m. – 2:30 p.m.	Linking Recreation Demand and Willingness To Pay With the Inclusive Value: Valuation of Saginaw Bay Coastal Marsh John Whitehead and Pete Groothuis, Appalachian State University
	2:30 p.m. – 2:45 p.m.	Discussant: Jamal Kadri, EPA, Office of Wetlands, Oceans, and Watersheds
	2:45 p.m. – 3:00 p.m.	Discussant: John Horowitz, University of Maryland
	3:00 p.m. – 3:30 p.m.	Questions and Discussion
3:30 p.m. – 3:45 p.m.	**Break**	
3:45 p.m. – 5:45 p.m.	**Session III: Invasive Species** Session Moderator: Maggie Miller, EPA, NCEE	
	3:45 p.m. – 4:15 p.m.	Models of Spatial and Intertemporal Invasive Species Management Brooks Kaiser, Gettysburg College, and Kimberly Burnett, University of Hawaii at Manoa
	4:15 p.m. – 4:45 p.m.	Policies for the Game of Global Marine Invasive Species Pollution Linda Fernandez, University of California at Riverside
	4:45 p.m. – 5:00 p.m.	Discussant: Marilyn Katz, EPA, Office of Wetlands, Oceans, and Watersheds
	5:00 p.m. – 5:15 p.m.	Discussant: Lars Olsen, University of Maryland
	5:15 p.m. – 5:45 p.m.	Questions and Discussion
5:45 p.m.	**Adjournment**	

April 24, 2007: Valuation for Environmental Policy

8:30 a.m. – 9:00 a.m.	**Registration**	
9:00 a.m. – 11:45 a.m.	**Session IV: Valuation of Ecological Effects** Session Moderator: William Wheeler, EPA, NCER	
	9:00 a.m. – 9:30 a.m.	Integrated Modeling and Ecological Valuation: Applications in the Semi Arid Southwest David Brookshire, University of New Mexico, Arriana Brand, Jennifer Thacher, Mark Dixon,Julie Stromberg, Kevin Lansey, David Goodrich, Molly McIntosh, Jake Gradny, Steve Stewart, Craig Broadbent and German Izon
	9:30 a.m. – 10:00 a.m.	Contingent Valuation Surveys to Monetize the Benefits of Risk Reductions Across Ecological and Developmental Endpoints Katherine von Stackelberg and James Hammitt, Harvard School of Public Health
10:00 a.m. – 10:15 a.m.	**Break**	
	10:15 a.m. – 10:45 a.m.	Valuing the Ecological Effects of Acidification: Mapping the Extent of Market and Extent of Resource in the Southern Appalachians Shalini Vajjhala, Anne Mische John, and David Evans, Resources for the Future
	10:45 a.m. – 11:00 a.m.	Discussant: Joel Corona, EPA, Office of Water
	11:00 a.m. – 11:15 a.m.	Discussant: David Simpson, Johns Hopkins University
	11:15 a.m. – 11:45 a.m.	Questions and Discussion
11:45 a.m. – 1:00 p.m.	**Lunch**	
1:00 p.m. – 4:15 p.m.	**Session V: Water Resources** Session Moderator: Adam Daigneault, EPA, NCEE	
	1:00 p.m. – 1:30 p.m.	Valuing Water Quality as a Function of Physical Measures Kevin Egan, Joe Herriges, John Downing, and Katherine Cling, Iowa State University
	1:30 p.m. – 2:00 p.m.	Cost-Effective Provision of Ecosystem Services from Riparian Buffer Zones Jo Albers, Oregon State University; David Simpson, Johns Hopkins University; and Steve Newbold, NCEE
2:00 p.m. – 2:15 p.m.	**Break**	
	2:15 p.m. – 2:45 p.m.	Development of Bioindicator-Based Stated Preference Valuation for Aquatic Resources Robert Johnston, Eric Shultz, Kathleen Segerson, Jessica Kukielka, Deepak Joglekar, University of Connecticut; and Elena Y. Besedin, Abt Associates

April 24, 2007 (continued)

	2:45 p.m. – 3:05 p.m.	Comparing Management Options and Valuing Environmental Improvements in a Recreational Fishery Steve Newbold and Matt Massey, NCEE
	3:05 p.m. – 3:20 p.m.	Discussant: Julie Hewitt, EPA, Office of Water
	3:20 p.m. – 3:35 p.m.	Discussant: George Parsons, University of Delaware
	3:35 p.m. – 4:05 p.m.	Questions and Discussions
4:05 p.m. – 4:15 p.m.	**Final Remarks**	
4:15 p.m.	**Adjournment**	

A Combined Conjoint-Travel Cost Demand Model for Measuring the Impact of Erosion and Erosion Control Programs on Beach Recreation

Ju-Chin Huang*
University of New Hampshire

George R. Parsons
University of Delaware

Min Qiang Zhao
The Ohio State University

and

P. Joan Poor
St. Mary's College of Maryland

Abstract

In this paper, we examine the impact of beach erosion and erosion control on the demand for beach trips. A contingent behavior setting of a hypothetical erosion control program, which employs a conjoint design to identify a program's potential effects (visible structure, poorer sand quality and so forth) on the beach environment in addition to preventing erosion, is incorporated into an in-person beach trip survey. Our results show that the recreation benefits of preventing erosion can be offset by the losses associated with the negative effects of erosion control. We also find that the economic values of erosion control vary across beaches that provide different activities and services. The findings may be used by policy makers to design economically efficient erosion control programs for beaches according to their specific characteristics.

Key Words: Beach Erosion, Contingent Behavior, Conjoint Design, Activity Specific Recreation Demand

JEL Codes: Q26, H41

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Abstract

In this paper, we examine the impact of beach erosion and erosion control on the demand for beach trips. A contingent behavior setting of a hypothetical erosion control program, which employs a conjoint design to identify a program's potential effects (visible structure, poorer sand quality and so forth) on the beach environment in addition to preventing erosion, is incorporated into an in-person beach trip survey. Our results show that the recreation benefits of preventing erosion can be offset by the losses associated with the negative effects of erosion control. We also find that the economic values of erosion control vary across beaches that provide different activities and services. The findings may be used by policy makers to design economically efficient erosion control programs for beaches according to their specific characteristics.

1. Introduction

Ocean beaches are important natural resources. Beach-related recreational activities in coastal areas also contribute significantly to local economies. According to the U. S. Army Corps of Engineers, close to half of the United States beaches are experiencing significant erosion problems. Beach erosion can be caused by a combination of human-induced development, global rising of the sea level, occasional violent weather systems, and chronic sediment transport by waves. Beach erosion results in losses of recreational beaches, tourist-related business, ocean front properties, land for aquaculture, and wildlife habitat.

Various erosion control programs/plans have been implemented in U.S. coastal areas. Most of the available erosion control methods have multiple effects, both positive and negative, on the beach and its surrounding environment. For example, some erosion control programs require installation of visible structures that can affect both the aesthetics of beaches and the overall experience of the beach trip itself. It is also possible for certain erosion control methods to initiate or accelerate erosion on neighboring beaches or affect coastal wildlife habitat. Some programs that require maintenance and adjustments may result in restricted use of beaches over a period of time.[1] If these effects are not considered when developing erosion control programs, non-optimal choices can result.

There are many studies examining the effectiveness and economic values of beach protection/preservation (e.g., Curtis and Shows, 1984; Bishop and Boyle, 1985; Lindsay et al., 1992; U.S. Army Corps of Engineers, 1994; Stronge, 1995; Dobkowski, 1998). However, none of these studies emphasizes the potential multiple effects of erosion control methods on the coastal environment and the associated tradeoffs. In his review of the empirical literature on the

[1] See the web site of Program for the Study of Developed Shoreline at Duke University for a description of erosion control devices and potential effects, http://www.nicholas.duke.edu/psds/Stabilization/Categories.htm.

economic value of marine recreation, Freeman (1995) points out that very few economic valuation studies have been done with a focus on the role of qualitative attributes of beaches.

The purpose of this study is to examine the impact of erosion and erosion control on beach recreation. A typical erosion control program is designed for the purpose of alleviating the effects of erosion. However, as discussed, it can also change the beach features and environment, visible structure on a beach, degraded conditions for wildlife viewing and so forth, thus directly affecting individuals' trip decisions. Further, beach visitors may react to various negative impacts differently, and the reaction to the impacts may be influenced by the type of activities that the visitors are engaged in. The variation in recreation activity across users is an important issue, yet less frequently addressed in empirical studies of recreation demand. A single trip demand model for all trips to a particular site assumes that all trips share common activities (or a single activity). Smith (1991) emphasizes that individuals are expected to have different demands for site services when they undertake different activities. Parsons (2003) argues that the more dissimilar the uses are, the greater the need is to disaggregate the model by type of use. Beach users clearly participate in different activities and the effects of erosion and erosion control programs are likely to vary across individuals given their different uses of the beach. Failure to recognize the differential effects of erosion control on beach activities may result in biased welfare measures.

In this paper, the multiple effects of a beach erosion control program on the beach environment are viewed as the 'attributes' of the program, and their impacts on demand for beach trips are examined. Contingent behavior data regarding program preferences and future beach trips are collected by randomly interviewing visitors at eight beaches in New Hampshire (NH) and Maine (ME). In the survey, individuals are presented with hypothetical erosion control programs that have varying effects on the beach environment. The conjoint questioning format enables us to value the potential negative effects of an erosion control program on recreational beach use. We also elicit detailed information on types of recreation activity and compile the beach characteristics database. These data are incorporated into our trip demand analysis. We estimate a pooled single site travel cost model ('pooled' across eight beaches) and a set of trip change equations to capture effects of erosion and control methods. Recreation values associated with erosion and erosion control are computed for various beaches that are characterized by their popular activities and services. We find that erosion control is not necessarily beneficial when the erosion is relatively small. Further, the same erosion control program can generate different recreation values at different beaches because of the heterogeneity across beaches.

The remainder of this paper is organized as follows. Section 2 describes the survey design and data collection. Section 3 presents the empirical model and the corresponding welfare measures. Section 4 discusses results of the data analysis and demonstrates the varying recreation values of erosion control across beaches due to different beach characteristics and recreational activities. Section 5 gives concluding remarks.

2. Conjoint Design of Contingent Behavior Beach Recreation Survey

We conducted three focus group meetings. These included seacoast residents, inland residents, and ocean front property owners in NH and southern ME. The purpose of these meetings was to investigate individuals' perceptions of beach erosion, erosion control devices and the impact of both on beach recreation. We found that most of the focus group participants were familiar with erosion control techniques. Most were supportive of the preservation of existing beaches through erosion control methods but were also concerned about the potential side effects of erosion control devices such as dangers to swimmers, impact on wildlife, impact on aesthetics, and water quality decline. The cost of implementing erosion control devices was of little concern to participants. They also felt that it would be difficult to evaluate the impact of erosion and erosion control if particular beach uses were not clearly described.

Based on the results of the focus groups, we developed an in-person, contingent behavior survey using a conjoint design to depict possible combinations of the side effects (impact attributes) of erosion control. In the conjoint questions, we asked people if erosion and the 'multi-attribute' erosion control programs would affect the number of trips taken to the beach. Posters with information on erosion and erosion control were shown while the survey was administered to ensure a basic understanding of the issues.

The in-person interviews were conducted at eight beaches in NH and Southern ME in August, 2002. Three of the eight beaches are in NH. Individual trip information including size of party, length of stay, beach activities, and demographics was collected. Beach activities were grouped in advance according to the factor analysis results in an unpublished study by Leeworthy, Meade, and Smith (1987) and reproduced in Smith (1991). Respondents were asked to check all activity groups that applied to their trips. They were presented with a hypothetical scenario regarding erosion at the beach where they were interviewed and asked if they would consequently change their trip behavior in the following year. Respondents were then presented with two hypothetical erosion control programs (one at a time) that would prevent the stated erosion, but these erosion control programs could potentially alter the beach environment. Under the premise that all proposed erosion control programs could prevent erosion, each program was described according to a set of five potential effects on the beach environment. Respondents were asked how their future beach trips would change with these erosion control programs. The five beach attributes affected by the programs include:

- visible structure (beach aesthetics)
- danger to swimmers
- wildlife viewing
- salt water quality
- sand quality.

The level of beach erosion and erosion control impact attributes were varied randomly across survey respondent according to an orthogonal main effects experimental design (Lorenzen and Anderson, 1993).[2] The design of erosion control programs is summarized in Table 1. In our contingent behavior analysis we use the following trip information from respondents:

- number of trips expected in the next year
- reported change in number of trips given a hypothetical level of beach erosion
- reported change in number of trips if an erosion control program (with certain impacts on beach environment) is put in place to prevent the beach erosion
- reported change in number of trips for an alternative erosion control program.

An example of our contingent behavior questions to elicit responses of reported changes in trips listed above is given in appendix A. We consider day trips only in this analysis.[3] Travel cost is assumed to be $0.35 per mile and the opportunity cost of travel time is assumed to be one third of the hourly wage rate (wage=Income/2080).[4] Table 2 summarizes the survey data and includes definitions of variables used in the regression analysis for the demand for day trips.

Approximately two-thirds of the survey respondents are NH or ME residents. On average, each survey respondent planned to take 17 trips in the following year. The median is 6 trips that the distribution is right skewed and close to ninety percent of respondents planned to

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[2] Specifically, a 2-factorial main effects with 5 factors experimental design, accompanying 6 levels of erosion, is employed.

[3] The ratio of day to total trips in the previous year was used to divide a change in total number of trips in response to the contingent behavior questions into changes in numbers of day and overnight trips in the following year. This was necessary because we did not ask people to report separately their changes in day and overnight trips in the contingent behavior questions.

[4] The opportunity costs of on-site time are not computed due to unavailability of data.

take 20 trips or less. One of the six levels of erosion (1, 4, 7, 10, 15, 25 feet/year) was randomly presented to respondents with an average of 10 feet. On average, erosion lead to1.36 fewer trips per respondent with 78% reporting no change in trips. When an erosion control program was introduced to prevent the stated erosion and some potential negative effects of erosion control device were presented, respondents still took fewer trips but the impact was attenuated--respondents now reported taking on average 1.01 fewer trips with 82% reporting no change in trips. The responses indicate that erosion control can be desirable but the potential negative impacts on the beach environment can offset the benefits of erosion control.

The beach recreation activity groups (A1 – A7) are also summarized in Table 2. Respondents may participate in more than one activity group during the same beach visit. The majority of the survey respondents did on-beach activities (A3). Observing wildlife, sightseeing, and walking/jogging constituted the second most popular group of activities (A1). Table 3 provides additional summary of characteristics and activities by beaches. The eight beaches in the survey are, from South to North, Hampton Beach State Park, Hampton Main Beach, Wallis Sands State Park, Long Sands, Ferry Beach, Old Orchard Beach, Crescent Beach, and Reid Beach State Park. Seven of these beaches currently have some erosion control device in place including seawalls, jetties, and sand dunes. By examining the summary of activities of survey respondents at the eight beaches, the beaches differ by activities that the visitors engaged in. For example, visitors at Ferry Beach and Old Orchard Beach are more likely to engage in activities in the A4 group (fishing, etc.) and visitors at Wallis Sands are noticeably less likely to have activities in the A1 group (wildlife viewing, sightseeing, etc.). In addition, four of the beaches have over half of their visitors from out of state. The average travel distance of visitors varies from 39 miles (Ferry Beach) to over 100 miles (Old Orchard Beach). It is perceivable that beach trip decisions are influenced by different characteristics and activities of beaches. If erosion and erosion control alter beach characteristics and activities, then the recreational impact of erosion and erosion control can differ across beaches. This is examined in the regression analysis.

3. Empirical Model and Welfare Measure

Our analysis involves three steps. First, we estimate a pooled single site recreation demand model using data on the total number of expected recreation trips next year as our dependent variable. Our focus in this step is on estimating the coefficient on travel cost which is used in our welfare analysis in step three. Second, we estimate two trip-change equations to predict how the demand for trips shifts with changes in erosion and erosion control programs. These models use the changes in day trips from our contingent behavior questions as dependent variables. Third, we use the quantity changes predicted in the second step and the travel cost coefficient in the first step to compute welfare measures using conventional welfare analytic methods.

We use a Poisson regression to estimate the demand function in the first step. An on-site, in-person survey ensures participation in the beach recreation of survey respondents. However, the random sample obtained on site does not readily represent the relevant population because those who visit the site more frequently are more likely to be sampled and an on-site sample does not include those who take zero trip in the studied period. To correct for the on-site sampling bias and truncation, we employ the model proposed by Shaw (1988) and use the following form in estimation

$$\Pr ob(Y_i = y_i) = \frac{e^{-\lambda_i} \lambda_i^{(y_i-1)_t}}{(y_i - 1)!} \quad y_i = 1, 2, ... \tag{1}$$

where Y_i is the quantity demanded for beach trips by individual i and λ_i is the expected value of Y_i. The above model resembles the standard Poisson model except for the subtraction of 1 from y_i. As usual, λ_i depends on the price of Y and individual characteristics.[5] Since our survey was conducted in eight different beaches in New Hampshire and Maine, we have a 'pooled' model which allows for variation in site characteristics. So, λ_i is specified to depend on beach characteristics as well.

$$\ell n\lambda_i = \alpha + \beta_p Cost_i + \beta' X_i + \gamma' W_i \tag{2}$$

where $Cost_i$ is the total travel cost per trip; X_i is a vector of individual i's characteristics including recreation activities at the beach; W_i is a vector of beach characteristics faced by the individual i; and α, β_p, β, and γ are parameters to be estimated.

As noted earlier, each respondent was asked a contingent behavior question about increased erosion and then two more questions about the installation of erosion control devices to forestall the erosion. In all cases, respondents were asked how they would adjust their trips in response to the hypothetical changes. We estimate two Poisson trip-change equations in step 2 – one for the erosion scenario and one for the two erosion control programs that prevent the erosion.

The basic form of the Poisson trip change models is $\Pr(M_{ji} = m_{ji}) = \dfrac{e^{-\omega_{ji}}\omega_{ji}^{m_{ji}}}{m_{ji}!}$, j=1,2. Let C_{1i} be the change in number of day trips due to erosion and C_{2i} be the change in number of day trips assuming the erosion is mitigated by erosion control and that there are some (negative)

[5] We estimated the Negative Binomial model without the correction for the on site sampling bias. The model fit was not as good as the Poisson model. We also attempted the estimation of the Negative Binomial model with the correction for truncation and on site sampling bias (Englin and Shonkwiler, 1995) and encountered convergence difficulties. Based on the model fit and stability, we chose to report the Poisson results in this paper.

impacts associated with that control. The expected values of the trip changes are specified as follows:

$$\omega_{1i} = \ell n(\overline{C}_{1i} + 1) = \delta_1 E_i + \delta_2 E_i/Width_j + \eta'(E_i{*}A_i) + \mu'(E_i{*}W_i) + \varphi'(E_i{*}X_i) \quad (3)$$

$$\omega_{2i} = \ell n(\overline{C}_{2i} + 1) = \kappa' ATT_i + \theta'(ATT_i{*}A_i) + \nu'(ATT_i{*}W_i) + \psi'(ATT_i{*}X_i) + \tau E_i/Width_j \quad (4)$$ [6]

where $\overline{C}_{1i}$ is the expected value of C_{1i}; E_i is the hypothesized level of beach erosion faced by individual i and $Width_j$ is the width of beach j in high tide to assess the severity of suggested erosion; A_i is a vector of beach activity groups (that in this study, 7 beach activity groups A=[A1, A2,…,A7]′ are identified); $\overline{C}_{2i}$ is the expected value of C_{2i}; ATT is the vector of impact attributes appearing in the conjoint question (visible structure, swim danger, wildlife impact, water quality, and sand quality); and δ_1, δ_2, η, μ, φ, κ, θ, ν, and ψ are parameters to be estimated.

The stated level of erosion (E) and the vector of impact attributes of an erosion control program (ATT) are the sole factors to induce the changes in trips in our conjoint questions. Consequently E is interacted with all explanatory variables in Equation (3) and ATT is interacted with all explanatory variables in Equation (4) except for the erosion severity variable E/Width. In the survey, respondents were told that the implementation of an erosion control program would prevent the occurrence of the stated erosion. However, the respondents could still be influenced by the stated severity of erosion even though it was eradicated by erosion control. For example, some survey respondents could be skeptical about the effectiveness of the proposed erosion control program if the stated severity of erosion was high. Because of the order of questions in the survey, the response to erosion control could also be influenced by the previous response to erosion. There might be other unobserved factors associated with the stated erosion level that affected the response to erosion control. Therefore, the erosion severity variable E/Width is included in Equation (4) as a testable hypothesis whether the trip change in response to erosion control is influenced by the hypothesized severity of erosion.

There is no intercept term in each of the trip change equations; this coupled with the addition of 1 on the left hand side of the equations to ensure that $\overline{C}_1$=0 when E=0 and $\overline{C}_2$=0 when ATT=0. Beach erosion and negative impacts of erosion control on the beach environment are in general perceived as "bad" in that the vast majority of beach goers responded by taking fewer trips. Less than one percent of the sample reported that they would increase their trips if erosion occurred. We deleted these observations from our sample.[7] The predicted trip changes (reductions) are computed from the estimation results of Equations (3) and (4) as $\hat{C}_{ji} = e^{\hat{\omega}_{ji}} - 1$, where j=1,2.

The expected quantity demanded for beach trips takes on a semi-log functional form (Equation (2)). As Hellerstein and Mendelsohn (1993) and Whitehead, et. al. (2000) show with this form of demand, the change in consumer surplus (ΔCS) due to a quality change is

$$\Delta CS = \frac{\hat{C}}{\hat{\beta}_p} \tag{5}$$

where $\hat{C}$ is the predicted change in the number of beach trips due to the introduction of the hypothetical erosion or erosion control scenario, estimated using Equations (3) and (4). $\hat{\beta}_p$ is the coefficient on travel cost and is estimated using equation (1). In the final step of our analysis, a variety of scenarios, varying degree of erosion and impact of erosion control will be considered

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[6] In Equation (4), the notations are used for easier comprehension. Algebraically the expressions (ATT_i*A_i), (ATT_i*W_i), and (ATT_i*X_i) should be written as (ATT_iA_i'), (ATT_iW_i'), and (ATT_iX_i'), respectively.

[7] It is debatable to exclude those who wanted to take more trips in response to the increased erosion in the analysis. In this paper, we exclude these observations to enable the use of the Poisson model to analyze the trip reductions due to erosion and erosion control.

for each of the eight studied beaches. Each scenario gives rise to a $\hat{C}$ and all use equation (5) to compute the welfare change.

4. Estimation Results

We estimate the demand for trips with corrections for on-site sampling bias and truncation using the Equations (1) and (2). For comparison, we also estimate the Poisson model without corrections for truncation and endogenous stratification. The results of both models, Model 1 without correction and Model 2 with correction, are reported in Table 4. In both models the coefficient of the travel cost variable is negative and significant as expected. Activity groups (A1 – A7) are included in the models. Each activity group is indicated by a keyword in Table 4, and the subsequent tables. The complete list of activities in each group is given in Table 2. All groups of beach activities significantly influence the demand for trips in different degrees. Ocean-front property owners and retirees take significantly more beach trips. Households with more adults or more children under an age of 13, take fewer beach trips. Sufficient bathhouse facilities (BathSuf) are important to trip decisions. The width of beach at high tide also matters. Beach goers tend to take fewer trips to those beaches with sand dunes and jetties, providing evidence that beach trip decisions are affected by the impacts of erosion control on the beach environment. Finally, the estimated coefficient of the travel cost variable is -0.013 in Model 1 and -0.014 in Model 2. The difference is small and marginally significant at the 0.1 level (Wald test statistic χ^2=2.87[1 d.f.]). We use the estimated coefficient of the cost variable from Model 2, the model corrected for on-site sampling bias, to perform the subsequent welfare analysis.

The trip change equation associated with erosion (Equation (3)) is estimated with two specifications. The explanatory variables in the *basic* model include only the proposed level of erosion and the relative size of erosion (as a proportion of the width of the beach at high tide). It describes the average impact of erosion on recreation for all beaches. The augmented *activity specific* model explores the differential effects of erosion on trip decisions according to individual specific beach uses by adding explanatory variables that interact erosion with groups of beach activities, as well as the interactions of erosion with location of the respondent's home and the presence of erosion control device. The estimation results are reported in Table 5. Note that the dependent variable indicates *fewer* trips taken as a result of beach erosion, so a positive coefficient on the erosion variable implies a reduction in beach trips when erosion occurs. As seen, erosion significantly reduces recreation trips. The relative size of erosion is not significant in the *basic* model but it becomes significant with twice as large magnitude in the *activity specific* model in which the heterogeneity of beaches is addressed. Most of the interaction terms are significant in the *activity specific* model, indicating that the magnitude of erosion impact on trip decisions depends on the individual beach activities and beach characteristics.

Based on the estimation results in Tables 4 and 5, and the summary of beach characteristics in Table 3, we compute the average changes in consumer surplus for two levels of beach erosion: one foot (slight) and ten feet (moderate) erosion, and report the estimates by beaches in Table 6.[8, 9] According to the *basic* model, the average change in consumer surplus per visitor per year is approximately $4 for one foot of erosion and $50 for ten feet of erosion. The welfare measures do not vary significantly across beaches since they are distinguished only by the relative size of erosion in the *basic* model. The *activity specific* model differentiates the beaches by the corresponding activities and characteristics. Based on the *activity specific* model,

[8] The general formula to compute the change in consumer surplus is: $(e^{\hat{\delta}_1 E+\hat{\delta}_2 E/Width+\hat{\eta}'E*A+\hat{\mu}'E*W+\hat{\varphi}E*X}-1)/\hat{\beta}_p$, where average values of the variables for each beach, as described in Table 3, are inserted in the formula.

the average changes in consumer surplus are quite different among the studied beaches. The benefits per visitor per year range from $1.7 (Hampton Main Beach) to $6.8 (Ferry Beach) for preventing one foot of erosion, and from $19.5 to $105.4 for preventing 10 feet of erosion. In general, the change in consumer surplus differs significantly across beaches. Every beach has its own characteristics and endowments, and attracts visitors to come for different activities. Taking into account the beach activities and characteristics helps discern the welfare effects of erosion on different beaches.

The regression analyses for trip reductions from the possible negative beach effects of erosion control (Equation (4)) are given in Table 7. The dependent variable indicates *fewer* trips taken due to the negative effects of erosion control so a positive coefficient estimate indicates a trip reduction. We first report a *basic* model that only includes the impact attributes (ATT1 – ATT5) of erosion control and the relative size of erosion as explanatory variables. In the *basic* model, all five impacts of erosion control significantly cause reduction of beach trips. The effect of erosion control on reduction of wildlife viewing has the largest impact on reducing beach trips. The variable of relative size of erosion is also significant, indicating that there are unobserved factors associated with the stated erosion to cause a significant reduction of future beach visits even when erosion control is in place to prevent the stated erosion. An augmented *activity specific* models interacting impact attributes with beach activities and characteristics is also reported.[10] The results show that if sand dunes are currently present, the trip reduction caused by visible structure due to erosion control is enhanced (positive coefficient on ATT1*SandDune). Conversely, beach visitors are less concerned about visible structure from

[9] In stead of welfare measures by beaches, we may compute changes in consumer surplus by activities. We report welfare measures by beaches to demonstrate the feasibility of using our models to derive welfare measures for any beach with a set of characteristics.

erosion control when a seawall is already present at the beach (negative coefficient on ATT1*SeaWall) possibly because visitors have grown accustomed to the visible seawall. The impact of erosion control attributes on trip changes depends on individual beach uses. For examples, those who come to beach to fish and camp are not adversely affected by visible erosion control devices (negative coefficient on ATT1*A4); those who come to enjoy the nature will take fewer trips if erosion control will result in a significantly less wildlife sighting (positive coefficient on ATT3*A1); those who engage in boating and kayaking will take fewer trips if water quality is affected by erosion control (positive coefficient on ATT4*A6). Similar to the *basic* model, the change in beach visits in response to erosion control is significantly affected by the stated relative size of erosion.

The changes in consumer surplus from the effects of erosion control by beaches based on the *basic* model are computed and reported in Table 8A. For comparison, we again compute welfare measures for two levels of stated erosion, one foot and ten feet. According to the *basic* model, given the stated erosion level to be one foot, on average the annual loss of consumer surplus per visitor from an erosion control program is approximately $15 if the program requires building a visible structure (ATT1), $19 if it results in a chance of minor injury to swimmers (ATT2), $23 if it reduces wildlife viewing (ATT3), $9 if deterioration of salt water quality results (ATT4), and $20 if sand quality is affected (ATT5). An erosion control device may have multiple impacts. For example, a jetty is visible and can affect water quality (ATT1 & ATT4) that on average the change in consumer surplus is about $25. If an erosion control device affects wildlife viewing and sand quality (ATT3 & ATT5) such as sand dunes, then the overall change in consumer surplus per visitor per year is approximately $49. Welfare effects for other

[10] In total, thirty-five attribute-activity interaction terms can be included in the estimation. We "trimmed" the specification by including the terms that are plausible and significant.

combinations of impact attributes can also be computed. Note that the change in consumer surplus of multiple impacts is not the sum of welfare changes from the individual impacts because of the nonlinearity in the Poisson model. Also, there is no significant difference of surplus changes across beaches for a hypothesized one-foot erosion. For a stated ten-foot erosion, on average the loss of consumer surplus for each of the erosion control impacts increases to about \$22, \$28, \$32, \$17, and \$30, respectively. The annual per-person loss in consumer surplus averages about \$35 if an erosion control program results in both visible structure and deteriorated water quality, and the average loss of per-person consumer surplus is close to \$61 if reduced wildlife viewing and lower sand quality result from the erosion control program. We also see differences in surplus changes across beaches. Under the hypothesized 10 feet of erosion, the negative effects of erosion control will result in the largest losses at Crescent Beach and smallest losses at Old Orchard Beach.

Comparing the changes in consumer surplus from erosion in Table 6 and from erosion control in Table 8A, it is clear that when the erosion is slight (e.g., 1 foot), erosion control is not beneficial since the losses of erosion do not outweigh the losses from the negative effects of erosion control. When erosion is moderate, erosion control can be beneficial. The shaded cells in Table 8A indicate the cases where losses of erosion are larger than the losses from the negative effects of erosion control. When erosion is 10 feet, any erosion control device that causes only one of the five negative effects generates an overall positive benefit at any of the beaches. However, erosion control programs that induce multiple negative effects are not necessarily desirable. For example, an erosion control program with a visible structure and reduced water quality is still beneficial at all eight beaches, while an erosion control program with reduced wildlife viewing and sand quality is not. The results show that certain negative impacts of erosion control are worse than the other. Reducing wildlife viewing is considered by beach visitors the most negative impact of erosion control. The findings suggest that certain erosion control devices are preferred by visitors for their less negative effects on beach environment.

Based on the *activity specific* model, the computed changes in consumer surplus associated with impact attributes of erosion control by beaches are reported in Table 8B. Among the five impact attributes, reduced wildlife viewing remains to be the most devastating impact of erosion control on recreation. The average annual per-person loss of reduced wildlife viewing due to erosion control is about $24 for a stated one-foot erosion and $31 for a ten-foot erosion.[11] Comparing across beaches, the recreation impact of the five effects of erosion control differs. For examples, adding a visible structure for erosion control causes the smallest loss in recreation value at Hampton Main Beach where seawall is already present and incurs the largest loss at the more natural Crescent Beach; deterioration of water quality results in more losses of recreation values at Wallis Sands and Ferry Beaches than at Old Orchards Beach; Ferry Beach incurs the largest loss of recreation value with a combination of visible structure and lower water quality from erosion control.

Comparing the welfare losses of erosion and losses from the negative effects of erosion control (the bottom half of Table 6 and Table 8B), the net welfare effect depends on the amount of erosion that is controlled. The net welfare effects of erosion control to prevent one foot of erosion will always be negative since the estimated losses of erosion control are larger than the losses of erosion. When erosion is 10 feet, the shaded cells in Table 8B indicate the cases where erosion control generates overall positive recreational benefits. For examples, an erosion control program with a visible device will have positive recreational benefits at most beaches except for

Hampton Beach State Park and Reid State Park; a program that reduces wildlife viewing will not be beneficial at five out of the eight beaches; all beaches will benefit from erosion control if the only negative effect is slight deterioration of water quality; half of the beaches will still have positive recreational benefits from erosion control when it results in visible structure and reduced water quality but only two beaches benefit from erosion control if it affects wildlife viewing and sand quality.[12] In sum, erosion control can be beneficial to prevent moderate to severe erosion that the welfare loss associated with the erosion is likely to exceed the loss due to erosion control disamenities. However, for small amounts of erosion, erosion control programs may bring on larger negative effects than the erosion itself.

5. Conclusion

We designed contingent behavior, in-person survey to value beach erosion control and employed a conjoint design in formulating the hypothetical erosion control to take into account the impacts of erosion control on the beach environment. The differential effects of erosion and erosion control on individual trip decisions due to varying trip activities and beach characteristics were demonstrated. We find that on average the loss of consumer surplus for a 10-foot erosion is approximately $50 per person, per year. However, this welfare loss is not completely recovered by erosion control due to potential negative effects of erosion control on the beach environment. The benefits of erosion control can be exaggerated if these negative erosion control effects are ignored. Further, the changes in consumer surplus due to erosion and erosion control vary with

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[11]As discussed previously, we find that relative size of erosion affects trip decisions even after the alleged erosion is to be prevented by erosion control. Consequently welfare measures associated with the negative effects of erosion control vary with the relative size of erosion.

[12] We also compute the changes in consumer surplus for a 25-foot (severe) erosion. As expected, erosion control generates overall positive recreational benefits at all beaches. We also examine the “critical size” of erosion at which a specific erosion control program becomes beneficial for each of the studied beaches. For example, for the erosion

individual beach activities and characteristics. Our findings reiterate the importance of distinguishing the purposes of recreational trips and incorporating beach characteristics in the welfare analysis of beach erosion control. The proposed survey questioning format and estimation strategies give rise to program and beach specific welfare measures that may be used by policy makers to design economically efficient erosion control programs at locations facing different beach uses.

In this paper, we study the impact of erosion control on the demand for day trips. It is expected that the effects of erosion on the demand for over-night trips will differ and will be studied in the future. Also, the focus of this study is the use value of beach erosion control. Huang and Poor (2005) find that beach preservation is valued by the general public for its contribution to property protection, protection of wildlife habitat, etc. The total benefits of beach erosion control must take into account both the use and non-use values, and further research to combine these values is warranted.

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control program that causes lower sand quality to be beneficial at Crescent Beach, the erosion has to be at least 6.5 feet. All these results are available upon request from authors.

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TABLE 1
Assigned Levels of Erosion and Erosion Control Effects in the Conjoint Design

Attributes of an Erosion Control Program (Variable Name)	**Levels**
Erosion	1, 4, 7, 10, 15, 25 (Feet/Year)
Visible structure on beach (**ATT1**)	Yes, No
1/1000 chance of minor injury to swimmers (**ATT2**)	Yes, No
Wildlife viewing reduced by 50% (**ATT3**)	Yes, No
Deterioration (10%) of salt water quality near beach (**ATT4**)	Yes, No
Sand quality: coarser sand with small rocks (**ATT5**)	Yes, No

TABLE 2
Variable Definition and Summary Statistics

Variable	Definition	N	Mean	Std Dev
DTripNY	Planned number of day trips in the following year	459	17.000	35.464
C_1	Decline in planned number of day trips due to erosion (22.2% of respondents reported nonzero decline)	459	1.362	5.200
C_2	Decline in planned number of day trips due to negative impacts of erosion control devices on beach environment (18.5% of respondents reported nonzero decline)	918	1.021	3.315
TtripTY	Total number of trips in the year of interview	459	17.431	33.460
TimeCost	Travel time cost ($) [=(income/2080)*hours*2]	459	14.428	16.345
TranCost	Out-of-pocket travel cost ($) [=$0.35*distance*2]	459	35.616	26.410
Cost	Total travel cost ($) [=TimeCost+TranCost]	459	50.044	38.427
SmlKids	Number of children under 13 of age in the household	459	0.625	0.955
Adults	Number of adults in the household	459	2.102	1.118
Income	Annual household income	459	59489	28088
NH	=1 if NH resident	459	27.7%	
ME	=1 if ME resident	459	39.7%	
Resident	=1 if resident of the state where the beach is located in	459	60.6%	
Distance	Travel distance (100 miles)	459	0.509	0.377
Ocean	=1 if own ocean front property	459	3.9%	
Retire	=1 if retired	459	10.0%	
A1	=1 if trip involved wildlife observation, photography, sightseeing, walking/jogging, bicycling, driving	459	61.9%	
A2	=1 if trip involved sports, concerts/plays, festivals, museums, hiking/trailing, horseback riding, back packing	459	19.2%	
A3	=1 if trip involved swimming, surfing, picnicking, family gathering, sunbathing, shell collecting	459	94.8%	
A4	=1 if trip involved camping, fishing	459	9.2%	
A5	=1 if trip involved pool swimming, golfing, tennis	459	8.9%	
A6	=1 if trip involved boating, canoeing, kayaking, sailing, water skiing	459	11.3%	
A7	=1 if trip involved theme parks, casinos	459	12.6%	
SandDune	=1 if sand dunes present at site	459	3 beaches	
Seawall	=1 if seawalls present at site	459	4 beaches	
Jetty	=1 if jetties present at site	459	2 beaches	
BathSuf	=1 if bath facilities sufficient according to beach manager	459	6 beaches	
Length	Length of beach (1000 ft)	459	5.101	5.104
WidthLT	Width of beach at low tide (100 ft)	459	2.858	1.356
WidthHT	Width of beach at high tide (100 ft)	459	0.761	0.356
SandQ	=1 if sand quality is good according to beach manager =0 if sand quality is ok or poor	459	86.5%	
Erosion	Proposed level of erosion [=1,4,7,10,15,25 ft]	459	10.211	7.646
EroRtLT	Ratio of proposed erosion to width of beach at low tide	459	0.051	0.060
EroRtHT	Ratio of proposed erosion to width of beach at high tide	459	0.179	0.189

TABLE 3
Summaries of Characteristics and Activities by Beaches

	Hampton Beach State Park	Hampton Main Beach	Wallis Sands	Long Sands	Ferry	Old Orchard	Crescent	Reid
WidthHT (width at high tide (ft))	82.5	82.5	100	35	50	150	30	115
Resident (% of visitors are residents)[a]	32.8%	13.0%	71.0%	7.6%	84.4%	33.7%	79.7%	96.7%
Distance (average travel distance, 100 miles)[a]	0.601	0.673	0.667	0.751	0.390	1.001	0.462	0.493
A1 (nature)[a]	62.6%	62.9%	34.5%	50.3%	73.1%	73.1%	52.9%	71.7%
A2 (sports)[a]	13.1%	38.4%	17.6%	8.1%	41.4%	21.2%	10.2%	20.5%
A3 (sunbath)[a]	95.8%	98.4%	97.1%	83.9%	100.0%	100.0%	96.7%	90.7%
A4 (fish)[a]	6.1%	2.2%	4.7%	3.8%	15.7%	17.1%	9.2%	13.1%
A5 (golf)[a]	6.5%	12.7%	2.8%	5.6%	10.2%	18.4%	6.5%	13.1%
A6 (boat)[a]	14.9%	6.0%	2.1%	1.4%	14.8%	7.8%	11.1%	15.3%
A7 (park)[a]	6.7%	38.3%	5.3%	7.4%	6.0%	12.6%	0.7%	12.2%
Sea Wall (=1 if seawalls present)	1	1	1	1	0	0	0	0
Sand Dune (=1 if sand dunes present)	1	0	0	0	0	0	1	1
Jetty (=1 if jetties present)	0	0	1	0	1	0	0	0

a The summary statistic is weighted by the visit frequency: $\sum_{i=1}^{n} \frac{x_i}{trip_i} \Big/ \sum_{i=1}^{n} \frac{1}{trip_i}$, where x_i is the characteristic or activity variable, and $trip_i$ is the total number of trips taken by individual i.

TABLE 4
Estimated Demand for Beach Trips

Dependent Variable: DTripNY		
	Model 1 (without correction)	Model 2 (with correction for truncation and on-site sampling bias)
Intercept	3.534*** (0.103)	3.534*** (0.107)
Cost	-0.013*** (0.0005)	-0.014*** (0.0005)
A1 (nature)	0.244*** (0.028)	0.261*** (0.029)
A2 (sports)	0.390*** (0.029)	0.416*** (0.030)
A3 (sunbath)	-0.546*** (0.043)	-0.582*** (0.044)
A4 (fish)	0.375*** (0.042)	0.403*** (0.043)
A5 (golf)	-0.335*** (0.047)	-0.356*** (0.049)
A6 (boat)	0.136*** (0.037)	0.136*** (0.038)
A7 (parks)	0.080** (0.039)	0.083** (0.040)
Ocean	1.186*** (0.033)	1.207*** (0.033)
SmlKids	-0.099*** (0.015)	-0.110*** (0.015)
Adults	-0.095*** (0.012)	-0.102*** (0.013)
Retire	0.262*** (0.031)	0.275*** (0.032)
Resident	0.451*** (0.035)	0.467*** (0.036)
SandDune	-1.253*** (0.071)	-1.352*** (0.074)
SeaWall	0.019 (0.045)	0.00042 (0.047)
Jetty	-0.716*** (0.068)	-0.771*** (0.071)
BathSuf	0.474*** (0.051)	0.515*** (0.053)

Length	-0.001 (0.005)	-0.003 (0.005)
WidthHT	0.096^{*} (0.052)	0.121^{**} (0.054)
LLF N	-5054.881 459	-5261.089 459

Note: Standard errors are in the parentheses. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

TABLE 5
Estimated Trip Changes When Erosion Occurs

Dependent Variable: $\log(C_1+1)$		
	Basic Model	***Activity Specific Model***
Erosion	0.050^{***} (0.004)	0.043^{**} (0.017)
Erosion/WidthHT	0.294 (0.204)	0.647^{**} (0.271)
Erosion*A1 (nature)		0.006 (0.005)
Erosion*A2 (sports)		0.001 (0.006)
Erosion*A3 (sunbath)		0.023^{*} (0.012)
Erosion*A4 (fish)		-0.016^{**} (0.008)
Erosion*A5 (golf)		-0.024^{***} (0.009)
Erosion*A6 (boat)		0.068^{***} (0.006)
Erosion*A7 (parks)		-0.027^{***} (0.009)
Erosion*Resident		-0.009 (0.006)
Erosion*Distance		-0.038^{***} (0.008)
Erosion*SeaWall		-0.016^{***} (0.005)
Erosion*SandDune		-0.014^{**} (0.007)
Erosion*Jetty		0.027^{***} (0.007)
LLF	-1452.370	-1355.272
N	459	459

Note: Standard errors are in the parentheses. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

TABLE 6
Annual Per-Person Losses from Beach Erosion ($)

	Hampton Beach State Park	Hampton Main Beach	Wallis Sands	Long Sands	Ferry	Old Orchard	Crescent	Reid
The Basic Model								
1 foot of Erosion	3.932 (0.236)	3.932 (0.236)	3.885 (0.251)	4.300 (0.270)	4.108 (0.218)	3.810 (0.281)	4.406 (0.320)	3.856 (0.262)
10 feet	50.565 (3.549)	50.565 (3.549)	49.803 (3.795)	56.638 (4.235)	53.437 (3.259)	48.615 (4.272)	58.452 (5.178)	49.337 (3.970)
The Activity Specific Model								
1 foot of Erosion	1.818 (0.410)	1.746 (0.390)	3.702 (0.405)	2.529 (0.470)	6.791 (0.468)	2.028 (0.596)	3.988 (0.365)	2.389 (0.435)
10 feet	20.392 (5.119)	19.498 (4.832)	46.897 (6.235)	29.693 (6.384)	105.445 (9.729)	23.059 (7.642)	51.479 (5.756)	27.805 (5.806)

Note: Standard errors are in the parentheses.

TABLE 7
Estimated Trip Changes in Response to Effects of Erosion Control on Beach Environment

Dependent Variable: $\log(C_2+1)$		
	Basic Model	***Activity Specific Model***
ATT1 (=1, visible structure)	0.179^{***} (0.045)	0.217^{**} (0.093)
ATT2 (=1, swim danger)	0.230^{***} (0.045)	0.260^{***} (0.046)
ATT3 (=1, wildlife viewing ↓)	0.268^{***} (0.045)	0.089 (0.069)
ATT4 (=1, water quality ↓)	0.115^{**} (0.045)	0.138^{*} (0.076)
ATT5 (=1, sand quality ↓)	0.245^{***} (0.047)	0.173^{***} (0.052)
ATT1*A4 (fish)		-0.357^{***} (0.136)
ATT1*SeaWall		-0.175^{**} (0.074)
ATT1*SandDune		0.167^{**} (0.085)
ATT1*Jetty		0.101 (0.106)
ATT2*A7 (parks)		-0.230^{**} (0.108)
ATT3*A1 (nature)		0.316^{***} (0.080)
ATT4*A1 (nature)		-0.147^{*} (0.082)
ATT4*A4 (fish)		-0.222 (0.137)
ATT4*A6 (boat)		0.354^{***} (0.101)
ATT4*Jetty		0.244^{***} (0.092)
ATT5*A2 (sports)		-0.382^{***} (0.089)
ATT5*A4 (fish)		0.968^{***} (0.131)
Erosion/WidthHT	0.617^{***} (0.105)	0.520^{***} (0.108)
LLF	-2138.326	-2072.547
N	918	918

Note: Standard errors are in the parentheses. The stars *, ** and *** indicate significance levels at 0.1, 0.05, and 0.01, respectively.

TABLE 8A
Annual Per-Person Losses due to Effects of Erosion Control on Beach Environment ($)
- The Basic Model

	Hampton Beach State Park	Hampton Main Beach	Wallis Sands	Long Sands	Ferry	Old Orchard	Crescent	Reid
Losses due to negative effect(s) of erosion control to prevent 1 foot of erosion								
ATT1 (=1, visible structure)	14.720 (3.950)	14.720 (3.950)	14.606 (3.947)	15.603 (3.981)	15.142 (3.964)	14.429 (3.941)	15.861 (3.991)	14.537 (3.945)
ATT2 (=1, swim danger)	19.207 (4.098)	19.207 (4.098)	19.088 (4.095)	20.136 (4.128)	19.651 (4.111)	18.901 (4.090)	20.407 (4.137)	19.015 (4.093)
ATT3 (=1, wildlife viewing ↓)	22.738 (4.293)	22.738 (4.293)	22.614 (4.289)	23.703 (4.324)	23.199 (4.307)	22.420 (4.284)	23.985 (4.335)	22.538 (4.287)
ATT4 (=1, water quality ↓)	9.354 (3.688)	9.354 (3.688)	9.248 (3.684)	10.182 (3.716)	9.750 (3.700)	9.081 (3.679)	10.424 (3.725)	9.182 (3.682)
ATT5 (=1, sand quality ↓)	20.647 (4.386)	20.647 (4.386)	20.526 (4.382)	21.591 (4.420)	21.098 (4.402)	20.336 (4.377)	21.866 (4.431)	20.452 (4.380)
ATT1=1 & ATT4=1	25.261 (5.805)	25.261 (5.805)	25.134 (5.801)	26.252 (5.841)	25.735 (5.822)	24.935 (5.795)	26.541 (5.852)	25.056 (5.799)
ATT3=1 & ATT5=1	49.014 (7.209)	49.014 (7.209)	48.856 (7.204)	50.248 (7.248)	49.604 (7.227)	48.608 (7.197)	50.607 (7.260)	48.759 (7.201)
Losses due to negative effect(s) of erosion control to prevent 10 feet of erosion								
ATT1 (=1, visible structure)	20.749 (4.275)	20.749 (4.275)	19.545 (4.189)	30.645 (5.336)	25.363 (4.696)	17.684 (4.077)	33.702 (5.773)	18.812 (4.142)
ATT2 (=1, swim danger)	25.549 (4.420)	25.549 (4.420)	24.282 (4.333)	35.958 (5.511)	30.402 (4.849)	22.325 (4.221)	39.173 (5.964)	23.511 (4.286)
ATT3 (=1, wildlife viewing ↓)	29.326 (4.632)	29.326 (4.632)	28.010 (4.541)	40.138 (5.767)	34.368 (5.080)	25.977 (4.423)	43.479 (6.238)	27.209 (4.491)
ATT4 (=1, water quality ↓)	15.009 (3.988)	15.009 (3.988)	13.880 (3.908)	24.291 (4.983)	19.337 (4.382)	12.134 (3.804)	27.159 (5.393)	13.192 (3.864)
ATT5 (=1, sand quality ↓)	27.089 (4.731)	27.089 (4.731)	25.803 (4.641)	37.663 (5.843)	32.020 (5.172)	23.814 (4.522)	40.929 (6.301)	25.020 (4.591)
ATT1=1 & ATT4=1	32.025 (6.141)	32.025 (6.141)	30.674 (6.056)	43.126 (7.159)	37.201 (6.545)	28.586 (5.943)	46.556 (7.581)	29.852 (6.009)
ATT3=1 & ATT5=1	57.433 (7.589)	57.433 (7.589)	55.751 (7.491)	71.250 (8.792)	63.876 (8.063)	53.153 (7.362)	75.519 (9.299)	54.728 (7.437)

Note: Standard errors are in the parentheses. By comparing the benefits and losses in Tables 6 and 8A, the shaded cells indicate the cases where recreation losses of erosion outweigh the losses from the negative effects of erosion control that preventing erosion generates overall positive recreational benefits.

TABLE 8B
Annual Per-Person Losses due to Effects of Erosion Control on Beach Environment ($)
- The Activity Specific Model

	Hampton Beach State Park	Hampton Main Beach	Wallis Sands	Long Sands	Ferry	Old Orchard	Crescent	Reid
Losses due to negative effect(s) of erosion control to prevent 1 foot of erosion								
ATT1 (=1, visible structure)	15.363 (6.780)	2.997 (5.387)	10.073 (7.299)	3.211 (5.379)	22.444 (9.082)	12.421 (7.699)	31.996 (6.497)	29.252 (6.325)
ATT2 (=1, swim danger)	20.472 (4.237)	14.008 (4.736)	20.648 (4.259)	21.100 (4.245)	20.996 (4.258)	18.965 (4.172)	22.791 (4.410)	19.150 (4.176)
ATT3 (=1, wildlife viewing ↓)	24.473 (4.450)	24.544 (4.453)	16.184 (4.576)	21.601 (4.425)	28.118 (4.666)	27.426 (4.647)	22.585 (4.428)	27.104 (4.615)
ATT4 (=1, water quality ↓)	6.896 (4.049)	5.092 (4.059)	28.414 (8.351)	5.644 (4.206)	25.359 (8.276)	1.734 (3.835)	7.285 (4.106)	4.604 (3.883)
ATT5 (=1, sand quality ↓)	14.849 (4.232)	3.921 (4.153)	12.152 (4.139)	15.288 (4.324)	13.881 (4.508)	21.358 (4.514)	19.487 (4.413)	18.199 (4.334)
ATT1=1 & ATT4=1	23.133 (8.064)	7.797 (6.390)	41.880 (10.828)	7.913 (6.394)	54.407 (13.201)	14.156 (8.752)	40.560 (8.451)	35.245 (8.100)
ATT3=1 & ATT5=1	43.651 (7.026)	29.166 (6.579)	30.540 (6.749)	39.815 (6.950)	46.198 (7.603)	56.493 (7.910)	46.135 (7.223)	51.612 (7.528)
Losses due to negative effect(s) of erosion control to prevent 10 feet of erosion								
ATT1 (=1, visible structure)	20.457 (7.240)	7.368 (5.759)	14.001 (7.713)	13.956 (6.616)	31.702 (10.100)	15.093 (7.912)	49.540 (8.192)	33.454 (6.523)
ATT2 (=1, swim danger)	25.864 (4.499)	19.023 (5.058)	25.083 (4.448)	34.407 (5.490)	30.112 (4.899)	21.844 (4.273)	38.780 (6.071)	22.932 (4.329)
ATT3 (=1, wildlife viewing ↓)	30.098 (4.743)	30.174 (4.746)	20.405 (4.793)	34.980 (5.711)	37.934 (5.393)	30.574 (4.767)	38.539 (6.148)	31.217 (4.793)
ATT4 (=1, water quality ↓)	11.494 (4.298)	9.585 (4.301)	33.221 (8.799)	16.738 (5.240)	34.903 (9.357)	4.067 (3.933)	20.654 (5.516)	7.782 (4.030)
ATT5 (=1, sand quality ↓)	19.913 (4.528)	8.346 (4.425)	16.179 (4.353)	27.763 (5.593)	22.298 (5.135)	24.314 (4.629)	34.917 (6.125)	21.941 (4.503)
ATT1=1 & ATT4=1	28.680 (8.503)	12.449 (6.730)	47.332 (11.398)	19.332 (7.530)	66.804 (14.610)	16.883 (8.963)	59.552 (10.026)	39.697 (8.295)
ATT3=1 & ATT5=1	50.397 (7.330)	35.066 (6.874)	35.449 (6.982)	55.802 (8.261)	57.789 (8.300)	60.564 (8.034)	66.069 (9.000)	56.743 (7.708)

Note: Standard errors are in the parentheses. By comparing the benefits and losses in Tables 6 and 8B, the shaded cells indicate the cases where recreation losses of erosion outweigh the losses from the negative effects of erosion control that preventing erosion generates overall positive recreational benefits.

Appendix A. Sample Conjoint-Contingent Behavior Questions in the Survey

Suppose that this beach were to erode by 1 foot next year if no erosion controls were undertaken. Would this affect the number of trips you take to this beach next year?

1. YES   2. NO

How would this affect the number of trips you take to this beach next year?

1. Take fewer trips ⇒ How many fewer? ________ FEWER TRIPS
2. Take more trips ⇒ How many more? ________ MORE TRIPS

As you have seen in the booklet and the impact information sheet, erosion control programs can help prevent erosion but at the same time they can also result in other impacts on the beach environment.

Suppose by the end of this year an erosion control program (Program A) were implemented at this beach to prevent the 1 foot of erosion from occurring. However, this erosion control program would also result in the following impacts on the beach environment at this beach.

Program A	
Impact:	
1. Beach aesthetics:	Visible structure/device installed
2. Swimmer impact:	No danger to swimmers
3. Wildlife viewing:	50% less
4. Salt water quality:	No change
5. Sand quality:	Coarser sand with small rocks

Given the implementation of this erosion control program and its impacts, would it affect your trip decision(s) to this beach next year?

1. YES   2. NO→ (**Skip to B_9**)

How would the implementation of this erosion control program affect the number of trips you take to this beach next year?

1. Take fewer trips ⇒ How many fewer? ________ FEWER TRIPS
2. Take more trips ⇒ How many more? ________ MORE TRIPS

Effects of Wetland Proximity and Type on Market Prices and Individual Choices of Residential Housing

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Abstract

Wetland ecosystems have long been recognized as serving important biological and economic functions. This study investigates specific economic effects of wetlands, namely the role that proximity to wetlands plays in residential housing markets. Using hedonic property price and discrete housing choice analyses, we find that proximity to wetlands in three counties in central Florida can either positively or negatively impact the prices of surrounding residential properties and the probability of choosing properties to purchase. Whether proximity has positive or negative amenity effects on market prices and individual choices is shown to be dependent upon the definition of a wetland and whether or not the wetland is protected from future development.

**Effects of Wetland Proximity and Type on
Market Prices and Individual Choices of Residential Housing**

I. Introduction

The overall goal of the project "A Consistent Framework for Valuation of Wetland Ecosystem Services Using Discrete Choice Methods" (EPA STAR Grant RD-83159801-0) is to develop and test a consistent framework to estimate the value of wetland services given that the diverse nature of wetland services undermines their complete valuation through a single method or data source. Our approach employs a joint modeling strategy to integrate revealed preferences (RP) from a discrete choice model of a housing market and stated preferences (SP) from a pairwise choice survey based upon public land acquisition. There are four interrelated objectives to the project: 1) To estimate the demand for proximity to wetlands and other water resources using discrete choice and hedonic property price models; 2) to estimate the demand for ecosystem services from different types of wetlands using a stated choice survey; 3) to develop and test a combined discrete choice model from the RP and SP data to produce a general valuation function for wetland ecosystem services; and 4) to estimate the implicit prices of wetland services in wetland mitigation banking markets.

This paper documents the data collection and construction aspect and reports estimation results specific to objective 1 of the project. Of interest is the effect of proximity to wetlands on the market prices and individual choices of residential housing. We investigate these effects across Orange, Volusia, and Polk counties in central Florida. In addition to the cross-county comparisons, we examine the sensitivity of the models to alternative definitions of wetlands. Specifically, wetlands are defined at various levels of aggregation, ranging from simply the nearest wetland to specific types of forested and non-forested wetlands. As central Florida wetlands also vary legally in terms of their ownership and potential to be converted into developed lands in the future, we also investigate the effects of their 'protection' status. The findings indicate significant amenity and disamenity effects of proximity to wetlands within each county and between counties and that the sign, magnitudes, and significance of the effects are sensitive to how wetland proximity is defined.

II. Background

A key aspect of both the revealed preference analysis reported in this paper and the stated preference land acquisition survey currently in the field is the use of GIS to identify, classify, and measure the composition of wetlands and alternative land uses within the landscape. For the revealed preference analysis, this information is integrated with property sales data obtained from the county tax appraisers. This section of the paper documents the approach and assumptions used for the construction of the spatial landscape variables and present summary statistics on the integrated datasets across the three county study region.

To begin, digital land cover/use maps were acquired from the two regional water management districts with jurisdiction in the respective counties (St. John's River Water Management District (SJRWMD) for Orange and Volusia counties; Southwest Florida Water Management District (SFWMD) for Polk county). These maps include data based on medium and low altitude flight imagery collected in 2000 and 2003 at scales of 1:24,000 and 1:6,000 resulting in an image resolution of 1 meter. The data were analyzed and interpreted into cover and land use types by the water management districts based on the Florida Land Use and Cover

Classification System (FLUCCS). The FLUCCS classifies hundreds of land types and includes more than 25 types of wetlands. These data are more accurate than the National Wetland Inventory produced by the U.S. Fish and Wildlife Service because the water management districts use the most recent flight imagery and the images are interpreted by local specialists.

The composition of the landscape in the three counties was aggregated into 6 mutually exclusive categories. These include: (1) residential land; (2) commercial and industrial land (including transportation, and utilities); (3) agriculture and rangeland (cropland, pasture, groves, dry prairie, brush land, and barren land); (4) upland forests (coniferous and hardwood); (5) water (lakes, rivers, and reservoirs); and (6) freshwater wetlands.

The portion defined as wetlands was divided into four mutually exclusive categories based on the dominant type of vegetation within the wetlands. These include: (1) wetland hardwood forests (loblolly bay, tupelo, and bottomland hardwoods); (2) coniferous forests (cypress, pond pine, and cabbage palm); (3) freshwater marshes (sawgrass, cattail, and other aquatic vegetation); and (4) wet prairies (emergent and sparse vegetation). The first two categories are distinguished by tree cover and crown closure whereas the latter categories are open habitats with short or no vegetation. These categories are consistent with prior hedonic pricing analyses of wetland values.

The composition of the landscape comprising the study area is summarized in Table 1. The data reveal sizable differences in the composition of the landscape within a given county and across the three counties. However, in each county about fifteen percent of the landscape is comprised of wetlands (17.9% in Orange county; 16.7% in Volusia county; 13.9% in Polk county). Considering the wetland categories, Orange and Volusia counties have comparable percentages of coverage in all cases, though Volusia county has about 30,000 more wetland acres than Orange county. For these counties, wetland hardwood forests and wetland coniferous forests are the dominant wetland types, comprising more than 70% of the total acreage defined as wetlands. Similar to Orange and Volusia counties, more than 70% of the total wetland acreage in Polk county is attributed to wetland hardwood forests and coniferous forests, with about 50% of the total acreage defined as wetland coniferous forest.

The property sales data used in the hedonic price and discrete housing choice analyses spans the three county study area over the period January 2000-December 2004. The data were obtained from the county tax appraisers, and all unqualified sales and other sales that did not appear to be arm's-length transactions were discarded in constructing the datasets. In addition to identifying the sales prices of single-family residential properties, dates of sale, and geographic locations, the data contains a variety of physical property attributes commonly included in property value analyses. For this study, a set of property attributes that were common and directly comparable between the counties are included in the datasets. These include the number of bedrooms and bathrooms; the square footage of the structure under central air/heating, the square footage of the land (or parcel); the age of the home; and the presence of a pool.

For generation of the spatial/environmental variables to include in the hedonic and discrete choice models, the property sales data were overlaid with GIS land use maps and maps identifying a variety of natural and human-made spatial attributes. Using mapping tools in ArcInfo 9.0, single family residential property sales were geo-located. The Euclidean distances between the centroid of each parcel and the edge of each of the nearest of the four types of wetlands and to other natural amenities (e.g., lakes and upland forests) were measured. In addition, the sizes of these nearest natural amenities were also measured.

The econometric analysis focused initially upon the hedonic property price model. Preliminary estimates of alternative specifications of the hedonic models revealed some counter-intuitive results, which lead to concern about possible mis-measurement of the distance and size (area) variables. To investigate, we selected a sample of properties to test for consistency in the distance calculations and identification of the correct land use. It was discovered that several factors could be attributed to potential mis-measurement of the variables. These included the temporal lags between the land use maps and the date property sales, the measurement of the centroids of the parcels, and inconsistencies between the GIS land use maps obtained from the water management districts and the county property appraiser tax rolls. The lags between the creation of the land use maps by the state water management districts relative to the continuous urban and rural developments in the three counties were believed in some cases to result in the identification of upland forests and wetlands within the landscape that no longer existed due to residential and commercial development.

Other measurement concerns arose because the county property appraisers and the water management districts categorize land uses differently, and the land use maps differed with respect to their distinctions between developed and undeveloped lands. This is noteworthy because identifying the location of the centroid of residential parcels is a necessary first step for calculating the distances between the parcels and the desired environmental attributes. As an example, it was found that in many cases the legal boundaries of lakefront parcels extended into their associated lakes, in which case the measured centroid of the parcels could be within the lakes. When the distances to the nearest lakes were measured for these parcels, rather than identifying the properties as being adjacent to lakes (i.e., lakefront), the GIS software would measure the distance to the next nearest lake. This was especially problematic with large lakes due both to the large number of parcels that surrounded such lakes and because the nearest of the other environmental amenities could be mis-identified, in which case the distances to these amenities was necessarily mis-measured.

To correct for this issue, the initial land-use maps were reconstructed. To begin, portions of Orange county were updated with land-use maps that were not available when the datasets were initially constructed. Next, all parcels that the assessor's office had identified as being residential, commercial, or industrial property were dissolved into a single land mass that was then removed from the land-use maps that identified upland forests and wetland areas. As a result, the total area identified as being forest or wetlands was reduced. Lastly, the boundaries of those lakefront properties that were identified as extending into the water were redefined by excluding the submerged portions of the parcels, and the centroids of the parcels were then redefined for the distance calculations.

An issue that arose in the process of reconstructing the land-use maps concerned the fragmentation of the undeveloped segments of the landscape. After dissolving and removing the residential, commercial, industrial land uses as discussed above, it was found that in many cases there were small portions of wetlands that were contained in the remaining area. These slivers were sufficiently small so as not to be identifiable with the naked eye in the aerial photos and were identified as being associated with both residential and commercial property development (i.e., small pieces of wetlands were contained between two or more developed parcels).

In developing a criterion to apply on a county-wide scale to distinguish these areas from other undeveloped areas, we found that the borders of the slivers were consistently defined by straight lines, whereas the borders of natural areas (wetlands and upland forests) tended to be curvilinear. Consequently, the ratio of edge length to interior area was considerably larger for the non-natural patches than for natural patches. GIS reference books document similar metrics that have been constructed for measuring habitat fragmentation and other ecological indicators.[1] One fragmentation index is the ratio of the patch perimeter to the patch area, which reflects the extent to which human dominated, regular shapes "fracture" otherwise continuous land cover areas.

Comparing the perimeter-to-area ratios between developed and natural environments revealed that patches of upland forests in Orange county that had ratios exceeding 0.04 were typically developed, while large and intact undeveloped patches consistently had ratios as small as 0.0015. By comparison, subdivisions and developed patches tended to have much larger ratios. Further, the perimeter-to-area ratios were found to vary between upland forests and the four wetland categories. Patches of upland forest tended to have very small ratios, (less than 0.04), whereas wetland prairies tended to have more 'feathery' shapes–with long perimeters and narrow interiors–resulting in perimeter-to-area ratios approaching 0.15. These differences were also true between counties. In Volusia county, which has many coastal areas and more topographical variation than Orange and Polk counties, the perimeter-to-area ratios tended to be greater than those ratios calculated in Orange and Polk counties.

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[1] See, for example, Stan Morain (Ed.). *GIS Solutions in Natural Resources Management*. Santa Fe: OnWord Press, 1998.

After completing this step of reconstructing the land-use maps, the upland forest and wetland areas were redrawn as new shapes in GIS and then cast into a new land use aggregation map. The areas and perimeters of the patches were then re-measured and the distances between the various land types and the residential parcels were re-calculated for inclusion in the hedonic price and discrete housing choice analyses.

In addition to the distance and area calculations, the composition of the land surrounding the residential parcels was measured from the revised land-use maps. This process entailed aggregating the land-types within the landscape into residential lands, commercial/industrial lands, agricultural lands, and undeveloped lands and waters. The size of the surrounding 'buffer' areas is defined as one square mile. To create the land-use buffers, we first attempted to create parcel-specific buffers (i.e., a buffer around each individual parcel) and then overlay the land-use maps so as to identify the composition of land-uses within each buffer. Despite the available computer power, this process proved to be computationally burdensome, given that the three-county datasets contain approximately 120,000 residential properties.

A second approach that was investigated entailed aggregated the landscape into two land-types: developed and undeveloped lands; however, the computational process remained problematic. The final approach that was investigated, and that which was adopted in this study, employed CADD (drafting) software to partition the counties into grids spanning one square-mile square. ArcGIS was then used to aggregate the landscape into four land-uses: residential lands, commercial/industrial lands, agricultural lands, and undeveloped lands and water. The percentage of each land-type contained in the square-mile grids were then calculated. The residential parcel map was then overlaid with the land-use grid so as to link the land-uses within the grids to the individual parcels. With this step, the final residential property datasets were complete, and estimation of the hedonic price and discrete housing choice models could proceed.

Table 2 reports summary statistics for the variables included in the revealed preference hedonic and discrete choice analyses. The data indicate that the average sales price (expressed in 2000 dollars) in Orange county is about $40,000 greater than in Volusia county, and about $60,000 greater than Polk county. The average heated area of the home is comparable between the counties; however, the average parcel area is notably smaller in Orange county relative to Volusia and Polk counties.

Considering the wetland characteristics, the distance to the nearest of each of the four wetlands categories exceeds 1000 meters on average. In all cases the average size of the nearest wetland hardwood forest and wetland coniferous forest exceeds 100,000 square meters. However, there is considerable variation in the sizes of the individual wetland parcels as indicated by the relative size of the respective standard deviations. In contrast, the average sizes of the nearest wetland marsh and wetland prairies are relative small, though considerable variation in the sizes of the parcels is again indicated by the respective standard deviations.

Table also reports the portions of wetlands that are designated as being protected from development. Protected wetlands in central Florida appear in two forms. First, wetlands contained in the Florida Natural Areas Inventory (FNAI) are designated as being regionally significant, are publicly owned, and are not subject to development in the future. In addition, other protected wetland areas were identified within the counties by land use codes that were designated as being set aside by developers and owned by neighborhood homeowner associations; these include conservation easements, undeveloped lands, and open spaces not available for future development. The portion of the number of protected wetlands varies within the counties by wetland type and across the counties for each wetland type. The values range from a minimum of 2.2 percent of wetland coniferous forest in Orange county to a maximum of 32.5 percent of wetland prairie in Volusia county.

Lastly, table 2 reports on the average composition of the land surrounding the residential properties that sold over the period. In all cases, the majority of the land contained in the square mile grid placed around the properties is developed and in residential use. About 20% of the surrounding land in all cases is defined as recreational, and the remainder is agricultural use.

III. Hedonic Property Price and Residential Housing Choice Analyses

The property sales data integrated with the land composition data is used to measure the amenity effects of proximity to wetlands. First, the effect of wetland proximity is investigated with respect to the sales prices of residential properties using hedonic price analysis. This approach defines a property as a bundle of physical characteristics located within a landscape, and which can be purchased in a competitive market, and then models the variation in property prices as a function of these physical and spatial attributes. Second, we estimate random utility models of individual housing choice in order to isolate the effect of wetland proximity on individual preferences (i.e., the parameters of an individual's indirect utility function). This approach has a long-standing history in modeling location choice and destination choice and is applied here to housing choice as a function of property attributes and spatially variant socioeconomic and environmental attributes. In both cases, the independent variables include those reported in table 2. For brevity, we do not detail here the technical aspects of the hedonic and discrete choice models; interested readers are referred to Haab and McConnell (2002) for technical details.[2]

In the proceeding analyses, the effects of proximity to wetlands is estimated for unprotected wetlands and the two categories of protected wetlands discussed above. To test for interactive effects of proximity to a given type of wetland (e.g., wetland hardwood forests), the respective distance variable is interacted with (i.e., multiplied by) the area of the wetland and with dummy variables identifying whether the respective wetland is a publicly protected wetland (FNAI Protected) or is informally protected through, for example, an easement or collective ownership by a neighborhood organization (Other Protected).

In addition, we examine the effect of wetland proximity under three definitions of a nearest wetlands; these differ in terms of their level of aggregation. The first wetland variable definition, referenced in the tables below by Nearest Wetland, includes that wetland which is nearest to a property, with no distinction made to its type (e.g., wetland coniferous forests vs. wetland marshes or prairies). The second wetland definition distinguishes between forested and non-forested wetlands and is referenced below by Nearest Forested Wetland and Nearest Non-forested Wetland. Thus, with this definition, there are two wetland distance variables, two wetland area variables, and four protection status dummy variables. The third wetland definition disaggregates the forested and non-forested wetlands into, respectively, wetland hardwood and wetland coniferous forests and wetland freshwater marshes and wetland prairies. These are

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[2] Timothy C. Haab and Kenneth E. McConnell, *Valuing Environmental and Natural Resources*. Cheltenham, UK: Edward Elgar Publishing Limited, 2002.

referenced below by their respective names (e.g., Nearest Wetland Prairie). Thus, there are four wetland distance variables, four area variables, and eight protection status dummy variables.

Hedonic Property Price Analysis

To proceed with the hedonic property price analysis an assumption must be made about the econometric specification of the hedonic price equation. To accommodate possible non-linearities between property prices and the continuous independent variables (e.g., the square footage of the home and its distance to a wetland), we use the commonly employed double-log specification, whereby the dependent and continuous independent variables are converted to natural logarithms.

Table 3 presents the estimation results specific to the wetland distance variables (the full set of estimation results is available in an appendix). For the specification that includes only the nearest wetland (Model 1) the results suggest that across all three counties the distance to wetlands is positively related to property prices on average as gauged by the positive and statistically significant coefficients on the bulk of the variables. Furthermore, the positive and significant coefficients on the protection status interactions indicate even larger positive effects on the mean property price as distance increases. One should be cautious, however, in considering the results with this specification of the model. Specifically, the results from model 2 reveal the aggregation problems embedded in model 1. For example, in Orange county the results from this second specification suggest that property prices increase on average as the distance to the nearest forested wetland decreases but that the mean price decreases in the case of non-forested wetlands. In contrast, the results for Volusia and Polk counties suggest that residential property prices tend to increase on average as distance increases for both forested and non-forested wetlands as gauged by the large number of positive and significant coefficients.

Aggregation effects also appear to be present in model 2 as indicated by the estimation results from model 3, which identifies the specific types of forested and non-forested wetlands. Similar to model 2, mean property prices are found to be negatively related to the distance to the nearest forested wetlands and positively related to the distance to non-forested wetlands. However, as the magnitudes of the coefficients differ by wetland type, the effects of wetland proximity on property prices are unique to each wetland type. Note, however, that although the estimation results differ between the three model specifications, the overall fit of the models is largely unaffected by the choice of wetland variables as gauged by the invariance of the adjusted R^2 statistics.

The primary interest in table 3 regards the signs, magnitudes, and significance of the coefficients. In addition, the estimation results may be used to calculate the implicit prices of distance (i.e., the marginal effects of distance) across the different types of wetlands and protection status categories within each county. These are reported in Table 4. As the distance variables are measured in meters, the implicit prices are interpreted as the change in the mean property price for a one meter change in distance to the nearest wetland of a given type. A negative sign indicates that distance is an amenity, with the property price increasing on average as the distance to the wetland decreases, and a positive sign indicates that distance is a disamenity. The results for the Nearest Wetland (model 1) specification indicate that wetland proximity is a disamenity in all three counties regardless of the protection status. Furthermore, the disamenity effect is larger for protected wetlands than unprotected wetlands.

However, similar to the results in Table 3, the aggregation effects resulting under the Nearest Wetland specification is revealed by the partially disaggregated (model 2) and fully disaggregated (model 3) specifications. For example, in Orange county the results for model 2 indicate that proximity to forested wetlands is an amenity, while non-forested wetlands have a disamenity effect on the mean property price. Relative to unprotected forested wetlands, the amenity effect is larger for FNAI-Protected wetlands and smaller for Other-Protected wetlands. Alternatively, relative to unprotected non-forested wetlands, the disamenity effect does not differ with FNAI-Protected wetlands but is significantly larger with other-protected wetlands. The amenity effect is differentiated between the specific types of forested and nonforested wetlands in model 3. In Orange county, proximity to wetland hardwood and wetland coniferous forests has small amenity effects, while proximity to non-forested wetlands has relatively large disamenity effects, most notably with freshwater wetland marshes. In contrast to Orange county, the only amenity effect that is identified in Volusia county is associated with wetland hardwood forests, while proximity to wetlands in Polk county is found to be a disamenity for all wetland definitions and categories of protection status.

Having examined the effects of wetland proximity on the market prices of residential properties, we turn next to the analysis of individual property choice. Here, we control for property prices and isolate the effect of proximity to the various categories of wetlands on housing choice. Assuming home buyers are utility maximizers, the property choice analysis may be used to measure individual preferences (i.e., marginal utilities) for proximity to the various categories of wetlands.

Discrete Housing Choice Analysis

To proceed with the random utility analysis of individual housing choice, two fundamental assumptions must be made. The first regards the specific form of discrete choice model to estimate. For this analysis, the conditional logit model is employed. The second necessary assumption regards the definition of the choice set (i.e., the set of alternative properties) from which an individual selects a property to purchase. In some applications (for example, survey based recreational site choice analysis), the researcher has individual-specific information that can aid in specifying choice sets.

However, with property choice analyses, and as recognized by others, very limited individual information is typically available; the present application is no exception. As such, we use the random draws approach to choice set generation, whereby an individual's choice set is defined by the chosen property and a set of alternative properties that is randomly drawn from all properties purchased within a temporal window around the sale date of the chosen property, similar to Banzaf and Smith (2007).[3] We define this window as the three-month period around the sale date (for example, if the property was purchased in April, the three-month period includes March, April, and May). For each home buyer we randomly draw 249 properties from all properties sold within this period; thus, each choice set is unique and contains 250 properties.

The sample of individuals used in the analysis is defined as those homeowners identified in the tax appraiser data as receiving a 'homestead exemption' on their property taxes. In Florida the exemption is assigned to a property if it is owned by a Florida resident who uses the property

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[3] H. Spencer Banzaf and V. Kerry Smith (2007), "Meta Analysis in Model Implementation: Choice Sets and the Valuation of Air Quality Improvements," forthcoming in *Journal of Applied Econometrics*.

as their primary residence. By defining the sample of home buyers in this way, we exclude nonresidents and individuals, partnerships, and corporations that purchase properties solely for investment purposes, and whose preferences may differ from those whose properties serve as their primary residence. This definition of the sample is also consistent with that employed in the stated preference wetland valuation survey referenced in the introduction (see objective 2).

Table 5 reports the conditional logit estimation results by county for the three specifications of the wetland variables (the full set of estimation results is available in an appendix upon request). In each case, the coefficient estimates on the distance and distance interaction variables, their standard errors, and significance levels are reported. In addtion, and similar to using the estimated hedonic models to calculate the implicit price of distance to a wetland, the estimated discrete choice models may be used to calculate the marginal utility of distance to gauge whether wetland proximity has amenity or disamenity effects on individual utility. For each of the three specifications of the model, Table 6 reports these estimated marginal utilities and their significance as gauged from the significance of the individual parameter estimates.

Considering the results reported in Table 5 and Table 6, the Nearest Wetland specification (model 1) indicates no significant difference between the effect of distance to unprotected and FNAI Protected wetlands in Orange county, and that the effect of distance appears solely through the area interaction variable. Further proximity to wetlands designated as Other Protected has amenity effects that differ significantly from those of the other two protection status categories. The results in Volusia county indicate significant amenity effects of distance to unprotected and Other Protected wetlands and significant disamenity effects with FNAI Protected wetlands, while distance has no significant effect in any case in Polk County. However, as with the hedonic price analysis, the aggregation effects of the Nearest Wetland specification are revealed by model 2 and model 3. Across all three counties proximity to forested wetlands has significant amenity effects for unprotected wetlands and for Other Protected wetlands in Orange county, while proximity to FNAI Protected wetlands has significant disamenity effects in Orange and Volusia counties. For non-forested wetlands in Volusia county there is no significant amenity effect for proximity to unprotected wetlands, but as with forested wetlands, proximity to FNAI Protected wetlands has significant disamenity effects. The results for forested wetlands in Polk county indicate amenity effects that do not differ significantly between protection status categories. Alternatively, the results from non-forested wetlands indicate disamenity effects that do not differ significantly by protection status.

Looking next at the wetlands within the forested and non-forested categories (model 3), the results indicate significant amenity effects for unprotected and Other Protected wetland hardwood forests and unprotected wetland coniferous forests, while proximity to FNAI Protected wetlands has disamenity effects for both types of forested wetlands in Orange county. In Volusia county, the only significant result is an amenity effect for wetland hardwood forests designated as Other Protected. And in Polk county the results indicate large and significant amenity effects for all protection status categories of wetland hardwood forests and significant disamenity effects of proximity to wetland coniferous forests in all cases.

Lastly, considering the specific types of non-forested wetlands, proximity to unprotected wetland marshes has large and significant disamenity effects in Orange county and significant amenity effects in Volusia and Polk counties. Again, amenity effects are associated with the Other Protected designation in the case of freshwater marsh in Orange county and disamenity effects in Volusia county. And proximity to unprotected wetland prairies has significant amenity effects in Orange and Polk counties, while the signs of the significant protection status interactions indicate both amenity and disamenity effects across the counties.

To summarize, the findings indicate significant amenity and disamenity effects of proximity to wetlands within each county and between counties. However, the sign, magnitudes, and significance of the effects are sensitive to how wetland proximity is defined.

IV. Conclusions

Wetland ecosystems have long been recognized as serving important biological and economic functions. This study investigated specific economic effects of wetlands, namely the role that proximity to wetlands plays in residential housing markets. Using hedonic property price analysis, we found that proximity to central Florida wetlands can either positively or negatively impact the prices of surrounding residential properties. Whether proximity has positive or negative amenity effects on property prices was shown to be dependent upon the definition of a wetland and whether or not the wetland was protected from future development. Similar conclusions about the amenity effects of proximity to wetlands were drawn from the random utility model of individual housing choice controlling for property prices.

A natural extension of the present study is to use the estimated hedonic and discrete choice models to measure the nonmarket values attached to wetlands in the study area. In the context of the property price analysis, and given that the housing markets are arguably unique to each of the three counties, the second stage of the hedonic model could be estimated in order to obtain the demand equation relating property prices to distance and estimate the consumer surplus associated with wetland proximity across the various wetland type and protection status categories. Alternatively, the discrete choice model may be used to estimate individual willingness to pay for changes in various attributes of the wetlands. Complementary to the hedonic analysis, this could entail calculating the value of proximity, but can also include valuing the loss of unprotected wetlands to development or changes in the protection status of the specific types of wetlands.

Table 1. Total Land Use Composition and Wetland Composition by Central Florida County in 2005

	Orange County		Volusia County		Polk County	
Description	Area (Hectares)	% Land Cover	Area (Hectares)	% Land Cover	Area (Hectares)	% Land Cover
All Land Types						
Residential	68,099	26.8	45,992	10.3	66,673	20.1
Commercial and Industrial	55,094	21.7	116,190	26.0	86,962	26.3
Agriculture and Rangeland	45,612	18.0	134,873	30.2	52,208	15.8
Water	24,309	9.6	31,330	7.0	41,076	12.4
Upland Forest	15,435	6.1	43,921	9.8	38,313	11.6
Wetlands	45,483	17.9	74,517	16.7	45,996	13.9
Total Area	254,031	100.0	446,823	100.0	331,228	100.0
Wetland Composition						
Wetland Hardwood Forest	15,754	34.6	25,508	34.2	10,303	22.4
Wetland Coniferous Forest	18,044	39.7	27,511	36.9	23,616	51.3
Wetland Freshwater Marsh	6,821	15.0	13,842	18.6	3,431	7.5
Wetland Prairie	4,864	10.7	7,656	10.3	8,646	18.8
Total Wetlands Area	45,483	100.0	74,517	100.0	45,996	100.0

Table 2. Summary Statistics on Samples of Central Florida Residential Housing Sales, January 2000-December 2004

			Orange County (N = 76,933)		Volusia County (N = 30,249)		Polk County (N = 19,716)	
Variable Description		Unit	Mean	Std Deviation	Mean	Std Deviation	Mean	Std Deviation
Property Characteristics								
Sales Price		2000 Dollars	173,785.60	151,625.70	134,361.40	80,317.46	115,455.10	70,952.82
Heated Area		Feet^2	1,813.55	746.27	1,682.71	565.50	1,630.87	608.75
Area of Parcel		Feet^2	11,699.95	18,511.56	19,126.90	41,457.09	18,231.50	44,644.88
Number of Bedrooms		--	3.29	0.74	2.92	0.61	2.90	0.56
Number of Bathrooms		--	2.15	0.68	2.02	0.50	1.85	0.59
Home Age		Years	17.04	13.09	19.97	15.12	25.92	20.48
% With Pool		--	0.24	--	22.95	--	21.64	--
% In Flood Zone		--	0.04	--	8.88	--	3.31	--
Locational/Spatial Characteristics								
Nearest Wetland Hardwood Forest:	Distance	Meters	1,554.15	1,273.64	2,226.90	1,662.21	1,128.49	890.64
	Area	Meters^2	307,792.90	1,927,734	181,448.10	374,925.00	245,917.9	882,989.70
	% Protected	--	29.39	--	30.90	--	14.97	--
Nearest Wetland Coniferous Forest:	Distance	Meters	1,303.41	1,119.03	1,670.15	1,061.82	1,794.20	1,183.91
	Area	Meters^2	96,383.88	519,952	334,626.30	1,579,265	183,072.70	640,792.90
	% Protected	--	2.21	--	22.68	--	22.25	--

Variable Description		Unit	Orange County (N = 76,933) Mean	Orange County Std Deviation	Volusia County (N = 30,249) Mean	Volusia County Std Deviation	Polk County (N = 19,716) Mean	Polk County Std Deviation
Nearest Wetland Freshwater Marsh:	Distance	Meters	1,359.60	1,241.12	1,535.66	1,015.61	1,002.93	1,467.88
	Area	$Meters^2$	14,060.85	24,000.10	15,310.99	41,094.71	27,640.18	84,362.32
	% Protected	--	19.01	--	9.27	--	11.28	--
Nearest Wetland Prairie:	Distance	Meters	1,133.10	800.74	1,166.62	687.84	1,076.05	773.01
	Area	$Meters^2$	18,030.85	26,887.24	20,491.71	41,353.43	30,044.61	174,951.00
	% Protected	--	32.49	--	9.49	--	5.48	--
Nearest Upland Forest:	Distance	Meters	1,266.21	1,046.11	1,597.71	1,000.42	989.75	654.65
	Area	$Meters^2$	124,814.50	408,266.80	1,612,130	3,978,746	93,661.45	195,949.30
	% Protected	--	23.15	--	52.80	--	13.13	--
Nearest Named Lake:	Distance	Meters	1,393.97	1,685.89	2,951.05	3,150.26	1,205.74	1,330.71
	Area	$Meters^2$	269.15	1,803.15	230,542.10	3,081,701	1,670,160	3,849,551
Nearest Other Water:	Distance	Meters	2,669.52	1,887.94	658.14	587.80	4,647.43	3,081.40
	Area	$Meters^2$	4,331.81	7,464.53	728,525.80	3,007,783	26,182.72	48,814.96
Central Business District:	Distance	Meters	13,183.94	5,982.58	25,848	14,323.75	53,395.70	44,337.53
Surrounding Land:	% Residential	--	48.77	--	63.48	--	37.94	--
	% Commercial/Industrial	--	27.36	--	14.89	--	18.27	--
	% Recreational	--	18.62	--	18.60	--	18.35	--
	% Agricultural	--	5.24	--	3.03	--	25.43	--
Latitudinal Coordinate		Degrees	0.53	0.04	0.61	0.04	0.71	0.05
Longitudinal Coordinate		Degrees	1.53	0.031	1.71	0.05	1.35	0.04

		Orange County (N = 76,933)		Volusia County (N = 30,249)		Polk County (N = 19,716)	
Variable Description	Unit	Mean	Std Deviation	Mean	Std Deviation	Mean	Std Deviation
Neighborhood Characteristics							
% of Population Caucasian	--	74.53	--	90.02	--	83.97	--
% of Population Black	--	12.54	--	5.03	--	9.33	--
% of Population Over 65 Years of Age	--	9.89	--	20.28	--	18.26	--
Median Household Income	2000 Dollars	52,237.78	18,038.46	41,266.18	10,015.86	42,023.18	12,089.82
Distribution of Sales by Year							
% of Sales in 2000	--	16.80	--	15.55	--	10.46	--
% of Sales in 2001	--	17.82	--	16.31	--	14.42	--
% of Sales in 2002	--	18.81	--	19.41	--	16.95	--
% of Sales in 2003	--	21.58	--	23.06	--	23.41	--
% of Sales in 2004	--	25.00	--	25.67	--	34.76	--

Table 3. Selected Estimates of Hedonic Property Price Models by County

		Orange County (N = 76,933)		Volusia County (N = 30,249)		Polk County (N = 19,716)	
Dependent Variable: Natural Logarithm of Sales Price		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Model 1:							
Nearest Wetland:	Ln(Distance)	0.002	0.001	0.020**	0.002	0.034**	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	-0.0002*	0.0001	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	0.005**	0.001	0.009**	0.001	0.003	0.002
	Ln(Distance) x Other Protected	0.004**	0.0003	0.007**	0.001	0.008**	0.001
		Adjusted $R^2 = 0.85$		Adjusted $R^2 = 0.83$		Adjusted $R^2 = 0.78$	
Model 2:							
Nearest Forested Wetland:	Ln(Distance)	-0.019**	0.001	0.002	0.002	0.023**	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	0.0004**	0.0001	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	-0.002*	0.001	0.002**	0.001	0.0005	0.001
	Ln(Distance) x Other Protected	0.001**	0.0004	0.0002	0.0004	0.007**	0.001
Nearest Non-Forested Wetland:	Ln(Distance)	0.011**	0.001	0.024**	0.002	0.028**	0.003
	Ln(Distance) x Ln(Area)	0.002**	0.0001	-0.0003*	0.0001	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	-0.001	0.001	0.003**	0.001	0.003	0.002
	Ln(Distance) x Other Protected	0.003**	0.0003	0.009**	0.001	0.003**	0.001
		Adjusted $^2 = 0.85$		Adjusted $R^2 = 0.83$		Adjusted $R^2 = 0.78$	

Table 3 Continued

Dependent Variable: Natural Logarithm of Sales Price		Orange County (N = 76,933)		Volusia County (N = 30,249)		Polk County (N = 19,716)	
		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Model 3:							
Nearest Wetland Hardwood Forest:	Ln(Distance)	-0.010**	0.001	-0.030**	0.002	0.021**	0.003
	Ln(Distance) x Ln(Area)	0.0002*	0.0001	0.001**	0.0002	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	0.002*	0.001	0.001	0.0004	0.001	0.002
	Ln(Distance) x Other Protected	0.004**	0.0003	0.001	0.001	0.005**	0.001
Nearest Wetland Coniferous Forest:	Ln(Distance)	-0.018**	0.001	0.037**	0.002	0.004	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	-0.001**	0.0001	-0.00002	0.0002
	Ln(Distance) x FNAI Protected	-0.006**	0.001	-0.002*	0.001	-0.001	0.002
	Ln(Distance) x Other Protected	---	---	0.0002	0.0004	0.013**	0.001
Nearest Wetland Freshwater Marsh:	Ln(Distance)	0.015**	0.001	-0.001	0.002	0.025**	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	0.001**	0.0002	-0.001**	0.0002
	Ln(Distance) x FNAI Protected	-0.002**	0.001	-0.001	0.001	0.0001	0.002
	Ln(Distance) x Other Protected	-0.003**	0.0003	-0.003**	0.001	0.002	0.001
Nearest Wetland Prairie:	Ln(Distance)	0.001	0.001	0.019**	0.002	0.015**	0.003
	Ln(Distance) x Ln(Area)	0.001**	0.0001	-0.001**	0.0001	0.001**	0.0002
	Ln(Distance) x FNAI Protected	0.013**	0.001	0.003**	0.001	-0.008**	0.002
	Ln(Distance) x Other Protected	0.002**	0.0002	0.012**	0.001	-0.005**	0.001
		Adjusted $R^2 = 0.86$		Adjusted $R^2 = 0.84$		Adjusted $R^2 = 0.77$	

Note: ** and * indicate significance at the 1% and 5% level, respectively. The full set of estimation results is available in an appendix.

Table 4. The Implicit Price of a 1 Meter Increase in Distance to Wetlands by County

		Orange County	Volusia County	Polk County
Model 1				
Nearest Wetland	Unprotected	$3.92	$2.98	$4.70
	FNAI Protected	5.14	4.48	5.28
	Other Protected	5.12	4.14	6.42
Model 2				
Nearest Forested Wetland	Unprotected	$-0.95	$0.65	$1.79
	FNAI Protected	-1.25	0.86	1.85
	Other Protected	-0.78	0.67	2.75
Nearest Non-Forested Wetland	Unprotected	4.89	2.80	3.88
	FNAI Protected	4.54	3.08	3.97
	Other Protected	5.09	2.82	5.20
Model 3				
Nearest Wetland Hardwood Forest	Unprotected	$-0.83	$-1.13	$0.99
	FNAI Protected	-0.64	-1.09	1.08
	Other Protected	-0.43	-1.09	1.46
Nearest Wetland Coniferous Forest	Unprotected	-0.55	2.16	0.25
	FNAI Protected	-1.34	2.02	0.20
	Other Protected	-0.55	2.18	1.12
Nearest Wetland Freshwater Marsh	Unprotected	3.06	0.31	2.23
	FNAI Protected	2.76	0.22	2.24
	Other Protected	2.68	0.07	2.42
Nearest Wetland Prairie	Unprotected	1.05	1.22	2.47
	FNAI Protected	3.09	1.54	1.60
	Other Protected	1.30	2.62	1.98

Note: Cells are shaded if the corresponding coefficients reported in Table 3 are significant.

Table 5. Conditional Logit Estimates of Residential Housing Choice by County

Dependent Variable: Housing Choice (1/0)		Orange County (I = 34,037)		Volusia County (I = 15,817)		Polk County (I = 10,825)	
Choice Sets: 250 Random Draws from 3 Month Window		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Model 1:							
Nearest Wetland:	Distance	0.0001	0.012	-0.055**	0.017	0.036	0.032
	Distance x Area	0.004*	0.002	-0.0004	0.001	0.001	0.002
	Distance x FNAI Protected	0.104	0.058	0.101*	0.044	0.093	0.074
	Distance x Other Protected	-0.086**	0.016	-0.280**	0.039	-0.050	0.063
		Pseudo $R^2 = 0.02$		Pseudo $R^2 = 0.004$		Pseudo $R^2 = 0.03$	
Model 2:							
Nearest Forested Wetland:	Distance	-0.052**	0.008	-0.030*	0.012	-0.060**	0.020
	Distance x Area	0.001	0.001	-0.001	0.001	-0.001	0.001
	Distance x FNAI Protected	0.146**	0.025	0.062**	0.019	0.051	0.062
	Distance x Other Protected	-0.077**	0.014	0.024	0.013	-0.014	0.038
Nearest Non-Forested Wetland:	Distance	0.019	0.011	-0.028	0.015	0.059*	0.029
	Distance x Area	0.086**	0.019	-0.005	0.021	-0.038	0.025
	Distance x FNAI Protected	-0.061**	0.037	0.144**	0.028	-0.003	0.102
	Distance x Other Protected	0.002	0.011	-0.174**	0.042	0.044	0.052
		Pseudo $R^2 = 0.02$		Pseudo $R^2 = 0.004$		Pseudo $R^2 = 0.03$	

Table 5 Continued

Dependent Variable: Housing Choice (1/0)		Orange County (I = 34,037))		Volusia County (I = 15,817)		Polk County (I = 10,825)	
Choice Sets: 250 Random Draws from 3 Month Window		Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Model 3:							
Nearest Wetland Hardwood Forest:	Distance	-0.023**	0.006	0.012	0.009	-0.087**	0.016
	Distance x Area	0.0002	0.0002	-0.002	0.001	-0.004**	0.001
	Distance x FNAI Protected	0.060**	0.012	0.010	0.009	0.059	0.054
	Distance x Other Protected	-0.052**	0.009	-0.050*	0.020	-0.014	0.044
Nearest Wetland Coniferous Forest:	Distance	-0.020*	0.009	-0.017	0.012	0.040**	0.011
	Distance x Area	0.0004	0.0006	-0.0004	0.0006	0.008**	0.002
	Distance x FNAI Protected	0.078*	0.031	0.023	0.027	-0.043	0.034
	Distance x Other Protected	---	---	0.008	0.011	-0.002	0.014
Nearest Wetland Freshwater Marsh:	Distance	0.087**	0.009	-0.029*	0.013	-0.068**	0.019
	Distance x Area	0.039*	0.018	-0.006	0.018	0.014	0.021
	Distance x FNAI Protected	-0.027	0.029	0.051**	0.017	-0.180	0.108
	Distance x Other Protected	-0.078**	0.018	0.041*	0.018	0.020	0.042
Nearest Wetland Prairie:	Distance	-0.046**	0.011	0.007	0.016	0.035	0.021
	Distance x Area	-0.012	0.020	0.034	0.019	-0.070**	0.023
	Distance x FNAI Protected	-0.038	0.041	0.085**	0.030	-0.145*	0.068
	Distance x Other Protected	0.052**	0.009	-0.092**	0.031	-0.012	0.045
		Pseudo $R^2 = 0.03$		Pseudo $R^2 = 0.004$		Pseudo $R^2 = 0.03$	

Note: ** and * indicate significance at the 1% and 5% level, respectively. The full set of estimation results is available in an appendix.

Table 6. The Marginal Utility of a 1 Meter Increase in Distance to Wetlands by County

		Orange County	Volusia County	Polk County
Model 1				
Nearest Wetland	Unprotected	0.003	-0.055	0.037
	FNAI Protected	0.108	0.046	0.130
	Other Protected	-0.083	-0.335	-0.013
Model 2				
Nearest Forested Wetland	Unprotected	-0.051	-0.033	-0.062
	FNAI Protected	0.094	0.029	-0.011
	Other Protected	-0.128	-0.010	-0.076
Nearest Non-Forested Wetland	Unprotected	0.031	-0.029	0.048
	FNAI Protected	-0.030	0.115	0.045
	Other Protected	0.033	-0.203	0.092
Model 3				
Nearest Wetland Hardwood Forest	Unprotected	-0.022	0.008	-0.096
	FNAI Protected	0.038	0.019	-0.037
	Other Protected	-0.073	-0.042	-0.110
Nearest Wetland Coniferous Forest	Unprotected	-0.020	-0.018	0.054
	FNAI Protected	0.058	0.005	0.011
	Other Protected	---	-0.011	0.052
Nearest Wetland Freshwater Marsh	Unprotected	0.092	-0.030	-0.064
	FNAI Protected	0.065	0.020	-0.244
	Other Protected	0.014	0.011	-0.044
Nearest Wetland Prairie	Unprotected	-0.048	0.014	-0.014
	FNAI Protected	-0.086	0.100	-0.130
	Other Protected	0.003	-0.077	0.003

Note: Cells are shaded if the corresponding coefficients reported in Table 5 are significant.

Linking Recreation Demand and Willingness to Pay with the Inclusive Value:

Valuation of Saginaw Bay Coastal Marsh[1]

June 13, 2007

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Introduction

Economists have use various methods for measuring the economic value of wetlands and results have differed depending on the location and the economic methods. Woodward and Wui (2001) performed a meta-analysis of published U.S. wetlands valuation studies for a number of services including flood control, water quantity and quality, hunting, fishing, wildlife watching, amenities, etc. Only a few studies have considered Great Lakes wetlands, beginning with Jaworski and Raphael's (1978) study of the value of fish, wildlife and recreation of Michigan's coastal wetlands. Several recent studies also address the value of various Midwest wetlands. These include a travel cost analysis for three small hunting sites (van Vuuren and Roy, 1993), a study of the value for commercial fisheries (Amacher, et al, 1989) and a study of Wisconsin wetlands (Mullarkey, 1997). In addition to these, more recent studies look at Michigan residents' willingness to accept different forms of wetlands mitigation (Lupi et al, 2002 and Hoehn et al, 2003).

Whitehead et al (2006) estimate the economic values of Saginaw Bay coastal marshes with multiple methods. Using the site selection travel cost model and conservative aggregation assumptions, an increase in 1125 acres of coastal marsh is valued at about $94,000 annually. The present value is $1.83 million. Willingness to pay for coastal marsh protection is estimated using the contingent valuation method. The annual value of protection of 1125 acres of coastal marsh is $113,000. The present value is $2.2 million.

We find that each acre of coastal marsh is worth $1,627 over a recreational user's lifetime. Over and above the recreational value are the other values estimated with the contingent valuation method. These values add $1,969 per acre over a lifetime. The recreation value and the willingness to pay value may be combined because analysis of the willingness to pay values indicated that they are not associated with increases in recreation trips. They are entirely nonuse values. The total value of each acre of coastal marsh is, therefore, $3,596 over the lifetime of a resident of the sampled region. The purpose of this paper is to further explore the additivity assumption adopted in Whitehead et al. (2006) by a combination of the revealed preference and stated preference data.

The combination of revealed preference and stated preference data for environmental valuation generally improves both types of willingness to pay estimates (Whitehead et al., 2005). Stated preference data can be used to estimate behavior and values beyond the range of revealed preference data, including nonuse values. Revealed preference data can be used to ground the stated preference data in reality and mitigate hypothetical bias. Also, additional observations may improve econometric efficiency of both types of estimates. McConnell (1990) provides the theory for data combination. Cameron (1992) empirically links a revealed preference model of continuous demand and a stated preference model of willingness to pay.

Whitehead (1995a) extends the McConnell (1990) results and identifies the price of recreation trips as an exogenous predictor of willingness to pay for quality change. One implication is that in an empirical model of willingness to pay the coefficient on recreation price provides an estimate of the change in demand (e.g., recreation trips) that would result from the quality change. Whitehead (1995b) argues that this result can be used to decompose willingness to pay into use and nonuse values. Willingness to pay and trip change models can be jointly estimated to more efficiently exploit the theoretical link (Huang, Haab and Whitehead 1997). In a more ad-hoc empirical specification Whitehead (2005) includes the predicted value of the change in trips using stated preference data with a quality change as a determinant of willingness to pay. This model is most appropriately used when measurement of recreation price is problematic. In addition, this model can also be used to decompose willingness to pay into use and nonuse values.

Revealed preference research has examined the linkage between discrete choice models of recreational site selection and continuous choice models of recreational intensity with the inclusive value -- an index of the expected utility gained from recreation trips (Parsons, Jakus and Tomasi 1999). No study to date has examined the linkage between discrete choice models of recreation site selection and stated preference models of willingness to pay. In this paper we link discrete choice recreation demand, continuous choice demand and willingness to pay models with the inclusive value. We use the Saginaw Bay watershed hunting and fishing license holders subset of the data used by Whitehead et al. (2006). These data include information on the typical county of Saginaw Bay coastal marsh-based recreation, the number of annual Saginaw Bay coastal marsh-based recreation trips and willingness to pay for coastal marsh protection. In general the approach presented here has the potential to (a) test the convergent validity of revealed and stated preference data, (b) provide an indirect test for scope and (c) examine the proportion of use and nonuse values in willingness to pay. Our more limited goal is to further examine the willingness to pay decomposition for the Saginaw Bay study.

The Linked Site Selection – Willingness to Pay Model

The travel cost method (TCM) is a revealed preference approach to environmental valuation that is used to estimate the benefits of outdoor recreation activities (Parsons, 2003). A variation of the travel cost method is the site selection (i.e., random utility) model (Parsons, 2003). In the random utility model (RUM), it is assumed that individuals choose their recreation site based on differences in trip costs and site characteristics (e.g., wetland acreage) between the alternative sites. Analysis of data on recreation site choice enables estimation of the monetary benefits of any change in site characteristics.

Consider an individual who considers a set of $j = 1,...,m$ recreation sites. The individual utility from the trip is decreasing in trip cost and increasing in trip quality:

$$(1) \qquad u_{ij} = v_{ij}(y_i - c_{ij}, q_j) + \varepsilon_{ij}$$

where u is the individual utility function, v is the nonstochastic portion of the utility function, y is income, c is the trip cost, q is a vector of site qualities, ε is the error term, i indexes individuals, $i = 1, \ldots, n$ and j indexes recreation sites, $j = 1, \ldots, s, \ldots m$. The deterministic part of the utility function is linear

$$(2) \qquad v_{ij} = \alpha_c c_{ij} + \alpha_q q_j + \alpha_k^{/} z$$

where c_{ij} is the travel cost of individual i to site j, q_j is the quality of site j and α_k is a vector of j – 1 alternative specific constants interacted with income and perhaps other individual-specific variables, z. The random utility model assumes that the individual chooses the site that gives the highest utility:

$$(3) \qquad \pi_{ij} = \Pr(v_{ij} + \varepsilon_{ij} > v_{is} + \varepsilon_{is} \quad \forall\ s \neq j)$$

where π_{ij} is the probability that individual i chooses site j.

A site choice RUM is estimated using the multinomial logit model where the dependent variable is a choice among a set of alternatives and the independent variables are alternative specific (Haab and McConnell, 2002). For example, a recreationist choosing among a set of recreation sites might consider the travel costs to each site and the characteristics of each site. If the error terms are independent and identically distributed extreme value variates then the conditional logit site selection model results

$$(4) \qquad \pi_i = \frac{e^{v_i}}{\sum_{j=1}^{m} e^{v_s}}$$

The inclusive value is the expected maximum utility from the cost, quality characteristics of the sites and other aspects of the choice. The inclusive value, *I*, is measured as the natural log of the summation of the site choice utilities

$$(5) \qquad I(c,q,z;\alpha) = \ln\left(\sum_{j=1}^{m} e^{v_j}\right)$$

Hanemann (1999) shows that the compensating variation from a change in quality characteristics is:

$$(6) \qquad CV = \frac{I(c,q,z;\alpha) - I(c,q+\Delta q,z;\alpha)}{\alpha_c}$$

where CV is the compensating variation measure of welfare for each choice occasion and the marginal utility of income is α_c. Haab and McConnell (2002) show that the compensating variation for a quality change can be measured as

(7) $$CV(\Delta q_k) = \frac{\alpha_k \Delta q_k}{\alpha_c}$$

where q_k is one element of the q vector. The compensating variation of site access is

(8) $$CV(j) = \frac{-\ln(1-\pi_{ij})}{\alpha_c}$$

These welfare measures apply for each trip taken by the individuals in the sample. If the number of trips taken is unaffected by the changes in cost and/or quality, then the total willingness to pay is equal to the product of the per trip compensating variation and the average number of recreation trips, $\bar{x}$. If the number of trips taken is affected by the changes in quality then the appropriate measure of aggregate welfare must be adjusted by the change in trips. There are several methods of linking the trip frequency model with the site selection model (Herriges, Kling and Phaneuf, 1999; Parsons et al., 1999), we choose the original approach that includes the inclusive value parameter as a variable in the trip frequency model (Bockstael, Hanemann and Kling, 1987)[5]

(9) $$x = x\left[I(c, q, z; \alpha), z\right]$$

These models are typically estimated with count (i.e, integer) data models such as the Poisson or negative binomial models (Haab and McConnell 2002). Count data makes adjustments for the fact that trips are not continuous variables but integers (e.g., 0, 1, 2, etc). Recreation demand count data tends to be clustered at zero and low integer values. The Poisson estimates the probability of trips at each integer value

[5] This is also referred to as a participation model.

$$\text{(10)} \qquad \Pr(x) = \frac{e^{-\lambda}\lambda^{x}}{x!}$$

$$\text{(11)} \qquad \ln(\lambda) = \beta_0 + \beta_1 I + \beta_2^{/} z$$

where $x = 0, 1, 2, \ldots$ is the number of trips, λ is the mean and variance of the trip distribution. The negative binomial model relaxes the equality restriction on the mean and variance of trips (Haab and McConnell, 2002).

Trips under various quality scenarios can be simulated by substitution of quality changes into the trip frequency model

$$\text{(12)} \qquad \hat{x}(\Delta q) = x\left[I\left(c, \Delta q, z; \alpha\right), z\right]$$

The total compensating variation of a quality change that might affect the number of trips is aggregated over the number of trips:

$$\text{(13)} \qquad CV(\Delta q_k) = \sum_{j=1}^{m}\left(\left[\hat{x}_j(\Delta q)\right]CV(\Delta q_k \mid j) + \left[\bar{x}_j - \hat{x}_j(\Delta q)\right]CV(j)\right)$$

The first component of the total value is the product of the average number of trips taken with the quality change and the value of the quality change. The second component of the willingness to pay is the product of the difference in trips and the willingness to pay for a trip to a particular site.

The contingent valuation method (CVM) can be used to estimate the willingness to pay for quality change (Mitchell and Carson, 1989; Boyle, 2003). The contingent valuation method is a stated preference approach that directly elicits willingness (and ability) to pay statements from survey respondents. Respondents are directly asked about their willingness to pay (i.e., change in compensating variation) for environmental improvement. The CVM involves the development of a hypothetical market via household surveys. In the hypothetical situation respondents are informed about the current problem and the policy designed to mitigate the problem. Other contextual details about the policy are provided such as the policy implementation rule (e.g., provision point design) and the payment vehicle (e.g., a special fund). Finally, a hypothetical question presents respondents with a choice about the improvement and increased costs versus the status quo. Statistical analysis of these data leads to the development of willingness to pay estimates.

Willingness to pay (*WTP*) for a quality change is

$$v_i(c, y_i - WTP_i, q) = v_i(c, y_i, q - \Delta q) \tag{14}$$

where c is a vector of travel costs and Δq is the change in quality. The dual definition of willingness to pay is

$$\begin{aligned} WTP_i &= e(c, q - \Delta q, v_i) - y_i \\ &= s(c, q, \Delta q, y_i) \end{aligned} \tag{15}$$

where $y = e\big(c, q, v(c, q, y)\big)$ and $s(\cdot)$ is the variation function. Willingness to pay is decreasing in travel costs, increasing in quality and increasing in income (Whitehead, 1995a). The variation function can be specified with utility theoretic variables

$$WTP_i = \gamma_0 + \gamma_1' c + \gamma_2 q' + \gamma_3 y + \gamma_4 z \tag{16}$$

where $q^{/} = q - \Delta q$. The negative of the coefficient on the travel cost variable, with an adjustment for the marginal utility of income across quality states, provides an estimate of the additional trips that would be taken with the quality change. The marginal willingness to pay for quality change can be obtained from the coefficient on the quality variable.

The proposal of this paper is that, alternatively, the inclusive value can be included as an index of travel costs, quality and income

$$(17) \qquad WTP_i = \gamma_0 + \gamma_1 I(c, q, z; \alpha) + \gamma_2 z$$

Oftentimes, alternative contingent valuation scenarios are necessary to obtain variation on quality in order to estimate its marginal value. In this case, marginal willingness to pay for changes in quality can be obtained from the coefficient on the inclusive value and simulated changes in the inclusive value

$$(18) \qquad \frac{\partial WTP_i}{\partial q} = \gamma_1 \frac{\partial I(c, q, z; \alpha)}{\partial q}$$

Alternative contingent valuation scenarios are not needed in order to obtain estimates of marginal willingness to pay for quality with the inclusive value.

Considering the revealed preference and stated preference approaches, a test of the convergent validity of the revealed preference (*CV*) and stated preference (*WTP*) methods is

$$(19) \qquad \begin{aligned} &H0 : CV(\Delta q) = WTP(\Delta q) \\ &HA : CV(\Delta q) \neq WTP(\Delta q) \end{aligned}$$

Equality of value estimates would lend validity to both methods.

Survey and Data

The purpose of the “Saginaw Bay Coastal Marshes Survey” is to generate data for use in developing economic values for coastal marsh protection. The survey describes Saginaw Bay coastal marsh resource allocation issues, elicits information about coastal marsh-related recreation, inquires about attitudes regarding economic development, describes a coastal marsh protection program and elicits willingness to pay. It also obtains socio-economic information.

Names and addresses of all sportsmen living within the Saginaw Bay watershed were obtained under a special use agreement with the Michigan Department of Natural Resources (DNR). From this list, names were randomly selected. Three rounds of surveys were mailed between February and June of 2005. Ten days after each mailing, a reminder card was sent to all survey recipients. To help increase the response rate, the third round of surveys included an incentive. Survey recipients were notified that $1000 would be divided among five winners. Winners were randomly selected from the third round respondents and a check was sent to each.

For each of the 18 versions of surveys sent to sportsmen, 79 names were randomly selected from the DNR list, for a total of 1422 surveys. We obtained a response rate of 22% and, after deletion of cases with item nonresponse on important variables, we have a sample size of 251 (Table 1). The typical license holder household has 3 people with 0.82 children. The license holder sample is 79 percent male and 97 percent white. The average age is 48 years. Thirty-seven percent are members of conservation and/or environmental organizations and 8 percent owned

Saginaw Bay shoreline property. The average number of years in school is 14. Household income is $49 thousand.[6]

Respondents are asked about their Saginaw Bay coastal marsh-related recreation activities. These activities are defined as any trip where the respondent was on or near the water including the marshes where the typical plants are cattails, rushes, grasses, and shrubs. Fifty four percent of the sample had visited the Saginaw Bay or Saginaw Bay coastal marsh area for outdoor recreation or leisure. The license holders took an average of 6 coastal marsh recreation trips. Not all license holders took trips to Saginaw Bay. The recreation participants took an average of 11 trips. The primary recreation activity was fishing with 55 percent of the sample anglers. The most popular county for recreation trips was Bay County with almost 50 percent visiting there on a typical trip.

The survey elicited the willingness to pay for coastal marsh protection using the contingent valuation method. Respondents are told that 9000 of 18,000 acres of Saginaw Bay coastal marshes are currently protected and that the remaining privately owned marshes could be purchased and protected. A hypothetical “Saginaw Bay Coastal Marsh Protection Program” was introduced. Voluntary contributions would go into a “Saginaw Bay Coastal Marsh Trust Fund”

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[6] We also obtained a sample of the general population with a similar response rate and sample size but focus our analysis on the license holders sample in this paper. The results from the general population are generally consistent with those of the license holders except that the linkage between willingness to pay and the inclusive value is nonexistent.

to purchase *X* acres of coastal marsh. The acreage amount, *X*, was randomly assigned from three amounts 1125, 2500 and 4500.

Respondents are told that “Money would be refunded if the total amount is not enough to purchase and manage *X* acres. If the amount of donated money is greater than the amount required to purchase and manage *X* acres, the extra money would be used to provide public access and educational sites at Saginaw Bay coastal marshes.” This is known as the provision point survey design (Poe, et al., 2002). The provision point design has been shown to minimize free riding bias in willingness to pay responses.

Then respondents are asked: “Would you be willing to make a one-time donation of money to the Saginaw Bay Coastal Marsh Trust Fund within the next 12 months?” For the license holder sample, 27 percent, 50 percent, and 23 percent would, would not, and did not know whether they would make a donation. Respondents who would be willing to make a donation are then told that “if about 1 percent (1 in 100) of all households in Michigan made a one-time donation of $*A*, the Trust Fund would have enough money to purchase and manage *X* acres of coastal marshes. Remember, if you made a one-time donation of $*A* into the Trust Fund, you would have $*A* less to spend on other things. Also remember that protected marsh would no longer be available for conversion to other uses.” The dollar amount, $*A*, was randomly assigned from the following amounts: $25, $50, $75, $100, $150 and $200. The dollar amounts were chosen based on revenue streams required to purchase *X* acres of coastal marsh if 1 percent of all Michigan households made the donation.

Respondents are asked if they **“**would make a one-time donation of $*A* to the Saginaw Bay Coastal Marsh Trust Fund within the next 12 months?” Sixty-two percent, 42 percent, 36 percent, 42 percent, 26 percent, and 19 percent of the license holders were willing to pay $25, $50, $75, $100, $150 and $200.

One problem that arises with contingent valuation method surveys is hypothetical bias (Whitehead and Cherry, forthcoming). Hypothetical bias exists if respondents are more likely to say that they would pay a hypothetical sum of money than they would actually pay if placed in the real situation. Since economic values are based on actual behavior, hypothetical bias leads to upward biased estimates of economic value. One method that is used to mitigate hypothetical bias is the certainty rating (Champ and Bishop, 2001).

For those respondents who said that they were willing to pay we asked: “On a scale of 1 to 10 where 1 is “not sure at all” and 10 is “definitely sure”, how sure are you that you would make the one-time donation of $*A*?” Thirty-four percent are definitely sure that they would pay and forty-percent are very sure that they would pay (i.e., their rating was 7, 8 or 9). To determine how likely respondents find the donation mechanism to work we ask “how likely do you think it is that 1 percent of all households in Michigan would make a one-time donation of $*A* to the Trust Fund within the next 12 months?” Forty-seven percent of the license holders thought that it would be somewhat likely or very likely.

Empirical Results

Revealed Preference

Recreation participants and non-participants are included in the analysis. Non-participants are those who took zero trips. The dependent variable for the site selection model is the typical county chosen for a coastal marsh-based recreation trip. We also include a nonparticipation choice for those who do not take trips. The most popular county for recreation trips is Bay County with almost 50 percent visiting there on a typical trip. Twelve percent go to Iosco and Arenac Counties, 11 percent goes to Tuscola County and 24 percent go to Huron County on a typical trip. Forty-six percent do not choose any county.

Data on wetlands acreage and other measures of site quality for each Saginaw Bay county was provided by Ducks Unlimited (Table 2). Other variables used to explain recreation site selection are the travel costs to the county site, the number of water access points in the county site and National Forest acreage. We compute distance traveled from the home zip code of the respondent to the zip code of the most commonly visited city in the county of the typical recreation trip destination using ZIPFIP software, d_{ij} (Hellerstein, 2005). Travel cost per mile is set at \$0.37, time costs are valued at one-third of the wage rate, and average miles per hour is 60: $c_{ij} = 0.37 \times 2 \times d_{ij} + [(0.33 \times y_i / 2000) \times (2 \times d_{ij})] / 60$. The average travel cost is \$56, the average number of wetland acres in each county is 42,000, the average number of access points is 6 and the average number of National Forest acres in each county is 10 thousand.

In Model 1, we include travel costs, wetland acres, access points and acres of National Forest land as independent variables (Table 3). As expected, the probability of site choice decreases as the travel costs to the site increases. The probability of site choice is not affected by wetland acres or acres of National Forest land. The probability of site choice increases with access points.

In Model 2, we also include alternative specific constants interacted with income. In this model, the probability of site choice decreases as the travel costs to the site increases. Surprisingly, the probability of site choice decreases with wetland acres. This is likely due to the inclusion of recreation nonparticipants in the model. In Whitehead et al. (2006), with nonparticipants excluded, the probability of site choice increases with wetland acreage. The probability of site choice increases with access points. The probability of site choice is not affected by National Forest land. The probability of site choice at each of the five counties, relative to nonparticipation, increases with income. This result indicates that coastal marsh recreation is a normal good.

We use the inclusive value computed from each of these models. We expect varying results depending on the inclusive value used and whether income is included in the linked models because the correlation coefficients between income and the inclusive values are significantly different. The correlation coefficient between the inclusive value from Model 1 and income is negative, $r = -0.33$. The correlation coefficient between the inclusive value from Model 2 and income is positive, $r = 0.52$. Nevertheless, the correlation coefficient between the inclusive values from Models 1 and 2 is positive, $r = 0.58$.

We estimate three negative binomial trip participation models. Model 1 includes the inclusive value estimated without income in the utility function (from Model 1 of Table 2) and a separate income variable. Trips increase with the inclusive value and income. The inclusive value coefficient primarily reflects the price effect. As travel costs fall (the individuals live closer to the recreation destination) the inclusive value increases.

Model 2 includes the inclusive value estimated with income in the utility function (from Model 2 of Table 2) without a separate income variable. Trips increase with the inclusive value. In this model, the inclusive value coefficient reflects the price effect and the income effect. As income increases, the individual is more likely to participate in recreation and, therefore, take more trips.

Model 3 includes the inclusive value estimated with income in the utility function (from Model 2 of Table 2) with a separate income variable. Trips increase with the inclusive value and decrease with income. Holding the effect of income on recreation participation constant, as income increases the individual takes fewer trips. From a statistical standpoint, Model 1 is preferred with a higher log-likelihood function value.

Stated Preference

The dependent variables in the willingness to pay analysis are whether the respondent is willing to pay something above zero ("donate") and, if so (n = 129), willing to pay more than the requested donation ("give"). Following Groothuis and Whitehead (2002) the "don't know" responses are recoded to "no" responses for a conservative estimate of willingness to pay. Since economic values are revealed by behavior, correction of hypothetical bias is necessary to develop more accurate willingness to pay estimates. We recode "give" responses where the respondent is not sure that they would be willing to pay, these respondents answered less than 7 on the follow-up certainty scale, to "no" responses. The natural log of the bid ($\$A$) amount is used to improve statistical fit.

The two willingness to pay decisions (e.g., donate and give) are analyzed separately with the logit model. The probability of a "yes" response is the probability that willingness to pay, *WTP*, is greater than the bid amount, A (Cameron, 1988)

$$\begin{aligned} \Pr(donate) &= \Pr(WTP > 0) \\ &= \Pr\left(\frac{\lambda' z}{\kappa}\right) \end{aligned} \tag{20}$$

$$\Pr(give) = \Pr(WTP > A) \tag{21}$$
$$= \Pr\left(\frac{\theta' z - \ln A}{\kappa}\right)$$

where λ and θ are vectors of coeffcients, z is a vector of independent variables and $\frac{-1}{\kappa}$ is the coefficient on the log of the bid amount. Median willingness to pay is (Haab and McConnell, 2002)

$$WTP = \exp(\kappa[\theta' z]) \tag{22}$$
$$= \exp(\gamma' z)$$

The t-statistics are developed using standard errors approximated by the Delta Method (Cameron, 1991).

The willingness to pay results are presented in Table 4. In addition to the inclusive value we include the log of the bid amount and the wetland acreage in both “donate” and “give” models. Since the data was collected with a mail survey respondents could read the entire survey before answering any question. It is therefore possible that price and scope effects may be found in the donate model, although theory would not guide the inclusion of these variables. Conservation and/or environmental organization membership and income are the only socioeconomic variables included. We also include a dummy variable equal to one if the respondent thinks it is likely that enough Michigan residents would make the required donation for the program to be a success. The variable is equal to zero otherwise.

We present four models. Model 1 includes the inclusive value estimated without income in the utility function (from Model 1 of Table 2) and a separate income variable. Model 2 includes the inclusive value estimated without income in the utility function and without income as a separate variable (from Model 1 of Table 2) without a separate income variable. Model 3 includes the inclusive value estimated with income in the utility function (from Model 2 of Table 2) with a separate income variable. Model 4 includes the inclusive value estimated with income in the utility function (from Model 2 of Table 2) without a separate income variable.

We first describe some general results and then turn our attention to the inclusive value. In each model, as the bid amount increases the probability of “donate” and “give” responses decreases. The bid variable influences the decision of whether to donate any amount of money and whether to donate the bid amount. In each model respondents who are organization members are more likely to be willing to donate some positive amount of money for coastal marsh protection and more likely to give more than the bid amount.

An important test of the validity of willingness to pay responses is whether willingness to pay increases with the quantity of the good being purchased. This is known as the scope test (Whitehead, Haab, and Huang, 1998). The scope test results are mixed. In models 1 and 3, with income included as a separate variable, increases in scope makes it more likely that the respondents will donate some amount of money. However, in none of the models is marsh acreage a significant determinant of whether the respondent would give more than the bid amount. Note that failure to pass the scope test does not necessarily invalidate the willingness to pay values. Economic theory only requires that willingness to pay be non-decreasing with quantity.[7]

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[7] Recent research in behavioral economics indicates that individuals do not always follow the

The provision point design is intended to provide respondents with incentives to reveal their true willingness to pay. One reason why respondents might state that they would not donate even if their willingness to pay is above the requested donation is that they believe the money would be wasted if total donations are not sufficient to fund the program. With the provision point design respondents are told that if that occurs, their money would be refunded. Survey respondents who did not believe that the donations would be sufficient were less likely to be willing to pay the bid amount. This result is further explored by Groothuis and Whitehead (2006).

Whitehead et al. (2006) adopt the theoretically preferred empirical specification by including the typical trip travel cost for users and the minimum travel cost for nonusers. The coefficient on this variable is not statistically significant which suggests that the willingness to pay estimates are nonuse values. The results with the inclusive value included in the willingness to pay model are mixed but generally support the results in Whitehead et al. (2006). In Model 1, with income excluded from the inclusive value but included separately in the model, the coefficient on the inclusive value is negative in the "donate" model and statistically insignificant in the "give" model. The same result is found in Models 2 and 3 without income in the inclusive value or as a separate variable and with income included in the inclusive value and included as a

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dictates of neoclassical consumer theory. Heberlein, et al. (2005) found that individual respondents do not pass the scope test internally for a variety of reasons. Market forces act to discipline irrational behavior for market goods. In valuation surveys this behavior is allowed to flourish. They conclude that behavior that flows from complex individual preferences and does not strictly follow neoclassical economic theory should not be considered invalid.

separate variable, respectively. The coefficient on income is positive and statistically significant in Models 1 and 3 in both willingness to pay decisions.

Models 1, 2 and 3 support an interpretation of willingness to pay as nonuse value since it does not vary in the expected direction with the inclusive. These results indicate that those with higher levels of expected maximum utility from coastal marsh recreation are less likely to be willing to donate anything for marsh protection. A naïve interpretation of this result is that it is consistent with the negative values for marsh protection found in the recreation demand model. However, the negative value result from the recreation demand model is likely due to the predominant choice of nonparticipation and the zero value of wetlands associated with that choice. Another interpretation of the willingness to pay result is that recreation nonusers hold nonuse values while recreation users do not hold nonuse values.

In contrast to Models 1-3, Model 4, with income included in the inclusive value and excluded as a separate variable, provides a different interpretation. The inclusive value is not a determinant of the decision to donate money to marsh protection but the probability of giving more than the bid amount is positively affected. This result suggests that willingness to pay is decreasing in travel cost and increasing in income and that willingness to pay contains a large component of use values. It is likely, however, that the inclusive value is picking up the income effect. It is most likely that the inclusive value is capturing ability to pay rather than the utility of recreational use of the coastal marsh.

Conclusions

We have explored the linkage between recreation demand and willingness to pay models. We have two goals. First, we further consider the decomposition of willingness to pay into use and nonuse values. If contingent valuation estimates of willingness to pay are comprised mostly of nonuse values then value estimates from revealed preference and stated preference models are additive. Second, we propose an alternative model for linking revealed preference and stated preference models of recreation when a single travel cost measure is difficult to obtain. We show that this model can be used to test convergent validity and offers an alternative scope test that does not rely on split-sample contingent valuation scenarios.

Our results with the Saginaw Bay coastal marsh data are mixed. In three of the four models estimated the inclusive value is negatively related to the willingness to donate but unrelated to the willingness to give more than the suggested bid amount. This result suggests that recreation nonusers hold nonuse values while recreation users do not hold nonuse values. As such, we believe that much of the willingness to pay estimate is comprised of nonuse values and the additivity assumption adopted by Whitehead et al. (2006) is appropriate.

The lack of an expected result may also arise from an incompatibility between the revealed preference and stated preference data. The stated preference data results from a scenario where respondents are asked to help protect an existing resource. Without this protection, the quality of future recreation resources might diminish. The revealed preference data results from existing opportunities. Future research should explore recreation demand and willingness to pay scenarios that are more tightly linked.

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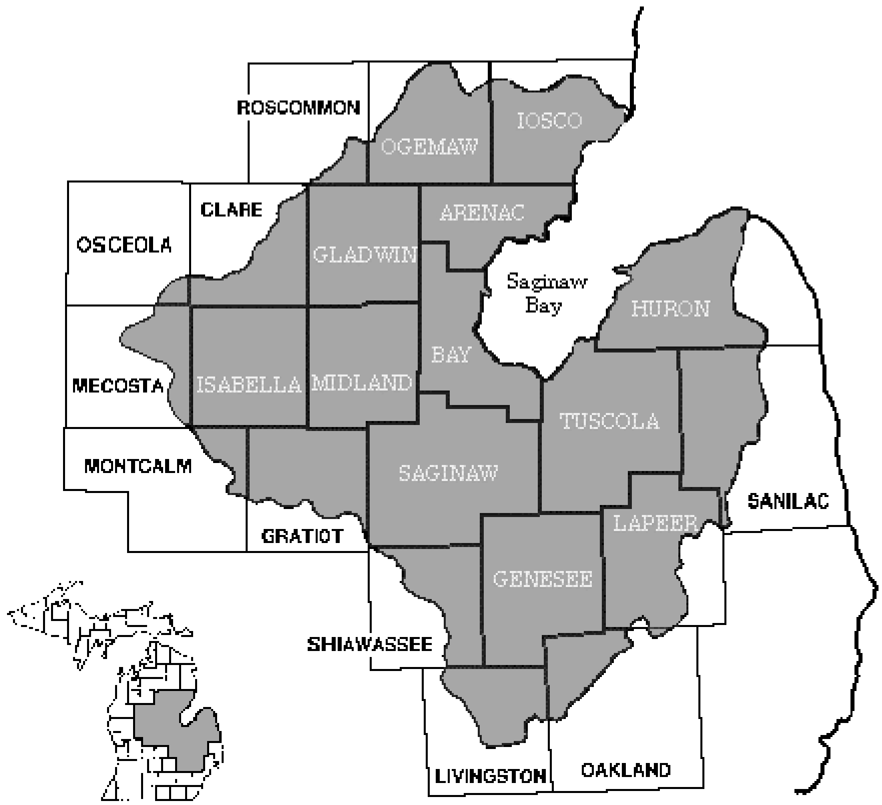
Figure 1. Saginaw Bay Watershed



Combining Stated and Revealed Preference: Comments on Huang-Parsons-Zhao-Poor, Milon-Scrogin, and Whitehead-Groothuis-Southwick

John Horowitz
University of Maryland

April 2007

Each of these papers combines a revealed preference analysis, either travel cost or hedonics, with a stated preference survey. Revealed preference on its own is informative but difficult: the data collection and model construction (making the imperfect data yield at least some welfare-relevant results) are always a steep challenge. Stated preference too is informative but difficult; model construction is easier, a bit, but data collection is harder. Revealed preference plus stated preference, as these authors have embarked on, is doubly ambitious. But is it informative? Is the whole greater than the sum of the parts?

1. Advantages and Disadvantages of Combining RP and SP

There are several ways in which the whole might be greater than the sum of the parts. Per-survey costs may be cheaper. A related advantage is that the stated-preference question can be targeted toward users, as both HPZP and WGS do. This may or may not be desirable, of course.

Perhaps the most important conceptual advantage is that the combination of stated and revealed preference data can provide a test of convergent validity. In the context of travel cost analysis, revealed preference reigns supreme: Actual visits to a recreation area tell us something about individual tastes towards the recreational experience. If stated-preference results do not reveal the same qualitative tastes then the particular stated-preference survey was probably poorly designed.

The potential disadvantage from combining RP and SP is that the stated preference survey gets insufficient attention. It gets insufficient attention both from the survey designer and the respondent. On-site valuation surveys, such as HPZP, are hectic affairs since respondents are almost always eager to get one with their recreation. There is not enough time for the subject to respond thoughtfully.

Mail surveys suffer because it is very difficult – impossible, really – because of the non-response problem. Mail surveys have low response rates (there are lots of unreturned surveys) and these non-respondents are not a random sample of values. I would like to urge the profession to drop mail surveys or, failing that, to explore the contexts in which mail surveys yield the same results as in-person (not telephone) surveys. Non-respondents likely do not represent a random sample of values even when demographic characteristics are the same for respondents and non-respondents. The unobserved component of tastes – that is, the component not related to income, education, location, or other variables – is important. But it is almost surely lost in a mail-survey unless there is a very high response rate.

2. Statistics

Economists rely too heavily on statistical significance. Many articles report significance without even mentioning the magnitude of the estimated coefficient and its implications. See McCloskey for a discussion of the prevalence of this feature in economic writing and a criticism. These research articles fall in with this pattern. WGS mention the statistical significance of their coefficient on Acres in their scope test but do not help the reader understand the actual coefficient. HGPZ do the same on their erosion measure. I urge the authors to focus on the estimated coefficients and what we can learn from them, leaving little more than a nod toward statistical significance.

The problem is that *0 is not a relevant null hypothesis for most valuation studies*. This problem is sufficiently widespread and sufficiently misunderstood (as was apparent at this EPA conference) that it is worth giving an example.

Suppose we wanted to know whether older individuals placed a higher value on a statistical life (VSL) than did lower individuals. An empirical investigation yields a coefficient of -0.2 on age (say, a dummy variable indicating whether the respondent is older than the author) with a standard error of 0.16. The absolute value of the t-statistic is 1.25, which indicates that the estimated coefficient is not significantly different from zero.

Does this result mean that older individuals have the same VSL as younger ones? Of course not; the researchers' *best guess* is that older individuals have a VSL that is 20 percent lower. Indeed, the whole point of estimation is that -0.2 is the researcher's considered assessment of this relationship. To argue that the VSL is the same for both groups is silly or, to be more accurate, is no more informative than arguing that the VSL for older individuals is *40 percent* lower. If a coefficient β is insignificantly different from 0, it is insignificantly different from 2β. If this latter conclusion seems fatuous, the reader should recognize that it is statistically analogous to the claim that the VSL is the same for the two groups.

Readers might wonder then whether t-statistics or standard errors have any role at all to play. For valuation, at least, the answer is "not much." Standard errors tell us how confident we can be about a coefficient. The policy context has to tell us the implication of this imprecision. To put this another way, the estimated magnitude of a relationship and the precision of our estimate are two separate findings. Statistical significance conflates these.

I refer readers to the insightful and voluminous work by McCloskey on this issue, including many concrete examples.

3. Relationship between WTP and Inclusive Value

WGZ look at the relationship between WTP and Inclusive Value, the latter a statistical construct from a nested logit. Their goal is admirable but the paper (as presented at the conference) did not characterize this relationship quite right. The correct relationship is:

WTP (for a change in acres) = *derivative* of Inclusive Value with respect to. Acres

Note that this relationship is definitional, not “explanatory.” Therefore, it does not yield an obvious role for any other explanatory variables. It is not clear how to “test” this relationship.

4. Willingness to Pay and the Voluntary Contribution Problem

WGS elicit willingness-to-pay by asking individuals for a potential contribution to a land conservancy. This set-up is fraught with peril. Individuals can contribute to a land conservancy independently from the survey. This opportunity makes it difficult to interpret the survey responses. If an individual says she is willing to donate $25 but has is not currently a donor and, perhaps, has never previously donated, then the researcher should be suspicious of the response.

This is not only a problem of survey design; it is a problem of free-riding, a problem that is notoriously difficult to overcome.

Note that most WTP models assume that the public good is available only through the proffered mechanism. This assumption is not valid for the land conservancy situation. It may be violated more widely, for lots of valuation circumstances, an issue that is worth investigating further. When the assumption is violated, WTP reflects a combination of utility parameters (individual taste) and market prices or opportunities. We are interested in a pure inference of the former. Separating these two is difficult.

5. Amenity Values and Ecological Values

I started my comments with the recognition that revealed preference analysis was difficult because of both data collection and model building. The MS research illustrates both of these points. The data collection and analysis are an astounding feat. This is a rich data set.

The model raises many difficult questions. Wetlands affect the location and quantity of land available for building; in other words, wetlands affect both demand and supply. In some instances, wetland preservation is endogenous (to the local community), so it is not always straightforward to examine the effects of preserved vs. non-preserved wetlands. Finally, even when these concerns can be dealt with, the remaining estimates tell us about the amenity value of a wetland (whether it is scenic; whether it smells) but not about its ecological value – namely, the services is provides to the general ecology. The ecological services are hard to define and measure but most of those services do not accrue specially to people who live close to the wetland versus 1, 5, or 10 miles away. Note that a painstaking exegesis of the ecological services is necessary in order to know how these services are used and how valuable or necessary proximity is to take advantage of these ecological services.

It is not hard to image a situation in which individuals prefer to live close to a sweet-smelling wetland when in fact a foul-smelling one provides a much higher volume of ecological services. The resulting housing-price gradient would reflect the amenity value (in this case negative), but the ecological value is missing.

Valuation for Environmental Policy: Ecological Benefits

A Workshop sponsored by U.S. Environmental Protection Agency's National Center for Environmental Economics (NCEE) and National Center for Environmental Research (NCER)

Crowne Plaza Washington National Airport Hotel
1480 Crystal Drive
Arlington, VA 22202

April 23-24, 2007

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U.S. Environmental Protection Agency (EPA)
National Center for Environmental Economics (NCEE) and
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Valuation for Environmental Policy: Ecological Benefits

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April 23-24, 2007

Agenda

April 23, 2007: Valuation for Environmental Policy

8:00 a.m. – 8:30 a.m.	**Registration**	
8:30 a.m. – 8:45 a.m.	**Introductory Remarks** Rick Linthurst, National Program Director for Ecology, EPA, Office of Research and Development	
8:45 a.m. – 11:30 a.m.	**Session I: Benefits Transfer** Session Moderator: Steve Newbold, EPA, NCEE	
	8:45 a.m. – 9:15 a.m.	Benefits Transfer of a Third Kind: An Examination of Structural Benefits Transfer George Van Houtven, Subhrendu Pattanayak, Sumeet Patil, and Brooks Depro, Research Triangle Institute
	9:15 a.m. – 9:45 a.m.	The Stability of Values for Ecosystem Services: Tools for Evaluating the Potential for Benefits Transfers John Hoehn, Michael Kaplowitz, and Frank Lupi, Michigan State University
9:45 a.m. – 10:00 a.m.	**Break**	
	10:00 a.m. – 10:30 a.m.	Meta-Regression and Benefit Transfer: Data Space, Model Space and the Quest for 'Optimal Scope' Klaus Moeltner, University of Nevada, Reno, and Randall Rosenberger, Oregon State University
	10:30 a.m. – 10:45 a.m.	Discussant: Matt Massey, EPA, NCEE
	10:45 a.m. – 11:00 a.m.	Discussant: Kevin Boyle, Virginia Tech University
	11:00 a.m. – 11:30 a.m.	Questions and Discussion
11:30 a.m. – 12:45 p.m.	**Lunch**	

April 23, 2007 (continued)

12:45 p.m. – 3:30 p.m.	**Session II: Wetlands and Coastal Resources** Session Moderator: Cynthia Morgan, EPA, NCEE	
	12:45 p.m. – 1:15 p.m.	A Combined Conjoint-Travel Cost Demand Model for Measuring the Impact of Erosion and Erosion Control Programs on Beach Recreation Ju-Chin Huang, University of New Hampshire; George Parsons, University of Delaware; Min Qiang Zhao, The Ohio State University; and P. Joan Poor, St. Mary's College of Maryland
	1:15 p.m. – 1:45 p.m.	A Consistent Framework for Valuation of Wetland Ecosystem Services Using Discrete Choice Methods David Scrogin, Walter Milon, and John Weishampel, University of Central Florida
1:45 p.m. – 2:00 p.m.	**Break**	
	2:00 p.m. – 2:30 p.m.	Linking Recreation Demand and Willingness To Pay With the Inclusive Value: Valuation of Saginaw Bay Coastal Marsh John Whitehead and Pete Groothuis, Appalachian State University
	2:30 p.m. – 2:45 p.m.	Discussant: Jamal Kadri, EPA, Office of Wetlands, Oceans, and Watersheds
	2:45 p.m. – 3:00 p.m.	Discussant: John Horowitz, University of Maryland
	3:00 p.m. – 3:30 p.m.	Questions and Discussion
3:30 p.m. – 3:45 p.m.	**Break**	
3:45 p.m. – 5:45 p.m.	**Session III: Invasive Species** Session Moderator: Maggie Miller, EPA, NCEE	
	3:45 p.m. – 4:15 p.m.	Models of Spatial and Intertemporal Invasive Species Management Brooks Kaiser, Gettysburg College, and Kimberly Burnett, University of Hawaii at Manoa
	4:15 p.m. – 4:45 p.m.	Policies for the Game of Global Marine Invasive Species Pollution Linda Fernandez, University of California at Riverside
	4:45 p.m. – 5:00 p.m.	Discussant: Marilyn Katz, EPA, Office of Wetlands, Oceans, and Watersheds
	5:00 p.m. – 5:15 p.m.	Discussant: Lars Olsen, University of Maryland
	5:15 p.m. – 5:45 p.m.	Questions and Discussion
5:45 p.m.	**Adjournment**	

April 24, 2007: Valuation for Environmental Policy

8:30 a.m. – 9:00 a.m.	**Registration**	
9:00 a.m. – 11:45 a.m.	**Session IV: Valuation of Ecological Effects** Session Moderator: William Wheeler, EPA, NCER	
	9:00 a.m. – 9:30 a.m.	Integrated Modeling and Ecological Valuation: Applications in the Semi Arid Southwest David Brookshire, University of New Mexico, Arriana Brand, Jennifer Thacher, Mark Dixon,Julie Stromberg, Kevin Lansey, David Goodrich, Molly McIntosh, Jake Gradny, Steve Stewart, Craig Broadbent and German Izon
	9:30 a.m. – 10:00 a.m.	Contingent Valuation Surveys to Monetize the Benefits of Risk Reductions Across Ecological and Developmental Endpoints Katherine von Stackelberg and James Hammitt, Harvard School of Public Health
10:00 a.m. – 10:15 a.m.	**Break**	
	10:15 a.m. – 10:45 a.m.	Valuing the Ecological Effects of Acidification: Mapping the Extent of Market and Extent of Resource in the Southern Appalachians Shalini Vajjhala, Anne Mische John, and David Evans, Resources for the Future
	10:45 a.m. – 11:00 a.m.	Discussant: Joel Corona, EPA, Office of Water
	11:00 a.m. – 11:15 a.m.	Discussant: David Simpson, Johns Hopkins University
	11:15 a.m. – 11:45 a.m.	Questions and Discussion
11:45 a.m. – 1:00 p.m.	**Lunch**	
1:00 p.m. – 4:15 p.m.	**Session V: Water Resources** Session Moderator: Adam Daigneault, EPA, NCEE	
	1:00 p.m. – 1:30 p.m.	Valuing Water Quality as a Function of Physical Measures Kevin Egan, Joe Herriges, John Downing, and Katherine Cling, Iowa State University
	1:30 p.m. – 2:00 p.m.	Cost-Effective Provision of Ecosystem Services from Riparian Buffer Zones Jo Albers, Oregon State University; David Simpson, Johns Hopkins University; and Steve Newbold, NCEE
2:00 p.m. – 2:15 p.m.	**Break**	
	2:15 p.m. – 2:45 p.m.	Development of Bioindicator-Based Stated Preference Valuation for Aquatic Resources Robert Johnston, Eric Shultz, Kathleen Segerson, Jessica Kukielka, Deepak Joglekar, University of Connecticut; and Elena Y. Besedin, Abt Associates

April 24, 2007 (continued)

	2:45 p.m. – 3:05 p.m.	Comparing Management Options and Valuing Environmental Improvements in a Recreational Fishery Steve Newbold and Matt Massey, NCEE
	3:05 p.m. – 3:20 p.m.	Discussant: Julie Hewitt, EPA, Office of Water
	3:20 p.m. – 3:35 p.m.	Discussant: George Parsons, University of Delaware
	3:35 p.m. – 4:05 p.m.	Questions and Discussions
4:05 p.m. – 4:15 p.m.	**Final Remarks**	
4:15 p.m.	**Adjournment**	

Models of Spatial and Intertemporal Invasive Species Management

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Brooks A. Kaiser, Gettysburg College and University of Hawaii, Manoa

Prepared for the NCEE
Valuation for Environmental Policy: Ecological Benefits Conference
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1. Introduction

Damages from invasive species are spatially and intertemporally variable. We define invasive species as those which have negative net benefits to society when introduced to an area in which they are non-native.[1] Valuation of these damages is often the first uncertain step in determining policy responses to invasive species problems.

As an invasive species spreads and increases in density across a landscape over time, the costs of locating and controlling it also change. Human intervention must therefore be spatially and temporally sensitive if it is to achieve the goal of minimizing net losses from the spread of invasive species. The three main, interdependent policy interventions are prevention, early detection and rapid response (EDRR), and control.

For clear guidance on optimal responses, all three policies require information on the likelihood of arrivals and establishment or re-establishment of an invasion, expected growth (spread), control costs, and expected damages. This is due to the recursive nature of the problem; spending large amounts of money to prevent a species that can be cheaply controlled at levels where it causes little actual damage if it establishes is a waste, while spending large amounts of money to control for a species that is likely to re-invade without integrated prevention decisions may also be a waste. Unfortunately, due in part to this recursivity but also due to the generally nonlinear nature of biological growth and spread, analytical solutions to a fully integrated, spatially and temporally explicit prevention and control problem even for a single species are generally intractable (see Smith et al. 2007, Burnett 2007).

Numerical solutions, with caveats and assumptions about transference of biological growth, expected costs, and damages from other locales, are possible for species with sufficient information about these parameters and the likelihood of invasion. A small but growing set of such case studies is evolving both in the economics and the ecological literatures, though few to date tackle both spatial and temporal issues together (Rejmanek and Richardson 1996, With 2002, Eiswerth and Johnson 2002, Burnett et al. 2006, Kaiser and Burnett 2007, Burnett et al. 2007). Certain locations encourage and facilitate analysis; the Hawaiian islands, the Cape of

[1] Many introductions are purposeful as they convey anticipated net benefits for those responsible for the introductions; in these cases there is the additional complication of unaligned incentives and distributional considerations in policy. We abstract from these considerations here, but mention them to highlight the fact that many of the consequences of invasive species are inflicted upon ecosystems (and their ecological benefits) rather than markets.

South Africa, Australia, and New Zealand, for example, all have fragile, isolated ecosystems where the rate of change in species introduction has rapidly increased with increased global integration over the past 400 (or fewer) years. These locations generate valuable benefits from biodiversity and are also, as they try to develop diversified global economies supporting growing populations and/or tourism, dependent on ecosystems for services like water quantity and quality, agricultural production, and aesthetics or other environmental factors that create a general satisfaction with life.

Due to the visible and significant threats these localities face, they are understandably at the forefront of efforts to manage invasive species problems. We focus on the Hawaiian Islands as a representation of the broader threat because in Hawaii the full problem, from establishment to eradication and back again, is writ large. We present three cases, described below, as analyzed independently in previous research, and draw comparisons and generalizations as possible from them.

First, we focus on measuring damages from an invasive species. This analysis does not inform policy decisions regarding prevention, EDRR, or control directly. Rather it demonstrates the first step in determining the expected damages. We examine the costs from frogs (*Eleutherodactylus coqui*) on the Big Island in Hawaii in terms of noise pollution effects on property values (Kaiser and Burnett 2006). We recap it and add it to the discussion here because it captures an essential consideration for ecosystem valuation and the threat from invasive species. In the words of Joni Mitchell: "you don't know what you've got till it's gone." The ability to value the anticipated losses from the frog depends on the losses that have already occurred due to the early stages of the invasion.

Second, we investigate optimal EDRR of a species with a possible, currently undetected, presence, the brown treesnake (*Boiga irregularis*) (Kaiser and Burnett 2007). Significant economic and ecological damages are anticipated from the snake's presence in Hawaii. The snake threatens some of the same ecosystem benefits as the tree (biodiversity) as well as the power supply and human health. Several specimens have been intercepted between Guam and Hawaii in the past 20 years, and it is possible that others have gone undetected. The appropriate policy tool in this case, EDRR, is explicitly spatial, as the searches, and their costs, are location specific.

Third, we investigate optimal control of a species with a limited presence already, the shrubby tree miconia (*Miconia calvescens*) (Burnett et al. 2007). Significant ecological damages are anticipated from the continued spread of the tree. Some of these damages have market connections, in particular ground water quantity, while others do not, in particular biodiversity.

From these three cases, we cull findings on the sensitivity of policy decisions to the parameters of import outlined above, namely arrivals, biological growth, control costs, and damages.

2. Case Studies

2.1 Coqui Frogs

Eleutherodactylus coqui, a small frog native to Puerto Rico, was introduced to Hawaii in the late 1980s, presumably as a hitchhiker on plant material from the Caribbean or Florida.. The frogs are present on the four main islands of Kauai, Oahu, Maui, and the island of Hawaii, although the populations are limited to specific areas on each island.

The primary economic effect of the frog is noise pollution. The combined lack of predation and competition for resources has resulted in densities reaching 55,000 frogs per hectare,[2] more than double the highest densities in the frog's native Puerto Rico (Beard and Pitt 2005). The males' calls, which are individually between 80-90 dBA at 0.5 m, now extend from an hour before sunset until dawn. The Hawaii Department of Health sets the threshold for minimizing impacts to human health and welfare at only 70 dBA (Department of Health, Hawaii Revised Statutes Section 324F-1). We concentrate on elucidating these damages through changes in property values. Economic theory suggests that property values for locations with noise pollution should be lower than comparable properties without. Since the frog's calls reach approximately 500 to 800 meters, we investigate whether properties within this range of a registered coqui complaint trade at lower prices than those beyond that perimeter.

We use a standard hedonic pricing model to evaluate the effect of registered coqui complaints on property values. Using this theory and a of real estate transactions from 1995 to 2005 for Hawaii county, we consider that individuals buy and sell properties as bundles of characteristics: here, the relevant characteristics for the properties are proximity of frog complaints, district, acreage, year of transaction, presence of housing structures, broad zoning class, and finely gradated neighborhoods as defined by the tax authority.[3] Our reduced form price function is:

$$P_i = f(D_i, F5_i, F8_i, A_i, M_t, L_i, Y_i, Z_i, N_i), \tag{1}$$

Where Pi = natural log of sales price of transaction i,

- D_i = district (Puna, South Hilo, North Hilo, Hamakua, North Kohala, South Kohala, North Kona, South Kona, Kau),
- $F5_i$ = indicator variable for frog complaint within 500 m previous to sale,
- $F8_i$ = indicator variable for frog complaint between 500-800 m previous to sale,
- A_i= natural log of acres for property *i*,
- M_t = natural log of average mortgage rate for month of transaction,
- L_i = indicator variable for housing structures on property,

[2] Densities of up to 133,000 per ha have been recorded on the island of Hawaii.

[3] Ideally, we would wish to include housing stock to control for effects of changes in supply. Unfortunately, this data is not available. The best we can do is use this time trend to broadly capture such differences. The neighborhood variables also help control for supply shifts, however these cannot be isolated as instruments so a two-stage estimation procedure is not possible.

Y_i = year of transaction,
Z_i = zoning class (agriculture, apartment, unimproved residential, improved residential, conservation, industrial, resort, commercial)
N_i = tax assessor's neighborhood classification (1736 groupings).

We have data from the Hawaii County Tax Assessor's office on 50,033 real estate transactions and properties from 1995-2005, shown in Figure 1. We omit unvalidated sales and sales that fall within the lowest 1% or highest 1% of prices to eliminate outliers and pricing irregularities. This results in 37,228 properties, each of which changes hands between 1 and 6 times (average 1.2 times), for a total of 46,405 transactions.

Table 1. District Level Summary Statistics

District	Number of transactions	Mean Transaction Price ($) (standard error)	Mean fraction of properties within 500m of frog complaints (standard error)
Puna	20,914	25,912 (40,177)	0.17 (0.38)
South Hilo	4,163	99,130 (81,389)	0.37 (0.48)
North Hilo	412	128,321 (110,007)	0.00 (0)
Hamakua	683	123,091 (109,196)	0.02 (0.13)
North Kohala	1,452	179,028 (153,884)	0.01 (0.09)
South Kohala	4,595	197,095 (176,779)	0.21 (0.41)
North Kona	7,871	187,438 (150,954)	0.33 (0.47)
South Kona	1,427	124,315 (154,234)	0.14 (0.35)
Kau	5,049	23,362 (43,874)	0.00 (0.04)

We expect that frog complaints cause a greater reduction in property values the closer they are. Currently, we have frog complaints reported to USDA/APHIS or the Big Island Invasive Species Committee (BIISC) from 1997-2001. We use geographical information systems (GIS) software (ArcView) to match the verified frog complaints to property transactions, and generate indicator variables for whether a property is within 500m of a previous complaint and whether it is within 800m of a previous complaint. We then generate an indicator variable for whether a property is between 500-800m of a previous complaint. Incentives of both buyers and sellers are such that properties with frogs should trade at prices lower than properties without frogs, and our reduced form estimates include loss in value to sellers as well as the lower willingness to pay of buyers.

The remaining variables control for other characteristics of properties affecting their value, and more detailed discussion can be found in Kaiser and Burnett (2006).

Table 2 shows the results for the regression including all of the districts (neighborhood controls not reported). Note that Puna is the omitted district and agriculture is the omitted zoning, so that the interpretation of the dummy variables is relative to the constant term representing Puna agricultural land transactions. Since we have transformed the continuous variables into logs, the results of our analysis will estimate elasticities. Thus, a one percent change in acreage, for example, will generate an estimated percent change in price indicated by the coefficient in column 2, Table 2, or 0.43 percent.

Table 2. Regression Results (dependent variable: Log Price)

Variable	Coefficient	Standard error	P-value
Frog500m	-0.16	0.01	0.00
Frog800m	-0.12	0.01	0.00
Log Acres	0.43	0.02	0.00
S_hilo_acres	-0.12	0.04	0.00
N_Hilo_acres	-0.15	0.07	0.03
Hamakua_acres	-0.06	0.04	0.09
N_Kohala_acres	-0.08	0.03	0.01
S_Kohala_acres	-0.24	0.03	0.00
N_Kona_acres	-0.26	0.03	0.00
S_Kona_acres	-0.31	0.05	0.00
Kau_acres	0.17	0.07	0.02
Log mortgate rate	-0.45	0.04	0.00
Residential structure	1.27	0.01	0.00
Year of sale	0.07	0.00	0.00
Improved Residential	0.23	0.14	0.10
Apartment	0.31	0.17	0.07
Commercial	0.14	0.26	0.58
Industrial	1.98	0.17	0.00
Conservation	-0.19	0.20	0.34
Resort	0.32	0.19	0.09
Unimproved Residential	0.53	0.33	0.11
Constant	-139.57	4.51	0.00

From the table, we see that most variables have the expected sign and influence on price. Virtually all variables are significantly different than zero at the 99% level (P-value < 0.01) (Huber-White robust errors correcting for heteroskedasticity due to the wide variation across districts). The overall fit of the regression is quite good, with an R^2 of 0.86.

The net impacts are in general fairly small, with only the residential structure and industrial property indicators, in addition to some neighborhood indicators (not reported), generating impacts on price greater than 1%.

The presence of frogs, however, does have a significant negative impact on property values. For properties within 500 meters of a complaint, property values decline 0.16%, or about 1/3 as much as values decline from a 1% increase in mortgage rates (-0.45%). For properties within 800m but not within 500 meters, property values decline less severely, at 0.12%. This is about ¼ of the drop from a 1% increase in mortgage rates.

Thus we have an estimate of net marginal damages from the spatial spread of the frog as a function of the properties in an invaded location. We could use this estimate, with additional estimates of damages to the floriculture industry, in conjunction with estimates of the cost of spread and the costs of capture to generate control policies for the frog. Misaligned incentives and missing information hinder this analysis, however. The floriculture industry, for example, is reluctant to share information on the frog's effects on their business.[4] The spread of the frog has been much faster and at a higher density than its behavior in its native range would suggest and so it has been underestimated over the last fifteen years. Early control techniques (e.g. spray caffeine) resulted in significant external costs to ecosystem health and had to be abandoned; new techniques (e.g. direct application of hydrated lime) are costly and not as effective. Hand capture is often possible for individual males because they can be located by their call, but female frogs do not call and also are believed to spend the days in the forest canopy, making them difficult control targets.

There is some risk that the frog is reducing native arthropod populations, but the science regarding the extent of this possibility remains unclear, as the frogs exhibit quite generalist eating behavior. While some might argue that the damages from the frog are not communal and that the frog should be treated like any household pest, left to the individual owners to treat or not treat, large source populations exist on public land. Control of these populations as well as prevention of the spread of the frog to new areas is clearly within the scope of public policy. The rule of thumb for such invasions has generally been that the quicker one acts the lower the overall costs. We examine this belief by examining the cases of miconia and the Brown treesnake, below.

2.2 Brown Treesnake

In this section, we address EDRR as an explicitly spatial policy instrument using the case study of the Brown treesnake on the island of Oahu, Hawaii. The brown treesnake is another well known potential invader of Hawaii and much effort has been expended to study the potential effects of an invasion to Hawaii. (Savidge 1987, Fritts et al. 1987, 1990, 1994, Burnett et al, 2006, Burnett, 2007, Burnett et al, 2007). There have been eight brown treesnakes captured at the ports on the island of Oahu and hundreds of other sightings reported throughout the island. EDRR technology has been developed in the form of specially trained teams based throughout the Pacific who are immediately deployed following a credible sighting of a Brown treesnake on Oahu or on other at-risk islands. Two such deployments have occurred in Hawaii in the last two years, one on the island of Maui and the other on Oahu, although neither effort produced a snake.

Using Geographical Information Systems (GIS) software, we analyze spatially-explicit EDRR policies given the reality that prevention of the snake's entry may already have failed or will eventually fail at least one of the most likely entry points, regardless of budget (Burnett et al. 2006, Olson and Roy 2005). EDRR policies comprise of search and destroy activities that occur beyond incoming crafts at points of entry (prevention) to target removal of uncertain but likely specimens throughout the potential habitat range that have evaded detection. Intertemporal and spatial differences in policies are compared given varying assumptions about planning and management horizons and the arrival of the snake.

[4] The frog is transported in nursery stock and the risk of its presence lowers willingness to pay and the costs of selling un-infested plants, because they do not want to admit the presence of the frog and incur these losses.

We divide Oahu into a grid, but we use a finer subdivision for the case of the snake and each grid cell measures only 4 ha each. The choice of grid cell has potentially large effects that we discuss in section 3. Each cell is assigned initial properties that include currently existent data on likelihood of snake presence (distance from points of entry, proximity to roads[5]), resource assets at risk (bird habitat, presence of power transmission lines, human population density) and accessibility of treatment (proximity of roads and trails, slope, and land ownership).

From these initial conditions, we estimate expected snake populations for each cell across a thirty year period based on the likelihood of the presence of snakes, the expected marginal damages (per snake) as a function of the resources at risk and the marginal costs (per 4 ha area) as a function of accessibility and terrain.

Using this information, we build a spatial-intertemporal model that minimizes the expected net damages from the brown treesnake on Oahu. Since treatment decisions are EDRR search decisions, the unit of decision is the spatial cell rather than the snake population directly. Net expected damages are calculated for each cell by assuming that treatment clears an area of snakes for that time period, so that population-based damages are avoided.

The theoretical model is formalized as:

$$\min_{x_{it}} \sum_i \sum_{t=0}^{T} \beta^t \left(d_i \left(n_{it} \left(x_{it}, \sum_i x_{it} \right) \right) + C_i(x_{it}) \right) \tag{2}$$

$$n_{it} = n(r,t,x) = \frac{\sum_i x_{i,t-1}}{I} g(n_{t-1}, r) * (1 - x_{it}) \tag{3}$$

$$\sum_i C_{it} \le A_t \tag{4}$$

Where d_i is the expected damage for cell i, n_{it} is the population of the cell at time t as a function of own-cell (x_{it}) and other-cell (x_{jt}) EDRR treatments, C_i is the cost of EDRR for cell i, I is the total number of cells, g is the biological growth function which depends spatially on the distance from the expected start of the invasive population, β represents the discount factor, and A_t represents a temporally constrained appropriations budget for EDRR.

[5] We have more specific information about habitat than distance from points of entry, but after extended discussions with several Brown treesnake scientists it has become clear that the main limiting factor in Hawaii will be the availability of prey, for which we do not have specific densities. Fortunately for our analysis though unfortunately for avoiding the spread of the snake, the one point of agreement between all of the scientists on this matter is that they believe there exists sufficient prey base for snake expansion in all habitats present on Oahu for a population explosion comparable to the one on Guam after its arrival. Thus, since there exists no scientific evidence or theoretical model to credibly believe that forest habitat is more amenable than urban, for example, we accept that there will be abundant prey in every habitat and that differences for the snake will be minimal.

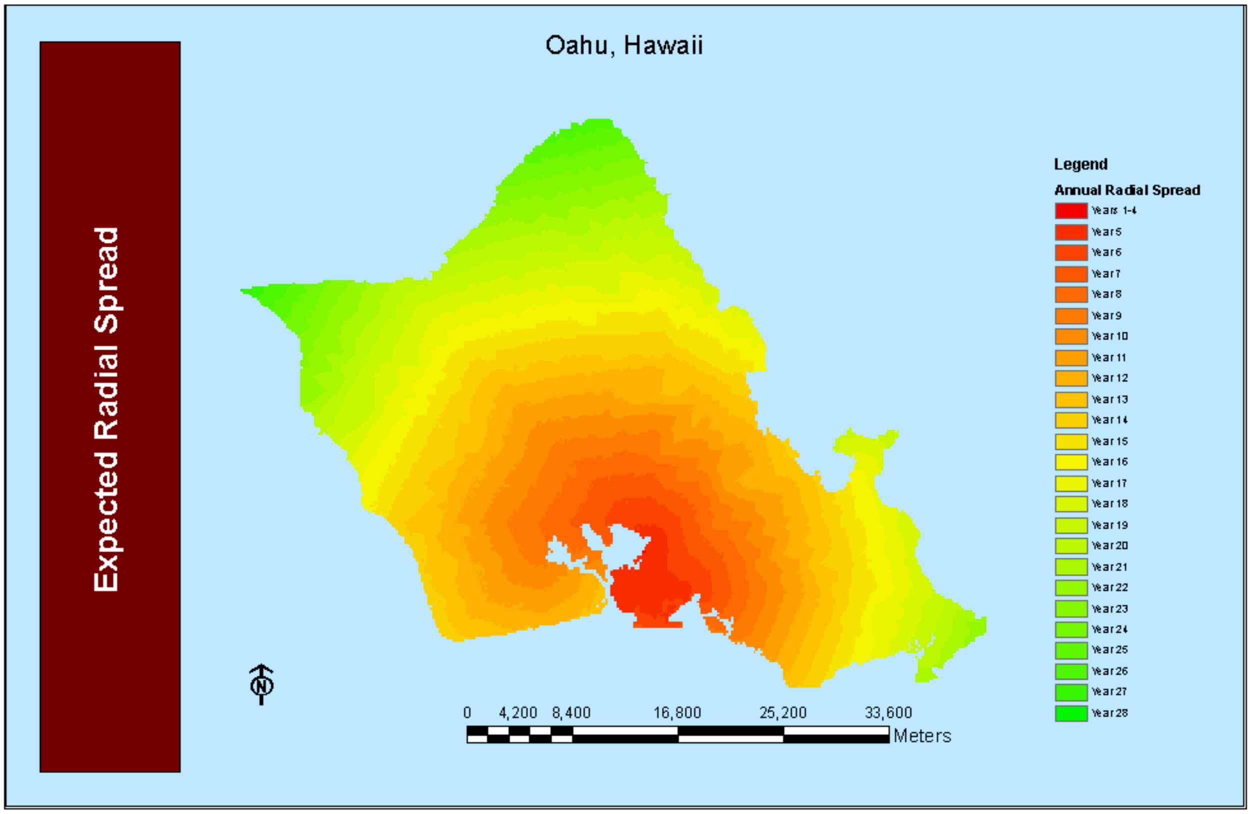
Spending C_i brings the population for period t to zero for an area, but invasion from other parts of the island, or anew from off-island, re-initiates growth in the next period. The larger the proportion of treated cells $\left(\frac{\sum_{i=1}^{I} x_{i,t-1}}{I} \right)$, the lower the rate of re-growth.

2.2.1 Snake Growth

The expansion path without intervention is based on the estimated expansion rate of 1.6 km/yr (Wiles et al. 2003) from the expected origins of the airport runways and Schofield facilities and the terrain through which the snakes must pass (Fig. 1d). Expected origins were weighted by capture experience on Oahu to date, with HNL being the most likely port of entry. Roads and trails are expected to provide the most rapid expansion paths (Timmins 2006); distance from roads and trails slows the radial spread.

Figure 1 illustrates the expected spread, with each change in color shade indicating another year's expansion of territory, from red to green. While there is a positive probability that the snake may appear in any cell at any time, the range is determined by the expected presence of at least one full snake.

Figure 1: Expected annual snake expansion



Note: Expected entry at Honolulu Airport (HNL) or the adjacent Hickam Air Force Base Airport (3/4 weight), Barber's Point Air Station (1/8 weight) or Schofield Barracks (1/8 weight)

Using the diffusion rate of 1.067 km^2/yr (Shigesada and Kawasaki 1997: 51), the average radii calculated from those illustrated in Figure 1, and the following expansion model, based on Fisher and Skellam (Shigesada and Kawasaki 1997), we determine the expected snake population in a given cell at a given time period. We assume the population changes as a function of both diffusion and internal growth:

$$\dot{n} = D\left(\frac{\partial^2 n}{\partial x^2} + \frac{\partial^2 n}{\partial y^2}\right) + \left(b - \mu n\right)n \qquad (5)$$

Where $n(x,y,t)$ is population at time t in spatial coordinate (x,y) as measured from the original specimen's location, D is the diffusion rate, b is the intrinsic growth rate, $\mu \geq 0$ captures intraspecific competition, and x and y are spatial coordinates, and the radial distance, r, is determined by $r^2 = x^2 + y^2$. The first term captures the rate of spread, the second captures population growth within the given coordinates. We estimate from maximum densities experienced on Guam that the maximum snake carrying capacity in any cell (K) is 200 snakes.

Because there is no explicit solution to this non-linear problem, in order to create a tractable model that incorporates both spread and internal growth, we use the solution to the Skellam model for exponential growth and spread until the population of the cell reaches the point where it diverges significantly from a logistic growth function with a capacity of 200 snakes, which occurs at approximately 40 snakes. From that point, we use a logistic growth function to determine population in an area. We do not simply use the logistic function because it does not allow for radial spread to and from other cells.

Assuming an initial distribution where n_0 individuals invade the origin at t=0, we have untreated populations

$$n(r,t) = \frac{n_0}{4\pi Dt}\exp\left(bt - \frac{r^2}{4Dt}\right), \tag{6}$$

until $n(r,t) \geq 40$. After this point,

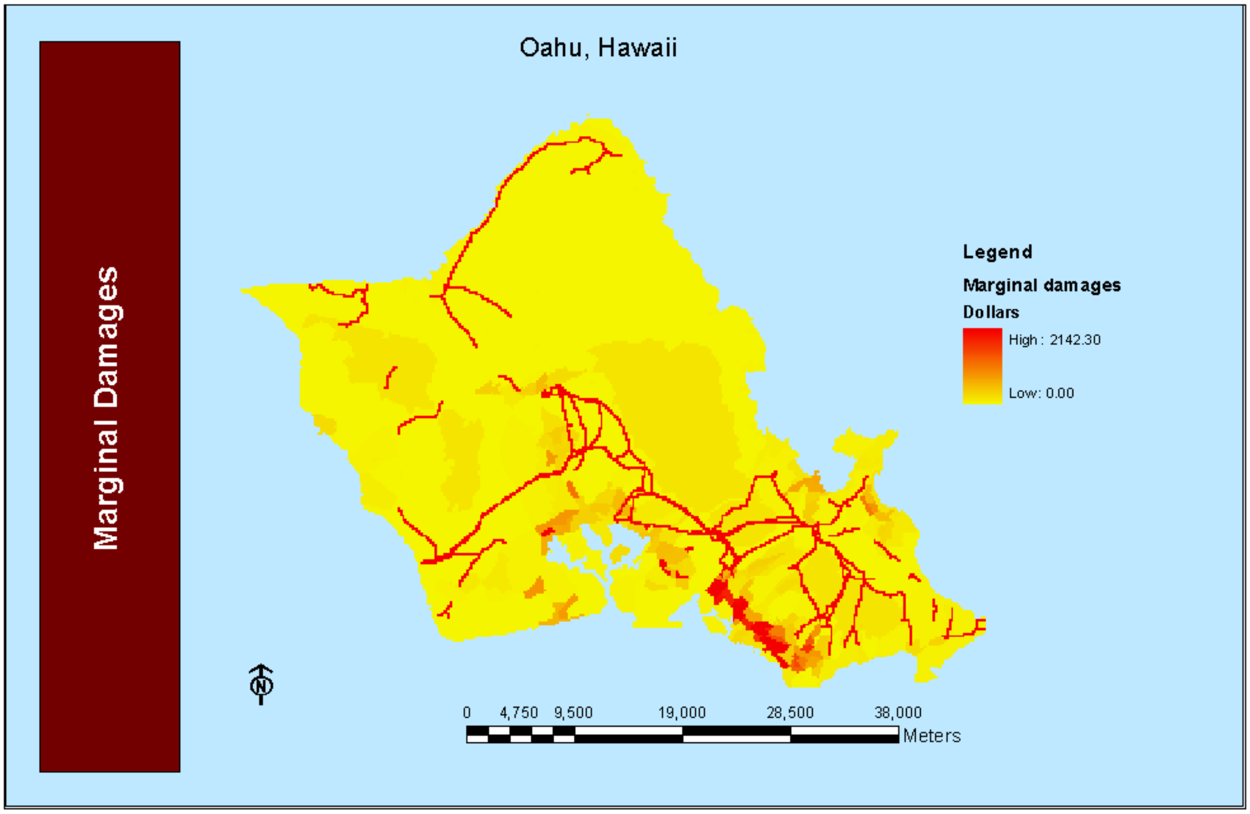
$$n(r,t) = n_r\left(\frac{Ke^{bt}}{K + n_r(e^{bt} - 1)}\right), \tag{7}$$

where n_r is the population (here, 40) when the growth function changes.

2.3.2 Damages

Figure 2 illustrates the range of damages across Oahu. Damages are calculated using a per snake linear coefficient that varies from a minimum of \$0 and a maximum of \$2143 (Fig. 2). Damages consist of three potential impacts: power outages, medical costs and human-snake interactions, and biodiversity losses. Details are available in Kaiser and Burnett 2007.

Figure 2: Total Damages



2.3.3 Snake Control Costs

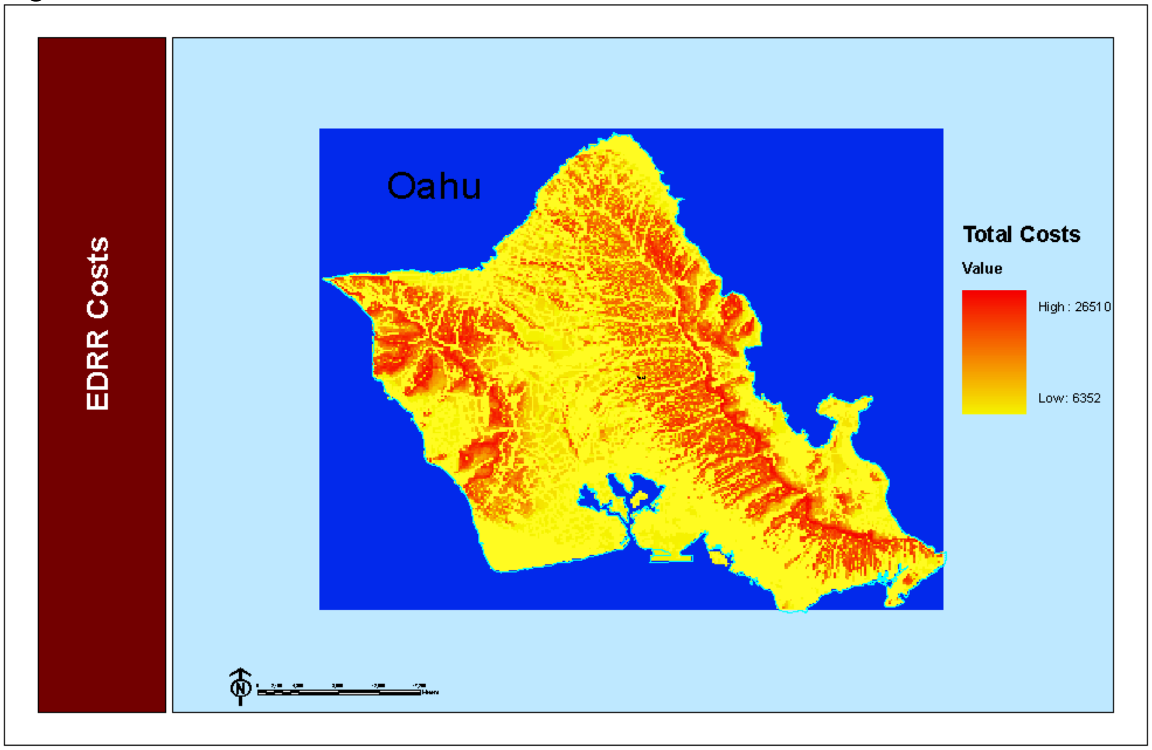
As discussed, a particular distinction between EDRR and other discussions of invasive species control is that with EDRR it is not known with certainty that there exists a population, while with control one generally assumes one can "harvest" a known population of the invasive species. Costs are therefore allocated spatially rather than as a function of population.

We describe EDRR treatment as consisting of preventative search, trapping and hand-removal (the only way to currently remove snakes too small to be trapped). Costs vary with terrain. Records on the costs of clearing an enclosed 5 ha plot on Guam (Rodda, personal communication) provide a least cost estimate of removing snakes from an area. Costs are scaled up from this base cost of \$6,352 per 4 ha cell to account for slope of the terrain and distance from a road. The steeper the grade, the more energy required to search the area. Since the cost of searching is a labor cost, we use a model of the American College of Sports Medicine to translate grade into energy expenditure, and then increase costs proportionally to the increase in effort. The energy expenditure rate (EER) is estimated to be:

$$EER = 0.1v + 1.8v \cdot a + 3.5 \tag{8}$$

Where v is the speed of walking and a is the percent grade (Sabatini et al. 2004). We assume a constant slow rate of walking at 0.5 km/hour to accommodate searching (Rodda, personal communication, Lardner, personal communication). Average slope for each cell is calculated from hillshade projections of Oahu in ArcGIS 9.1. Figure 3 illustrates total costs.

Figure 3: Snake Control Costs



For each cell, we first calculate the energy expenditure rate, EER. We then generate an energy expenditure ratio where we divide the cell's EER by the EER when the slope is zero, which provides an estimate of how much more difficult clearing the cell is than clearing the 5 ha test plot (which was on level ground) cost. This ratio is therefore multiplied by the base cost of $6352.[6]

Costs also increase with the distance of the cell needing treatment from accessible roads. We use analogous methodology to determine distance costs from roads by using ArcView Spatial Analyst to calculate the least cost distance path. First, based on the EER from the nearest road to the cell, we determine the least cost EER path from the nearest road to the cell. Then we create a ratio of this distance cost to the linear distance from the road. We then multiply this ratio by the labor cost of reaching the cell, estimated at $60 per unit. The maximum access cost is approximately $3420, while the average is approximately $540. The total cell cost is then the sum of the in-cell treatment cost and the distance (access) cost.[7]

[6] The maximum cost for thoroughly searching a cell for EDRR purposes using this formula is approximately $27,500, while the average cost is $11,700.

[7] Note this does not allow for treatment in multiple adjacent cells at discounted distance cost. However, since this method also assumes only one treatment time necessary (rather than repeated nights of search) the net effect is unclear. We leave this for later modeling. We also delay modeling of any external cost to accessing private land. One possibility is to assume that gaining access to private land and/or convincing private landowners to engage in search activities themselves is one of the main purposes of awareness campaigns, and that expenditures targeting awareness of a species can be considered additional costs of treating private land. In the case of the Brown treesnake in Oahu, this amounts to only about $3 per cell of private land, thus we have ignored this cost for now.

2.3.4 Snake Results

Currently, no known snake populations exist on Oahu, but there is general agreement amongst the scientific community that there may be between 0 and 100. We begin our analysis with $n_0=1$.[8] Thus, our initial application is for search only. Current search on Oahu occurs only after a suspected sighting, while all other funds are expended on Guam and are targeted at preventing snake arrival at defined points of entry. Previous research (Burnett et al. 2006) indicates that this may actually focus too much on the points of entry if snakes have already evaded detection there. Our results concur.

We calculate the spatial-temporal treatment schedule that minimizes the overall net damages and costs in present value terms for a thirty year period.

We find a present value of expected damages of $371 million accumulated over 30 years from an initial invasion of a single snake at one of three possible entry locations with no EDRR action. We start the optimization with treatments indicated for all cells when and where the current year damages exceed the current year costs, treatment of which will certainly reduce the social welfare losses. We then test whether treating these cells or neighboring cells before the damages exceed the current year costs reduces the present value of net damages by reducing the future populations and their damages. We find that under our parameters for the discount rate, growth, costs and damages, it does not.

We find that treatment reduces social welfare losses to $101 million dollars. Over the thirty year period, we find the need to treat just over 3000 cells, or 8% of the island. The treatment plan also delays any search until the 12th year after an invasion. This result is driven by the interplay between the discount rate and the growth function; the chances of finding snakes when they are spreading out across the potential habitat and are at low densities, and causing low damages, mean that waiting discounts the costs more than the growth in the damages.

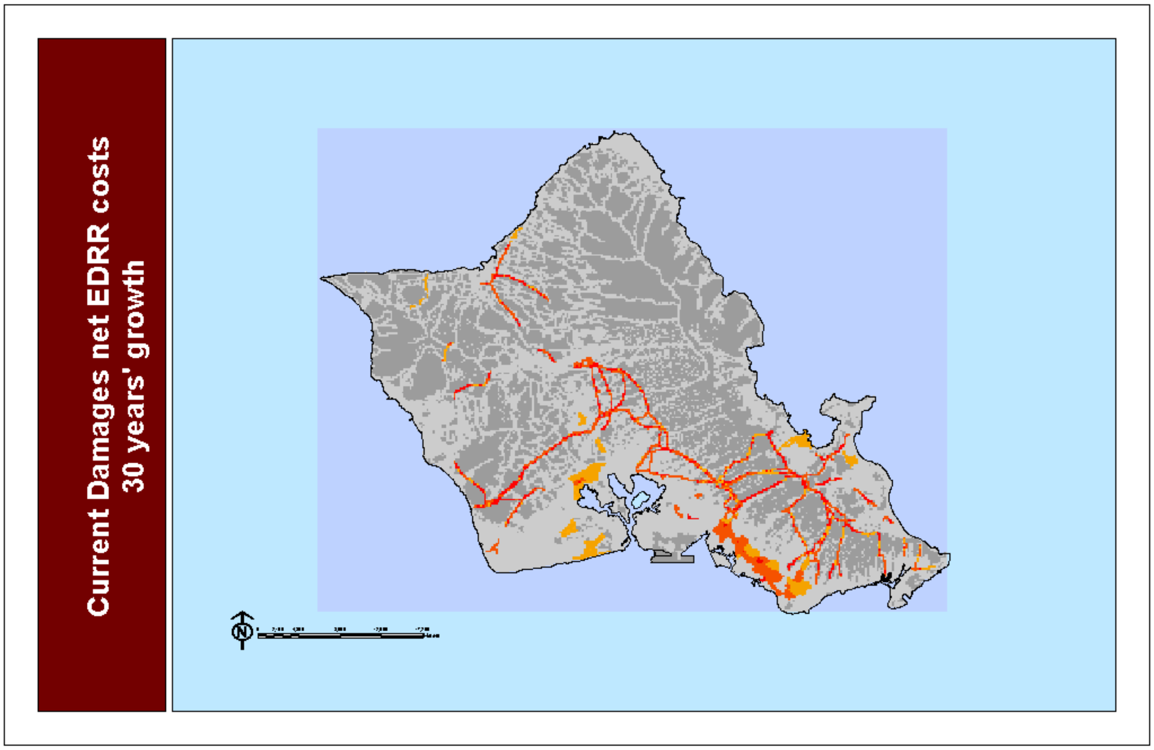
The hazard rate (the probability of arrival during the intervals between arrivals) should affect these results in two ways. We have used a thirty year time frame in part because this is the time, given the growth parameters, that it should take for the entire island to have snake populations. In this time frame, damages have just grown to exceed the present value of costs for an entire-island sweep (which occurs in year 28, see section 3), which suggests that is the appropriate time to switch from an EDRR policy to a control policy, where removal of the snake population is undertaken directly.

Figure 4 shows a snapshot of the net current damages (i.e. only the damages in that year) that would occur if all cells were treated in the last year of invasion. In a significant majority of cells, the current damages are below the current EDRR costs (shown in grayscale), and intervention cannot be justified on the basis of current damages alone. The area for which damages do exceed costs (shown increasingly from orange to red), so that EDRR treatment is cost-effective

[8] Mitochondrial DNA evidence suggests that the entire population of snakes on Guam may have originated from a single female.

in this single period, are obviously also the areas where optimal EDRR should be targeted. One can see that these cells integrate damages, costs, and the biological spread in such a way that EDRR treatment, when there is only funding for sporadic and incomplete treatment, should focus on not just the areas closest to the most likely point of entry (HNL airport) but also along roadways with major power lines adjacent and in locations where human-snake interactions would be high (the orange areas along the southeastern coast in Figure 4 are the densely populated Honolulu and Waikiki areas).[9]

Figure 4: Current net damages across first 30 years of invasion



If opportunities for effective EDRR are missed, the snake population will need to be managed as an existing invader, where the marginal costs of the population of an area are weighed against the marginal benefits. We examine the current case of Miconia calvescens to illustrate the different policy implications.

2.3 Miconia calvescens

One well known significant threat to Hawaii's forest ecosystems comes in the form of the woody shrub, *Miconia calvescens*. A member of the Melastomataceae family from Central America, the plant was purposefully introduced to Hawaii. Starting in a handful of back yards and arboretums four decades ago, it has been spreading with increasing rapidity on the islands of Maui and Hawaii. It is also present on Kauai and Oahu, though it has not yet claimed significant acreage in either location. Miconia is not thought to be present on the island of Molokai. The length of

[9] In spite of the level of urbanization, scientists assure us there is plenty of prey available, and as the snake is nocturnal and reclusive snake, it is likely to do well in an urban environment with many places to hide.

time from the initial invasion and the considerable efforts that have been expended in controlling and surveilling for the tree's expansion over the last two decades mean that there is sufficient data to generate estimates of growth and control costs. Extracting this data from the resource managers and processing it into a useable form is a challenge we discuss at greater length in section 3.

When considering optimal management of Miconia, two spatial considerations matter. First, the likelihood and magnitude of the invasion (as measured by population growth over time) will vary spatially according to the current population and dynamics of growth. Second, the natural capital assets may be unevenly distributed across space.

We use Geographical Information Systems (GIS) to map the current and future populations of miconia on the island of Oahu, Hawaii, and the potential damages to water quantity, water quality, endangered bird habitat, and native habitat housing endangered plants, snails, and insects. We develop a control cost function that includes locating and treating miconia plants. Using optimal control theory, we find the spatially dependent optimal population levels of miconia and the paths to these populations over time.

We define our problem so that we minimize the expected costs and damages from the presence of and control activities undertaken against the invading species. In an advance over the current literature, we allow costs and damages to vary spatially as well as temporally. Thus the objective function is:

$$\underset{x_{it}}{Max} \int_0^\infty -e^{-rt} \sum_i \left(\int_0^x c(n_{it}) d\gamma + D(n_{it}) \right) dt \tag{9}$$

subject to:

$$\dot{n}_i = g(n_i, n) - x_i \tag{10}$$

$$0 \le x_{it} \le n_{it} \tag{11}$$

$$n_0 = n(0), \tag{12}$$

where *i* denotes the spatial location (grid cell), *t* represents the time period, n_{it} and $\dot{n}_{it}$ are the population of the invasive species in a given location and its associated time derivative, n_t is the total population at *t*, $g(n_{it}, n_t)$ the growth function of the invasive, x_{it} represents the number of removals, $c(n_{it})$ the marginal cost function for removals, which varies with population level, and $D(n_{it})$ the damages incurred at population n_{it}. In the following, we drop the time subscripts for ease of notation.

Defining the current value Hamiltonian for each location as:

$$H_i = -\int_0^{x_i} c(n_i)d\gamma - D(n_i) + \lambda_i[g(n,n_i) - x_i]\,. \tag{13}$$

Applying the Maximum principle and rearranging the subsequent first order conditions, we find

$$D'(n_i) = rc(n_i) - c(n_i)g'(n,n_i) - c'(n_i)g(n,n_i) \tag{14}$$

In this way, we see that at an optimal population, the marginal damages should be equated with the costs of maintaining that population for the location. Were marginal damages to be higher (lower), additional (fewer) trees could be removed, reducing the overall losses. Areas with higher marginal damages, then, will have more trees removed.

We divide Oahu into 16 ha plots, or cells, to analyze the optimal management of miconia for the island over space and time. Each cell contains information on habitat quality and the current presence of the invading plant. We assume that the current invasion has already been underway for 37 years, and was initiated by purposeful individual plantings.

2.3.1 Miconia Growth

Invasive species managers on the heavily invaded island of Hawaii estimate that the densest areas contain approximately 100 trees per acre. Our spatial cells are 16 hectares each. Carrying capacity per cell is thus 3,952 trees.

For population, we use the same functional form expressed for brown treesnake in equations (6) and (7). In the case of the tree, however, the transition between the exponential growth and spread and internal logistic growth occurs at 20 trees in a cell with a maximum snake carrying capacity in any cell (*K*) of 3,952 trees. Further details are available in Burnett et al. 2007.

2.3.2 Miconia Damages

We estimate damages from Miconia as evolving from indirect ecosystem services as well as non-market goods like biodiversity. Particularly significant threats are a reduction in habitat for endangered species and a shift in the hydrological cycle that may reduce freshwater recharge and increase runoff and sedimentation. Details of the damage estimates are available in Burnett et al. 2007. In short, marginal damages for any given location will be calculated according to:

$$d_{it} = d_{bird\ habitat\ or\ range} + d_{water} + d_{native\ habitat}\,. \tag{15}$$

Because not all locations will have all of these characteristics and because water damages will vary by aquifer, marginal damages will vary spatially. We find that in our analysis marginal damages range from \$0.22 per tree to \$19.06 per tree. Marginal damages from bird habitat losses range from \$0.00 to \$6.34 per tree; damages from watershed losses range from \$0.22 to \$0.70 per tree; damages from native habitat losses range from \$0.00 to \$12.02 per tree.

2.3.3 Control Costs

The marginal cost of searching and treating *x* trees is:

$$c(n_i) = \left(\frac{\$39,520}{n_i^{1.6258}} + 13.39 \right) \qquad (16)$$

There are two separate activities that must occur – the trees must first be found, then treated, so that the cost function consists of two parts, the "search" component and the "treatment" component. While the unit cost of treating a tree with herbicide and/or cutting a tree may be constant across population levels, the cost of finding a tree is rapidly decreasing in population size.

We determine the two components for Oahu in the following manner. The search component involves a fixed cost which depends on the island's potential habitat acreage and which decreases with increased access to that habitat. Based on discussions with resource managers, searching one average acre for Miconia costs approximately \$1,000. The numerator of the search component for each spatial cell on Oahu is \$1,000 per potential acres, or \$39,520 per 16 ha cell.

The ability to search an island's habitat will also depend on several characteristics of the surrounding area, such as density of vegetation, the steepness of the terrain, etc. One major determinant is ease of access into the potential habitat. We use the combined length of roads and trails as a proxy for this variable. The length of roads and trails as compared to Molokai, the most expensive island to search because it has the fewest roads and trails per acre of habitat, is used to determine the exponent on population in the denominator of the search component. Higher values imply greater ease of access, which translate into lower search costs. Due to the number of well maintained roads and trails throughout Oahu's forests, Oahu has the highest search coefficient of all islands, at 1.6258. Additional details on the specification of the cost function are in Burnett et al. 2007.

2.2.4 Miconia Results

If left untreated, the damages from miconia will grow at an increasing rate into the foreseeable future. Unchecked damages over the next 40 years have a present value of approximately \$627 million dollars using a 3% discount rate.[10] This is the cost of doing nothing.

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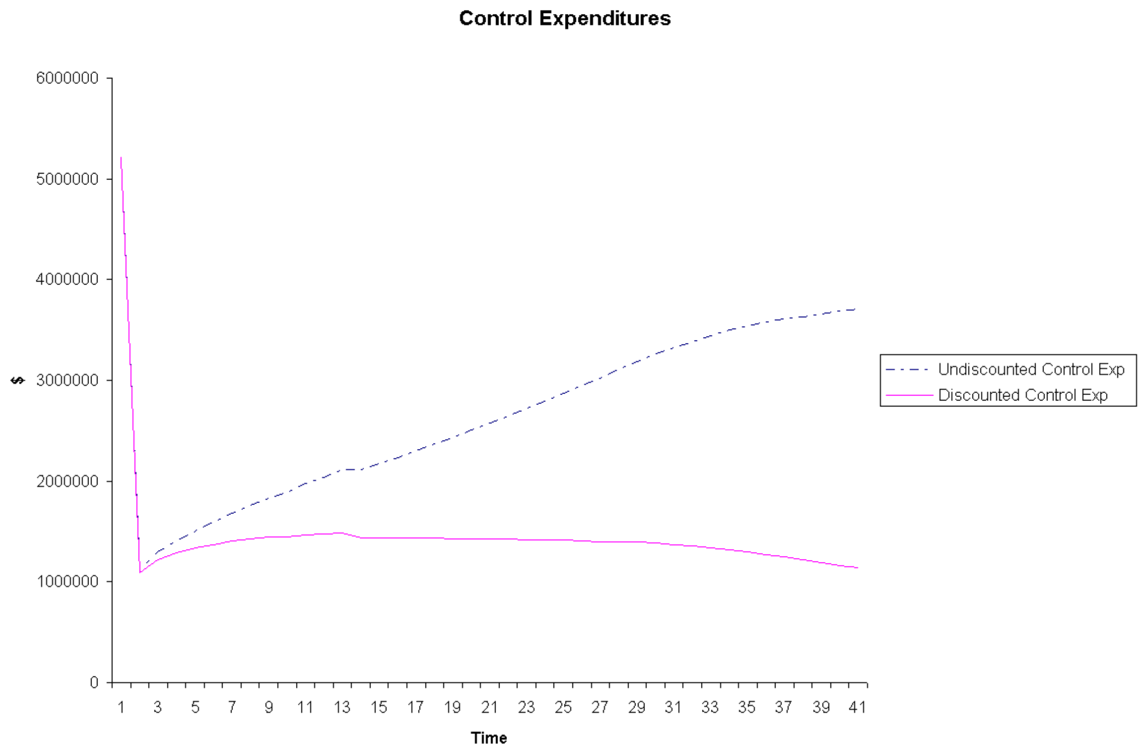
[10] Under our parameterization of the spread, it will take approximately 80 more years for miconia to blanket its potential habitat on Oahu in the way that it now covers Tahiti. In part because planning horizons are short and in part because new treatment technologies are likely to evolve in the long run that will change control costs, we focus on the more immediate future and investigate the benefits of management over a forty year time horizon. In particular, remote sensing technology already can identify large stands of Miconia, and improvement in this technology may allow for quick identification of smaller Miconia populations. Additionally, since the loss of an endangered species is irreversible and the demand for groundwater is likely to change over time as well, damages may not be constant over the long run either.

Using the parameterization described above, we solve for the optimal populations in each spatial location over time. We find that 9616 ha need immediate treatment at an expected cost of $5.21 million dollars. This should be followed by spending that keeps the population in each location cell somewhere between 43 and 705 trees per 16 ha plot. Over 40 years, this cost will increase from $1.12 million per year to $3.71 million per year. The total present value of control costs from now until 40 years into the future should be $54.5 million, using a 3% discount rate.

Figure 5: Miconia control costs over time



As shown in Figure 5, the initial large immediate outlay of $5.21 million should be followed by continuous control expenditures. Note that while these expenditures are increasing in current dollars, after year 12 they are decreasing in present value. We therefore emphasize that long run planning is essential to optimal management; it will become increasingly difficult to find new funds for management, so that setting aside funds for future management so that they can keep pace with the discount rate will be helpful to achieving optimal management goals.

Figure 6: Optimal control vs. no control over time

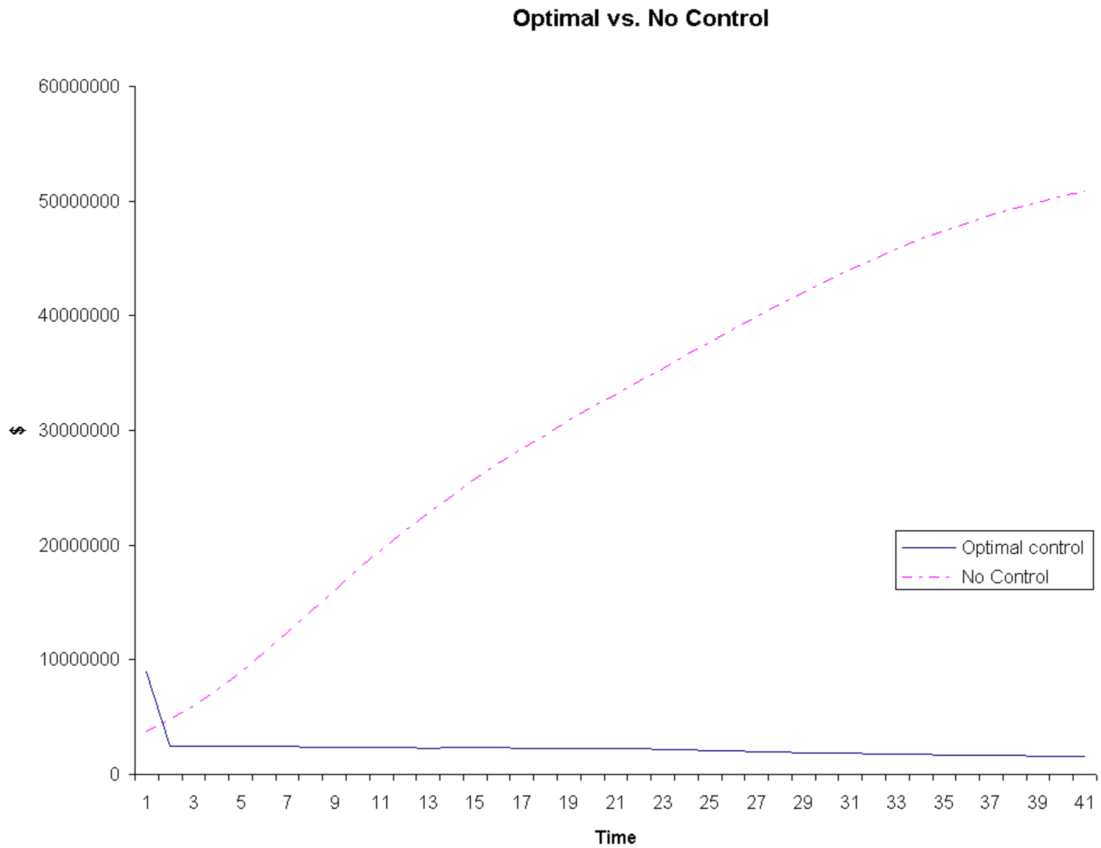


Figure 6 shows the comparison outcomes of no control, as measured by damages, to those of optimal control, as measured by damages from untreated trees plus the control costs for treated trees. We find that the returns to control grow in present value over time. In the first year of management, current expenditures and damages ($9.0 m) are more than current untreated damages ($3.8 m) by $5.2 million. By the second year, however, optimal management costs $2.2 million less than untreated outcomes and the benefit: cost ratio increases to just over 10:1 by year 40, with annual present value net benefits between $14 m - $17 m beginning in year 12. Net benefits over the forty year period from optimal control are $534 million.

3. Discussion

3.1 Parameter choices

3.1.1 Grid cell size

Grid cell size matters in determining optimal policy for several reasons. Foremost, because the cost of search exhibits economies of scale that are spatially dependent, the finer the gradation is, the flatter the marginal costs as a function of population will be. Flatter marginal costs tend to increase the optimal population level. In the case of miconia, we see that including finer gradation in the analysis significantly increases the population of trees. When we analyze the entire Hawaiian islands as one continuous habitat, the optimal population of trees is 31,295 (Burnett et al. 2006). When we subdivide the analysis by island, we see that the optimal population of trees for Oahu is 5495 and the optimal population for the state is 63,504 (Kaiser et al., 2007). Finally, when we subdivide Oahu into 16 ha plots, the optimal population for the island will eventually reach almost 1 million trees and seedlings (52 years from the present), though the population in each 16 ha plot will range from only 40 to 705 trees and seedlings. (Burnett et al., 2007).

Additional considerations include the availability of reliable GIS data at finer resolutions and the computational limitations of perhaps millions of choices across cells, even if the choices are binary. In the case of miconia, habitat cells could not be reliably determined at any smaller resolution. In addition, there was little benefit from smaller units of analysis because helicopter searches can cover several acres in one pass. In the case of the snake, search is time-consuming and only small areas can be searched in any one night. Since the island of Oahu is considered all potential snake habitat, the resolution did not affect this parameter. Finally, since treatment was a binary decision to search or not search, having over 1 million cells, though cumbersome, was not impossible with the application of constraints from theory. In the miconia case, while theory guides the population levels in the cells, the populations are continuous and the reduction in cell numbers dramatically increases the ability to solve the problem.

3.1.2 Growth

Both the internal growth parameters, here 0.3 for miconia and 0.6 for snakes, and the diffusion rates, here 0.208 km2 for miconia and 1.067 km2 for Brown treesnakes, are important factors in determining optimal policy. Combined with marginal damages, faster growth will increase the need for immediate treatment and increase the probability that delaying efforts will result in having to choose accommodation of the invasion over eradication or control at a small population. Faster growth will also lower marginal costs of treatment more quickly so that delay again is less beneficial.

Not only is delay more costly, inadequate control efforts are more wasteful. If control is applied at levels where growth continues to expand within a cell, the benefit of that control effort is lost to future damages. The faster the growth rate, the greater the penalty will be.

3.1.3. Costs

For most invasive species, detecting the species is a significant portion of costs, at least at low densities. The area for which search costs are defined, then, will affect the marginal costs as a function of population and the optimal population, as described above. When costs are determined spatially, however, this concern is alleviated. If the species is known to be present in an area, like miconia is, then it is inappropriate to apply costs spatially since it does not allow the optimal population to vary within the area. Optimal population may indeed vary as a function of damages, growth, and costs. If there is no known population, however, and if the optimal population were its presence detected was low or zero, as it is in the case of the brown treesnake (Burnett et al. 2006, Burnett 2007), then costs can be applied spatially. EDRR is a valuable and distinct management tool that needs greater analytical attention.

3.1.4 Damages

Though damages for ecological benefits are often very uncertain, in all of our cases we have at least one market good to which we can tie damages, providing lower bound estimates. Thus we need not fear that our damage estimates are too high and that accommodation of these invasive species is actually the optimal policy. We may need to be concerned with upper bounds, however. If damages are significantly underestimated, it may be that eradication is the optimal policy in spite of high search costs or the inability to prevent future entries. This inability to prevent future entries, however, requires prevention and possibly EDRR activities be considered in this optimal policy decision.

EDRR is again an appropriate policy for considering the range of damages that might matter. Under our parameterization, we find that spending on EDRR for the snake should occur when the present expected damages exceed the present costs. Thus if one fears that an endangered species is undervalued, for example, then cells in which the species is present may deserve more EDRR effort. The essential finding that management activities must simultaneously incorporate expected costs, damages, and growth does not change.

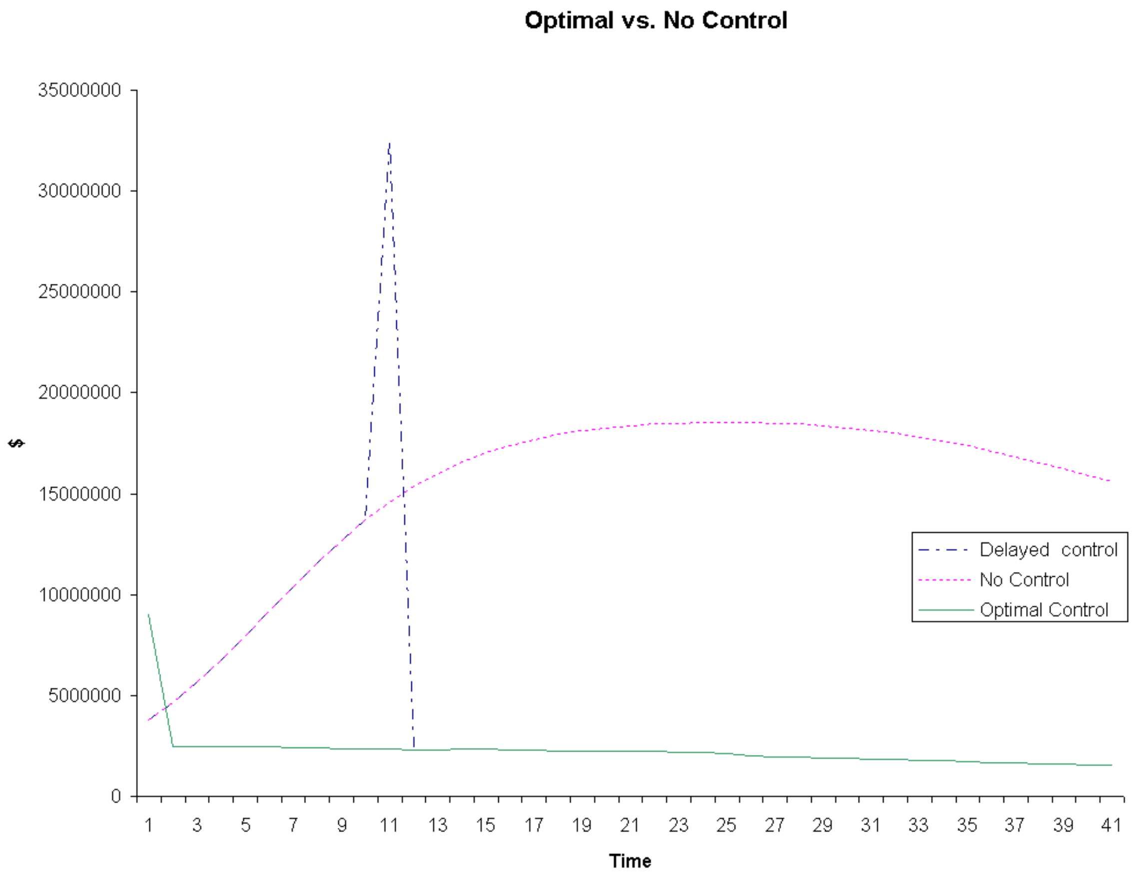
3.2 Temporal Application of Policy

3.2.1. Delays in Policy Initiation

The annual expenditures that maintain the optimal populations of miconia are, as figure 5 shows, around one to 1.5 million dollars. (Note that a steady state population is not reached in 40 years because the population of trees has not reached all habitat in that time.) Delaying the start of treatment will increase the need for current outlays when treatment does begin, as more trees will need to be removed. Figure 7 illustrates. In spite of the large returns that can be gained from delayed control, it is evident from figure three that there may well be a point at which it is too late, and accommodation should be favored over expensive removals and permanent control because the present value of uncontrolled net damages will be lower than that of controlled damages and costs.

The specific time at which this switch would occur, however, is a decreasing function of the discount rate and an increasing function the time horizon under consideration. An infinite time horizon is preferable to our current short term analysis, especially given the irreversible nature of many of the ecosystem benefits, and we do not seek to calculate this. In the case presented here, though net benefits of control fall from \$534 m to \$448 million, a loss of \$86 million over just ten years, it is still worthwhile to initiate delayed control.

Figure 7: Cost of Delayed Control



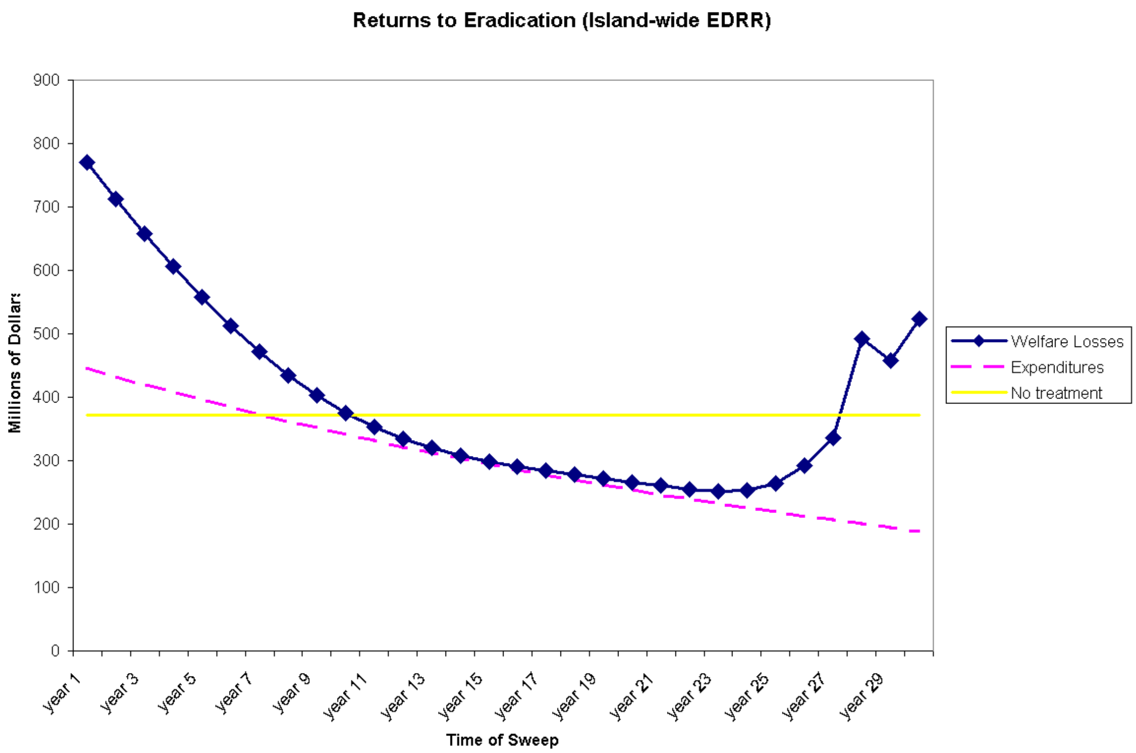
In the case of the snake, though delaying initial search until the 12th year after an invasion appears optimal, two caveats are offered that suggest additional benefits to earlier search. First, in an island-wide sweep, scientists may become confident that an early eradication is complete at a lower total cost than $447 million as they gain evidence from the search experience. Second, our damage function is not currently applicable to extension beyond thirty years because of the expected irreversible loss of the elepaio bird species. The 11 bird species extirpated on Guam were lost in fewer than 40 years, and a similar time frame for Hawaii can be expected. Thus if eradication efforts are deferred, the irreversible loss of the species imposes a dramatic threshold damage penalty and reduces the expected benefits of further action, which will then only serve to reduce human-snake interactions and electrical supply damages.

3.2.2 Application of inappropriate policy for the level of invasion

Eradication is almost always a stated goal for agencies charged with managing invasive species. The snake may be a case where eradication or at least low populations are optimal (Burnett et al. 2006, Burnett 2007). Under our specifications, a full island search would rid the island until the next arrival, therefore there may be some benefit, though not economically optimal, to periodic island-wide sweeps. We investigate the returns to island-wide sweeps at various stages to highlight these tradeoffs. The cost of a complete island search is estimated at just under $447 million. In the worst case scenario, if an island-wide search is conducted, and then another snake enters in the following year with no follow-up treatments, the total social welfare losses are $771 million, far more than never conducting the search.

However, if a single island-wide search is conducted between years 11 and 27, the net benefits of the search are positive, even with re-infestation the next year. Social savings range from $18 million to a peak of $120 million before they begin to fall again and become negative after year 27. This is due to the fact that the damages grow exponentially with the expansion of the snake, so that while the present value of the costs is constantly falling, the damages from the spread of the snake outpace the discounting of the future damages. Waiting until year 30, for example, will have total social losses of $523 million. Thus, the use of a lower discount rate might actually deter EDRR activities because the costs will appear higher for a longer period; using a 3% discount rate, the damages do not start to grow rather than decrease until year 16.[11] Figure 8 illustrates.

Figure 8: Returns to Eradication (Island-wide EDRR)



Extensive but random search, however, is likely to raise costs more than reduce damages, unless it is comprehensive (island-wide) and occurs between the 11th and 27th year of a successful invasion. Note then that early, incomplete search may work against long run efforts at snake prevention and control, since repeated failure to produce a snake may significantly reduce the public perception of the magnitude of the problem and their willingness to devote resources to it. When search is random but incomplete, the present value of social costs regularly lies between $450 and $750 million. Successful damage-minimizing EDRR activities target areas that have

[11] At year 15, even with exponential growth, no cell has more than 28 snakes, just over 10% of carrying capacity. This begins to change rapidly in years 15 to 30.

high expected net damages, either because they have a combination of high expected populations, high asset values, and low search costs. Small changes in treatment allocations that explicitly weigh expected damages, population growth, and treatment costs can dramatically improve random solutions. Thus, random or incomplete efforts may not be better than doing nothing, but strategic action can dramatically improve outcomes.

3.2.3 Changes in optimal policy when funds are uncertain

In the case of a potential invader like the brown treesnake, we determined that the optimal policy for EDRR is not to search until populations are high enough that there is a chance to find them at a reasonable cost, here in the 12th year of an invasion.

A likely restriction for managers, however, is the inability to plan for EDRR funds over a long period of time. We investigate what the optimal policy should be if funding can only be secured in 5 year increments. In this case, we find that at the end of the first 5 years, if there is uncertainty regarding future funding, one is best off treating a small number of cells with high net expected damages, reducing the overall expected cost by about $150 m to $227m. Treating a slightly larger group of high expected damage cells after another five years reduces damages to $142 m, while additional treatments at years 15 and 20 reduce the damages to $126 m. Compared to the periodic island-wide sweeps, this targeted EDRR activity is preferable, in spite of the fact there may still be snakes present. Furthermore, it suggests that taking decisive and targeted EDRR action, even though it may not be the optimal action, is more likely to reduce overall damages than to increase expenditures, especially when those expenditures are large.

4. Conclusions

Optimal management of invasive species will minimize total losses from invasion, including ecological damages, economic damages, and the costs of managing these invasions. The primary instruments for managing invasive species are prevention, early detection/rapid response, and control. Efficient management programs will vary across time and landscapes. In this paper we explore efficient spatial and intertemporal management for three invasive species in Hawaii, the coqui frog, miconia, and the brown treesnake.

We begin by considering economic damages from the coqui frog. We find that the presence of the frogs has a significant negative impact on property values. For properties within 500 meters of an official coqui complaint, property values decline 0.16%. While we do not explicitly model efficient management of the frog in this work, we produce an estimate of net marginal damages from the spatial spread of the frog as a function of the properties in an invaded location. In future work, this estimate will be used in conjunction with spread and capture cost estimates to generate optimal management policies for the frog.

For miconia, we find that optimal control entails treating immediately treating approximately 9,616 hectares on the island of Oahu, at an expected cost of $5.21 million. This should be followed by spending that keeps the population in each location cell between 43 and 705 trees per 16 ha plot, depending on the spatial location of each plot, across an eventual total of about 53,000 ha.

In the case of the potential invader, the brown treesnake, we find that the optimal management program entails EDRR on less than 10% of the island of Oahu over a thirty year period. While the cost of inaction is approximately $371 million, optimal treatment reduces social welfare losses to $101 million dollars. This analysis confirms that search and removal should be focused not only on likely areas of entry, but around potentially high damage areas as well. We further find that after approximately 30 years, the benefits of EDRR should begin to be supplemented by direct control.

We conclude by investigating the sensitivity of policy decisions to key model components. We find that results are sensitive to grid cell size, as this affects the steepness of the marginal cost function and the resolution at which other parameters can be applied. Rate of growth will also influence the optimal program. Faster growth will increase the need for immediate treatment and will lower marginal costs of treatment more quickly. Specification of growth will also be related to the adequacy of management levels. Inadequate control efforts are found to be wasteful. If control is applied at levels where growth continues to expand within a cell, the benefit of that control effort is lost to future damages. The faster the growth rate, the greater these losses will be.

Deliberation consideration of space in the model improved our understanding and ability to model costs of control and damages from miconia and the brown treesnake. Temporal insights were advanced from previous work as well. For miconia, despite the large returns that can be gained from delayed control, we find a point at which it is too late, and accommodation should be favored over expensive removals and permanent control. For the brown treesnake, it appears that delaying initial search until the 12th year after an invasion is preferred to initiating search immediately.

Current policy regimes often tout eradication as the most favorable management option. Under our parameterization, we are not able to find any case in which full eradication and maintenance of a zero population is optimal. We also find that random or incomplete efforts may not be better than doing nothing, although strategic, efficient action can obviously improve outcomes.

Finally, because the dedication of future funding to invasive species efforts is often unknown or extremely limited, we investigate optimal brown treesnake policy under funding that can only be secured in 5 year increments. In this case, we find that treating cells with the highest expected damage first will reduce total losses by the most. This is an important result for policymakers in Hawaii and the Pacific, as limited brown treesnake funds are currently focused on searching around likely points of entry, rather than around high-valued assets at risk.

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Economic Evaluation of Policies to Manage Aquatic Invasive Species

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1. Introduction

Ships transporting goods, people and services between different places represent a vector for spreading invasive species throughout the world's oceans (Hayes and Sliwa, 2003). Ships are mobile aquaria as species ranging from pathogens to fish hitchhike in ships' ballast water and attached to a ship's hulls as biofouling (Fofonoff et al., 2003). The main impacts of invasive species are negative impacts on human health and decreases in economic production activities based on marine environments and resources such as fisheries, aquaculture, tourism and marine infrastructure (Pimental et al., 2005).

Approximately 50% of shipping traffic to California takes place within 200 miles of the coastal mainland, primarily from vessel traffic between Mexico and Canada, two of California's largest trading partners through the North American Free Trade Agreement (NAFTA) (GAO, 2002). These vessels are not subject to any regulations for ballast water nor biofouling. Time and fuel considerations by shippers on the north-south route have not prevented the introduction of these species. For example, Levings et al. (2004) shows that ships traveling north from California and Mexico transport large numbers of invasive species into British Columbia, Canada. Therefore, current U.S. and Canadian policy to prevent the spread of marine invasive species in the Pacific coast of North America is inadequate.

New policies are needed to promote biosafety and address invasive species along coastlines on a multinational scale. In 2004 the International Maritime Organization (IMO) formulated a numerical limit guideline for ballast water emissions (IMO, 2004). Biofouling emissions did not receive the same attention. Ultimately, the control effort will depend on the actions taken by shippers that in turn depend on economic incentives. The paper seeks to analyze the potential for reducing the threat of invasive species under a few policy options.

There is a paucity of economic analysis of policies to regulate the biological pollution problem of invasive species. Lovell et al. (2006) provides a helpful review of the economic literature as it applies to invasive species (aquatic and otherwise) that deal with various aspects other than specifically policy options for solving the problem. When there are some estimates of damages due to invasive species, there have been some quantitative analyses assessing incentives and strategies to solve the biological pollution problem [(Fernandez, 2006), (Fernandez, 2007)]. However, those analyses have focused on amount of abatement needed and ways in which multiple locations can coordinate efforts rather than explicitly reviewing policy options to spark abatement. Preventative policy measures exist but there has not been an economic analysis of their general cost effectiveness and the incentives for shippers and ports.

The present paper should be viewed as the case of a discussion of the framework for policies that require more damage estimates through careful economic valuation techniques in order to quantitatively work out the details. Hence, the following paragraphs will outline with analytic simplicity some basis for exploring policies that can benefit from efforts to quantify damages and benefit for avoiding invasive species in the marine environment in order to formally measure all of the positive aspects of the policies discussed.

Biologists assert prevention is necessary to abate invasive species due to risk and uncertainty of locating exact emissions per ship from both vectors (ballast water and biofouling) uniformly across time and space and ineffective eradication (Ruiz and Carlton, 2003). Social benefits of preventative measures that are unobservable with positive externalities lead to suboptimal levels of private investment. There's a reason to investigate the feasibility of public policy intervention to promote prevention.

The dependence of one port's security on the behavior of others may partially or in some cases almost completely negate the payoffs it receives from its own investment in protective measures. This case of conditional dependence of protection should be addressed in any efforts to regulate invasive species possibly traveling between connected ports. The decision to invest in monitoring or controls necessarily means balancing the cost of doing so with the reduction in the risk of an invasion from a ship not only from those ships entering their port first from outside of a country's Exclusive Economic Zone (EEZ), but also from within the EEZ, as mentioned previously of the North-South traffic as well as the East West traffic along the Pacific coast of North America. The incentive by one port to invest is greatly decreased if other ports fail to adopt protective measures, thereby leading to greater threats overall. The decision for no protection may be a Nash equilibrium even though there are net benefits to everyone from protection. However, unlike a Prisoner's Dilemma, there may be a Nash equilibrium where some agents want protection. The role for public sector intervention to overcome the decreasing incentive for investing in prevention if more ports do not coordinate should consider coordinating mechanisms to induce some protection and reduce the need for what appears to be futile eradication efforts.

How can one port insure that enough ports will invest in prevention so that others follow to avoid invasive species altogether? That question is addressed in the first part of the paper that deals with policies between ports. Then, the other realm is to deal with the interaction between the port and ships. That context is dealt with in the second part of the paper.

The analysis involves a model of interdependence of ports for the invasive species problem with a negative externality that creates a disincentive to invest in prevention. The policy goal is then to internalize the externality.

1 A. Port Model

A basic picture is a one period model of N risk neutral seaports designated by S_i, i = 1...N . The seaports represent the public resource managers deciding on protection. The choice can be seen as discrete: invest or not. Alien invasive species population is A_i, i = 1...N for various ports. The risk of loss is: D A_i. It is possible to further define A_i as a function of how much abatement is applied as will be described below in terms of M . The probability of a loss arising on seaport if it has not invested is p so expected loss is pD A_i. If the seaport has invested in prevention, risk=0. Assume for really simplistic math to motivate the discussion that ports are symmetric and identical. An additional risk from another port that did not inspect or stop a ship from spreading invasive species beyond its port is x.

On any given ship trip there is a probability p that a seaport without a preventative plan accepts a ship with invasive species that invades its own port. The probability x refers to a ship from another port arriving to invade a second port. If there are N ports greater or equal to 2 seaports the probability per trip that this ship will be transferred from seaport i to j is x/(N-1). The probability per trip that a ship at a port without a prevention system will invade is probability p + x. Assume that D A_i from one invasion is as harmful as from multiple invasions, so D A_i is not additive. As probability is low and the D A_i may be catastrophic, a single occurrence is all most consider for making the decision about protection at the port.

The seaport has perfect information on risk and costs of protection and has to make a choice between investing in protection M or not. Think of M as monitoring a discharge permit or some other form of inspection. The following table has payoffs for 2 ports (S_1, S_2) where R is the revenue for a port.

	M	No M
M	R-C, R-C	R-C-xD A_i , R-pD A_i
No M	R-pD A_i , R-C-xD A_i	R-[pD A_i +(1-p)xD A_i], R-[pD A_i +(1-p)xD A_i]

The cost per ship of investing in monitoring protection is C. The payoffs if both seaports invest is R-C for each. And, the rest of the table is straightforward.

It is imperative to ask what conditions will lead seaports to invest in protective monitoring? For monitoring to be a dominant strategy R-C > R-pD A_i and R-C-xD A_i > R-pD A_i - (1-p)xD A_i . The first inequality indicates C < pD A_i where the cost of protection is less than expected loss. This can be a condition for an isolated seaport. The second inequality from above reduces to C < pD A_i -pxD A_i =pD A_i (1-x). This is definitely a tighter inequality reflecting the possibility of influence from a second seaport. This influence reduces incentive to invest in monitoring. In isolation there is complete freedom from risk by investing in protective monitoring.

With interdependencies between ports, there is no such guarantee. Even if a few invest there remains a risk of loss due to the other ports having influence. Investing in protection buys little assurance when there is the possibility of influence from others.

In a 2 agent problem with identical costs, one can determine optimal behavior of each seaport without communication. In this noncooperative environment if C < pD A_i (1-x), then both seaports will want to invest in protective measures (M,M); if C >pD A_i then neither agent will want to invest in protection (N,N). If pD A_i (1-x) < C < pD A_i then there are two Nash equilibria and the solution is undetermined.

If seaports have different costs of investing in protection measures, then there may be a Nash equilibrium when one seaport invests and the other does not. Specifically, let C_1 and C_2 be the costs of the two seaports, then (N,M) will be the Nash equilibrium if $C_1 >$ pD A_i and $C_2 <$ pD A_i (1-x). This mixed equilibrium requires that the two costs differ by at least pxD A_i.

A general case of N identical seaports all symmetrically placed means if all but 1 of the seaports have invested in protection, then risk facing the remaining one is identical to what would be in isolation; there is no risk of influence from others. At the other extreme, suppose non of the other N-1 seaports have invested in protection; then if the remaining agent is protected it still faces risk originating at N-1 other locations.

If three ports are the focus of S_i, i=1,2,3, then define E(3,0) as the expected negative externality to any seaport i that has protection if the rest of the three seaports have no such protection. E(3,0) is given by (x/2)[1-x/2)]D A_i. When one other seaport has installed protection then the expected negative externality is given by (x/2)D A_i since there is only one seaport without protection and it transfers a questionable ship to the first seaport with probability x/2. If there are four seaports then the expected negative externality is as follows, based on how many adopt protection: E(4,2) = (x/3)D A_i; E(4,1)=(x/3)[1+(1-x/3)]D A_i; E(4,0)=(x/3)[1+(1-x/3)+(1-x/3)²]D A_i.

For N>1 seaports, this can be generalized as

(1.1) E (N,0) = [x(n-1) $\sum_{t=0}^{n-2} [1-x/(n-1)]^t DA_i = [1-[1-x/(n-1)]]^{n-1}]DA_i$

The limit on this expression as n approaches infinity is:

$$\lim_{n\to\infty} E(n,0) = (1-e^{-x})DA_i .$$

When there are n seaports the payoff to seaport i from not investing when n-1 do not invest is

(1.2) R-pD A_i -(1-p)E(n,0).

The payoff to port i from investing is

(1.3) R-C-E(n,0).

Comparing (1.2) and (1.3), investing is the better strategy if and only if

(1.4) C < p[D A_i -E(n,0)] .

Equation (1.4) implies that there is less incentive to invest in protection with higher negative externalities associated with seaport interdependence. What is the structure of a set of possible Nash equilibria? For the two port case (M,M) is the dominant strategy if C <pD(1-x) and a Nash equilibrium if C<pD A_i . The strategy (N,N) is a dominant strategy if C > pD A_i and a Nash equilibrium if C > pD A_i (1-x).

There is an interval pD A_i (1-x) < C <pD A_i in which both (M,M) and (N,N) are Nash equilibria. For the N port case, (M,…,M) is the dominant strategy if C< p[D A_i -E(n,0)] and [N,…,N] is the dominant strategy if C > pD A_i . When C is between 2 values, there are 2 equilibria.

1 B. Policies Between Ports

Insurance discourages investment in protection if insurers face moral hazard problems due to their inability to detect careless behavior on the part of the insured ports who know that they will receive compensation should they suffer a loss. In this case, one can lose a (M,…,M) equilibrium if the ports are allowed to insure themselves against losses. If moral hazard problems can be eliminated through the terms of the insurance contract (deductibles, coinsurance) and/or monitoring and inspection, then insurance with actuarily fair premiums encourage a risk averse port operating in violation to adopt protection whenever the cost of the measure is less than the reduction in expected losses.

It is necessary to deal with the externalities created by other ports who do not invest in protection and due to interdependencies cause damage to other ports. Suppose that an invasion happens in port 2 due to lack of investment by port 1, and port 1's insurer is required to pay for the damage to port 2. This is not how current insurance practice operates. An insurer who provides protection to S_i is responsible for losses incurred by port i no matter who caused the damage. If the damage from insured risk is due to negligence or intentional behavior there are normally clauses in the insurance policy that indicate that losses are not covered (such as with arson). One reason for this contractual arrangement between insurer and insured is the difficulty in assigning causality for a particular invasion. A single insurance program that provided coverage to all ports would, however, want to internalize the externality.

It may help to illustrate this point with the interdependent port case with 2 identical seaports (S_1, S_2) where each port has its own insurer who charged a premium based on expected losses. If S_1 contacts its insurer inquiring about a premium reduction for undertaking a protective measure, knowing that C<pD A_i. If the insurer knows or suspects that S_2 has not invested in protection, it will only be willing to reduce the premium by p(1-x)C because of the interdependent effects from S_2 to S_1. On the other hand, a single insurer covering both ports that commands the market (monopolist) or represents a social insurance program can require both S_1 and S_2 to invest in the protective measure and in return give each port a premium reduction of pD A_i.

The real world example of insurance related to marine invasive species pollution involves New Zealand. All costs associated with inspection, cleaning and abatement are the responsibility of the importer in a program run by the New Zealand government.

If a port that caused damage to other ports by not adopting a protective measure were held liable for these losses, then the legal system would internalize externalities due to interdependencies. For the two port example, suppose that S_1 knew that by not investing in protection it would be liable for damage that it caused to S_2. It would invest in protection whenever $C < (p+x)D A_i$. Although the liability approach has attractive theoretical properties, it faces practical problems due to high transactions costs related to determining causes of loss. The discussion presented in the context of ports and shippers below combines liability with other policies based on the limitation of liability alone. And, the framework for suggesting liability below is through the formal program, International Ship and Port Facility Security (ISPS) Code that already exists.

Because of the difficulty of attributing damage ex post to a shipper through liability involving legal proceedings, Segerson (1995) suggests combining liability with an ex ante instrument. For invasive species, an ex ante instrument is relevant in order to foster needed prevention and formally internalize the externalities. The IMO has regulations related to the prevention, operation and maintenance for flagged states and ships (Llacer, 2004). The statutorily imposed liability for general marine pollution through flagging and registering a ship for ocean transportation is the context for a more focused policy on invasive species. The ship can be held liable regardless of the amount of care exercised. The form of joint and several liability where the court can apportion one party responsible for full damages regardless of relative contribution would make this parallel to strict liability for shippers. In principle, the anticipation of the liability can be incentive enough to reduce risk of damage. However, this incentive may be less effective if polluters face limited financial liability and avoid paying damages by becoming insolvent (Sterner, 2003).

This paper addresses risk of damages and asymmetric information between the regulator and shipper in the context of two emissions vectors (ballast water and biofouling) that require more than one policy to address them. The optimal regulatory policy depends on information provided by the shipper since they know more about what abatement happens on the ship than the regulator. The difficulty of attributing damage ex post to a shipper under liability motivates the study of the efficacy of ex ante measures.

The choice of optimal regulatory policies with two vectors (ballast water and biofouling) of emissions is examined under conditions of (1) risk surrounding the potential magnitude of the damages and (2) asymmetric information between the regulating port and the shipper regarding the shipper's potential liability for any damage costs. A combination of two policies is used to address the market failures. The combination consists of liability and subsidies as well as liability and taxes.

The analysis of these policies is contrasted with an initial Case 1 that does not formally recognize both sources of emissions and possible damages. Case 2, where both sources of emissions and damages are fully accounted for, approaches reality and enables the variety of policies to be assessed for the potential to help address marine invasive species pollution. The modeling approach considers incentives for both the regulating port and the shipper facing any regulation and evaluates the optimality of possible policies for both key entities. Specifically, Case 2 contains the following components: (1) the IMO emissions standard; (2) both the shipper and regulating port realize the potential for biofouling damage that has a risk distribution; (3)

strict legal liability of the shipper for any damages; (4) a per cubic meter subsidy; (5) a fixed fee to pay for an emissions monitoring program and any necessary damage abatement costs, where the fee depends on a ship-reported estimate of the potential severity of damages, should they occur. Assuming there is asymmetric information on the potential severity of damage, should it occur, the shipper has more information than the regulator on potential the severity due to knowledge of the abatement.

Results show incentive-based policies (subsidy with liability rule or tax with liability rule) help avoid marine invasive species pollution when there are uncertain damages and asymmetric information between shippers and the regulating port. When liability is high, shipper profits are higher and social welfare is lower under regulation. Liability does not affect abatement choices, only the distribution of rents. Subsidies and taxes achieve the same level of abatement and welfare. While shipper profits are slightly lower with profits, damages are significantly lower.

2. Model of Ship and Port Regulator

The model takes the IMO standard on ballast water emissions to the ocean as a given policy and seeks to determine how best to regulate impacts from more than ballast water emissions in order to also address biofouling emissions. The analysis reflects the second best, fragmented nature of current environmental regulation. The shipper is assumed to know the standard. The environmental goal of the IMO standard is a numerical goal of risk reduction in a safety-first manner, focused on ballast water emissions.

The regulating port minimizes total social costs of shipping including any potential environmental costs subject to meeting the IMO standard. The shipper maximizes expected profits. Assume that shipping has constant returns technology, so any changes in shipping costs translate to changes in production costs per cubic meter of emissions.

Two cases are modeled. In the first model, biofouling emissions are imposed on the IMO ballast water standard. Then, the shipper chooses the amount of ballast water emissions to release to the ocean to meet the IMO standard at least cost. Without biofouling damages formally accounted for in setting the standard, the shipper's choice matches the regulator's socially-optimal (second-best, given the level of the IMO standard) selection.

The second model considers a regulatory framework that may help regulating ports avoid some of the "unintended consequences" of uncontrolled invasive species. This model allows for (1) the possibility of both ballast water emissions and biofouling emissions with damages in formulating the regulations and (2) asymmetry regarding estimates of the shipper's potential liability for any invasive species impacts. Thus, this model provides a realistic description of most pollution regulation decisions. The regulatory instruments to be tested in this model include liability, subsidies and taxes. The subsequent sections derive sequentially the optimal emissions and policy levels. It will be shown that liability combined with subsidies has similar results as liability in combination with taxes. Functional forms are based on the empirical setting with properties for computational ease.

2.1 Case 1 with IMO Emission Standard Regulation

The shipper maximizes profits by selecting a combination of ballast water emissions $B_1$and biofouling emissions B_2 for ocean release to meet the IMO standard. Table 1 lists model symbols. Equation (2) indicates the IMO standard for ballast water augmented by adding biofouling emissions, another vector of invasive species released by ships to the ocean.

The model is developed on a "per cubic meter of emissions" basis to indicate a volume measure for aqueous emissions commonly used in the maritime shipping context, containing an amount (percentage) of invasive species. Equation (1) indicates that the shipper maximizes profit per cubic meter of emissions, π, by choosing to release to the ocean some amount of ballast water emissions B_1 in the tank and volume of biofouling emissions B_2 attached to the ship hull. Prior to release to the ocean, ballast water treatment onboard serves to filter and remove invasive species in the ship's emissions. Since marine invasive species can be sessile as well as suspended in aqueous emissions, biofouling consists of the volume of invaders attached to the ship as it moves from one port to another with wet weight not dry weight. It is necessary to also measure this vector of emissions in cubic meters from which sessile invaders can be filtered and removed. Prevention to address both emissions will be discussed later.

Equation (2) describes the IMO constraint on invasive species released to the ocean from ship emissions. Equation (2) describes the fixed-proportions relationship that exists between the emissions vectors and the standard $\bar{I}$. The IMO standard, $\bar{I}$, is set at a numerical limit of 0.02 that is based on a percentage of invasive species (allows for various species and sizes) (Ambroggi, 2004). While the IMO has focused on B_1, it is useful to include B_2. There are fixed dimensions of ballast water tank size and surface area for ships to follow the form of equation (2). For example, typically 30% of a ship's weight is the quantity of ballast water capacity for that ship (Langevin, 2003). The shipper's profit maximization problem is:

$$\text{(1)} \quad \max_{B_1, B_2} \pi = r(B_1 + B_2) - c_1 B_1 - c_2 B_2$$

$$\text{(2)} \quad \text{subject to}: a_1 B_1 + a_2 B_2 \leq \bar{I}$$

Non-negativity constraints on B_1 and B_2 are: $B_1 \geq 0$ and $B_2 \geq 0$. Parameter r in equation (1) is the shipper's transportation profit margin per cubic meter of emissions. In this manner the shipper's earnings can be tied to the transportation activity he performs separately from the trade revenue. This distinction helps to investigate the transportation realm where r is the monetary value multiplied by the amount of invasive species emissions released to the ocean from the tonnage transported. The amount of shipping can be gauged by r and the following production relationship links emissions to shipping, r=F(V). The technology F(V) indicates the amount of invasive species emissions produced (and released) when the current shipping of the port is r in a manner that has been modeled in the environmental economics literature by Forster (1973). In this case, V is made up of both B_1 and B_2, according to $V=B_1+B_2$.

The shipper's profit margin, r, is approximately \$0.27 per cubic meter of emissions carried by the ship (Helling and Poister, 2000).

Parameters a_1 and a_2 in equation (2) represent the percentage of invasive species per cubic meter of biofouling and the percentage of invasive species per cubic meter of ballast water emissions, respectively. Fofonoff et al. (2003) indicate reference values for both a_1 and a_2 based on time series data of the percentage of invasive species per cubic meter of ballast water and hullfouling emissions. Parameter a_1 is 0.35 percent per cubic meter of ballast water emissions, based on the typical dry weight of invasive species in the liquid volume of ballast water emissions (Ruiz and Carlton, 2003). Parameter a_2 is 0.18 percent per cubic meter of biofouling emissions.

The cost parameters c_1 and c_2 in equation (1) are the costs to filter, remove and release the invasive species per cubic meter of ballast water emissions (c_1) and biofouling emissions (c_2), respectively. Shipper's costs for biofouling emissions are 9-13 cents per cubic meter based on a range of six technology options for anti-fouling coatings that have different enzyme and phytochemical bases (Johnson and Miller, 2002). Fouling growth creates enough friction, or "drag" to slow boats and increase fuel consumption, in some cases by 30% (Younqlood et al. 2003). The cost of biofouling due to reduced fuel economy is 4 cents per cubic meter due to up to 10% drag that translates into a 1% loss of fuel from biofouling emissions (Milne, 1990). This amount is then subtracted from the biofouling cost as a gain to fuel economy by the ship. Hence, c_2, is set at the midpoint of the cost range, seven cents per cubic meter of biofouling emissions.[1] The sealants are variable costs in terms of the rate of application and maintenance, to release biofouling emissions off the hulls. In the event of fixed costs, they can be adjusted to annual figures using a discount rate of 5% for an equipment lifetime of 10 years. The 10 years lifetime is determined by the assessment of duration of effectiveness by Johnson and Miller (2002). The fixed costs are proportional to cubic meters of emissions since they are based on flow capacity. Then, it is possible to sum variable and fixed costs in the per cubic meter estimate of costs.

The cost of ballast water emissions, $c_{1,}$ is approximately $2.38 per cubic meter of emissions, the midpoint of a range of a couple technology choices, that imply emissions are gleaned thereby lowering the concentration of invasive species. Since ballast water exchange is not reliable it is important to include the costs of alternative technology that includes physical and chemical processes of deoxygenation and ultra violet treatment [(Taylor et al., 2002), (Tamburri et al., 2002)]. In this case, the variable and fixed costs are calculated on a per cubic meter basis for the cost range stated above that are applied to glean the volume of ballast water emissions, where the fixed costs are adjusted through discounting over the equipment lifetime to combine with variable costs by applying a 5% discount rate and an equipment lifetime of 20

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[1] Parameter values indicate the estimate of biofouling emissions per cubic meter is an average of the range of biofouling treatment costs reduced by the fuel economy savings.

years. The lifetime is referenced from Taylor et al. (2002). These fixed costs are proportional to cubic meters of emissions.

The linear constraint in equation (2) that adds both types of emissions (sessile organisms from the ship hull and suspended organisms in ballast water) arriving at the port facing the IMO standard is aligned with trend evidence from Fofonoff et al. (2003) and implies a corner solution where one of the two decision variables is positive as determined by the relative values of the parameters c_1, c_2, a_1 and a_2. When $r-a_1/c_1 < r-a_2/c_2$ (as is the case for ballast water emissions and biofouling emissions), the solution to the linear programming problem (1)-(2) is given by equations (3):

$$(3)\ B_1^0 = 0, B_2^0 = \frac{\bar{I}}{a_2},$$

The firm chooses to use $B_2^0 = 0.11$ cubic meters of biofouling emissions (and zero percent of ballast water) to meet the IMO standard $\bar{I}$, given that there is incentive to cut down on drag weight from growth on the ship hull that demands additional fuel. Eventually, fouling growth leads to damage to hull and vessel deterioration (Rolland and DeSimone, 2002). These effects would be another incentive on the part of shippers to implement some action to prevent fouling as a vector of marine invasive species. Without emissions from both vectors, both the firm and the regulating port focus on biofouling emissions to meet the IMO standard, at least cost.

2.2 Case 2 with Regulation Accounting for Dual Vectors of Biofouling and Ballast Water Emissions

This case considers the shipper's ex-ante decision on emissions and the regulating port's ex-ante decision for regulating the *potential* for dual vectors of emissions (biofouling and ballast water). The IMO standard in equation (2) was set based only on damages from ballast water emissions (IMO, 2004). Therefore, the following model includes quadratic damage costs from biofouling emissions explicitly in addition to damages from ballast water emissions accounted for in the IMO standard. The damage costs of biofouling do not overlap with the content of equation (2) where the standard is set based on ballast water emissions only. The biofouling added in equation (2) indicates the typical dry weight amount if one attempts to divide between two sources of invasive species: ballast water and biofouling.

The regulating port defines expected social welfare E(W) as expected shipper profits less invasive species damages. The explicit specification here of biofouling damages compensates for the fact that equation (2) was not set with consideration for biofouling damages, only those of ballast water. So, the previous section was an attempt to augment the standard by including biofouling. However, biofouling damages had not been formally measured in that case. Ex-post estimates of the invasive species damages are measured per cubic meter of biofouling emissions and are quadratic in B_2, that is, invasive species damages per cubic meter of biofouling emissions as $D \cdot (B_2)^2$ with an exponential probability distribution. An index of invasive species damage, D, indicates damage to native shellfisheries which have commercial and recreational value. Ex-post estimates of average invasive species damage costs range from \$0.06 to \$0.16 per cubic meter of biofouling emissions, including cleanup costs for the Pacific coast of North America [(Department of Fisheries and Oceans Canada, 2002), (Estado de Baja, 2003), (Zentner et al., 2003)]. The upper limit of this range is considered a lower bound of actual damage costs due to limited data that does not cover the entire Pacific coast of the three NAFTA countries. Estimates from Alaska Dept. of Fish and Game (2002), Department of Fisheries and Oceans Canada (2002), EDAW, Inc. (2003), Estado de Baja (2003), Hanemann (2003) are for locations along the Pacific coast from the same time period that could be associated with a per cubic meter biofouling emissions in terms of impacts on production quantity and values of shellfisheries (market and nonmarket values are averaged for the damage measure). These estimates provide the factor income valuation approach where the per cubic meter marginal unit of biofouling emissions displaces a quantity of native shellfish that have the commercial and recreational value indicated in the estimates obtained for the damages.

The mid-point of the range of ex-post damage cost estimates is \$0.11 per cubic meter of biofouling emissions. This midpoint serves as the regulating port's ex-ante estimate of mean damage costs per cubic meter of biofouling emissions. Mean damage cost corresponds to the actual amount of biofouling emissions, $B_2^0 = \frac{\bar{I}}{a_2} = 0.11$, and enables solving for the mean value of the damage severity index, denoted $\overline{D}$, as: $\$1.00 = \overline{D} \cdot (B_2^0)^2 = \overline{D} \cdot (0.11)^2 \Rightarrow \overline{D} = 82.64$. The 0.11 is damage per unit of aqueous biofouling emissions, while the \$1.00 is per unit dry weight of invasive species in aqueous biofouling emissions.

The ex-post value of D is a random variable, ex-ante, from the perspective of both the port and the shipper. Suppose it is common knowledge, ex ante, that D follows an exponential probability density function with location parameter λ, (i.e., $p(D) = \lambda e^{-\lambda D}$) because this form has qualitative properties such as the shape that enables modeling unexpected events. For the exponential density function, $\overline{D}$ =1/λ; hence, $\lambda = 1/\overline{D}$ = 0.0121, based on initial estimates of the biofouling emissions damages to native shellfisheries, commercial and recreational values (in U.S. dollars) in Mexico, U.S. and Canada. The probability density function from the exponential distribution and quadratic damages indicates that the ex ante probability of small multiple externality damages is high, and the ex ante probability of large multiple vector damages is low. The biological basis is from Williamson and Fritter (1996) who developed a statistical or probability based approach for characterizing the outcomes of an invasion known as the tens rule where, over various steps of a possible biological invasion, each step has a one in ten probability of leading to ultimate invasion (from initial dispersal, arrival, spread, establishment, damage). This rule is thought to be applicable to marine invasive species by several marine scientists [(Ruiz and Carlton, 2003) and Orr (2003)].

With this specification of potential multiple vector damage costs, the port chooses ballast water emissions, B_1, and biofouling emissions, B_2, to maximize expected welfare subject to the IMO constraint. The regulating port's problem is:

$$(4)\quad \max_{B_1,B_2} E(W) = \int_0^{\infty}\left[r(B_1+B_2) - c_1B_1 - c_2B_2 - DB_2^2\right]\cdot\left(\lambda e^{-\lambda D}\right)dD$$
$$\text{subject to}: a_1B_1 + a_2B_2 \le \bar{I} \quad \text{(IMO constraint)}$$

Solving the constraint for B_2 and substituting into the objective function:

$$(5)\quad \max_{B_1} E(W) = \int_0^{\infty}\left[r(B_1+B_2) - c_1B_1 - c_2\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}B_1\right) - D\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}B_1\right)^2\right]\cdot\left(\lambda e^{-\lambda D}\right)dD,$$

the first order condition for the problem is:

$$\frac{\partial E(W)}{\partial B_1} = \int_0^{\infty}\left[r - c_1 + c_2\frac{a_1}{a_2} + 2D\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right) - 2D\left(\frac{a_1}{a_2}\right)^2 B_1\right]\cdot\left(\lambda e^{-\lambda D}\right)dD \equiv 0,$$

or, defining $M_1 \equiv r + c_2(a_1/a_2) - c_1$, and distributing the integral across the terms of the integrand:

$$\frac{\partial E(W)}{\partial B_1} = M_1\cdot\int_0^{\infty}\left(\lambda e^{-\lambda D}\right)dD + \left[2\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right) - 2\left(\frac{a_1}{a_2}\right)^2 B_1\right]\cdot\int_0^{\infty} D\cdot\left(\lambda e^{-\lambda D}\right)dD \equiv 0.$$

Evaluating the left-hand integral above via the method of u-substitution (with $u = -\lambda D$), and the right-hand integral via the method of integration by parts (with $u = D$ and $v = -e^{-\lambda D}$), leaves:

$$(6)\quad \frac{\partial E(W)}{\partial B_1} = M_1 + \left[2\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right) - 2\left(\frac{a_1}{a_2}\right)^2 B_1\right]\left(\frac{1}{\lambda}\right) \equiv 0$$

Solving (6) for the port's optimal value of B_1:

$$(7)\quad B_1^* = \frac{M_1 + 2\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right)\left(\frac{1}{\lambda}\right)}{2(a_1/a_2)^2\left(\frac{1}{\lambda}\right)}.$$

Equations (7) and (8) take into account damages, costs and relative contributions of ballast water emissions and biofouling emissions into the adjusted IMO limit, instead of one emissions vector. The port's optimal value of B_2 is obtained via the IMO pollution regulation constraint:

(8) $B_2^* = (\bar{I}/a_2) - (a_1/a_2)B_1^*$

2.2.1 The Role of Liability

The form of shipper's liability is joint and several liability arising from shipping registration. Shippers are parties to the share of costs that lies between zero and one (a percentage), and the shipper's expectation is that the share is α. This share can be viewed as the probability of damage detected being attributed to the shipper to assume liability. Without ex ante regulation, the shipper chooses B_1 and B_2 to maximize expected profit (including any multiple vector damages for which the shipper is liable), $E(\pi)$, subject to the IMO regulation constraint and its anticipated share of any multiple externality damages. Given the parameters, the shipper bears damage costs αDB_2^2, contingent on the probability of pollution, and this is subtracted from the previous profit maximization. The revised profit maximization is shown in the appendix.

As the shipper's anticipated liability share α decreases, the new abatement value of $\hat{B}_1$ decreases and $\hat{B}_2$ increases, deviating from the socially-optimal values for treatment of B_1^* and B_2^* derived previously. Thus, strict liability encourages precaution when there is a risk of damages. Joint and several liability may result in less than optimal control of both biofouling and ballast water emissions. Preventative action with liability could take place within the existing framework of ship registration. The registration involves certifying security measures that include addressing marine pollution. The International Ship and Port Facility Security Code that ships must abide by after July 1, 2004 (IMO, 2002), could emphasize that ships maintains pollution control in order to be able to engage in shipping activity.

2.2.2 Use of a Subsidy Incentive Policy

The regulator uses a subsidy[2], s, per unit of B_1 to ensure that the firm's chosen levels of B_1 and B_2 are consistent with the planner's optimal levels B_1^* and B_2^*. The subsidy is viable through an existing program such as the Experimental Ballast Water Treatment Systems STEP Program run by the U.S. Coast Guard for allocating funds to offset costs of alternative gleaning technology (U.S. Coast Guard, 2004). The socially-optimal subsidy depends on the shipper's anticipated liability share for invasive species damages α. Since the instrument is on a per cubic meter unit basis, it enables flexibility for the shipper to choose amongst technology alternatives depending on vessel characteristics (surface area and ballast water capacity). In this manner, the instruments allow for heterogeneity of ships and can be considered more efficient than a uniform instrument. There is asymmetric information between the shipper and the regulating port regarding α. The shipper's *true* anticipated liability share α_t is known only to the shipper from filtering and removal efforts. The shipper may choose to *report* a liability share α_r different from the *true* share α_t in an attempt to manipulate the regulating port and increase expected shipper profits. This is a plausible feature of the model since the existing W. Coast Ballast Water Reporting Program simply collects information that shippers report to ports. No verification is made. In addition to the per unit subsidy s, the regulating port pays the firm a lump-sum

[2]Ballast water reporting and offloading fees for ships according to the California State Lands Commission are lower than actual costs, thereby representing a subsidy.

subsidy[3] S (derived in the appendix) to ensure that the shipper reports its true anticipated liability share.

The difference between these values and those in equation (10) is that the subsidy in the numerator of B_1 will mean more emissions are filtered and removed before release since the marginal savings to the shipper from the amount of ballast water emissions and biofouling emissions is equal to the contribution to the emissions target, taking into account the subsidy.

The port determines the per-unit ballast water subsidy rule $s(\alpha_r)$ necessary to ensure optimal abatement B_1^* under the assumption that the lump-sum subsidy $S(\alpha_r)$ will ensure that the shipper will report its true liability share, that is, under the assumption that $\alpha_r = \alpha_t$ (this assumption is verified in Appendix 1). The ideal regulation is one with incentive (expected profit) for the shipper to reveal the truth.

The per unit subsidy offered for the shipper to abate works assumes the shipper knows that this is used to determine the lump sum subsidy. It is plausible since the lump sum subsidy programs of the U.S. Coast Guard are announced to shippers based on some form of cost sharing. This lump sum does not require additional terms such as the probability of auditing if the subsidy were based on verifying that the shipper had implemented the optimal B_1 and B_2.

2.2.3 Use of a Tax Incentive Policy

In this section, although optimality conditions may be the same as under optimal subsidies, the number of shippers will be lower in the long run under taxes as profits will be lower (Baumol and Oates, 1988).

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[3] Since the model is parameterized on a cubic meter basis, this subsidy is drawn from the current ballast water reporting fee uniformly charged per boat to cover some administration costs (California State Lands Commission, 2003). This fee can be adjusted based on the potential severity of invasive species costs. For example, the current fee of $0.012 per cubic meter of untreated ballast water is not sufficient to cover cleanup costs or reporting costs for all boats, and it could be raised to $0.048-$0.21. The lump-sum subsidy S can be envisioned as a *reduction* in the ballast water fee.

The port uses a per unit tax, t, assessed per unit of B_2, to ensure that the shipper's chosen levels of B_1 and B_2 are consistent with socially-optimal levels B_1^*, B_2^*. As shown in the Appendix, the socially-optimal tax depends on the shipper's anticipated liability share for multiple vector damages α. There is asymmetric information between the shipper and the port regarding α. Only the shipper knows the *true* liability share α_t. In addition to the per unit tax t, the port imposes a lump-sum fee F (derived in the Appendix) on the shipper to ensure that the shipper reports the true liability share. Both the per unit tax t and the optimal lump-sum fee are functions of α, that is, $t(\alpha)$ and $F(\alpha)$. The shipper may choose to *report* a liability share α_r different from the *true* share α_t in an attempt to manipulate the port's choice of t and F and increase shipper profit. The shipper's problem under tax regulation is to maximize expected profit $E(\pi)$, including any invasive species damage liability, per-unit ballast water tax t, and lump-sum fee F, by choosing B_1 and B_2 subject to the IMO constraint.

The level of both types of emissions is based on the marginal benefit to the firm equal to the marginal expected tax, taking into account liability and the contributions of these emissions to the IMO standard as shown in the Appendix.

The shipper's profit-maximizing choice of α_r under tax regulation in the Appendix shows that the incentive mechanism, the lump-sum fee F offered by the port to the shipper will ensure that the shipper's reported α_r equals the true α_t.

With parallel logic from the derivation of the subsidy, the following relates to investigation of the optimization components that depend on liability. Under the assumption that the lump-sum fee F ensures that $\alpha_r = \alpha_t$, the regulated shipper's expected profit $E(\pi(\ddot{B}_2(\alpha_t)))$ varies with the <u>*true*</u> liability share α_t.

3. Numerical Results for the Multiple Ship Externality Model

Table 2 indicates the parameter values used in the derivation of numerical results in subsequent tables (3 and 4). Table 3 results are presented in four panels. Panel a gives the regulating port's choice of per-unit ballast water subsidy s and lump-sum subsidy S based on the shipper's reported multiple vector damage liability share α_r. Notice that the subsidies vary inversely with respect to one another as the shipper reports larger values of α_r. If the shipper reports a small value of α_r, that is, if the shipper reports that its liability share for multiple vector damages will likely be small, then a large per-unit ballast water subsidy, s, is chosen by the regulating port, because an unregulated shipper would otherwise largely discount multiple vector damages and select an inefficiently low level of ballast water control and an inefficiently high level of biofouling control. As the shipper's reported value of α_r increases, the shipper's increasing liability for multiple vector damages serves as an increasingly sufficient incentive for the firm to select the socially-optimal combination of ballast water emissions and biofouling emission. As a result, the per-unit ballast water subsidy necessary to ensure that the firm selects the socially-optimal combination decreases.

If the regulator relied on the ballast water subsidy alone as the sole policy instrument, the firm would have an incentive to report small values of α regardless of the true liability share in order to manipulate the regulating port into providing large ballast water subsidies. The regulating port uses the lump-sum subsidy S to combat the shipper's incentive to report false values of α. If the shipper's reported value α_r is small, the shipper receives a large lump-sum subsidy. The size of the lump sum subsidy decreases as the shipper reports larger values of α. As shown in the model description, the regulating port's rules for selecting values of s and S that vary inversely with one another ensure that the shipper cannot increase its profits by reporting a false value of α.

Panels b and c of Table 3 illustrate how the shipper's ballast water emissions B_1 and biofouling emissions B_2 vary with the shipper's true invasive species damage liability share α_t and the shipper's reported liability share α_r. As the shipper's true vector liability share α_t increases, the shipper gleans more ballast water emissions B_1, which helps reduce pollution, and gleans biofouling B_2. As the shipper's reported liability share α_r increases, the shipper receives smaller ballast water subsidies, and as a result the shipper treats less B_1 and more B_2.

The results presented in panel d of Table 3 confirm that the shipper cannot increase its expected profit $E(\pi)$ by reporting a liability share α_r that differs from the shipper's true liability share α_t . As a result, it is assumed that the shipper will report its true liability share. The results in panel d indicate that as the shipper's true liability share increases, the shipper's expected profit decreases under the incentive mechanism.

The diagonal elements of panels b and c give the shipper's chosen values of B_1 and B_2 under the incentive mechanism, that is, when $\alpha_r = \alpha_t$. As the shipper's true liability share increases when under the incentive mechanism, the shipper's socially-optimal selections of B_1 and B_2 do not change—the true liability share influences the distribution of rents between the firm and the rest of society, but it does not influence the determination of socially-optimal activity levels.

As indicated by the results in panel a, in order to implement the incentive mechanism, the regulating port would have needed to pay the shipper a per-unit subsidy s of from \$0.01 to \$0.54 per cubic meter of ballast water emissions and a lump-sum subsidy S of from \$0.02 to \$0.04 per cubic meter.

Table 4 also contains 5 panels of results with a lump sum tax and per unit tax. From panel a in Table 4, the taxes vary inversely as the per unit tax decreases, the lump sum tax increases with the increased values of α_r. Values in panels b and c of Table 4 are similar to panels b and c of Table 3. Hence, the taxes work as do subsidies to encourage a balance between B_1 and B_2. The shipper has incentive to report a small liability share from biofouling damages. Hence a large per unit tax, is chosen because the shipper will otherwise choose a low level of hullfouling gleaning to discount the damages. As the reported value of α_r increases, the increase in liability for damages is enough incentive for the shipper to choose the optimal combination of hullfouling and ballast water.

Clearly there is a difference in welfare between the two sets of instruments. Panel d in Table 4 indicates a lower profit for the shipper facing taxes rather subsidies.

4. Conclusions

The results of this study show there is potential for a combination of incentive policies to help avoid marine invasive species in situations involving risk of damages and asymmetric information between ports and shippers.

The incentive policies can involve a combination of liability with subsidies or liability with taxes. The port's selected values of the two subsidies (a lump sum and per cubic meter) vary inversely with one another to ensure that the shipper reports a true estimate of its invasive species damage liability. As the shipper's liability increases, the shipper's expected profit decreases under the incentive policy. However, when shipper's liability is high, a shipper regulated under the incentive policy earns higher profits than would an unregulated firm. Changes in liability do not affect the shipper's socially-optimal selections of emissions reduction—liability influences the distribution of rents between the shipper and the rest of society, but it does not influence the determination of socially-optimal activity levels. The benefits of regulation to the shipper are higher when liability and invasive species damages are high. Alternatively, benefits of regulation in terms of social welfare are higher when liability and invasive species damages are low.

Although the subsidy-based policy achieves the (second-best) social optimum, there are alternative mechanisms such as taxes that achieve the same efficiency result with different equity outcomes. Under the tax-based policy, a per-unit tax of 0.5 to 28 cents per cubic meter in combination with a lump-sum fee of 0.05 to 0.10 cents (panel a, Table 4), depending on the shipper's multiple emissions vectors damage liability, result in the shipper's selection of the socially-optimal combination of emissions reduction (compare panels b and c of Table 3 and Table 4). Of course, under the tax-based policy, the shipper's profits are lower (compare panel d in Table 2 with panel d in Table 4), but expected social welfare remains the same (compare panel e in Table 3 with panel e in Table 4). The tax-based model shows that the same efficiency result can be achieved in alternative ways depending on equity goals and other constraints.

The model for the analysis draws on existing policy channels for potential regulatory action to formally address both shipping vectors of marine invasive species. The IMO guideline recommendation as the emission standard used in the model is presented in the mode of offering the flexibility to the shipper to be less or equal to the amount of emission allowed. Drawing on some measures of damages pertaining to biofouling meant that a distribution of damage risk was specified to derive analytical and numerical results. However, there are other aspects to the invasive species pollution problem that are truly uncertain where there would hardly be a risk probability distribution to specify. In some cases, such as with uncertainty in determining which shipper is at fault or uncertainties in the legal process, etc, which may prevent the shipper from bearing full financial responsibility for any damage, the parameter α made sense in that it allows the possibility of a range rather than a point estimate to explore the variation in the liability policy with some uncertainty. However, with other aspects of uncertainty, the model would have to be stated with stochastic and general functional forms that may not have the definitive magnitudes in which to offer some of the interpretations found here with different policy options. This analysis can be viewed as offering a foundation for further analysis to ponder present and future policy options.

The implementation of the liability, subsidy and tax incentive policies can occur through existing but refined policies. Currently, the port fee for reporting ballast water filter and removal of emissions does not depend on the shipper's reported liability. However, this fee could be adjusted to correspond to the lump-sum fee in the tax-based incentive mechanism to induce the shipper to reveal its true liability. The subsidy for technology is not set according to a measure of actual impact of invasive species, and this amount could be modified to accomplish emission reductions of the analysis in order to properly address marine invasive species through both shipping emissions vectors. The U.S. Commission on Ocean Policy suggests collecting adequate levels of resource rent for ocean space in terms of the port access fees that can be used to protect the public ocean (U. S. COP, 2004). The tax mechanisms suggested here can serve towards this goal.

The purpose of the model presented here is to provide an illustration of how incentive mechanisms might be applied to "real-world" invasive species regulation. Rather than a focus on hypothetical policy, the existing channels for the incentive mechanisms are studied, thereby making it more plausible that the pollution problem can be addressed from the results. Refining current policy involves: (1) tying current technology subsidies of the U.S. Coast Guard to liability; (2) Tying current ballast water reporting fee to the port security liability rule; (3) Ship registration liability under port security law post 2004 is more prominent and can help with environmental regulation of ships. U.S. Senate Bill 770 Section 1.C mentions liability as a plausible policy to assign civil penalty for not addressing invasive species introductions related to shipping in the U.S. Exclusive Economic Zone. The Invasive Species Specialist Group of the IUCN has called for the development of liability and criminal penalties for the consequence of unchecked, purposeful introductions of marine invasive species with responsibility for all costs associated with control, enforcement, and damages (Invasive Species Specialist Group, 2000).

The Ecological Society of America recommends actions that include focus on commercial shipping pathways, quantitative analysis, and study of incentives for cost-effective regulation. This research provides such action. The analytical method and policies apply to other settings beyond the Pacific Coast of North America by making appropriate modifications to choice variables, functional forms, sources of uncertainty and asymmetric information for those settings.

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Appendix 1

(9) $$\max_{B_1,B_2} E(\pi) = \int_0^\infty \left[r(B_1+B_2) - c_1B_1 - c_2B_2 - \alpha DB_2^2\right]\cdot\left(\lambda e^{-\lambda D}\right)dD$$

$$\text{subject to}: a_1B_1 + a_2B_2 \le \bar{I} \quad \text{(IMO pollution constraint)}$$

Solving the unregulated shipper's problem with methods analogous to those used in the port's problem, the unregulated shipper's profit-maximizing B_1 and B_2, denoted $\hat{B}_1$ and $\hat{B}_2$, are:

(10) $$\hat{B}_1 = \frac{M_1 + 2\alpha(\bar{I}/a_2)(a_1/a_2)(1/\lambda)}{2\alpha(a_1/a_2)^2(1/\lambda)}, \quad \hat{B}_2 = (\bar{I}/a_2) - (a_1/a_2)\hat{B}_1$$

If the shipper's anticipated liability share $\alpha = 1$, that is, if the shipper expects to bear full liability for any and all multiple vector damage costs, then the unregulated shipper's choices of B_1 and B_2 correspond to the shipper's optimal values B_1^* and B_2^*.

The following maximization includes subsidies s and S as functions of α, that is, $s(\alpha)$ and $S(\alpha)$. The regulated shipper's problem is to maximize expected profit, including any multiple vector damage liability, ballast water subsidy s, and lump-sum subsidy S, by choosing B_1 and B_2 subject to the IMO regulation constraint:

(11) $$\max_{B_1,B_2} E(\pi) = \int_0^\infty \left[r(\overline{B}_1+\overline{B}_2) - (c_1 - s(\alpha_r))B_1 - c_2B_2 - \alpha_t DB_2^2 + S(\alpha_r)\right]\cdot\left(\lambda e^{-\lambda D}\right)dD$$

$$\text{subject to}: a_1B_1 + a_2B_2 \le \bar{I} \quad \text{(IMO constraint)}$$

Solving the IMO constraint for B_2 and substituting into the objective function:

(12)

$$\max_{B_1} E(\pi) = \int_0^\infty \left[r(\overline{B}_1+\overline{B}_2) - (c_1 - s(\alpha_r))B_1 - c_2\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}B_1\right) - \alpha_t D\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}B_1\right)^2 + S(\alpha_r)\right]\cdot\left(\lambda e^{-\lambda D}\right)dD$$

The FOC for the problem is:

(13) $$\frac{\partial E(W)}{\partial B_1} = \int_0^\infty \left[M_1 + s(\alpha_r) + 2\alpha_t D\frac{\bar{I}}{a_2}\left(\frac{a_1}{a_2}\right) - 2\alpha_t D\left(\frac{a_1}{a_2}\right)^2 B_1\right]\cdot\left(\lambda e^{-\lambda D}\right)dD \equiv 0$$

Solving the regulated shipper's problem using methods analogous to those used in the social planner's problem, the regulated shipper's profit-maximizing values of B_1 and B_2, denoted $\overline{B}_1$ and $\overline{B}_2$, are given by:

(14) $\overline{B}_1 = \dfrac{M_1 + s(\alpha_r) + 2\alpha_t(\bar{I}/a_2)(a_1/a_2)(1/\lambda)}{2\alpha_t(a_1/a_2)^2(1/\lambda)}$, $\overline{B}_2 = (\bar{I}/a_2) - (a_1/a_2)\overline{B}_1$

The use of subsidies should result in $\overline{B}_1 = B_1^*$ or

$$\frac{M_1 + s(\alpha_r) + 2\alpha_t(\bar{I}/a_2)(a_1/a_2)(1/\lambda)}{2\alpha_t(a_1/a_2)^2(1/\lambda)} = \frac{M_1 + 2\alpha_t(\bar{I}/a_2)(a_1/a_2)(1/\lambda)}{2\alpha_t(a_1/a_2)^2(1/\lambda)}$$

(15) $s(\alpha_r) = -(1-\alpha_r)\cdot M_1$

Since $M_1 = r + c_2(a_1/a_2) - c_1$, the subsidy in the numerator would be adjusted according to α.

The shipper chooses α_r to maximize $E(\pi(\overline{B}_1, \overline{B}_2))$. Recalling expression (11) above, the shipper's problem is now:

$$(16) \quad \max_{\alpha_r} E(\pi(\overline{B}_1, \overline{B}_2)) = \int_0^\infty \left[r(\overline{B}_1 + \overline{B}_2) - (c_1 - s(\alpha_r))\overline{B}_1 - c_2\overline{B}_2 - \alpha_t D\overline{B}_2^2 + S(\alpha_r)\right]\cdot\left(\lambda e^{-\lambda D}\right)dD$$

Using the IMO constraint to substitute for $\overline{B}_2$, the shipper's problem becomes:

$$\max_{\alpha_r} E(\pi(\bullet)) \int_0^\infty \left[r(\overline{B}_1 + (\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\overline{B}_1)) - (c_1 - s(\alpha_r))\overline{B}_1 - c_2\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\overline{B}_1\right) - \alpha_t D\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\overline{B}_1\right)^2 + S(\alpha_r)\right]\cdot\left(\lambda e^{-\lambda D}\right)dD$$

The first order condition for this problem is:

$$(17) \quad \frac{\partial E(\pi(\vec{B}_1))}{\partial \alpha_r} = \int_0^\infty \left[M_1 \frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} + \frac{\partial s}{\partial \alpha_r}\overline{B}_1 + s\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} + \alpha_t M_2 \frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} \right.$$

$$\left. - 2\alpha_t M_3 \overline{B}_1 \frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} + \frac{\partial S}{\partial \alpha_r}\right]\cdot\left(\lambda e^{-\lambda D}\right)dD \equiv 0,$$

where $M_2 \equiv 2D(\bar{I}/a_2)(a_1/a_2)$, and $M_3 \equiv D(a_1/a_2)^2$. Expression (17) implicitly defines the regulated shipper's profit-maximizing choice of α_r.

Verifying Lump-sum Subsidy S Ensures $\alpha_r = \alpha_t$.

To verify that a lump-sum subsidy S ensures $\alpha_r = \alpha_t$, it is sufficient to show that the shipper cannot increase profits by changing its reported value α from α_t to some other value α_r; that is, it is sufficient to show that

$$\text{(A.1)}\quad \left.\frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_r}\right|_{\alpha_r=\alpha_t} = 0\,.$$

Substituting $\frac{\partial s}{\partial \alpha_r} = M_1$, $\frac{\partial \overline{X}_1}{\partial s} = \frac{1}{2\alpha_t (a_1/a_2)^2 (1/\lambda)}$,

$$\frac{\partial S(\alpha_r)}{\partial \alpha_r} = c_1 \frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} - \frac{\partial s}{\partial \alpha_r}\overline{B}_1 - s\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} - c_2\left(\frac{a_1}{a_2}\right)\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} - 2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r}$$

$$+ 2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{r_1}{r_2}\right)^2 \overline{X}_1 \frac{\partial \overline{X}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} + \left(\frac{1}{\lambda}\right)\left(\left(\frac{\bar{I}}{r_2}\right) - \left(\frac{r_1}{r_2}\right)\overline{X}_1\right)^2 - \frac{B_1^2}{4\left(\frac{r_1}{r_2}\right)^2\left(\frac{1}{\lambda}\right)},$$

and the expressions for M_1, M_2, M_3, and $\overline{B}_1$ into equation (17), yields:

$$\frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_r} = \int_0^{\infty}\left[2\alpha_t D\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} - 2\alpha_t D\left(\frac{a_1}{a_2}\right)^2 \overline{B}_1 \frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} - 2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r}\right.$$

$$\left. + 2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{a_1}{a_2}\right)^2 \overline{B}_1 \frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r}\right]\cdot\left(\lambda e^{-\lambda D}\right) \equiv 0\,.$$

Carrying-out integration (via the methods of u-substitution and integration by parts),

$$\frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_r} = 2\alpha_t\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} - 2\alpha_t\left(\frac{1}{\lambda}\right)\left(\frac{a_1}{a_2}\right)^2 \overline{B}_1 \frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} - 2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}\right)\left(\frac{a_1}{a_2}\right)\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r}$$

$$+ 2\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{a_1}{a_2}\right)^2 \overline{B}_1 \frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_r} \equiv 0\,.$$

Evaluating the last expression above for $\alpha_r = \alpha_t$ verifies that $\left.\frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_r}\right|_{\alpha_r=\alpha_t} = 0$. Then, the incentive is viewed as incentive compatible and individually rational for the shipper.

The Port's Choice of Lump-Sum Subsidy S

Under the assumption that the lump-sum subsidy S ensures that $\alpha_r = \alpha_t$, the regulated shipper's expected profit $E(\pi(\overline{B}_1))$ varies with its *true* liability share α_t as:

(18)

$$\frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_t} = \int_0^\infty \left\{ M_1\left[\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_t} + \frac{\partial \overline{B}_1}{\partial \alpha_t}\right] + \frac{\partial s}{\partial \alpha_t}\overline{B}_1 + s\left[\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_t} + \frac{\partial \overline{B}_1}{\partial \alpha_t}\right] + M_2\overline{B}_1 + \alpha_t M_2\left[\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_t} + \frac{\partial \overline{B}_1}{\partial \alpha_t}\right]\right.$$
$$\left. - M_3\overline{B}_1^2 - 2\alpha_t M_3\overline{B}_1\left[\frac{\partial \overline{B}_1}{\partial s}\frac{\partial s}{\partial \alpha_t} + \frac{\partial \overline{B}_1}{\partial \alpha_t}\right] - D(\overline{I}/a_2)^2 + \frac{\partial S}{\partial \alpha_t}\right\} \cdot \left(\lambda e^{-\lambda D}\right) dD$$

As the lump-sum subsidy S (derived below) ensures that $\alpha_r = \alpha_t$ (as verified in Appendix 1), (17) helps simplify (18) via the envelope theorem yielding:

$$(19)\quad \frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_t} = \int_0^\infty \left\{ -D(\overline{I}/a_2)^2 + M_1\left[\frac{\partial \overline{B}_1}{\partial \alpha_t}\right] + s\left[\frac{\partial \overline{B}_1}{\partial \alpha_t}\right] + M_2\overline{B}_1 + \alpha_t M_2\left[\frac{\partial \overline{B}_1}{\partial \alpha_t}\right]\right.$$
$$\left. - M_3\overline{B}_1^2 - 2\alpha_t M_3\overline{B}_1\left[\frac{\partial \overline{B}_1}{\partial \alpha_t}\right]\right\} \cdot \left(\lambda e^{-\lambda D}\right) dD$$

From section 2.2.4, it follows that $\frac{\partial \overline{B}_1}{\partial \alpha_t} = \frac{-M_1}{2\alpha_t (a_1/a_2)^2 (1/\lambda)}$. Hence, expression (19) becomes:

$$(20)\quad \frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_t} = \int_0^\infty \left\{ \frac{DM_1^2 - 2M_1^2(1/\lambda)}{4(a_1/a_2)^2(1/\lambda)^2}\right\} \cdot \left(\lambda e^{-\lambda D}\right) dD,$$

or, $$\frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_t} = \left(\frac{M_1^2}{4(a_1/a_2)^2}\right)\int_0^\infty \left\{\frac{D}{(1/\lambda)^2}\right\} \cdot \left(\lambda e^{-\lambda D}\right) dD - \left(\frac{M_1^2}{2(a_1/a_2)^2}\right)\int_0^\infty \{\lambda\} \cdot \left(\lambda e^{-\lambda D}\right) dD.$$

Evaluating the left-hand integral in the expression above via the method of integration by parts (with u = D and v = $-e^{-\lambda D}$), and the right-hand integral via the method of u-substitution (with u = $-\lambda D$), leaves:

$$(21)\quad \frac{\partial E(\pi(\overline{B}_1))}{\partial \alpha_t} = \frac{-M_1^2}{4(a_1/a_2)^2(1/\lambda)}.$$

The portion of $E(\pi(\overline{B}_1))$ that varies with α contains the following terms:

$$(22)\quad \int_0^{\infty}\left[(r - c_1 - s(\alpha_r))\overline{B}_1 - c_2\left(-\frac{a_1}{a_2}\overline{B}_1\right) - \alpha_t D\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\overline{B}_1\right)^2 + S(\alpha_r)\right]\cdot\left(\lambda e^{-\lambda D}\right)dD.$$

Expression (22) is equal to the integral of expression (21) multiplied by the density function of α, $p(\alpha)$, where $p(\alpha)$ is uniformly distributed over support (0,1), based on the description of liability under shipping rules facing limited liability as well as joint and several liability that yields a flexible range of possible outcomes. The integral is taken over α from $\alpha = 0$ to $\alpha = \alpha_t$, that is:

$$(23)\quad \int_0^{\infty}\left(\left[r - c_1 - s(\alpha_r))\overline{B}_1 - c_2\left(-\frac{a_1}{a_2}\overline{B}_1\right) - \alpha_t D\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\overline{B}_1\right)^2 + S(\alpha_r)\right]\cdot\left(\lambda e^{-\lambda D}\right)dD$$

$$= \int_0^{\alpha_t}\frac{-M_1^2}{4(a_1/a_2)^2(1/\lambda)}\cdot p(\alpha)\, d\alpha\,.$$

Evaluating the integral on the left-hand side of expression (23), and recalling that $p(\alpha) = \frac{1}{1-0}$ for a uniform distribution with support (0,1), expression (23) becomes:

$$r - (c_1 - s(\alpha_r))\overline{B}_1 + c_2\left(\frac{a_1}{a_2}\right)\overline{B}_1 - \alpha_t\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2} - \frac{a_1}{a_2}\overline{B}_1\right)^2 + S(\alpha_r) = \int_0^{\alpha_t}\frac{-M_1^2}{4(a_1/a_2)^2(1/\lambda)}\cdot\left[\frac{1}{1-0}\right]d\alpha\,.$$

Evaluating the integral on the right-hand side of the expression above, yields:

$$(24)\quad r-(c_1-s(\alpha_r))\overline{B}_1+c_2\left(\frac{a_1}{a_2}\right)\overline{B}_1-\alpha_t\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}\overline{B}_1\right)^2+S(\alpha_r)=\frac{-M_1^2\alpha_t}{4(a_1/a_2)^2(1/\lambda)},$$

from which the port's rule for determining the lump-sum subsidy S as a function of the shipper's reported value of α is recovered:

$$(25)\quad S(\alpha_r)=(-r+c_1+s(\alpha_r))\overline{B}_1-c_2\left(\frac{a_1}{a_2}\right)\overline{B}_1+\alpha_r\left(\frac{1}{\lambda}\right)\left(\frac{\bar{I}}{a_2}-\frac{a_1}{a_2}\overline{B}_1\right)^2-\frac{M_1^2\alpha_r}{4(a_1/a_2)^2(1/\lambda)}$$

The Regulated Shipper's Expected Profit $E(\pi(\overline{B}_1))$ Under the Incentive Mechanism

The regulated shipper's expected profit under the incentive mechanism $E(\pi(\overline{B}_1))$ is found by adding the portion of $E(\pi(\overline{B}_1))$ that varies with α, equivalent to the right-hand side of expression (24), to the portion of $E(\pi(\overline{B}_1))$ that does <u>not</u> vary with α, namely $r-(c_2\bar{I}/a_2)$:

$$E(\pi(\overline{B}_1))=r-(c_2\bar{I}/a_2)-\frac{M_1^2\alpha_t}{4(a_1/a_2)^2(1/\lambda)}$$

For each following subsection, the results of the analysis are similar to the per unit lump sum subsidy analysis with the difference that fees represent an additional cost and subsidies, a reduction in costs.

2.2.8.1 The Regulating Port's Problem

The regulating port's problem under tax regulation is identical to that under subsidy regulation and produces identical results B_1^*, B_2^*.

2.2.8.2 The Unregulated Shipper's Problem

The unregulated shipper's problem under tax regulation is identical to that under subsidy regulation and produces identical results: B_1^*, B_2^*. As the unregulated shipper's anticipated liability share α decreases from its maximum value of 1, $\hat{B}_1$ decreases and $\hat{B}_2$ increases, deviating from their socially-optimal values B_1^*, B_2^*.

$$(27)\quad \max_{B_1,B_2} E(\pi(= \int_0^\infty \left[r - c_1 B_1 - (c_2 + t(\alpha_r))B_2 - \alpha_t D B_2^2 - F(\alpha_r)\right] \cdot \left(\lambda e^{-\lambda D}\right) dD$$

$$\text{subject to}: a_1 B_1 + a_2 B_2 = \bar{I} \quad \text{(IMO constraint)}$$

Solving the constraint for B_1 and substituting into the objective function:

$$(28)\quad \max_{B_2} E(\pi(= \int_0^\infty \left[r - c_1\left(\frac{\bar{I}}{a_1} - \frac{a_2}{a_1}B_2\right) - (c_2 + t(\alpha_r))B_2 - \alpha_t D {B_2}^2 - F(\alpha_r)\right] \cdot \left(\lambda e^{-\lambda D}\right) dD$$

The FOC for the problem is:

$$(29)\quad \frac{\partial E(\pi(}{\partial B_2} = \int_0^\infty \left[M_4 - t(\alpha_r) - 2\alpha_t D B_2\right] \cdot \left(\lambda e^{-\lambda D}\right) dD \equiv 0, \qquad \text{where } M_4 \equiv r + c_1 a_2 / a_1 - c_2 .$$

Evaluating the integral in (29) using methods analogous to previous sections, the resulting expression for the shipper's profit-maximizing values of B_1 and B_2 is solved under tax regulation, denoted $\dddot{B}_1$ and $\dddot{B}_2$:

$$(30)\quad \dddot{B}_2 = \frac{M_4 - t(\alpha_r)}{2\alpha_t (1/\lambda)}, \qquad \dddot{B}_1 = (\bar{I}/a_1) - (a_2/a_1)\dddot{B}_2$$

2.2.8.4 The Port's Choice of Per-Unit tax t

The port determines the per unit tax $t(\alpha_r)$ necessary to ensure that $\dddot{B}_2 = B_2^*$ under the assumption that the lump-sum fee $F(\alpha_r)$ (derived below) will ensure that $\alpha_r = \alpha_t$:

$$\dddot{B}_2 = B_2^*$$

$$\frac{M_4 - t(\alpha_r)}{2\alpha_t (1/\lambda)} = \frac{M_4}{2(1/\lambda)}$$

$$(31)\quad t(\alpha_r) = (1 - \alpha_r) \cdot M_4$$

The per unit tax is similar to the form of the per unit subsidy.

2.2.9 The Shipper's Choice of Reported Liability α_r

The regulated shipper knows that the port's per unit tax rule $t(\alpha_r)$ and lump-sum fee $F(\alpha_r)$ depend on the shipper's report α_r. The regulated shipper chooses α_r to maximize $E(\pi(\dddot{B}_1, \dddot{B}_2))$. Through the first order necessary condition derived from equation (28) above:

$$(32) \qquad \max_{\alpha_r} E(\pi(\dddot{B}_1(\dddot{B}_2), \dddot{B}_2)) = \int_0^\infty \Bigg[r - c_1\left(\frac{\bar{I}}{a_1} - \frac{a_2}{a_1} \cdot \dddot{B}_2(s(\alpha_r), \alpha_t)\right)$$

$$- (c_2 + t(\alpha_r)) \cdot \dddot{B}_2(s(\alpha_r), \alpha_t) \;\; - \alpha_t D\left(\dddot{B}_2(s(\alpha_r), \alpha_t)\right)^2 - F(\alpha_r)\Bigg] \cdot \left(\lambda e^{-\lambda D}\right) dD$$

The first order condition for this problem is:

(33)

$$\frac{\partial E(\pi(\dddot{B}_2))}{\partial \alpha_r} = \int_0^\infty \left[M_4 \frac{\partial \dddot{B}_2}{\partial t}\frac{\partial t}{\partial \alpha_r} - \frac{\partial t}{\partial \alpha_r}\dddot{B}_2 - t \cdot \frac{\partial \dddot{B}_2}{\partial t}\frac{\partial t}{\partial \alpha_r} - 2\alpha_t D \dddot{B}_2 \frac{\partial \dddot{B}_2}{\partial t}\frac{\partial t}{\partial \alpha_r} - \frac{\partial F}{\partial \alpha_r} \right] \cdot \left(\lambda e^{-\lambda D}\right) dD \equiv 0$$

$$(34) \qquad \frac{\partial E(\pi)}{\partial \alpha_t} = \int_0^\infty \Bigg\{ M_4 \left[\frac{\partial \dddot{B}_2}{\partial t}\frac{\partial t}{\partial \alpha_t} + \frac{\partial \dddot{B}_2}{\partial \alpha_t}\right] - \frac{\partial t}{\partial \alpha_t}\dddot{B}_2 - t \cdot \left[\frac{\partial \dddot{B}_2}{\partial t}\frac{\partial t}{\partial \alpha_t} + \frac{\partial \dddot{B}_2}{\partial \alpha_t}\right]$$

$$- 2\alpha_t D \dddot{B}_2 \left[\frac{\partial \dddot{B}_2}{\partial t}\frac{\partial t}{\partial \alpha_t} + \frac{\partial \dddot{B}_2}{\partial \alpha_t}\right] - D\dddot{B}_2^{\,2} - \frac{\partial F}{\partial \alpha_t}\Bigg\} \cdot \left(\lambda e^{-\lambda D}\right) dD$$

As the lump-sum fee F (derived below) ensures that $\alpha_r = \alpha_t$, we may use (33) to simplify (34) via the envelope theorem to find:

$$(35) \qquad \frac{\partial E(\pi)}{\partial \alpha_t} = \int_0^\infty \left\{ M_4 \left[\frac{\partial \dddot{B}_2}{\partial \alpha_t}\right] - t \cdot \left[\frac{\partial \dddot{B}_2}{\partial \alpha_t}\right] - 2\alpha_t D \dddot{B}_2 \left[\frac{\partial \dddot{B}_2}{\partial \alpha_t}\right] - D\dddot{B}_2^{\,2} \right\} \cdot \left(\lambda e^{-\lambda D}\right) dD$$

Recognizing that $\frac{\partial \dddot{B}_2}{\partial \alpha_t} = \frac{-M_4}{2\alpha_t^2 (1/\lambda)}$, and evaluating the integral in expression (35) using methods analogous to those in section 2.2.1, yields:

$$(36) \qquad \frac{\partial E(\pi)}{\partial \alpha_t} = \frac{-M_4^2}{4(1/\lambda)}.$$

Define *the portion of E(π) that varies with* α as:

$$(37)\quad \int_0^\infty \left[c_1(a_2/a_1)\ddot{B}_2 - (c_2 + t(\alpha_t))\ddot{B}_2 - \alpha_t D\ddot{B}_2^{\,2} - F(\alpha_r)\right]\cdot\left(\lambda e^{-\lambda D}\right)dD\,.$$

Expression (37) is equal to the integral of expression (36) multiplied by the density function of α, $p(\alpha)$, where $p(\alpha)$ is uniformly distributed over support (0,1), and where the integral is taken over α from $\alpha = 0$ to $\alpha = \alpha_t$, that is:

$$(38)\quad \int_0^\infty \left[c_1(a_2/a_1)\ddot{B}_2 - (c_2 + t(\alpha_t))\ddot{B}_2 - \alpha_t D\ddot{B}_2^{\,2} - F(\alpha_r)\right]\cdot\left(\lambda e^{-\lambda D}\right)dD$$

$$= \int_0^{\alpha_t} \frac{-M_4^2}{4(1/\lambda)}\cdot p(\alpha)\,d\alpha \;=\; \int_0^{\alpha_t} \frac{-M_4^2}{4(1/\lambda)}\cdot\left[\frac{1}{1-0}\right]d\alpha \;=\; \left.\frac{-M_4^2\alpha}{4(1/\lambda)}\right|_0^{\alpha_t} \;=\; \frac{-M_4^2\alpha_t}{4(1/\lambda)}\,.$$

After evaluating the integral on the left-hand side of (38), the regulating port's rule for determining the fixed fee F as a function of the shipper's reported value of α is found:

$$(39)\quad F(\alpha_r) = c_1(a_2/a_1)\ddot{B}_2 - (c_2 + t(\alpha_r))\ddot{B}_2 - \alpha_r(1/\lambda)\ddot{B}_2^{\,2} + \frac{M_4^2\alpha_r}{4(1/\lambda)}$$

2.2.11 The Regulated Shipper's Expected Profit E(π) Under the Incentive Mechanism

The regulated shipper's expected profit under the incentive mechanism $E(\pi(\ddot{B}_2))$ is found by adding *the portion of E(π) that varies with* α*,* equivalent to the right hand side of expression (38), to *the portion of E(π) that does* _not_ *vary with* α, namely $r - (c_1\bar{I}/a_1)$:

$$(40)\quad E(\pi(\ddot{B}_2)) = r - (c_1\bar{I}/a_1) - \frac{M_4^2\alpha_t}{4(1/\lambda)}$$

This profit should be lower than the subsidy case.

Table 1. Model notation.

π = shipper net profits per cubic meter
r = shipper profits per cubic meter of emissions
B_1 = cubic meters of ballast water emissions
B_2 = cubic meters of biofouling emissions
c_1 = cost per-cubic meter of ballast water emissions
c_2 = per-cubic meter of biofouling emissions
$\bar{I}$ = IMO emissions standard constraint in percent of invasive species
a_1 = percent per cubic meter content of invasive species in ballast water emissions B_1
a_2 = percent per cubic meter content of invasive species in biofouling emissions B_2
s = subsidy per cubic meter
S = lump sum subsidy
α_t = shipper's true liability share
α_r = shipper's reported liability share
D = invasive species damage index
p(D) = probability density function of random variable D
λ = location parameter of exponential probability density function
$M_1 \equiv c_2(a_1/a_2) - c_1$, derived parameter
$M_2 \equiv 2D(\bar{I}/a_2)(a_1/a_2)$, derived parameter
$M_3 \equiv D(a_1/a_2)^2$, derived parameter
$M_4 \equiv c_1 a_2/a_1 - c_2$, derived parameter

Table 2. Parameter values

Parameter	Value
r	0.65
c_1	\$2.38
c_2	\$0.07
a_1	0.35
a_2	0.18
$\bar{I}$	0.01
B_2^0	0.11
λ	0.0121

Table 3. Solution values for the multiple externality model, with subsidy incentive mechanisms.

Panel a.--Subsidy values, s*, S*

	α_r 0.5	0.75	0.99
s*	1.121944	0.560972	0.022439
S*	0.060001	0.090001	0.118802

Panel b.—Ballast Water, $\overline{B}_1$

α_t	α_r 0.5	0.75	0.99
0.5	0.53479	0.51648	0.49889
0.75	0.54701	0.53479	0.52307
0.99	0.55293	0.54367	0.53479

Panel c.-Biofouling, $\overline{B}_2$

α_t	α_r 0.5	0.75	0.99
0.5	0.07123	0.10685	0.14104
0.75	0.04749	0.07123	0.09403
0.99	0.03598	0.05397	0.07123

Panel d.—Shipper's expected profit, $\mathrm{E}(\pi)$, per cubic meter

α_t	α_r 0.5	0.75	0.99
0.5	0.268167	0.268167	0.268167
0.75	0.267140	0.267140	0.267140
0.99	0.266153	0.266153	0.266153

Panel e.—Expected social welfare, $\mathrm{E}(\mathrm{W})$, per cubic meter

α_t	α_r 0.5	0.75	0.99
0.5	0.146110	0.145083	0.142163
0.75	0.145654	0.146110	0.145689
0.99	0.145103	0.145869	0.146110

Table 4. Solution values for the multiple externality model, with tax incentive mechanisms.

Panel a.--Tax and Fee values, t*, F*

	α_r 0.5	0.75	0.99
t*	0.57700	0.28850	0.01154
F*	0.00411	0.00616	0.00813

Panel b.—Ballast Water, $\overline{B}_1$

α_t	α_r 0.5	0.75	0.99
0.5	0.53479	0.51648	0.49889
0.75	0.54701	0.53479	0.52307
0.99	0.55293	0.54367	0.53479

Panel c.-Biofouling, $\overline{B}_2$

α_t	α_r 0.5	0.75	0.99
0.5	0.07123	0.10685	0.14104
0.75	0.04749	0.07123	0.09403
0.99	0.03598	0.05397	0.07123

Panel d.-Shipper's expected profit, $\mathrm{E}(\pi)$, per cubic meter

α_t	α_r 0.5	0.75	0.99
0.5	0.139945	0.139945	0.139945
0.75	0.138917	0.138917	0.138917
0.99	0.137931	0.137931	0.137931

Panel e.-Expected social welfare, $\mathrm{E}(\mathrm{W})$, per cubic meter

α_t	α_r 0.5	0.75	0.99
0.5	0.146110	0.145083	0.142163
0.75	0.145654	0.146110	0.145689
0.99	0.145103	0.145869	0.146110

Valuation for Environmental Policy: Invasive Species

Discussant:
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Models of Spatial and Intertemporal Invasive Species Management

by Burnett and Kaiser

3 Models/Case Studies

i) Hedonic pricing model to value invasive species damages – noise pollution from *coqui* frogs

ii) Spatial model of control – *Miconia calvescens*

iii) Spatial model of early detection and control – *Boiga irregularis* (Brown Treesnake)

Relatively few spatial economic models of invasive species management

- Huffaker, Bhat and Lenhart (1992) examine how dispersal between 2 sites affects control and the invasion size
- Brown, Lynch and Zilberman (2002) examine a static model of spatial control with dispersal from a source located some distance from agricultural production. They focus on source control and barrier zones as a means of reducing invasive species impacts.
- Sharov and Leibhold (1998), Sharov, Leibhold and Roberts (1998) and Sharov (2004) examine the use of barrier zones to slow the spread of an invasive species. "Slow the Spread" program used to manage the gypsy moth in N. America.
- Several ongoing efforts under USDA's PREISM program

Invasive species management is complicated

- spatial considerations (control costs, damages, dispersal)

- intertemporal considerations – current control costs mitigate current and future damages – damages caused by invasion growth

Most research focuses on static models or steady-state analysis of a dynamic, homogeneous invasion

Very few careful case studies consider spatial and dynamic considerations

Burnett and Kaiser provide a useful step in this direction

Typology of optimal control models:

- dynamic, homogeneous invasion

- static, spatial

- dynamic, “parametric” spatial interactions

- dynamic, fully endogenous spatial interactions

Dynamic, homogeneous invasion

$$\min \sum_{t=0}^{\infty} \delta^t \left[c(n_t)x_t + D(n_t)\right] \quad \text{subject to: } n_{t+1} = n_t + g(n_t) - x_t$$

Optimal steady state (necessary conditions):

$$c(n) = \frac{D'(n) + c'(n)g(n) + c(n)g'(n)}{r}$$

mar. cost of control = mar. benefit of control compounded
at rate r indefinitely

mar. benefit = marginal damages avoided adjusted by the effect
a change in the invasion size has on control costs

Burnett/Kaiser spatial model (discrete time version)

$$\min \sum_{t=0}^{\infty} \delta^t \sum_{i=1}^{k} \left[c_i(n_{it}) x_{it} + D_i(n_{it}) \right] \qquad \text{s.t. } n_{it+1} = n_{it} + g_i(n_{it}, n_t) - x_{it}$$

$n_t =$ total invasion size

influences control cost, damages and growth in patch i

Optimal steady state (necessary conditions):

$$c_i(n_i) = \frac{D_i'(n_i) + c_i'(n_i) g_i(n_i, n) + c_i(n_i) \dfrac{\partial g_i(n_i, n)}{\partial n_i}}{r}$$

Total invasion size affects management in patch *i* parametrically (each patch is “small” relative to whole)

Complete spatial, dynamic model

$$\min \sum_{t=0}^{\infty} \delta^t \sum_{i=1}^{k} \left[c_i(n_{it}) x_{it} + D_i(n_{it}) \right] \quad \text{s.t. } n_{it+1} = n_{it} + g_i\left(n_{it}, \sum_{i=1}^{k} n_{it} \right) - x_{it}$$

Optimal steady state (necessary conditions):

$$c_i(n_i) = \frac{D_i'(n_i) + c_i'(n_i) g_i(n_i, n) + c_i(n_i) \frac{\partial g_i(n_i, n)}{\partial n_i} + \sum_{j=1}^{k} c_j(n_j) \frac{\partial g_j(n_j, n)}{\partial n}}{r}$$

Control in patch *i* has non-negligible effect on future control costs in other patches

One note of caution:

Models of invasive species management are similar to models of renewable resource management, with one important difference. Renewable resources provide social benefits while invasive species impose social costs.

A larger renewable resource biomass is associated with a larger opportunity set for social welfare

In contrast, a larger invasion size is associated with a smaller opportunity set for social welfare

Economic models of renewable resources typically maximize a concave objective function subject to a concave transition function (resource growth function)

Economic models of invasive species minimize social costs subject to the transition function that governs growth and spread in the invasion size

Since all invasions are bounded, the transition function is necessarily non-convex. Hence, commonly used second-order conditions are not automatically satisfied. Invasive species management problems are potentially non-convex.

Brown Treesnake – Early detection and rapid response

Divide an island into K cells

A model of “search and destroy”

When to treat each cell, given invasion size and proportion of cells treated in previous period?

Potential extensions:

Extend spatial analysis to incorporate endogenous spatial interactions – effect of patch *i* on growth in other patches – neighborhood dispersion (vs. long distance dispersion)

Adaptive management and uncertainty – treatment in cell *i* provides information about invasion size in other cells that can be used to inform future policy choices

Economic analysis of surveillance and monitoring

Economic Evaluation of Policies to Manage Aquatic Invasive Species   by Linda Fernandez

Invasive species management can be improved by identifying pathways of introduction and directing policy toward those pathways

A major pathway of aquatic introductions is maritime shipping – ballast water and/or biofouling

Potential for strategic interactions – mitigation by one agent (port or shipper) affects incentives for other agents

Models of aquatic “biological pollution”:

- Shippers maximize profits subject to emission limit. Linear programming model of ballast water and biofouling emission reductions.

- Uncertain damages from biofouling. Port maximizes shipper profits less expected damages subject to emission limit.

- Shippers face liability for damages. Asymmetric information. Ports use a combination of fees and subsidies/taxes to induce shippers to reveal true liability and to choose port’s target emissions

Extensions:

Mitigating risk associated with pathways is dependent on technology.

Exs: Ballast water management and biofouling
Wood packing material (ISPM N. 15)

Can policy be used to bring about better technology to manage pathway risk?

Relationship between policy and induced technological change in the context of invasive species.

Institutional barriers

International Convention for the Control and Management of Ships Ballast Water & Sediments was adopted in February, 2004.

Entry into force 12 months after ratification by 30 States, representing 35% of world merchant shipping tonnage

As of March 31, 2007, 8 States (3.2% of tonnage) had ratified.

States raised concerns about liability in relation to the Convention on Biological Diversity

International invasive species problems involve repeated interactions between self-interested parties (international trade).

Literature on repeated games suggests that cooperation may be sustainable when the payoffs to all parties exceeds their minimax payoff.

A better understanding of the circumstances under which cooperation is a sustainable equilibrium for invasive species management is needed.

Valuation for Environmental Policy: Ecological Benefits

A Workshop sponsored by U.S. Environmental Protection Agency's National Center for Environmental Economics (NCEE) and National Center for Environmental Research (NCER)

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April 23-24, 2007

Agenda

April 23, 2007: Valuation for Environmental Policy

8:00 a.m. – 8:30 a.m.	**Registration**	
8:30 a.m. – 8:45 a.m.	**Introductory Remarks** Rick Linthurst, National Program Director for Ecology, EPA, Office of Research and Development	
8:45 a.m. – 11:30 a.m.	**Session I: Benefits Transfer** Session Moderator: Steve Newbold, EPA, NCEE	
	8:45 a.m. – 9:15 a.m.	Benefits Transfer of a Third Kind: An Examination of Structural Benefits Transfer George Van Houtven, Subhrendu Pattanayak, Sumeet Patil, and Brooks Depro, Research Triangle Institute
	9:15 a.m. – 9:45 a.m.	The Stability of Values for Ecosystem Services: Tools for Evaluating the Potential for Benefits Transfers John Hoehn, Michael Kaplowitz, and Frank Lupi, Michigan State University
9:45 a.m. – 10:00 a.m.	**Break**	
	10:00 a.m. – 10:30 a.m.	Meta-Regression and Benefit Transfer: Data Space, Model Space and the Quest for 'Optimal Scope' Klaus Moeltner, University of Nevada, Reno, and Randall Rosenberger, Oregon State University
	10:30 a.m. – 10:45 a.m.	Discussant: Matt Massey, EPA, NCEE
	10:45 a.m. – 11:00 a.m.	Discussant: Kevin Boyle, Virginia Tech University
	11:00 a.m. – 11:30 a.m.	Questions and Discussion
11:30 a.m. – 12:45 p.m.	**Lunch**	

April 23, 2007 (continued)

12:45 p.m. – 3:30 p.m.	**Session II: Wetlands and Coastal Resources** Session Moderator: Cynthia Morgan, EPA, NCEE	
	12:45 p.m. – 1:15 p.m.	A Combined Conjoint-Travel Cost Demand Model for Measuring the Impact of Erosion and Erosion Control Programs on Beach Recreation Ju-Chin Huang, University of New Hampshire; George Parsons, University of Delaware; Min Qiang Zhao, The Ohio State University; and P. Joan Poor, St. Mary's College of Maryland
	1:15 p.m. – 1:45 p.m.	A Consistent Framework for Valuation of Wetland Ecosystem Services Using Discrete Choice Methods David Scrogin, Walter Milon, and John Weishampel, University of Central Florida
1:45 p.m. – 2:00 p.m.	**Break**	
	2:00 p.m. – 2:30 p.m.	Linking Recreation Demand and Willingness To Pay With the Inclusive Value: Valuation of Saginaw Bay Coastal Marsh John Whitehead and Pete Groothuis, Appalachian State University
	2:30 p.m. – 2:45 p.m.	Discussant: Jamal Kadri, EPA, Office of Wetlands, Oceans, and Watersheds
	2:45 p.m. – 3:00 p.m.	Discussant: John Horowitz, University of Maryland
	3:00 p.m. – 3:30 p.m.	Questions and Discussion
3:30 p.m. – 3:45 p.m.	**Break**	
3:45 p.m. – 5:45 p.m.	**Session III: Invasive Species** Session Moderator: Maggie Miller, EPA, NCEE	
	3:45 p.m. – 4:15 p.m.	Models of Spatial and Intertemporal Invasive Species Management Brooks Kaiser, Gettysburg College, and Kimberly Burnett, University of Hawaii at Manoa
	4:15 p.m. – 4:45 p.m.	Policies for the Game of Global Marine Invasive Species Pollution Linda Fernandez, University of California at Riverside
	4:45 p.m. – 5:00 p.m.	Discussant: Marilyn Katz, EPA, Office of Wetlands, Oceans, and Watersheds
	5:00 p.m. – 5:15 p.m.	Discussant: Lars Olsen, University of Maryland
	5:15 p.m. – 5:45 p.m.	Questions and Discussion
5:45 p.m.	**Adjournment**	

April 24, 2007: Valuation for Environmental Policy

8:30 a.m. – 9:00 a.m.	**Registration**	
9:00 a.m. – 11:45 a.m.	**Session IV: Valuation of Ecological Effects** Session Moderator: William Wheeler, EPA, NCER	
	9:00 a.m. – 9:30 a.m.	Integrated Modeling and Ecological Valuation: Applications in the Semi Arid Southwest David Brookshire, University of New Mexico, Arriana Brand, Jennifer Thacher, Mark Dixon,Julie Stromberg, Kevin Lansey, David Goodrich, Molly McIntosh, Jake Gradny, Steve Stewart, Craig Broadbent and German Izon
	9:30 a.m. – 10:00 a.m.	Contingent Valuation Surveys to Monetize the Benefits of Risk Reductions Across Ecological and Developmental Endpoints Katherine von Stackelberg and James Hammitt, Harvard School of Public Health
10:00 a.m. – 10:15 a.m.	**Break**	
	10:15 a.m. – 10:45 a.m.	Valuing the Ecological Effects of Acidification: Mapping the Extent of Market and Extent of Resource in the Southern Appalachians Shalini Vajjhala, Anne Mische John, and David Evans, Resources for the Future
	10:45 a.m. – 11:00 a.m.	Discussant: Joel Corona, EPA, Office of Water
	11:00 a.m. – 11:15 a.m.	Discussant: David Simpson, Johns Hopkins University
	11:15 a.m. – 11:45 a.m.	Questions and Discussion
11:45 a.m. – 1:00 p.m.	**Lunch**	
1:00 p.m. – 4:15 p.m.	**Session V: Water Resources** Session Moderator: Adam Daigneault, EPA, NCEE	
	1:00 p.m. – 1:30 p.m.	Valuing Water Quality as a Function of Physical Measures Kevin Egan, Joe Herriges, John Downing, and Katherine Cling, Iowa State University
	1:30 p.m. – 2:00 p.m.	Cost-Effective Provision of Ecosystem Services from Riparian Buffer Zones Jo Albers, Oregon State University; David Simpson, Johns Hopkins University; and Steve Newbold, NCEE
2:00 p.m. – 2:15 p.m.	**Break**	
	2:15 p.m. – 2:45 p.m.	Development of Bioindicator-Based Stated Preference Valuation for Aquatic Resources Robert Johnston, Eric Shultz, Kathleen Segerson, Jessica Kukielka, Deepak Joglekar, University of Connecticut; and Elena Y. Besedin, Abt Associates

April 24, 2007 (continued)

	2:45 p.m. – 3:05 p.m.	Comparing Management Options and Valuing Environmental Improvements in a Recreational Fishery Steve Newbold and Matt Massey, NCEE
	3:05 p.m. – 3:20 p.m.	Discussant: Julie Hewitt, EPA, Office of Water
	3:20 p.m. – 3:35 p.m.	Discussant: George Parsons, University of Delaware
	3:35 p.m. – 4:05 p.m.	Questions and Discussions
4:05 p.m. – 4:15 p.m.	**Final Remarks**	
4:15 p.m.	**Adjournment**	

Integrated Modeling and Ecological Valuation: Applications in the Semi Arid Southwest[1],[2]

David S. Brookshire[3], L. Arriana Brand, Jennifer Thacher, Mark D. Dixon, Karl Benedict, Juliet C. Stromberg, Kevin Lansey, David Goodrich, Molly McIntosh, Jake Grandy, Steve Stewart, Craig Broadbent and German Izon

May 17, 2007

I. Introduction

Conservation of freshwater systems is critical in the semi-arid Southwest where groundwater and flood regimes strongly influence the abundance, composition, and structure of riparian (streamside) vegetation. At the same time these systems are in high demand for competing human use (Stromberg et al. 2007, Alley et al. 2002). To address this conflict, natural scientists must evaluate how anthropogenic changes to hydrologic regimes alter ecological systems. A broad foundation of natural science information is needed for ecological valuation efforts to be successful. The goal of this research is to incorporate hydrologic, vegetation, avian, and economic models into an integrated framework to determine the value of changes in ecological systems that result from changes in hydrological profiles.

[1]This research is supported by the U.S. Environmental Protection Agency, "Integrated Modeling and Ecological Valuation," EPA STAR GRANT Program #2003-STAR-G2 and in part by SAHRA (Sustainability of semi-Arid Hydrology and Riparian Areas) under the STC Program of the National Science Foundation, Agreement No. EAR-9876800 (work related to the avian component), and with in kind contributions from the U.S. Department of Agriculture Research Service, Hawks Aloft Inc and The Nature Conservancy. We would like to thank, John Loomis and Bonnie Colby who participated in a workshop in Albuquerque 2006 and offered significant insights and suggestions to the overall survey design.
[2] Presented at the USEPA "Valuation for Environmental Policy: Ecological Benefits" workshop April 23, 24, 2007 in Washington D.C. Comments are welcome. Please send to David Brookshire (brookshi@unm.edu)
[3] Respectively, Professor of Economics and Director of the Science Impact Laboratory for Policy and Economics, University of New Mexico (UNM); Research Associate, Sustainability in semi-Arid Hydrologic Riparian Areas, University of Arizona (UA); Assistant Professor of Economics (UNM); Assistant Professor of Biology, University of South Dakota; Senior Research Scientist, Earth Data Analysis Center, (UNM); Associate Professor, School of Life Sciences, Arizona State University; Professor of Civil Engineering, (UA); Research Scientist, US Department of Agriculture; Attorney at Law and Bilingual Mediation and Facilitation, NM; Middle Rio Grande Conservancy District, Research Scientist, Sustainability in semi-Arid Hydrologic Riparian Areas, (UA), Research Assistant, (UNM); and Research Assistant, (UNM).

We have developed a hydro-bio-economic framework for the San Pedro River Region (SPRR) in Arizona that considers groundwater, stream flow, and riparian vegetation, as well as abundance, diversity, and distribution of birds within a protected area encompassing the San Pedro Riparian National Conservation Area (SPRNCA). In addition, we are developing a similar framework for the Middle Rio Grande of New Mexico (MRG). Distinct valuation studies are being conducted for each site with benefit-transfer tests to be conducted between the two sites. This research is novel in that it provides much more detailed scientific information for economic valuation models than is typically available

In the absence of integrated science information, stated-preference valuation studies are typically must rely on vague program descriptions and imperfect measures of the change in resource quality or quantity. The lack of a scientific foundation for economic valuation studies typically occurs either because (1) targeted scientific research on the topic of interest is lacking, or (2) scientific studies that do exist have not been adequately designed to directly inform valuation questions. Ideally, existing scientific information should provide forecasts for the area of interest, contain well-defined timescales, and speak in terms that are relevant and understandable to the lay public. This study attempts to address these issues through use of an integrated scientific/economic framework. The research team includes hydrologists, ecologists, ornithologists, geospatial geographers, facilitators, and economists, most of whom are centrally involved in varying degrees with research projects in both the SPRR and the MRG.

There are five research components for this project: (1) scenario specification and the hydrologic model, (2) the riparian vegetation model, (3) the avian model, (4) methods for displaying the information gradients in the survey instrument, and (5) the economic framework. As such, our modeling framework begins with the identification of factors that influence spatial and temporal changes in riparian vegetation on the two rivers. For the SPRR this is principally through impacts on the availability of surface water and groundwater, while in the MRG the impacts are through regulation of flooding and human restoration activities. We use the construct of "current conditions" as a basis for making spatial predictions of vegetation change and avian populations in both river systems through linked modeling frameworks. This framework utilizes the best available information through the direct focus on science-based linkages between flow regimes, habitat quality, birds, and human values.

The goal of this paper is to provide a brief overview of the research project to date and discuss some of the issues that have been encountered in designing an integrated framework for each river system. In addition we broadly discuss issues relating to the workings of an interdisciplinary team, issues associated with defining appropriate attributes to be valued based on the scientific information available as well as how the definition of the attributes might change depending upon the goals of the valuation exercise.

II. Study Areas

This project required the added complexity of selecting study areas based on natural science considerations in addition to demographic and socio-economic concerns with selecting a benefit transfer site. It was necessary, from the science perspective, to restrict the transfer site to a region having similar physical and ecological conditions to the SPRR; thus our focus was on lowland (<5,000 feet), semi-arid, Southwestern riparian vegetation. This provides sites where conflicts between human use and riparian needs are most pronounced, visitation characteristics are similar, and riparian vegetation in the recent past (i.e. past century) was historically dominated by cottonwood, willow and mesquite. On each river, environmental stresses (e.g. groundwater depletion, altered flood regimes) have led to partial replacement of these species by non-native species better suited to the effects of anthropogenic change, specifically stands of salt cedar or Russian olive. Further, given the types of data required for the valuation exercise, we were also limited by areas for which appropriate datasets (e.g. vegetation maps, bird transect data) were available.

Two study areas for this project were selected based on both natural and social science concerns. The SPRNCA in southern Arizona encompasses an approximately 40-mile stretch of the San Pedro River between the U.S.- Mexico border and St. David, Arizona. The San Pedro flows north from Cananea, Mexico, enters the U.S. near Sierra Vista, and eventually reaches the Gila River, a tributary to the Colorado River (Figure 1). The San Pedro is a free-flowing river containing stretches of gallery riparian forest and represents an extremely important semi-arid flyway. The SPRR provides critically important habitat for resident, breeding, and migratory birds, but may be threatened by groundwater decline due to pumping of the regional aquifer. Over 400 bird species have been recorded in the SPRR; more than 200 of these are neo-tropical migrants (Krueper 1999).

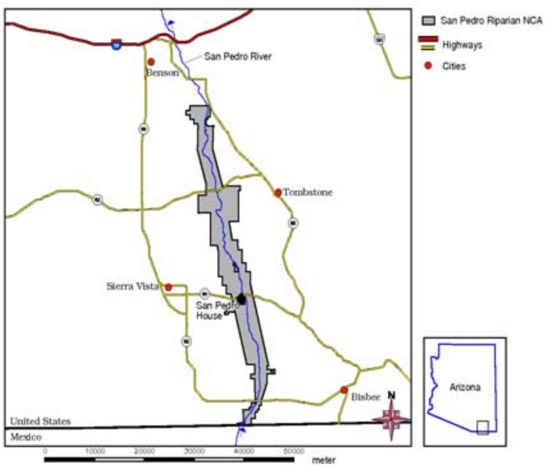


Figure 1: SPRR and SPRNCA

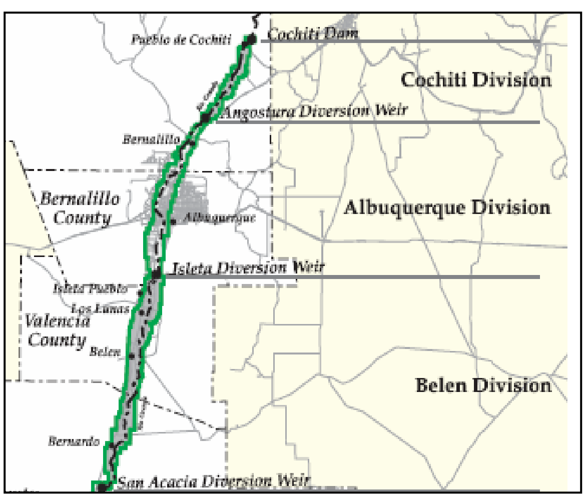


Figure 2: Middle Rio Grande

The MRG covers the area from Cochiti Dam (North of Albuquerque) to the San Acacia gage (above Elephant Butte reservoir). The study area is approximately 140+ miles of river and includes the Rio Grande State Park, located in the Albuquerque vicinity (Figure 2). As in the SPRR, the riparian system is essentially a wooded riparian area (bosque). Even though there have been serious impacts on the riparian corridor through agricultural activities and urban development, it remains a biologically diverse community in the Southwest, providing a wealth of habitat for breeding, wintering, and migrating birds.

III. Overview of Project Components

a. Ecosystem Alteration Drivers, Decision Support Frameworks, and Scenarios

Extensive human use of dryland rivers has resulted in many changes to their biota. For example, on parts of the SPRR groundwater depletion and overgrazing by livestock have contributed to shifts from cottonwood-willow (*Populus-Salix*) forests to *Tamarix* shrub lands (Stromberg 1998; Lite et al. 2005). The riparian ecosystem on the MRG has been impacted by flood control facilities, river channelization, land clearing, and agricultural activities. More recently, mechanical removal of introduced invasive species, motivated by both aesthetics and fire control, has influenced vegetation patterns in the MRG. Significant research effort has been allocated toward understanding the impacts of groundwater pumping on the SPRR biota and developing policy options that could be used to mitigate the impacts of groundwater pumping. Since agricultural activities have largely been eliminated from the SPRNCA region, the focus on policy options falls into four principal categories:

1) Infrastructure changes: changing the location of subdivisions and groundwater wells or recharge basins in order to reduce groundwater declines near the river;

2) Water augmentation: increasing the amount of water in the basin via inter-basin transfers;

3) Water conservation: decrease the consumption in the region through regulations and incentives;

4) Combination of all of the above

A Decision Support System (DSS) has been developed with the aid of systems dynamic modeling software (Tidwell et al., 2004 as an illustrative application of a DSS) by the San Pedro Partnership to provide the basis for understanding the impacts of alternative policy decisions and to identify the effectiveness of alternative water conservation measures for the Upper SPRR (Sumer and Lansey, 2004; Ritcher 2006[4]). The DSS, designed with the aid of systems dynamic modeling software, incorporates a USGS groundwater model, surface water supply, groundwater storage, and residential/commercial water uses. It allows temporally and spatially variable future population growth and associated water consumption. Each policy measure or combination of policies can be simulated for a 50 year period or less. The impacts of activities such as groundwater pumping can be determined spatially relative to specific river reaches.

Our research places additional demands upon the DSS, particularly the need to understand groundwater levels as well as changes in riparian vegetation with more spatial and temporal precision than is needed by SPRR water managers. Because the DSS is funded primarily by other entities, the more sophisticated features that this research requires can only be incorporated into major revisions of the DSS.

While operational, the DSS is still undergoing development. Additional features such as the condition class model, upon which much of this research is based, are being added to each new version of the model. Because the current version of the DSS does not include the condition class model to generate vegetation changes, we relied upon scientists' (D. Goodrich, personal communication) best estimate of the magnitudes of likely groundwater level changes in status quo, high growth and low growth/high conservation scenarios garnered from the understanding

[4]The USPP DSS has not been published in its entirety as it is still be vetted by the Upper San Pedro Partnership.

of the USGS groundwater model currently incorporated in the DSS (scenarios 4 - 7) in addition to uniform (scenarios 1 – 3), and end-member cases (scenarios 8 and 9) groundwater changes.

Scenario 1 = 0.5 m uniform decline in groundwater;

Scenario 2 = 1 m uniform decline in groundwater;

Scenario 3 = 0.5 m uniform increase in groundwater;

Scenario 4 = Continued and increased agricultural pumping near Palominas; new developments in unincorporated areas of Palominas and Hereford near SPRNCA;

Scenario 5 = Increasing cone of depression in Sierra Vista, Ft. Huachuca, and Huachuca City with impacts toward the lower Babocomari and northern SPRNCA;

Scenario 6 = Large increases in groundwater due to recharge and conservation efforts in Sierra Vista and Bisbee;

Scenario 7 = combined from scenarios 4 & 5, representing effects of both agricultural pumping in the south and increasing cone of depression;

Scenario 8 = Low extreme - river essentially dries up;

Scenario 9 = High extreme - river essentially has surface flows throughout SPRNCA[5].

Figure 3 depicts the impact on SPRNCA of the above hydrologic scenarios. Each graph shows SPRNCA divided into 14 reaches. Based on research from project ecologists, reaches have been classified into one of three types (condition classes): wet, intermediate, dry. This classification reflects variables such as annual surface water permanence, depth to groundwater, and vegetation composition (Lite and Stromberg 2005, Stromberg et al. 2006). The SPRNCA currently consists primarily of wet and intermediate reaches; in our scenario analysis we assume

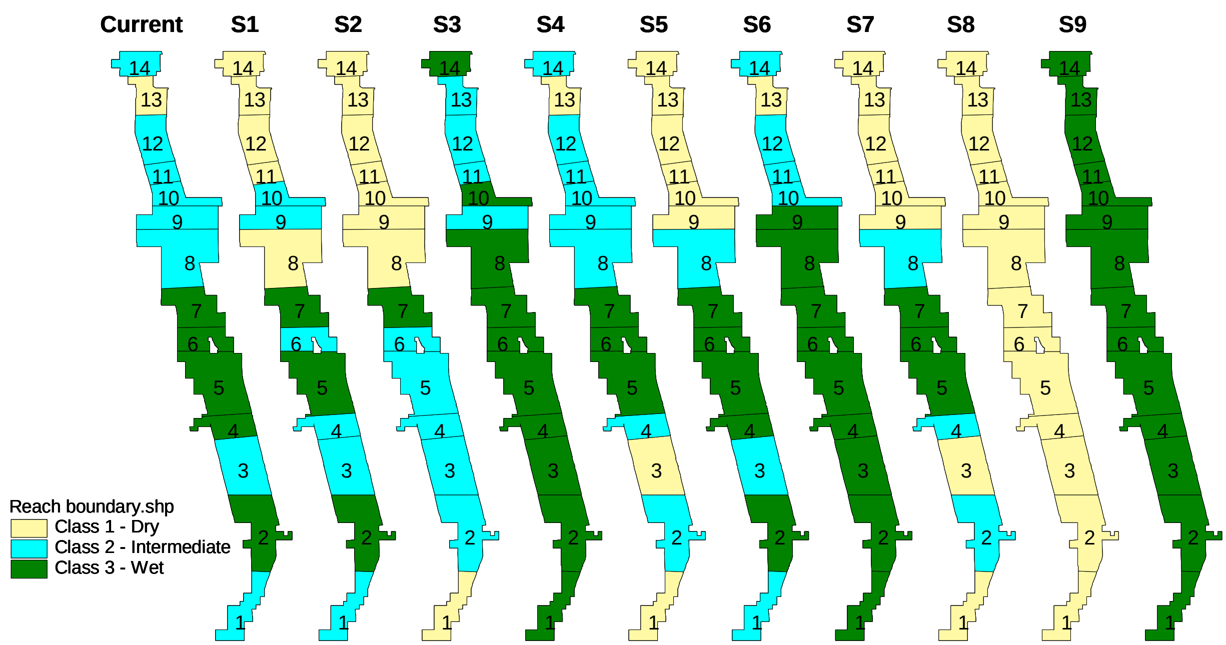
[5]The importance of developing plausible scenarios became apparent during the May 2006 focus groups where participants were generally frustrated with the choice question because the scenarios causing the changes in attribute levels was intentionally left ambiguous.

that changes in groundwater levels from actions such as pumping and recharge results in shifts between stream classes.

b. Riparian and Avian Components

One of the core challenges of this project has been to quantitatively link models across the natural science disciplines, and in turn, provide usable outputs for ecological valuation. The

Figure 3: Changes in San Pedro Riparian Condition Classes by Scenario



riparian and avian components each began with different goals. The objective of the riparian component was to determine how riparian vegetation distribution, composition, and structure respond to changes in surface flow and groundwater levels in the SPRNCA. As noted above, prior riparian research yielded a condition class model based on underlying hydrologic conditions. The objective of the avian component was to determine the impact of hydrologic and vegetation changes on bird populations and communities for the different reaches of the SPRNCA, and then express these outputs in terms of bird abundance as inputs into the ecologic valuation models. Bird abundances were assessed by migratory status, nest height, and the degree of water-dependence.

The next step was to link the riparian condition class model with avian datasets. The modeling framework used the raw data that was available for vegetation and birds (e.g. average proportion of different habitat types within a condition class and bird densities by habitat type and hydrologic class), and projected how changes in groundwater, as reflected in the condition class vegetation model, would impact bird abundances as a function of the different hydrologic scenarios by reach. While the components of this work were not new (for example, the developed methodology applied some basic approaches in space-for-time substitution modeling and the delta method to calculate errors propagated across the vegetation and bird modeling levels), the development and programming of this model was specific to the data and problem at hand. This linkage was the key step required to provide a scientific foundation to the economic valuation effort[6].

c. Survey Component

The foundation of the survey research program is framed by the following questions:

1) What is the ideal set of physical, natural, and social science information on which to build an economic research program to value ecological service flow changes?

2) Can alternative suites of natural science information coupled with socio-behavioral information lead to a better understanding of both intra-site and inter-site benefit transfer functions?

The research incorporates two stated preference techniques, Contingent Valuation (CVM) and Choice Modeling (CM), with three alternative information gradients, “Fine”, “Coarse” and

[6]Linking models across disciplines is inherently challenging and requires quantitative skill. As such, future interdisciplinary efforts should not underestimate the work involved in developing methods to link disciplines, since each effort is likely to require a novel methodology and approach. The research team feels that because of their quantitative nature, such efforts would also be enhanced by hiring a qualified, experienced statistician to aid with the development of methodology and programming.

"Traditional" for each technique. To date there have been few published comparisons of CVM and CM (Stevens et al. 2000; Margat et al. 1998; Barret et al. 1996; Boxall et al. 1996; Ready et al. 1995; Mackenzie 1993; Desvousges et al. 1987). All of these studies found substantial differences in willingness to pay (WTP) estimates between the various forms of CVM and CM analyses for equivalent policies. Various reasons for the disparity have been offered: first, CVM is a one shot procedure vs. the iterative nature of the CM (Takatsuka 2003); second, the presentation of alternative policies in the CM format suggests substitute (alternative) policies not available in CVM (Boxall et al. 1996; Ready et al. 1995); third, CMs allow explicit recognition of complements that CVMs may not (Morrison 2000, Stewart et al. 2002); fourth, the effects of data structure used for conditional logit vs. standard logit estimation vary (Stewart et al. 2002). In addition to these comparisons, benefit transfers will be conducted between the two test sites. The literature on benefit transfers predominately relies on the science as given (Desvousges et al. 1998). Few studies have examined the role of models across disciplines in a benefit transfer setting (Brookshire et al., 2007; Brookshire and Chermak, 2007), while few cross-method comparisons exist (Boxall et al. 1996; Stevens et al. 2000; Takatsuka, 2003).

CM, a variant of conjoint analysis, elicits an individual's preferences by asking the subject to consider a series of alternatives. In contrast to CVM, which asks individuals to explicitly state their willingness to pay for a proposed policy change, CM requires the individual to choose from a series of possible alternatives, each having different levels of the attributes (birds, in-stream flow, riparian vegetation and cost, for example). This allows the researcher to obtain the marginal value (implicit price) of each attribute, as well as welfare measures for any policy that has attributes contained within the span of those presented in the survey. Both the CVM and CM models utilize a random-utility framework to explain individuals' preferences for alternative profiles and are directly estimable from the CVM and CM data (Roel et al. 1996; Stevens el at. 1997). Several iterations of the coarse scale CM surveys have been drafted with emphasis on the educational and scenario components. The educational component forms the foundation of all three information levels for both the CM and CVM surveys.

Information gradients are represented through different levels of spatial representation and / or levels of detail of ecological attributes. The "Traditional" scale will provide minimal spatial representation of the attributes[7], the "Coarse" scale will provide reach scale spatial representation[8] with the "Fine" scale providing reach scale spatial representation giving survey participants the option to 'drill-down' to more detailed information on hydrologic, vegetation, and avian attributes[9]. In this regard different levels of scientific information are coupled with the ability to present the attributes in more advanced forms. To ensure that responses are representative of the population, both mail and internet versions of the surveys are being developed. Figure 4 shows the types of comparisons that can be made across modeling

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[7] The notion of the traditional scale is that much of the scientific research has enabled an understanding of the ecological processes of the river systems in spatial detail. If this work had not been done, we would have been faced with what might be a more traditional informational setting. That is, rather than being able to divide the river into stretches as they relate to groundwater levels, we would have been faced with information such as 35% is cottonwood, 50% mesquite, etc.

[8] Coarse scale information uses the best available science in a spatial setting but omits within the survey some of the available detail such as reference to all types of birds.

[9]The fine scale incorporates within the structure of the attribute set all of the available information. For instance, the 'drill-downs' will allow the respondent to examine in detail changes in a particular bird species.

approaches and the types of tests that can be conducted using a benefit transfer.

Figure 4: Benefit Transfer Tests

		Traditional Survey	Coarse Survey	Fine Survey
Choice Questions	San Pedro	No spatial vegetation and bird information	*Spatial vegetation and bird information*	*Spatial vegetation and bird information, plus the ability to drill down by reach for additional information*
Choice Questions	Rio Grande		Spatial vegetation and bird information	
DC / CVM	San Pedro		*Policy attribute chosen by scientist*	
DC / CVM	Rio Grande		Policy attribute chosen by scientist	

Educational component is the same

Educational component is the same

d. Focus Groups

To date, three focus groups have been conducted using a draft of the "Coarse" scale CM SPRNCA survey. These focus groups aimed to obtain specific written and oral feedback for each section of the survey as well as comments on the overall structure of the survey. Feedback indicated that although the cognitive burden of the survey was high due to the complexity of the issue, many participants wanted access to more information. Interestingly this desire was in contrast to their desires for the survey to be shorter. This apparent conflict prompted the inclusion of 'drill-downs' in the "Fine" scale surveys. Feedback also indicated that the overall presentation of the material needed to be changed to reduce redundancy and eliminate irrelevant information to reduce the cognitive burden of the survey. This feedback has significantly streamlined the surveys. At the writing of this paper future focus groups have been planned for the SPRNCA CM survey, utilizing laptops for presentation purposes.

IV. Reflections on the Interdisciplinary Process for Organizing the Science Information

An overarching goal of this project is to build a broad foundation across the natural and social sciences that will allow us to address the critical issue of conservation of riparian systems in the Southwest. This project has tackled the challenging task of identifying a set of feasible policy options that lead to groundwater changes that, in turn, affect vegetation and birds. The survey then presents the resulting scientific information for an educational component for survey respondents about the scientific details of the attributes to be valued within the CM framework. An important lesson learned from this process has been that the goals of the valuation process affect the instruments' attribute structure. Consider four possible stylized goals of the valuation process:

1) Focus only on the SPRR ecosystem: The valuation process will use the best available science information to uniquely reflect the attributes in the SPRR. No consideration will be given in the design to the issues associated with transferring the valuation results to other semi-arid riparian areas. This would lead to a more traditional benefit transfer exercise where the transfer from the SPRR to MRG are only a "rough" fit with regards to the attributes.

2) Focus only on the MRG ecosystem: The valuation process will use the best available science information to uniquely reflect the attributes in the MRG. No consideration will be given in the design to the issues associated with transferring the valuation results to other semi-arid riparian areas.

3) Design the valuation instruments with the SPRR as a base, attempting to account for the disparity in scientific information between the SPRR and the MRG (e.g. differences in types and amounts of scientific information and differences in the ecosystems themselves including the different species assemblages found in the two areas). This would engender a more robust set of benefit transfer exercises.

4) Design the valuation instruments in tandem, with the goal of creating a set of ecosystem values that are transferable to most semi-arid regions in the Southwest.

Depending on the goal desired, one would follow a different process, where the results of each goal may be in conflict with each other. Below we outline in more detail the oppositional nature of these goals and the process by which a compromise was achieved.

a) Idealized Representation of the Scientific Knowledge

In defining the attributes, the research team faced the immediate problem that the scientists ideally would like a more complete representation of the ecological processes and outputs. For instance, in the development of the SPRNCA condition class model, 9 different riparian vegetation attributes are measured (Stromberg et al 2006; Lite and Stromberg 2005) where only 4 vegetation attributes are represented in the economic survey. Likewise the avian component estimated over 45 possible single-species and 21 grouped-species abundance attributes for breeding and migratory birds as well as species richness and nest success with only 3 attributes being used in the ecological valuation study.

Clearly the level of detail normally addressed by science goes far beyond the cognitive burden of survey respondents and beyond the study design requirements for the ecological modeling effort. Structuring and simplifying the science inputs from the ecologic models has required an iterative and multi-pronged process. First, based on the initial attempts of the ecologists, plant and bird species were isolated and aggregated into groups that best represent the primary impacts of hydrologic and/or restoration change profiles on both birds and vegetation. Second, feedback from focus group surveys were presented back to the ecologists. Finally, simplification of the science has depended on the needs of the experiment and study design of the ecological valuation models. Thus, the final set of vegetation and bird attributes represent a compromise between maintaining a foundation in meaningful and accurate scientific findings and simplifying the results so that survey designers and respondents can handle the cognitive burden.

Different Goals would Lead to Different Approaches

In what follows, we will briefly detail the compromise from the scientific perspective, first noting the key "drivers" of ecological change (e.g. ground water depletion) followed by a discussion as to the resulting structure of the information for vegetation and birds. We will then discuss the compromises from the perspective of designing a CM framework followed by extracted text from the "Coarse" SPRNCA survey to illustrate the final form that the compromise took.

i. Goal 1-Focus only on the SPRR:

Physical Drivers: The master variable that is driving changes in the SPRR riparian ecosystem is availability of surface water and groundwater. Groundwater pumping in concert with natural variations in stream hydrogeomorphology has created gradients of depth to groundwater along the river.

Vegetation: The riparian vegetation, in response to changes in surface and groundwater hydrology, change species composition and growth form. To best represent this, vegetation information attributes have been presented for each river reach in terms of:

1. Abundance of tall, flood-dependent, wetland trees (i.e., Fremont cottonwood and Goodding willow);
2. Abundance of short, flood-dependent, drought-tolerant shrubs (i.e., saltcedar);
3. Abundance of wetland ground cover and stream surface water.

Birds: Riparian birds, in response to both the physical drivers and changing vegetation, have changed in bird species composition and abundance. To best represent this, bird attributes would be presented for each river reach in terms of:

1) Canopy vs. non-canopy, where canopy nesting birds decline with the loss of tall trees on the SPRNCA occurring from the transition of wet or intermediate reaches to dry reaches.

2) Degree of water dependence, where water obligate birds (e.g. wading, swimming, or shorebirds) decline with loss of perennial surface water, this occurs from the transition of condition class from wet to intermediate or dry reaches.

3) Migrating birds, which have an overall decline with the loss of tall trees.

ii. Goal 2-Focus only on the MRG:

Physical Drivers: The master variable that is driving changes in the MRG riparian ecosystem is alteration of the flood disturbance regime. Secondarily, human restoration actions are driving changes, where changes in the system have occurred as a result of channelization, land clearing, agricultural use, and urban use.

Vegetation: As a result of the reduction in river flooding caused by dam management, the species composition of the riparian vegetation has changed and the density of the vegetation has increased. Some parts of the MRG floodplain support tall, old, flood-dependent cottonwood forests with a very dense understory of smaller, flood-intolerant trees. Some of the understory trees are introduced species (such as Russian olive); others are native (such as New Mexico olive). As a result of changes in the pattern of river flooding (and perhaps in water table depth), other parts of the floodplain no longer support cottonwood but support dense stands of the shrub salt cedar. Restoration actions are shaping the vegetation by mechanically clearing non-native plants in the dense mid-story vegetation. To best represent this goal, the information would be presented by each river reach in terms of:

1. Abundance of tall, flood-dependent, wetland trees (i.e., Fremont cottonwood and Goodding willow);

2. Abundance of short, flood-intolerant trees.

    a. Abundance of short, flood-intolerant trees that are native

    b. Abundance of short, flood-intolerant trees that are introduced

3. Abundance of short, flood-dependent, drought-tolerant shrubs (i.e., saltcedar)

<u>Birds</u>: As a result of changing vegetation, riparian birds change in terms of composition and abundance. To integrate the response of vegetation, information should be presented for each river reach in terms of:

1. Canopy, mid-story and understory (ground/low-shrub) nesting birds. The canopy nesting birds are predicted to increase with removal of monotypic stands of salt cedar and restoration of tall cottonwood-willow forests in the southern study area of the MRG. Mid-story and possibly understory nesting birds decline with mechanical thinning of the non-native mid-story in the short term.

2. Migrating birds may show an overall decline with loss of tall trees or from the loss of understory shrubs or trees due to mechanical thinning.

The distinct physical differences and anthropogenic pressures between the MRG and the SPRR illustrate that goals 1 and 2 would lead to a different set of vegetation and bird attributes if each site were considered individually. For vegetation this is exemplified by the different stressors, physical drivers, and species present at the two sites. On the SPRR natural flood regimes exist with the stressor of concern being groundwater decline. The vegetation attributes of concern are those related to changes in groundwater depth (shifts from cottonwood-willow to saltcedar) and surface flow permanence (loss of herbaceous wetland plants). On the MRG, the alteration of flood regimes by upstream dams and bank stabilization structures is the primary stressor, with groundwater having a lesser role. This necessitates a shift in focus from plant traits related to drought tolerance/groundwater depth on the SPRR, to one dealing with responses to flooding or the lack thereof (i.e., increased abundance of flood intolerant smaller trees) on the MRG. In addition, the functional group approach, rather than a species-based approach, becomes necessary when both systems are considered, because of the differences in the species present in the SPRR and MRG (e.g., Russian olive is absent from the SPRR).

For birds, emphasis on canopy versus non-canopy nesting birds for the SPRR would need to be expanded for the MRG to emphasize the differences that occur in the mid-story and understory from mechanical thinning of the vegetation. The different attributes show how different physical and anthropogenic drivers on two river systems (alteration of groundwater regime on the SPRR; active mechanical thinning on the MRG) impact the difference in bird attributes. While the degree of water dependence is an important variable for the SPRR as obligate birds decline with loss of perennial surface water, this group would likely not be as important on the MRG as there is less expected variation in availability of surface water between current conditions and restoration scenarios. While little is known thus far how migrating birds will respond to vegetation changes on the MRG, they are included as an attribute since feedback from the focus groups have emphasized migrating birds.

iii. Goal 3 - The SPRR is the base, but a close eye is kept on the MRG as a transfer site:

Physical Drivers: Groundwater and flood regimes are two key driving variables that structure dryland riparian ecosystems across the SPRR and MRG river systems, while mechanical thinning of understory vegetation ("restoration") is an important physical driver for the MRG.

Vegetation: To capture the effects of changes in these master variables on riparian vegetation of unconstrained, low gradient, historically perennial rivers of the American Southwest, information should be presented for each river reach on:

1. Abundance of tall, flood-dependent wetland tree species (e.g., Fremont cottonwood, Goodding willow);
2. Abundance of short, flood-dependent drought-tolerant shrub species (e.g., saltcedar);
3. Abundance of short, flood-intolerant trees (e.g., Russian olive, velvet mesquite);
4. Abundance of herbaceous wetland vegetation and surface water.

Birds: The master variables that are driving changes on SPRR and/or MRG bird communities are availability and composition of riparian vegetation and surface water availability. To capture these more general influences, information should be presented on the union of attributes from the SPRR and MRG:

1. Canopy, mid-story and understory (ground/low-shrub) nesting birds. The canopy nesting birds decline with loss of cottonwood on the SPRR, while they increase with clearing of monotypic stands of salt cedar and restoration of tall riparian trees (e.g., cottonwood forests) in the southern study area of the MRG. Mid-story and possibly understory nesting birds decline with mechanical thinning of the non-native under story in the short term on the MRG.
2. Degree of water dependence. Water obligate birds decline with loss of perennial surface water on the San Pedro; this group will not likely be as important on the MRG as on the San Pedro.Water obligate birds decline with loss of perennial surface water on the SPRR; this will not likely to be a very important group on the MRG.
3. Migrating birds decline with loss of tall trees on the SPRR, and may or may not show an overall decline with loss of tall trees on the MRG.

The distinction between goals 1 or 2 with goal 3 show that the set of vegetation and bird attributes would need to be the union, or combination, of attributes for the two individual rivers systems. If each site were considered individually it would be important to have the set of attributes that best represented the specific physical drivers occurring on that river system. However, when looking across river systems the attributes would need to be expanded accordingly.

iv. Goal 4 - Assume Goal 3 is satisfied but the taxonomy needs to be robust to all semi-riparian areas.

Environmental Drivers: There are many key variables that shape semi-arid riparian areas in the Southwest such as hydrologic regimes (groundwater flows, base flows, flood flows) and geomorphic regimes (sediment flows and other geomorphic processes). Other key drivers include water quality (including salinity and nutrients), fire, climate, and activities of mammals including beavers (an ecosystem engineer), large herbivores, and people (including restoration actions). The approach would need to encompass the wide range of flows regimes (ephemeral, intermittent, perennial), watershed sizes and stream orders (flood magnitude), stream geomorphologies (stream gradient, floodplain width), elevations and geographic locations found throughout the region.

Anthropogenic Changes: A taxonomy of the major types of human actions that can alter riparian areas in the Southwest needs to be created. Key actions include those that would alter water availability (diversions, pumping, interbasin transfers), flood patterns (dams, land use changes), water quality (effluent discharge, agricultural and urban runoff), stream morphology (channelization, berming), vegetation area (conversion to agriculture, urban), and herbivory levels (livestock grazing).

Vegetation: To link changes in vegetation attributes to the above anthropogenic changes, one would create a taxonomy of riparian ecosystem types in the Southwest. One would then gather empirical and/or theoretical information pertaining to vegetation responses to changes in the environmental drivers addressed above. Efforts have been undertaken to link specific environmental changes to riparian vegetation response for specific stream types, but many scientific gaps remain.

Birds: To develop riparian bird attributes across Southwestern rivers it would be necessary to assess how birds respond to the larger set of physical drivers It would then be possible to develop a meta-analytic dataset (pulling in existing data from the literature) to look at ecological and life-history traits of birds that respond strongly to changes in riparian vegetation across all riparian areas in the Southwest. This would encompass, among other things: variations in response of birds to vegetation composition, structure and arrangement, availability of surface, water, livestock grazing, and surrounding land cover. Grouped species predictions would then be possible, however probably only in some sort of index form such as a ranking of bird abundances (not absolute abundances).

One primary distinction between goals 1 and 3 versus goal 4 is that we likely won't have an original dataset that spans Southwestern rivers. Thus implementation of goal 4 would require the development of some sort of index to predict what is going on in a new river system without collecting a lot of additional data. Prediction to novel locations, based on existing empirical or theoretical knowledge in the natural sciences (both vegetation and birds) represents a major scientific endeavor. Because of its difficulty and novelty the scientific effort required to provide prediction to new locations as foundation to ecological valuation work should not be taken for granted or underestimated.

Indices are often used in ecological valuation and benefit transfer studies as proxies for specific benefits since there is often insufficient time and resources to study each attribute for which ecological valuation studies would be beneficial. Ecological indices may provide an efficient means to guide management and conservation decisions. Indices based on a relatively small set of ecological metrics have been used as substitutes for more intensive and/or expensive measurements of ecological conditions (O'Connell et al. 2000, Canterbury et al. 2000; Stromberg et al. 2004). While indices deliberately simplify complex ecological systems, they are intended to provide an efficient means to assess broad regions when more detailed studies are impractical or impossible (Karr 1991, Canterbury et al. 2000). From the natural science perspective, creation of meaningful ecological indices requires prediction of conditions in previously unstudied locations. While identification of larger ecological principles that may be operating across sites within a given region is one of the key goals of the science of ecology, it is by no means simple (Côté and Reynolds 2002).

In order for an index to be meaningful, it needs to be founded in ecological theory and be empirically based. For this project developing a predictive approach for the natural science inputs to the benefit transfer was a monumental task. Development of an appropriate index would have required collection of data across Southwestern riparian systems facing different physical drivers, and if only from the literature were available the use of meta-analysis would be required. Since the distribution of many species of birds may not cover an entire region of interest, use of ecological traits of species would have provided a means to predict expected responses of birds to changes in hydrologic and vegetation conditions across sites (Brand 2004).

Similarly, because species composition of riparian plants varies across the region, classification of plants by functional traits would have provided a means to predict riparian vegetation responses across sites. In addition to the substantial effort and time required to develop such indices, the primary stumbling block that we faced was that the structure of the ecological attributes would have been very different if an index were used for the benefit transfer site, while a non-index (e.g. bird abundance estimated from data) was used for the SPRR. Future efforts can and should be allocated to the development of predictive models in the natural sciences that begin to fulfill the need in ecological valuation for ecological indices that are meaningful across sites within a region, and are empirically and theoretically based.

V. Issues from the Choice Modeling Perspective

From the CM perspective, the biggest issues faced have been:

1. Accurately portraying the science results in a way that is comprehensible to survey respondents;

2. Defining the good in a way that keeps the 'best science' available from SPRNCA but allows transfer to other sites;

3. Removing the inherent correlation that comes from using integrated scientific results.

Based on feedback from the focus groups and considerations arising from the benefit transfer we drafted a new version of the coarse SPRNCA CM survey. We sought to find a balance between the vast detail of information available from the scientific outputs and respondent comprehension level. This version was shared around the research team so that all could check the greatly "aggregated" science content for accuracy in presentation.

To put this in perspective, we had available data on 33 individual species of birds by reach with over 15 different ways that our ornithologist could potentially group this species-specific data. The final attributes that were chosen for selection in the choice question include:

1. Miles of surface water;
2. Three possible condition classes of riparian vegetation with a spatial distribution;
3. Bird abundance by condition class;
4. Cost.

This final choice of attributes represents a trade-off between scientific detail, benefit-transfer needs, and CM requirements. For example, the condition classes represent the ’best available science’ at the coarse level of the SPRNCA, where the identification of a reach as wet, dry, or intermediate is based on a large number of variables that include groundwater, surface water, and vegetation types. This aggregation of information into one of three types was both a blessing and a challenge in terms of survey design. On the positive side presentation of these three types encapsulated a good deal of information in a way that was easy for individuals to understand. However this starting point created significant challenges for the economists.

A goal of the study was to determine a marginal value of water. We dealt with this by separating out surface water as an attribute and emphasizing the ground water/vegetative components of the condition classes. Although we spent significant time and energy identifying a Southwestern riparian area that was similar in many ways to the SPRR, as noted earlier, the policy drivers and the issues of concern are very different along the SPRR and MRG. In some ways the SPRR is quite unique. The ’best science’ for the SPRR was designed so as to best describe the SPRR, not necessarily other Southwestern rivers.

As discussed above, the challenge facing benefit transfer in this study, just as with any study, is that the models you would choose with benefit transfer in mind may be very different than what you would choose to describe a particular study area. What drove the best science at the SPRR is not necessarily the most salient issue in the MRG. Without conducting primary science on the MRG, it is essentially impossible to create riparian condition classes that are comparable to the SPRR. This fact has caused us to emphasize the vegetative characteristics of the condition classes. This has also resulted in additional complexity in the SPRNCA survey, as we bring in an additional vegetative component (short, flood-intolerant trees such as mesquite on the SPRR and Russian olive on the MRG) that did not change among the condition classes in the SPRNCA but varies among sites and is a focus of vegetation manipulations on the MRG.

While birds have been significantly easier to deal with from a transfer perspective, they have resulted in a fair amount of additional complexity. For example, we have six different bird categories: breeding/low-shrub; ground, breeding/high-shrub, breeding/canopy, breeding/water-dependent; breeding/non-water-dependent and migratory. Originally we had chosen categories of breeding/canopy, breeding/non-canopy, breeding/water-dependent and breeding/non-dependent to best capture the actual important changes that would occur in the SPRR from groundwater pumping. As total number of birds was predicted to stay relatively constant, total number of species did not capture the whole story; instead the important difference was in the composition of birds. Migratory was included because of the importance that focus groups bestowed on this category. Once the benefit transfer site was included, non-canopy had to be widened to encompass the real changes that are happening on the MRG. More specifically, while groundwater pumping that affects birds may be the primary concern in SPRR, it is restoration in response to fire concerns that affects birds in the MRG. The types of birds that are affected by these two policies are not the same. Thus, non-canopy was further sub-divided into low-shrub/ground and high-shrub. In trying to cover just two sites, the complexity has increased remarkably.

Finally a comment must be made from the choice-modeler's perspective. A goal of efficient CM is to create a design with independence between attributes. This is completely at odds with the idea of ecosystem services, which by their very nature are strongly linked; the desire for attribute independence has been troubling to the economists . The very heart of the scientific model employed in this study was to link disparate disciplines in creating an integrated model. Vegetation modelers linked their results to groundwater models and bird modelers based their model on the condition class model. What is the independent-attribute choice modeler to do? By its very design, the attributes of bird density are linked to condition class. One way we have tried to break these correlations is through the information presented to respondents. For example, respondents will be presented with information on miles of surface water; while this depends on condition class, it is not perfectly linked because of uncertainty in the surface water estimates and the spatial nature of the condition classes.

The agreement that has been made is that traditional design methods will be used, ignoring the correlations. The choice pairs will then be presented to the scientists for their review, so as to weed out any blatantly unobtainable combinations. Tests will then be run to check that the remaining combinations in the design will allow the economists to estimate the marginal values of interest. Because of the underlying science, we will then be able to use the estimated marginal values to estimate willingness to pay for scientifically predicted outcomes from potential groundwater changes. Once the marginal values are obtained, WTP estimation will be based on the scientific estimation of attribute levels. This represents the primary difference between traditional CM methods and our integrated approach.

VI. The Surveys

In the following section, we present some extracted text from the “Coarse” SPRNCA survey, to illustrate the final form of the compromise.

a. The “Coarse” SPRNCA Survey

The structure of the “Coarse” SPRNCA CM and the CVM survey will have the following:

1. Introduction, and discussion of the importance of riparian zones;
2. Background information of three important characteristics of the SPRNCA;
3. Discussion of water (focusing on surface and groundwater interactions), vegetation (focusing on types and relationships to water availability) and birds (focusing on types and relationship to vegetation cover);
4. Current conditions for the three riparian condition classes;
5. Relevant policy measures (appropriate variations for CVM);
6. Choice or dichotomous questions (appropriate variations for CVM)
7. Socio/economic/activity information.

Respondents are presented with a summary of each of the current condition classes, and provided with information about the average surface flow and density of birds by type. This is shown in Figures 5 through 7. Figure 5 shows this information for the wet condition class depicting which reaches of the SPRNCA are currently classified as wet. Figure 6 shows this information for the intermediate condition class depicting which reaches of the SPRNCA are currently classified as intermediate. Figure 7 shows this information for the dry condition class depicting which reaches of the SPRNCA are currently classified as dry.

Figure 5: Wet condition class

Characteristics of Average Wet Stretch

Surface Water Flow:
•99% of the year

Mix of Vegetation
No salt cedar
Predominantly cottonwood-willow (89%)
Some mesquite (11%)
Contains river marsh grasses

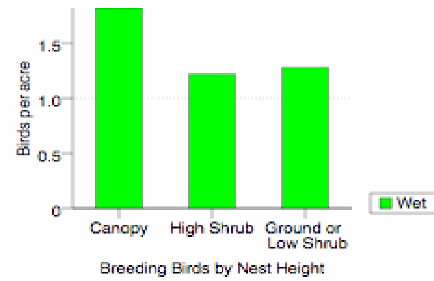
Birds
•Breeding birds by nest height
- Canopy: 1.8 per acre
- High Shrub: 1.2 per acre
- Low Shrub/Ground: 1.3 per acre

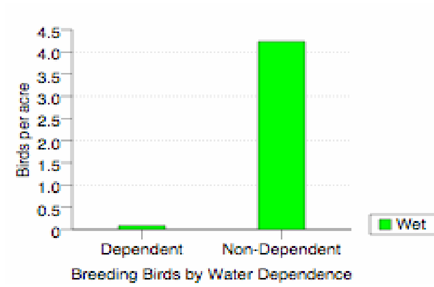
•Breeding birds by surface-water dependency
- Non-dependent: 4.2 per acre
- Dependent: 0.1 per acre

• Migratory birds: 3.3 per acre

Current Conditions for Wet Stretches in SPRNCA

●5 wet stretches, consisting of 601 acres (30 % of the total area of SPRNCA)
●On an average day, 14.5 miles of surface water
●3.3 migratory birds per acre





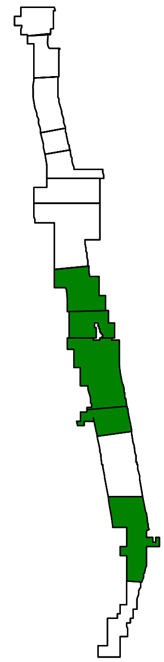


Figure 6: Intermediate condition class

Characteristics of Average Intermediate Stretch

<u>Surface Water Flow</u>
•70% of the year

<u>Mix of vegetation</u>
21% salt cedar
63% cottonwood-willow
16% mesquite
Contains no river marsh grasses

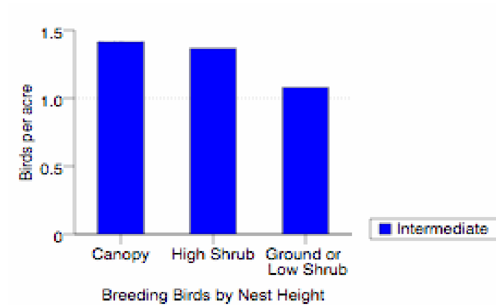
<u>Birds</u>
•Breeding birds by nest height
- Canopy: 1.4 per acre
- High Shrub: 1.4 per acre
- Low Shrub/Ground: 1.1 per acre

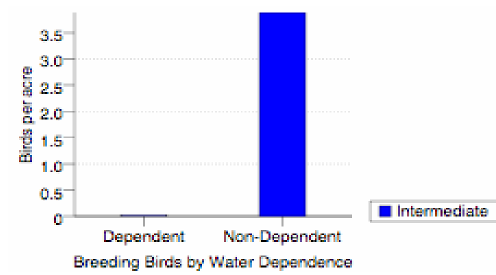
• Breeding birds by surface-water dependency
- Non-dependent: 3.9 per acre
- Dependent: 0.02 per acre

Migratory birds: 3.3 per acre

<u>Current Conditions for Intermediate Stretches in SPRNCA</u>

- 8 intermediate stretches, consisting of 1175 acres (60% of the total area of SPRNCA)
- On an average day, 14.9 miles of surface water
- 3.3 migratory birds per acre





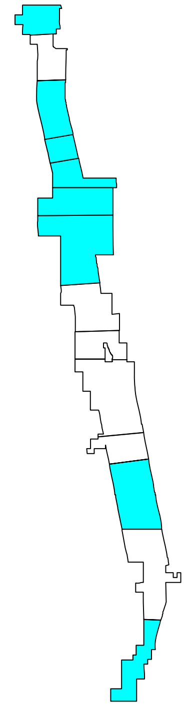


Figure 7: Dry condition class

Characteristics of Average Dry Stretch

Surface Water Flow
• 46% of the year

Mix of vegetation
Primarily salt cedar (73%)
17% mesquite
10% cottonwood-willow
Contains no river marsh grasses

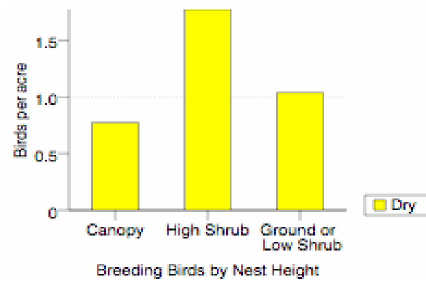
Birds
•Breeding birds by nest height
  • Canopy: 0.8 per acre
  • High Shrub: 1.8 per acre
  • Low Shrub/Ground: 1.0 per acre

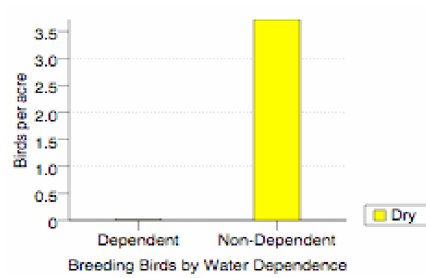
• Breeding birds by surface-water dependency
  • Non-dependent: 3.7per acre
  • Dependent: 0.01 per acre

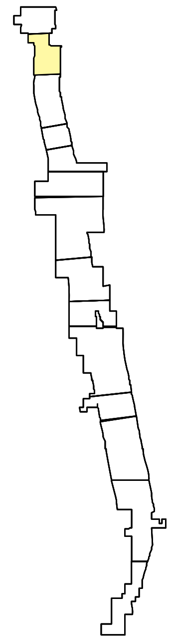
• Migratory birds: 3.8 per acre

Current Conditions for Dry Stretches in SPRNCA

- 1 dry stretch, consisting of 196 acres (10 % of the total area of SPRNCA)
- On an average day, 1.1 miles of surface water
- 3.8 migratory birds per acre







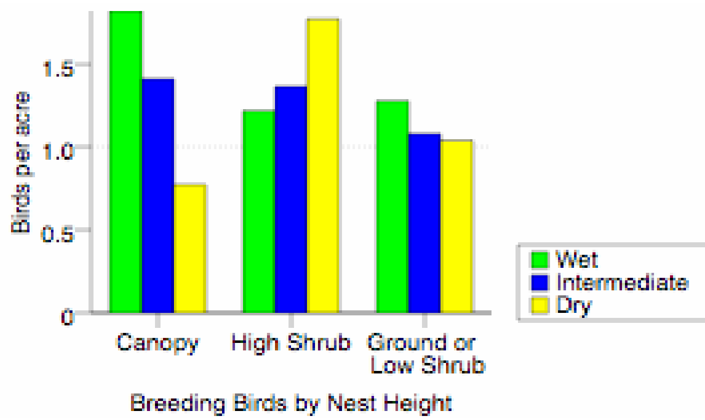
b. Current Conditions Summary

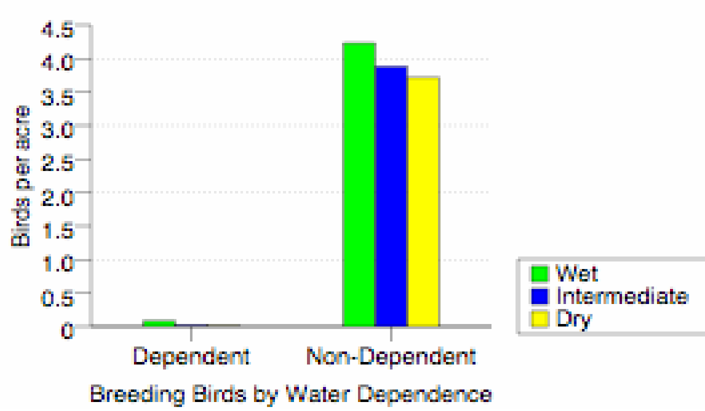
The information from each of the condition classes is then summarized into a single graphic (Figure 8). This graphic forms the status quo alternative and shows the format that is used to describe each of the choice alternatives.

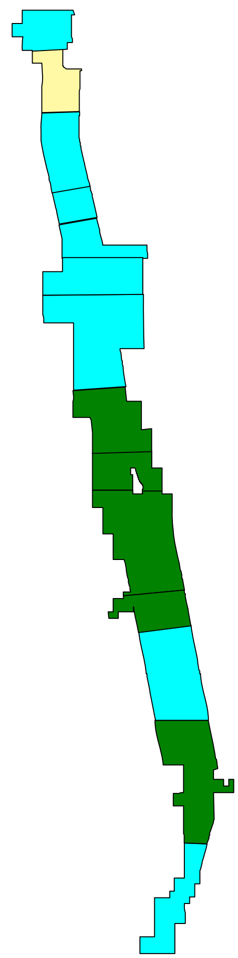
Figure 8: Current condition class

<u>Current Conditions for SPRNCA</u>

- Consists of 5 wet stretches totalling 601 acres (30% of SPRNCA), 8 intermediate stretches totalling 1175 acres (60% of SPRNCA), and 1 dry stretch of 196 acres (10 % of SPRNCA)
- On an average day, there are 30.5 miles of surface water
- 3.4 migratory birds per acre







VII. Reflections

This paper has presented a case study, highlighting some of the complexity involved in creating an integrated scientific/economic framework. As discussed in this paper, difficulties in creating such a framework for a single site include: the inherent contradictions in separately valuing ecosystem services as distinct, independent attributes; the cognitive difficulties posed for survey research in having primary scientific output; the challenges of integrating disparate disciplines; and the need to develop novel methods for connecting the output between the disciplines. These difficulties, while surmountable, are made even more challenging when the goal is to conduct benefit transfer between sites, as the 'best science' is traditionally geared towards understanding a specific site as opposed to broadly describing a set of sites. Accommodating scientific differences between sites and trying to remain scientifically accurate increases the cognitive burden placed on survey respondents while limiting the level of detail at which the problem can be addressed. The necessary result has been a number of pragmatic compromises.

While we present this experience with the hope of sparking discussion, we do so retaining the belief that while complex, the effort to integrate the disciplines remains essential. Working with other disciplines has been an interesting experience, highlighting the lack of full understanding of natural systems that economists bring to valuation exercises. In order to develop meaningful welfare estimates that can contribute to policy discussion, economists must better understand the possible trade-offs resulting from policy choices. In order for the science results to have policy impact, scientists must strive to make their results understandable and transferable. Additionally they must engage with policymakers. Better environmental policy requires integrated research.

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CONTINGENT VALUATION SURVEYS TO MONETIZE THE BENEFITS OF RISK REDUCTIONS ACROSS ECOLOGICAL AND DEVELOPMENTAL ENDPOINTS

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ABSTRACT: We report the results of several contingent valuation (CV) surveys to develop willingness-to-pay (WTP) estimates to reduce environmental risks facing wildlife and unborn children as a result of hypothetical exposure to polychlorinated biphenyls (PCBs) in fish. Three surveys are developed: Two have a parallel structure in which respondents are first asked about a single endpoint, either ecological (EcoFirst), or human (HHFirst), and a second set of questions asks about the combined effects across endpoints. The third survey asks only about the combined effects (combined). We randomize two ecological and human health endpoints for each survey: the ecological endpoints include reducing risks associated with potential reproductive effects of PCBs on eagles, and the second is based on a "species sensitivity distribution" (SSD) that quantifies the risk reduction across all bird species. The human health endpoints include a probability of a 6-point reduction in IQ, and the other a probability of a 7-month reduction in reading comprehension. We evaluate sensitivity of WTP to the magnitude of the risk reduction for each endpoint. Survey respondents were willing to pay incrementally more for human health endpoints in the EcoFirst survey than they were for ecological endpoints in the HHFirst survey, but the results for the combined versus single endpoints are not statistically distinguishable. The survey results show that WTP for an individual endpoint is approximately proportional to the magnitude of the risk reduction for the Eagle and IQ as endpoints, but not for SSD and reading comprehension endpoints.

This is the first survey that evaluates WTP for potential risk reductions associated with exposure to chemicals in the environment specifically in terms of ecological or developmental health benefits within a risk assessment context. We reported the results of the human health endpoints previously. The focus of this paper is on the ecological endpoints.

1.1 Introduction

Risk assessment is the process of quantifying the probability that humans or animals will develop adverse health effects as a result of exposure to stressors, such as chemicals, in the environment. Increasingly, there is pressure to defend proposed risk-protection regulations or policies designed to reduce exposure to chemicals (*e.g.,* Superfund cleanups) on the basis of cost-benefit or cost-effectiveness (EPA *et al.,* 2000; EPA-SAB, 2000). Although the benefits associated with risk reductions do not require monetization, monetary units facilitate comparison across disparate endpoints and costs. In the absence of observable markets for risk reductions, CV and other stated preference methods that rely on an analysis of the hypothetical choices made by individuals are virtually the only means for deriving economic values for the benefits associated with predicted risk reductions.

Human health effects resulting from environmental exposures can be acute (immediate) or chronic (longer term). Acute effects can often be ameliorated if the source of the exposure is removed (*e.g.*, asthma attacks as a result of air pollution), while chronic effects by definition tend to extend beyond the period of exposure (*e.g.*, the asthma itself, or developmental effects). In addition, with chronic effects, there can also be a latency period (*e.g.*, cancer, liver disease and other diseases that might not reveal themselves until long after exposure has ceased). The bulk of the CV studies found in the literature are for respiratory exposures (Van Houtven *et al*., 2003 provide a meta-analysis of 136 studies) leading to episodes of asthma or angina attacks, and there were no studies identified that specifically addressed mild cognitive deficits. Likewise, ecological CV studies tend to focus on endangered species or biodiversity, and we were unable to identify any studies that evaluated a reduction in potential reproductive effects. This study is designed to evaluate willingness-to-pay for a subtle effect (in humans) that occurs with a fairly large probability (20% chance if exposed) relative to typical cancer risks at Superfund sites, and to evaluate willingness-to-pay for a significant effect in ecological receptors (reproductive capability), consistent with the risk assessment framework.

The contingent valuation surveys presented here are designed around a case study of exposure to PCBs in the environment using the modeling tools and dataset available for the Hudson River Superfund Site. This case study provides the specific endpoints and risk reductions to serve as the basis for the valuation questions to demonstrate the feasibility of integrating WTP with risk assessment results to monetize the benefits associated with risk reductions.

1.2 Methods

1.2.1 Survey Design and Development

The surveys were designed over a one-year period and involved several informal pilot surveys, focus groups, and a pretest. The surveys were designed to be administered over the Internet using a professional survey firm, Knowledge Networks. The research goal was to evaluate whether a CV might provide a feasible method for obtaining economic values for endpoints consistent with how they are expressed in a typical risk assessment framework (drawing from the experience of the lead author at an actual Superfund site) and explore how people respond to questions regarding potential effects to children and wildlife as a result of exposure to a specific chemical in the environment. To that end, the surveys asked numerous open-ended questions for which respondents could provide comments as they progressed.

The primary objective of the surveys was to elicit an approximation of the monetized loss in utility experienced by respondents resulting from potential effects associated with exposure to PCBs in the environment that would be consistent with economic theory. Another objective of the surveys was to measure WTP for risk reductions, consistent with the results that an existing set of modeling tools provided. The surveys were designed so that members of the general public could follow and understand the issues, and the surveys asked various questions throughout to gauge what respondents already knew (or thought they knew) concerning chemicals in the environment and how they felt, in a general sense, about exposure to chemicals (*e.g.*, whether they thought it was a serious issue, or even feasible that the kinds of effects described in the survey could really occur). The surveys are based on a hypothetical, generic site located in the respondent's State (there are numerous actual PCB-contaminated freshwater systems across the United States and it is likely that there is at least one in the general area in which the respondent lives). Respondents are left to consider which specific waterbody the surveys refer to, and despite the generic nature of the site, the surveys were designed to be plausible and the payment vehicle realistic and believable.

Respondents to the survey are first told that government officials in their State are responsible for allocating resources and are interested in individual opinions to inform potential policies. The first question asks respondents to rate the importance of several issues facing regulators. The second question asks respondents to consider whether current State budget allocations should be reduced or increased, keeping in mind that overall expenditure cannot be increased without an increase in revenue. Respondents are reminded that State policy makers are responsible for allocating resources, and that people may feel differently about these allocations depending on their own beliefs and knowledge. Respondents are told that State policy makers are interested in learning how taxpayers feel about specific issues.

The survey then proceeds to frame the specific valuation question, which involves the potential effects of a specific chemical (PCBs – we ask "have you ever heard of PCBs?") in a large, unnamed freshwater system in the state in which the respondent resides. This system is contaminated, and the company or companies ostensibly responsible went out of business some years ago. Therefore, the State is contemplating setting up a special "cleanup" fund to be funded through a one-time increase in the State income tax.

The question states that the risk will decrease if the cleanup is conducted if the income tax is raised by the bid amount for all, not just for the respondent (Johansson-Stenman, 1998), which has been shown to generate values consistent with economic theory. However, not all States have an income tax, and this was not explicitly acknowledged. The cleanup is described as occurring over several years, and the survey also states that even after cleanup is complete, it will still take several years for concentrations in fish to decrease, and for wildlife receptors to recover. In addition, the risks will never decrease to zero as there will always be some residual contamination.

A particular issue that arises with double-bounded CV estimates from the literature is a failure to achieve consistency (Hanemann, 1991; Hanemann and Kaninnen, 2001; McFadden and Leonard, 1993). We used a double-bounded dichotomous choice (Hanemann, Loomis and Kanninen, 1991) which has been shown to substantially increase the statistical power of the WTP estimate, at the expense of a downward bias in the estimate because the second response is not incentive-compatible (Carson *et al*., 2003). There is evidence that in some cases, responses to the second bid are inconsistent with responses to the first bid. Some authors (*e.g.,* Alberini, 1995a; 1995b; 1995c) have shown that pooling the responses to the first and second bids leads to some bias in the coefficient estimates, but a gain in efficiency. Respondents are presented with an initial bid randomized from a bid vector ranging from $25 to $400. If the respondents agree to the initial bid, they are presented with a bid that is double the first bid (if they agree to $400 initially, then they are asked if they would be willing to pay at $800). If respondents do not agree to the initial bid, then they are presented with a bid that is half as much ($10 if they did not agree to $25 initially).

The bid vector for the total valuation question across all endpoints in the EcoFirst and HHFirst surveys takes as its starting point the next highest bid that was agreed to for the individual endpoint valuation question. One could randomize the bid vector, but true randomization would inevitably lead to a bid being offered for the combined valuation that could be less than what a respondent had already agreed to for an individual endpoint. One could randomize the bid amount offered for the combined endpoints starting with the next highest bid above what had already been agreed to, but that cannot be considered true randomization. Therefore, we offered respondents the next highest bid following the one already agreed to for the single endpoint (except in the case where a respondent said No-No to the first bid: in that case, we randomized the total valuation bid as well). Table 1 shows the relationship between the bid amounts for the individual endpoints in the first part of each survey and the bid amounts for the total valuation question across both endpoints for the EcoFirst and HHFirst surveys. The combined survey uses this same bid vector.

The next set of questions asks about respondent confidence for stated WTP for the endpoints individually and jointly. Another question asks whether respondents feel they can separately consider ecological and human endpoints from a valuation standpoint.

Another set of questions asks about familiarity with PCBs, concern about chemicals in the environment, and whether the respondent believes that exposure to PCBs really can cause these effects. Finally, respondents are asked to rate their trust on a one to five scale concerning the information they receive from a number of sources, including different web sites, print media and television.

We develop three versions of the survey: EcoFirst (n=405), in which WTP for risk reductions to ecological receptors (randomized by eagle, SSD, and specific risk reduction) are asked first, followed by the total WTP for both human and ecological endpoints; HHFirst (n=400), in which WTP for risk reductions to unborn children (randomized by IQ, RC, and specific risk reduction) are asked first, followed by the total WTP for both human and ecological endpoints; and combined (n=200), a survey which does not attempt to separate human and ecological endpoints but provides a risk reduction for each endpoint and questions respondents about total WTP across endpoints.

1.2.1.1 Endpoint Selection

The specific endpoints for this survey are taken from the risk assessment case study. The individual ecological and human health endpoints are discussed next.

Ecological Endpoints

For the ecological outcomes, we are interested in how people perceive environmental threats to ecological resources, what they might be willing to pay to reduce that threat, and how those results can be incorporated into a risk assessment.

While Superfund human health risk assessment typically focuses on the "hypothetical" individual, ecological risk assessment strives to evaluate the potential for risk in terms of the population or ecosystem (EPA-RAF, 1998). There are two distinct ways in which ecosystem structure and function are typically evaluated within a risk assessment context and these are used as the basis for developing the CV questions so that the economic values derived from the surveys can be integrated into a risk model. The first focuses the analysis on a set of single species that have been selected to represent high-end exposure and sensitivity. Within the ecological risk assessment framework, the assessment endpoints (that which is being protected) generally do not define specific species (*e.g.,* a typical assessment endpoint is the protection and sustainability of wildlife populations). The associated measurement endpoint(s) for that assessment endpoint might include comparing predicted doses to the selected species with doses from the toxicological literature associated with specific effects. This deterministic analysis can be expanded to include a joint probability model that quantifies the probability of an increasing magnitude of effect using a dose-response model for a single species (*e.g.*, reduction in fecundity). Alternatively, the probability of exceeding a threshold value can also be modeled. Under this approach, a valuation for a single "high-profile" species will implicitly value those aspects of the ecosystem that support this species (Loomis and White, 1996). The valuation questions respondents on their willingness-to-pay to reduce the probability of an effect on a single species. Management actions are designed to reduce risks for the presumed highest risk species. We evaluate potential risks specifically to the eagle, following the ecological risk assessment for the Hudson River (EPA, 2000b), and this endpoint is referred to as "eagle" in the surveys.

The second approach is slightly different. Rather than relying on a single dose-response relationship for one species, the analysis develops species sensitivity distributions (SSD). These distributions quantify the probability of the proportion of species that will be affected (*e.g.,* there is a 20% probability that 80% of the species will experience adverse reproductive effects). Under this approach, the analysis does not focus on one particular species but rather considers the probability of impacting multiple species. This is referred to as the "SSD" endpoint in our surveys.

Human Health Endpoints

The weight-of-evidence for a relationship between *in utero* polychlorinated biphenyl (PCB) exposure and developmental outcomes has been well established and continues to grow (Schantz *et al*., 2003; EPA, IRIS). Both epidemiological as well as animal studies demonstrate statistically significant increases in developmental delays and effects with increasing maternal PCB exposure (Jacobson and Jacobson, 2002b; Jacobson *et al.,* 2002;

Levin *et al.,* 1988; Schantz *et al*., 1989, 1991; ATSDR, 2000). These effects can be seen in newborns as measured by the Bayley Scales of Infant Development to older children, measured either directly in terms of IQ or from other, related tests.

Much of our understanding of the implications of slight declines in cognitive ability across a population is based on work done relative to lead exposures (Schwartz *et al*., 1985; Schwartz, 1994). The research conducted in this area shows that slight declines in IQ, which are difficult to detect in individuals and which may or may not lead to noticeable adverse effects on an individual basis, are significant on a population level in terms of a population shift in IQ. Other cognitive effects include other kinds of developmental delays such as declines in reading comprehension to levels below grade level, low scores on analytical tests and tests of simple math problems, and behavioral responses.

The risk reductions used in the surveys are based on the results from Jacobson *et al*. (2002) who present a linear relationship between lipid-normalized breast milk concentration of PCBs and outcomes including a 6-point reduction in IQ and a 7-month deficit in reading comprehension as evidenced by scores on the WISC-R at eleven years for the Michigan cohort. This dose response relationship is used together with exposure assumptions from the risk assessment case study (Chapter 4) to obtain the specific risk reductions used in the survey.

1.2.1.2 Sensitivity to Scope and Risk Reduction

Sensitivity of estimated WTP to the magnitude of the risk reduction is one technique used as a diagnostic test of the performance of the survey instrument (Arrow *et al*., 1993; Hammitt and Graham, 1999). Sensitivity to scope can take several forms. Typically, these are referred to as *regular* embedding, (part-whole bias), and *perfect* embedding, (sensitivity of WTP to the stated risk reduction, *e.g.,* demonstrating a higher WTP for a larger risk reduction). There are two "part-whole" aspects to these surveys: one is within an endpoint, and the other is across endpoints. Within an endpoint, ecological part-whole bias is easier to evaluate through the difference between WTP for the specific ecological endpoint. That is, we evaluate the difference between WTP for eagle and SSD, controlling for risk reduction. The human health endpoints do not demonstrate additivity since the potential human health effects of *in utero* exposures to PCBs include a panoply of developmental effects, all or some of which may or may not occur.

There has been increasing discussion in the CV literature concerning the effect of the placement of a particular good or endpoint within a valuation sequence and the influence that has on respondent valuation (Carson and Mitchell, 1995; Diamond, 1996; Bateman and Willis, 2001). Different WTP estimates are obtained depending on the order in which the benefits are presented, and additionally, the summation of the individual WTP values is often not the same as the overall WTP obtained without specifying individual endpoints. This is the issue of embedding, or part-whole bias, across endpoints. We explore this by administering three different versions of the survey.

We evaluate perfect embedding by randomizing two different risk reductions for each endpoint across respondents as shown in Table 2. That is, each respondent sees only one risk reduction per developmental and ecological endpoint, but there are two risk reductions for each endpoint randomized across each subsurvey. We focus a number of the analyses on the risk reduction coefficient across surveys and endpoints.

Figure 1 provides a sample from the survey for effects to eagles, and Figure 2 shows a sample for the species sensitivity distribution. The values in brackets are the final risks, thus, the risk reductions in each case are 15 in 100 and 10 in 100 (0.15 and 0.10) for eagles, and 25 in 100 and 40 in 100 (0.25 and 0.40) for SSD. Risks are described both as a probability (percentage) and as a frequency (one in some number). There is a substantial body of evidence showing that people are generally more capable of understanding frequencies than they are probabilities, and this is the focus of much research in the "innumeracy" literature (Gigerenzer, 2002).

1.2.1.3 Motivation Questions

The survey contains a number of questions related to respondents' knowledge and beliefs regarding chemicals in the environment, PCBs in the environment, potential effects of PCBs, and trust in different sources of information (*e.g.*, industry scientists, media, academia). The survey contains several followup questions designed to elicit motivation for agreeing to a particular bid. One question asks respondents to rate on a scale from not important to very important some specific reasons why they might be willing to pay to reduce potential risks to wildlife, while another asks the same question about developmental effects. We asked this follow-up question if the respondent answered N-Y, Y-N, or Y-Y (*e.g.,* they agreed to any bid amount). Likewise, for those respondents who answered N-N and were not willing to pay any amount, we questioned their motivation.

These kinds of motivational questions are important for evaluating how and why respondents made the decisions they did, and allow us to test hypotheses concerning the role of behavior in eliciting preferences relative to WTP (Dubourg *et al.,* 1997; Nunes and Schokkaert, 2003; Heberlein *et al.,* 2005).

We evaluated the responses to the "motivational" questions using factor analysis to determine whether those responses should be represented by few variables since it is likely that these responses are correlated and originate from a common behavioral denominator. We used varimax rotation as this assumes independence across factors and provides the most convenient and suitable interpretation of results. We fail to reject the hypothesis that four factors are sufficient across all nine questions from the pooled dataset as shown in Table 3. The first three questions showed the highest loading (altruism, bequest, nonuse) representing, broadly speaking, a nonuse component to the motivation. The correlation across these responses suggests that they have a common motivational origin. The second factor is most highly loaded on a broad-based support for a cleanup irrespective of risk or WTP. The third factor is most highly loaded on altruism for potential effects in children exposed to PCBs. Finally, the last factor is most highly loaded on use or option to use the ecological resource (*e.g.*, the respondent enjoys seeing eagles and wildlife or rates highly the option of doing so). Based on these results, each respondent is assigned a value for each factor based on the combination of responses to each individual motivational question, and these factors are used in the regression models in place of the original responses. These results are consistent across both datasets as shown in Table 3.

1.2.1.4 Survey Administration

A professional survey firm, Knowledge Networks (KN), administered the survey to a panel representative of the US general population via a web-based survey mechanism during Spring 2005. The statistical foundation of the research panel stems from the application of probability-based sample selection methodologies to recruit panel members. The KN web-enabled panel is the only available method for conducting Internet-based survey research with a nationally representative probability sample (Couper, 2001; Krotki and Dennis, 2001).

The Knowledge Networks Panel, recruited randomly through Random Digit Dialing, represents the broad diversity and key demographic dimensions of the U.S. population. The web-enabled panel tracks closely the U.S. population on age, race, ethnicity, geographical region, employment status, and other demographic elements. The differences that do exist are small and are corrected statistically in survey data (*i.e.*, by non-response adjustments). The web-enabled panel is comprised of both Internet and non-Internet households, all of which are provided the same equipment for participation in Internet surveys. Internet-based surveys are increasingly showing favorable comparisons to mail and telephone survey methods (Berrens *et al*., 2003).

1.2.2 Survey Analysis

The statistical model for CV responses must satisfy both statistical and economic criteria (Hanemann and Kaninnen, 2001). CV responses can be modeled as discrete dependent variables with binary responses since respondents can either state “yes” or “no” to a particular bid value. An equivalent but alternative modeling form takes the bid interval agreed to by an individual respondent as the dependent variable. In economic terms, the statistical model for CV responses must be consistent with the theory of utility maximization inherent in economic models. This assumes individuals show preferences for market commodities (x) and nonmarket amenities (q) as represented by a utility function $U(x,q)$ which is continuous and non-decreasing (Hanemann, 2001). Individuals face budget constraints based on income (y) and prices of the market commodities (p). Individuals are assumed to be utility-maximizers given a budget constraint (*e.g.,* disposable income). Willingness-to-pay, or the compensating variation (C) is the maximum an individual is willing to pay to secure an increase to the nonmarket amenity. In this case, the nonmarket amenity is expressed as a risk (r); therefore, a decrease in the risk increases utility $U(x, r)$.

Each respondent to the survey has an indirect utility function for which one can plot the tradeoff between risk and income while maintaining utility as given by the slope of that curve.

The economic measure of value is given as:

$$v(p, r_1, y\text{-}C) = v(p, r_0, y) \qquad \text{(Eq. 1)}$$

where C = the amount of money at which the individual is indifferent between a lower probability of risk and higher income, and r_0 and r_1 are different levels of:

- Risk to the reproductive capacity of eagles (eagle)
- Risk to the reproductive capacity of an avian population (SSD)
- Risk of a 6-point reduction in IQ to an unborn child given maternal exposure (IQ)
- Risk of a 7-month deficit in reading comprehension given maternal exposure (RC)

We evaluate two different risk reductions across endpoints as shown in Table 2. The assumption is that a smaller risk relative to baseline improves well-being so compensating variation, or WTP, should be positive. Under this framework, expected utility is roughly proportional to risk; consequently WTP should be approximately proportional to risk reduction and we use the survey results to test this hypothesis. As individuals spend more money, the utility loss increases. However, WTP is likely small with respect to income and so an income effect is also likely to be negligible.

The double-bounded dichotomous choice elicitation format used here is analogous to interval-censored survival data in medical and engineering settings in which time to illness or failure of a component is modeled. In this case, we know the interval within which WTP for any individual respondent lies; for example, for the yes-yes response, it is known that the interval lies somewhere between the highest amount the respondent agreed to and their household wealth. The actual bid P_i that the respondent is willing to pay is somewhere between the upper and lower bids or $P_L < P_i < P_U$. In addition, each respondent provides a vector of explanatory variables including bid amount (P_i), income, age, other sociodemographic variables, knowledge about chemicals and/or PCBs in the environment, and other attitudinal variables.

The WTP model takes the form:

$$LNWTP_i = \beta_0 + \beta_1 LN(\Delta Risk) + \beta_2 LNIncome + \beta_x X + \varepsilon \qquad \text{(Eq. 2)}$$

where

WTP = WTP for the i^{th} individual in the interval (intervals shown in Table 4)
ΔRisk = is the risk reduction (0.1 or 0.15 for Eagle; 0.25 or 0.4 for SSD)
Income = respondent household income
X = vector of respondent-specific attributes (as given in Table 6)
ε = error term

The log likelihood function can be maximized assuming a particular parametric distribution (*e.g,* lognormal) or by using the Turnbull nonparametric modification of the Kaplan-Meier estimator, which makes no assumptions about the shape of the underlying WTP distribution (Carson *et al*., 2003; Hanemann and Kanninen, 2001). We evaluate several parametric forms for each risk reduction variable and use both visual goodness-of-fit, statistical tests, and theory to determine the most appropriate parametric form.

As there are three distinct surveys (EcoFirst, HHFirst, and combined), we first test to determine whether the survey results can be pooled (Henscher *et al.,* 1999). We then develop two datasets: The first uses WTP for the single endpoint as the dependent variable with dummy variables for each endpoint (IQ, RC, Eagle, SSD), and whether the survey asked about ecological endpoints or human health endpoints first. The second dataset uses total WTP across all endpoints with appropriate dummy variables for survey type (HHFirst, EcoFirst, or combined) and specific endpoint. We also develop models using the single endpoints from each individual survey. This paper focuses on the results for the ecological endpoints.

Parameter estimation is accomplished through maximum likelihood methods to obtain values of unknown statistical parameters most likely to have generated the observed data. All models use the interval-censored bid interval as the dependent variable. The first set of models includes only the risk reduction variable(s) and the dummy variables for survey order and endpoint. The second set of models includes all potential covariates of interest. Tests of significance are based on t-tests under the test of the null hypothesis that the slope parameter of an independent variable is equal to zero. Proportionality of the risk reduction with respect to WTP is evaluated by testing the hypothesis that $\beta_1 = 1$.

All analyses are conducted using S-Plus 6.2 (Insightful Corporation, 2004) and Microsoft Excel.

1.3 Results

1.3.1 Descriptive Statistics

Table 4 presents the frequencies of response to the bid vectors across the surveys. The frequency of Yes responses decreases as the offered bid increases, and a $\chi 2$ test rejects the null hypothesis that responses do not systematically vary with bid amount.

Table 5 provides a summary of the demographic characteristics of the sample stratified by endpoint from the first valuation question from each individual survey, and for comparison purposes, data from the 2000 census. In general, the demographics from the surveys compare favorably to the demographics of the general population. For the EcoFirst survey, the sample shows a lower proportion of individuals with less than a high school education as compared to the general public, and a higher proportion of individuals with at least an associate's degree. When considering the error associated with these percentages, they still compare favorably, and it is not clear that more traditional survey methods (*e.g.,* direct mail and/or telephone) would have reached a higher proportion of this fraction of the population.

Table 6 provides a brief summary of potential covariates in the model, and provides means from the surveys, stratified by specific endpoint.

1.3.2 Models of WTP

Figures 3 and 4 present the visual goodness-of-fit plots across distribution types for the ecological and human health endpoints, respectively. Figures 5 and 6 show the WTP functions for the ecological and human health endpoints, respectively. Of the parametric model forms, the Weibull and lognormal assumptions provide the most explanatory power across distribution types, but are not statistically distinguishable. In addition, both parametric models lead to statistically indistinguishable coefficients for the covariates across models; therefore, we present only the lognormal results as this distributional assumption has favorable properties in terms of the interpretation of the results.

Table 7 presents the results using the results of the single endpoint (ecological) questions from the EcoFirst survey. This table shows that the risk reduction coefficients are positive for the eagle and negative for SSD, although neither is statistically significant in Model 1, which includes all potential covariates of interest. Positive statistically significant predictors for the eagle as endpoint in Model 1 include motivational variables, such as concern about PCBs in the environment, belief that PCBs can cause reproductive effects to eagles, and the motivational factor scores. A different picture emerges for the SSD endpoint as shown in the next column of Table 7. In this case, the same motivational factors are statistically significant predictors, but the risk reduction coefficient is negative, and is closer to significance than the risk reduction coefficient for the eagle endpoint at p=0.17.

Model 2 was only run for the Eagle endpoint since the risk reduction coefficient for the SSD endpoint is negative, which violates economic theory and is difficult to interpret within a policy context. Model 2, which includes a stepwise deletion of all nonsignificant predictors, Table 7 shows that the "motivational" variables are more highly statistically significant than the single socioeconomic statistically significant predictor (dual income). The risk reduction coefficient is significant at the 0.10 significance level (p=0.08) eagle and is proportional, consistent with what classical macroeconomic theory would predict.

Table 8 presents the results of the pooled model for the first valuation question. EcoFirst indicates whether the endpoint was human or ecological. IQ indicates whether the specific human endpoint was IQ or reading comprehension (RC), while Eagle indicates whether the specific ecological endpoint was Eagle or the species sensitivity distribution (SSD). Each of the models includes the four risk reduction variables.

This first column in this table (the reduced model) shows that none of the risk reduction coefficients are statistically significant, and the coefficients for RC and SSD are actually negative. Although both the Eagle and IQ risk reduction coefficients are not statistically significant (p=0.7 and p=0.14), they are positive.

The second column shows the results for the model including all potential covariates. When including all potential covariates, the risk reduction coefficients remain insignificant but change in magnitude. In the reduced model, the risk reduction coefficient for IQ is nearly proportional but insignificant at p=0.14, while in the full model, it is less than proportional and insignificant at p=0.4. For the eagle risk reduction coefficient, the reduced model shows that it is much less than proportional and insignificant, while in the full model, it is nearly proportional but still insignificant (p= 0.17). Statistically significant predictors in the full model include predominantly motivational and attitudinal variables, including concern about PCBs in the environment, confidence in the stated WTP, concern about PCBs specifically with regard to exposure by children, and altruism as a motivating factor (only for the Y-N, N-Y, and Y-Y respondents).

Table 9 presents the results for the models using total WTP across all endpoints. This model pools the results from all three surveys (EcoFirst, HHFirst, and combined). The first column presents the reduced model using just the risk reduction variables and dummy variables indicating survey order and endpoint as predictors. The risk reduction coefficients show the same pattern as the models for individual endpoint WTP. Eagle and IQ are positive; while SSD and reading comprehension are negative. Only the SSD coefficient in the stepwise model is statistically significant (column 2 of Table 9).

In both the reduced and full models, the EcoFirst survey leads to higher total WTP. Those respondents who answered questions concerning ecological receptors first had approximately 80% higher WTP than the HHFirst survey respondents. IQ and Eagle as endpoints are associated with significantly higher WTP than SSD and RC. Statistically significant predictors in the full model (column 2) include the specific endpoint, age, and motivational variables such as concern about chemicals, and PCBs specifically, in the environment, concern about PCBs and children, and concern about the risks facing children. Significant predictors are related to child exposure rather than wildlife exposure.

The risk reduction coefficients are more stable for the combined (total) endpoint valuation shown in Table 9 than in the single endpoint valuation shown in Table 8. That is, the magnitude and potential significance of the risk reduction coefficients are very different across models in Table 8, and much less so in Table 9.

1.3.2.1 Median Household WTP

Median WTP per household is estimated from the regression models at the sample mean of the covariates. Median WTP is typically quite stable at the covariate means and is reasonable to estimate even if individual coefficients are not significant. We used the reduced models (*e.g.*, risk reduction variables, and dummy variables for survey type and endpoint) to estimate WTP. Table 10 and Figure 7 present these results. The letters on the x-axis in Figure 7 refer to the specific risk reductions and endpoints as shown in Table 10. For example, "A" refers to the total WTP across both the Eagle and reading comprehension endpoints from the EcoFirst survey, and the risk reduction 0.1 in both cases.

These results show that although the combined survey total WTP is higher than for the individual endpoints, the results are not statistically significant. In addition, there is very little difference between the total and individual endpoint median WTP from the individual surveys.

1.4 Discussion

These survey results show that when evaluated as a whole, WTP is not particularly sensitive to risk reduction across endpoints. Typically, this kind of insensitivity to scope is attributed to survey design and elicitation format (Bateman and Brouwer, 2006; Smith and Osbourne, 1996). Others have argued that respondents do not demonstrate well-constructed preferences and therefore the CV method does not achieve the goals necessary to develop estimates of WTP consistent with standard economic welfare theory (Bateman and Brouwer, 2006). Both the IQ and eagle endpoints consistently demonstrate positive coefficients, suggesting that respondents understood the survey questions as presented to them, which makes the interpretation of the consistently negative coefficients for reading comprehension and SSD slightly more problematic (*e.g.,* it is difficult to argue that respondents were unable to understand what was presented to them, since they appear to demonstrate an understanding of two of the four endpoints).

As shown in Table 7 for the single ecological endpoint model from the EcoFirst survey and employing a stepwise backward selection method which removes the most insignificant variable until all remaining variables are significant the p=0.10 level results in a model for which the risk reduction coefficient for eagle is both proportional and statistically significant at p=0.09. On the one hand, both of these results suggest at scope sensitivity under some assumptions for eagle and IQ as endpoints. On the other hand, the instability of the risk reduction coefficients and the inconsistency across models and stratification variables highlights the tenuous nature of the sensitivity to scope and the obvious concern in using such results as justification for policy development or remedy selection.

Interestingly, there is a statistically significant difference in the self-expressed confidence that respondents had in their responses to bids. Table 11 shows that those respondents who answered Yes-Yes (*e.g.*, did not provide the highest bid amount they would be willing to pay) had a statistically significant higher confidence in their responses than did the No-No or Yes-No/No-Yes respondents (Kruskal-Wallis $\chi 2$ $p<0.001$ across surveys) for total WTP. The No-No respondents had the lowest confidence in their results, and this difference was statistically significant.

We ran several stratified models as shown in Table 12 using the results for the single endpoint valuation question to evaluate differences in responses across the stratification variables. Stratifying the data on the basis of whether respondents were able to think about ecological endpoints separately from human health endpoints showed that for those respondents who indicated they were *not* able to think about ecological and human endpoints separately, the risk reduction coefficient for the IQ endpoint was positive and statistically significant in Model 1 (first valuation question). In a model of total WTP across both human and ecological endpoints (second valuation question), Model 3 shows that again, respondents who indicated they were not able to separately consider human and ecological endpoints showed positive and statistically significant risk reduction coefficients for both eagle and IQ. For those respondents who indicated they *were* able to think about the endpoints separately, the risk reduction coefficients were negative for RC and SSD across both the single endpoint model (Model 2) and the total endpoint model (Model 4). In that case, the negative coefficients for reading comprehension and SSD were statistically significant for the total valuation in Model 4. For Model 2, the single endpoint model, none of the risk reduction coefficients were statistically significant. Those respondents who admitted that it was difficult, if not impossible, to separately value human health and ecological outcomes had more consistent responses for two of the endpoints, in terms of economic theory and *a priori* expectation than did those respondents who felt confident that they were able to separately evaluate the endpoints.

The results presented here lend themselves to several interpretations. On the one hand, the insensitivity to scope lends support to critics of the CV method that fundamental assumptions of economic welfare theory are violated. On the other hand, these surveys were designed to be exploratory, including four endpoints (two human, two ecological), two risk reductions per endpoint, many independent variables, and the generally unfamiliar nature of the survey (*e.g.,* potential risks associated with exposure to chemicals, with risks experienced by ecological receptors and babies). Given these constraints, the models are not designed to achieve the power necessary to be directly applicable in a policy context. Therefore, these results do not necessarily undermine the CV method, nor are they necessarily shortcomings of the survey itself. Rather, these results suggest ways in which the CV method might be refined in order to be successfully applied in a risk assessment context. Although two-thirds of respondents felt they were able to provide WTP estimates for human health and ecological endpoints individually, the analysis revealed poor performance.

One result of these surveys is that respondents were willing to pay an additional amount when asked about ecological effects first and human health effects second, but were not willing to pay an additional amount when asked about human health endpoints first and ecological endpoints second. This observed order effect across endpoint type is not particularly surprising. This result highlights the potential difficulties in asking respondents about ecological effects, and the role of risk reductions to ecological receptors in situations in which there are benefits across receptor types.

The concept of risk remains a difficult one for individuals to grasp under any circumstances. In this case, respondents were asked to consider risks to ecological receptors (species-wide or specifically to eagles) or to children exposed *in utero*. In terms of the ecological receptors, respondents were not asked to consider extinction, which has a very explicit definition, but rather the more nebulous concept of population viability. Respondents were informed that species would have "trouble reproducing" as opposed to being in any particular danger of extinction.

Corso *et al*. (2001) tested several graphic forms for conveying risk reductions, and found that the form of the visual aid is a statistically significant predictor of WTP. In the case of the SSD, the visual aid we used (Figure 2-2) is difficult to understand, and likely presents too much information to the respondent. However, it is also possible that respondents did not find the larger risk reduction believable or plausible, in which case one would expect a smaller WTP for the larger risk reduction. Respondents may also have flat preference functions over the range of risk reductions evaluated, although in the case of SSD, the risk reductions are substantial. Another issue may be "metric bias" (Boyle *et al.,* 1994; Mitchell and Carson, 1989) which can arise when a respondent measures the risk reduction on a different scale than was intended by the researcher.

For those respondents who had a stated WTP (*e.g.,* Y-Y, Y-N, or N-Y), we asked them to rate on a scale of 1 to 5 (not important to extremely important) their motivation for agreeing to a particular bid. Across both the EcoFirst and HHFirst surveys, more than half the respondents with a positive WTP indicated that they supported a cleanup of the environment on principle. 53% of respondents rated seeing birds in general as extremely important as compared 32% who rated seeing eagles in particular as extremely important. More respondents for the SSD endpoint rated bequest value as extremely important than for the eagle endpoint (53% versus 45%). These results are shown in Table 13.

For those respondents who did not have a stated WTP (*e.g.,* N-N), we asked them why they didn't agree to any bid amount (Table 14). Respondents were also allowed an "open ended" response in which they could type in their thoughts as to why they did or didn't agree to any bid amount. In the EcoFirst survey, 46% (of 140 respondents) and 48% (of 86 respondents) chose to type in a response for the single and combined endpoints, respectively. Overwhelmingly, these responses indicated a level of distrust that the government would "spend the resources wisely." Some felt that the "one-time tax" referendum was merely a ruse and that the government would find other ways to keep the tax year after year. A typical (verbatim) open ended response was: "The government wants to do things only if we pay for it, this should be done and that's it. I think the government already receives enough revenue to do this clean up. They have plenty of money to go to war!!!!!!!!!!!!!!" Several respondents indicated that the risk reduction that would be achieved was not enough to warrant the cost, while several others indicated that the predicted cost (per taxpayer) was too low and therefore it was not believable that the cleanup program would work. For human health effects, a number of respondents indicated that because there were fish consumption advisories in place in their particular State, they felt the risks were lower than what had been portrayed in survey, although the survey clearly states that the risks are only to those individuals who consume fish. The implication was that since there are institutional controls in place, actual risks are lower.

There was considerable resistance on the part of the No-No respondents to various aspects of the payment, including resistance to the tax vehicle ("They need to learn to manage the insane amount of tax money we already pay now," "The money never goes to such things," "Business should pay," and so on). This suggests a potential bias arising from a framing effect (Kahneman *et al.,* 1999). This set of surveys utilized one payment vehicle (*e.g.,* a one-time increase in the State income tax), thus, it is not possible to test for the effect of the payment vehicle. However, the results suggest this is an issue for further exploration.

In addition to distrust of the government, approximately 70 of these open-ended responses suggested that the "companies responsible" should pay. A few individuals remarked that they would be willing to pay to reduce risks to humans but not to animals (this question, of course, having been asked prior to the questions related to WTP for developmental effects). Another factor is that costs are borne by all (*e.g.,* a one-time increase in the State income tax earmarked for a cleanup), but the developmental benefits are only experienced by those who are actually exposed (*e.g.,* consume freshwater fish), and the ecological benefits likely have very little direct relevance for most respondents.

A possible hypothesis for the negative association between risk reduction and WTP for the SSD endpoint might be that respondents are insensitive to the actual risk reduction because they support a cleanup irrespective of the actual risks. In a pooled model using the interval-censored bid amount for a single endpoint regressed against risk reduction, endpoint, and level of support for a cleanup (the original motivational variable prior to the factor analysis), the cleanup coefficient is positive and statistically significant, but none of the risk reduction coefficients were statistically significant.

Another hypothesis is that respondents did not find the larger risk reduction plausible. In this case, we would expect a smaller WTP for a larger risk reduction. Although we cannot directly test for whether respondents found the risk reduction plausible, we do have information on how significant respondents perceive the risk to be (one question is "do you believe PCBs can cause these kinds of effects?" and another question asks respondents to rate on a scale of one to four how serious the risks are facing ecological and human receptors), and these are included as predictors in the models. 35% of respondents felt that the risks facing wildlife were "very" or "extremely" serious, and 37% of respondents felt that the risks facing unborn babies were "very" or "extremely" serious. Most respondents felt that the risks were "somewhat" serious (38% for wildlife and 33% for unborn children).

There are several complicating factors specifically with regard to the assumptions inherent in utility maximization in this particular case. Risks to ecological receptors are, of course, risks not directly experienced by the respondents. The risk is framed in terms of a risk to the reproductive capacity of the eagle population specifically or the avian population generally. The implication, although never directly stated, is that the *number* of eagles, or avian species overall, would likely decrease given these risks, but the absolute number of animals that could or would be affected is not given, consistent with the risk assessment format. There have been a number of other CV studies that have asked respondents directly about numbers of animals and these have led to the current controversy in the literature regarding insensitivity to scope.

Dubourg *et al*. (1997) found that stated preferences for road safety exhibited considerable imprecision and were insensitive to variations in the quantity and quality of the safety improvements offered to respondents. In that study, respondents were asked to value a *personal* safety, as opposed to the endpoints evaluated here. Those authors argue that assuming a precise preference structure is unrealistic, given that they were unable to elicit values even for a personal good, and using an instrument that had been shown to be robust and well-designed. Payne *et al.* (1999) argue that "preference measurement is best viewed as an architecture," rather than an elicitation of deeply-held values, and present a set of "building codes" to follow when designing surveys.

Respondents' environmental preference structures are not necessarily linked to biophysical needs (Limburg and Folke, 1999) and are likely lexicographic in that "some things are more important than others, and cannot be substituted for lower level wants or needs." (Farber *et al*., 2002). This means that respondents may only have a WTP for a reduction in risk to ecological endpoints insofar as higher-order preferences have already been met. Existence, bequest, and option values are considered “services” that the ecosystem can provide, but these are likely to go largely unrecognized by respondents. That is, “the intrinsic values of natural system features and processes within the natural system itself may possess different abundance and functional value properties than their corresponding economic values.” (Farber *et al.,* 2002).

These results may lend credence to the argument that WTP estimates obtained using CV are not consistent with economic theory and should not be used as the basis for policy development. We take a more circumspect view. The evidence that contingent valuation represents a reasonable approach continues to grow, particularly as more surveys are done, people become more familiar with the method, respondents become better survey-takers, and analysts develop more sophisticated modeling approaches to characterize the results. Further, denying the contingent valuation method, or having argument with its results, in no way changes the fact that there are ecosystem service flows that have economic benefit, and therefore value, which cannot (currently) be quantified in any other way (*e.g.,* particularly nonuse values such as existence, bequest, option), and therefore have significant implications for policy development. Those who would argue that costs (*e.g.,* of restoration) should form the basis of valuation fail to make the distinction between cost and value.

This is, to our knowledge, the first CV survey to pose valuation questions in a way that allows an explicit linkage to the results of a hypothetical risk assessment. In addition, rather than asking about a certain outcome, this set of surveys allowed for a risk that does not go to zero. The closest survey of this kind was conducted under the Natural Resource Damage Assessment for the Montrose site in California (NRDA, 1994b) and elicited WTP for time to recovery for selected species. The time to recovery was given as a fixed number of years under different remedial scenarios. In our surveys, there is always a small reproductive risk associated with exposure to PCBs because it is acknowledged that the contaminated water body can never be completely remediated.

1.5 Conclusions

The results of the surveys show insensitivity to scope as demonstrated by statistically insignificant risk reduction coefficients across endpoints in the pooled models. There is some suggestion that eagle and IQ as endpoints fared better than reading comprehension and SSD, which actually showed a negative relationship between risk reduction and WTP, by developing individual models for single endpoints from each survey individually. For SSD, it is likely that the graphic used to convey the risk reduction was inadequately understood by respondents. However, that is not the case for reading comprehension which used the same graphic as eagle and IQ. Stratifying the combined endpoint total valuation model on the basis of whether respondents thought they could separately evaluate ecological and human health endpoints resulted in greater than proportional statistically significant risk reduction coefficients for eagle and IQ as endpoints for those respondents who admitted they were *not* able to separate the endpoints.

In developing environmental policies and deciding how to best allocate scarce resources, it is necessary to develop estimates for the benefits of risk reductions, and ideally these estimates should be monetized to facilitate comparison to costs, for cost-effectiveness ratios, and to compare across disparate endpoints. For nonmarket "goods" such as existence and bequest value, or for morbidity endpoints for human health, stated preference methods are the primary tool for eliciting these values under the theoretical framework of utility maximization. However, respondents in these surveys are probably not revealing a structured set of preferences, as utility theory requires, but rather constructing their preferences in response to the questions being posed. Does that necessarily invalidate the results of CV surveys? What are the options? Much more needs to be done in this area, but using CV methods represents a reasonable approach to developing monetary estimates of benefits associated with management actions, particularly regarding risk reductions. Risk assessment is a process that is used in many contexts to determine the potential human health and ecological impacts of contaminants in the environment, including permitting and development of remedial alternatives. Therefore, it is important to explore methods that link risk assessment and economics in ways that benefit both disciplines and continue to conduct studies that further our understanding and basis for decisionmaking.

When CV surveys fail to show sensitivity to scope in whatever form, the first criticism is always imperfect questionnaire design, followed closely by invalidation of the method overall. Despite the results presented here, we are not inclined to argue either view. The basis for the questionnaire was reasonable and represents the situation at a number of sites across the United States. The risk reduction coefficients for two of the endpoints

(IQ and eagle) are positive, and under some assumptions and model forms, statistically significant.

The number of risk reductions, endpoints, and randomization lead to small sample sizes for any given survey (approximately 200). These sample sizes are too small to have much power. However, they provide an initial evaluation into the question of benefits associated with potential risk reductions, and in particular, ecological benefits, which tend not to be quantified let alone monetized and yet which may represent a significant proportion of the overall benefit of management actions taken to mitigate or manage environmental contamination.

Successful integration of analyses across disciplines requires attention to the form of the outputs from each analysis. The goal of this effort was to explore one possible method for integration, namely, eliciting WTP for a particular set of risk reductions. It may be that the risk reductions need to be translated into a set of benefits that are less cognitively burdensome to survey respondents. For example, instead of asking about a probability of an impact to a percentage of species (as in the species sensitivity distribution approach), it may make more sense to translate the difference in risks across alternatives to a difference in the fraction of species affected. On the other hand, although the listerature suggests it is difficult for most people, even "technical" people, to work with probabilities, there is a very real and, in some ways, misleading difference between describing a probability of an effect (which never actually goes to zero) and the certainty of a small effect (*e.g.,* a certain difference in the fraction of species affected). In addition, there are cognitive issues associated with probabilities and frequencies (Gigerenzer, 2002), although individuals don't seem to have a problem reading the odds for sports teams or playing such games as *Deal or No Deal*, a current television program popular with many Americans. In the environmental context, engaging people through surveys of this kind, publications, and the media moves the dialogue forward and is a continuing source of education to people about the potential impacts of chemicals in the environment and the allocation of scarce resources for the purpose of directing environmental policy.

The results presented here also highlight the importance of obtaining and evaluating behavioral and motivational variables when developing CV models. Virtually none of the socioeconomic variables were statistically significant in the regression models, but the behavioral and motivational variables were highly statistically significant predictors of WTP. Other studies have shown that these variables can account for a lack of sensitivity to scope (*e.g.,* Nunes and Schokkaert, 2003; Heberlein *et al.,* 2005). Further cross-disciplinary efforts between survey researchers, behaviorists, and economics will increase our understanding of what motivates people to make the tradeoffs for potentially unfamiliar goods that we ask them to make through these surveys.

The limitations discussed in each of the papers highlights the difficulties of developing CV surveys and interpreting the results. However, limitations of the method in no way deny the fact that there are nonuse benefits associated with particular ecosystem service flows, and that these benefits have a value. The only question is, how can the methods for eliciting these values be improved, and are there other economic paradigms (e.g., "steady-state" versus "consumption and growth") that will lead to other theoretical constructs suitable for developing environmental policies.

1.6 References

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TABLES

TABLE 1: Initial Bid Vectors and Followup Bids for the CV Surveys

	Bid vectors based on final response in first section and are given as initial bid, upper, lower:			
Initial Bid	Y-Y[1]	Y-N[1]	N-Y[1]	N-N
$25	C ($100, $200, $50)	B ($50, $100, $25)	A ($25, $50, $10)	random
$50	D ($200, $400, $100)	C ($100, $200, $50)	B ($50, $100, $25)	random
$100	E ($400, $800, $200)	D ($200, $400, $100)	C ($100, $200, $50)	random
$200	F ($800, $1000, $400)	E ($400, $800, $200)	D ($200, $400, $100)	random
$400	G ($1000, $1500, $800)	F ($800, $1000, $400)	E ($400, $800, $200)	random
$800	H ($2000, $1500, $800)	G ($1000, $1500, $800)	F ($800, $1000, $400)	random

Notes:
1 – It is possible, in the followup, to respond “no” to a value for the total that had already been agreed to in the previous section. In that case, respondents are shown the following prompt: “You already agreed you'd be willing to pay this amount for ecological benefits alone. Now we’re asking about the total you’d be willing to pay”

TABLE 2: Risk Reductions in the Surveys

Endpoint	Context	Small Risk Reduction	Large Risk Reduction
Eagle	Probability of reproductive impairment significant enough to affect viability of the population	10 in 100	15 in 100
Species Sensitivity Distribution (SSD)	Probability of reproductive significant reproductive effects to 20% of all avian species in a freshwater ecosystem	25 in 100	40 in 100
Reading Comprehension	Probability of reading at approximately 7 months below grade level	10 in 100	15 in 100
IQ	Probability of a 6-point reduction in IQ	10 in 100	15 in 100

TABLE 3: Factor Analysis for the Motivational Responses (N-Y, Y-N, Y-Y)

	EcoFirst and HHFirst pooled (n=808)				All data pooled (n=1003)			
	Factor 1	Factor 2	Factor 3	Factor 3	Factor 1	Factor 2	Factor 3	Factor 4
Question	Loading	Loading		Loading	Loading	Loading	Loading	Loading
Altruism	**0.83**	0.21	0.14	0.24	**0.84**	0.22	0.13	0.21
Bequest	**0.76**	0.18	0.19	0.28	**0.76**	0.18	0.16	0.27
Nonuse	**0.78**	0.30	0.21	0.26	**0.80**	0.3	0.17	0.23
Use	0.47	0.13	0.15	**0.83**	0.52	0.11	0.14	**0.73**
Option	0.30	0.28		**0.38**	0.33	0.27		**0.40**
Eco Cleanup	0.31	**0.84**	0.18	0.18	0.29	**0.87**	0.13	0.17
My Child			0.37				0.36	
HH Altruism	0.12	0.18	**0.82**		0.13	0.23	**0.82**	
HH Cleanup	0.20	**0.49**	0.47		0.21	**0.60**	0.38	
Proportion of Variance:	26%	40%	53%	65%	28%	43%	55%	65%
	$\chi 2=5.6$, df=6, $p = 0.46$				$\chi 2=10.4$, df=6, $p = 0.11$			

Rate on a scale of 1 to 5 where 1 is not important and 5 is very important

TABLE 4: Proportion of Respondents in Each Bid Interval for the Ecological Endpoints

ECOFIRST SINGLE	EAGLE (n=193)					SSD (n=210)				
Bid Amount	n	Y-Y	Y-N	N-Y	N-N	n	Y-Y	Y-N	N-Y	N-N
A ($25, $50, $10)	36	12%	3%	3%	1%	37	11%	1%	1%	4%
B ($50, $100, $25)	38	10%	3%	3%	4%	36	9%	4%	1%	3%
C ($100, $200, $50)	22	2%	7%	1%	2%	30	3%	4%	1%	6%
D ($200, $400, $100)	32	5%	6%	2%	5%	34	3%	6%	1%	6%
E ($400, $800, $200)	33	2%	4%	3%	9%	39	4%	5%	2%	8%
F ($800, $1000, $400)	32	3%	4%	2%	8%	34	4%	1%	2%	9%

HHFIRST TOTAL	Eagle (n=211)					SSD (n=191)				
Bid Amount	n	Y-Y	Y-N	N-Y	N-N	n	Y-Y	Y-N	N-Y	N-N
A ($25, $50, $10)	11	1%	2%	0%	1%	12	1%	2%	1%	3%
B ($50, $100, $25)	20	1%	1%	3%	4%	23	2%	3%	3%	5%
C ($100, $200, $50)	50	5%	5%	9%	6%	44	6%	5%	8%	4%
D ($200, $400, $100)	39	3%	2%	7%	7%	27	2%	3%	4%	5%
E ($400, $800, $200)	30	1%	3%	5%	5%	33	1%	3%	8%	7%
F ($800, $1000, $400	37	2%	1%	9%	7%	29	2%	3%	5%	6%
G ($1000, $1500, $800)	12	2%	1%	2%	1%	10	1%	2%	1%	1%
H ($1500, $2000, $1000)	7	2%	0%	1%	0%	8	3%	0%	1%	0%

TABLE 2-4: Proportion of Respondents in Each Bid Interval for Human Health Endpoints

HHFIRST -- Single Endpoint	**IQ (n=208)**					**RC (n=196)**				
Bid Amount	n	Y-Y	Y-N	N-Y	N-N	n	Y-Y	Y-N	N-Y	N-N
A ($25, $50, $10)	35	11%	3%	0%	3%	35	12%	2%	1%	4%
B ($50, $100, $25)	36	8%	4%	1%	5%	32	7%	5%	4%	2%
C ($100, $200, $50)	27	3%	3%	2%	5%	21	3%	1%	2%	3%
D ($200, $400, $100)	30	4%	3%	2%	4%	33	4%	4%	2%	7%
E ($400, $800, $200)	41	2%	5%	4%	8%	40	4%	5%	2%	10%
F ($800, $1000, $400)	33	4%	1%	1%	9%	32	3%	4%	2%	7%

ECOFIRST -- Total Bid for Both Endpoints	**IQ (n=194)**					**RC (n=208)**				
Bid Amount	n	Y-Y	Y-N	N-Y	N-N	n	Y-Y	Y-N	N-Y	N-N
A ($25, $50, $10)	11	0%	2%	2%	2%	14	2%	0%	1%	3%
B ($50, $100, $25)	16	2%	3%	2%	3%	18	1%	3%	2%	2%
C ($100, $200, $50)	37	11%	5%	6%	3%	47	10%	5%	5%	3%
D ($200, $400, $100)	47	6%	8%	7%	4%	39	3%	8%	6%	2%
E ($400, $800, $200)	30	0%	7%	5%	4%	31	3%	2%	4%	5%
F ($800, $1000, $400	32	3%	1%	6%	8%	32	5%	1%	6%	3%
G ($1000, $1500, $800)	10	2%	2%	2%	0%	11	1%	1%	3%	0%
H ($1500, $2000, $1000)	5	2%	0%	1%	0%	9	3%	0%	1%	0%

TABLE 2-4, continued: Proportion of Respondents in Each Bid Interval for the Combined Survey

COMBINED	**Combined (n=204)**				
Bid Amount	n	Y-Y	Y-N	N-Y	N-N
A ($25, $50, $10)	37	11%	4%	0%	3%
B ($50, $100, $25)	41	9%	6%	0%	5%
C ($100, $200, $50)	23	4%	2%	1%	4%
D ($200, $400, $100)	34	5%	4%	2%	5%
E ($400, $800, $200)	35	2%	5%	1%	9%
F ($800, $1000, $400)	29	3%	3%	0%	8%

TABLE 5: Demographics for Each Subsurvey and the US Census

	ECOFIRST		HUMANFIRST		COMBINED	
Demographic	Eagle (n=193)	SSD (n=210)	RC (n=196)	IQ (n=208)	Combined (n=204)	US Census Data[1]
Some high school, no diploma	7%	8%	19%	11%	16%	20%
High school	29%	30%	29%	35%	32%	29%
Some college, no degree	23%	20%	21%	24%	21%	21%
Associate's degree (AA, AS)	15%	12%	7%	5%	6%	6%
Bachelor's degree	17%	19%	16%	19%	14%	16%
Master's degree	4%	7%	7%	5%	9%	6%
Other	5%	4%	2%	2%	1%	3%
Black, Non-Hispanic	10%	12%	12%	15%	12%	12%
Hispanic	9%	15%	17%	9%	11%	13%
Other, Non-Hispanic	5%	5%	4%	4%	5%	0%
White, Non-Hispanic	76%	68%	67%	72%	72%	75%
Female	57%	50%	48%	51%	52%	51%
Male	43%	50%	52%	49%	48%	49%
Income						
Less than $10,000	12%	10%	12%	13%	13%	10%
$10,000 to $14,999	11%	5%	9%	8%	4%	6%
$15,000 to $19,999	5%	4%	5%	4%	8%	6%
$20,000 to $24,999	8%	10%	6%	8%	5%	7%
$25,000 to $29,999	8%	7%	10%	6%	5%	6%
$30,000 to $34,999	7%	7%	5%	4%	8%	6%
$35,000 to $39,999	4%	10%	10%	10%	9%	6%
$40,000 to $49,999	9%	11%	10%	6%	15%	11%
$50,000 to $59,999	10%	9%	7%	13%	7%	9%
$60,000 to $74,999	10%	9%	8%	12%	12%	10%
$75,000 to $99,999	11%	9%	12%	6%	7%	10%
$100,000 to $124,999	2%	3%	5%	5%	5%	5%
$125,000 to $149,999	1%	2%	1%	1%	2%	3%
$150,000 to $174,999	1%	1%	1%	0%	2%	2%
$175,000 or more	2%	2%	2%	0%	1%	2%
Divorced	12%	15%	13%	20%	14%	10%
Married	52%	50%	48%	46%	52%	54%
Separated	2%	2%	3%	4%	1%	2%
Single (never married)	26%	28%	28%	26%	29%	27%
Widowed	7%	5%	7%	4%	3%	7%

1: Data provided for males and females combined (except gender); therefore, percentages may not equal 100 due to combining. Data from: factfinder.census.gov, 2000 Census

TABLE 6: Means for the Covariates across Surveys

		Eagle (n=193)	SSD (n=210)	IQ (n=208)	RC (n=196)	Combined (n=204)
		ECOFIRST		HHFIRST		COMBINED
Parameter	Parameter Name	Mean	Mean	Mean	Mean	Mean
Education (1 for college and above, 0 otherwise)	EDUCAT	0.53	0.61	0.55	0.53	0.50
White (1 for yes, 0 otherwise)	WHITE	0.76	0.68	0.72	0.67	0.71
Black (1 for yes, 0 otherwise)	BLACK	0.09	0.12	0.15	0.12	0.22
Hispanic (1 for yes, 0 otherwise)	HISPANIC	0.09	0.15	0.09	0.17	0.14
Gender (1 if Female, 0 if Male)	MALE	0.57	0.50	0.52	0.48	0.52
Natural log of income	LNInc	10.36	10.46	10.41	10.41	10.38
Married (1 if yes, 0 otherwise)	MARRIED	0.52	0.50	0.46	0.48	0.52
Live in a metropolitan area (1 if yes, 0 if no)	METRO	0.83	0.82	0.83	0.84	0.79
Natural log of ecological risk reduction	LNEcoRR	-2.09	-1.17	-1.67	-1.60	-2.11
Natural log of human health risk reduction	HHLNRR	-2.09	-2.09	-2.09	-2.09	-2.09
Have you ever heard of PCBs (1 if yes, 0 otherwise)	PCBs	0.48	0.50	0.45	0.43	0.41
Confidence in response to single endpoint valuation (scale of 1 to 5 where 1 is not confident and 5 is very confident)	ConfWildlife	4.39	4.16	3.70	3.62	na
Confidence in total	ConfTotal	4.55	4.06	3.67	3.60	3.31
Are you able to think about ecological endpoints separately from human (1 if yes, 0 if no)	eco.sep	0.78	0.72	0.71	0.77	na
Are you able to think about ecological benefits separately from human health benefits? (1 if yes, 0 otherwise)	eco.ben.sep	0.62	0.63	0.62	0.64	na
Concerned about chemicals in the environment (1 if yes, 0 otherwise)	ChemConcern	3.12	2.96	3.04	2.89	3.03

TABLE 6: Means for the Covariates across Surveys

Concerned about PCBs in the environment (1 if yes, 0 otherwise)	PCBConcern	2.96	2.77	2.69	2.62	2.87
Do you believe PCBs can cause reproductive effects in wildlife? (1 if yes, 0 otherwise)	PCBWildlife	0.66	0.59	0.59	0.60	0.60
Do you believe PCBs can cause developmental effects in children exposed *in utero* ? (1 if yes, 0 otherwise)	PCBChild	0.61	0.54	0.65	0.60	0.59
Rate the risks facing eagles in this state (0 = not sure, 1 = not serious, 2 = somewhat serious, 3 = very serious, 4 = extremely serious)	risk.wldlf	2.14	2.04	1.94	1.94	2.08
Rate the risks facing unborn babies in this state (0 = not sure, 1 = not serious, 2 = somewhat serious, 3 = very serious, 4 = extremely serious)	risk.baby	2.22	2.01	2.17	2.11	2.16
How often do you watch programs on television about wildlife (1 = never, 2 = rarely, 3 = sometimes, 4 = often)	tv.wldlf	2.99	2.91	2.75	3.03	2.90
Do you live near freshwater (1 = yes, 0 = no)	live.fw	0.69	0.64	0.60	0.60	0.66
How much time do you spend on a river, lake, or stream? (1 = never, 2 = rarely, 3 = sometimes, 4 = often)	time.fw	2.60	2.65	2.49	2.61	2.62
How often do you eat recreationally caught fish (0 = never, 1 = a few times a year, 2 = a few times a month, 3 = a few times a week)	eat.fish	2.50	2.53	2.51	2.47	2.57
How much confidence do you have in information you receive from government sources (1 = none, 2 = some, 3 = a lot)	conf.gov	1.85	1.78	1.93	1.85	1.85

TABLE 6: Means for the Covariates across Surveys

How much confidence do you have in information you receive from industry scientists (1 = none, 2 = some, 3 = a lot)	conf.sci.ind	1.88	1.82	1.85	1.81	1.86
How much confidence do you have in information you receive from university scientists (1 = none, 2 = some, 3 = a lot)	conf.sci.univ	2.25	2.27	2.21	2.20	2.31
How much confidence do you have in information you receive from television sources (1 = none, 2 = some, 3 = a lot)	conf.tv	1.70	1.68	1.72	1.70	1.71
How much confidence do you have in information you receive from government web sites (1 = none, 2 = some, 3 = a lot)	conf.gov.web	1.87	1.78	1.87	1.83	1.81
How much confidence do you have in information you receive from commercial web sites (1 = none, 2 = some, 3 = a lot)	conf.comm.web	1.69	1.62	1.61	1.59	1.65
How much confidence do you have in information you receive from nonprofit web sites (1 = none, 2 = some, 3 = a lot)	conf.np.web	2.10	2.09	2.04	2.02	2.05
How much confidence do you have in information you receive from university web sites (1 = none, 2 = some, 3 = a lot)	conf.uni.web	2.21	2.20	2.12	2.06	2.15
How much confidence do you have in information you receive from print media (1 = none, 2 = some, 3 = a lot)	conf.print	1.86	1.88	1.84	1.81	1.88

TABLE 7: Model Results for Ecological Endpoints in EcoFirst Survey

	Model 1 All Covariates for the Eagle Endpoint β (std error)	Model 2 All Covariates for the SSD Endpoint β (std error)	Model 3 Stepwise Model for the Eagle Endpoint β (std error)
Intercept	1.6 (2.2)	-0.5 (2.7)	2.6 (1.4)*
Risk Reduction	0.9 (0.7)	-0.9 (0.7)	1.0 (0.6)*
Age	-0.002 (0.009)	-0.005 (0.01)	
Dual Income Household	0.4 (0.3)	0.4 (0.3)	0.5 (0.2)*
Education	-0.2 (0.3)	0.6 (0.4)*	
Race (reference = White)			
Other	0.7 (0.6)	0.06 (0.7)	
Black	0.06 (0.5)	-0.8 (0.5)	
Hispanic	0.9 (0.5)*	0.5 (0.4)	
Male	0.07 (0.3)	-0.06 (0.3)	
Confidence	0.4 (0.1)***	0.5 (0.2)**	0.3 (0.1)**
Married	-0.1 (0.3)	-0.04 (0.4)	
Live in a metro area	0.5 (0.4)	0.1 (0.4)	
Concerned about PCBs	0.7 (0.2)****	1.2 (0.3)****	0.8 (0.1)****
Watch television on wildlife	0.2 (0.2)	0.3 (0.2)*	0.3 (0.1)**
Live near freshwater	0.2 (0.3)	-0.5 (0.4)	
Spend time near freshwater	0.1 (0.1)	-0.1 (0.2)	
Nonuse	-0.4 (0.1)***	-0.2 (0.2)	-0.4 (0.1)***
Use/Option	0.2 (0.1)*	-0.02 (0.2)	0.2 (0.1)*
Cleanup	-0.2 (0.2)	-0.1 (0.2)	
-2*Log-Likelihood	462	472	470
	n=192	n=208	n=193
* p<0.10, ** p<0.05, *** p<0.01, **** p<0.001			

Dependent variable is interval-censored WTP for a single endpoint

TABLE 8: Model Results Using Pooled Dataset
for the Single Endpoint Valuation Question[1]

	Model 1 Reduced Model β (std error)	Model 2 Full Model β (std error)
Intercept	4.6 (1.6)***	-0.03 (1.6)
EcoFirst	0.4 (2.5)	1.9 (2.4)
IQ	2.6 (2.2)	1.5 (2.1)
Eagle	-0.0009 (0.3)	-0.4 (0.3)
Eagle Risk Reduction	0.2 (0.8)	1.0 (0.7)
SSD Risk Reduction	-0.4 (0.6)	-0.7 (0.6)
IQ Risk Reduction	1.1 (0.7)*	0.5 (0.7)
Reading Comprehension Risk Reduction	-0.1 (0.7)	-0.2 (0.7)
Age		-0.004 (0.005)
Education		0.2 (0.2)
Race (ref = White)		
Other		0.5 (0.4)
Black		0.03 (0.2)
Hispanic		0.4 (0.2)*
Income		0.04 (0.2)
Married		0.07 (0.2)
Live in a metropolitan area		0.2 (0.2)
Heard of PCBs?		-0.4 (0.2)**
QALY		0.1 (0.04)****
Confidence		0.3 (0.08)****
Concerned about PCBs Generally		0.7 (0.2)****
Concerned about Chemicals Generally		0.2 (0.1)*
Concerned about PCBs and Wildlife		0.07 (0.2)
Concerned about PCBs and Children		0.6 (0.2)***
Risks to wildlife		0.09 (0.1)
Risks to babies		0.09 (0.1)
Watch TV programs about wildlife		0.06 (0.09)
Live near freshwater		-0.03 (0.2)
Spend time at freshwater		-0.004 (0.08)
Consume self-caught freshwater fish		-0.01 (0.09)
Nonuse		-0.2 (0.08)***
Cleanup		-0.02 (0.08)
HH altruism		-0.3 (0.09)****
Use/Option		-0.04 (0.08)
-2*Log-Likelihood	2127	1833
	n=808	n=791
* p<0.10, ** p<0.05, *** p<0.01, **** p<0.001		

TABLE 9: Model Results using Pooled Data for Total WTP (HH and Eco Endpoints)[1]

	Model 1 Reduced Model β (std error)	Model 2 Full Model β (std error)
Intercept	2.9 (0.9)***	0.08 (0.9)
Combined (no single endpoint)	-0.2 (0.2)	0.02 (0.2)
EcoFirst	0.4 (0.1)****	0.4 (0.1)***
IQ	2.6 (1.3)**	2.5 (1.3)**
Eagle	1.4 (0.9)	1.7 (0.9)*
Eagle Risk Reduction	0.3 (0.4)	0.4 (0.4)
SSD Risk Reduction	-0.6 (0.4)	-0.7 (0.5)*
IQ Risk Reduction	0.7 (0.5)	0.7 (0.5)
Reading Comprehension Risk Reduction	-0.6 (0.4)	-0.6 (0.4)
Age		-0.009 (0.004)**
Education		0.08 (0.1)
Race (ref = White)		
Other		-0.2 (0.3)
Black		0.05 (0.2)
Hispanic		0.2 (0.2)
Income		0.02 (0.1)
Married		-0.03 (0.1)
Live in a metropolitan area		-0.02 (0.2)
Heard of PCBs		-0.2 (0.1)
Concerned about PCBs Generally		0.4 (0.1)****
Concerned about Chemicals Generally		0.3 (0.1)**
Concerned about PCBs and Wildlife		0.1 (0.2)
Concerned about PCBs and Children		0.5 (0.2)***
Risks facing wildlife		0.07 (0.08)
Risks facing babies		0.1 (0.07)**
Watch TV programs about wildlife		0.08 (0.07)
Live near freshwater		0.01 (0.1)
Spend time at freshwater		0.03 (0.07)
Consume self-caught freshwater fish		0.06 (0.08)
Nonuse		0.1 (0.07)
Cleanup		-0.04 (0.06)
HH altruism		0.03 (0.07)
Use/Option		0.02 (0.07)
-2*Log-Likelihood	3222	2952
	n=1003	n=992
* p<0.10, ** p<0.05, *** p<0.01, **** p<0.001		

1 - Dependent variable is interval-censored WTP for both endpoints (total WTP)

TABLE 10: Risk Reduction and Median WTP at Covariate Means Across Models

Model	Reading Comprehension Risk Reduction	Eagle Risk Reduction	WTP Median Prediction	WTP 95% LCL	WTP 95% UCL	Survey Identifier
Ecofirst -- Both Endpoints	0.10	0.10	$ 276	$ 198	$ 387	A
(n=403)	0.10	0.15	$ 241	$ 173	$ 336	B
	0.15	0.10	$ 263	$ 188	$ 368	C
	0.15	0.15	$ 229	$ 166	$ 317	D
Humanfirst -- Both Endpoints	0.10	0.10	$ 180	$ 128	$ 252	E
(n=404)	0.15	0.10	$ 171	$ 122	$ 240	F
	0.10	0.15	$ 157	$ 113	$ 218	G
	0.15	0.15	$ 149	$ 108	$ 206	H
Combined	0.10	0.10	$ 115	$ 64	$ 206	I
(n=204)	0.10	0.15	$ 150	$ 83	$ 270	J
	0.15	0.10	$ 127	$ 74	$ 218	K
	0.15	0.15	$ 165	$ 93	$ 295	L
Ecofirst -- Single Endpoint	na	0.10	$ 150	$ 114	$ 197	M
(Eagle; n=193)	na	0.15	$ 163	$ 128	$ 209	N
Humanfirst -- Single Endpoint	0.10	na	$ 118	$ 96	$ 146	O
(RC; n=204)	0.15	na	$ 146	$ 116	$ 184	P
Humanfirst -- Single Endpoint	0.10	na	$ 125	$ 85	$ 184	Q
(IQ; n=208)	0.15	na	$ 154	$ 106	$ 225	R
MINIMUM			$ 115	$ 64	$ 206	
MAXIMUM			$ 276	$ 198	$ 387	

TABLE 11: Confidence Level by Response Category

DBDC Response	n	Mean	Standard Deviation
<< ------- COMBINED SURVEY ------------------------->>			
Yes-Yes	70	4.4	0.9
No-No	71	2.2	1.4
Yes-No or No-Yes	62	3.3	0.8
<< ------- Pooled Data Across All Surveys -------------->>			
Yes-Yes	244	4.2	0.9
No-No	280	3.1	1.4
Yes-No or No-Yes	483	3.6	0.9

Kruskal-Wallis $\chi 2$ p <0.001 that means are significantly different

TABLE 12: Model Results for Stratified Models Using
Pooled Dataset for a Single Endpoint (Models 1 and 2) and Total Endpoint (Models 3 and 4)

	Model 1 Single Endpoint EcoSep = 0 β (std error)	Model 2 Single Endpoint EcoSep = 1 β (std error)	Model 3 Total Endpoint EcoSep = 0 β (std error)	Model 4 Total Endpoint EcoSep = 1 β (std error)
Intercept	9.4 (3.7)***	2.8 (1.8)	5.7 (2.2)***	0.8 (1.3)
Eco Endpoints First	-4.9 (5.5)	2.1 (2.8)	0.6 (0.3)**	0.4 (0.2)***
IQ	1.8 (4.8)	2.8 (2.6)	5.9 (2.9)**	2.9 (1.6)*
Eagle	0.2 (0.6)	-0.06 (0.3)	3.8 (2.4)*	0.7 (1.3)
SSD Risk Reduction	0.7 (1.2)	-0.8 (0.7)	0.2 (0.8)	-0.9 (0.5)**
Eagle Risk Reduction	-0.7 (1.7)	0.4 (0.8)	2.0 (1.0)**	-0.3 (0.5)
Reading Comprehension Risk Reduction	2.3 (1.7)	-1.1 (0.8)	0.3 (0.9)	-1.5 (0.6)***
IQ Risk Reduction	3.0 (1.5)**	0.3 (0.8)	3.0 (0.9)***	0.004 (0.5)
-2*Log-Likelihood	544	1556	684	1999
	n=205	n=597	n=204	n=597

* p<0.10, ** p<0.05, *** p<0.01, **** p<0.001

EcoSep = 0; respondents not able to separately value human health and ecological endpoints
EcoSep = 1; respondents are able to separately value human health and ecological endpoints

TABLE 13: Responses to Y-N, N-Y, Y-Y Followup Questions

	Eco Valuation Questions (n=550)						HH Valuation Questions (n=576)		
Rating	Altruism	Bequest	Nonuse	Use	Option	Cleanup	Altruism	My Child	Cleanup
1 - Not Important	2%	3%	2%	5%	8%	2%	2%	34%	2%
2	3%	4%	4%	7%	10%	7%	4%	7%	6%
3	26%	22%	26%	24%	36%	21%	18%	16%	20%
4	26%	27%	29%	25%	21%	25%	21%	10%	27%
5 - Extremely Important	43%	44%	40%	39%	26%	46%	55%	33%	45%

Notes:
Altruism: I think it's important to preserve [EAGLES / WILDLIFE] not just for my enjoyment but for everyone
Bequest: I would like my children to have the opportunity to see [EAGLES / WILDLIFE]
Nonuse: I think it's important to protect [EAGLES / WILDLIFE] – it's important to me know that they are ok
even if I don't see them directly
Use: I enjoy seeing [EAGLES / WILDLIFE]
Option: It's not very important to me right now if see [EAGLES / WILDLIFE], but I would like the option of doing so in the future
of doing so in the future
Cleanup: I support a cleanup no matter what the risk might be (I don't like the idea of chemicals in the environment generally)
Altruism (HH): I'm worried about the potential risk to unborn babies generally
My Child (HH): I'm worried about the potential risk to my own unborn children
Cleanup (HH): I support a cleanup no matter what the risk might be (I don't like the idea of chemicals in the environment generally)

TABLE 14: Responses to N-N Followup Questions

Agree?	Ecological Valuation Questions (n=253)				HH Valuation Questions (n=230)			
	Not Worth the Money	Difficult for Household to Pay	Don't Believe a Cleanup Will Work	Some Other Reason	Not Worth the Money	Difficult for Household to Pay	Don't Believe a Cleanup Will Work	Some Other Reason
No	81%	62%	69%	59%	87%	62%	68%	56%
Yes	19%	38%	31%	41%	13%	38%	32%	44%

FIGURES

D.1. Scientists predict that eagles will have a 20 in 100 (or 1 in 5) chance of failing to produce young if exposed to PCBs. Put another way, if there are 100 eagles, then 20 of them will be unable to produce young. Each dot below represents one eagle. The red dots represent the eagles that won't be able to reproduce.

••

••

If the river is cleaned up, scientists predict that the risk will drop to [1 in 10 / 1 in 20], or that [10 out of 100 / 5 out of 100] animals will be affected. There will always be some chance that eagles will have trouble reproducing because the sediments can't be totally cleaned up. Each dot below represents one eagle: the red dots represent the eagles that will still have trouble reproducing after the river is cleaned up.

[APPROPRIATE DOTS]

FIGURE 1: "Dots" Graphic for Risk Reduction from the Surveys

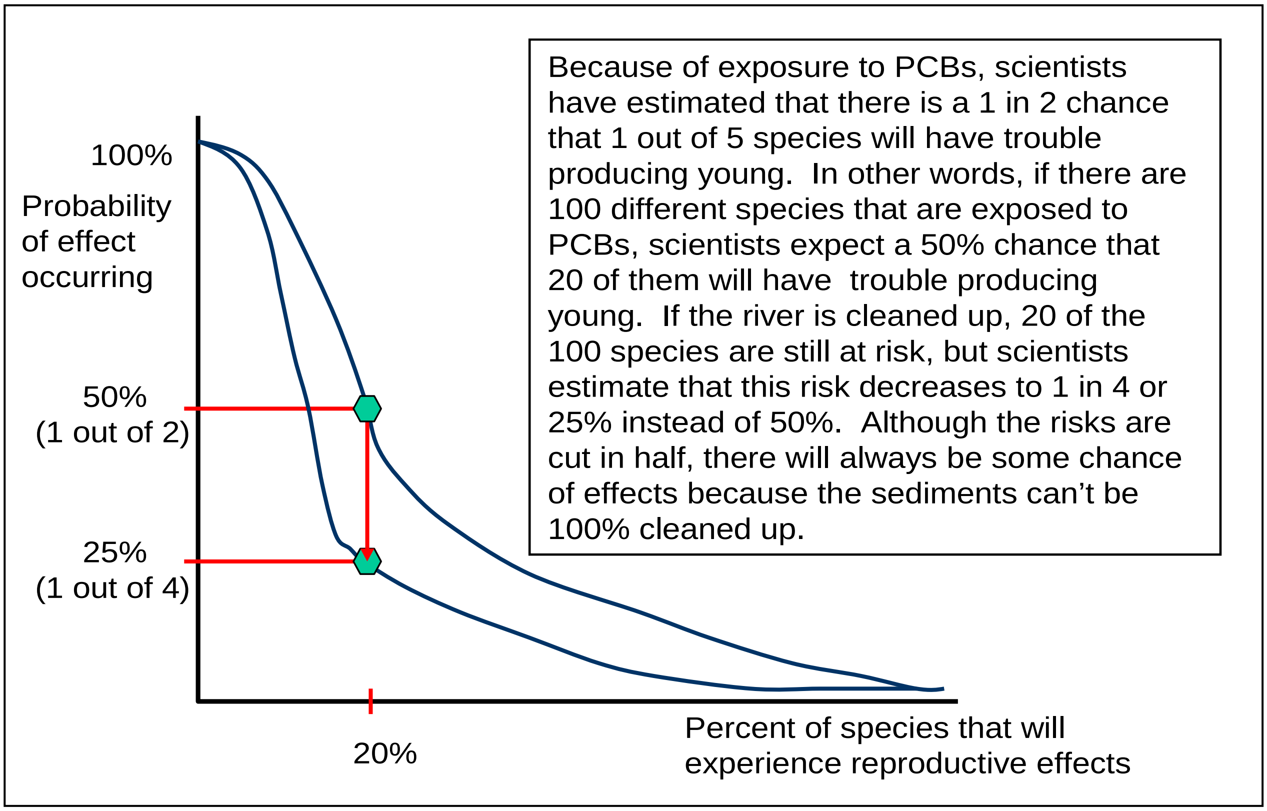

FIGURE 2: Species Sensitivity Distribution (SSD) Graphic from the Surveys

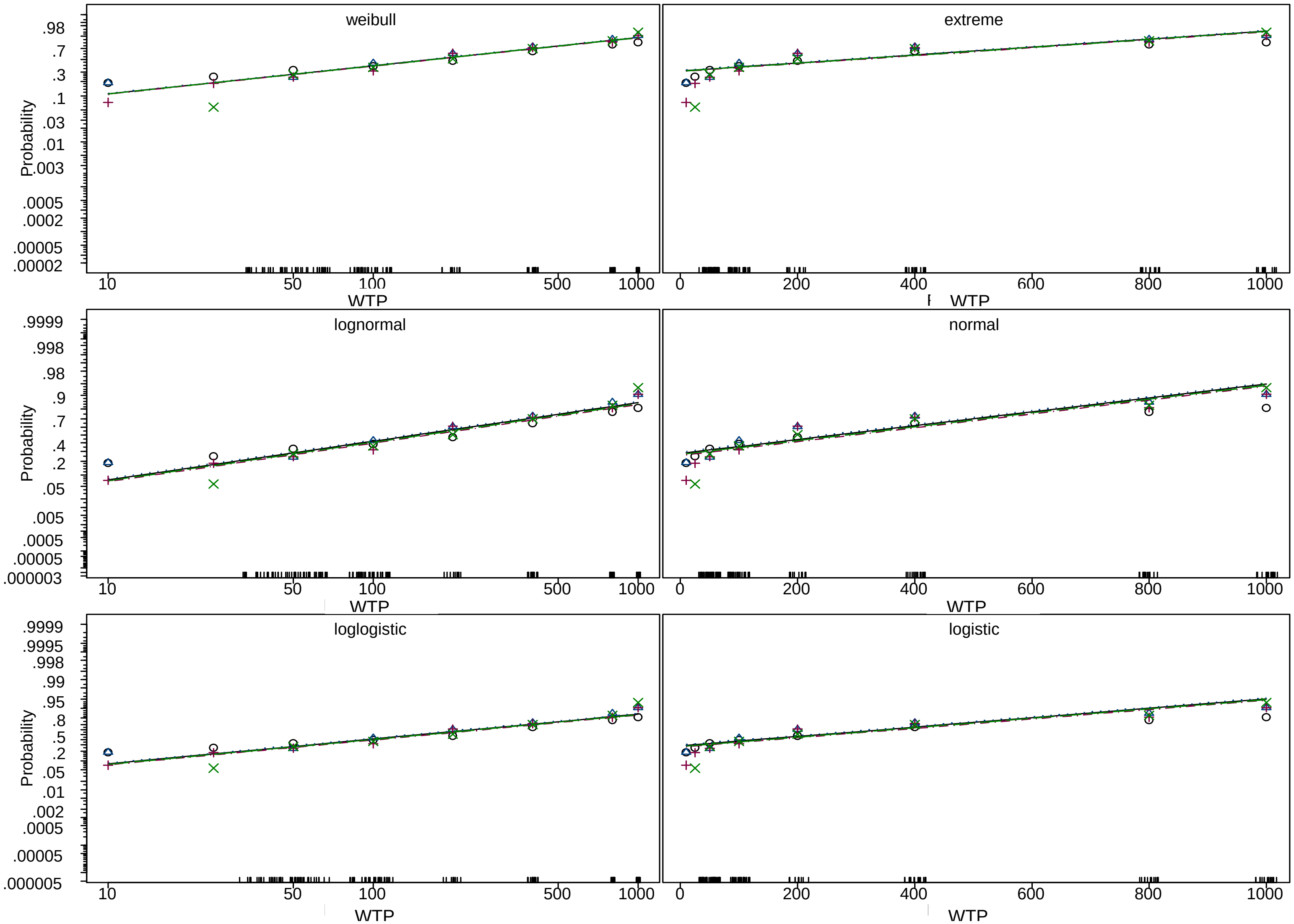

FIGURE 3: Probability Plots for the Ecofirst Single Endpoint

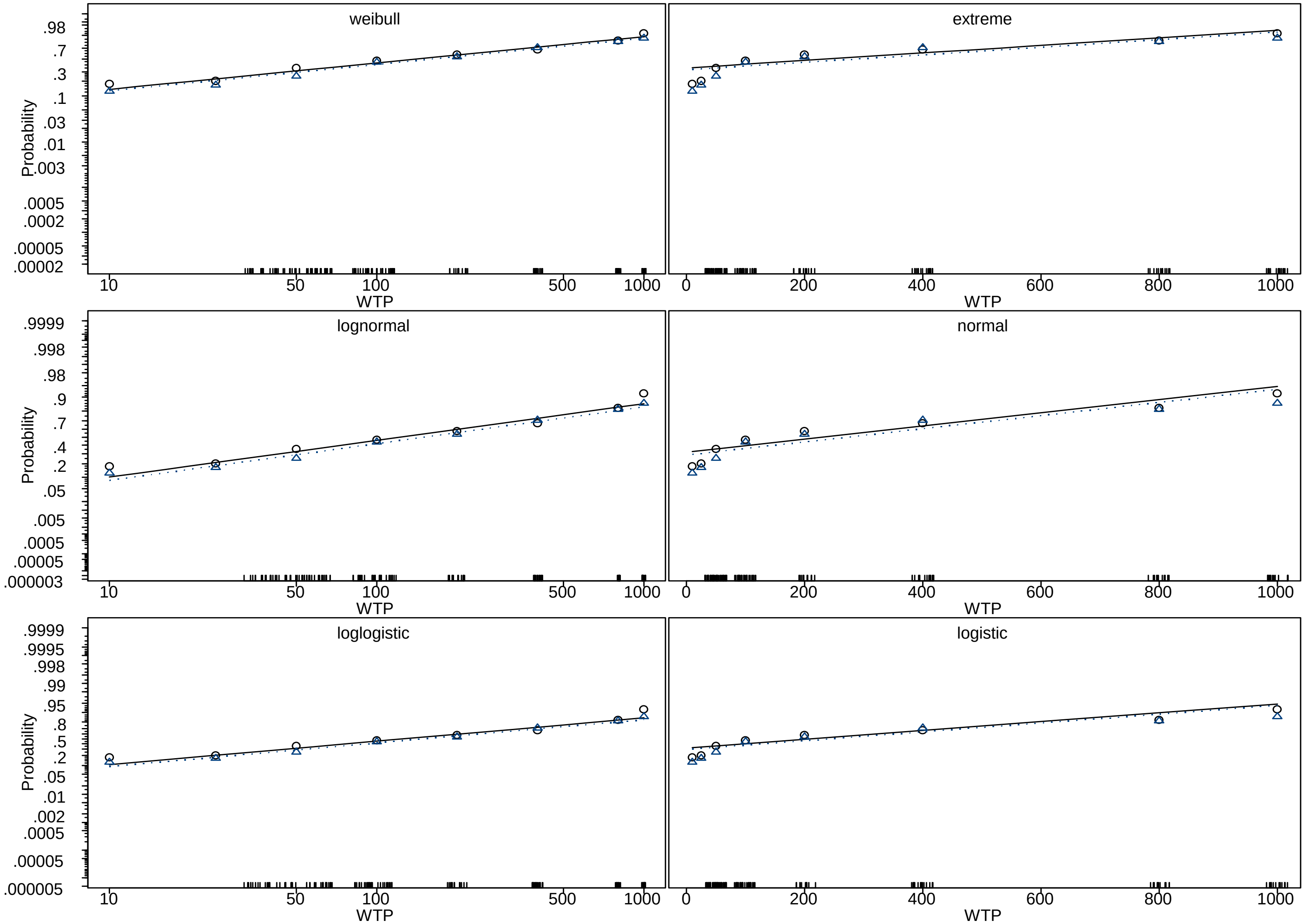

FIGURE 4: Probability Plots for the HHFirst Single Endpoint

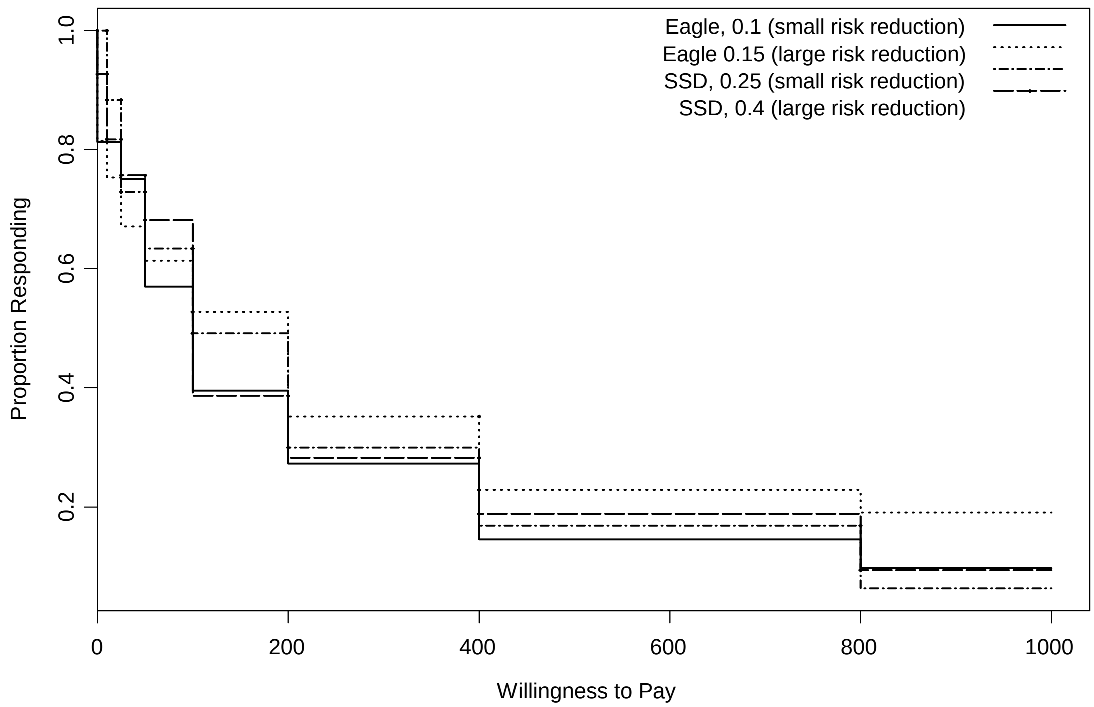

FIGURE 5: Willingness to Pay Across Risk Reductions for Ecological Endpoints

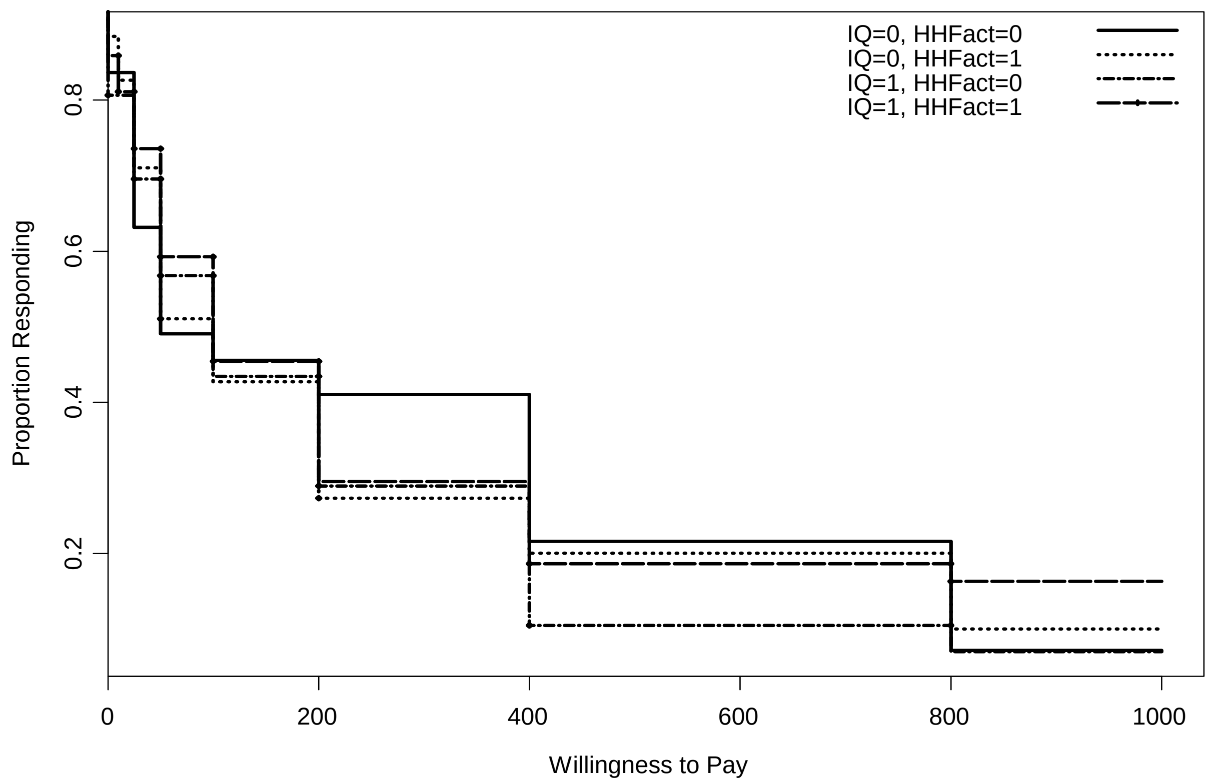

FIGURE 6: Willingness to Pay Across Risk Reductions for Human Health Endpoints

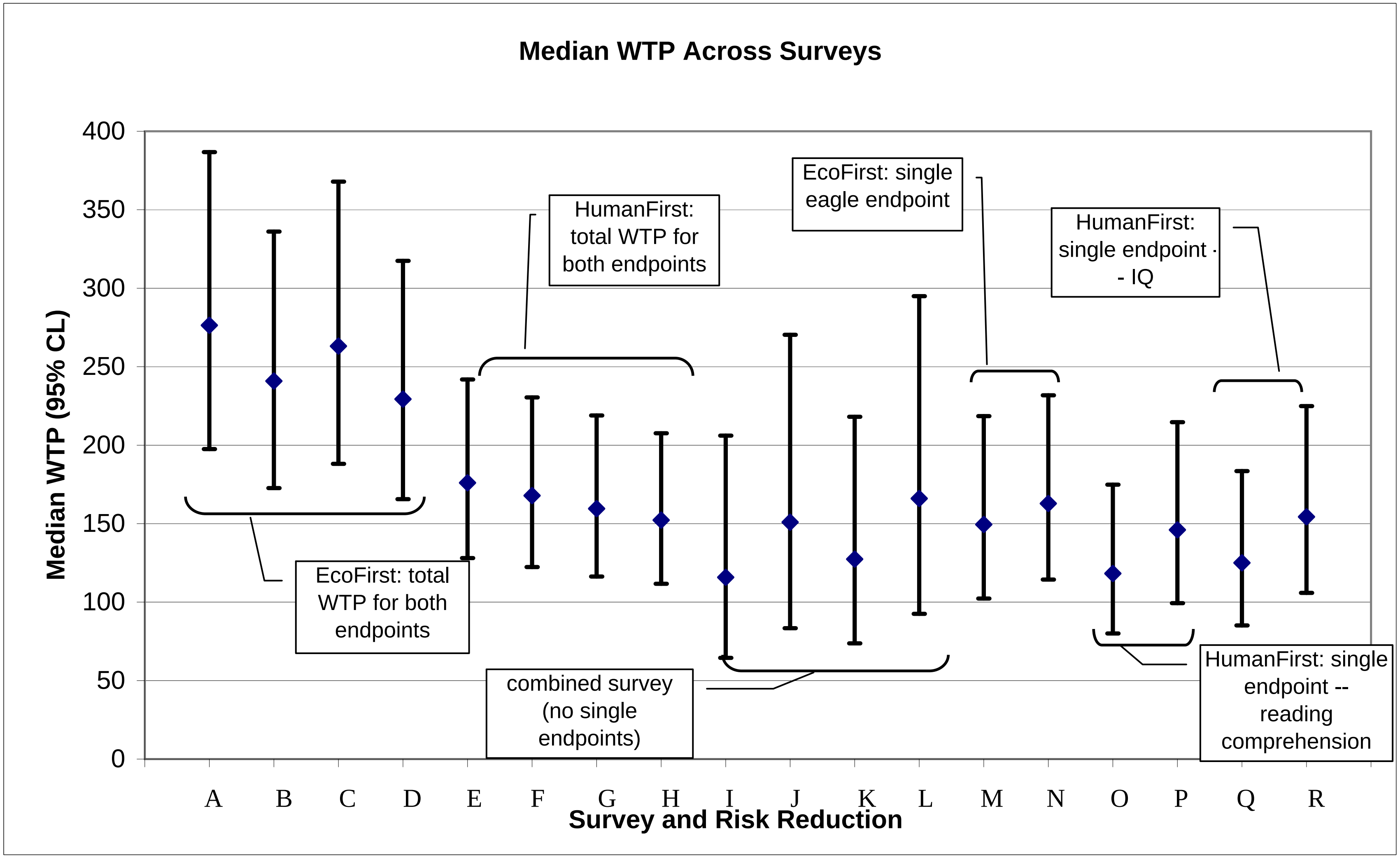

FIGURE 7: Willingness to Pay Across Surveys, Endpoints, and Risk Reductions

Valuing the Ecological Effects of Acidification

Mapping the Extent of Market and Extent of Resource in the Southern Appalachians

Shalini P. Vajjhala, Anna Mische John, and David A. Evans

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Valuing the Ecological Effects of Acidification: Mapping the Extent of Market and Extent of Resource in the Southern Appalachians

Shalini P. Vajjhala, Anna Mische John, David A. Evans

Abstract

Identifying the appropriate survey population and defining the extent of resource are among the most fundamental design decisions for stated preference surveys. However, there is often little information on the perceptions of the general population regarding the scope of the resource being valued (extent of resource) and who in the population holds measurable value for the resource (extent of the market). This paper presents a novel approach using mental mapping interview techniques to provide information about the extent of market and the extent of resources for the design of stated preference surveys that elicit willingness to pay (WTP) for reducing environmental damages. The approach was developed and tested as part of an ongoing study on environmental degradation associated with acidification in the Southern Appalachian Mountain region. While damage from acidification in the study region is broad, it is not clear if residents of this region are particularly concerned about degraded resources in the states where they live, in neighboring states, on public lands, or more broadly across the region. Based on a pilot study with a convenience sample of former residents of North Carolina and Virginia, we find that participants' show a significant home-state preference in the number and size of natural areas that they value within the Southeastern United States and the larger Southern Appalachian region. This study lays the groundwork both methodologically and analytically for integrating spatial considerations into conventional contingent valuation and choice experiment designs.

Contents

Valuing the Ecological Effects of Acidification: Mapping the Extent of Market and Extent of Resource in the Southern Appalachians

Shalini P. Vajjhala, Anna Mische John, David A. Evans*

Introduction

Identifying the appropriate survey population and defining the resource to be valued are among the most fundamental design decisions for stated preference (SP) surveys. However, , a researcher does not necessarily know the distribution of those who hold measurable value for the resource or what particular part of the resource to focus on (i.e. the extent of the market and the definition of the commodity). Limited resources prevent casting a large net and capturing every potential individual or household that values the resource in question. Furthermore, there is often little information on the perceptions of the general population regarding the scope of the resource being valued. These challenges are particularly true for resources associated with significant nonuse values. Both of these drivers, limited sampling budgets and the desire for a credible payment vehicle, along with the preferences of the survey sponsor, often result in the use of convenient, implicit, or ad-hoc definitions of the extent of the market.

This paper presents a novel approach using mental mapping interview techniques from geography and psychology literature as a complement to traditional focus-group interviews to provide an early characterization of the extent of market and the extent of resources for the design of SP surveys that elicit willingness to pay (WTP) for reducing environmental damages in large regions. The approach was developed and tested as part of an ongoing study on environmental degradation associated with acidification in the Southern Appalachian Mountains. While damages from acidification in the study region are broad, it is not clear if residents of this region are particularly concerned about degraded resources in the states where they live, in neighboring states, on public lands, or more broadly across the region.

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As a region that covers parts of eight different states, the Southern Appalachian Mountain region does not have clear jurisdictional boundaries, making it difficult to develop a standard and credible payment vehicle for all potential survey participants in region. In order to better characterize both the resource and the survey population before making instrument design decisions and engaging in focus group interviews, we developed a pilot study with a convenience sample of 30 former residents of either North Carolina or Virginia, currently living in the Washington D.C. metropolitan area.

Study participants were provided with a base map of the region, and asked during one-on-one interviews, to add information to the maps about their use of and value for different parts of the region. Respondents mapped features including 1) places that they visited regularly while living in the region, 2) the five natural areas in the region that they valued most and thought were most important, and 3) any areas they perceived as degraded. The resulting maps from each interview were then coded (in a process similar to transcribing an interview) to allow for quantitative evaluation and comparisons of the sizes, types, and locations of the areas/resources marked on participants' maps.

By providing preliminary spatial characterization of both the extent of market and the extent of resource, this approach demonstrates how mapping can inform the design of SP surveys of both contingent valuation and conjoint forms. Section 2 describes in detail the motivation for using spatial analysis as an introductory component of SP survey instrument design. Section 3 provides a review of the mapping literature and outlines the potential contributions of the method to the economic literature and SP research. Section 4 details the elements of our methodological approach and mapping study design. Section 5 then presents a pilot application evaluating the extent of market and extent of resource for damages from acidification in the Southern Appalachian Mountain region. Section 6 highlights our early analyses and findings, and Section 7 concludes with a discussion of the strengths and weaknesses of the method for wider application to different resources, regions, and related benefits-transfer techniques and also highlights several areas for further study.

Motivation for Spatial Analysis

Eliciting individuals' value for different environment attributes or areas is an inherently spatial problem dependent on the locations of key resources and populations. SP surveys, in particular, require clear definitions of the resource being valued and a careful consideration of the population from which to select a survey sample. However, a researcher often has little information about who cares about the resource ex-ante and therefore develops a definition of the extent of the market (at least for sampling purposes) based on other objectives and study constraints. For example, in related valuation study focused on the Adirondack Mountains in upstate New York (Banzhaf et al. 2006), the survey population was defined as all New York State residents to allow for the use of an incentive-compatible payment vehicle (state income tax) that corresponded with a credible management agency (New York State) for the resource in question (the Adirondacks Park).[1] While New York State residents are likely to have higher average WTP for improvements to this resource, it is also likely that residents of neighboring states, like Vermont, would receive similarly significant benefits from improvements to the resource. Given the scale of the resource and the design complexities associated with surveying a larger population, it was decided that estimating Vermont residents' WTP was outside the scope of the study. These constraints, while typical, are particularly important in the case of very large resources, where unlike the Adirondacks, oversight and payment options are less obvious.

For some surveys, the resource of interest corresponds to a clear administrative authority through which management decisions and environmental improvements are made. If the jurisdiction encompasses all of those that have a measurable WTP for improvements to that resource, then the design the SP survey is relatively straightforward, as described above. But this is not always the case. The boundaries of many other natural resources do not correspond to administrative and jurisdictional boundaries under which resource management decisions are made. Instead these resources, including major national parks and forests, cross state boundaries and are surrounded by and encompass a variety of different populations, ecosystems, and land uses. Similar issues arise for resources that are encompassed by one jurisdictional boundary but managed by a higher level of government. In these cases, using mapping as a complement to traditional SP methods provides opportunities to elicit perceptions of the resource from a sub-set of the largest potential survey population to develop a baseline spatial characterization and assessment of the extent of both the resource and the market for the resource. Furthermore, because mapping interviews are typically open-ended, it is possible to use this approach to identify other resources for which residents could have significant nonuse values.

[1] While this study only estimated the WTP for improvements to the Adirondacks from reduced acid deposition from New York State residents, the information gathered by the survey is still very useful information when conducting a benefit-cost analysis of the benefits of reducing acid deposition precursors. The total WTP of all New York residents can be viewed as a lower-bound of the total value of the improvement to the resource.

Defining the commodity and understanding the extent of market

Two parallel challenges in developing a stated preference survey are 1) defining the commodity of interest and 2) determining the extent of the market (and thus who to survey). In cases where the resource is sufficiently large to encompass a variety of different attributes and features, it is unclear if individuals within a given distance of the larger area value, for example, the whole area or simply the parts of the resource closest to their home, the parts of the resource with the greatest amenities, or the parts of the resource that they have visited or used the most. In cases of valuing ecosystem improvements over large areas, it is beyond a study budget to conduct a survey where the definition of the commodity is the entire area of interest (in our example, the Southern Appalachians). In these cases, it is more realistic to consider multiple surveys, where each survey describes a particular commodity (or part of the larger region) whose improvement is particularly salient to the population of interest. Implementing this approach and determining which areas are valued within a larger, shared natural resource, requires a methodology that can elicit subjects' mental models and identify any systematic variations, preferences, or biases in how different sub-sets of a survey population might perceive or value parts of a larger resource differently.

Furthermore, individual use and existence values for different environmental resources (commodities) are not confined to geographic or political boundaries, and it is conceivable that almost anyone could have some value for a resource in question. Thus, the extent of the market could vary depending on whether or not people have any value for parts of a resource 1) far from their home, 2) in another state, and 3) with many other competing resources or substitutes available. Understanding who cares about a resource and how much is in part a feature of any given resource such as its size, quality and location. In most cases it is assumed that the market for a (non-market) resource is generally proximate to the resource itself, but this may not be the case. Cast over a wide population, the mapping approach proposed here can be used broadly to inform these questions and help identify the extent of the market for diverse commodities.

The process of conducting mapping interviews has additional related benefits with respect to interpreting WTP questions and designing the SP survey. For example, in order to be able to correctly interpret WTP responses from the survey, it is critical to have clear characterization of these potential differences *before* administering an SP survey. Moreover identifying a locally relevant incentive compatible payment vehicle is essential, and although there might be several federal agencies with authority over a large resource, in most cases a payment vehicle at a federal scale would be incompatible with smaller markets for a resource.

Defining the extent of resource

Without a clear, straightforward political or geographic definition of a resource it is impossible to assure that individuals share the same definition of a study area when responding to valuation questions. Moreover, it is unclear the extent to which individuals are able to identify with very large scale resources, resulting in problems if respondents consider only a limited sub-region that they associate with the larger resource or if they similarly cognitively truncate a larger area based on their prior experiences and perceptions (Fischoff et al. 1993).[2] To this end, the primary goal of this approach is to develop a method to elicit individuals' perceptions of the size and shape of a large resource and use it to inform SP instrument design decisions.

Defining the extent of the resource in the case of large resources refers to formally eliciting and evaluating 1) if potential survey participants identify with the resource in its entirety or with specific features or sub-regions within the resource instead, 2) where the boundaries of the resource are in their perceptions of the region, and 3) how these boundaries compare with other established political or geographic boundaries, such as state or national park borders.

Background on Mapping: A Review of the Literature

As a technique widely applied and tested both in geography and psychology literature, mapping is a tool that has the potential to reduce ambiguity about extent of market and extent of resource in valuation research. In psychology the process of cognitive mapping has been tested widely over many decades. Beginning in the 1940s with Tolman's (1948) landmark study that first recognized the term cognitive mapping, both geographers and psychologists have conducted experiments and studies to understand how individuals perceive different types and scales of spaces and to characterize systematic biases and distortions in map representations. A primary distinction between the two fields' approaches to mapping is the focus on *internal maps* in psychology versus *external maps* or representations of spaces in geography (Downs and Stea 1973, 1977; Golledge and Zannaras 1973; Golledge 1976).

More recently these literatures have come together around research on defining the theoretical underpinning of digital mapping tools, such as Geographic Information Systems

[2] With very large areas research has shown significant embedding effects, in that respondents in CV surveys are incongruently willing-to-pay the same amount for improvements to a large area as they are for improvement to a smaller sub-region of the same area. Fischhoff et al. (1993) describe several different methodological reasons for these effects and outline strategies for overcoming such biases.

(GIS), in order to develop and evaluate if the tools are responsive to how individuals navigate and think about spaces (Tversky 1993; Mark and Frank 1996). Although there has been significant research on variations in spatial perceptions and comprehension at different scales from the very small (a single room) to the very large (continent-level), a majority of research on spatial cognition to date has focused on built environments and less on natural environments. For this reason, we focus on bringing together elements from both the geography and psychology literature that focus on natural resources to develop an interview method to elicit a participatory map of a large, natural environment.[3]

The method applied here (Vajjhala 2005) extends traditional participatory mapping techniques using a semi-structured interview format to elicit survey respondents' individual maps of a region and their perceptions of a resource and to provide a quantifiable justification for follow-on SP instrument design. The potential contributions of this approach to SP literature and research include: extending valuation studies to larger scales more reliably and robustly, making more informed decisions about the relevant population to survey, helping to better understand what people think they are paying for, and laying the groundwork for further evaluation of benefits transfer methods. The next section describes our general approach to designing a mapping study as a front piece within a larger SP survey design and implementation process, and Section 5 details the implementation of this pilot methodology in the Southern Appalachians.

Study Design and Methodological Approach

The focus of this paper is both methodological (how to incorporate mapping into larger SP studies) and applied (what are the results of an application to an ongoing study in the Southern Appalachians). This section outlines our basic methodological framework for incorporating mapping into a planned SP survey project and the next section highlights our applied example. It is important to emphasize that this experiment is not a freestanding research effort; and although the instrument design framework outlined in this section can be used for full mapping studies, it is modified and tailored to SP survey design. Because this approach is intended to be as streamlined, the focus was on gathering essential baseline information from a small sub-set of the potential survey population as early in the design process as possible.

[3] A participatory map is typically defined very broadly as any map created through participation-based methods for eliciting and recording spatial data, including sketch mapping, scale mapping, and transect walking, among others (Chambers 1994; Craig et al. 2002). Maps resulting from a participatory process can vary from drawings on the ground with sticks or chalk to paper sketches to three-dimensional physical site models.

In order to most effectively contribute to the larger SP survey, we take a mental models interview approach (Morgan et al. 2002) and use a semi-structured format with selected open-ended questions to elicit sizes and locations of the natural resources that individual's value within a large region. Like most mental models studies we also find that a relatively small sample (~30 participants) provides a sufficiently complete characterization of a region to inform future research. Recognizing the time and budget limitations that constrain most survey projects, the approach described here uses 45-minute to 1-hour individual mapping interviews to elicit any systematic variations in how individuals characterize the types of areas and resources that they value within a larger region. There are many additional questions that could be asked, and the proposed approach is simply intended to serve as an outline for a wider range of applications.

Within an integrated mapping-SP methodology, some basic research questions will likely be consistent across all studies, including the following: Who cares about a resource? Where do individuals perceive boundaries of the resource? Is this perception consistent across the survey population or are there systematic differences in how people view and value the resource? Are there parts or sub-regions within a resource that people value and is there the potential for embedding and related biases when considering these areas? Addressing these questions requires (as with the design of any survey) that the research build on existing data to define hypotheses of how residents of a large region might value a shared resource. For example, in some regions recreation data might suggest that individuals use resources close to home most frequently, or conversely, that a single highly-visited or high-profile area dominates a larger region.

Depending on the hypotheses, the next steps in the design of the mapping study are to develop a mapping interview protocol and a base map. The base map is the main focus of the mapping interview and the primary medium in which interview responses will be recorded. As a result, it is extremely important that the map and protocol be developed in parallel with any relevant scientific constraints and careful consideration of scale and the features included in describing the region. Since the goal is to encourage participants to add as much information as possible by drawing on to the map itself, it is critical that the base map is sparse and serves primarily as a frame of reference. The map should not have so much information or text that it appears complete leading participants to re-create features already on the map or to refrain from adding information altogether because they assume it is already there.

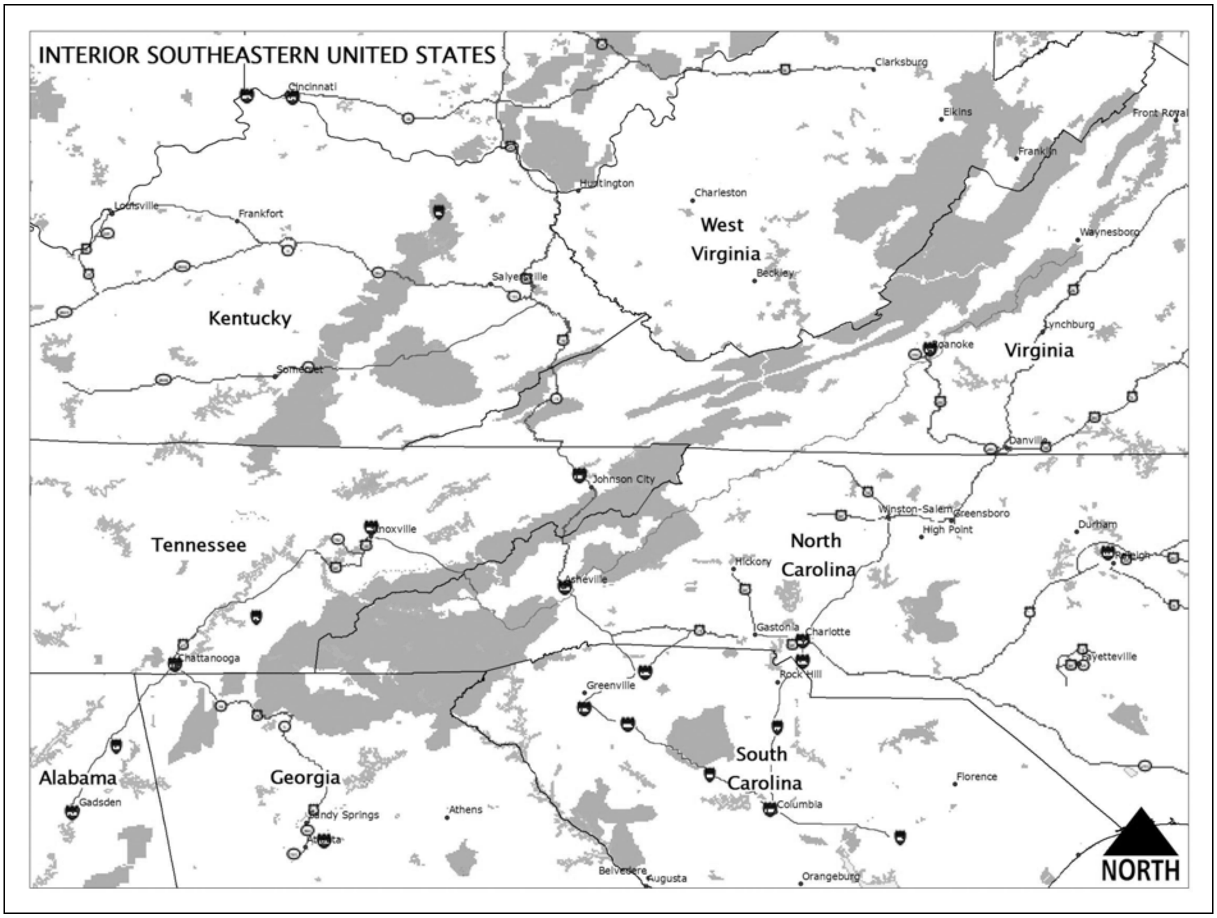


Figure 1. Base map with the Southern Appalachian Mountain Region at the center and portions of all eight states comprising the larger region. Geographic identifiers include state boundaries and names, shaded areas representing all national park and forestland, and selected major highways for spatial reference. Maps were labeled as "Interior Southeastern United States" to avoid framing effects when using the term "Appalachian."

The framing of the base map (what features are included, which ones are not, and at what scales) is highly likely to influence the scale of participants' responses. As a result, the overall area should be defined sufficiently broadly to encompass the resource being studied and relevant surrounding areas while still leaving room for new information, such as areas and boundaries at the edges of a study region that participants might identify. Similarly, the printed maps used in interviews should be sufficiently large-size, such as 18-inches by 24-inches, to allow participants to add information clearly at different scales. It cannot be emphasized enough that each base map must be tailored to the questions being asked, the region being evaluated, and the context of the larger study and extensively pre-tested in order to be effective.

Figure 1 is the base map used in this study. Existing data on the Appalachians ecosystems, acidification, and recreational patterns in the region suggest that the region includes large parts of eight states, extending from Alabama to Virginia, and this base map provides very basic information including state borders and names, major highways, and light shading highlighting general forest and water resources in the region. The map is deliberately designed without any labels to avoid framing and anchoring effects (Kahneman et al. 1982). Additionally, the map is titled "Interior Southeastern United States" to avoid leading participants to focus too narrowly on the Appalachians or any social, cultural or political association with the term and to avoid competing resources much less relevant to the study such as the Atlantic Coast.

As a complement to the base map, the interview protocol is divided into three main sections (see Appendix A for full protocol). The first section asks about patterns of use and travel in the study region to elicit basic spatial information, develop a general picture of individuals' use values for the resource, and allow individuals to grow accustomed to the process of adding information to the base map in response to interview questions. The second section of the protocol, the main focus of the study, asks individuals to think about areas that they value. There are a number of different, valid approaches to structuring these questions, and depending on the goal of the larger study, questions could focus on eliciting 1) a boundary for the region as a whole, 2) specific points people care about within the region, or 3) broader areas or sub-parts of the region. In order to allow for faster coding of the collected data, different colored markers and pens can be used to differentiate types of place added to the maps.[4]

In all cases the questions should be sufficiently broad to allow for follow-up once the participant has responded. This process is discussed further in the context of the particular application described below. The last section of the interview protocol focuses on degraded areas to determine how participants perceive the environmental damages being evaluated and identify any biases or common misconceptions. The final module of the proposed methodology is a short written survey including demographic questions, and basic ranking and follow-on questions relevant for the larger SP study (Appendix B).

Taken as a whole, this methodology, consisting of the design of a base map and implementation of a mapping interview protocol and survey, is intended to be part of a larger

[4] Because this methodology is applied to a small sample, we do not address any issues of inter-coder reliability that might emerge. All interviews and map coding for this study were completed by a single interview/transcriber.

effort, and the methods can be applied in as much or as little detail as a project requires. Because the goal of this approach is to provide a structured framework for informing and interpreting the results of larger focus group interviews, this section deliberately presents a very basic, streamlined approach to integrating mapping and SP survey design to inform, without duplicating, information being elicited in the larger survey about natural resources, damages and willingness to pay for improvements. The next section places the proposed methodology in context and discusses an application focused on the Southern Appalachians.

Acidification in the Southern Appalachians: An Application

The Southern Appalachian Mountain region (SAMR) is a large, mountainous area surrounding the Appalachian mountain chain that stretches from Alabama and Georgia in the South to Virginia and West Virginia in the North. The full region covers approximately 37 million acres (SAA 1996), encompassing parts of eight different states and a wide variety of ecosystems, land uses, and management authorities, including National Park and Forest Service lands, state parks and recreation areas, private properties, and agriculture lands, among others (see Figure 1 for reference). The region is characterized by at least two main anchors – the Great Smoky Mountain National Park (GSMNP) in North Carolina/Tennessee and the Shenandoah National Park (SNP) in Virginia. These two parks and the surrounding forest and stream resources in the region are currently at-risk of significant damages from acid deposition, and the issue has emerged as a policy priority for the affected states and the region as a whole.

The scale of this resource makes both environmental evaluation and policy making difficult, and the absence of estimates of the economic value of improvements in ecological systems has hindered policymakers' attempts to set efficient regulation and environmental policy goals. The larger study (to which this mapping pilot study is designed to contribute) focuses on characterizing the potential damages to forests and streams from acid deposition based on the best available science, and eliciting WTP estimates for environmental improvements in the region. The study includes contingent valuation (CV) as well as a choice experiment (CE) surveys to generate a lower-bound estimate of ecological improvements from reduced acidification. This work also builds closely on a recently completed CV study of the total value of ecological improvements from reduced acidification in the Adirondacks (Banzhaf et al. 2006), and allows for comparisons of the competing SP techniques, and to examine the potential for benefits transfer for different types of resources.

Although both the Adirondacks and the Appalachians are mountainous areas with similar forest resources and highly used recreational sites, containing sensitive ecological receptors that have received high levels of acid deposition to date, the regions are fundamentally different from one another in scale and location. As discussed earlier, the Adirondacks are entirely contained within the state of New York, making the CV survey designed for the Adirondacks difficult to adapt and modify for use in an areas as large as the SAMR. Moreover, the types of aquatic features in both regions are significantly different with lakes dominant in Adirondacks and streams dominant in the Appalachians.

The greatest challenge for survey implementation in the SAMR is the multiple jurisdictional boundaries within the region. Since the resources of interest for this study are regional, and not easily defined by any single administrative boundary like the Adirondacks, the fundamental goals of a survey instrument design process are, 1) to construct a well-defined description of the affected area that is relevant to how people view the resource, and 2) to identify the primary survey population from which to sample. The later will help in the identification of an appropriate payment vehicle with which to elicit WTP estimates. The mapping methodology outlined above is applied here to provide a preliminary assessment of how residents perceive the region and its natural resources and to lay the groundwork for scenario development and sampling decisions in the larger study.

Survey Population

In this application and test of the methodology, our interview protocol focused on eliciting and characterizing the types, sizes, and location of places that individuals value in the larger Southern Appalachian region. Given the limited time and resources for this preliminary effort, we chose to sample from two Southern Appalachian Mountain Region states, North Carolina and Virginia. These two states were selected because they each contain a large national park affected by acid deposition, which comprise a sufficiently large portion of SAMR to provide different characterizations of the full region and resource. Furthermore, we hypothesized that residents of the region would focus on the GSMNP and the SNP as high-profile resources, and residents of the states containing those resources would likely have the greatest value for them compared with residents of other states across the region. To test this hypothesis we recruited a convenience sample of former residents of North Carolina and Virginia currently living in the Washington D.C. area.

Participants were recruited through online advertisements, and 15 respondents from North Carolina and 15 from Virginia were chosen from approximately 135 responses. All respondents were screened to select participants who had lived in the study region for a minimum of 5 years since the age of 16. Additionally, in order to avoid overlap between groups of participants from the two states, candidates were screened to eliminate any prospective volunteers who had lived in both North Carolina and Virginia. Gender balance and geographic distribution with the state were also considered when recruiting participants. The interviews where conducted from October 2006 to January 2007.

The final sample included approximately equal numbers of men and women from each state aged between 23 years and 66 years old, averaging approximately 34 years of age. The sample also included participants from a wide range of educational backgrounds ranging from "some college, but no degree" to "post-graduate degree" with the majority of participants holding Bachelor's or Associate degrees. Median household income across all participants was in the \$50,000 to \$84,999 bracket.

Interview Process

Each mapping interview was scheduled and conducted on an individual basis, and began with a brief general introduction to the goals of the study as outlined in the attached protocol. The process was described as a "mapping interview" and no mention was made of the Appalachians, environmental degradation, or acid deposition. Study participants were then provided with a colored marker and an 18-inch by 24-inch base map of the region showing state boundaries, unlabeled shaded areas representing public lands, and select highways and cities (see Figure 1). Significant emphasis was placed on carefully considering the sizes, shapes, and relationships between locations they added to their maps.

As discussed earlier the semi-structured interview protocol asked participants to 1) identify places on the map that the participant visited regularly or as a significant destination while living in the region, 2) add the center points and boundaries of five natural areas in the region that they value or care about most to their maps, and 3) identify any areas and causes of improvement or environmental deterioration in the region. In this format the second set of questions was deliberately broad to encourage respondents to identify areas that they care about but may not actively use, thereby allowing for early identification of key resources and areas for which there may be nonuse values.

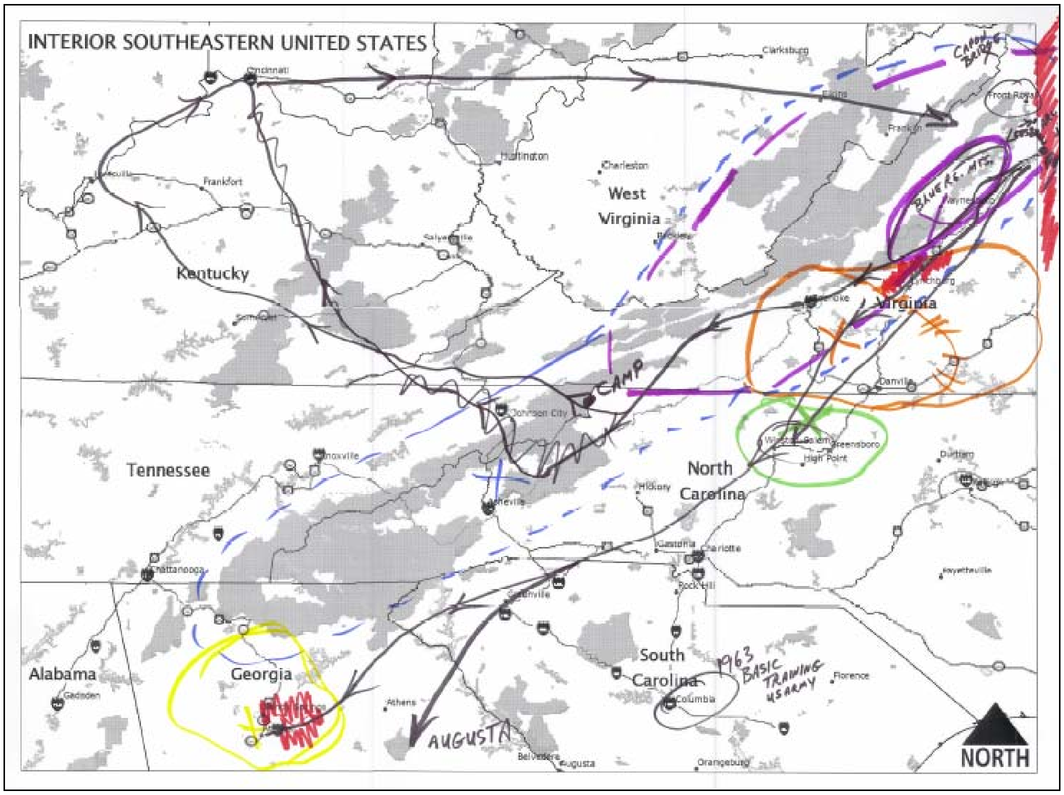
After adding the center point for a valued natural area, participants were prompted to carefully consider and explain what defined the size and boundary of the marked area. For example, prompts included *"I noticed that you didn't include this (town/highway/etc.) in the area you marked, do you consider it part of this resource? If not, what defines the start of this edge for you?"* Respondents were given time after adding each area to consider the size, boundary, location and relationship to other areas and allowed to make any corrections or changes. At all points during the interview, participants were asked to both respond to questions by adding information to their maps and explaining their response verbally to allow the interviewer to follow-up and add prompts to keep the dialogue moving forward. Finally, each interview was followed by a short written survey with additional demographic questions and WTP and questions about the region and specific places marked on their own maps.

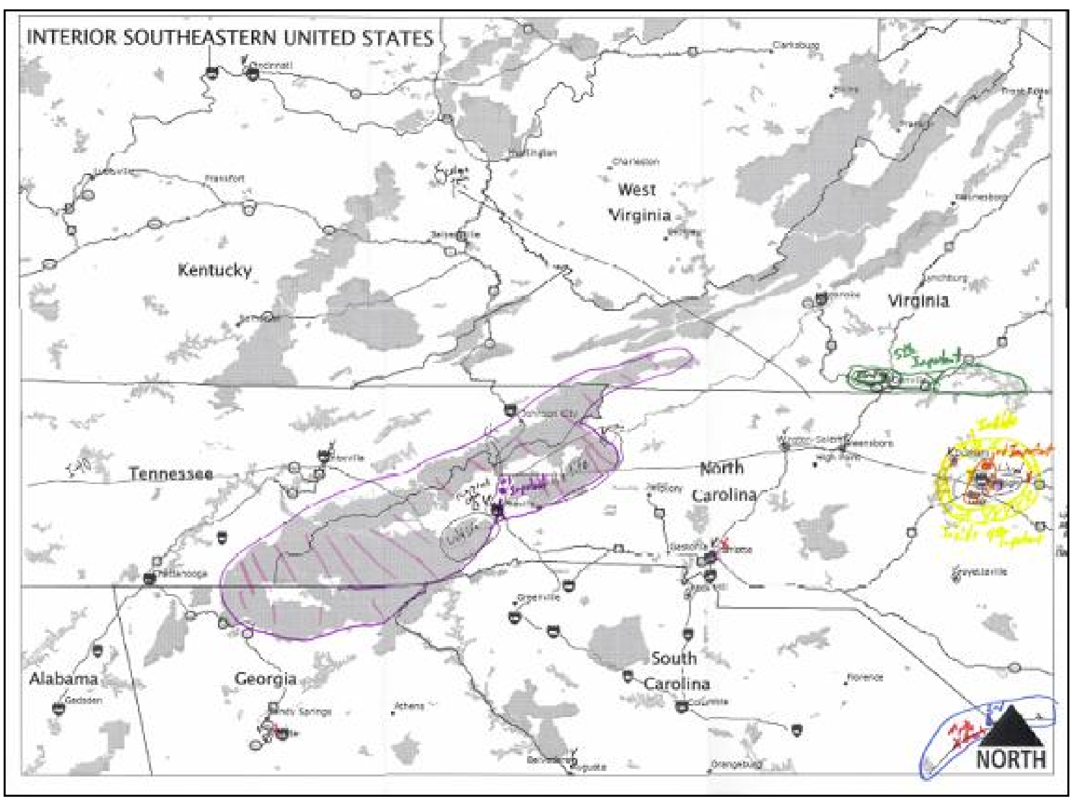
The pairing of the mapping interview and survey also allow for quantitative evaluation of the strength of respondents' preferences for maintaining or improving the environmental quality of different valued resources using implicit (by order of addition on their map) and explicit rankings (written survey question). Of central importance in these rankings is whether or not a respondent even included a particular resource or part of the region as a valued place on their map. By also asking respondents to identify an important natural resource outside of the mapped region and re-rank the five valued areas with this additional resource, the survey elicited the importance of potential substitutes or competing resources in the larger region (see Appendix B).

Overall, the information from the mapping interviews provides more general (ordinal, not cardinal) data than would typically be gathered from a SP survey focused on a specific researcher-defined resource. However, because the mapping protocol questions are not structured around questions soliciting WTP (i.e. a referendum) and limited to a single source of damages, they are more flexible and thus require less intensive sampling to get a sense of the extent of the market for a particular resource. This method is also an improvement on the use of recreational and market data to understand the extent of the resource as it does not preclude identifying significant nonuse values, which have been shown to be important components of average WTP in other studies (Banzhaf et al. 2006).

Maps, Data Analysis, and Study Results

Results from the 30 mapping interviews and written surveys were transcribed and coded after all interviews were completed. Data compiled from the maps included counts of places visited and valued by state, type of resource (forest, water, other), size of resource, and order in which places were added to the maps, among other more specific attributes. Figures 2 and 3 are examples of the types of maps collected during the study that show the diversity in the types and sizes of natural areas that individuals' marked as valued places. As participants were prompted to consider what defined the boundary of the area they cared about, participants highlighted a wide variety of defining characteristics for specific resources and areas.





Figures 2 and 3. VA participant map (above) and NC participant map (below) showing major areas visited and traveled (black), five most valued natural areas (multiple colors), and degraded areas (red).

For example, some participants referenced ecosystem characteristics in defining the boundaries of specific areas and areas were drawn to include all of a specific "type" of environment, such as the sandhills of North Carolina, which one participant stated "are a separate area because the topography and vegetation are difference from the area around it." Still other participants marked the borders of their valued areas where changes in natural features occurred, such as the increasing "hilliness" west of Asheville, NC as marking the start of the Smokies. Participants also used distances from cities, highways, and state boundaries to mark the start or edge of a natural area, and ownership or management (public versus private) to clarify why they had drawn their boundary at a specific location. In several cases, valued areas overlapped, partially or completely (like the two areas in Figure 3 marked near the Smokies), highlighting the potential for mapping to help with early identification of potential embedding problems.

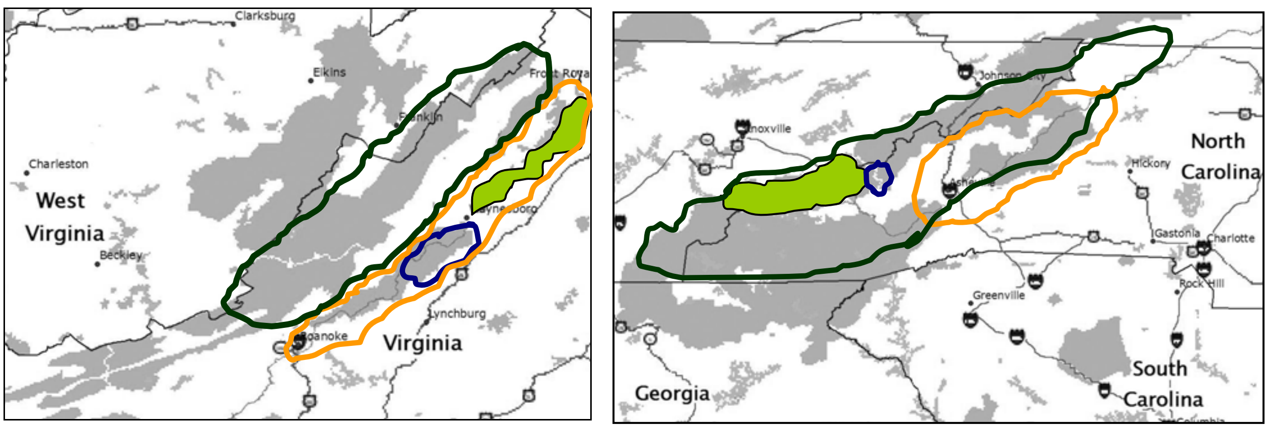


Figure 4. Sizes and locations of "the Shenandoah" relative to the SNP (left) and "the Smokies" relative to the GSMNP (right) as marked on selected participants' maps.

Across all participants, a large majority included either a natural area representing the Smokies or the Shenandoah; however, the sizes and shapes of the resources varied significantly. Figure 4 illustrates these differences and shows the SNP in solid green (left) and the GSMNP (right) overlaid with selected participants' boundaries and locations for valued areas they generally marked as "the Smokies" or "the Shenandoah".[5]

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[5] The parks will serve as a frame of reference for the following discussion. This will simplify the discussion such that the focus can be on the information that can learned with the mapping protocol. That said, the SP surveys that this analysis will inform will not necessarily be limited to describing improvements in these parks. Indeed, the extent of market analysis is also intended to inform the scope of the resource that should be described in the survey. That is, is it necessary to solicit the WTP for improvements to ecoystems in national and private forests as well as national parks?

Extent of Market

Through the mapping interviews we hoped to inform the extent of the market question by learning if residents of a given state are only likely to value (or to assign greater value) to resources in their home states. For example, do North Carolinians mark only the GSMNP, or both the GSMNP and the SNP on their maps, and vice versa for Virginians? If residents of both Virginia and North Carolina marked both park areas on their maps, then this argues for the design of a common SP survey for both populations with scenarios of regional environmental improvements and correspondingly larger payment vehicles and management agencies.

Alternatively, if participants from one state marked both GSMNP and SNP and the majority of participants from the other state marked only one of these areas then two SP instruments could be used, one asking residents only about the resources within their home-state and a second asking residents about both resources. Finally, if participants only marked the park in their own state it would support a decision to administer different surveys to residents of each state with any environmental improvements described as occurring solely within their state.

To examine how participants valued areas vary by state, coded data from all maps was used to conduct basic statistical analysis, such as comparing the counts of visited and valued places added across all maps. Participants from both North Carolina and Virginia added an average of 18 places that they had visited or cared about in the study region. As Figure 5 shows, North Carolinians added more places to their maps on average, and a majority of these places were within North Carolina. The former Virginia residents marked fewer places on average and their maps also reflected greater out-of-state travel for the areas marked. Because the population surveyed includes only former residents of either state, we expect (that as people who have moved out-of-state) study participants are likely to be more highly traveled than other residents of the region. As a result, the balance between within-state and out-of-state additions to each map is likely to represent an

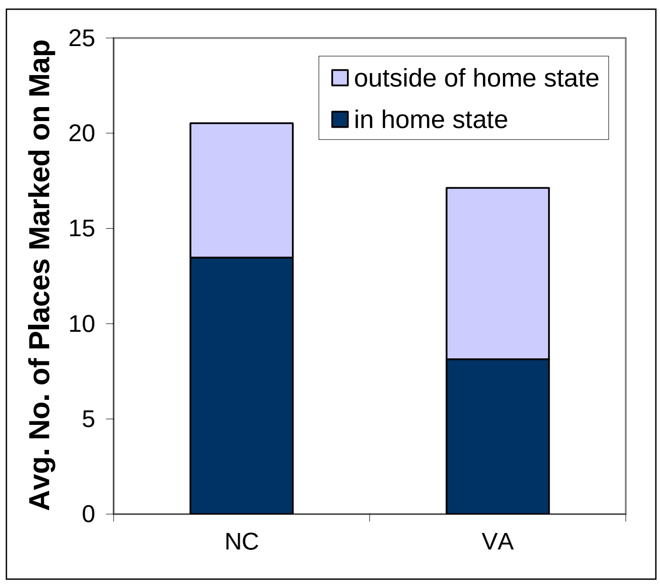

Figure 5. Differences in additions to respondents' maps.

upper bound for out-of-state additions, and we would expect an even stronger home-state preference to emerge with current residents of the region.

Similarly evaluating the five natural areas respondents marked on the maps reveals a home-state preference for valued as well as visited resources. Across all participants, more than 60% of the center points and areas that each individual marked among the areas that they valued were located entirely within their home state. This average was slightly higher for respondents from North Carolina who on average had 4 out of their 5 valued places in North Carolina. Participants were also far more likely to include the national park in their home state (the GSMNP in North Carolina and the SNP in Virginia) than the park outside their state.

Across all participants 53% of North Carolinians and 67% of Virginians only included the park in their state (see Figure 6), and one-third of all participants included both parks. The participants who included both park areas on their map, always ranked the park area within their own state higher than the other park.[6] None of the participants marked only the park outside of their home state, and all but one participant from each state included a general area, incorporating part or encompassing the whole park in their home state among the five areas that they valued.[7]

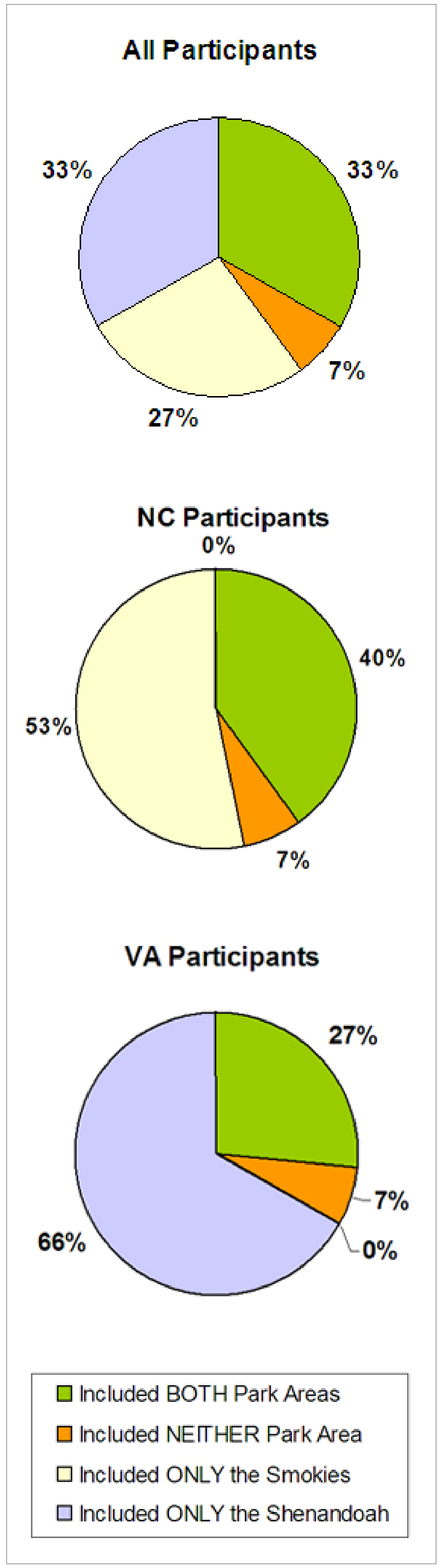

Figure 6. Percent of participants who value the GSMNP and/or SNP.

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[6] Although we emphasized that respondents should respond as if they had the same prferences and perspective as when they were living in the study region, it is important to note that North Carolinians may have a higher percent of respondents that marked both parks because they now live closer to the resources in Virginia.

[7] When ranking their five valued areas implicitly or explitily, on average the ranking of the Smokies and the Shenandoah were at least 1.4 ranks apart with the resource in the home state ranked higher. This gap actually increased for those that put both parks on their map. However, this is too small number to treat as a reliable sample.

These results support the hypothesis that people are more likely to value natural resources in their own state than resources outside their state.[8] This further suggests that the extent of the market in the Southern Appalachian Mountain Region is affected by state boundaries, but not to the point where values for natural resources in different parts of the region are limited solely to the state with the resource. This is still a very preliminary stage of analysis and at this point, it is work is still in progress as to how these results should be interpreted in the context of the larger SP instrument design; however, these results do provide an important baseline suggesting that state WTP estimates are likely to be an upper-bound relative to all other states in a region, if one chooses to survey any given state's residents about only the resources in their own state.

Extent of Resource

Like the counts and locations of valued areas that allowed for a preliminary evaluation of the extent of market, analyses based on the sizes of the mapped valued areas were used to examine the extent of resource. Defining five size categories based on the sizes of areas on all maps with 1 corresponding to the smallest area (less than 500 square miles) to 5 corresponding to the largest areas (those greater than 8,000 square miles) the sizes of all of the valued area were estimated for each map and assigned codes for their equivalent size category. A majority of valued areas across all maps and participants were in the smallest two size categories, 1 or 2; however, most participants included a variety of area sizes on their maps.

Of those participants who marked either the Smokies or the Shenandoah on their maps, most marked the area that they valued as the GSMNP or SNP as significantly larger than the actual park boundaries, as highlighted in Figure 4. Interestingly, of those participants who included both parks on their maps, participants marked the area representing the park outside their home state as significantly larger than the corresponding park within their home state. As Figure 7 illustrates 75% of Virginians who included a GSMNP area on their map drew it larger than the park boundaries compared to 50% of North Carolinians; 100% of North Carolinians who included a SNP area on their map drew it larger than the park boundaries compared to 77% of Virginians. Additionally, the average sizes of both the GSMNP and the SNP as marked on

[8] Similar results have been shown in SP surveys where there is a discrete drop in the gradient of willingness to pay to the distance from the resource at the boundary of the jurisdiction in which the resource lies (Reed et al. 2001). It is unknown if this is due to preferences that are provincial in nature or because the individual outside the jurisdiction cannot influence the authority managing the resource.

participants' maps were substantially larger than the average size of all other valued areas that respondents marked on their maps.

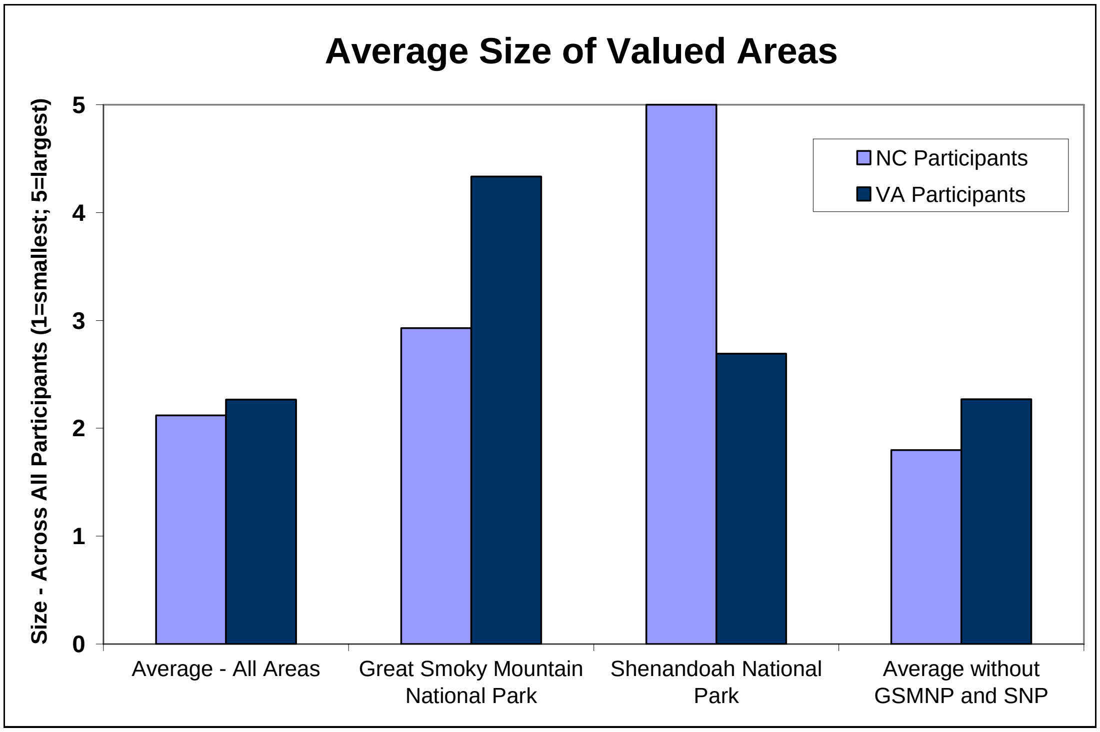

Figure 7. Of the participants who included either or both areas labeled or referenced as the Smokies or the Shenandoah among the five natural areas that they valued, the average sizes of these places were significantly different for participants from North Carolina and those from Virginia. Of the participants who marked the resource in the other state (either the Smokies or the Shenandoah) participants from both states marked this resource as much larger than their in-state counterparts.

It is interesting to note that participants seem to overestimate the size of the more distant resource. This distance-weighted relationship with the perceived size of a resource could indicate that residents may assign disproportionate value (based on a skewed perception of scale) to a less familiar and more distant resource.[9] This result, though preliminary, is in contrast to findings suggesting that WTP drops with distance, and further study is necessary to confirm these hypotheses. Together these initial analyses and results suggest that the extent of resource for the

[9] Generally speaking the researcher usually feels that they have defined the resource to be valued. However, we know that if the resource to described in the survey is particularly incongruent with the resource the respondent believes is most relevant, then embedding or a similar phenomena may occur that undermine the reliability of the WTP estimates.

Southern Appalachian Mountain region is significantly larger than current national park boundaries; however, residents do not necessarily value the region as a single large contiguous resource. Instead based on these early results, it appears that although a majority of residents have higher values for resources within their home states, a significant percentage of residents value other sub-parts of the resource, such as the GSMNP and the SNP suggesting that these two parks could be either complements or substitutes as regional natural resources.

Conclusions and Future Work

Taken as a whole, this study develops and illustrates a methodology for integrating mapping into SP survey design. Application of the proposed methodology to the Southern Appalachians reveals that the method does allow for preliminary analysis of extent of market and extent of resource issues; however, the scope of this study would need to be significantly expanded to further test the efficacy of the method for other applications and locations. At this point, initial results reveal that individuals value a greater number of resources in their home states and assign higher rankings to these resources than those in other states in the region. Based on this preliminary finding, we would expect that an SP instrument that focuses only on resources/damages in a single state would generate higher average WTP values from residents of that same state than those from other states.

Other analyses also show that using only national park or forest boundaries in an SP survey may underestimate the extent of the resource people value. Participants who indicated that they valued a mountainous area in North Carolina or Virginia overwhelmingly identified areas larger than corresponding national park boundaries for the Great Smokey Mountains National Park and Shenandoah National Park, respectively. All of the results presented here are based on very early stages of analysis, and further study to test both the method and evaluate the contributions to SP survey implementation are required. At this stage, by providing preliminary spatial characterization of both the extent of market and the extent of resource, this approach demonstrates how mapping can both inform the design of SP surveys and aid in the interpretation of WTP results.

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Appendix A: Mapping Interview Protocol

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Survey number

INTERIOR SOUTHEASTERN U.S. MAPPING INTERVIEW

Briefly introduce the project to the subject. Begin with a description of the type of maps the project is trying to collect and how the subjects' participation is important. The process should take less than 40 minutes. Participants will add information onto the base map in response to a series of interview questions. The primary goal is to gather information about the areas individuals "value" in the region. Emphasize that drawing skills or map-making skills are not required; however, the subject should carefully consider the sizes, shapes, and boundaries of the areas they add to the map and how they relate to one another.

Hello my name is Anna. I'm here today from Resources for the Future. We are conducting a study on the Interior Southeastern U.S. We would like you to help us by taking part in a mapping exercise. You don't have to have any experience with drawing or map-making, so please don't worry! What I would like you to think carefully about is the natural places you care about in this region. I'm going to ask you to add information onto the base map in front of you, and I'd like you to think about the sizes, shapes, and boundaries of these areas as you add them to your map and also how they relate to one another.

The goal of this whole interview is for you to create a map of the <u>areas you care about</u>, <u>the places that are important to you</u>, and <u>spaces that you value</u> in the Interior Southeastern United States. The base map in front of you shows parts of 8 states in this region, and there are colored markers here for you to use. First, take a minute to look over this base map. Do you have any questions?

As I ask you questions I'd like you to answer each out loud (there is a tape recorder here) and also to answer each question by adding the areas and locations that you identify on to your map. If you aren't sure about a specific answer – don't worry- you can always go back and add places, change your map, or make corrections. The point is just for you to carefully identify the natural areas that are important to you in this region and draw these areas on your map. Do you have any questions about the project? Okay, let's begin.

Places You Go [Black]

1. The first few things I am going to ask you are general questions about where you used to live in this region and any major places you went to regularly. For all of these questions, I would like you to <u>focus only on the time during which you lived in this region</u>. This is very important, so I really want to emphasize that I would like you to you think only about places you went when you lived in this area.

2. First, I'd like you to start by taking a look at the base map in front of you and begin by finding the general location for where you used to live (this doesn't have to be exact, just take your best guess). Here is a BLACK marker. Using this marker, mark the location of your home (when you lived in the region) on the map. You can use any symbol you would like to identify your home, and please write the name of the town and your former zip-code (if you remember it) next to your symbol.

3. *Have you lived in other places in this region? If so add these "homes" to the map as well and label them too.*

4. Now I am going to ask you a few questions about some of your activities and trips in this region <u>during the time you lived here</u>.

5. Think carefully about where you used to go <u>outside of the town or city where you used to live in the region.</u> These are places that you might have gone somewhat frequently, that were not part of your everyday routine, like work or the grocery store. *Please mark each place and label it. (Give the subject time to add a few places)* For example, are there any specific places you used to go at least once a month or a few times a year?

How about places you might have gone for *(say these prompts one at a time, give the subject enough time to think about it between each prompt and either add places or say "no")…*

- General recreation / outdoor activities? Parks? Campsites? Hunting? Fishing? Hiking?
- Observing wildlife/photography
- Vacations or other travel?
- Trips to visit family/friends?
- Seasonal activities? White water rafting? Fruit picking?

6. Look back on the places that you already have drawn on your map. Would you like to add any places in any of these **other states** *(point generally to blank areas on the subject's map)*?

   Is there any place that you went to often or think is important that is not already on the map? If there is, add it now.

Places You Value [Multiple Markers]

Ok, now I'm going to ask you to switch markers. Don't worry if there are places that you've forgotten to add up to this point, you can always go back and add these places. Remember this process is not about finding exact locations, instead its more important for you to think carefully about the size of each area you add to the map and where the edges are relative to the other points you've drawn on your map

Now I would like you to think about the areas that you <u>cared about</u> in this region during the time you lived here. I would like you to focus on ***natural places****, not cities or man-made destinations like a family farm or friend's home. Instead I would like you to think about any type of natural environment or area that was personally important to you.* ***This can include places you like and value <u>even if you never went there often or at all. It can even include places that you wanted to go to, but haven't visited.</u>***

I am going to ask you to add your <u>five most important</u> areas to the map ***one at a time****. Before you add any information to your map, try to think about how these spaces relate to one another. Each area can be as big or as small as is important to you.*

7. Now I'd like you to use the RED marker, and start by thinking about the first of these places you value. Begin by marking the center of this place on your map with an **X and labeling it**.

8. Now think carefully about the size of this whole "place" on your map. How big is the area that you cared about and think is important? What defines this area around the center point you selected? Now I want you now to draw a boundary of this space and explain what features define or form the edges or boundaries of this area. *What makes up the edge of this area?*

9. Why did you choose to add this area as a natural place you cared about?

10. Now here is a BLUE marker. I would like you to repeat this same process for the next place you care about and think is important. Start again by marking the center of this second natural place that you value on your map with an **X and label it**.

11. Again I'd like you to think carefully about the size of this place on your map and also how it relates to the first area you added. Draw the boundary of this area.

    What defines this boundary? (Take notes here at each of these explanations)

12. Why did you choose to add this area as a natural place you cared about?

Continue with the third (ORANGE), fourth (YELLOW) and fifth (GREEN) places, always asking the subject to mark the center of each place on your map with an ***X and a label****. Remind the subject to consider how each new place relates to the others already on the map, and then ask the subject to carefully draw the boundary of each area.*

13. With the orange/yellow/green marker mark the center/boundary of a third/fourth/fifth natural area that you most care about, even if you never visited it.

    Why did you choose that as the center?

    I noticed that you included/avoided

    Does that overlapping area include this other area you've marked over here?

14. Excellent. Now I want you to take a minute to look over your whole map. Is there anything you would like to add or to change about these places you value or their boundaries? Do you think that anything should be bigger or smaller? Are the center points where you would like them to be?

15. Have you visited any of these places on your map? If so, when/what for/how often? *(Take notes here)*

Negative and Deteriorated Places

1. For the last drawing section I would like you to use this PURPLE marker. Look closely at the region on your map and the five places that are important to you, and think about any major changes you saw during your time in the region. Are there any areas that you think were degraded or have deteriorated significantly while you lived in the region? If so, mark these areas on the map, and explain why you think these areas are degraded and what the causes are?

Okay, Congratulations- you're almost finished! I would like you to just take one final look at your map, and see if there is anything missing or anything you would like to change. Do you have any questions for me?

As a final wrap up, I have a brief written survey that I would like you to complete about the places on your map and some general demographic questions. This shouldn't take more than 5 minutes. As you go through the survey feel free to ask me any questions you might have, and you can just hand it to me when you are finished.

Once they've handed in their survey, explain the payment process… parking, etc.

Give them the letter and let them know that if they have any questions or would like to follow-up they can contact us at the email/phone on the letter, and thank them very much for their time…

Appendix B: Mapping Survey

INTERIOR SOUTHEASTERN UNITED STATES

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1. Of the five important natural places that you marked on your map, please rank these places in order of importance from 1 being most important to 5 least important. (Please write your answers in the spaces below using the same names that you used on your map. Feel free to refer back to your map.)

1. ____

2. ____

3. ____

4. ____

5. ____

2. If you were to add any other natural place outside of this map region to the list of natural places that you care about, what would it be? *(Please write your answer in the space below)*

____

3. How would you rank this place relative to the other natural places you ranked above? *(Check only one box.)*

- ❑ Above number 1
- ❑ Between numbers 1 and 2
- ❑ Between numbers 2 and 3
- ❑ Between numbers 3 and 4
- ❑ Between numbers 4 and 5
- ❑ Below number 5

4. How many years did you live in the entire region represented on your map <u>since you were 16 years old</u>?

- ❑ Less than 5 years
- ❑ 5-15 years
- ❑ 16-30 years
- ❑ More than 30 years

5. Please write the name of your home state (from the map) in the space below.

____

6. How many years has it been since you last lived in this state?

______ **years** *(Please write the total number of years in the space to the left.)*

7. How many years <u>total</u> did you live in this state only?

- ❑ Less than 5 years
- ❑ 5-15 years
- ❑ 16-30 years
- ❑ More than 30 years

8. If you were given $100 to distribute for making environmental improvements in the region on your map, how would you divide this money across the 8 states in the region shown on your map? ***(Please write a number in the blank next to each state, the total for all states should add up to $100.)***

_____________ Alabama

_____________ Georgia

_____________ Kentucky

_____________ North Carolina

_____________ South Carolina

_____________ Tennessee

_____________ Virginia

_____________ West Virginia

9. When you lived in the area on your map, did you ever <u>hunt</u> in your home state?

- ❑ No **(SKIP TO Question 11)**
- ❑ Yes (Continue to Question 10)

10. If yes, on average about how many <u>days per year</u> (from 1 day to 365 days) did you <u>hunt</u> in your home state? *(Write your answer in average number of days per year in the blank to the left.)*

____________ Days

11. When you lived in this area, did you ever <u>hunt</u> in any of the other states in the region *outside* of your home state?

- ❑ No **(SKIP TO Question 13)**
- ❑ Yes (Continue to Question 12)

12. If yes, on average about how many <u>days per year</u> (from 1 day to 365 days) did you <u>hunt</u> in each of the areas below? *(Write your answers in average number of days per year in the blanks below.)*

____________ in the <u>entire region</u> outside of your home state

____________ in Virginia only

____________ in North Carolina only

____________ in Tennessee only

13. When you lived in the area on your map, did you ever <u>fish</u> in your home state?

- ❑ No **(SKIP TO Question 15)**
- ❑ Yes (Continue to Question 14)

14. If yes, on average about how many <u>days per year</u> (from 1 day to 365 days) did you <u>fish</u> in your home state? *(Write your answer in average number of days per year in the blank below.)*

____________ days

15. When you lived in this area, did you ever <u>fish</u> in any of the other states in the region *outside* of your home state?

- ❑ No **(SKIP TO Question 17)**
- ❑ Yes (Continue to Question 16)

16. If yes, on average how many days per year (from 1 day to 365 days) did you fish in each of the areas below? *(Write your answers in average number of days per year in the blanks to the left.)*

____________ in the entire region outside of your home state

____________ in Virginia only

____________ in North Carolina only

____________ in Tennessee only

17. When you lived in the area represented on the map, did you ever take any trips at least one mile from your home to observe wildlife in your home state?

❑ No **(SKIP TO Question 19)**

❑ Yes (Continue to Question 18)

18. If yes, on average about how many trips at least one mile from your home did you make to observe wildlife in your home state? *(Write your answer in number of trips in the blank below.)*

____________ Trips per year

19. When you lived in this area, did you ever take any trips to observe wildlife in any of the other states in the region *outside* of your home state?

❑ No **(SKIP TO Question 21)**

❑ Yes (Continue to Question 20)

20. If yes, on average how many <u>trips per year</u> did you make to <u>observe wildlife</u> in each of the areas below? *(Write your answers in trips per year in the blanks to the left.)*

____________ in the <u>entire region</u> outside of your home state

____________ in Virginia only

____________ in North Carolina only

____________ in Tennessee only

21. Would you describe yourself as an environmentalist?

- ❑ Yes, definitely
- ❑ Yes, somewhat
- ❑ No

22. What is the maximum tax increase for your household that you would accept to pay for making improvements to parks and the natural environment in the entire area represented on your map? *(Write your answer in the box below.)*

I would accept a tax increase of at most $ [ ] per year for the next 10 years to pay for this program.

23. Please write your age in the space to the right. _________ **years**

24. What is your gender?

- ❑ Male
- ❑ Female

25. What is the highest degree or level of education that you have completed?

- ❑ Less than high school
- ❑ Graduated from high school - Diploma or Equivalent (GED)
- ❑ Some college, no degree
- ❑ Bachelor's degree or Associate degree
- ❑ Postgraduate degree

26. Please indicate the category that best represents your total household income in the past 12 months before taxes. Was it...

- ❑ Less than $19,999
- ❑ $20,000-$34,999
- ❑ $35,000-$49,999
- ❑ $50,000-$84,999
- ❑ $85,000-$124,999
- ❑ $125,000 or more

Thank you for completing this survey!

Please hand-in your completed survey to your map interviewer.

Valuation for Environmental Policy: Ecological Benefits

Session IV: Valuation of Ecological Effects

Joel Corona

US EPA

Arlington, VA

April 24 2007

Session IV: Valuation of Ecological Effects

- **Integrated Modeling** and Ecological Valuation: Applications in the Semi-Arid Southwest (Brookshire et al.)
- Contingent Valuation Surveys to Monetize the Benefits of **Risk Reductions** Across Ecological and Developmental Endpoints (von Stackelberg and Hammitt)
- Valuing the Ecological Effects of Acidification: **Mapping** the Extent of Market and Extent of Resources in the Southern Appalachians (Vajjhala et al.)

Brookshire et al.

- Integrated framework includes hydrological model, riparian model, avian model, survey instrument and valuation
  - Still in initial stages
  - Intention to test benefits transfer between two sites

<u>Value to EPA:</u>

- Integrated framework
- Different information gradients (traditional, coarse, fine)

von Stackelberg and Hammitt

- Estimates WTPs through CVs for both ecological and human health endpoints in a risk assessment framework
    - Issues with estimates (IQ, eagle positive, reading comprehension, SSD negative)
    - WTP higher when asked about ecological effects first

<u>Value to EPA:</u>

- Value in including both types of endpoints
- Value in using risk assessment framework

Vajjhala et al.

- Ongoing study, tackles extent of market and extent of natural resource through mapping
  - Initial results suggest individuals place higher value on within-state natural resources
  - Individuals identified areas larger than corresponding national park boundaries

<u>Value to EPA:</u>

- Concept of mapping during pilot to help set natural resource boundaries
- Mapping to help identify relevant populations

Overall

- Benefits Transfer
- Well-proven methods to new scenarios/endpoints
- Methodological Advances

Discussant Comment by David Simpson:

I was asked to discuss three papers on the valuation of ecological resources. It may, then, seem strange that the first image that popped into my head was of a man acting like a giant chicken.

By way of explanation, let me first say that the approach that each of these papers take involves stated preferences: conducting surveys to ask, either directly or indirectly, how much respondents value ecological resources at risk. Stated preference[1] methods in general remind me of an old joke. The adult children of an aging couple have not returned to the family farm for many months. When they do arrive, they're shocked by what they see. Their father is strutting about the yard, pecking and clucking. "Mom, what's happened to Dad?" the son asks.

"He thinks he's a chicken," the mother replies.

"Oh my goodness! This is terrible!" say the children. "Have you taken him to a doctor?"

Well, I've been meaning to," says the mother, "but I just need the eggs too bad."

What does this have to do with valuation using stated preferences? In short, "we just need the eggs too bad." We all recognize that there are things which we as a society care about preserving, but that, to borrow Douglas Larson's [1993] helpful characterization, do not leave enough of a "behavioral trail" for their values to be estimated using conventional (that is to say, "revealed preference") methods. What do we do in such "hopeless cases"?[2]

The answer to that question depends crucially not on whether we "*need* the eggs" – we certainly do – but on whether stated preference methods deliver them. The profession is deeply divided on this question. Some ten years ago now V. Kerry Smith wrote

> Indeed, there is a curious dichotomy in the research using C[ontingent] V[aluation] for nonmarket valuation. Environmental economists actively engaged in nonmarket valuation continue to pursue very technical implementation or estimation issues, while the economics profession as a whole seems to regard the method as seriously flawed when compared with indirect methods. They would no doubt regard this further technical research as foolish in light of what they

[1] I'll use the term "stated preference" broadly to encompass contingent valuation, choice modeling, and other approaches that ask respondents to consider hypothetical scenarios rather than inferring values from actual, budget-constrained, choices.

[2] This time I am adopting A. Myrick Freeman's [2002] characterization of situations in which separable preferences between market and nonmarket goods preclude conventional estimation.

> judge to be serious problems with the method. (Smith, 1997; p. 42)

These issues seem no closer to resolution today than they were a decade ago. In fact, it would appear that many economists have, as Smith suggested, simply washed their hands of the whole issue, while a small but active group continue to pursue "further technical research". This is a deeply unsatisfying state of affairs. The papers I have been asked to discuss both underscore the divisions within the profession and point to some possible ways out of the impasse.

The von Stackelberg and Hammett paper reports on a number of interesting findings. The ones I want to focus on concern evidence on "embedding" in survey answers. They ask different respondents questions concerning their willingness to pay to prevent human health effects arising from contamination, and/or their willingness to pay to prevent ecological effects on nonhuman species. One of the intriguing answers they obtain is that people are, on average, willing to pay more in total for both programs when they are asked about ecological effects first and human health effects second.

To those of us who are skeptical about the reliability of stated preference studies, this finding has a read interpretation. First, respondents will, in general, want to express their willingness to do *something*; to "purchase moral satisfaction", in Kahnemann and Knetsch's memorable characterization. Second, however, respondents see human health as "important," saving wildlife as less so. Consequently, when you ask them about their willingness to pay for something "important" after asking them to pay for something more frivolous, they're likely to think "Oh, that's really important, I'd better pay something more". Conversely, if you ask them to pay for something more frivolous after already getting a pledge from them for something "important," they're more likely to say "Sorry, I've already given".

Now I hasten to point out that the explanation I've suggested is nothing more than my own subjective narrative, informed by nothing more than my own opinions and prejudices. Yet I offer it because it seems to me to be no less compelling than any other narrative offered to explain anomalous – or, for that matter, any other – stated preference results. The justification researchers often suggest for whatever results they derive is typically "that's what people told us".[3]

If I were to offer a criticism of the von Stackelberg and Hammett paper, then, it is that it pulls its punches when it has the opportunity to say something more concrete about the reliability of stated preference work. The authors note that the finding I have summarized above

> . . . may lend credence to the argument that WTP estimates obtained using CV are not consistent with economic theory . . . [but] We take a more circumspect view . . . denying the contingent valuation method . . . in no way changes the fact that

[3] I might note in passing that Harvard economist Edward Glaeser has recently reported very interesting work as to why people might profess some objectively very unreasonable things.

> there are ecosystem service flows that have economic benefit, and . . . therefore have significant implications for policy development. (p.33)

I fear that the authors are creating a false dichotomy. I, for one, do not quarrel with the view that "ecosystem service flows . . . have economic benefit". I think the more important question, though, is whether stated preference approaches of the type the report provide any useful information for prioritizing the sources of such benefits and choosing how to allocated limited conservation expenditures. I'm not convinced that they do. In any event, however, I'm disappointed that von Stackelberg and Hammett, having done a great deal of careful work come right to the brink of issuing venturing conclusive findings, but back down rather than join the controversy.

We do not yet have a sense from the Brookshire, *et al*., work as to whether it will speak to the reliability of the methods it employs. In his remarks David Brookshire concurred with the view that economists have simply agreed to disagree as to whether results from stated preference studies are inconsistent with received theory (a view associated with, among others, MIT economist Peter Diamond). I am concerned that no progress can be made under such circumstances. Results, if they are to be "scientific", must be *falsifiable*, and it is certainly problematic if the claim is simply that the answers simply are what they are, with no agreement as to when they would not be accepted.

For this reason, my main concern about the outline of work Professor Brookshire presented at the workshop is with the criteria that are being followed in refining the questions to be asked of respondents. It would appear that a great deal of work is being done to hone questions with focus groups, and this is certainly a worthwhile activity. However, I would be concerned if the purpose of these exercises cannot be phrased in more objective and operational terms. In discussion, Professor Brookshire indicated that (to the best of my recollection) questions were being refined so as to communicate the understanding that natural scientists on the project team deemed needed to be communicated. One can see the concerns that arise by considering slightly different phrases to describe what that might be: "respondents should *understand* the complexity of the systems involved" vs. "respondents should *appreciate* the complexity of the systems involved," for example. I don't mean to suggest that any such semantic slanting is underway – I certainly have no reason to suspect that it would be – but only to say that, given the state of the debate, it behooves one to be as circumspect as possible in avoiding any appearance of slanting results.

I found the Vajjhala, et al., paper perhaps the most interesting of those I was asked to review, and regret that I expended too much of my time at the workshop on the first two at the expense of the third. Most regrettably, I spent the time I had dwelling on the negative rather than the positive aspects of the paper. To quickly recap, the negative aspect of the paper is that, *from the perspective of received theory*, the mapping exercise reported in the paper might be obviated. The researchers asked people familiar with particular scenic and natural areas of the country to report on those areas' salient aspects. To the extent that such aspects are appreciated more by people in closer proximity to those areas, or at least with greater experience with them, valuation might be effectively accomplished with revealed preference methods. For example, people who enjoy recreation in the Great Smoky Mountains National Park might choose to purchase year-round or vacation homes near the park, or to reveal their preferences with their travel choices. Hedonic pricing or travel cost methods might, then, be used to estimate values.

My sense, however, is that the real contribution of the paper may not lie in informing existing valuation methodologies so much as in illuminating the processes of decision-making. My own sense is that stated preference studies do not contribute enough to better decision-making as to be worth the expense of conducting them. Regrettably, however, I'm not entirely confident that revealed preference studies have much more to recommend them. I hasten to add that this is not for want of creativity and effort on the part of researchers. This is just extraordinarily hard work! We'd probably do well to remember that nonmarket goods are nonmarket goods precisely because of the great difficulties inherent in putting prices on them.[4]

Given this state of affairs, it seems to me that we should be thinking outside the box, or perhaps, in this case, "off the map" is a better way of putting it. In economics we would like to think of people making rational choices in response to well-formed information. However, work such as that undertaken by Vajjhali and her colleagues may prove to be more valuable by helping us think about how people form values rather than how to induce them accurately to report the values they have formed.

While I am optimistic about this work, however, I would like to see it made a little more transparent. It was clear *what* had been done: respondents indicated areas on maps and reported related information. However, it was not always clear, or I as a reader was not always sure, what was to be inferred from the markings, annotations, and responses people made. It would have been helpful to have had some more narrative in the paper as to what the exercises were intended to show, and perhaps some explicit hypotheses as to the patterns that might have been expected to, and/or which did, in fact, appear.

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[4] Although non-excludability raises somewhat related, but distinct difficulties as well.

Valuation for Environmental Policy: Ecological Benefits

A Workshop sponsored by U.S. Environmental Protection Agency's National Center for Environmental Economics (NCEE) and National Center for Environmental Research (NCER)

Crowne Plaza Washington National Airport Hotel
1480 Crystal Drive
Arlington, VA 22202

April 23-24, 2007

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U.S. Environmental Protection Agency (EPA)
National Center for Environmental Economics (NCEE) and
National Center for Environmental Research (NCER)
Valuation for Environmental Policy: Ecological Benefits

Crowne Plaza Washington National Airport Hotel
1480 Crystal Drive
Arlington, VA 22202
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April 23-24, 2007

Agenda

April 23, 2007: Valuation for Environmental Policy

8:00 a.m. – 8:30 a.m.	**Registration**	
8:30 a.m. – 8:45 a.m.	**Introductory Remarks** Rick Linthurst, National Program Director for Ecology, EPA, Office of Research and Development	
8:45 a.m. – 11:30 a.m.	**Session I: Benefits Transfer** Session Moderator: Steve Newbold, EPA, NCEE	
	8:45 a.m. – 9:15 a.m.	Benefits Transfer of a Third Kind: An Examination of Structural Benefits Transfer George Van Houtven, Subhrendu Pattanayak, Sumeet Patil, and Brooks Depro, Research Triangle Institute
	9:15 a.m. – 9:45 a.m.	The Stability of Values for Ecosystem Services: Tools for Evaluating the Potential for Benefits Transfers John Hoehn, Michael Kaplowitz, and Frank Lupi, Michigan State University
9:45 a.m. – 10:00 a.m.	**Break**	
	10:00 a.m. – 10:30 a.m.	Meta-Regression and Benefit Transfer: Data Space, Model Space and the Quest for 'Optimal Scope' Klaus Moeltner, University of Nevada, Reno, and Randall Rosenberger, Oregon State University
	10:30 a.m. – 10:45 a.m.	Discussant: Matt Massey, EPA, NCEE
	10:45 a.m. – 11:00 a.m.	Discussant: Kevin Boyle, Virginia Tech University
	11:00 a.m. – 11:30 a.m.	Questions and Discussion
11:30 a.m. – 12:45 p.m.	**Lunch**	

12:45 p.m. – 3:30 p.m.	**Session II: Wetlands and Coastal Resources** Session Moderator: Cynthia Morgan, EPA, NCEE	
	12:45 p.m. – 1:15 p.m.	A Combined Conjoint-Travel Cost Demand Model for Measuring the Impact of Erosion and Erosion Control Programs on Beach Recreation Ju-Chin Huang, University of New Hampshire; George Parsons, University of Delaware; Min Qiang Zhao, The Ohio State University; and P. Joan Poor, St. Mary's College of Maryland
	1:15 p.m. – 1:45 p.m.	A Consistent Framework for Valuation of Wetland Ecosystem Services Using Discrete Choice Methods David Scrogin, Walter Milon, and John Weishampel, University of Central Florida
1:45 p.m. – 2:00 p.m.	**Break**	
	2:00 p.m. – 2:30 p.m.	Linking Recreation Demand and Willingness To Pay With the Inclusive Value: Valuation of Saginaw Bay Coastal Marsh John Whitehead and Pete Groothuis, Appalachian State University
	2:30 p.m. – 2:45 p.m.	Discussant: Jamal Kadri, EPA, Office of Wetlands, Oceans, and Watersheds
	2:45 p.m. – 3:00 p.m.	Discussant: John Horowitz, University of Maryland
	3:00 p.m. – 3:30 p.m.	Questions and Discussion
3:30 p.m. – 3:45 p.m.	**Break**	
3:45 p.m. – 5:45 p.m.	**Session III: Invasive Species** Session Moderator: Maggie Miller, EPA, NCEE	
	3:45 p.m. – 4:15 p.m.	Models of Spatial and Intertemporal Invasive Species Management Brooks Kaiser, Gettysburg College, and Kimberly Burnett, University of Hawaii at Manoa
	4:15 p.m. – 4:45 p.m.	Policies for the Game of Global Marine Invasive Species Pollution Linda Fernandez, University of California at Riverside
	4:45 p.m. – 5:00 p.m.	Discussant: Marilyn Katz, EPA, Office of Wetlands, Oceans, and Watersheds
	5:00 p.m. – 5:15 p.m.	Discussant: Lars Olsen, University of Maryland
	5:15 p.m. – 5:45 p.m.	Questions and Discussion
5:45 p.m.	**Adjournment**	

April 24, 2007: Valuation for Environmental Policy

8:30 a.m. – 9:00 a.m.	**Registration**	
9:00 a.m. – 11:45 a.m.	**Session IV: Valuation of Ecological Effects** Session Moderator: William Wheeler, EPA, NCER	
	9:00 a.m. – 9:30 a.m.	Integrated Modeling and Ecological Valuation: Applications in the Semi Arid Southwest David Brookshire, University of New Mexico, Arriana Brand, Jennifer Thacher, Mark Dixon,Julie Stromberg, Kevin Lansey, David Goodrich, Molly McIntosh, Jake Gradny, Steve Stewart, Craig Broadbent and German Izon
	9:30 a.m. – 10:00 a.m.	Contingent Valuation Surveys to Monetize the Benefits of Risk Reductions Across Ecological and Developmental Endpoints Katherine von Stackelberg and James Hammitt, Harvard School of Public Health
10:00 a.m. – 10:15 a.m.	**Break**	
	10:15 a.m. – 10:45 a.m.	Valuing the Ecological Effects of Acidification: Mapping the Extent of Market and Extent of Resource in the Southern Appalachians Shalini Vajjhala, Anne Mische John, and David Evans, Resources for the Future
	10:45 a.m. – 11:00 a.m.	Discussant: Joel Corona, EPA, Office of Water
	11:00 a.m. – 11:15 a.m.	Discussant: David Simpson, Johns Hopkins University
	11:15 a.m. – 11:45 a.m.	Questions and Discussion
11:45 a.m. – 1:00 p.m.	**Lunch**	
1:00 p.m. – 4:15 p.m.	**Session V: Water Resources** Session Moderator: Adam Daigneault, EPA, NCEE	
	1:00 p.m. – 1:30 p.m.	Valuing Water Quality as a Function of Physical Measures Kevin Egan, Joe Herriges, John Downing, and Katherine Cling, Iowa State University
	1:30 p.m. – 2:00 p.m.	Cost-Effective Provision of Ecosystem Services from Riparian Buffer Zones Jo Albers, Oregon State University; David Simpson, Johns Hopkins University; and Steve Newbold, NCEE
2:00 p.m. – 2:15 p.m.	**Break**	
	2:15 p.m. – 2:45 p.m.	Development of Bioindicator-Based Stated Preference Valuation for Aquatic Resources Robert Johnston, Eric Shultz, Kathleen Segerson, Jessica Kukielka, Deepak Joglekar, University of Connecticut; and Elena Y. Besedin, Abt Associates

April 24, 2007 (continued)

	2:45 p.m. – 3:05 p.m.	Comparing Management Options and Valuing Environmental Improvements in a Recreational Fishery Steve Newbold and Matt Massey, NCEE
	3:05 p.m. – 3:20 p.m.	Discussant: Julie Hewitt, EPA, Office of Water
	3:20 p.m. – 3:35 p.m.	Discussant: George Parsons, University of Delaware
	3:35 p.m. – 4:05 p.m.	Questions and Discussions
4:05 p.m. – 4:15 p.m.	**Final Remarks**	
4:15 p.m.	**Adjournment**	

Valuing Water Quality as a Function of Physical Measures[1]

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April 10, 2007

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Abstract

Employing a unique and rich data set of physical water quality attributes in conjunction with detailed household characteristics and trip information, we develop a mixed logit model of recreational lake usage. Our empirical analysis shows that individuals are responsive to the full set of physical water quality measures used by biologists to identify the impaired status of lakes. WTP estimates are reported based on improvements in these physical measures. This implies that cost benefit analysis based on physical water quality measures can be used as a direct policy tool.

1 Introduction

More than three decades have elapsed since the passage of the 1972 Clean Water Act (CWA), yet progress toward meeting the standards set forth in the CWA has been slow in the area of nonpoint source pollution. The most recent National Water Quality Inventory (USEPA,[21]) categorizes forty-five percent of assessed lake acres in the U.S. as impaired, with the leading causes of these impairments being nutrients and siltation. Moreover, few states have developed the priority ranking of their impaired waters or determined the Total Maximum Daily Loads (TMDLs) as required under Section 303(d) of the CWA.[1] Legal actions by citizen groups have prompted renewed efforts toward developing both the priority listing and associated TMDL standards.[2] However, the task facing both the EPA and state regulatory agencies remains a daunting one. The prioritization process alone, which is all the more important given current tight budgets, requires information on the cost of remediation and the potential benefits that will flow from water quality improvements. Both types of information are in short supply. The purpose of this paper is to help fill this gap by providing information on the recreational value of water quality improvements as a function of detailed physical attributes of the water bodies involved. The water quality values are obtained from a recreation demand model of lake usage in the state of Iowa, combining trip and socio-demographic data from the Iowa Lakes Valuation Project and an extensive list of physical water quality measures collected by Iowa State University's Limnology Laboratory.

Recreation demand models have long been used to value water quality improvements, but studies typically rely on limited measures of water quality. The most commonly used indicators are fish catch rates (e.g., [4], [15]). However, catch rates are themselves endogenous,

[1] TMDLs specify the amount of a pollutant that a water body can receive and still meet existing water quality standards.

[2] As of March 2003, there have been approximately 40 legal actions taken against the USEPA in 38 states concerning the implementation of Section 303(d) of the CWA.

depending on both fishing pressure and the abilities of the anglers, and provide only indirect measures of the underlying water quality. Physical water quality measures, such as Secchi depth and bacteria counts, are used only sparingly, in large part because of limitations in available data. Phaneuf, Kling, and Herriges [18] use fish toxin levels in their model of Great Lakes fishing, but the toxin levels were available only for a limited number of aggregate sites in the region. Parsons and Kealy [17] use dummy variables based on dissolved oxygen levels and average Secchi depth readings to capture the impact of water quality on Wisconsin lake recreation. Similarly, Parsons, Helm, and Bondelid [16] construct dummy variables indicating *high* and *medium* water quality levels for use in their analysis of recreational demand in six northeastern states. These dummy variables are based on pollution loading data and water quality models, rather than on direct measurements of the local water quality. In all of these studies, the physical water quality indicators are found to significantly impact recreation demand, but, because of the limited nature of the measures themselves, provide only a partial picture of value associated with possible water quality improvements.

Bockstael, Hanemann, and Strand's [3] analysis of beach usage in the Boston-Cape Cod area has perhaps one of the most extensive lists of objective physical water quality attributes included in a model of recreation: oil, fecal coliform, temperature, chemical oxygen demand (COD), and turbidity. However, the study also points out one of the frequently encountered problems in isolating the impact of individual water quality attributes - multicollinearity. Seven additional water quality measures were available to the analysts: color, pH, alkalinity, phosphorus, nitrogen, ammonia, and total coliform. These latter variables were excluded from the analysis because of correlations among the various groups of water quality measures. The five water quality variables used were chosen because they were either directly observable by recreationists or highly publicized. While these choices are certainly reasonable given limitations in the available data, the lack of direct information on how nutrient levels (phosphorus and nitrogen) impact recreational usage is unfortunate in the context of setting standards in Midwestern states, where nutrient loadings are of particular concern.

The contribution of the current paper lies in our ability to incorporate a rich set of physical water quality attributes, as well as site and household characteristics, into a model of recreational lake usage. Importantly, the full set of water quality variables used by biologists to classify lakes as impaired by the EPA, and therefore potentially in need of policy action, are included. Trip data for the study are drawn from the 2002 Iowa Lakes Survey, the first in a four-year project aimed at valuing recreational lake usage in Iowa. The survey was sent to a random sample of 8,000 Iowa households, eliciting information on their recreational visits to Iowa's 129 principal lakes, along with socio-demographic data and attitudes toward water quality issues. The unique feature of the project, however, is that a parallel inventory of the physical attributes of these lakes is being conducted by Iowa State University's Limnology Laboratory.[3] Three times a year, over the course of a five-year project, thirteen distinct water quality measurements are being taken at each of the lakes, providing a clear physical characterization of the conditions in each lake. Moreover, because of the wide range of lake conditions in the state, Iowa is particularly well suited to identifying the impact of these physical characteristics on recreation demand. Iowa's lakes vary from a few clean lakes with up to fifteen feet of visibility to other lakes having some of the highest concentrations of nutrients in the world, and roughly half of the 129 lakes included in the study are on the EPA's list of impaired lakes.

A second unique contribution of this study is the application of careful model specification and fitting procedures to identify the best set of explanatory variables, and their functional form, for the estimated model. Since economic theory does not provide guidance to the analyst on these issues, ex ante selection of model variables and structure will often fail to

[3]The limnological study is funded by the Iowa Department of Natural Resources.

achieve the best model fit. On the other hand, specification searching on a given data set leads to the well known problem of incorrect standard error estimates (Leamer, [13]). Thus, we exploit our large sample size by splitting the sample into three equal parts. With the first sample, we extensively explore various specifications of the model, including a variety of variables and their functional form. The second sample was reserved for clean model estimation, allowing us to generate unbiased estimates of precision for all of the parameter estimates. The third split of the sample was used to perform out-of-sample prediction to provide an overall assessment of the model fit.[4]

The remainder of the paper is divided into five sections. Section 2 provides an overview of the two data sources. A repeated mixed logit model of recreational lake usage is then specified in Section 3. The mixed logit model allows for a wide variety of substitution patterns among the recreational sites and for heterogeneity among households in terms of their reaction to individual site characteristics. (See, e.g., [9],[14], and [20].) The specification search procedure and parameter estimates are reported in Section 4.[5] In Section 5, we illustrate not only the implications of the model in terms of recreational value of meeting the objectives of the CWA (i.e., removing all of the lakes in the state from the impaired water quality list) but also how the model can be used to prioritize the remediation task. Conclusions of the paper are provided in Section 6.

2 Data

Two principal data sources are used in developing our model of recreational lake usage in Iowa: the 2002 Iowa Lakes Survey and the physical water quality measures collected by Iowa State University's Limnology Laboratory. As noted earlier, the 2002 Iowa Lakes Survey is

[4] We are aware of only one other recreation demand study that has adopted this procedure. Creel and Loomis ([5], [6]) use this procedure to identify the key explanatory variables for deer hunting in California.

[5] The current paper highlights the results of the specification and estimation stages. A more detailed analysis, including out-of-sample predictions findings, is provided in a companion paper [8].

the first survey in a four-year study of lake usage in the state. The focus of the survey was on gathering baseline information on the visitation patterns to Iowa's 129 principal lakes, as well as socio-demographic data and attitudes towards water quality issues. After initial focus groups and pre-testing of the survey instrument, the final survey was administered by mail in November 2002 to 8,000 randomly selected households in the state. Standard Dillman procedures ([7]) were used to ensure a high response rate.[6] Of the 8,000 surveys mailed, 4,423 were returned. Allowing for the 882 undeliverable surveys, this corresponds to an overall response rate of sixty-two percent.

The survey sample was initially paired down to 3,859 households as follows. Those individuals who returned the survey from out of state were excluded (thirty-eight observations). It is not feasible to ascertain whether these respondents have permanently left the state or simply reside elsewhere for part of the year. Respondents who did not complete the trip questions or did not specify their numbers of trips (i.e., they simply checked that they had visited a given lake) were excluded (224 observations). Lastly, anyone reporting more than fifty-two total single-day trips to the 129 lakes were excluded (133 observations). In the analysis that follows, only single-day trips are included to avoid the complexity of modeling multiple-day visits. Defining the number of choice occasions as fifty-two allows for one trip per week to one of the 129 Iowa lakes. While the choice of fifty-two is arbitrary, it seems a reasonable cut-off for the total number of allowable single-day trips for the season.[7] This last step eliminated approximately three percent of the returned surveys. Finally, because of the large number of respondents, the overall sample was randomly divided into three segments; specification, estimation, and prediction portions, each component using just under 1,290 observations. Once the estimation stage is reached, the results will be free from any form

[6] Complete details of the survey design and implementation can be found in [2].

[7] Sensitivity analysis, raising the allowable number of trips per year above fifty-two, indicated that the results were not sensitive to the choice of this cut-off.

of pretest bias and the standard errors will be not be biased by the extensive specification search.[8]

Table 1 provides summary statistics for the full sample regarding trip and the socio-demographic data obtained from the survey. The average number of total single-day trips for all 129 lakes is 6.68, varying from some respondents taking zero trips and others taking fifty-two trips. In general, the survey respondents are more likely to be older, male, have a higher income, and to be more educated than the general population. Schooling is entered as a dummy variable equaling one if the individual has attended or completed some level of post-high school education.

The physical water quality measures used in modeling recreational lake usage in Iowa were gathered by Iowa State University's Limnology Laboratory as part of the ongoing state lake monitoring program. Table 2 provides a listing of the water quality attributes and 2002 summary statistics for the 129 lakes used in our analysis. All of the physical water quality measures are the average values for the 2002 season. Samples were taken from each lake three times throughout the year, in spring/early summer, mid-summer, and late summer/fall to cover the range of seasonal variation.

Each of the water quality measures help to characterize a distinct aspect of the lake ecosystem. Secchi transparency is one of the most widely applied limnological parameters and approximately reflects the lake depth at which the bottom of the lake can still be seen. Chlorophyll is an indicator of phytoplankton plant biomass which leads to greenness in the water. Three nitrogen levels were gathered. Total nitrogen is the sum of all dissolved and particulate forms. NH3+NH4 measures ammonium nitrogen that derive from fertilizer or anaerobic conditions and can be toxic. NO3+NO2 measures the nitrate level in the water that derives from aerobic nutrient contributions. Total phosphorus is an important indicator

[8] Creel and Loomis [5] use a similar procedure in investigating alternative truncated count data estimators.

of nutrient conditions in freshwater systems and is usually the principal limiting nutrient which determines phytoplankton (algae?) growth. Silicon is important to diatoms, a key food source for aquatic organisms. The hydrogen ion concentration of the water is measured by pH with levels below 6 indicating acid conditions and levels above 8 indicating extreme basicity. As Table 2 notes, all of the pH levels in this sample are clustered between 7.3 and 10. Alkalinity is a reflection of the buffering capacity of the water and is expressed as the concentration of calcium carbonate in the water. Plants need carbon to grow and most carbon comes from alkalinity in lakes; therefore, alkalinity is an indication of the availability of carbon to plant life. Inorganic suspended solids (ISS) consist of soil and silt suspended in the water through erosion, whereas volatile suspended solids (VSS) consists of suspended organic matter. Increases in either ISS or VSS levels decrease water clarity.

Table 2 demonstrates that there is considerable variation in water quality conditions throughout the state. For example, average Secchi depth varies from a low of 0.09 meters (or 3.5 inches) to a high of 5.67 meters (over 18 feet). Total phosphorus varies from 17 to 453 μg/L, spanning the range of concentrations seen in the world (Arbuchle and Downing, [1]). An additional unique aspect of Iowa lakes is that the diversity of land uses in the watershed contributing to them leads to a low degree of collinearity among the water quality measures.

In addition to trip and water quality data, two other data sources were used. First, the travel costs, from each survey respondent's residence to each of the 129 lakes, were needed. The out-of-pocket component of travel cost was computed as the round-trip travel distance multiplied by $0.25 per mile.[9] The opportunity cost of time was calculated as one-third the estimated round-trip travel time multiplied by the respondent's average wage rate. Table 3 provides summary statistics for the resulting travel cost variable. The average price of a recreational trip to a lake is $136, although perhaps a more meaningful statistic is the

[9] *PCMiler (Streets Version 17)* was used to compute both round-trip travel distance and time.

average price of a lake visit, $85.

Second, lake site characteristics were obtained from the Iowa Department of Natural Resources [11]. Table 3 provides a summary of these site characteristics. As Table 3 indicates, the size of the lakes varies considerably, from 10 acres to 19,000 acres. Four dummy variables are included to capture different amenities at each lake. The first is a "ramp" dummy variable which equals one if the lake has a cement boat ramp, as opposed to a gravel ramp or no boat ramp at all. The second is a "wake" dummy variable that equals one if motorized vessels are allowed to travel at speeds great enough to create wakes and zero otherwise. About sixty-six percent of the lakes allow wakes, whereas thirty-four percent of lakes are "no wake" lakes. The "state park" dummy variable equals one if the lake is located adjacent to a state park, which is the case for 38.8 percent of the lakes in our study. The last dummy variable is the "handicap facilities" dummy variable, which equals one if handicap amenities are provided, such as handicap restrooms or paved ramps. A concern may be that handicap facilities would be strongly correlated with the state park dummy variable. However, while fifty of the lakes in the study are located in state parks and fifty have accessible facilities, only twenty six of these overlap. Finally, a "fish index" variable is included that varies from zero to four representing the number of fish species for which the lake is considered one of the "top 10" sites for the species in the state.[10]

3 The Model

The mixed logit model was chosen because it exhibits many desirable properties, including that "...it allows for corner solutions, integrates the site selection and participation decisions in a utility consistent framework, and controls for the count nature of recreation demand" (Herriges and Phaneuf, [9]).

[10] The candidate fish species are Bluegill, Brappie, large-mouth bass, catchfish, bullhead, and walleye. See [12] for details.

Assume the utility of individual i choosing site j on choice occasion t is of the form

$$U_{ijt} = V\left(X_{ij}; \beta_i\right) + \varepsilon_{ijt},\ \ i = 1, ..., N;\ \ j = 0, .., J;\ \ t = 1, ..., T \tag{1}$$

where V represents the observable portion of utility, and from the perspective of the researcher, ε_{ijt}, represents the unobservable portion of utility. A mixed logit model is defined as the integration of the logit formula over the distribution of unobserved random parameters (Revelt and Train, [19]). If the random parameters, β_i, were known then the probability of observing individual i choosing alternative j on choice occasion t would follow the standard logit form

$$L_{ijt}\left(\beta_i\right) = \frac{\exp\left(V_{ijt}\left(\beta_i\right)\right)}{\sum\limits_{k=0}^{J} \exp\left[V_{ikt}\left(\beta_i\right)\right]}. \tag{2}$$

Since the β_i's are unknown, the corresponding unconditional probability, $P_{ijt}(\theta)$, is obtained by integrating over an assumed probability density function for the β_i's. The unconditional probability is now a function of θ, where θ represents the estimated moments of the random parameters. This repeated Mixed Logit model assumes the random parameters are $i.i.d.$ distributed over the individuals so that

$$P_{ijt}\left(\theta\right) = \int L_{ijt}\left(\beta\right) f\left(\beta|\theta\right) d\beta. \tag{3}$$

No closed-form solution exists for this unconditional probability and therefore simulation is required for the maximum likelihood estimates of θ.[11]

Following Herriges and Phaneuf [9], a dummy variable, D_j, is included which equals one for all of the recreation alternatives ($j = 1, \ldots, J$) and equals zero for the stay-at-home option ($j = 0$). Including the stay-at-home option allows a complete set of choices, including in the population those individuals who always "stay at home" on every choice occasion and

[11] Randomly shifted and shuffled uniform draws are used in the simulation process (Hess, Train, and Polak, [10]). The number of draws used in the simulation is 750.

do not visit any of the sites. It is convenient to partition the individual's utility into the stay-at-home option or choosing one of the J sites, with

$$U_{ijt} = \begin{cases} \tilde{\beta}' z_i + \varepsilon_{i0t} \\ \beta_i' x_{ij} + \alpha_i + \varepsilon_{ijt}, \ \ j = 1, ..., J, \end{cases} \tag{4}$$

where α_i is the random parameter on the dummy variable, D_j, which does not appear since it equals one for $j = 1, ..., J$ and zero for $j = 0$. The vector z_i contains socio-demographic data such as gender, age, and education, and x_{ij} represents the site characteristics that vary across the lakes, including attributes such as facilities at the lake as well as water quality measures. Notice that the parameters associated with the socio-demographic data are not random as this information does not vary across the sites.[12]

The random coefficient vectors for each individual, β_i and α_i, can be expressed as the sum of population means, b and a, and individual deviation from the means, δ_i and γ_i, which represents the individual's tastes relative to the average tastes in the population (Train, [20]). Therefore, we can redefine

$$\beta_i' x_{ij} = b' x_{ij} + \delta_i' x_{ij} \tag{5}$$

$$a_i = a + \gamma_i \tag{6}$$

and then the partitioned utility is

$$U_{ijt} = \begin{cases} \tilde{\beta}' z_i + \eta_{i0t} \\ b_i' x_{ij} + a + \eta_{ijt}, \ \ j = 1, ..., J, \end{cases} \tag{7}$$

where

$$\eta_{ijt} = \begin{cases} \varepsilon_{i0t} & \qquad i = 1, ..., N; \ \ t = 1, ..., T \\ \delta_i' x_{ij} + \gamma_i + \varepsilon_{ijt}, \quad j = 1, ..., J; & i = 1, ..., N; \ \ t = 1, ..., T \end{cases} \tag{8}$$

is the unobserved portion of utility. This unobserved portion is correlated over sites and trips because of the common influence of the terms δ_i and γ_i, which vary over individuals. For example, an individual who chooses the stay-at-home option for all choice occasions

[12]It is possible to interact the socio-demographic data with the sites if one believed, for example, that age would affect which lake was chosen.

would have a negative deviation from a, the mean of α_i, while someone who takes many trips would have a positive deviation from a, allowing the marginal effect to vary across individuals. However, the parameters do not vary over sites or choice occasions; thus, the same preferences are used by the individual to evaluate each site at each time period. Since the unobserved portion of utility is correlated over sites and trips, the familiar IIA assumption does not apply for mixed logit models.

In particular, we model the utility individual i receives from choosing lake j on choice occasion t as

$$U_{ijt} = \begin{cases} \tilde{\beta}' z_i + \varepsilon_{i0t} \\ -\beta^P P_{ij} + \beta^{q'} Q_j + \beta_i^{a'} A_j + \alpha_i + \varepsilon_{ijt}, \ j = 1, ..., J \end{cases}, \tag{9}$$

where the vector z_i consists of socio-demographic characteristics, P_{ij} is the travel cost from each Iowan's residency to each of the 129 lakes, as calculated with PCMiler. The vector Q_j denotes the physical water quality measures and A_j represents the attributes of the lake. As shown in equation (9), notice that the parameters on the lake attributes and the dummy variable, D_j, are random.

4 Specification and Estimation

While the mixed logit model provides the general framework for our analysis, it does not determine the specific variables to use in the model (e.g., which water quality measures) or the functional form they should take in equation (9) (e.g., linear versus logarithmic). Moreover, economic theory provides little or no guidance in terms of these choices. In order to investigate the model specification issue, we divided the full survey sample into three portions, with one portion each dedicated to model specification, estimation and out-of-sample prediction. We begin this section with a discussion of the model specification process.

4.1 Specification

There are, of course, a large number of potential model specifications given the range of water quality, site characteristics, and household characteristics identified in Tables 1 through 3. We focus on modeling the role of water quality characteristics in determining recreation demand patterns, holding constant the manner in which both socio-demographics and other site characteristics impact preferences. Specifically, socio-demographic characteristics are assumed to enter through the "stay-at-home" option. They include age and household size, as well as dummy variables indicating gender and college education (See Table 1). A quadratic age term is included in the model to allow for nonlinearities in the impact of age. Site characteristics, identified in Table 3, are included with random coefficients. This is to allow for heterogeneity in individual preferences regarding site characteristics, such as wake restrictions and site facilities, observed in previous studies (e.g., Train, [20]). For example, some households may prefer to visit less developed lakes with wake restrictions in place, while others are attracted to sites allowing the use of motorboats, jet skis, etc. It is assumed that the random parameters (β_i^a) are each normally distributed with the mean and dispersion of each parameter estimated.

Even restricting our attention to the water quality characteristics in Table 2, there are a large number of potential model specifications. We focus on five groups of water quality characteristics for the Q_j in equation (9):

- Secchi depth;
- Chlorophyll;
- Nutrients (Total Nitrogen and Total phosphorus);
- Suspended Solids (Inorganic and Organic); and

- Bacteria (Cyanobacteria and Total).

The first four characteristic groups directly impact the visible features of the water quality, making it more likely that households respond to them. Bacteria is included because surveyed households report it to be the single most important water quality concern (See [2]).

Our initial intent was to consider three possible specifications for each of these groups of variables: inclusion linearly, inclusion logarithmically, or exclusion. However, preliminary analysis indicated that these variables individually and as groups were consistently significant at a five percent level or better. Thus, we chose to focus on determining whether each group of factors should enter the model in a linear or logarithmic fashion. This required estimating a total of $2^5 = 32$ versions of the model. The preferred model (see [8] for details) has Secchi depth and suspended entering the model linearly, with the remaining variables entering in a logarithmic fashion. This model is referred to as Model A below. A more complex model, including the remaining water quality variables of pH, alkalinity, silicon, nitrates, and ammonium nitrogen) is referred to as Model B below. These additional variables are entered in a linear form, except for pH which is included quadratically.

4.2 Estimation Results

Given the results from the specification search, three models were using the second third of the sample: Models A and B and a model including only Secchi depth as a measure of water quality (referred to as Model C hereafter). We include Model C to illustrate the consequences of relying on a single measure of water quality, in this case one that is often available to analysts. The resulting parameter estimates are presented in two Tables, 4a and 4b. For all three models, the coefficients for the socio-demographic data, price, and the random coefficients on the amenities are given in Table 4a. Table 4b lists the coefficients for the physical water quality measures in all three models. All of the coefficients are significant at the one percent level except for a few of the socio-demographic data. For model B, with thirteen physical water quality measures, only the "male" dummy variable is not significant. In model A, household size and the quadratic term on age are insignificant. Note that the socio-demographic data are included in the conditional indirect utility for the stay-at-home option. Therefore, higher-educated individuals, and larger households are all more likely to take a trip to a lake. Age has a convex relationship with the stay-at-home option and therefore has a concave relationship with trips. For model B, the peak occurs at about age 37, which is consistent with the estimate of larger households taking more trips, as at this age the household is more likely to include children. The price coefficient is negative as expected and virtually identical in all three models.

Turning to the site amenities, again all of the parameters are of the expected sign. As the size of a lake increases, has a cement boat ramp, gains handicap facilities, or is adjacent to a state park, the average number of visits to the site increases. Notice, however, the large dispersion estimates. For example, in model A the dispersion on the size of the lake indicates 11.1 percent of the population prefers a smaller lake, possibly someone who enjoys a more private experience. The large dispersion on the "wake" dummy variable seems particularly appropriate given the potentially conflicting interests of anglers and recreational boaters. Anglers would possibly prefer "no wake" lakes, while recreational boaters would obviously prefer lakes that allow wakes. It seems the population is almost evenly split, with 56.9 percent preferring a lake that allows wakes and 43.1 percent preferring a "no wake" lake. Lastly, the mean of α_i, the trip dummy variable, is negative, indicating that on average the respondents receive higher utility from the stay-at-home option, which is expected considering the average number of trips is 6.7 out of a possible 52 choice occasions.

The physical water quality coefficients are reported in Table 4b and are relatively stable across the two models. For all three models, the effect of Secchi depth is positive, while in both Models A and B organic and inorganic (volatile) suspended solids have a negative impact, indicating the respondents strongly value water clarity. However, the coefficient on chlorophyll is positive, suggesting that on average respondents do not mind some "greenish" water. The negative coefficient on total phosphorus, the most likely principal limiting nutrient, indicates higher algae growth leads to fewer recreational trips. High total nitrogen levels also have a statistically significant and negative impact on recreational utility associated with a site.

Continuing with the additional measures in model B, alkalinity has a positive coefficient, consistent with alkalinity's ability to both act as a buffer on how much acidification the water can withstand before deteriorating and as a source of carbon, keeping harmful phytoplankton from dominating under low CO_2 stress. Since all of the lakes in the sample are acidic (i.e., pH greater than seven), a positive coefficient for alkalinity is expected. The positive coefficient on silicon is also consistent since silicon is important for the growth of diatoms, which in turn are a preferred food source for aquatic organisms. Lastly, pH is entered quadratically, reflecting the fact that low or high pH levels are signs of poor water quality. However, as mentioned, in our sample of lakes all of the pH values are normal or high. The coefficients for pH show a convex relationship (the minimum is reached at a pH of 8.2) to trips, indicating that as the pH level rises above 8.2, trips are predicted to increase. This is the opposite of what we expected.

5 Welfare Calculations

Given the random parameters β_i, the conditional compensating variation associated with a change in water quality from Q to Q' for individual i on choice occasion t is

$$CV_{it}(\beta_i) = \frac{-1}{\beta^p}\left\{\ln\left[\sum_{j=0}^{J}\exp\left(V_{ijt}\left[Q';\beta_i\right]\right)\right] - \ln\left[\sum_{j=0}^{J}\exp\left(V_{ijt}\left[Q;\beta_i\right]\right)\right]\right\}$$

which is the compensating variation for the standard logit model. The unconditional compensating variation does not have a closed form, but it can be simulated by

$$CV_{it} = \frac{1}{R}\sum_{r=1}^{R}\frac{-1}{\beta^p}\left\{\ln\left[\sum_{j=0}^{J}\exp\left(V_{ijt}\left[Q';\beta_i^r\right]\right)\right] - \ln\left[\sum_{j=0}^{J}\exp\left(V_{ijt}\left[Q;\beta_i^r\right]\right)\right]\right\}$$

where R is the number of draws and r represents a particular draw from its distribution. The simulation process involves drawing values of β_i and then calculating the resulting compensating variation for each vector of draws, and finally averaging over the results for many draws. Following Von Haefen [22], 2,500 draws were used in the simulation.

Three water quality improvement scenarios are considered with the results from model A used for all the scenarios. The first scenario improves all 129 lakes to the physical water quality of West Okoboji Lake, the clearest, least impacted lake in the state. Table 5 compares the physical water quality of West Okoboji Lake with the average of the other 128 lakes. All of West Okoboji Lake's measures are considerably improved over the other 128. For example, West Okoboji Lake has slightly over five times the water clarity, measured by Secchi depth, of the other lakes. Given such a large change, the annual compensating variation estimate of $249 for every Iowa household seems reasonable (Table 7). Aggregating to the annual value for all Iowans simply involves multiplying by the number of households in Iowa, which is 1,153,205.[13] Table 7 also reports the average predicted trips before and after the water quality improvement. Improving all 128 lakes to the physical water quality

[13]Number of Iowa households as reported by Survey Sampling, Inc., 2003.

of West Okoboji Lake leads to an increase in average number of trips to 15.2. As expected, the predicted trips to West Okoboji Lake fall by 19.8 percent, from 0.39 average trips per Iowa household to 0.31. Iowans could then choose the nearest lake with the attributes they prefer, instead of traveling further to West Okoboji Lake.[14]

The next scenario is a less ambitious, more realistic plan of improving nine lakes to the water quality of West Okoboji Lake (see Table 5 for comparison). The state is divided into nine zones with one lake in each zone, allowing every Iowan to be within a couple of hours of a lake with superior water quality. The nine lakes were chosen based on recommendations by the Iowa Department of Natural Resources for possible candidates of a clean-up project. The annual compensating variation estimate is $40 for each Iowa household. As expected, this estimate is 16.0 percent of the value if all lakes were improved, even though the scenario involves improving only 7.0 percent of the lakes. This suggests location of the improved lakes is important and, to maximize Iowan's benefit from improving a few lakes, policymakers should consider dispersing them throughout the state.

The last scenario is also a policy-oriented improvement. Currently of the 129 lakes, 65 are officially listed on the EPA's impaired waters list. TMDLs are being developed for these lakes and by 2009 the plans must be in place to improve the water quality at these lakes enough to remove them from the list. Therefore, in this scenario, the 65 impaired lakes would be improved to the median physical water quality levels of the 64 non-impaired lakes. Table 8 compares the median values for the non-impaired lakes to the averages of the impaired lakes. The table indicates that the median values of the non-impaired lakes seem an appropriate choice, with physical water quality measures higher than the averages of the 65 impaired lakes but much below those of West Okoboji Lake. This scenario is valued considerably lower than the first two water quality improvement scenarios. The estimated compensating

[14] West Okoboji Lake, while one of the most popular lakes in the state currently, is far from most population centers in Iowa.

variation per Iowa household is \$151. Consistent with this, the predicted trips only increase three percent over the predicted trips with no improvement in water quality. A reasonable conclusion is that Iowans have an abundance of lakes at this threshold level, and bringing the low-quality lakes up to this level is not much of a benefit.

6 Conclusions

The first-year survey of the Iowa Lakes Project gathered information about the recreational behavior of Iowans at 129 of Iowa's principal lakes. These data were combined with extensive physical water quality measures from the same set of lakes gathered by the Iowa State University Limnology Lab. Our analysis, which employs the repeated mixed logit framework, shows that individuals are responsive to physical water quality measures, and it is possible to base willingness-to-pay calculations on improvements in these physical measures. In particular we considered three improvement scenarios, with the results suggesting that Iowans value more highly a few lakes with superior water quality rather than all recreational lakes that have only adequate levels (i.e., sufficient to not be listed as impaired by the Environmental Protection Agency).

A number of important practical findings come directly from this work. Limnologists and other water quality researchers should be interested in the results of this paper, since the general belief is that visitors care about water clarity as measured by Secchi depth (how many meters beneath the surface of the water a Secchi dish is visible) or water quality in general. By estimating the partial effects of a list of physical measures, we have determined which measures significantly affect recreationists' behavior. Limnologists and water resource managers can use this information about what physical lake attributes visitors' trip behavior responds to in designing projects for water quality improvements. Our results indicate water clarity is very important as evidenced by the Secchi dish and suspended solids parameters.

Also, high concentrations of nutrients, in general, are found to decrease recreational trips.

The findings of this study also have direct relevance for environmental protection managers and citizens concerned with water quality in that they can be used to prioritize clean-up activities to generate the greatest recreational benefits for a given expenditure. Not only can the findings be used to determine which lakes to target and in what order to clean them but also the most efficient levels of improvement can be identified.

Table 1. 2002 Iowa Lakes Survey Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Total Day Trips	6.44	10.22	0	52
Male	0.68	0.46	0	1
Age	53.34	16.09	15	82
School	0.66	0.46	0	1
Household Size	2.61	1.30	1	12

Table 2. Water Quality Variables and 2002 Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.
Secchi Depth (m)	1.17	0.92	0.09	5.67
Chlorophyll (ug/l)	41	38	2	183
NH3+NH4 (ug/l)	292	159	72	955
NO3+NO2 (mg/l)	1.20	2.54	0.07	14.13
Total Nitrogen (mg/l)	2.20	2.52	0.55	13.37
Total Phosphorus (ug/l)	106	81	17	453
Silicon (mg/l)	4.56	3.24	0.95	16.31
pH	8.50	0.33	7.76	10.03
Alkalinity (mg/l)	142	41	74	286
Inorganic SS (mg/l)	9.4	17.9	0.6	177.6
Volatile SS (mg/l)	9.4	7.9	1.6	49.9
Cyanobacteria (mg/l)	295.8	833.1	0.01	7178.1
Total Bacteria (mg/l)	304.8	835.2	3.99	7178.6

Table 3. Summary Statistics for Lake Site Characteristics

Variable	Mean	Std. Dev.	Min.	Max.
Travel Cost	135.79	29.47	94.12	239.30
Acres	672	2,120	10	19,000
Ramp	0.86	0.35	0	1
Wake	0.66	0.47	0	1
State Park	0.39	0.49	0	1
Handicap Facilities	0.39	0.49	0	1
Fish Index	1.01	1.14	0	4

Table 4a. Repeated Mixed Logit Model Parameter Estimates (Std. Errs in Parentheses)[a]

	Model A: 8 WQ Measures		Model B: 13 WQ Measures		Model C: Secchi Depth	
Variable	Mean	Dispersion	Mean	Dispersion	Mean	Dispersion
Male	-7.88^*		-5.93^*		-6.65^*	
	(0.56)		(0.57)		(0.45)	
Age	1.13^*		0.31^*		-0.23^*	
	(0.09)		(0.09)		(0.08)	
Age^2	-0.007^*		-0.001		0.006^*	
	(0.0008)		(0.0008)		(0.0007)	
School	-2.12^*		-3.09^*		5.81^*	
	(0.55)		(0.58)		(0.53)	
Household	0.75^*		-0.29		-0.68^*	
	(0.20)		(0.22)		(0.18)	
Price	-0.49^*		-0.49^*		-0.49^*	
	(0.0012)		(0.001)		(0.001)	
Log(Acres)	4.70^*	3.81^*	4.42^*	4.34^*	4.02^*	3.00^*
	(0.09)	(0.07)	(0.10)	(0.08)	(0.07)	(0.06)
Ramp	12.49^*	16.86^*	12.71^*	15.58^*	11.51^*	17.30^*
	(0.93)	(0.90)	(0.89)	(0.86)	(0.88)	(0.65)
Facilities	2.07^*	13.46^*	2.01^*	12.89^*	1.37^*	13.95^*
	(0.29)	(0.34)	(0.28)	(0.33)	(0.26)	(0.29)
State Park	3.90^*	12.35^*	3.50^*	11.81^*	4.04^*	13.99^*
	(0.32)	(0.28)	(0.31)	(0.27)	(0.31)	(0.27)
Wake	3.80^*	11.73^*	1.94^*	11.89^*	3.88^*	13.98^*
	(0.31)	(0.27)	(0.34)	(0.26)	(0.30)	(0.34)
Fish Index	0.04	6.36^*	-0.16	6.06^*	-0.12	5.41^*
	(0.12)	(0.12)	(0.13)	(0.13)	(0.12)	(0.11)
α	-11.90^*	2.76^*	-11.92^*	2.59^*	-11.80^*	2.76^*
	(0.05)	(0.04)	(0.05)	(0.04)	(0.04)	(0.03)

* Significant at 1% level.

[a] All of the parameters are scaled by 10, except α (which is unscaled).

Table 4b. Repeated Mixed Logit Model Parameter Estimates (Std. Errs. in Parentheses)[a]

Variable	Model A: 8 Water Quality Measures	Model B: 13 Water Quality Measures	Model C: Secchi Depth Only
Secchi Depth (m)	2.40* (0.10)	2.44* (0.10)	1.77* (0.06)
Log(Chlorophyll (ug/l))	2.37* (0.16)	2.97* (0.19)	
NH3+NH4 (ug/l)		0.003* (0.0007)	
NO3+NO2 (mg/l)		−0.14 (0.09)	
Log(Total Nitrogen (mg/l))	−1.16* (0.10)	−1.80* (0.34)	
Log(Total Phosphorus (ug/l))	−2.83* (0.17)	−4.36* (0.22)	
Silicon (mg/l)		0.33* (0.04)	
pH		−109.59* (10.01)	
pH^2		6.41* (0.59)	
Alkalinity (mg/l)		0.05* (0.003)	
Inorganic SS (mg/l)	−0.006 (0.005)	−0.027* (0.006)	
Volatile SS (mg/l)	−0.02 (0.02)	−0.03 (0.02)	
Log(Cyanobacteria)	−2.44* (0.12)	−2.27* (0.14)	
Log(Total Bacteria)	3.44* (0.15)	2.92* (0.17)	
LogLik	-37,626.94	-37,579.04	-37,759.20

*Significant at the 1% level.

[a] All of the parameters are scaled by 10.

Table 5. West Okoboji Lake vs. the other 128 Lakes

	West Okoboji Lake	Averages of the other 128 Lakes	Averages of the 9 Zone Lakes
Secchi Depth (m)	5.67	1.14	1.23
Chlorophyll (ug/l)	2.63	41.01	40.13
Total Nitrogen (mg/l)	0.86	2.21	3.64
Total phosphorus (ug/l)	21.28	105.99	91.11
Inorganic SS (mg/l)	1.00	9.45	9.52
Volatile SS (mg/l)	1.79	9.38	8.42
Cyanobacteria (mg/l)	22.00	295.76	948.00
Total Bacteria (mg/l)	24.06	304.78	953.37

Table 6. 64 Non-impaired Lakes vs. the 65 Impaired Lakes

	Median of the 64 Non-impaired Lakes	Averages of the 65 Impaired Lakes
Secchi Depth (m)	1.27	0.81
Chlorophyll (ug/l)	23.25	56.67
Total Nitrogen (mg/l)	1.11	2.31
Total phosphorus (ug/l)	58.79	139.91
Inorganic SS (mg/l)	3.51	14.78
Volatile SS (mg/l)	6.02	12.93
Cyanobacteria (mg/l)	42.96	516.96
Total Bacteria (mg/l)	47.48	528.65

Table 7. Annual Compensating Variation Estimates

a. Using Model A

Average CV	All 128 Lakes Improved to W. Okb.	9 Zone Lakes Improved to W. Okb.	65 Impaired Lakes Improved to Median
Per choice occasion	$4.80	$0.77	$0.29
Per Iowa household	$249.43	$40.12	$15.06
For all Iowa households	$287,648,000	$46,261,000	$17,363,000
Predicted Trips (11.04 with current water quality)	15.22	11.72	11.33

b. Using Model C

Average CV	All 128 Lakes Improved to W. Okb.	9 Zone Lakes Improved to W. Okb.	65 Impaired Lakes Improved to Median
Per choice occasion	$3.95	$0.64	$0.13
Per Iowa household	$205.40	$33.05	$6.82
For all Iowa households	$236,863,000	$38,117,000	$7,862,000
Predicted Trips (11.23 with current water quality)	14.75	11.80	11.37

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Cost-effective provision of ecosystem services from riparian buffer zones

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Abstract

The main objective of this paper is to determine the optimal spatial arrangement of riparian buffer zones (RBZs) for protecting salmon species on a branched river network. First, we develop a stylized analytical model of salmon survival on a stream network with three reaches, which reveals some of the general conditions under which RBZs should be concentrated on a few reaches or spread more evenly among multiple reaches. Next, we present a series of simulation experiments based on a calibrated version of the model, which allows us to numerically solve for the optimal distribution of RBZs under a range of initial conditions and parameter values. These simulation experiments reinforce the intuition behind our analytical results and help to further illuminate the quantitative influence of the key parameters of the model, including the spatial distribution of spawning areas, initial temperature conditions, and the size of the conservation budget. This research can help to improve riparian buffer protection guidelines and inform the design of economic incentive schemes for meeting TMDL requirements for a variety of non-point source pollutants including nutrients and high water temperatures.

1 Introduction

Riparian buffer zones are stream-side strips of natural vegetation that serve a variety of ecosystem functions, including filtering polluted non-point source runoff before it enters streams, preventing erosion by stabilizing stream banks, providing nutrients and microhabitat structure from inputs of leaf litter and coarse woody debris, and regulating stream temperature by shading the water surface. These functions in turn contribute to a variety of ecosystem services, including the protection of valued fish stocks and other aquatic species. In this paper we focus on the role of riparian buffer zones in regulating stream temperatures and thereby contributing to the survival of cold water migratory fish species such as salmon.

When Meriwether Lewis and William Clark visited what is now the northwestern U. S. in the early nineteenth century Clark remarked that the number of salmon they encountered was "incredible to say."[1] The explorers grew heartily sick of the ubiquitous fish. Expedition member Patrick Gass recorded that "Being again reduced to fish . . . we made an experiment to vary our food by purchasing a few dogs, and ... felt no disrelish to this new dish."[2] It is ironic that two centuries later several runs of Pacific Salmon are now listed as Federal threatened or endangered species. This situation has led to a number of calls to conserve them. As one might expect of a commercially valuable species with a complicated life cycle ranging over thousands

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[1] Journal of William Clark, 17 October 1805. Available online at http://www.ccrh.org/comm/river/docs/lcww.htm accessed 7 April 2007.

[2] Journal of Patrick Gass, 10 October 1805. The explorers' purchases did create some cultural conflicts, however. The natives were revolted. Gass went on to note that the Nez Perce with whom they traded "have great numbers of dogs, which they employ for domestic purposes, but never eat; and our using the flesh of that animal soon brought us into ridicule as dog-eaters." Quoted in "Lewis and Clark from Other Side", online at http://redwebz.org/modules.php?name=News&file=article&sid=1408 accessed 6 April 2007. Part of the Lewis and Clark expedition's aversion to salmon may also be attributed to ignorance of their biology. Salmon die shortly after spawning and the explorers, on seeing so many dead fish, presumed they must have been diseased.

of kilometers of both fresh and saltwater habitat, the conservation options are as diverse as is the range of the fish. Policies advocated include:

- land use restrictions and best management practices intended to preserve the upstream habitats in which adult fish spawn, eggs hatch, and young fish grow;
- total maximum daily load (TMDL) restrictions on various pollutants that may adversely affect salmon survival, including high temperatures;
- restricting water use to assure adequate flows over dam spillways, road transport of juvenile fish around generating turbines, and—the most extreme option—breaching major dams on the Snake, Columbia, and other rivers;
- programs to control predation from Caspian terns and other animals that feed on salmon in the Columbia Estuary and elsewhere (USACE 1999, Roby *et al.* 2002); and
- reducing fishing pressures on mature fish in marine environments.

The existence of so diverse a range of options guarantees that any particular choice will be controversial. The (opportunity) costs borne by a specific group, be it developers, ranchers, fisherman, or others, differ markedly depending on the option, which guarantees disagreement about the appropriate policy choice. In addition, the best approach may well be a collection of specific policies, but coordinating policy over such a broad range of options, actors, and locations can overwhelm governance systems. The policy of the United States Fish and Wildlife Service in its interpretation and enforcement of the Endangered Species Act suggests a societal commitment to the preservation of Pacific Salmon. Salmon conservation policy, then, might be considered a classic candidate for cost-effectiveness analysis. What is the least expensive way to achieve this objective? What combination of the options under consideration is the best?

Both natural scientists and economists have weighed in on this topic. The scales at which different authors have addressed the issues have varied greatly. Some researchers have developed models to determine the optimal buffer width at a location given the local terrestrial and stream conditions at that point (e.g., Weller *et al*. 1998, Sparovek *et al*. 2002, Matero 2004, Frimpong *et al*. 2005, Tomer *et al*. 2005). This strand of research has inspired policy guidance on the width of RBZs and the composition of vegetation and placement of woody debris within the streams. Moreover, some jurisdictions offer incentives for landowners to establish and maintain RBZs, such as the federal-state partnerships between the USDA and Oregon and Washington that uses the Conservation Reserve Enhancement Program to protect salmon and trout through RBZs.[3]

However, by focusing exclusively on local conditions, these studies and associated policy recommendations take no account of the larger scale, landscape level spatial interactions that also can have a strong influence on the overall effectiveness of RBZs. Considering that conservation budgets often are severely limited, RBZ protection and restoration efforts should be spatially targeted in such a way that the manager's overall conservation goals are achieved as cost-effectively as possible.

Other researchers have developed larger-scale models that explicitly account for the spatial arrangement of buffers in the landscape, typically to maximize the mass of pollutants filtered by RPZs before they enter a river system (e.g., Ferarro 2001, Azzaino *et al*. 2002, and Cerucci and Conrad 2003, Yeo *et al*. 2004). These studies take advantage of the spatial heterogeneity in terrestrial conditions that contribute to NPS pollution at a basin-wide scale to

[3] www.fsa.usda.gov/dafp/cepd/crep.htm

increase the overall cost-effectiveness of RBZ expenditures, but they typically ignore any in-stream processes such as water flows, pollution decay or dilution, or species exposures and mortality rates that also may have strong effects on the provision of ecosystem services.

Research by Wu and colleagues has begun to address the question of optimal allocations of conservation expenditures in the presence of threshold effects in the ecosystem service production functions (Wu and Boggess 1999, Wu *et al*. 2000, Wu and Skelton-Groth 2002). Using the John Day Watershed in Oregon as a case study, Wu and colleagues combined data on standing stocks of fish per reach, a detailed water temperature and flow model, and a cost effectiveness analysis to identify priority reaches for RBZs given various management goals. Their central result places RBZs in fish-bearing, upper reaches of the watershed. Although this research provides useful information and integrates economic and ecological data, the focus on a particular river system and their use of a complex water temperature simulation model make it difficult to identify the drivers of their main results and derive generalizable lessons for other watersheds. Furthermore, Wu and colleagues use data on the relative abundances of spawning salmon as a measure of habitat quality for targeting conservation efforts. No model of salmon migrations is included, so their analysis does not account for the key spatial interaction effects inherent in such a system. In this paper we develop a stylized model of fish and water movement to determine the optimal placement of RBZs in a watershed as a clear function of the parameters of the model. Our policy goal of maximizing the number of fish that survive to the mouth of the river system recognizes that the salmonid lifecycle requires movement through connected reaches in the watershed and accounts for spatial externalities of RBZ restoration.

Another recent contribution to the economic literature on salmon conservation falls, in a sense, at the other end of the spectrum relative to the work of Wu and colleagues. Rather than focusing on watershed protection measures along low order streams, Halsing and Moore (2006) consider 76 management options along the mainstem of the Columbia River for salmon recovery and rank them by their costs effectiveness. The options considered include various combinations of strategies for managing or removing dams, controlling predators, and restricting fishing effort; they do not consider interventions focusing on spawning habitat, as they are unable to obtain sufficient data. Nevertheless, Halsing and Moore's analysis seems a powerful motive for applying cost-effectiveness analysis to upstream habitat conservation options. In their work they find that between 80 and 90 percent of recovery options are clearly dominated by lower-cost alternatives. It would seem, then, quite likely that careful consideration of upstream recovery options via habitat conservation might either reveal them to dominate higher cost strategies in Halsing and Moore's set of preferred alternatives, or to be dominated by them. We are now reporting work in progress that has not yet been fully calibrated to facts on the ground, but we expect the gains from that calibration and comparison to other alternatives will be quite informative to policy.

2 An Analytical Model of Optimal Conservation Efforts

In this section we develop an analytical model of salmon survival on a simplified river network. A set of conditions will emerge that indicate whether expenditures on RBZ protections should be targeted toward a single reach or spread more evenly among multiple reaches. These conditions also will provide a foundation for interpreting some of the numerical results in the following section. Let us consider, then, a simple river network consisting of a downstream reach, which we will identify with a subscript 3 in the following exposition, and two upstream reaches, identified with subscripts 1 and 2. See Figure 1. Note that this is a very general specification; it could describe any situation above and below the confluence of two streams.

Let N_i denote the number of young salmon hatched in reach *i*. Now suppose that policy makers can devote expenditures, denoted by x_i, along each reach to enhance salmon habitat. Note that these expenditures (or more generally "conservation efforts") could come in a variety of forms, e.g., dollar outlays on restoration projects, opportunity costs of habitat protections, the amount of land set aside or restored to RBZs, etc.

We will suppose that fish survival along reach *i*, p_i, can be described by a logistic function of expenditures on that reach (to allow for threshold effects that are thought to characterize many dose-response functions) as well as expenditures on upstream reaches (because water flows downstream, water quality in upstream reaches influences water quality in downstream reaches). Thus, for our three-reach river network, we have

$$p_1 = \frac{k_1}{1 + \beta_1 e^{-\alpha_1 x_1}}, \tag{1}$$

$$p_2 = \frac{k_2}{1 + \beta_2 e^{-\alpha_2 x_2}}, \tag{2}$$

and

$$p_3 = \frac{k_3}{1 + \beta_3 e^{-(\gamma_1 x_1 + \gamma_2 x_2 + \alpha_3 x_3)}}, \tag{3}$$

where α_i determines the influence of expenditures on reach *i* on fish survival on reach *i*, γ_i determines the influence of expenditures on reach *i* on fish survival on the downstream reach, and k_i and β_i determine the minimum and maximum fish survival on reach *i*.

The following properties of the logistic specification, $p(x) = \frac{k}{1 + \beta e^{-\alpha x}}$, will be useful for deriving some of our main qualitative results:

$$p(0) = \frac{k}{1+\beta},$$

$$\lim_{x \to \infty} p(x) = k,$$

$$\frac{\partial p}{\partial x} = \alpha p \left(\frac{k-p}{k} \right),$$

and

$$\frac{\partial^2 p(x)}{\partial x^2} = \alpha^2 p \left(\frac{k-p}{k} \right) \left(\frac{k-2p}{k} \right);$$

that is, the function has an inflection point at $x = \ln(\beta / \alpha)$, where $p = k/2$. We will find it easier to demonstrate our subsequent results if we first invert expressions (1) through (3). Doing so, we have

$$x_1 = \frac{1}{\alpha_1} \ln \frac{\beta_1 p_1}{k_1 - p_1}, \tag{4}$$

$$x_2 = \frac{1}{\alpha_2} \ln \frac{\beta_2 p_2}{k_2 - p_2}, \tag{5}$$

and, since

$$\gamma_1 x_1 + \gamma_2 x_2 + \alpha_3 x_3 = \ln \frac{\beta_3 p_3}{k_3 - p_3},$$

$$x_3 = \frac{1}{\alpha_3}\ln\frac{\beta_3 p_3}{k_3 - p_3} - \left(\frac{\gamma_1}{\alpha_1\alpha_3}\ln\frac{\beta_1 p_1}{k_1 - p_1} + \frac{\gamma_2}{\alpha_2\alpha_3}\ln\frac{\beta_2 p_2}{k_2 - p_2}\right). \tag{6}$$

Using these facts, the total cost of the overall conservation program is

$$x_1 + x_2 + x_3 = \frac{1}{\alpha_3}\ln\frac{\beta_3 p_3}{k_3 - p_3} + \frac{\alpha_3 - \gamma_1}{\alpha_1\alpha_3}\ln\frac{\beta_1 p_1}{k_1 - p_1} + \frac{\alpha_3 - \gamma_2}{\alpha_2\alpha_3}\ln\frac{\beta_2 p_2}{k_2 - p_2}. \tag{7}$$

In general we might consider the problem of conserving fish as a constrained optimization exercise: given a specified limit on the sum of expenditures in expression (7), how would we allocate those expenditures across reaches to maximize the expected number of surviving fish? Such a problem is typically set up as a Lagrangean maximization exercise with a multiplier that reflects the shadow value of the constraint, which reveals the cost of saving the "marginal fish." For our expositional purposes here, however, it will be convenient to treat a somewhat simpler problem. Suppose that the manager is offered a price per fish saved and then maximizes "profits," defined as the price times the expected number of fish saved less the expenditures devoted to saving them. The answer derived using this approach will be exactly the same as that which would emerge from more general problem when the "price" is exactly equal to the shadow value of the multiplier, but by phrasing the problem in this way we simplify required calculations below.[4] So, suppose that the manager's objective is to maximize

$$\phi p_3\left(p_1 N_1 + p_2 N_2\right) - \left(\frac{1}{\alpha_3}\ln\frac{\beta_3 p_3}{k_3 - p_3} + \frac{\alpha_3 - \gamma_1}{\alpha_1\alpha_3}\ln\frac{\beta_1 p_1}{k_1 - p_1} + \frac{\alpha_3 - \gamma_2}{\alpha_2\alpha_3}\ln\frac{\beta_2 p_2}{k_2 - p_2}\right), \tag{8}$$

[4] The reason for this is that derivation of second-order (sufficient) conditions for an optimum in a Lagrangean optimization problem require verification of determinant conditions on a 4 x 4 bordered Hessian matrix of second derivative. By assuming a fixed price of fish we can confine our attention to the 3 x 3 sub-matrix of second derivatives in what follows.

where ϕ is the price of fish. Note the implication of inverting expressions (1), (2), and (3) to derive (4), (5), and (6) , and, by extension, (7) and (8). We treat the manager as choosing probabilities of survival along each reach and, in so doing, committing to the expenditures required to achieve those survival probabilities. First-order conditions for this optimization problem are, with respect to p_1,

$$\phi p_3 N_1 - \frac{\alpha_3 - \gamma_1}{\alpha_1 \alpha_3} \frac{k_1}{p_1 \left(k_1 - p_1\right)} \leq 0, \tag{9}$$

with respect to p_2,

$$\phi p_3 N_2 - \frac{\alpha_3 - \gamma_2}{\alpha_2 \alpha_3} \frac{k_2}{p_2 \left(k_2 - p_2\right)} \leq 0, \tag{10}$$

and with respect to p_3,

$$\phi p_1 N_1 + \phi p_2 N_2 - \frac{k_3}{\alpha_3 p_3 \left(k_3 - p_3\right)} \leq 0. \tag{11}$$

Each of these conditions could be an inequality. None of the p_i's can be less than $k_i / \left(1 + \beta_i\right)$. In other words, it is not possible to free up further resources to apply along reach *j* by sacrificing survival along reach *i* if the latter is already as low as $k_i / \left(1 + \beta_i\right)$.

Note also that the left-hand sides of expressions (9) and (10) would be positive if $\alpha_3 < \gamma_i$, $i = 1, 2$. Referring back to expressions (1) and (2), this would occur if one unit of expenditure on one of the *upstream* reaches had a greater impact on the survival of fish in the *downstream* reach than did one unit of expenditure there. To give an example, this might be the case if controlling temperature or pollution upstream were more important to survival downstream than were expenditures made downstream to control mortality there directly.

To consider further cases under which the first-order conditions might *not* hold as equalities, suppose that expression (9) *is* an equality,

$$\phi N_1 = \frac{\alpha_3 - \gamma_1}{\alpha_3 \alpha_1} \frac{k_1}{p_3 p_1 \left(k_1 - p_1\right)}, \tag{12}$$

and consider the circumstances under which this would imply a contradiction. The denominator on the right-hand side of equation (12) would reach its maximum when p_3 equals its maximum value k_3 and p_1 approaches $k_1/2$. (As will be demonstrated momentarily, satisfaction of the second-order conditions for maximization requires that $p_1 > k_1/2$.) Hence the *minimum* possible value of the right-hand side of (12) is $\frac{\alpha_3 - \gamma_1}{\alpha_1 \alpha_3} \frac{4}{k_1}$. There seems no reason *a priori* to rule out values of the parameters α_1, α_3, γ_1, and k_1 such that certain combinations of the number of fish hatched on reach 1, N_1, and the value assigned to surviving fish, ϕ, were not large enough to justify positive expenditures along reach 1.

Let us proceed for now, however, on the assumption that the first-order conditions (9) – (11) are equalities and continue to characterize the conditions under which interior solutions obtain; that is, the conditions under which it is optimal to devote some expenditures on RBZ protections on all three reaches (and of course when these conditions are not satisfied a corner solution will be optimal). Combining (9) and (10) with (11) when each is an equality,

$$\frac{\alpha_3 - \gamma_1}{\alpha_1} \frac{k_1}{k_1 - p_1} + \frac{\alpha_3 - \gamma_2}{\alpha_2} \frac{k_2}{k_2 - p_2} - \frac{k_3}{k_3 - p_3} = 0 \,. \tag{13}$$

While expressions for the relationships between survival probabilities can be reasonably compact, closed-form solutions for the probabilities themselves are not. In general they admit multiple roots, begging the question of which root corresponds to the optimal allocation of expenditures. To further analyze this question, we derive the second-order conditions for optimization. The matrix of second derivatives of the objective function is

$$\begin{pmatrix} \dfrac{\alpha_3-\gamma_1}{\alpha_1\alpha_3}\dfrac{k_1\left(k_1-2p_1\right)}{p_1{}^2\left(k_1-p_1\right)^2} & 0 & \phi N_1 \\ 0 & \dfrac{\alpha_3-\gamma_2}{\alpha_2\alpha_3}\dfrac{k_2\left(k_2-2p_2\right)}{p_2{}^2\left(k_2-p_2\right)^2} & \phi N_2 \\ \phi N_1 & \phi N_2 & \dfrac{k_2\left(k_3-2p_3\right)}{\alpha_3 p_3{}^2\left(k_2-p_3\right)^2} \end{pmatrix} \tag{14}$$

and simplifying by substituting from the first-order conditions,

$$\phi\begin{pmatrix} p_3N_1\dfrac{k_1-2p_1}{p_1\left(k_1-p_1\right)} & 0 & N_1 \\ 0 & p_3N_2\dfrac{k_2-2p_2}{p_2\left(k_2-p_2\right)} & N_2 \\ N_1 & N_2 & \left(p_1N_1+p_2N_2\right)\dfrac{k_3-2p_3}{p_3\left(k_3-p_3\right)} \end{pmatrix}. \tag{15}$$

For the second-order conditions to be satisfied each of the diagonal terms must be negative. This requires that each p_i exceeds its corresponding $k_i/2$. In other words, the optimal expenditure along each reach will be positive if diminishing returns obtain along each.

Another necessary condition for the second-order conditions to be satisfied is that the principle minors must alternate in sign, which implies that

$$p_3^2N_1N_2\frac{k_1-2p_1}{p_1\left(k_1-p_1\right)}\frac{k_2-2p_2}{p_2\left(k_2-p_2\right)}>0,$$

$$\left(p_1N_1+p_2N_2\right)\frac{k_2-2p_2}{\left(k_2-p_2\right)}\frac{k_3-2p_3}{\left(k_3-p_3\right)}>p_2N_2,$$

and

$$\left(p_1N_1 + p_2N_2\right)\frac{k_1 - 2p_1}{\left(k_1 - p_1\right)}\frac{k_3 - 2p_3}{\left(k_3 - p_3\right)} > p_1N_1 .$$

A sufficient condition for the first of these conditions to be met is that the conditions on the diagonal elements are met. A sufficient condition for the second and third conditions to be met is that each p_i exceeds its corresponding $2k_i/3$.

The final necessary condition for the second-order conditions to be satisfied is that the determinant of the entire matrix is negative, which will be true if

$$\left(p_1N_1 + p_2N_2\right)\frac{k_1 - 2p_1}{p_1\left(k_1 - p_1\right)}\frac{k_2 - 2p_2}{p_2\left(k_2 - p_2\right)}\frac{k_3 - 2p_3}{\left(k_3 - p_3\right)} < N_2\frac{k_1 - 2p_1}{p_1\left(k_1 - p_1\right)} + N_1\frac{k_2 - 2p_2}{p_2\left(k_2 - p_2\right)} . \qquad (16)$$

A *sufficient* condition is that each p_i exceeds its corresponding $2k_i/3$.

These analytical results may not be immediately transparent, so it may be useful to attempt an intuitive explanation of our findings. Recall that the logistic function has an inflection point at $p_i = k_i/2$. It is not surprising, then, that $k_i/2$ is an important benchmark for our results. If none of the p_i's were as large as its corresponding $k_i/2$, there would be increasing returns to additional expenditures on each reach, and all expenditures should be dedicated to the reach for which the marginal contribution to the probability of survival is highest.

These results also reveal that as more money is allocated to restoring salmon—in our model, as a higher price, ϕ, is put on the salmon that survive—it will make sense to allocate expenditures across more than one reach: diminishing returns will eventually set in along the first reach to which expenditures are allocated. The other conditions we derive for an optimum indicate that the probability of survival must rise to some level discretely greater than $k_i/2$ along each of two reaches before it becomes optimal to allocate expenditures across all three reaches simultaneously. Heuristically, it will be the case that the marginal product of expenditure in enhancing the likelihood of survival along each of the reaches to which positive expenditures are allocated is declining when the probability of fish survival along each of two reaches receiving positive expenditure is greater than $k_i/2$. However, that marginal product still may exceed the marginal product of expenditure in enhancing the likelihood of survival along the last of three reaches to which effort is allocated.

That an interior solution requires decreasing returns to each input is a familiar condition for any constrained optimization problem, but these second order conditions play a key role in determining the nature of the optimal allocation of RBZs and they arise due to the particular structure of our model system: with threshold effects in the survival functions along each reach, under some conditions the objective function will exhibit increasing returns. Thus, as in other ecosystem management problems, the non-convex ecological production functions require special attention and can give rise to outcomes such as "specializing" or focusing policy on one area even when the two areas are identical (Swallow *et al*. 1997, Wu and Boggess 1999), and can lead to difficulties for management including multiple local optima and the inability of decentralized incentive schemes to generate efficient outcomes (Dasgupta and Maler 2004).

3 Simulation Experiments

In this section we present simulation results from a numerical version of the model analyzed above. This requires calibration of the logistic function parameter values to represent the stream temperature-fish survival relationship (plus some modest changes in notation in the process, which we point out as they arise). Specifically, we calibrated the model to match the following temperature dose-response relationship estimated by McHugh *et al*. (2003) using data from the Snake River in Oregon:

$$S_t = \exp\left[-\left(\frac{T_t}{27.0271}\right)^{10.74}\right], \tag{17}$$

where S_t is the daily survival rate of spring Chinook salmon and T_t is the average daily temperature. To estimate survival probabilities for the entire portion of the life cycle during which young salmon migrate from their spawning streams to the mainstem, McHugh *et al*. assumed that daily survival probabilities are independent, which implies that the overall survival probability is the product of the daily survival probabilities that constitute the full duration of this portion of the life cycle.

To calibrate our simulation model, we translated this resulting seasonal survival probability to a logistic form, where the average seasonal temperature was the argument of the logistic function. (We assumed a day-to-day coefficient of variation of 0.3, which also is loosely consistent data shown in McHugh *et al*.) Figure 2 shows the match between the McHugh model and the logistic model with $\alpha = 1.25$ and $\beta = 1/5{,}700{,}000$. The match is not exact, but it is close enough to ensure that our numerical simulation model will produce realistic results.

Next, we assume a simple linear relationship between riparian shading and average stream water temperatures. On the two upstream reaches the average stream temperatures are

$$T_i = T_i^{\max} + \left(T_i^{\min} - T_i^{\max}\right) x_i \quad i = 1,2, \tag{18}$$

and on the downstream reach the average stream temperature is

$$T_3 = T_3^{\max} + \left(T_3^{\min} - T_3^{\max}\right)\left(x_3 + \gamma_1 x_1 + \gamma_2 x_2\right), \tag{19}$$

where x_i is the fraction of reach i with restored riparian buffers, $T_i^{\max}$ is the current stream temperature on reach i (with no riparian restoration), $T_i^{\min}$ is the stream temperature on reach i under pristine conditions (if riparian buffers were fully restored along all three reaches), and γ_i is the influence of riparian restoration along (upstream) reach i ($i = 1,2$) on the temperature of the downstream reach. Note that our control variables here, the x_i's, represent the fraction of the reach where buffers are restored and so are bounded between 0 and 1 (rather than representing "expenditures" as in the previous section, which were unbounded from above). Furthermore, note that it is the combination of parameters $T_i^{\max}$, $T_i^{\min}$, α_i, and β_i that determine the upper and lower bounds on fish survival along each reach rather than the ("reduced form") parameters k_i, α_i, and β_i used to derive our qualitative analytical results above.

In this application the γ_i's summarize the rate at which heat is gained and lost from the flowing water, and their values will depend on a variety of physical factors including latitude, water flow rates, reach widths, and air temperatures. We expect the γ_i's to be positive but less than one—riparian restoration on a reach should have a stronger influence on the water temperature in that reach than restoration upstream—but otherwise we have no basis for estimating a realistic value for these parameters. Thus, we present results based on a range of γ values, from 0 to greater than 0.5.

The survival probability for salmon migrating through a reach is based on the logistic function, as in the previous section, but here it is calibrated to match the McHugh *et al*. model, and so the argument of the logistic function is the average stream temperature, T_i,

$$p_i = \frac{1}{1+\beta_i e^{\alpha_i T_i}} . \tag{20}$$

The total number of salmon that survive the migration to the downstream end of reach three, F, is the number of salmon hatched in reach 1 that survive migration down reaches one and three, the number hatched in reach 2 that survive migration down reaches two and three, and the number hatched in reach 3 that survive migration down reach three, i.e.,

$$F = \left(N_1 p_1 + N_2 p_2 + N_3\right) p_3 . \tag{21}$$

Equation (21) is the objective function, which will be maximized by choosing x_1, x_2, and x_3 in Equations (18) and (19) subject to a constraint on the sum of the x's, i.e., $x_1 + x_2 + x_3 \leq X$, which essentially assumes a homogeneous and fixed marginal cost of buffer restoration. (And from the perspective of the dual problem, the sum of the x's chosen optimally give the lowest possible cost of riparian buffer restoration for achieving the resulting level of salmon production, F.)

As discussed in the previous section, this optimization problem may be non-convex (here depending on the values of the $T_i^{\max}$'s), so a simple optimization approach using a gradient-based search or first-order conditions alone may not guarantee the globally optimal solution. Thus, we use an exhaustive combinatorial search method—checking every possible combination of x's that sum to the budget constraint, X (in increments of X/500)—to ensure the globally optimal solution for any combination of parameters and starting values. This approach is straight-forward and feasible for our current example with only three reaches, but the curse of dimensionality would quickly set in as more reaches are added. Thus, more efficient optimization algorithms will be needed to address real-world cases on river systems that may consist of dozens of reaches. In the meantime, the stylized examples analyzed here can help to build some intuition about what the optimal configuration of riparian buffer restoration will look like under various conditions.

Preliminary sensitivity analyses revealed that, in addition to interior solutions, virtually all combinations of corner solutions are possible. Rather than presenting an exhaustive accounting of all possible combinations, we show in Figures 3 through 5 a few key results that illustrate the effects of the most important model parameters. In each figure, the upper panels graph the fraction of each reach where RBZs are restored (the vertical axis) against the size of the budget (the horizontal axis). The corresponding lower panels in each figure show the number of fish that survive to the mouth of the system at each budget level.

First, consider Figure 3, which illustrates the effect of the initial temperature conditions on the optimal distribution of RBZ restoration. In Panel A the initial temperatures are just beyond the inflection point of the logistic survival curve (refer back to Figure 2), so decreasing returns prevail on each reach. However, since the objective is a multiplicative function of survival along reaches 1 and 3 and 2 and 3, i.e., RBZ restoration on reach 3 enhances the survival prospects of fish hatched on both reaches 1 and 2, when the budget is small it is optimal to target all restoration effort to the downstream reach. If the budget is large enough, then an interior solution is optimal; restoration effort should be split between the three reaches, with equal amounts devoted to each of the two upstream reaches. In Panel B, the initial temperatures are well below the inflection point of the logistic survival curve, so increasing returns prevail on each reach initially. Thus, when the budget is large enough to justify some restoration effort being devoted upstream, that effort should be targeted to one of the two upstream reaches rather than split evenly between them (even though the initial conditions are the same on the two upstream reaches). At still higher budgets the threshold for the upstream focal reach is achieved and RBZ expenditures occur on all three reaches.

Figure 4 illustrates the influence of the strength of the spillover effects from upstream RBZ restoration on the optimal allocation of restoration effort. In Panel A, γ equals 0.25, which means one unit of RBZ restoration on either reach 1 or 2 will reduce the average temperature on the downstream reach by the same amount as 0.25 units of RBZ restoration on reach 3. These results are qualitatively similar to those in Panel B of Figure 2 where there were no spillover effects, but the switching points between the various corner solutions occur at lower levels of the budget. In Panel B of Figure 4, γ is increased even further to 0.51, which is sufficient to cause a qualitative change in the optimal pattern of RBZ restoration: now at low budgets RBZ restoration efforts should be targeted to one of the two upstream reaches rather than the downstream reach. This concentration of effort occurs because the spillover effects are strong and there are increasing returns to RBZ restoration initially.

Next, Figure 5 illustrates the influence of one of the key spatial features of the objective function on the optimal allocation of RBZ restoration. Here all spawning occurs on only one of the two upstream reaches and there are no spillover effects, so the branching feature of the system is effectively eliminated. Thus, this example isolates the serial (multiplicative) nature of overall fish survival due to the fact that salmon must travel through multiple reaches on their journey to and from the ocean. In our simplified case, the number of fish that survive to the downstream end of reach 3 is the number hatched in reach 1 that survive their migration through both reach 1 and then reach 3. In Panel A the initial temperatures are above the inflection point of the logistic survival function, so, as we might expect, restoration effort is split evenly between the two reaches. However, in Panel B the initial temperatures are well below the inflection point, so we might expect that, at least when the budget is low, restoration effort should be targeted towards one of the two reaches rather than split evenly between them. However, it turns out that the multiplicative nature of the objective function leads to a switch in the sign of the second derivative compared to the analogous case with an additive objective function.[5] This further highlights the influence of the particular spatial structure of our study system on the qualitative nature of our results. This finding also qualifies one of Wu's key analytical results—that at low budgets and in the presence of threshold effects optimal conservation efforts should be spatially aggregated rather than dispersed (Wu and Boggess 1999)—which apparently depends in part on the fact that their objective was an additive function of watershed-level outputs.

Finally, note that in several of the cases illustrated here, the optimal amount of RBZ restoration does not increase monotonically along each reach as the budget increases (Panel B of Figure 3, and Panels A and B of Figure 4). This can have important consequences for the manager whose budget is not a once-and-for-all endowment but rather comes in regular (typically annual) installments that are often provisional, i.e., not guaranteed and conditional on

[5] The reader can confirm this by comparing a simple "serial" case, $F = p_1(x_1)p_2(X - x_1)$, with an analogous "parallel" case, $F = p_1(x_1) + p_2(X - x_1)$, where the $p_i(\bullet)$'s are based on the logistic function, and taking first and second derivatives of each with respect to x_1.

a variety of factors out of the manager's control. In these cases, if the manager targets funds as they become available to RBZ restoration in areas with the currently highest marginal benefits, and if RBZ restoration projects are not easily reversible, then the manager may find she is stuck with a sub-optimal pattern of RBZs. Thus, in the general case a forward-looking dynamic programming approach will be needed to solve this problem.

4 Conclusions

The ecological and policy literature on salmonid conservation and RBZs contains sometimes conflicting ideas about where to place RBZs in a watershed. Some recommend that RBZs be placed along reaches with warm water that is close to threshold or lethal levels, while others recommend that they be placed upstream where they keep cool water cool. Some state and federal regulations prohibit harvesting trees from riparian areas of salmonid-bearing streams and innovative programs encourage further riparian management of forests (Oregon Forest Practices Act, Kline *et al*. 2000). Recent research has emphasized the contribution of fishless headwater streams to downstream habitat and have called for RBZs in those reaches (IMST 1999, Thompson *et al*. 2007). It appears that there are scientific reasons to have RBZs in many parts of a watershed but, in a world of limited budgets, prioritizing amongst locations is difficult.

The stylized model developed in this paper identifies the role of key parameters and initial conditions in determining where in a watershed to invest in RBZs. In different settings as characterized by these parameter values, the optimal placement of RBZs varies. It seems that no simple rule of thumb will apply uniformly across an ecologically heterogeneous region. However, our results can serve as a starting point for developing some general guidelines based on a few readily observable characteristics of specific cases. For example, when thresholds in survival matter, and when initial conditions are highly degraded and the budget is small, focusing efforts on a subset of reaches conserves more fish than spreading effort across all reaches. Second, when upstream habitat conditions contribute significantly to downstream species protection, RBZ expenditures should create those spillovers by emphasizing upstream riparian conservation. Third, stream reaches that affect many fish—such as downstream migration corridors—or that are particularly important in the probability of survival—such as those in which salmonids live for extended periods in order to grow strong enough to survive the ocean—should be high priorities because the probability of survival there plays a large role in the overall survival rate. With these state-based rules of thumb in mind, there are situations in which it is best to place RBZs downstream, upstream, and in fishless headwaters but also situations in which those placements are not preferred.

Such rules of thumb can be a useful starting point for managers trying to meet landscape or basin scale species conservation goals, but the real power of this framework will come in specific applications to real-world cases. By expanding the model to a full river network and calibrating it to current temperature conditions and fish survival rates, it should be possible to determine the theoretically optimal distribution of riparian buffer protections and then make concrete suggestions for future RBZ restoration efforts.

Current RBZ regulations and conservation incentives typically do not vary across settings except between fish-bearing and fishless streams. Many policies target stream temperatures for different portions of the salmonid lifecycle but tradeoffs across reaches and watersheds and the connectivity of reaches are not considered. Even the establishment of critical habitat for salmon has faced boundary difficulties that constrain those designations away from linking conservation upstream to downstream in order to take advantage of spillovers and characteristics of salmonid migration. All of this suggests that significant improvements in the cost-effectiveness of RBZ conservation programs should be possible if the key spatial interactions and tradeoffs across watersheds are properly accounted for in the targeting process.

The framework developed in this paper forms the foundation for several next steps. The work presented here is quite preliminary and our first research priority is to further explore this simple branching system with water and fish movement, with particular attention to identifying characteristics of a setting that lead to different allocations of RBZs across a watershed. One direction of future research involves a fuller representation of the habitat needs across the lifecycle of salmonids and the impact of lifecycle characteristics on the relative importance of reaches within a watershed. A somewhat different direction of research incorporates the RBZ framework developed here into a broader model that elucidates tradeoffs between policy options to conserve salmonids, including breaching dams, limiting harvests, and riparian management. In future work we also intend to calibrate the model to a real river system and attempt to solve the larger network optimization problem and the more general dynamic programming problem accounting for uncertain budgets and discounting. This framework also can serve as a foundation for evaluating the effectiveness of various watershed trading schemes or riparian buffer mitigation banking designs.

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Figures

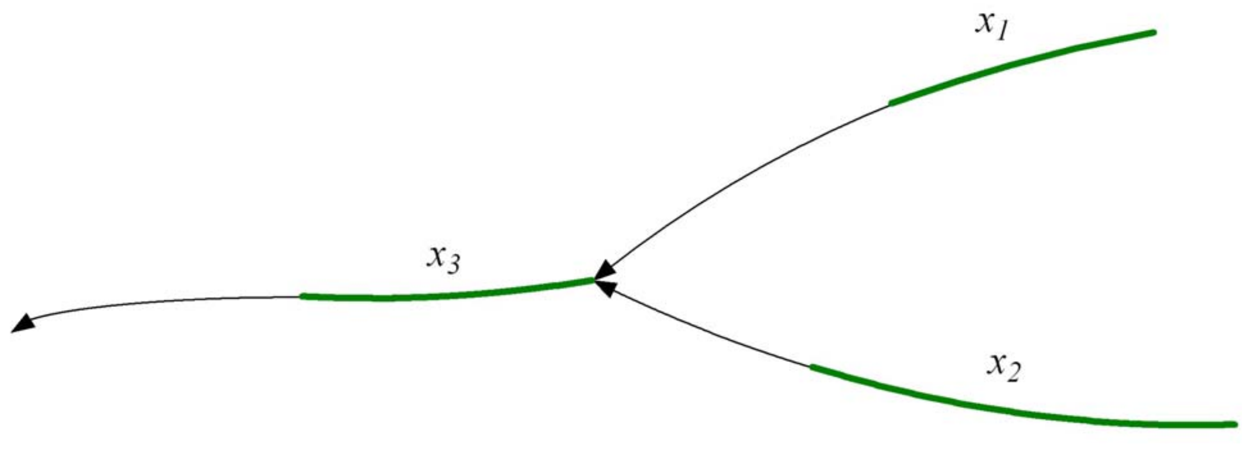


Figure 1 – Schematic representation of a branched stream network, with partial coverage of riparian buffers on each reach.

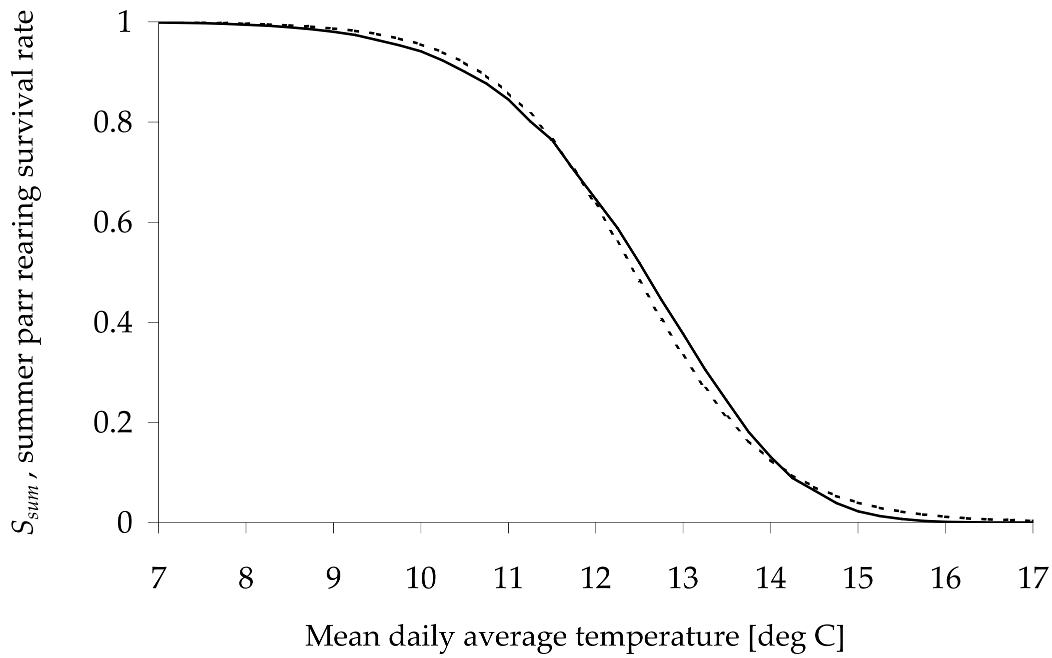
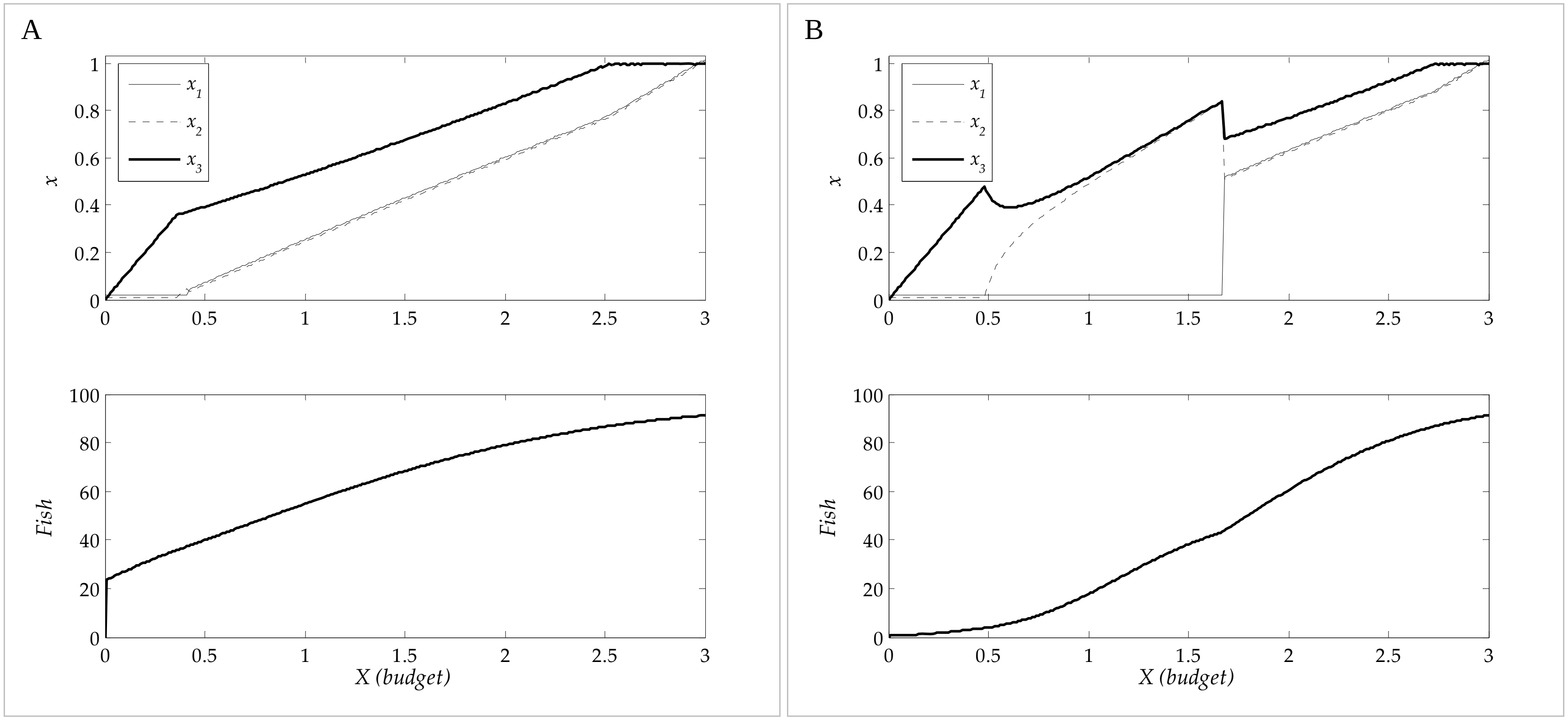


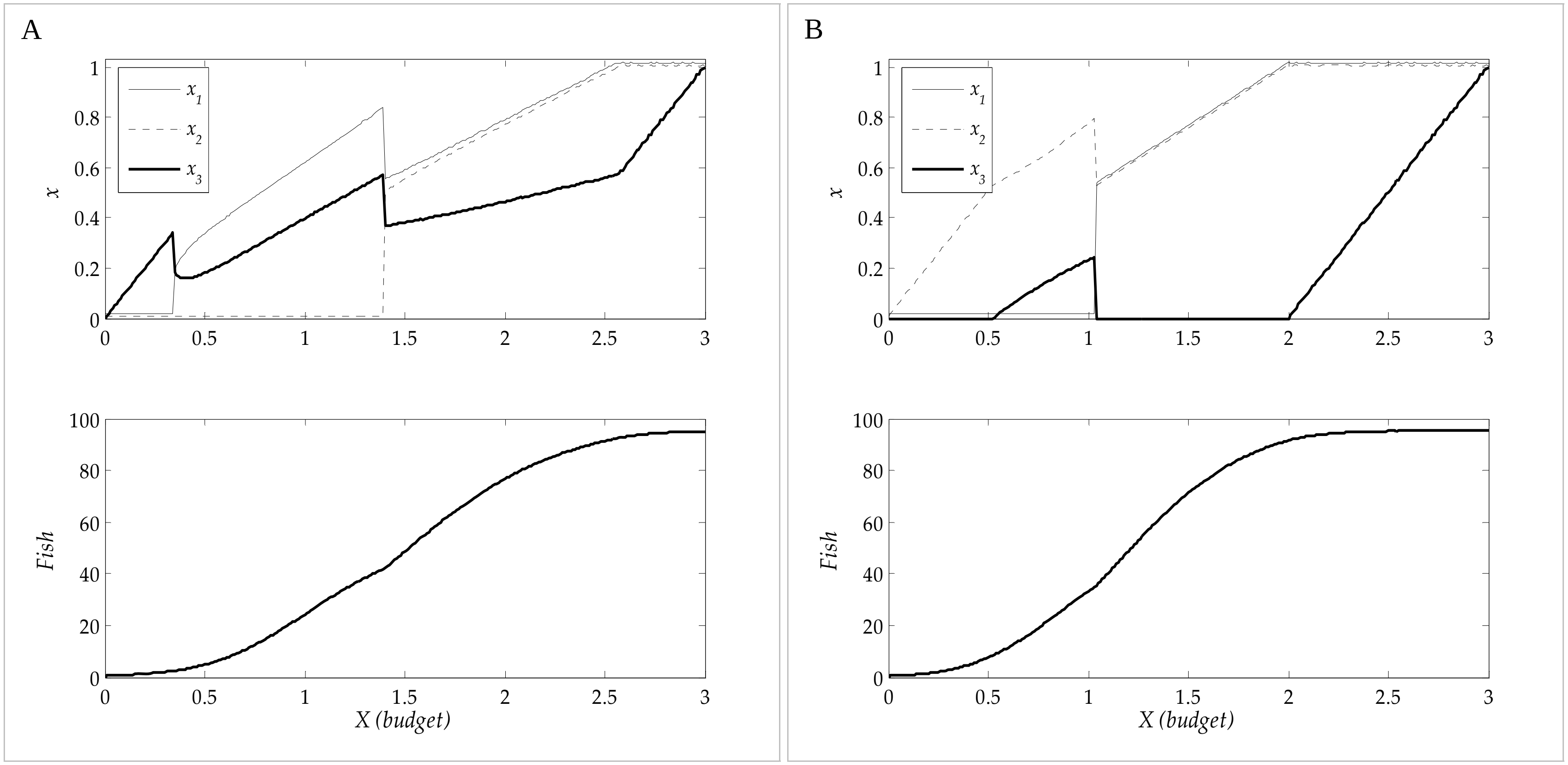
Figure 2 – Seasonal survival probability using the model from McHugh *et al*. (2003) (solid line) and using our calibrated logistic survival function (dotted line).



Reach	1	2	3
N	50	50	0
T^{max}	12.5	12.5	12.5
T^{min}	10	10	10
γ	0	0	--

Reach	1	2	3
N	50	50	0
T^{max}	14.5	14.5	14.5
T^{min}	10	10	10
γ	0	0	--

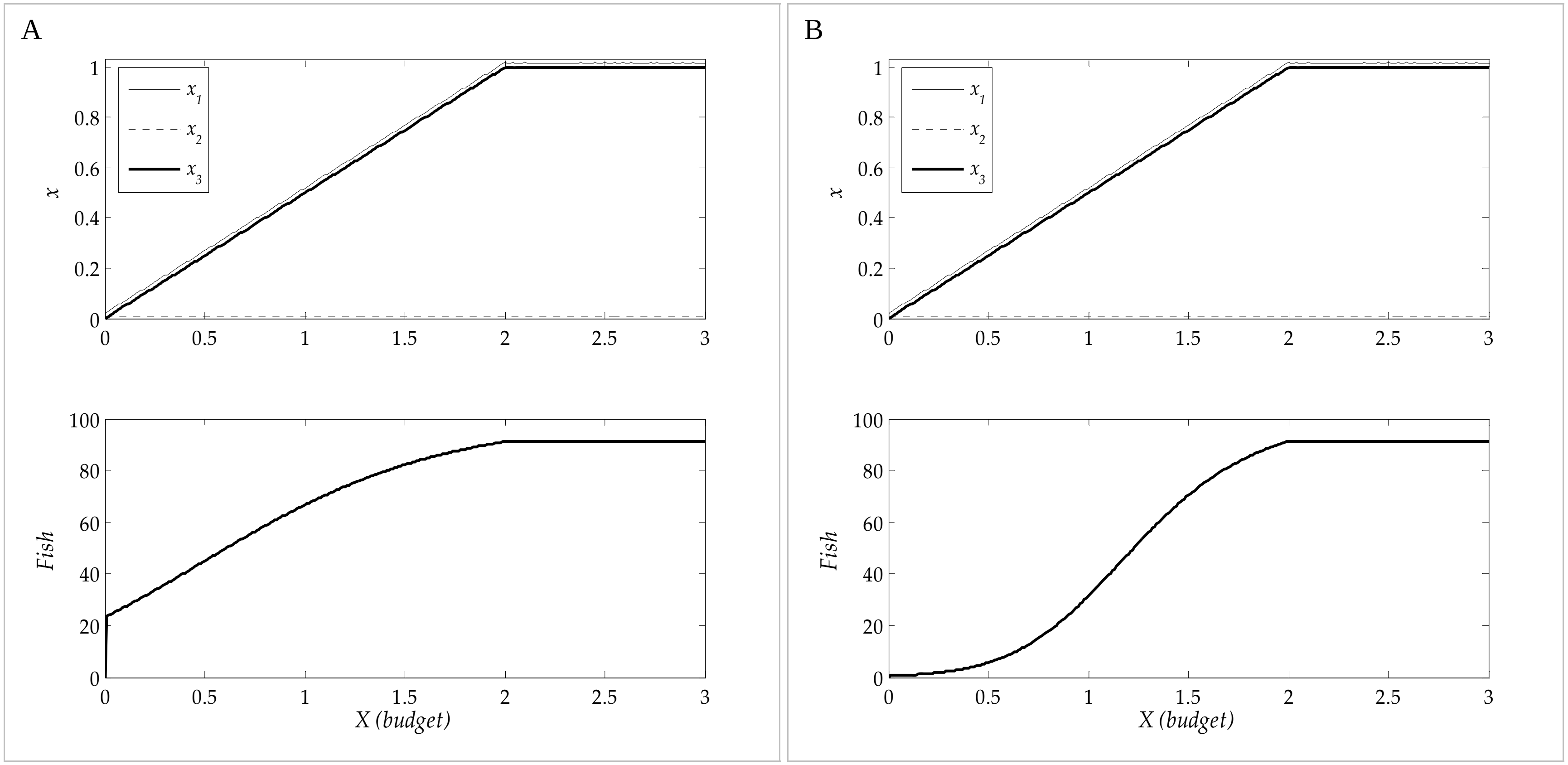
Figure 3 – The influence of initial temperature conditions on the optimal allocation of RBZs.



Reach	1	2	3
N	50	50	0
$T^{\max}$	14.5	14.5	14.5
$T^{\min}$	10	10	10
γ	0.25	0.25	--

Reach	1	2	3
N	50	50	0
$T^{\max}$	14.5	14.5	14.5
$T^{\min}$	10	10	10
γ	0.51	0.51	--

Figure 4 – The influence of the strength of downstream spillovers on the optimal allocation of RBZs.



Reach	1	2	3
N	100	0	0
T^{max}	12.5	12.5	12.5
T^{min}	10	10	10
γ	0	0	--

Reach	1	2	3
N	100	0	0
T^{max}	14.5	14.5	14.5
T^{min}	10	10	10
γ	0	0	--

Figure 5 – The influence of the multiplicative objective function on the optimal allocation of RBZs.

Development of Bioindicator-Based Stated Preference Valuation for Aquatic Resources

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Abstract

Stated preference (SP) survey techniques are often used to estimate willingness to pay (WTP) for ecological improvements. Describing ecological improvements in a stated preference survey is a challenging task, however, because ecologists often choose assessment endpoints that are relevant to the overall integrity and functioning of the ecosystem but that are not directly linked to economic values or easily understood by survey respondents. This paper presents ongoing progress for an EPA/STAR funded research project, *Improved Valuation of Ecological Benefits Associated with Aquatic Living Resources: Development and Testing of Indicator-Based Stated Preference Valuation and Transfer.* The paper highlights issues related to improving SP estimation of use and non-use values for a specific type of aquatic habitat policy—the restoration of fish passage for diadromous species. We begin by outlining conceptual and practical issues related to the estimation of use and non-use values for aquatic habitat restoration. We then discuss potential limitations in current SP methods used to value aquatic ecosystem changes, and present the framework and theory underlying a proposed, innovative approach to valuation. This approach, denoted Indicator-Based Stated Preference Valuation, seeks to provide more appropriate modeling and representation of aquatic ecosystem attributes within SP valuation, through a more solid grounding in ecological models and a more appropriate communication of ecological change. The paper concludes with an illustration of preliminary survey materials currently under development, grounded in the ISPV framework.

Introduction

Stated preference (SP) valuation methods are often used to estimate the amount individuals would be willing to pay (WTP) for ecological improvements or to avoid a ecological degradation.[1] A number of recent studies, for example, apply SP techniques to assess WTP for policies that affect the ecology of aquatic systems (e.g., Whitehead 1992; Loomis et al. 2000; Johnston et al. 2002; Johnston et al. 2002; Morrison et al. 2002; Boyer and Polasky 2004; Morrison and Bennett 2004; Flores and Shafran 2006). The validity of associated value estimates, however, depends on the appropriate combination of ecological and economic information to derive value estimates (Johnston et al. 2002). A common criticism of SP approaches to aquatic resource valuation is that they do not appropriately reflect the richness and potential complexity of the ecological resources being valued (Simpson 1998; Turner 1999), or are not linked systematically to ecological models (Johnston et al. 2006). There is also disagreement concerning whether this limitation is due to a fundamental and unbridgeable difference between economic and ecological sciences (Turner 1999) or arises from simple miscommunication and/or misinterpretation of ecological models by those seeking to estimate economic values (Simpson 1998).

This paper presents ongoing progress for an EPA/STAR funded research project, *Improved Valuation of Ecological Benefits Associated with Aquatic Living Resources: Development and Testing of Indicator-Based Stated Preference Valuation and Transfer.* The paper highlights issues related to improving SP estimation of use and non-use values for a specific type of aquatic habitat policy—the restoration of fish passage for diadromous species. We begin by outlining conceptual and practical issues related to the estimation of use and non-

[1] In principle, tradeoffs can also be measured using "willingness to accept" measures. However, in practice most applications use WTP because it is more readily estimated.

use values for aquatic habitat restoration in general, and the restoration of fish passage in specific. We then discuss potential limitations in current SP methods used to value aquatic ecosystem changes, and present the framework and theory underlying a proposed, innovative approach to valuation. This approach, denoted Indicator-Based Stated Preference Valuation, seeks to provide more appropriate modeling and representation of aquatic ecosystem health (and change) in SP valuation, through a more solid grounding in ecological models and empirical data and a more appropriate communication of ecological change. Finally, we illustrate preliminary choice experiment questions developed within the ISPV framework, and discuss the differences between such questions and those that are typical within contemporary SP valuation.

Economic Value, Valuation Methods, and Ecological Restoration

Within deliberations for potential natural resource policy changes, natural scientists typically provide data on the components and processes of natural systems. These data may derive from the predictions of ecological models or from the results of empirical field studies of particular systems. From an economic perspective, many of the features of these natural systems represent ecological services that may have value to the public, related to either direct or indirect impacts on human welfare or well-being. The total value realized from policies that restore functions of ecological systems can derive from numerous sources. For example, the restoration of diadromous fish passage yields: (1) potential effects on commercial fisheries may generate market values, (2) impacts on recreational fisheries and other recreational activities (visiting a stream to watch fish runs) may generate substantial non-market use values, as well as (perhaps) market values, (3) restoration of associated ecological functions and condition may generate a wide range of additional use and non-use values.

The remainder of this paper focuses on stated preference valuation of aquatic habitat restoration, and more specifically the restoration of fish habitat or passage in streams and rivers. Stated preference methods, including choice experiments, use surveys to estimate the value people hold for well-defined changes in the quantity or quality of a resource and its services, as measured by what they are willing to give up (in the form of other goods and services they value) in exchange. These approaches in effect construct a hypothetical market using carefully developed survey scenarios. For example, choice experiments present individuals with a set of choices among multiattribute policies, allowing survey respondents to "vote" for the policy they prefer, or to reject all policies in favor of the status quo. By observing respondents' choices over a large number of policies that differ across a range of attributes (including household cost), it is possible to estimate preferences and WTP for different types of restoration programs.

Valid estimation of stated preferences and WTP requires that surveys and estimation methods comply with a wide variety of requirements and guidelines. One of the critical requirements in valuation of ecological restoration is that respondents are provided with sufficient information; analyses of economic value must be based on sound ecological understanding (Bingham et al. 1995), such that respondents can accurately predict the expected influence of the proposed ecological change(s) on their well-being, and hence make rational choices. Put another way, values estimated using SP methods must be viewed as contingent upon the information available to respondents—either as provided by the survey or derived from other sources (e.g., preexisting knowledge) (Bergstrom and Stoll 1989; Bergstrom et al. 1989; Hoehn and Randall 2002; Cameron and Englin 1997). In the view of many ecologists and other natural scientists (as well as some economists), however, stated preference survey instruments often fail to provide sufficient information to enable respondents to understand potential effects of ecological change on welfare (Spash and Hanley 1995). Moreover, the attributes communicated in these surveys are often ambiguously linked to underlying ecological models or available field study data, providing no clearly defensible means to link estimated preference functions to measurable (or predictable) policy outcomes (Johnston et al. 2006). Finally, the incomplete specification of ecological outcomes may lead respondents to assume particular ecological production function relationships that do not correspond with those identified by ecologists. The following section addresses some of these potential shortcomings, and outlines potential solutions based on the combination of economic stated preference valuation methods with established ecological methods and indicators used to characterize aquatic ecosystem condition.

Valuation of Aquatic Habitat Restoration: Limitations of Current Approaches

Flores and Shafran (2006) review recent studies that seek to estimate values for river and stream restoration. Of 23 studies reviewed (completed since 1999), none address fish passage. Various other studies address improvements in the ecological condition of rivers and watersheds (e.g., Morrison et al. 2002; Holmes et al. 2004; e.g., Morrison and Bennett 2004; Hanley et al. 2006), yet again we are aware of no recently published studies that explicitly address attributes related to the restoration of fish passage through the provision of fish ladders and/or removal of dams. Hence, while aquatic habitat restoration is addressed by a substantial number of past works, the provision of fish passage has been given little attention in the valuation literature.

One of the key issues in survey design is how to define and describe the improvement to ecosystem function (Flores and Shafran 2006, p. 272). While not made explicit by most published SP studies (for an exception, see Holmes et al. 2004), this is most often accomplished using some form of ecological indicator(s). Ecologists have developed a suite of indices to measure community health and to measure the level of community impacts from stressors, such as species richness and diversity indices and dominance by opportunistic species that is characteristic of a disturbed community (e.g., Davis and Simon 1995; Bortone 2005; Jorgensen et al. 2004). Within stated preference (SP) or survey-based valuation, the role of such ecological indicators is to communicate changes in resource quality or quantity, such that meaningful expressions of value may be elicited (Spash and Hanley 1995). Such information must not only be placed in a format that is readily understood by respondents, but that also provides an accurate representation of the policy change being valued (Mitchell and Carson 1989; Bateman et al. 2002; Spash and Hanley 1995). As stated by Schiller et al. (2001), "effective communication of ecological indicators involve[s] more than simply transforming scientific phrases into easily comprehensible words. [It requires] language that simultaneously fit[s] within both scientists' and nonscientists'…frames of reference, such that resulting indicators [are] at once technically accurate and understandable."

Despite the significant attention given to indicator development in the ecological literature, ecological indicators used within SP surveys are often based on *ad hoc* metrics unrelated to formal models of ecosystem change. Measures of change in aquatic living resources presented in SP surveys: (1) rarely correspond to formal indicators presented in the published ecological literature; (2) rarely address uncertainty associated with prediction and measurement; (3) are often ambiguously linked to quantifiable and measurable long-term policy impacts, and; (4) are often based on arbitrary or vague measurement units (Jackson et al. 2000, Ebert and Welsch 2004). For example, Holmes et al. (2004) use an ordinal (hig h, medium, low) "index of naturalness" as an attribute characterizing riparian ecosystems in North Carolina. In the context of river restoration, Morrison and Bennett (2004) incorporate an attribute communicating the percentage of the river with "healthy riverside vegetation and wetlands." While perhaps easily understandable by respondents, these scales may have little clear meaning within the context of formal ecological models. From the ecologist's perspective, such SP indicators are inadequate.

Indicators commonly used in SP surveys may also fail to communicate critical and welfare-relevant attributes. For example, focus group results reveal that respondents typically view aquatic ecosystem changes relative to historical or pristine conditions (Besedin and Ranson 2004; Johnston et al. 2006b). Common cardinal metrics used in surveys (e.g., 1 million juvenile fish; 20,000 sea birds), in contrast, may have little meaning to respondents.[2] Indeed, with the exception of a few of well-known and tested metrics (e.g., the RFF water quality ladder, Vaughn and Russell 1982), there has been little attention devoted to the development of meaningful (Ebert and Welsch 2004), consistent ecological indicators in SP research.

Using poorly defined indicators may also yield an ambiguous understanding of the goods being valued (i.e., inadequate information regarding specific ecological attributes that influence utility). For example, when presented with an attribute indicating changes in fish populations related to fish passage or other changes, it may be unclear whether resulting WTP estimates reflect a value for the *fish populations themselves*, a value for fish as a proxy for *broader ecological condition*, or a value for fish as a proxy for *some other valued ecosystem function or service*. Do respondents care directly about the loss of a specific number of fish, or do they instead care about other commodities—such as ecosystem health or the probability that fish populations will persist into the future—and use fish numbers as a proxy for the attributes of real concern? Models underlying valuation efforts provide few answers to such questions. In still

[2] This may be one reason why contingent valuation estimates based on such cardinal indicators have been shown to fail scope tests in past assessments (cf. Heberlein et al. 2005).

other cases, SP survey scenarios may confound management *approaches* (what is done) with ecological *outcomes* (what results in terms of measurable ecological change), again leading to the potential for inappropriate respondent assumptions to bias welfare estimates. For example, Yonts et al. (2003) illustrates an SP survey addressing forest biodiversity preservation that characterizes policy outcomes primarily in terms of *what is done* (e.g., the percent of biodiversity reserves, endangered species habitat, and salmon runs either protected or restored; the forest age management approach applied). Left unstated are the measurable ecological improvements that might result, leading to the possibility that respondents may assume an (unstated and likely incorrect) relationship between management actions and ecological outcomes. The resulting ambiguity has significant implications for the validity and transferability of welfare estimates.

The Theoretical Issue

In formal neoclassical economic terms, the question regards the structure of utility. For example, assume that respondent *i*'s utility is of the form $U_i(E(F))$, where $E(\cdot)$ is ecosystem integrity, biodiversity or some other assessment endpoint, and F is the number of diadromous fish (e.g., river herring, shad) passing upstream (or some other measurement endpoint or quantifiable indicator). If the respondent cares about F solely because of its impact on $E(\cdot)$, then a valuation question framed solely in terms of F effectively asks the respondent to directly value changes in the *input* rather than changes in the *output* which influences utility.

The first implication of this is an obvious potential for bias. It is well-known that a preference function of the form $U_i(E(F))$ can be mathematically collapsed to $W_i(F)$. However, if individuals value $E(\cdot)$ directly, the specification of valuation scenarios solely in terms of F will likely lead to biased WTP estimates, because this requires respondents to assume their own (almost certainly incorrect) ecological production function (i.e., to assume a relationship between

F and $E(F)$). As noted by Carson (1998, p. 23), "[r]espondents will tend to fill in whatever details are missing in the CV survey with default assumptions. These may differ considerably from what the researcher perceives." This is particularly true for complex ecological resources and functions, over which respondents may have little baseline information (e.g., Carson 1998; Spash and Hanley 1995). For this reason, it is critical to know if preferences take the form $U_i(E(F))$ rather than the often assumed form $U_i(F)$.

The potential for bias is compounded if utility takes a more complex form such as $U_i(E(F),H(F),F)$, where $H(F)$ represents a second valued ecological attribute influenced by F. For example, $H(\cdot)$ might represent expected quality of recreational fishing for non-diadromous species (e.g., bass), where diadromous fish could have a positive ($\partial H(\cdot)/\partial F > 0$) or negative ($\partial H(\cdot)/\partial F < 0$) marginal effect on recreational fisheries, depending on ecological relationships.[3] Here, F influences utility directly, as well as indirectly its influence on both $E(F)$ and $H(F)$. Moreover, the indirect effects may not be universally positive. In this context, appropriate modeling of utility is critical to obtaining understanding and obtaining unbiased estimates of values for policies that influence F, $E(F)$ and $H(F)$.

The use of oversimplified ecological indicators, moreover, may not yield meaningful valuation for policy purposes. Assume, for example, that ecologists have developed and tested multi-metric indicators of overall ecosystem condition (see additional discussion of these indicators below) that are designed to proxy for true underlying ecosystem condition, $E(\cdot)$, that influences individuals' well being. As a simple illustration, assume that the multimetric indicator W is a formal indicator or measure of $E(\cdot)$ developed by ecologists. However, the

[3] For example, in some cases diadromous fish may serve as prey for valued recreational species. In other cases diadromous fish may compete for food with various life stages of recreational fish. The balance of such effects may be positive or negative.

survey designer, concerned that respondents will not be able to understand *W* (or unaware of the appropriate ecological literature), instead uses a simplified indicator (e.g., high-medium-low), which we denote $\widetilde{W}$. The difficulty is that respondents must infer $E(\cdot)$ based on $\widetilde{W}$, with no provided function or information to make this inference; there is no formalized relationship between $\widetilde{W}$ and either *W* or $E(\cdot)$.[4] Hence, the model estimates WTP for a derived attribute, $\widetilde{W}$, which has no formal ecological meaning or interpretation.

A Proposed Solution: Indicator-Based Stated Preference Valuation

Indicator-Based Stated Preference Valuation (ISPV) is proposed here as a novel approach to welfare evaluation that integrates previously established ecological indicators within SP valuation methodology. ISPV provides a formal basis in established and measurable ecological indicators, a clear structure linking these indicators to specific attributes influencing individuals' well-being, a clear set of criteria to ensure that indicators are consistent and meaningful, and a consequent ability to link welfare measures to measurable and unambiguous policy outcomes. The proposed approach allows the use of measurable indicators within utility-theoretic valuation models, while providing ecological linkages among indicators and assessment endpoints. The result is a multidisciplinary approach to ecological valuation, distinguished from the often *ad hoc*, piecemeal use of ecological information by existing SP valuation.

Figure 1 outlines the basic structural linkages that form the integrated economic-ecological model underlying ISPV. As shown by the illustrated framework, ISPV recognizes that the "assessment endpoints" or fundamental outcomes of fish restoration—as is the case with most environmental policies—are often directly unobservable (US EPA 1998). These are shown

[4] This lack of formalized relationship may be realized at either the researcher level (i.e., researchers have not specified any formal relationship) or at the respondent level (i.e., researchers may have specified a relationship, but this is unknown or poorly understood by respondents. In applied stated preference valuation, the former is (arguably) most common.

as “ecological impacts” in figure 1. For the case of fish passage, ecological impacts may include changes in the survival of fish passing upstream annually, the size and composition of fish populations, and community-level characteristics such as diversity, trophic structure, productivity and resilience. These impacts also represent the attributes that influence people’s well-being (utility).

While often not directly observable, ecological impacts may be measured (and represented) through a set of matching ecological indicators (or measurement endpoints) developed by natural scientists (US EPA 1998). Some of these indicators may be simple and relatively direct—such as the use of fish counter data to measure the number of fish passing upstream. Others are more complex, less direct, and require additional interpretation—such as indices of biological diversity and overall ecological condition. These indicators are mapped to the underlying impacts through established (although sometimes controversial) ecological models (Davis and Simon 1995; Jorgensen et al. 2004; Bortone 2005).

For example, the ecological literature provides numerous integrative, multimetric indices that formally assimilate multiple ecosystem components and are widely used as indicators of ecosystem health or condition (e.g., Davis and Simon 1995; Jorgensen et al. 2004; e.g., Bortone 2005). These indicators (e.g., Index of Biotic Integrity (IBI) and the Estuarine Biotic Integrity Index (EBI)) represent measurement endpoints that can be calculated from data on ecological inputs and can serve as proxies for assessment endpoints that affect utility. Ecologists who have been focused more specifically on species at risk have also developed methods (e.g., population viability analysis or PVA) for projecting population-level uncertain outcomes under alternative management strategies (Lee and Rieman 1997; Beissinger 2002; Jager 2006). If integrated appropriately into valuation models, indices of population viability or ecosystem integrity provide a basis to distinguish utility gained from specific elements of the ecological system (e.g., populations of specific species) from utility associated with certain elements of overall system condition (e.g., the long term viability of species in given ecosystems).

Primary elements distinguishing ISPV from traditional stated preference valuation hence include:

1. clear distinction between ecological impacts (or assessment endpoints) and indicators (measurement endpoints), as well as between management approaches (what is done) and outcomes (what results);
2. explicit recognition of the potential divergence between actual ecological production functions and those that might be assumed by uninformed survey respondents;
3. explicit recognition of the potential relationship between higher- and lower-level indicators[5] in respondents preference functions, and the possibility that the latter may be used to infer the former;
4. related clear criteria for both indicators and information incorporated in SP surveys, designed to (a) impose an unambiguous link between survey scenarios and well-defined, measurable ecological outcomes and/or ecological model predictions (b) prevent divergence between ecological relationships assumed by respondents and those modeled by ecologists or policy experts (see discussion below), and;

[5] In the context of fish passage restoration, a "higher-level indicator" might include an index of biological integrity, designed to characterize the overall condition and integrity of the aquatic ecological system in question (Karr 1991). Lower-level indicator might include such measures as the number of diadromous fish passing upstream, the percentage of total fish biomass comprised of diadromous species, or the presence of certain indicator species such as freshwater mussels. Respondents may have preferences (and values) over both higher- and lower-level indicators, and may (appropriately or inappropriately) assume relationships between the two.

5. associated improvements in the ability to model linkages between policy impacts and economic values, and hence derive more defensible welfare estimates for ecological policy changes.

To be sure, there are numerous examples of stated preference survey instruments addressing aquatic habitat valuation that incorporate ecological indicators—either simple or complex—as elements in survey scenarios (Morrison et al. 2002; Holmes et al. 2004; Morrison and Bennett 2004; Hanley et al. 2006). *Moreover, it is entirely possible for non-ISPV surveys to derive valid welfare estimates in some cases.* However, the lack of a clear framework conceptualizing distinctions between ecological impacts and ecological indicators—as well as the potential linkages among different types of impacts and indicators—can lead to ambiguity regarding the interpretation of model results, skepticism among natural scientists and potential bias in welfare guidance to policymakers.

Relationships Between Indicators and Survey Attributes

ISPV clearly identifies most attributes presented in stated preference survey scenarios as *indicators* that proxy for the underlying, largely unobservable attributes that influence utility. This recognition also highlights the fact that survey respondents may not be aware of the specific linkages between indicators and underlying conditions assumed by natural scientists. *Hence, unless provided with sufficient information and a set of indicators that map to attributes in their underlying utility functions, individuals may draw erroneous conclusions based on the specific indicator set provided.* This recognition is largely absent from the existing stated preference literature, which typically assumes that respondents will answer questions based solely on the attributes presented in survey scenarios (i.e., that the attributes that are presented are the attributes that directly enter the utility function).

For example, focus group respondents often reflect general concerns for the overall ecological condition of water bodies affected by policy changes (e.g., Besedin and Ranson 2004). In reaction, surveys such as those of Morrison and Bennett (2004) and Morrison et al. (2002) incorporate a wide range of individual ecological indicators, for example providing information on the presence/absence (or number) of various species and the percentage of river miles supporting "healthy vegetation and wetlands" (Morrison and Bennett 2004). Such surveys, while clearly well-designed according to the standards of the literature, can lead to potential bias and ambiguity when viewed within a more formal ecological-economic framework. For example, figure 1 makes it clear that attributes such as the number of native fish species present can serve as *indicators* for at least two types of underlying assessment endpoints that influence utility: 1) those dealing directly with the size and composition of fish populations, and 2) those dealing with overall system health or integrity. Which of these elements is being valued by respondents who react to the presented "native fish species" attribute is unclear. Moreover, the functional relationship used by respondents to derive information on (2) from the presented survey attributes is also unclear, and almost certainly diverges from that presented in the ecological indicators literature.

For the case of fish restoration, ISPV addresses these challenges through the inclusion of specific "lower-level" indicators for each of the resource-specific attributes that focus groups suggest influence individuals' utility. For example, one might include indicators representing the number of fish passing upstream to spawning areas, the size of spawning areas available to diadromous fish, changes in rare or threatened species that are ecologically dependent on migratory fish, and similar indicators. Following the structure of figure 1, however, one would also include at least one representation of the change in overall ecosystem condition or population viability resulting from the provision of fish passage. Finally, one would include specific information providing at least some detail regarding the relationship between various indicators presented in survey scenarios (i.e., ecological production functions)—to avoid the potential for erroneous assumptions among respondents.

All ecological indicators, including those representing population and ecosystem status, are also scaled relative to clear benchmarks, providing respondents with unambiguous referents. For example, Population Viability Analysis provides an example of an approach that yields benchmarks on the status of individual species in the system. PVA is a process wherein demographic features (abundance, population structure), genetic characteristics, and environmental variability are modeled to yield predictions of the likelihood that a population will persist for a specified period of time under different scenarios (Boyce 1992). Indices of Biotic Integrity provide comparable benchmarks on a system-wide level; they are conventionally scaled relative to least-impacted, relatively pristine reference sites (Jackson et al. 2000).[6] Other lower-level indicators such as fish-counter data may be scaled relative to either historical measures or comparisons to established regional reference sites. The use of well-defined reference points for both baseline conditions and potential ecological change both provides a clear link between survey attributes and established ecological models and practice, and also provides information critical to enable respondents to understand the scope of changes under consideration.

Finally, recognizing the importance of linking estimated preference functions to measurable policy outcomes, ISPV imposes a requirement that indicators used in surveys are both unambiguous from the perspective of natural scientists and are grounded either in

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[6] Both PVA and IBI analyses are now commonly used to inform species conservation efforts and/or resource management decisions, and their use in ISPV will therefore strengthen the integration of ecological science and resource management with valuation methods.

potential/actual predictions of established ecological models or in ecological field data that is either currently available or could be made available using standard methods. Moreover, to the extent possible given respondents' cognitive limitations, the basis in measurable data or ecological models should be communicated, at least at a basic level.

While the informational and developmental requirements of ISPV are somewhat greater than those of standard stated preference approaches, the result is a clearer understanding of the attributes driving survey responses, a reduced likelihood that responses are influenced by inappropriate ecological assumptions, and more valid information about public values regarding ecosystem protection. Moreover, the information presentation required for ISPV can be accomplished using established methods—such as the use of video and graphical devices during survey implementation (e.g., Opaluch et al. 1993, Johnston et al. 1999, Johnston et al. 2002).

Criteria for Indicators and Survey Attributes

The proposed valuation approach is designed to generate welfare measures that can be *unambiguously linked to models of ecosystem function*, are based on *measurable outcomes*, and can be more *easily incorporated into benefit cost analysis*. In addition, the approach provides clear mechanisms to distinguish the role of attributes as valued components in and of themselves, versus as indicators of broader ecological condition. As noted above, these goals lead to a set of systematic criteria for survey attributes that are unique to ISPV. These criteria are in addition to the well-known guidance for survey attributes provided by the stated preference literature (e.g., Mitchell and Carson 1989; Bateman et al. 2002; Arrow et al. 1993), and include the following:

1. Ecological survey attributes must have a *systematic linkage to measurable*

indicators representing data that is either commonly available to resource managers, or that could be reasonably obtained using established field methods.[7]

2. Ecological survey attributes must have a *clear, quantitative basis* that is both understood by survey respondents and is meaningful to natural scientists.
3. Ecological survey attributes must be viewed as largely *consistent and meaningful* by natural scientists (subject, of course, to controversies regarding the appropriateness of certain indicators that are a long-standing characteristic of the ecological literature).
4. Ecological survey attributes must be *grounded in identifiable reference conditions*, both in terms of the best and worse outcomes within the realm of practical possibility.
5. Ecological survey attributes must be clearly *associated with specific ecological services* within potential respondents' utility functions.
6. Ecological survey attributes must cover the *full range of primary ecological services* that are both affected by proposed policies (in a significant manner) and valued by the public.
7. To the extent warranted by preliminary research on public preferences (e.g., focus groups), *attributes must communicate both policy approaches (what is done) and ecological outcomes (what results)*.

Violation of any of the seven above-noted criteria can lead to situations in which

[7] Ad hoc or after the fact linkages are insufficient. For example, one might attempt to link a "high-medium-low" scale to measurable bioindicators using a variety of assumptions. However, unless clearly specified to survey respondents prior to completing survey questions, such linkages are ad hoc and non-unique, and will likely lead to biases related to divergence between respondents' perceptions and actual ecological relationships.

associated WTP estimates are either biased or cannot be securely linked to measurable policy outcomes. Hence, while their use may present an additional burden to SP survey designers, these criteria also help ensure that resulting welfare measures are both valid and viewed as appropriate by natural scientists. For example, violation of criterion #1 leads to a potential disconnect between attributes valued by survey respondents and policy outcomes that are either measured or predicted by ecologists. Violation of criterion #6, in contrast, might lead respondents to draw unintended conclusions regarding valued ecosystem services that are nonetheless omitted from survey scenarios (see Johnston and Duke (2007) for a closely related discussion of technical issues in discrete choice preference modeling). As described above, these conclusions will likely be based on incorrect inferences drawn from those ecological attributes that *are* presented in survey scenarios. Similar causal links to welfare estimation biases or limitations may be shown for each of the seven above-noted criteria. Review of SP survey instruments in the published literature, however, shows widespread violation of these criteria. While this does not imply that associated welfare measures are *necessarily* biased, it does lead to questions regarding the interpretation of results for policy guidance.

Within this framework, multimetric indicators of ecological integrity present a particular challenge, given that (1) a variety of such indicators are available, with relatively standardized formats and scaling, (2) the development of such indicators can be highly site-specific, (3) such indicators have not been developed for most aquatic areas, and (4) these indicators can be controversial. Hence, when specifying such indicators in survey scenarios, it may be necessary to generalize at least somewhat, such that subsequently-developed multimetric indicators can be "plugged-in" to estimated preference functions. For example, one might specify survey scenarios based on a multimetric Index of Biotic Integrity (IBI) modeled closely after those reported in the literature (Jorgensen et al. 2004; Karr 1991), even though a specific IBI has not been developed for the water body in question. This IBI would be specified with the same standardized scales present in published IBIs, such that site-specific IBI results could be later combined with estimated preference functions to provide more exact welfare estimates.[8]

Implications for Benefit Transfer

The proposed ISPV framework and attribute criteria are also designed to promote SP valuation functions that are better suited to benefit transfer. Function-based benefit transfer (including that based on meta-analysis) requires reconciliation of valued policy changes (e.g., changes in valued ecological services) at study site(s) and policy site(s) (Smith et al. 2002). This reconciliation is complicated by the wide array of different measurements and units often applied in SP research to communicate essentially similar ecological changes. Moreover, as noted above, many of these metrics have unspecified or ambiguous linkages to accepted ecological models or data collected by management agencies. The proposed methods, in contrast, are developed around established, well-defined indicators drawn from data commonly collected by management agencies (e.g., the number of diadromous fish passing upsteam, as commonly measured using fish counters installed on fish ladders or other fish passage devices). Hence, the resulting valuation functions are more likely to be directly commensurate with data available for policy sites, allowing more defensible benefit transfer. The proposed methods will also allow more defensible *tests* of benefit transfer performance, as the unambiguous definition

[8] In such cases, respondents would be provided with information regarding the general components of the IBI, but would not be given detailed information regarding the specific mathematical composition of the index. Even if site-specific IBI results were available, it is unlikely that respondents would have the experience or education to understand the complex mathematics that form the basis of many multimetric indicators. Hence, the challenge is to provide sufficient information such that respondents and experts share the same fundamental interpretation of the index, without the requirement that respondents be provided with complex mathematical details.

and common availability of incorporated indicators will ensure that transfer tests are drawn from an appropriate "apples to apples" comparison of ecological change.

Preliminary Survey Scenarios

The proposed approach is currently under the process of empirical development and testing for the valuation of fish passage in New England water bodies. As a result, quantitative results are not yet available. However, numerous expert interviews, four focus groups and significant ecological background research have been conducted over the past 18 months. In addition, the project has drawn from prior results from one dozen transcribed focus groups conducted during the design of a prior stated preference survey for US EPA, addressing similar issues related policy impacts on fish and associated effects on aquatic ecosystem health and integrity (US EPA 2005), as well as evidence gained by the authors in numerous prior stated preference studies addressing WTP for ecological improvements (e.g., Johnston et al. 1999; 2002).[9] This combined research has led to the development of preliminary templates for survey choice questions.

Figures 2a and 2b illustrate an example of the current format of choice experiment questions currently under further development and testing. As shown by figure 2b, survey attributes represent effects on six primary vectors over which focus groups indicated respondents maintain preferences. These vectors characterize (1) the size of aquatic habitat areas restored, or made newly available to diadromous fish, (2) the number of diadromous fish that use the provided fish passage devices to reach the restored upstream river areas, (3) effects on recreational fishing for non-diadromous fishes, (4) effects on rare and threatened aquatic species,

[9] This project addressed use and nonuse values associated with the reduction of entrainment an impingement losses of fish in US water bodies.

(5) effects on other fish dependent wildlife, and (6) effects on overall ecological integrity. Survey attributes provide data both on what is done by managers (e.g., how many acres of habitat are restored) and the ecological outcomes that result (e.g., how many fish pass upstream, effects on freshwater mussels, etc.). Attributes also represent both lower- (e.g., acres restored, fish passing upstream) and higher-level (e.g., ecological integrity) ecological indicators, and survey information materials provide at least rudimentary information on the relationships between the two indicator types.

Each attribute is represented in relative terms, with regard to upper and lower reference conditions defined in survey informational materials. The provided scores represent the percent progress towards the upper reference condition (100%), starting from the lower reference condition (0%). The scenario also presents the cardinal basis for this relative score (e.g., number of acres, number of fish). As noted above, all attributes are grounded in measurable indicators. Prior survey informational materials clarify the specific interpretation of each attribute, the associated reference conditions, and the reason for their inclusion in survey scenarios. These descriptions balance a need to provide sufficient ecological detail with a need to provide concise information that will not exceed the cognitive capacity of respondents.

For example, the Migratory Fish score is described in the survey using the simple text, "the Migratory Fish Score shows the number of fish that swim upstream each year. The score shows the number of fish, as a percent of the maximum possible in the river." The lower (0) and upper (1.2 million) are clearly identified, and are drawn from established models used by the Rhode Island Department of Environmental Management (RIDEM 2006; O'Brien 2006). Prior informational materials also clearly describe the effect of fish passage restoration on migratory fish, along with mechanisms whereby fish passage restoration impacts the other ecological attributes characterized by the survey question.

The Freshwater Mussels score, in contrast, is motivated by focus group respondents' clear concerns for rare and threatened species, where freshwater mussels are the primary rare species that would be significantly affected by the restoration of fish passage in Rhode Island rivers (Raithel and Hartenstine 2006; O'Brien 2006). The survey first describes the ecological basis for this effect ("…some animals require migratory fish to survive, such as certain freshwater mussels whose larvae need to attach to river herring.") The survey attribute is then characterized: "[t]he Freshwater Mussels Score is based on the presence of rare mussels. These mussels require fish to complete their life cycle. They are indicators of ecosystem health and are endangered in many states. The score shows the percentage of these species that are common in restored areas." Finally, the survey scenario characterizes the effect on these species, relative to the lower (0 species) and upper (5 species) reference baselines (cf. Raithel and Hartenstine 2006), and the current level in the non-restored area (0 species). Similar information and baselines are provided for each survey attribute, as based on preliminary ecological research, interviews with policy and ecological experts, and focus groups with Rhode Island residents. Initial pretests with these questions and attributes have been promising, but further testing and development is required prior to survey implementation.

In addition to the specific attributes present in draft choice questions, the survey booklet also provides information to assist respondents in understanding the general policy and ecological context. For example, respondents in early focus groups requested clarification regarding "whether this issue was important" from a broader ecological perspective, and the extent to which fish passage had been diminished relative to its historical maximum. For this reason, the survey provides numerous maps and other graphics to illustrate and quantify the broader effects of fish passage on ecological systems, as well as the historical and present extent of habitat available to these species. For example, Figures 3 and 4 represents maps and accompanying text included in the survey materials to illustrate the present and historical extent of fish passage in Rhode Island and the Pawtuxet Watershed; these maps were designed explicitly for the survey based on ecological data from RIDEM and RIGIS map templates (Erkan 2002).

As noted above, these survey materials are under development, with a number of focus groups and expert interviews planned prior to survey implementation. It is likely that numerous changes will be made to survey materials, based on input from these sources. The current illustrations, however, show up-to-date progress towards a survey instrument that complies with the guidelines and criteria of ISPV developed during the initial phases of the research, as summarized above. The goal of these developmental activities is to design a survey instrument that is viewed as equally appropriate by (1) potential respondents, (2) policymakers, (3) ecologists and other natural scientists, and (4) valuation practitioners and other economists.

Conclusion

Current stated preference valuation methods may in many cases provide insufficient information to enable meaningful, unbiased WTP estimation of the value of ecological changes. The research presented here, although still in its early stages, is designed to extend the frontier of valuation research at the intersection of ecology and welfare economics, with a specific emphasis on the critical nature of measurement metrics and structural linkages between ecological and economic models. Unlike prior work, here we emphasize the role of ecological indicators not only as simple and interchangeable means to communicate "well-known" ecological information (the common economic perspective)—but as a fundamental means to bridge the gap between ecological and economic treatments of policy outcomes. Despite numerous prior efforts to merge ecological and economic information for neoclassical valuation purposes, divergent disciplinary perspectives often lead to an ad hoc treatment of ecological attributes—with little reference to the extensive (and sometimes controversial) work by ecologists to model and measure ecosystem health and condition. The purpose of this research is to ground SP welfare evaluation—both theoretically and empirically—in exactly the types of ecological indicators and associated models developed and tested within the ecological sciences, as well as measurable data available to policymakers. This research also formalizes this "grounding" using a set of derived guidelines and criteria for the development of SP surveys and incorporated ecological indicators. This formal grounding offers many advantages, but also significant challenges, which we will be addressing as we further develop survey materials over the coming months. The goal is a more defensible structure for ecological valuation, as well as applied welfare evaluation viewed as more appropriate by natural scientists.

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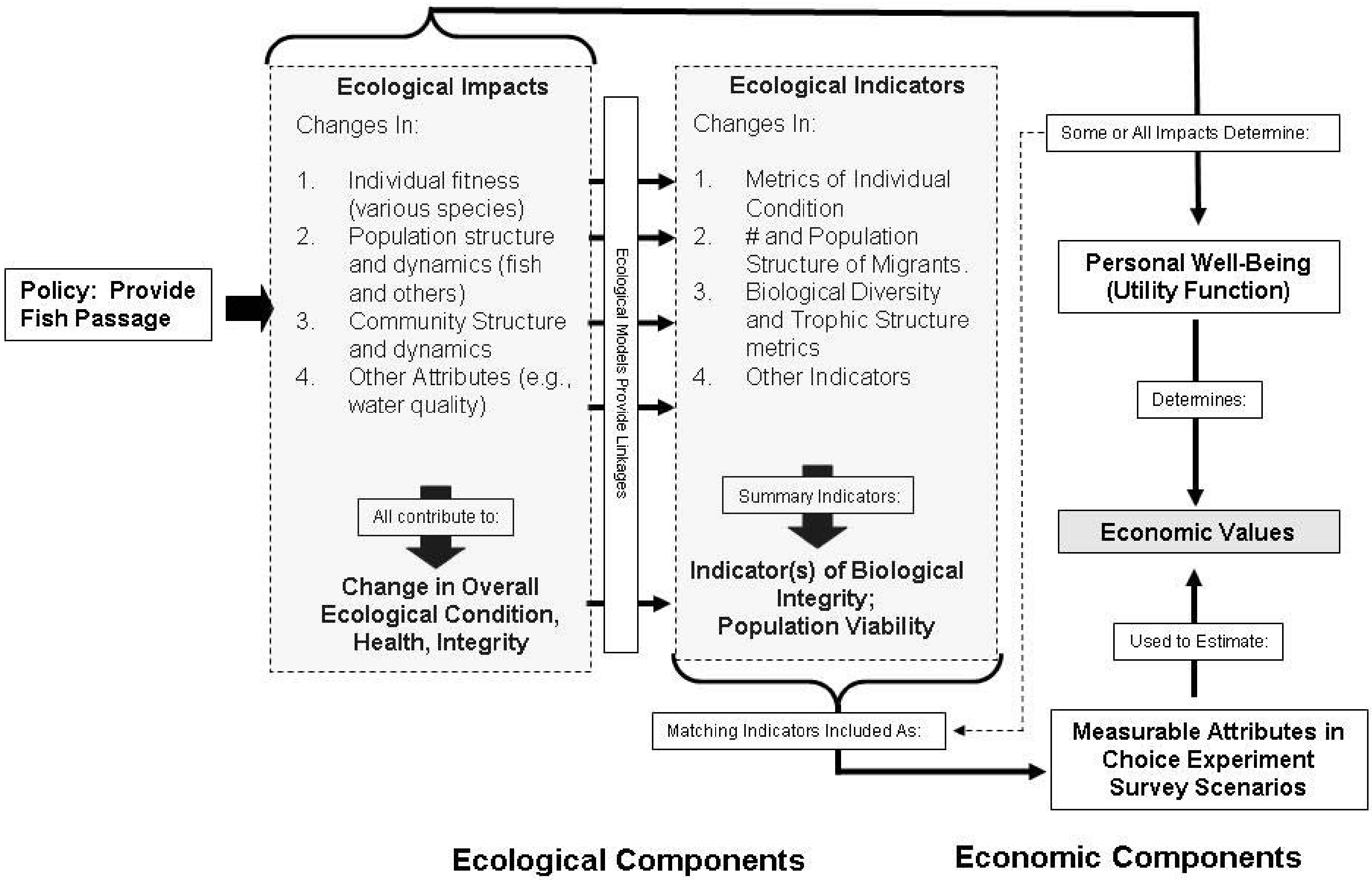


Figure. 1. Conceptual Framework of Indicator-Based Stated Preference Valuation

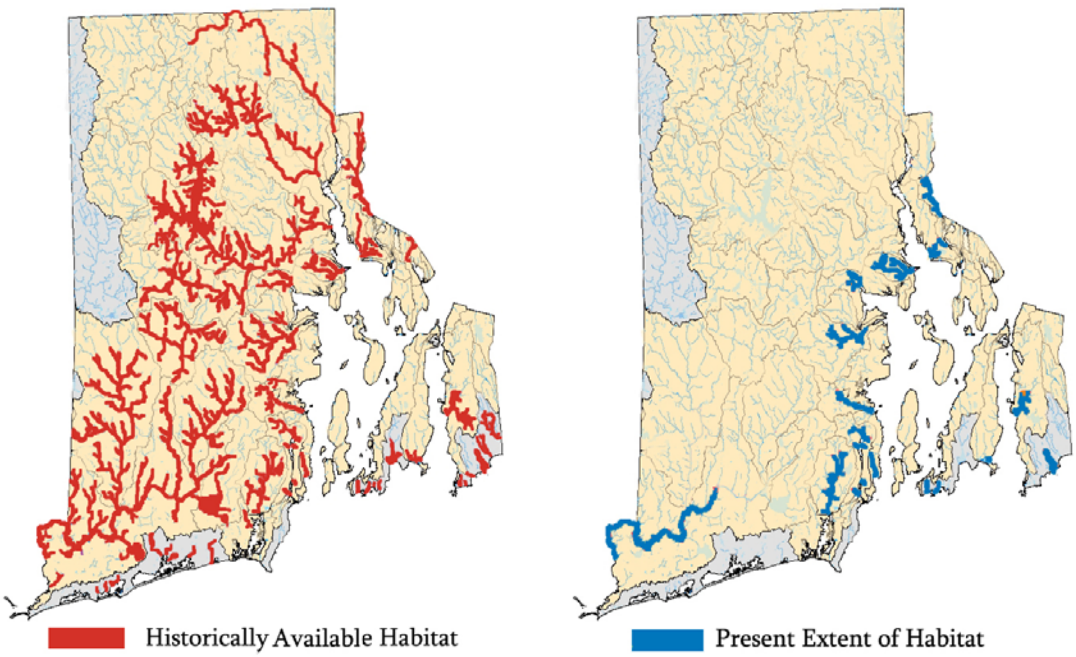
Question 3. Assume **Options A** and **B** are different Fish Passage Restoration Options for the Pawtuxet Watershed, and that the **Current Situation** is the status quo with no restoration. Unless otherwise indicated, scores show effects in restored area of the river only. **How would you vote?**

Figure 2a. Preliminary Choice Experiment Question Text

Effect of Restoration	Current Situation (no fish ladder)	Fish Ladder Option A	Fish Ladder Option B
	SCORE OUT OF 100	SCORE OUT OF 100	SCORE OUT OF 100
 Fish Habitat	0 0 of 4347 watershed acres restored	3 125 of 4347 watershed acres restored	4 160 of 4347 watershed acres restored
 Migratory Fish	0 0 fish out of 1.2 million possible in watershed	9 100,000 out of 1.2 million possible in watershed	10 125,000 out of 1.2 million possible in watershed
 Angler Catch	50 Anglers catch the limit on 50% of trips	50 Anglers catch the limit on 50% of trips	50 Anglers catch the limit on 50% of trips
 Freshwater Mussels	20 1 of 5 species native to RI are common	20 1 of 5 species native to RI are common	20 1 of 5 species native to RI are common
 Fish-Dependent Wildlife	50 4 of 8 species native to RI are common	62 5 of 8 species native to RI are common	62 5 of 8 species native to RI are common
 Ecological Condition	20 Ecological Health Index	25 Ecological Health Index	25 Ecological Health Index
$ Cost to your Household per Year	**$0** **Increase in Annual Taxes and Fees**	**$3** **Increase in Annual Taxes and Fees**	**$7** **Increase in Annual Taxes and Fees**
HOW WOULD YOU VOTE? (CHOOSE ONE ONLY)	" I would vote for **NO FISH LADDERS**	" I would vote for **OPTION A**	" I would vote for **OPTION B**

Figure 2. Preliminary Choice Experiment Question Template

DAMS AND MIGRATORY FISH IN RHODE ISLAND



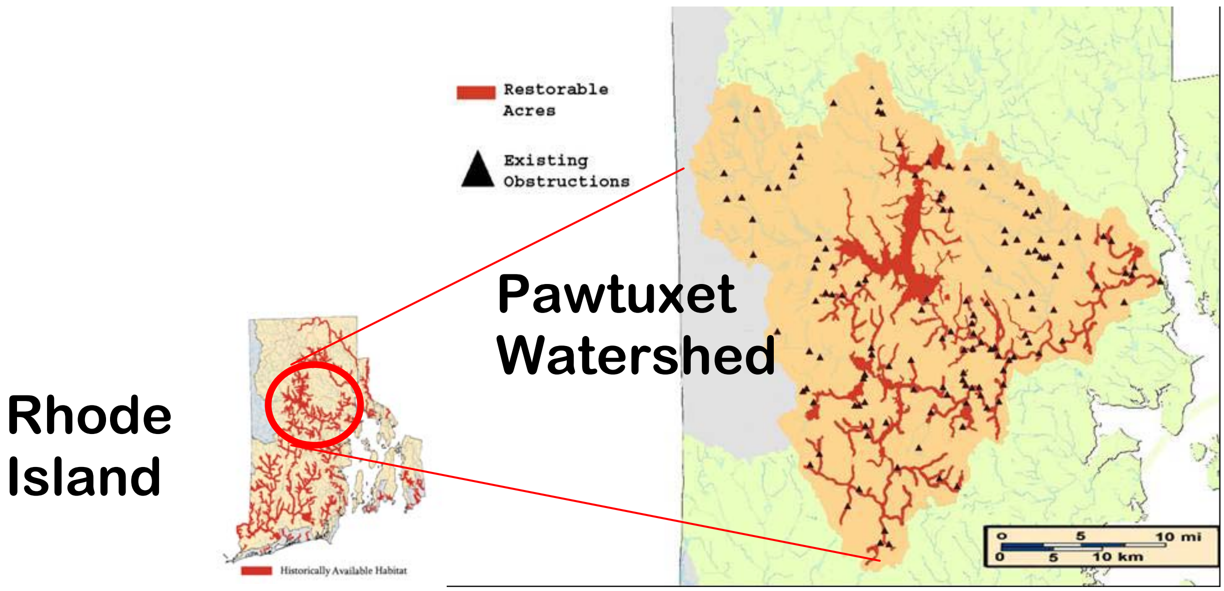
The two maps above show Rhode Island rivers where migratory fish used to live before humans arrived (left side), and rivers where these fish live today (right side).

Many Rhode Island rivers used to support annual runs in excess of 300,000 fish, now the largest measured run is only 50,000 fish. Most are much smaller.

Figure 3. Excerpt from Survey Information Booklet: Historical and Present Fish Passage (graphics edited from RIGIS data).

THE PAWTUXET WATERSHED

The Pawtuxet Watershed provides 38% of all restorable migratory fish habitat in Rhode Island, and all of this habitat is blocked by 22 obstructions (mostly dams). As a result, the Pawtuxet provides no upstream habitat.



If fish ladders were built over all 22 dams, it would provide 4347 new acres of fish habitat. Most realistic projects, however, are much smaller.

Figure 4. **Excerpt from Survey Information Booklet: Restoration of Fish Passage in the Pawtuxet Watershed (graphics edited from RIGIS data).**

Valuing environmental changes in managed fisheries

Steve Newbold & Matt Massey

U.S. EPA,

National Center for Environmental Economics

April 2007

General motivation

- In previous work, we estimated the value of water quality improvements in a recreational fishery using results from a RUM model of recreational site choices and a model of fish population dynamics (Massey *et al*. 2006).

- Additional ongoing work is attempting to formally define the potential welfare bias resulting from using reduced form models

- A quick example to illustrate …

Is integration necessary?

- If q is an exogenous environmental attribute:

$$I_i = \ln\left(e^{\theta_0} + e^{\theta_1 q - \theta_4 c_i}\right)$$

$$WTP = \frac{O}{\theta_4}\sum_i \frac{\partial I_i}{\partial q} = T\frac{\theta_1}{\theta_4}$$

→A recreation demand model alone is sufficient.

- If y is expected catch and is endogenous:

$$I_i = \ln\left(e^{\theta_0} + e^{\theta_1 y - \theta_4 c_i}\right)$$

$$WTP = \frac{O}{\theta_4}\sum_i \frac{\partial I_i}{\partial \alpha}\frac{\partial \alpha}{\partial q} = \frac{O}{\theta_4}\left[\frac{\sum_i p_i}{\beta/(\eta\theta_1) + \eta O\sum_i p_i\left(1-p_i\right)}\right]\frac{\partial \alpha}{\partial q}$$

→ An integrated model is needed.

General motivation

- Previously, however, we have ignored the management regime in the fishery.

- It is well known that the benefits generated by a renewable natural resource are strongly influenced by how the resource is managed.

General motivation

- Consider the standard model of a commercial fishery:
  - If open access, all rents are dissipated.
  - If landings (really fish mortality) is taxed at the proper level, social benefits are maximized.

- Natural resource economists have explored these issues in great detail for commercial fisheries.

General motivation

- Should we expect the same in a recreational fishery?
- If unregulated, will all benefits from water quality improvements be dissipated by new participants?
- Environmental economists have done some preliminary work on valuing different management regimes, e.g., by adding indicator variables to site choice models.

General motivation

- Reduced form recreation demand models on their own may not be sufficient for comparing the welfare effects of different fishery management strategies or environmental improvements.

- Ecological modeling on its own may not be sufficient for comparing the biological impacts.

- In many cases these processes need to be modeled jointly.

General motivation

- In this project we address both sides of this issue—management and valuation—using an integrated model of angler behavior and fish population dynamics, including fish growth.

Harvest regulations

- A variety of approaches are available to recreational fishery managers for restricting harvests:
  - Bag limits, size limits, trip fees, landing taxes, season licenses, season closures, ITQ's, …

- The relative performance of these options will depend on the anglers' preferences, the biological characteristics of the fish stock, and implementation costs.

Harvest regulations

- In general, the welfare effects of each management option will depend on the relative values of each trip attribute—total catch, take home catch, and average length of catch—and how each trip attribute is changed by the management option.

- In equilibrium, these trip attributes will depend on both the anglers' preference parameters and the reproduction, growth, and survival parameters of the fish stock.

Valuing water quality changes

- The value of a change in water quality also will depend on the nature of the management regime in the fishery.
- For example, suppose a water quality improvement causes the average catch rate to increase from 1 to 2 fish per trip.
- What is the value of this improvement to the anglers if there is a 1 fish bag limit in place in the fishery?
- What if there were a minimum size limit in the fishery instead of a bag limit?

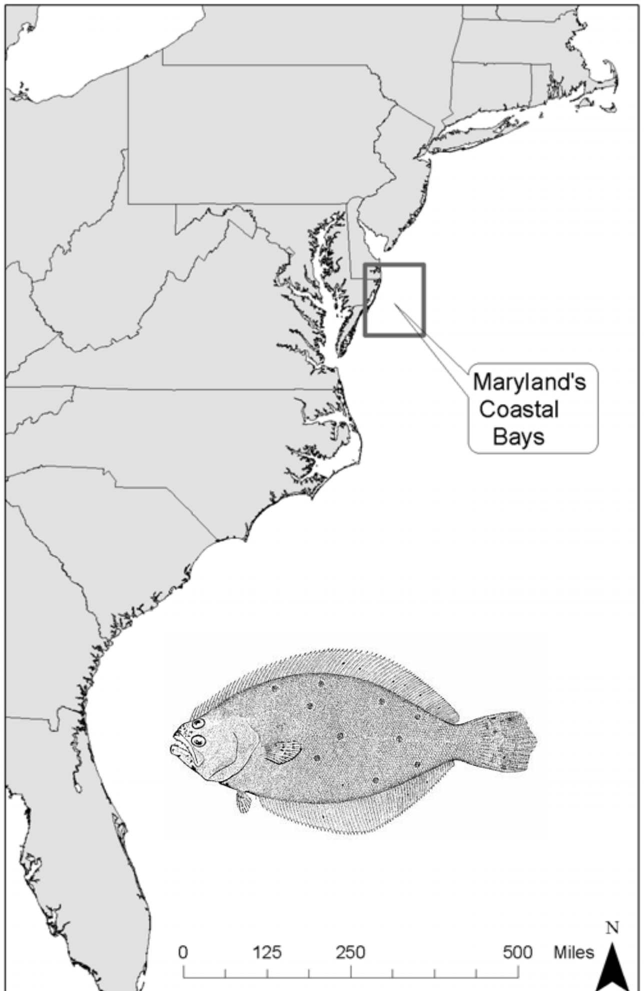
Questions to be addressed

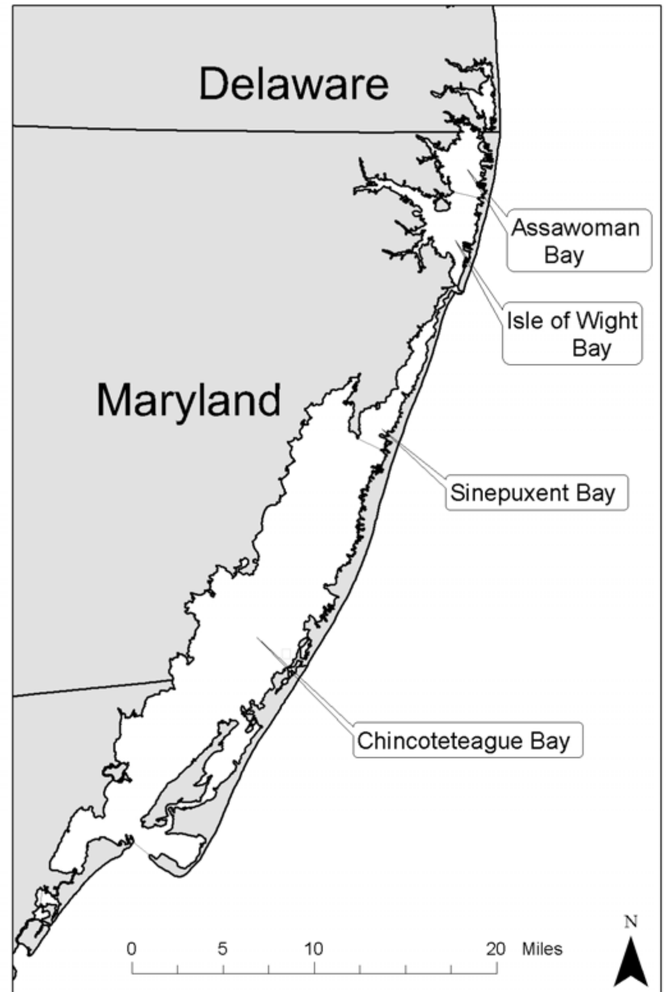
1. What is the optimal management regime for a particular recreational fishery (i.e., for a given set of angler preferences and biological parameters)?

2. How does the nature of the management regime—whether optimal or not—affect anglers' valuation of water quality changes?

Previous work

Summer flounder fishing in Maryland's coastal bays





Framework: Angler preferences and behavior

Indirect utility of fishing or doing something else:

$$V_i = \theta_1 y + \theta_2 y_h + \theta_3 l + \theta_4 \left(m_i / O - c_i \right)$$
$$V_{0i} = \theta_0 + \theta_4 \left(m_i / O \right)$$

Probability of taking a fishing trip:

$$p_i = \frac{e^{V_i}}{e^{V_{0i}} + e^{V_i}}$$

Expected max utility per choice occasion:

$$u_i^{\max} = \ln\left(e^{V_{0i}} + e^{V_i} \right)$$

Total number of fishing trips:

$$T = O \times \sum_i p_i$$

Framework: Fish growth and population dynamics

Age structure (constant mortality):

$$n(a)=\begin{cases} n_R e^{-m(a-a_R)} & a_R \le a < \hat{a} \\ n_R e^{-m(\hat{a}-a_R)-(m+f)(a-\hat{a})} & \hat{a} \le a < \infty \end{cases}$$

Growth (von Bertalanffy):

$$l(a)=l_\infty-\left(l_\infty-l_R\right)e^{-\mu(a-a_R)}$$

Reproduction (logistic):

$$n_R=\int_{a_R}^{\infty} r(a)n(a)\,da=\int_{a_R}^{\infty}(\alpha-\beta N)n(a)\,da=\alpha N-\beta N^2$$

Equilibrium stock size:

$$N=\frac{1}{\beta}\left[\alpha-\frac{m}{1-\left(f/(m+f)\right)e^{-m(\hat{a}-a_R)}}\right]$$

Framework:
Bio-economic linkages

Expected catch:

$$y = \eta N$$

Expected take-home catch (catch is a Poisson process):

$$y_h = \sum_{y=0}^{\hat{y}} y e^{-\eta N_h} (\eta N_h)^y / y! + \hat{y}\left(1 - \sum_{y=0}^{\hat{y}} e^{-\eta N_h} (\eta N_h)^y / y!\right)$$

Average length:

$$len = \frac{n_R}{N}\left[\frac{l_\infty e^{-m(\hat{a}-a_R)}}{m+f} - \frac{(l_\infty - l_R)e^{-(\mu+m)(\hat{a}-a_R)}}{\mu+m+f}\right]$$

Total harvest:

$$H = fN_h = y_h T$$

Recreation Demand Model:

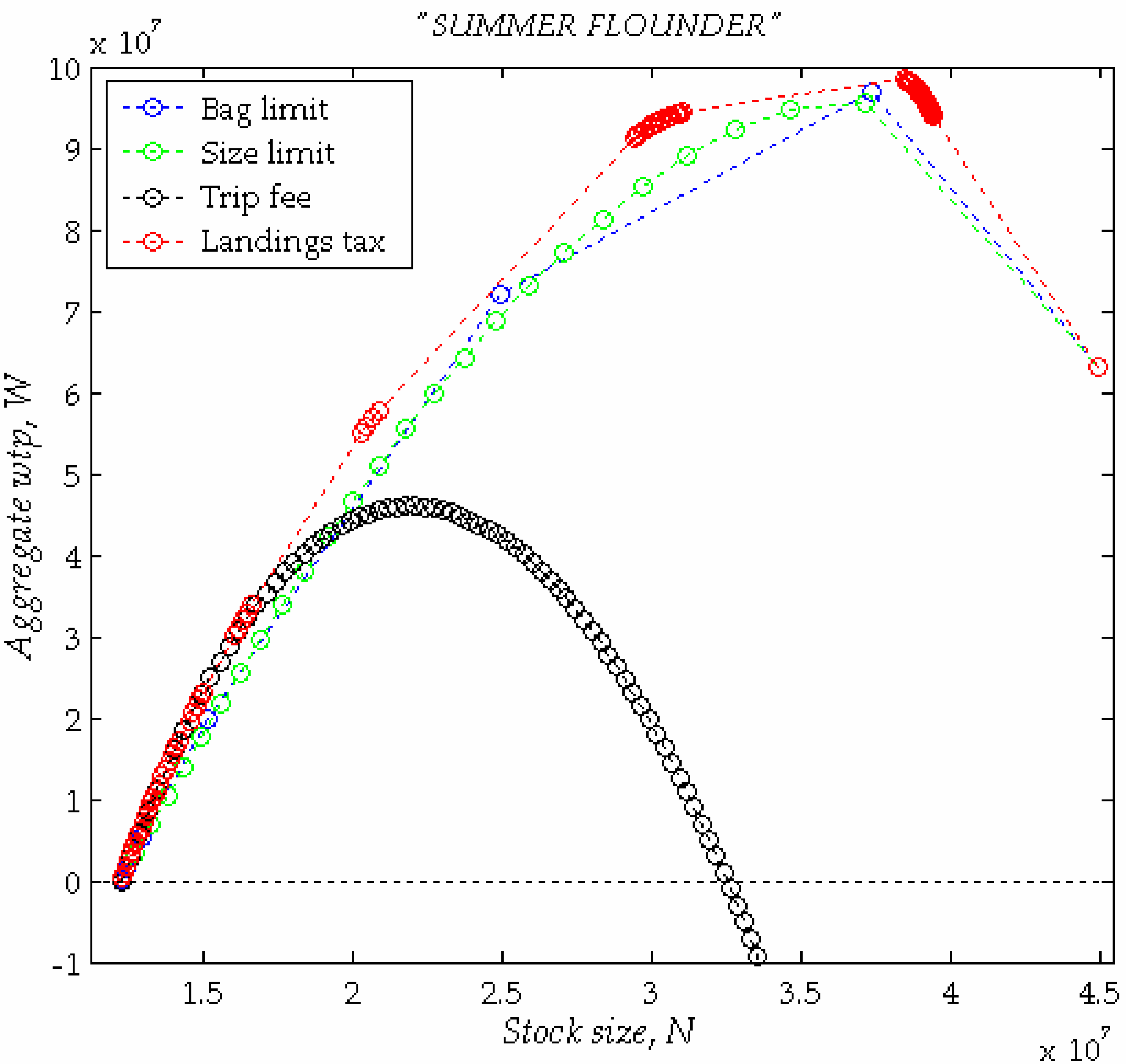
Variable	Estimate	t-stat
No Trip Dummy (NTD)	1.2616	7.555
Participant characteristics:		
NTD*Boat Owner	-0.0143	-0.122
NTD*Non-White	0.3496	1.564
NTD*Male	-0.3728	-1.402
NTD*Attended College	0.1616	1.346
NTD*Work Fulltime	-0.4701	-4.040
NTD*Daysfished	-0.0080	-1.492
Trip characteristics:		
Travel Cost	-0.0132	-13.419
Expected Total Catch	0.6183	18.216
Bag Limit	0.4770	18.322
Size Limit	0.2685	24.645
Other fishing Good	0.3148	7.416
Other fishing Bad	-0.4374	-10.913
Number of Respondents	2392	
Number of Observations	9568	
Mean Log-likelihood	-0.829243	

Example 1: summer flounder

- While there is certainly skill in hooking flounder, they are not a “fighting” species.
- Bigger is better, but fishermen do not normally target trophy flounder.
- Flounder fishermen are generally most concerned with take home catch.

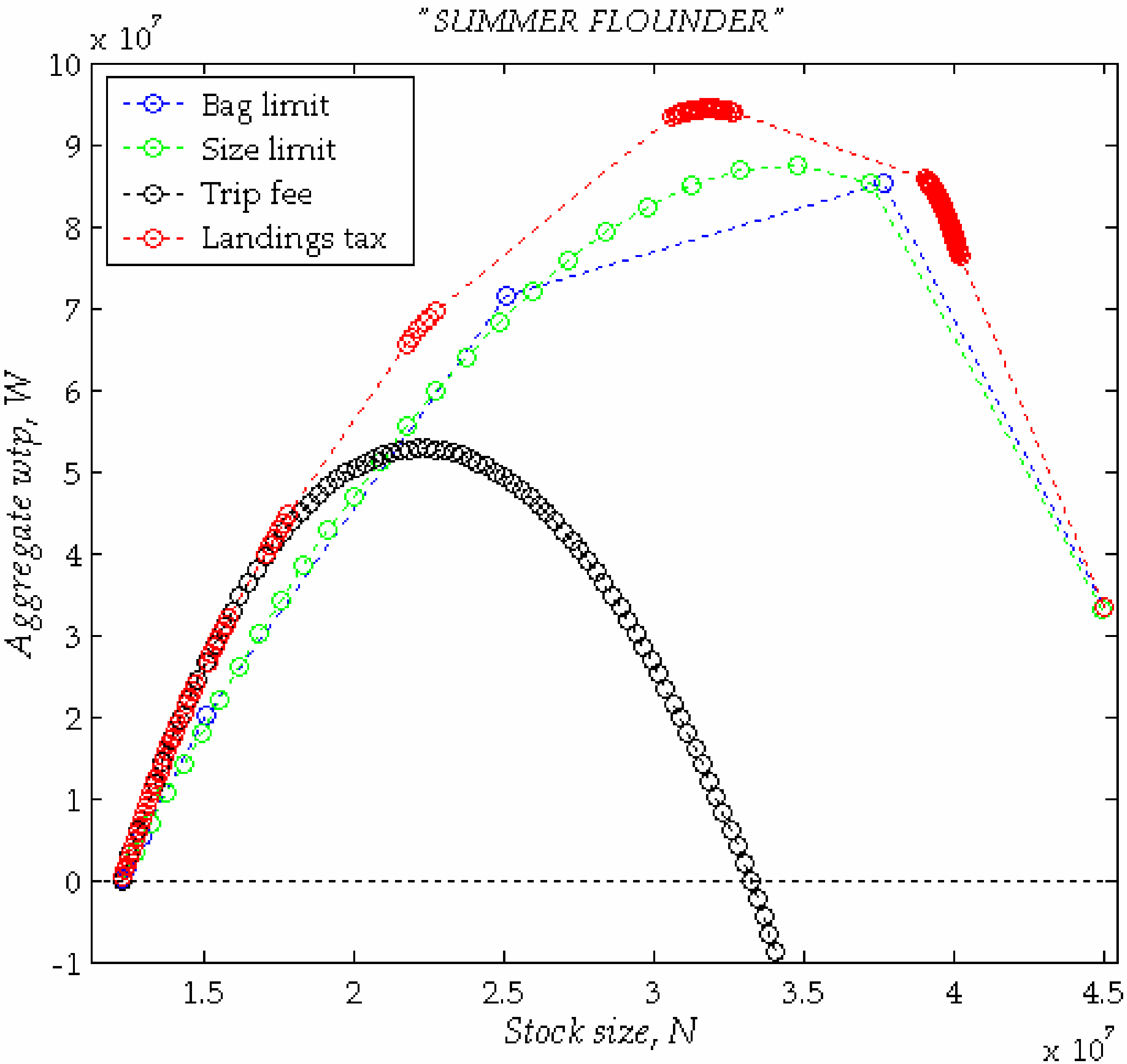
Expected take home catch

= 0.4770*.75



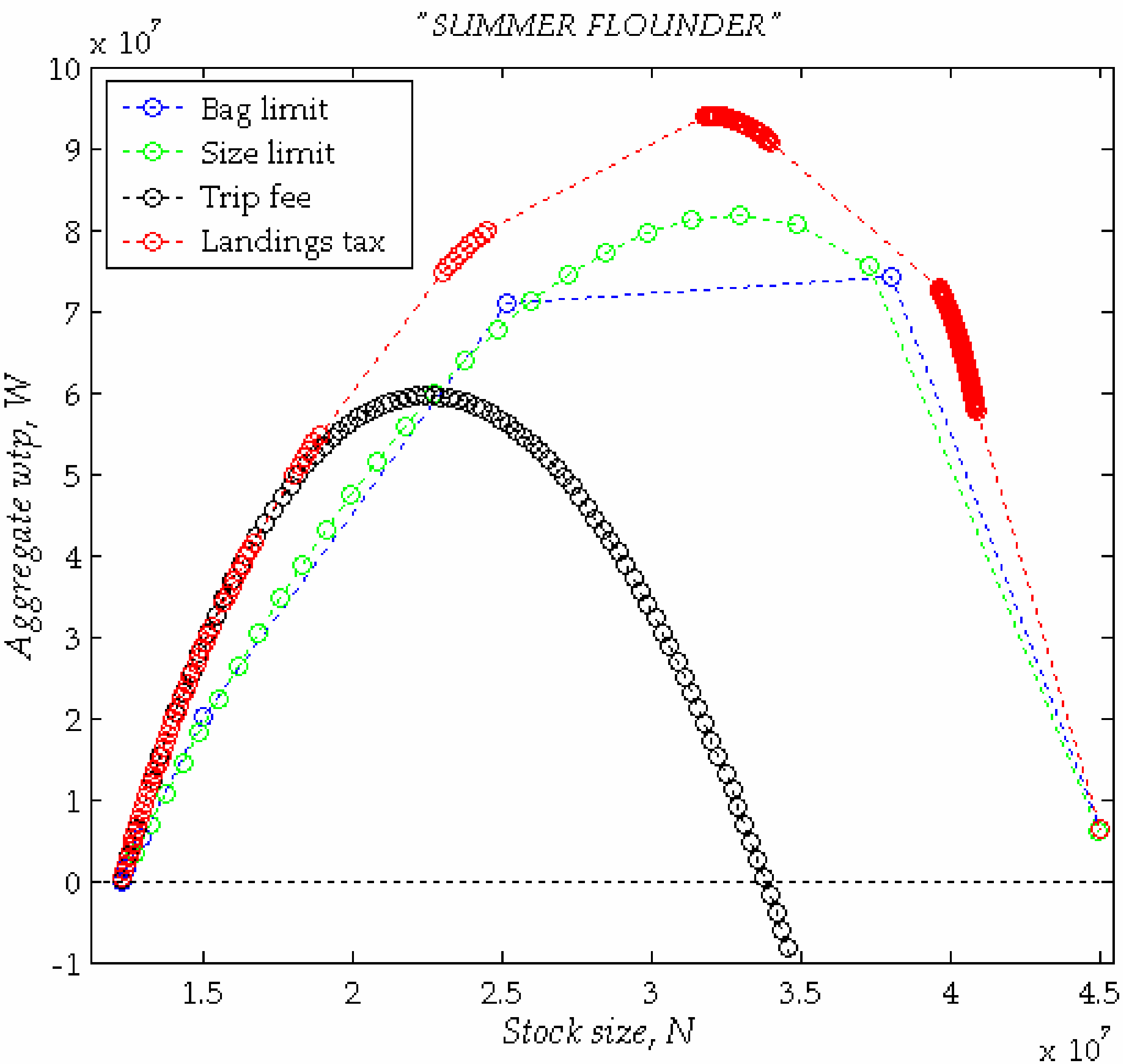
Expected take home catch

= 0.4470 (Baseline)



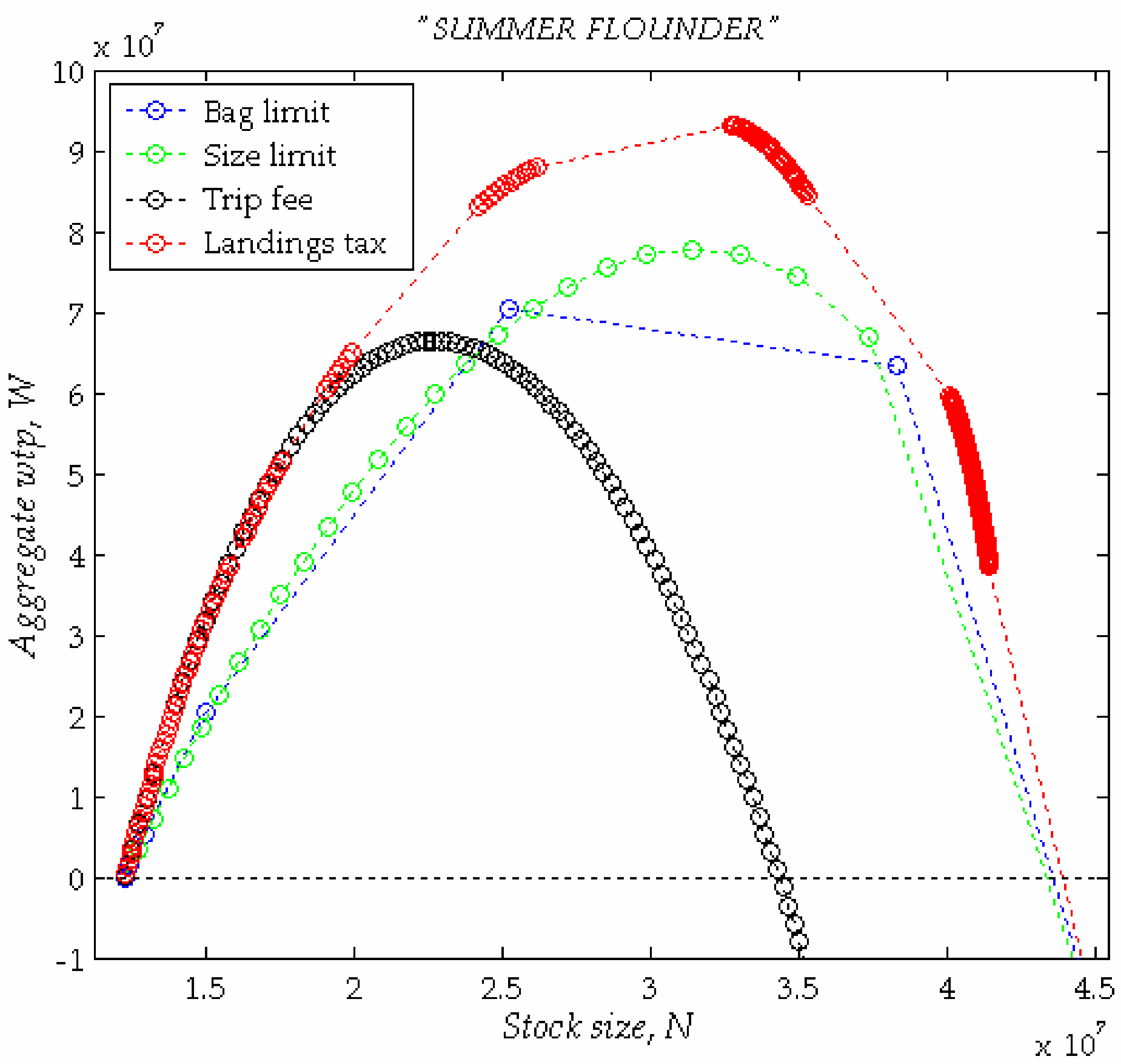
Expected take home catch

= 0.4770*1.25



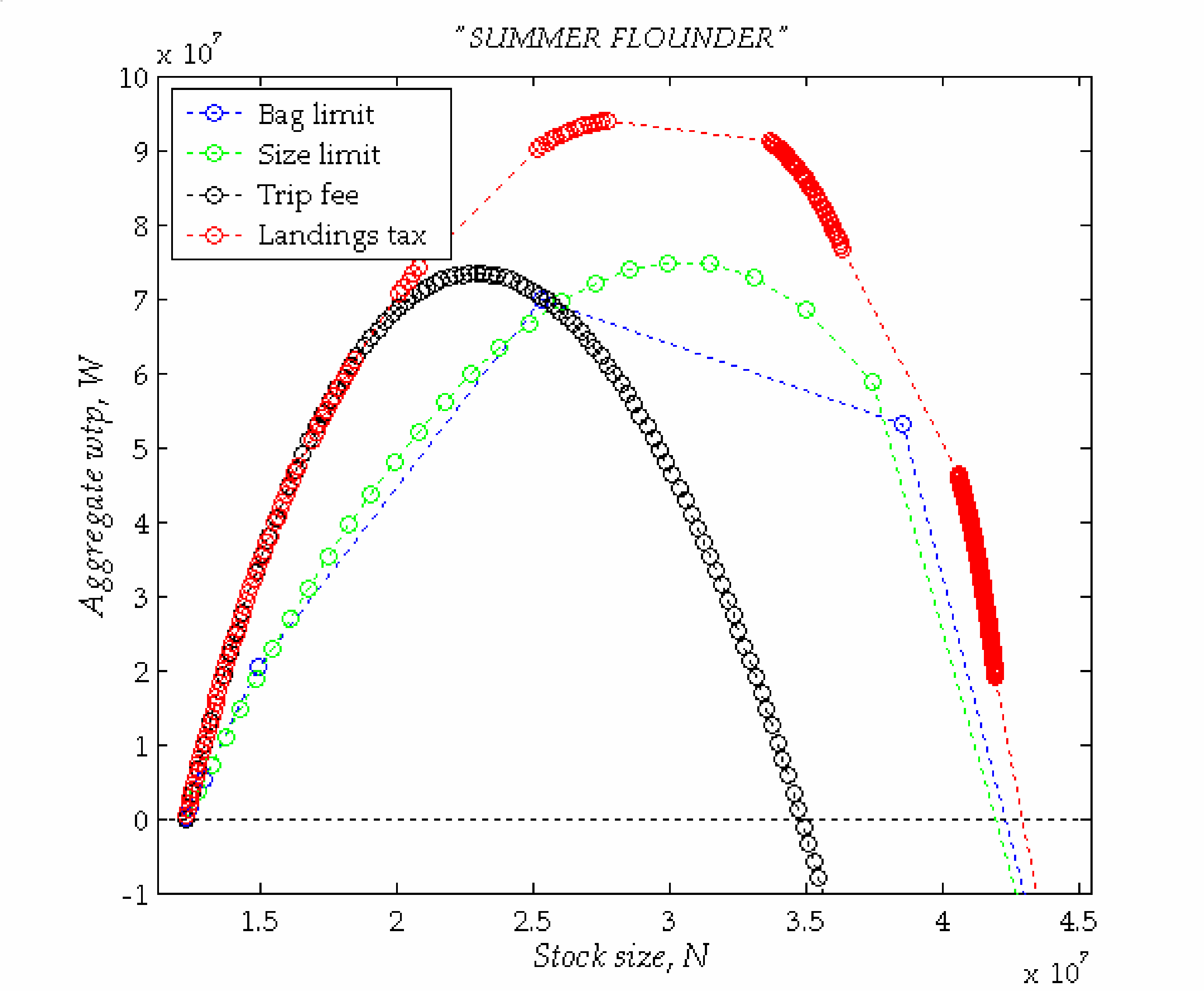
Expected take home catch

= 0.4770*1.5



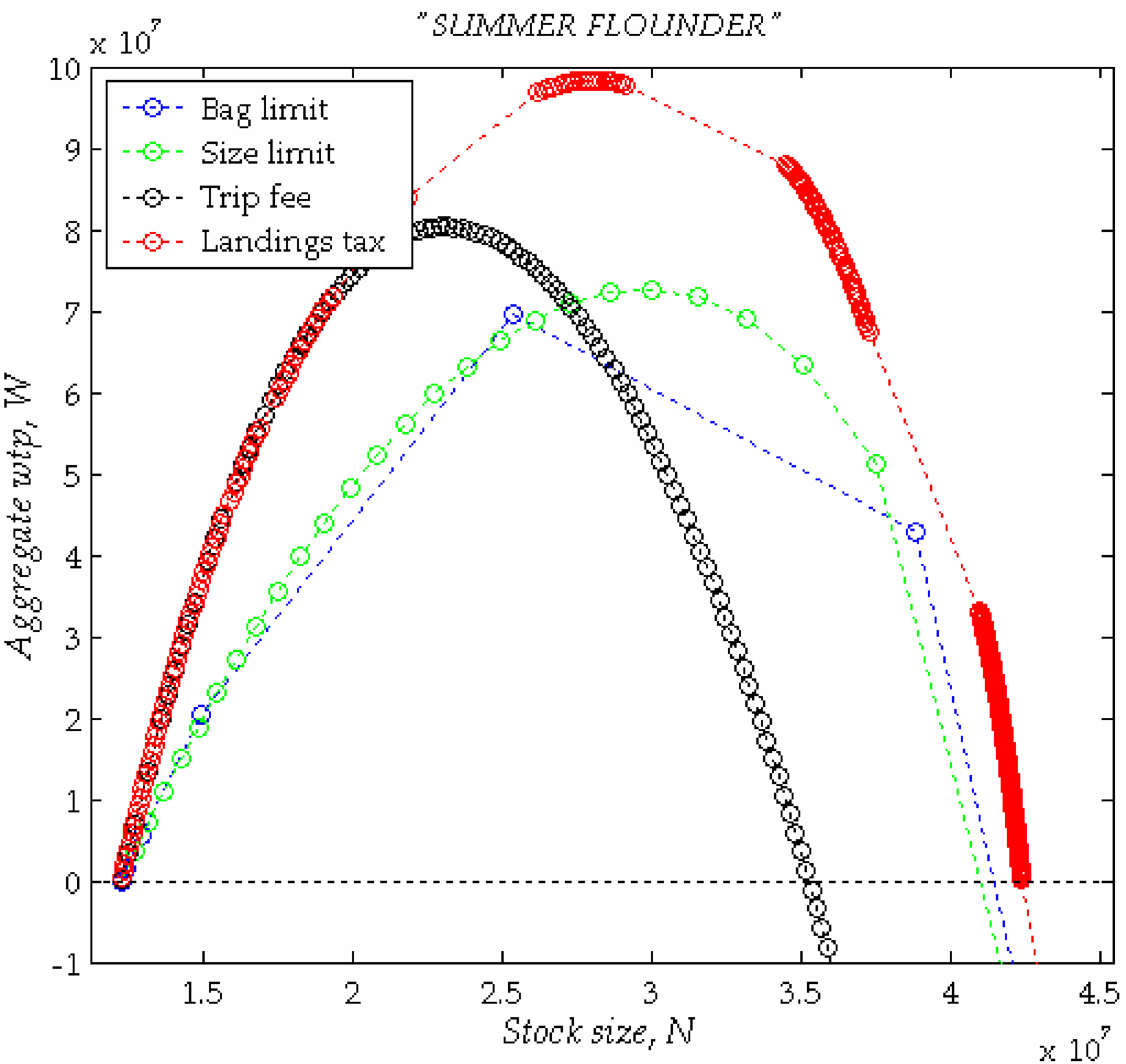
Expected take home catch

= 0.4770*1.75



Expected take home catch

= 0.4770*2



As the value of take home catch increases:

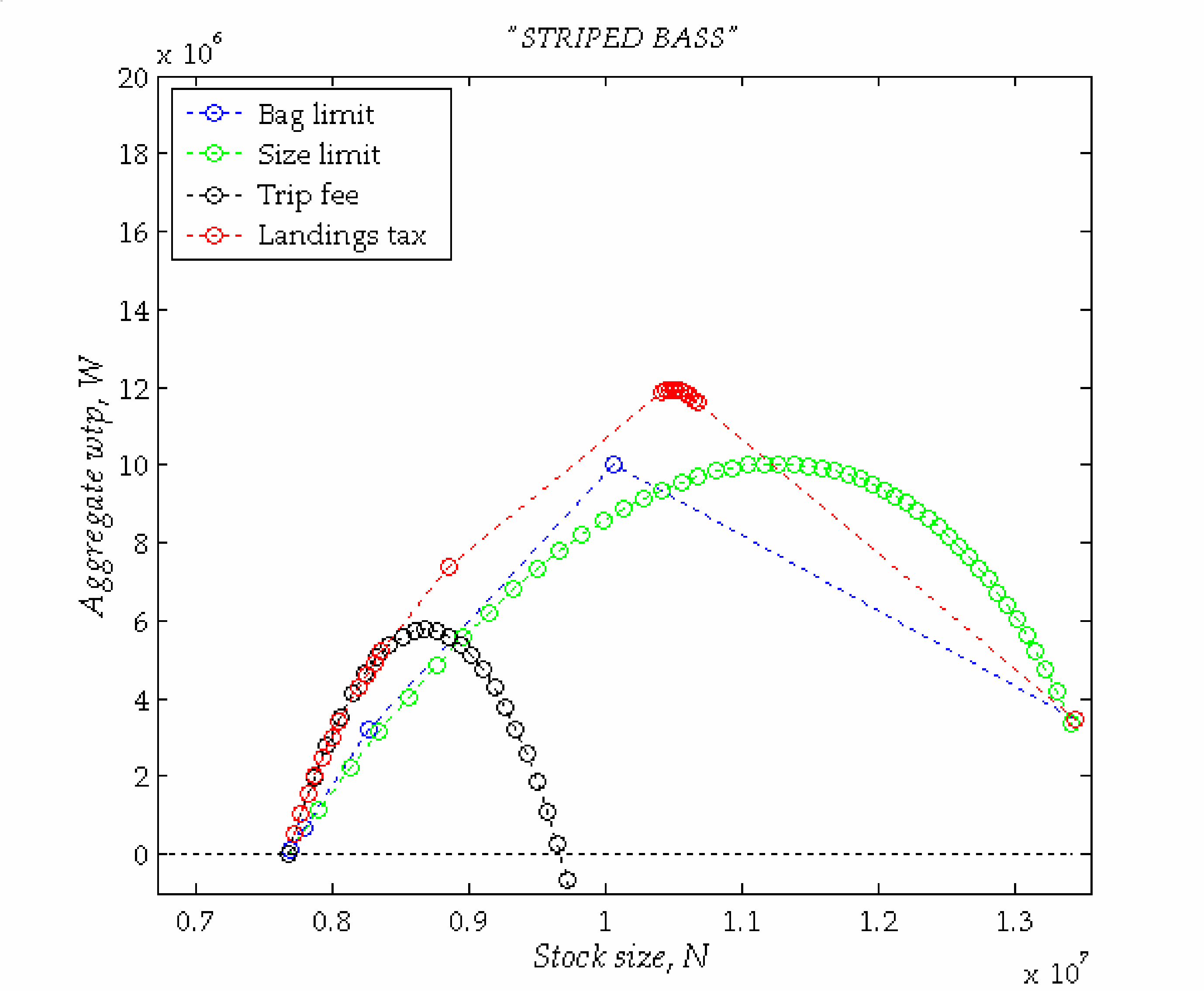
- Optimal stock size decreases
- A landings tax is always the optimal management option
- The biological methods (bag and size limits) are very similar
- Biological methods become less optimal because they restrict the number of fish you take home
- Optimal trip fee increases

Example 2: striped bass

- Striped bass are a very charismatic species and are well known for being a “fighting” fish.
- Many fishermen would value catching one large striped bass more than catching several smaller ones.
- Because we are aware of no studies that estimate angler preferences for striped bass management options, we adjust the estimated flounder parameters to increase the value for large fish and decrease the value for take home catch.

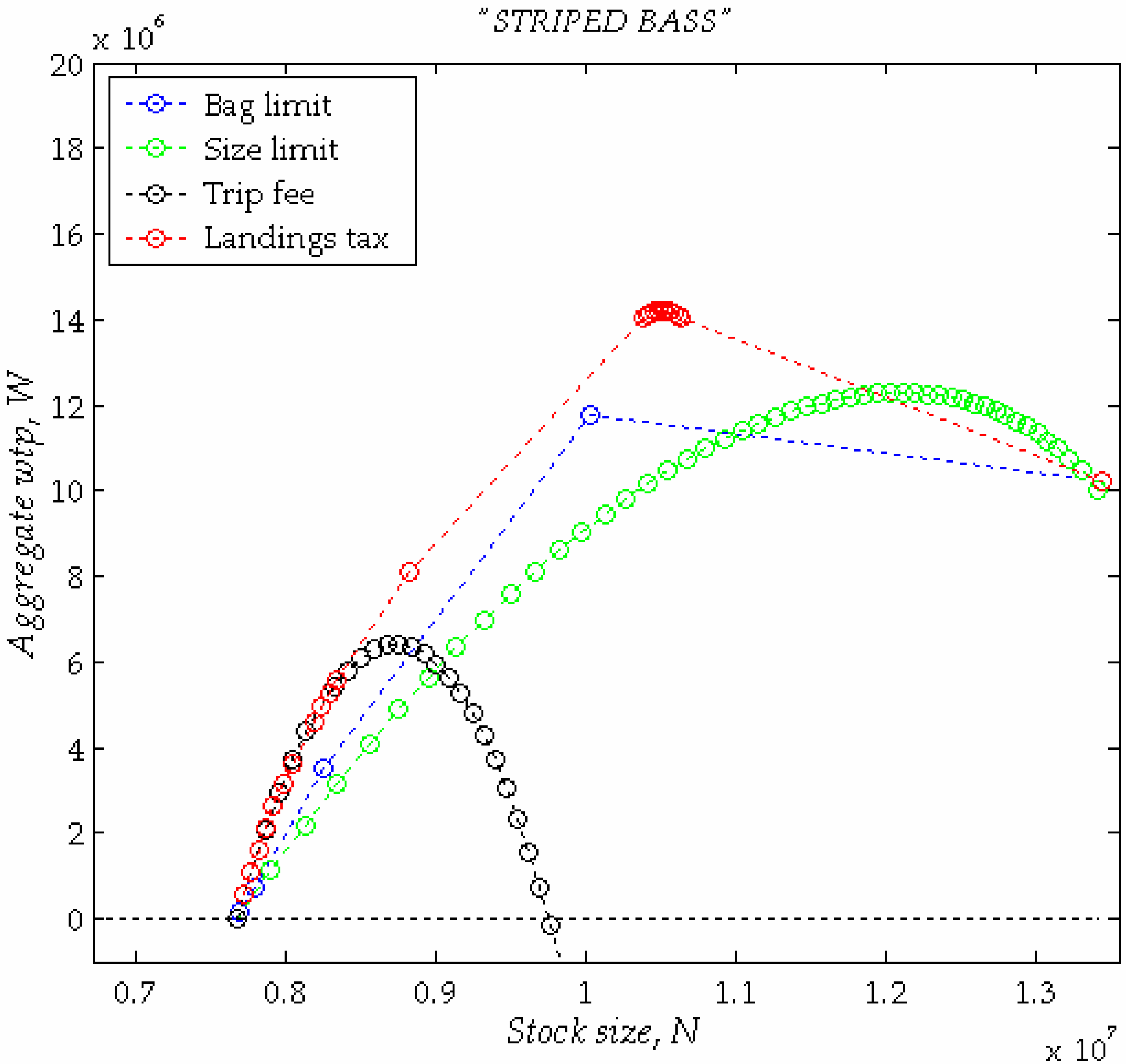
Average length of catch

= 0.2685*.5



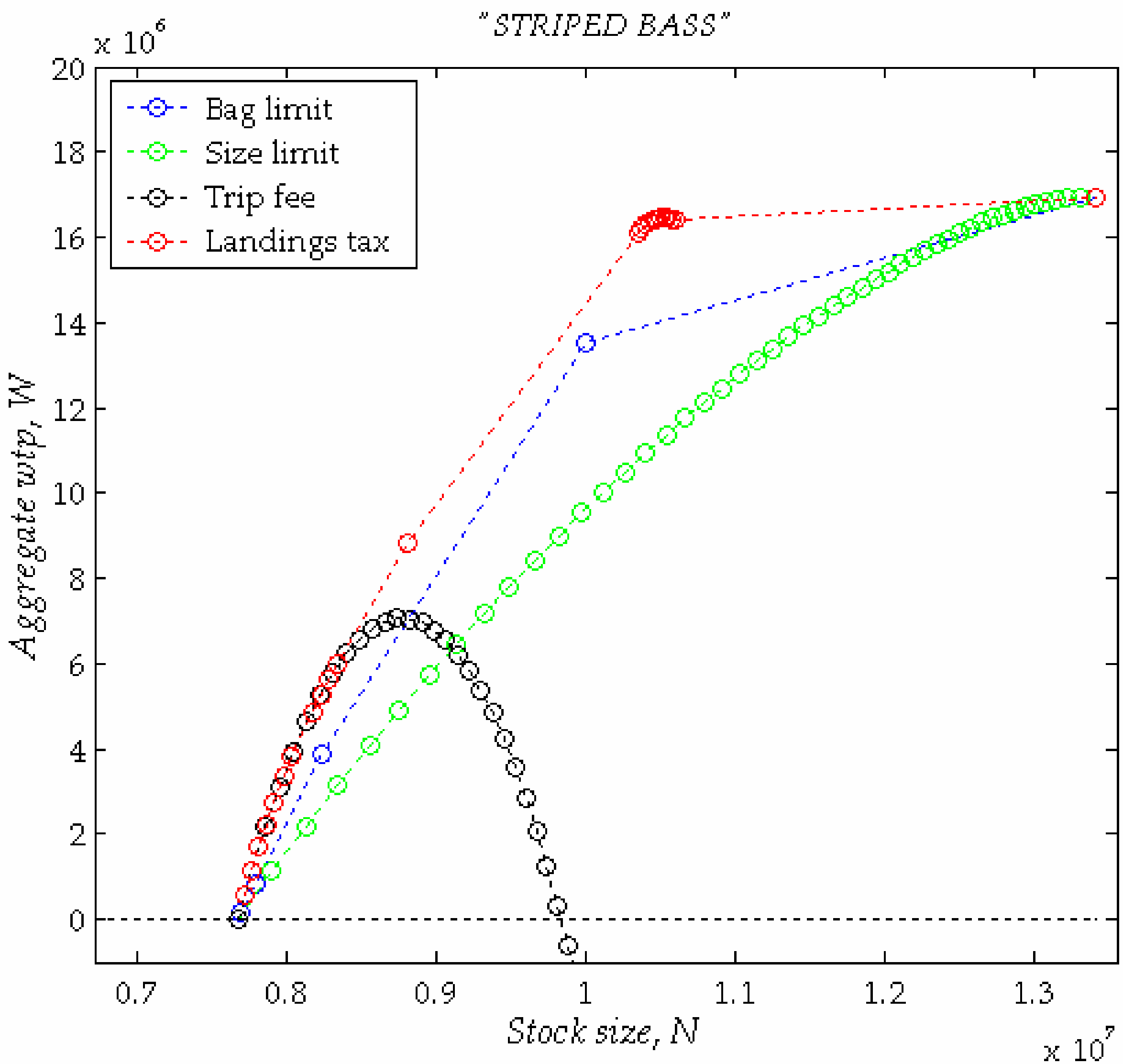
Average length of catch

= 0.2685 (Flounder Baseline)



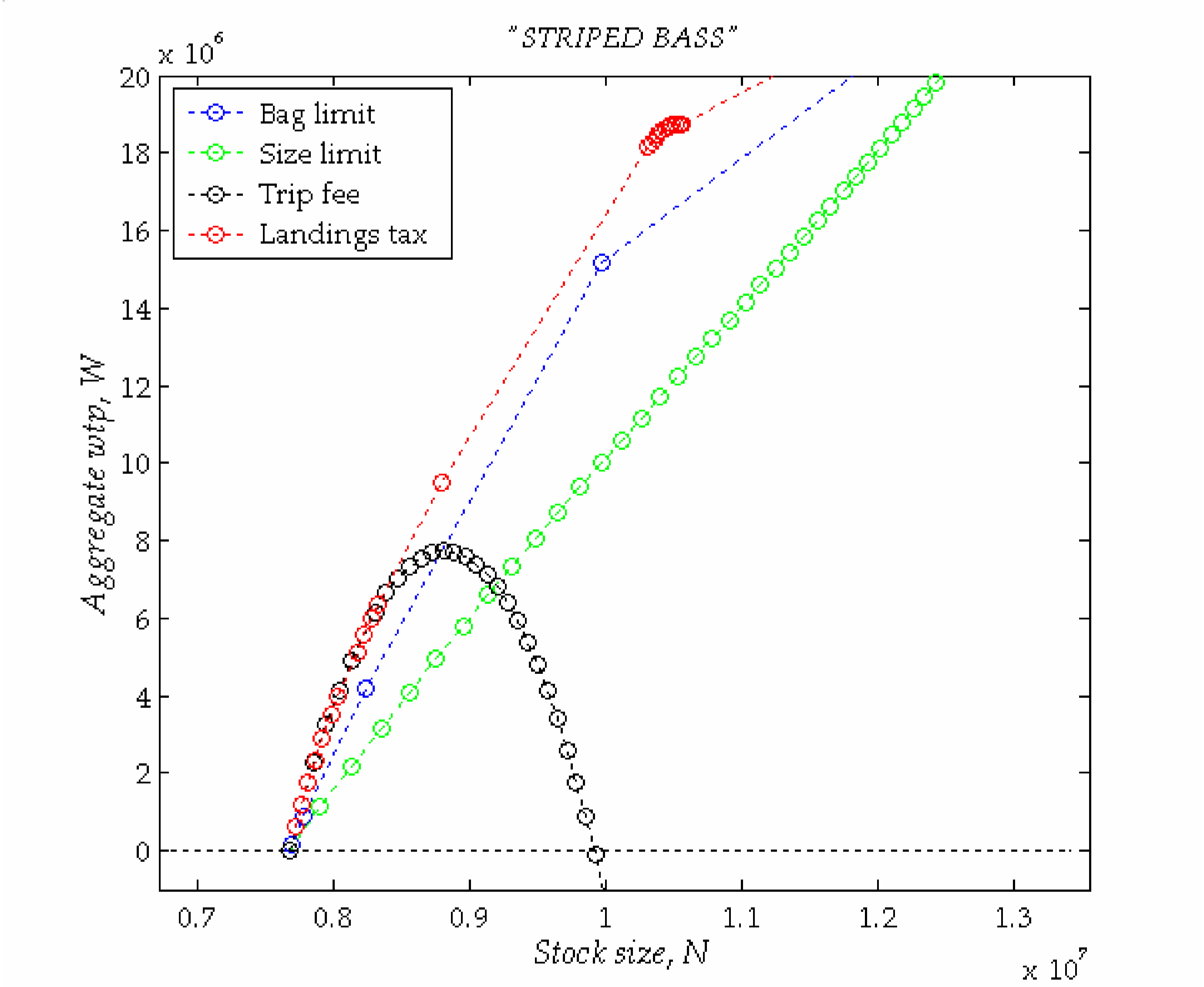
Average length of catch

= 0.2685*1.5 (striped bass baseline)



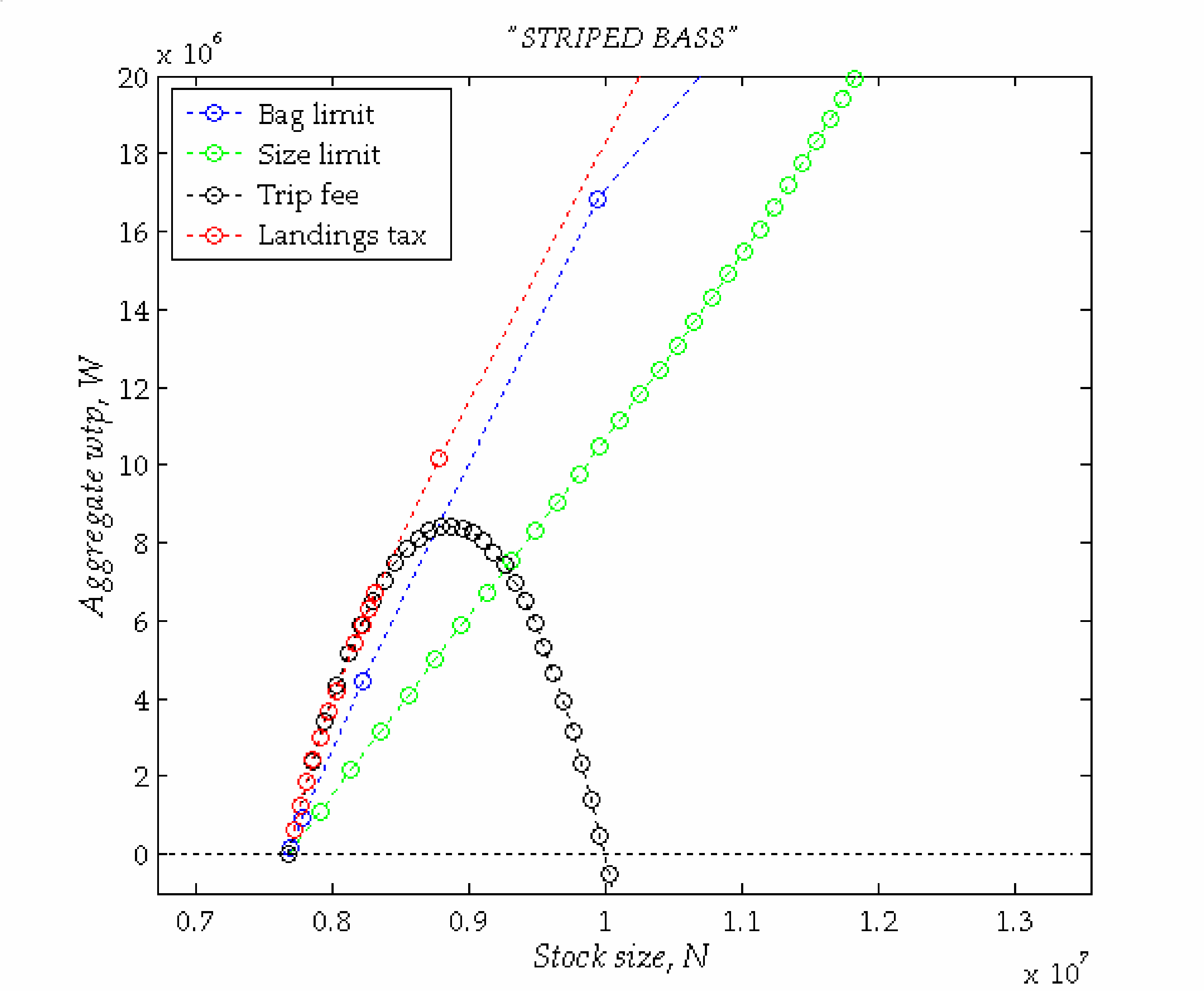
Average length of catch

= 0.2685*2



Average length of catch

= 0.2685*2.5



As the value of length of catch increases…

- The model predicts a shift to a catch and release fishery.
- A landings tax is always the optimal management option.
- Bag limits are preferred to size limits.
- Bag limits are relatively close to the optimal tax.
- Optimal trip fee increases.

Valuing environmental improvements

Management regime	Summer flounder $W(1.01\alpha) - W(\alpha)$	Striped bass $W(1.01\alpha) - W(\alpha)$
Unregulated	2.57E+06	1.27E+06
Optimal bag limit	2.54E+06	8.98E+05
Optimal size limit	2.99E+06	9.18E+05
Optimal trip fee	3.09E+06	1.29E+06
Optimal landings tax	3.49E+06	8.98E+05

Summary

- Optimal management in a recreational fishery will depend on the preferences of the anglers and the biological characteristics of the fish stock.
- In some cases harvest restrictions via bag or size limits can perform nearly as well as economic incentives.
- Early results suggest that the management method can affect the magnitude of welfare estimates

Next steps

- Add discard mortality and commercial fishing to the model
- Evaluate season licenses
- What is the optimal mix of management methods?
- Apply to several managed fisheries using harvest data and calibration
- How does the adjustment path of each management techniques to the long run equilibrium differ?
- Jointly estimate biological and economic parameters

Valuation for Environmental Policy: Ecological Benefits

Water Resources Session

April 24, 2007

Julie Hewitt

Outline

- General comments
- Iowa Lakes study
- Riparian Buffer Zones study
- Indicator-based Stated Preference Valuation study
- General Conclusion
  - The Value of Non-use Value
  - Other comments

General Comments

- All papers received on schedule
- All papers well-written

- All leave me a little wanting

Iowa Lakes study

- Careful collection of environmental data
  - Allows choice of specification
- Split sample for model development, estimation and prediction
- Provides (half of) information that decision makers need

Iowa Lakes study, cont.

- Not ecological, per se
  - Focus is on recreational trips
- Only single day trips
- Sociodemographic parameters aren't random because this info doesn't vary across the sites
  - Vajjhala et al. is suggestive that it does
  - Could key to local sociodemographic info

Riparian Buffer Zones

- Motivated by paper that ignores upstream spawning but uses CEA
- Hard for me to judge whether modeling assumptions are appropriate
- Simulations show interesting differences
  - Optimal solution depends on downstream spillovers

Riparian Buffer Zones, cont.

- Based on exhaustive combinatorial search
  - Won’t work on real-world problems
- Analysts determine reach definition
- Not valuation, per se

IbSPV

- Do preferences take form $U_i(E(F))$ or $U_i(F)$?
  - Formal incorporation of focus group process
- List of 7 criteria for applying IbSPV
  - Note that existing studies don't generally meet
  - Suggest validity still possible under "certain conditions" (begs the question)
- Relationships among indicators and impacts need to be described
  - Span the range, science can follow

IbSPV, cont.

- No results, per se
- Concern about cognitive burden
- Can we learn anything about order of presenting impacts/indicators?
- Is this really new?
  - Does not mean it's not a useful articulation
- Promontory Point
  - Ideal of analysis vs. real-world

General Conclusion

- Session is appropriately titled
- Is the workshop?
  - STAR grant results and progress
  - Ecological benefits

The Value of Non-use Value

- We have to ask the question, “have we incorporated non-use values?”
- Do we have to report non-use values to answer that question?
  - Recreational use is easy to measure
  - Ecological use is not so easily measured

Other Thoughts

- Incentive compatibility of choice experiments
- Multi-purpose or multi-day trips

Comments on Session V: Water Resources
George Parsons

1. Valuing WQ (Kevin Egan)

   - ➡ Omitted Variable Bias?
     - WQ Correlated w/ Missing Amenities
   - ➡ Why not estimate dispersion terms for WQ?
   - ➡ Recreation Types
   - ➡ Repeat this Analysis w/ same data
   - ➡ Small dispersion terms on no-trip constant
   - ➡ Dropping heavy users?
   - ➡ Policy Implications

2. Indicator Based SP (Rob Johnston)
    - ➡ Are 'full information' values correct for policy?
        - Pathways
        - Value of Information

3. Riparian Buffer Zones (Heidi Albers)
    - ➡ When will the model be ready for prime time?