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Essays on improving nonmarket valuation techniques

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Chapter 1. General Introduction

I. Introduction

Nonmarket valuation techniques are widely used to obtain welfare measures associated with environmental goods and services. These welfare measures are, in turn, important to policymakers when conducting cost-benefit analyses involving proposed changes to environmental amenities, such as programs to clean up nutrient contamination in lakes or to protect a given threatened species. The goal of this dissertation is to improve on existing nonmarket valuation techniques by incorporating three sources of information rarely used in the literature: (a) prior information on (and uncertainty about) the distribution of willingness-to-pay (WTP), (b) individual perceptions regarding environmental quality, and (c) contingent behavior data based on hypothetical environmental quality improvements. Consideration of each of these information sources constitutes an essay in the dissertation.

The first essay focuses on incorporating prior information on the distribution of WTP when designing dichotomous choice referendum (DCR) surveys. The DCR format is a stated preference approach to nonmarket valuation in which survey respondents are presented with a hypothetical change to the environment (e.g., an improvement in water quality) and asked if they would vote yes on a referendum to provide this change with a given cost to them of \$*B*. The bid (*B*) is varied across individuals in the sample, allowing the analysts to estimate the distribution of willingness to pay (WTP) for the change using standard discrete choice models (e.g., logit or probit). Two broad approaches have been employed to choose the bids used in discrete choice setting: the classical (or frequentist) approach and the Bayesian approach. The classical design approach (e.g., Kanninen, 1993) uses assumed values for the parameters that characterize the distribution of interest. The problem is that these are the very parameters the survey is seeking to estimate. Moreover, such designs typically do not take into account uncertainty about these parameters in the design. In contrast, the Bayesian design approach, much of it developed in the bioassay literature, explicitly considers prior information (and uncertainty) about the distributional parameters in constructing optimal design (See, e.g., Tsutakawa, 1972, 1980; Chaloner and Larntz; 1989). However, relatively little attention has been paid to Bayesian designs in the non-market valuation literature. Kanninen's (1991) dissertation appears to be the only study to consider Bayesian optimal design in contingent valuation. Much has changed in the Bayesian design literature since Kanninen's work in this area.

In this first essay of my dissertation, I propose a Bayesian optimal design for use in DCR surveys. As part of developing the design, I incorporate three design features. First, I employ recently developed algorithms for computing the expected posterior variance of WTP, i.e., beyond the normal approximation used by Kanninen. Second, rather than relying on direct optimization routines (e.g., Nelder-Mead simplex, etc.), I use Müller and Parmigiani's (1995) curve-fitting approach. Third, in addition to providing a single-stage Bayesian design, I develop an optimal sequential design in which the bid design considers both (a) the optimal sample allocation between a survey pre-test and final survey administration and (b) the optimal bid design for each stage.

In addition to stated preference approaches, behavioral data (i.e., revealed preferences) can be used model recreation demand, which can in turn be used to value environmental goods and services. Recreation demand models link the environmental attributes of a recreational site and the frequency with which the site is visited to infer the value placed in these environmental amenities. However, they typically do not take into account the linkage between the physical water quality attributes and an individual's perceptions of them. In particular, according to a recent survey (the Iowa Lakes Survey), Iowa lakes are used extensively by residents for recreational boating, fishing, swimming, with over sixty percent of the households visiting at least one lake in 2002 and the average number of trips per year exceeding eight (Azevedo *et al.*, 2003). Yet there is substantial concern about the water quality of these, with the USEPA designating roughly half of the lakes in the Iowa Lakes Survey as being impaired (EPA Water Quality Inventory for the State of Iowa, 2003). This observation raises two issues as to whether individual perceptions regarding lake quality are consistent with the actual physical conditions and what form of quality attributes drives individual's site choice decision: observed physical measures or water quality perceptions?

The second essay focuses on individual perceptions regarding water quality. Two questions emerge. First, how big is the disparity between the quality measures perceived by individuals and those reported by scientists? Second, which of these measures (perceptions or physical attributes) have a greater impact on the recreation behavior of individuals? Disparity in these quality measures is of interest to policymakers from the standpoint of welfare measure. Adamowicz *et al.* (1997) found that welfare estimates based on perceptual data are smaller than those using objective quality measures. Leggett (2002) showed the welfare estimates are biased if they do not properly control for the quality perception of individuals.

In the second essay of my dissertation, I utilize detailed data on trip behavior and water quality assessments of lakes collected from Iowa Lakes Survey 2003, along with physical quality measures collected by the Iowa State University Limnologist laboratory, to investigate the impact of both water quality perceptions and physical measures on recreational lake usage. The related hypotheses, survey result, correlation coefficients and regression estimates linking reported water quality perceptions with trip behavior and physical measures are discussed in Chapter 3. A Repeated Mixed Logit Model is employed to estimate recreational demand and test the hypotheses.

Finally, while recreation demand models typically benefit from considerable variation in the price of the good in question (i.e., the travel cost), they often have available little variation in the quality of the good being valued. To address this limitation, the recreation demand literature increasingly makes use of contingent behavior (CB) data; i.e., asking households how they would change their visitation patterns given a hypothetical change to environmental conditions. Yet little is known as to whether the stated changes to these hypothetical water quality changes are consistent with how household respond to actual quality changes. Do they respond more to hypothetical water quality changes (e.g., with the hope of influencing policy change, or because they ignore their budget constraint)? Alternatively, do they respond less because they do not believe the changes will actually occurs?

In the third essay, I measure the impact of hypothetical water quality improvements on recreation demand patterns using data collected from the 2004 Iowa Lakes Survey. In the survey, households were asked about how many trips they took in 2004, as well as how many trips they anticipate taking in 2005 under both current and improved water quality. I develop the model incorporating all three trip data sets in order to separately quantify the impact of hypothetical water quality improvements and test for consistency with observed household response to actual water quality. The model, related hypotheses, survey result are discussed in Chapter 4 below. Similar to the second essay, a Repeated Mixed Logit Model is employed to estimate recreation demand and test the hypotheses.

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Chapter 2. Bayesian Experimental Design: Application to Contingent Valuation

I. Introduction

The dichotomous choice referendum format is used extensively in contingent valuation studies designed to estimate the value of environmental goods and services. In this format, survey respondents are presented with a hypothetical change to the environment (e.g., an improvement in wager quality) and asked if they would vote yes on a referendum to provide this change with a given cost to them of $\$B$. The bid ($B$) is varied across individuals in the sample, allowing the analysts to estimate the distribution of willingness to pay (WTP) for the change using standard discrete choice models (e.g., logit or probit). The problem is that each person provides only limited information about their WTP (i.e., whether it is above or below the threshold B), making the choice of B's presented to survey respondents an important determinant of the precision with which the WTP distribution can be estimated for a fixed sample size. This issue is analogous to the problem in the bioassay literature, where dosages must be specified in medical experiments.

Two broad approaches have been used to choose the bids in the discrete choice setting: the classical (or frequentist) approach and the Bayesian approach. The classical design approach uses assumed values for the parameters that characterize the distribution of interest. The problem here, of course, is that these are the very parameters the experiment is seeking to estimate. Moreover, such designs typically do not take into account uncertainty about these parameters in the design. Examples of classical design studies include Finney (1971), Abdelbasit and Plackette (1983), Minkin (1987) and Wu (1987).

The Bayesian design approach, on the other hand, takes into account prior information (and uncertainty) about the distributional parameters in constructing optimal design. Key papers on such designs in the bioassay literature include Tsutakawa (1972, 1980) and Chaloner and Larntz (1987). They show that both the number of bids used and their spread increase with the uncertainty about the distributional parameters.

Relatively little attention has been paid to Bayesian designs in the non-market valuation literature. Indeed, Kanninen's (1991) dissertation appears to be the only study to consider Bayesian optimal design in contingent valuation. In the third chapter of her dissertation, she considers the utility difference model of Hanemann (1984) and a standard logistic distribution in developing the optimal bid design. The criterion she uses is to minimize expected posterior variance of WTP based on a normal approximation to posterior variance of WTP, essentially the same approach used by Tsutakawa (1980) and Chaloner and Larntz (1989). One problem with the utility difference approach used by Kanninen (1991) is that the median willingness to pay is the ratio of two normally distributed random variables. In this case, the WTP distribution does not have finite moments. In addition, Sun, Tsutakawa and Lu (1996) show that posterior distribution may include values substantially larger than those expected by the approximating distribution.

In this chapter of my dissertation, I develop a Bayesian optimal design for use in contingent valuation based on bid function approach suggested by Cameron (1988). The advantage in doing so is that this avoids focusing on the ratio of two random parameters (as is the case with the utility difference approach). As part of developing the design, I incorporate three additional design features. First, I use alternative algorithms for computing the expected posterior variance of WTP, i.e., beyond the normal approximation used by Kanninen. Specifically, I investigate the use of Tierny's (1986) Laplace approximation and Markov Chain Monte Carlo methods. Second, rather than relying on direct optimization routines (e.g., Nelder-Mead simplex, etc), I use Müller and Parmigiani's (1995) curve-fitting approach. Third, in addition to providing a single-stage Bayesian design, I develop an optimal sequential design in which the bid design considers both (a) the optimal sample allocation between a survey pre-test and final survey administration and (b) the optimal bid design for each stage.

The remainder of this chapter is divided into five sections. Section II provides an overview of both the utility and bid function approaches to modeling discrete choice referendum questions. Section III then summarizes both classical and Bayesian design approaches (including C- and D-Optimality and Fiducial method in the classical approach), alternative Bayesian design procedures, and recent developments in this area such as simulating the exact expected posterior variance. Results using bid function and curve fitting approaches in a single stage experimental design are presented in Section IV. In Section V describes the two-stage Bayesian design results, with concluding remark following in Section VI.

II. Welfare Measures under Referendum Format

Dichotomous choice referendum (DCR) format is a value elicitation procedure used extensively in the environmental area. It is the one mechanism recommended by NOAA panel (Arrow *et al.*, 1993) for use in non-market valuation exercises, in part because of the simplicity of the question format. Subsequent research has also touted the incentive compatibility of this elicitation procedure (e.g., Carson, Groves and Machina, 2000). The referendum procedure involves first establishing the attributes of the public good or resource amenity to be provided under a proposed program. The respondents are then asked whether or not they would vote in favor of the program given a specific direct cost to them. For example, following by a description about hypothetical improvement of water quality in Storm Lake, a DCR question might ask "Would you vote 'yes' on a referendum to improve the water quality in Storm Lake to the level described above? The proposed project would cost you $\$B$." The bid values ($B$) are varied across respondents. This questioning strategy is attractive because it generates a scenario for each consumer which is similar to that encountered in day-to-day market transactions. A hypothetical price B is stated and the respondents merely decide whether to "take it or leave it". This is less stressful than requiring respondents to state a specific value for the program and circumvents much of the potential for strategic response bias. The drawback of the DCR format is that it provides only an upper or lower bound on the respondent's true valuation.

Two basic approaches have been used to model DCR responses: the utility difference approach developed by Hanemann (1984) and the bid function approach developed by Cameron (1988). I briefly review each of these methods for welfare estimation.

The utility difference approach assumes that an individual's utility depends upon whether the good in question (e.g., a water quality improvement) is provided, money income y, and a vector of individual characteristics, s. Let the index j denote the provision of the good in question, where j=1 if the good is provided and =0 otherwise. The individual's utility is assumed to take the form

$$u(j,y;s) = v(j,y;s) + \varepsilon_j, \tag{1}$$

where ε_j is *i.i.d.* random variable capturing unobservable aspects of the individual's preferences. The utility function is typically assumed to be linear in income, with

$$u(j,y;s) = \alpha_j(s) + \beta \cdot y_j + \varepsilon_j, \tag{2}$$

where $y_0 = y$ and $y_1 = y - B$. The individual is assumed to vote in favor of the program if

$$u(1, y - \$B; s) > u(0, y; s). \tag{3}$$

This inequality gives rise to

$$\begin{aligned} &\alpha_1(s) + \beta(y - \$B) + \varepsilon_1 > \alpha_0(s) + \beta\, y + \varepsilon_0 \\ &\Rightarrow \alpha_1(s) - \alpha_0(s) - \beta\, B > \varepsilon_0 - \varepsilon_1. \end{aligned} \tag{4}$$

Given $\eta \equiv \varepsilon_0 - \varepsilon_1$ and $\alpha(s) \equiv \alpha_1(s) - \alpha_0(s)$, then a "yes" vote implies that

$$\Delta v \equiv \alpha(s) - \beta \cdot B > \eta \,. \tag{5}$$

If the unobservables are assumed to be *i.i.d.* and drawn from an extreme value distribution, then η follows logistic distribution. The probability that an individual will accept a bid is then given by

$$P_1 = F_\eta(\Delta v) = 1/\{1 + \exp(-(\alpha(s) - \beta \cdot B))\} \,, \tag{6}$$

and the probability that he/she will not accept the offer is $P_0 = 1 - F_\eta(\Delta v)$. Since WTP is defined to be amount of money that equates utilities from two states, we can write

$$WTP = \frac{\alpha(s)}{\beta} + \frac{\eta}{\beta} \,. \tag{7}$$

That is, WTP is a random variable with mean $\mu = \alpha(s)/\beta$ and variance $\sigma^2 = \mathrm{var}(\eta)/\beta^2$.

Cameron (1988) focuses on the fact that, in the DCR question, the offered bid values B provide a direct threshold on the individual's WTP. Indeed, because the threshold amounts are varied across respondents, one is able to identify both the location and scale of the underlying WTP distribution. This result is obscured in the utility function approach. Instead, the utility theoretic approach focuses on estimating the "probability" that a respondent would benefit from the proposed environmental change.

Cameron's bid function approach begins by assuming that the unobserved continuous dependent variable is the respondent's true WTP for an environmental quality improvement, W, such as water quality. The underlying distribution of W is assumed to be conditional on a vector of explanatory variables, s, with a mean of $\delta(s)$. In the standard binary logit model, we would assume that

$$W_i = \delta(s) + u_i \,, \tag{8}$$

where u_i is assumed to have logistic distribution with mean 0 and scale parameter κ. Given a bid value B_i, we assume that respondents will say "yes" to the referendum question if their true WTP is greater than B_i. Hence

$$\begin{aligned}\Pr(yes) &= \Pr(W_i > B_i) \\ &= \Pr(u_i > B_i - \delta(s)) \\ &= \exp\{-(B_i - \delta(s))/\kappa\}/[1+\exp\{-(B_i - \delta(s))/\kappa\}].\end{aligned} \tag{9}$$

For both the utility and bid function approaches, the precision with which the parameters of the model are estimated (for a given survey sample size) depends on the choice of bid values B_i. This problem is the same as the optimal experimental design of dose level in quantal analysis in bioassay field. I review the experimental design in the following section.

III. Experimental Design

Much of the experimental design literature in a discrete choice setting has evolved in the bioassay (or dose-response field). Dose-response models are used to characterize the effect on laboratory animals of varying doses of a given substance or treatment. Most often, the effect is measured in terms of the percentage of animals that die when administered a specific dose. The model estimated is a probability curve (called tolerance distribution), often assumed to be logistic. The specific quantity of interest varies, but analysts are often interested in the effective dose level (ED_γ) at which γ percentile of animals will respond. ED_{50}, for example, would indicate the dosage level at which half of the sample would be expected to die. This is analogous in the non-market valuation situation where analysts are interested in the median WTP (i.e., the program cost at which half the population would vote "yes").

Since responses of animals are not observable before the experiment is conducted, parameters in the probability model of interest are not observable either. There are two approaches for optimal design which vary in terms of how these unknown parameters are handled in the design process. The classical approach treats the parameters of interest as if they are known prior to the experiment; e.g., drawn from prior studies or relying on a best guess. On the other hand, the Bayesian approach takes into account uncertainty about the parameters by assigning prior distribution to them. Each of these design approaches are described in the following subsections.

A. The Classical Design Approach.

The optimal design for an experiment will, of course, depend upon the criteria or objective function used to evaluate the outcome of the experiment. Three criteria are prominent in the classical literature: D-Optimality, C-Optimality and Fiducial method.

1. D-Optimality.

D-Optimality uses as its objective the maximization of the determinant of the Fisher information matrix; i.e., the negative of the expected value of the Hessian of the log likelihood function. The information matrix is asymptotically equivalent to the inverse of the covariance matrix for maximum likelihood estimators. Thus, maximizing the determinant of this matrix given a logistic response function corresponds, in some sense, to jointly minimizing the asymptotic variances of the estimators. Minkin (1987) shows that the D-Optimal design for estimating ED_{50}, consists of two dosage levels $\mu - 1.5434 \cdot \sigma$ and $\mu + 1.5434 \cdot \sigma$ (where μ and σ are respectively the median and standard deviation of the underlying response distribution), with each dosage level administered to half of the sample. The problem, of course, from a practical point of view is that neither μ nor σ is typically known with certainty prior to the experiment.

2. C-Optimality.

A C-Optimality design minimizes the variance of a function of the estimated coefficients. For example, consider a simplified version of the utility theoretic approach to model the DCR response, where $\alpha(s) = \alpha$. The corresponding median WTP becomes (α / β). The C-Optimal design would seek to minimize the asymptotic variance of ($\hat{\alpha} / \hat{\beta}$), where $\hat{\alpha}$ and $\hat{\beta}$ are maximum likelihood estimates of the model parameters. Wu (1987) shows that efficient estimation of the median occurs with all design points at the median value, i.e., a one-point design.

3. The Fiducial Method.

Another criterion that might be considered useful is the minimization of the length of the fiducial (or confidence) interval (Finney, 1978) associated with a function of the estimated parameters.[1] Under fiducial interval criterion, the optimal design is a 2-point design distributed symmetrically around median of the response distribution when the sample size is even and a 3-point design when the sample size is odd. Kanninen (1993) shows in the context of DCR and the utility function approach that it is again optimal to have two bid points ($\mu - 0.6105 \cdot \sigma, \mu + 0.6105 \cdot \sigma$) distributed symmetrically around the median when the sample size is 500.[2]

B. Bayesian Optimal Design Criteria

1. Overview

Lindley (1972) presented a two-part decision theoretic approach to experimental design, which provides a unifying theory for most work in Bayesian experimental design. Lindley's approach involves specification of a suitable utility function reflecting the purpose

[1] The fiducial and C-Optimal designs will be equivalent when the function of interest is linear in the parameters.
[2] The fiducial designs will generally depend on the sample size.

and costs of the experiment. The best design is then selected to maximize expected utility.

Specifically, suppose that design points **B** are selected from some set **D.** The response outcome vector **y** from a sample space **Y** will then be observed with probability $p(y \mid B)$. Based on **y**, a decision $r(y)$ will be chosen from some set **A**. Thus, the problem has two parts: first the selection of **B** and then the choice of a terminal decision rule $r(y)$ based on observation **y**. The unknown parameters are θ and the parameter space is Θ. A general utility function is of the form $U(r(y), \theta, B, y)$. For any design **B**, the expected utility of the best decision is given by

$$\Psi(B) = \int_{Y} \max_{r(y) \in A} \int_{\Theta} U(B, r(y), \theta, y) p(\theta \mid y, B) p(y \mid B) d\theta dy \tag{10}$$

and the Bayesian solution to the experimental design problem is provided by the design $\mathbf{B}^*$ maximizing equation (10). In other words, Lindley's argument suggests that a good way to design experiments is to specify a utility function reflecting the purpose of the experiment, to regard the design choice as a decision problem and to select a design that maximizes the expected utility.

To fix ideas, suppose that the problem at hand was one of testing a new drug. The decision variable, $r(y)$, in this case might be whether to put the drug on the market, which will depend upon the outcomes of the drug testing. The utility function would ideally reflect the cost of the testing, the value of the drug if it is found to be effective and the costs associated with any ill effects (including death) from its use. The design points (B) could include both dosage levels and sample sizes.

As in the case of classical designs, the optimal dosages (or bids in the valuation context) depend upon the specific criteria used (i.e., the utility function in equation 10). If, for example, $U(\cdot)$ is the expected gain in Shannon information (i.e., the Kullback-Leibler divergence) between the prior and the posterior distribution on the parameters of interest, then a Bayesian version of D-Optimality results. In this dissertation, I follow the bulk of the existing literature by using a squared error loss function, resulting in a Bayesian version of C-Optimality.

Suppose that the only quantity to be estimated is a function of the coefficient $g(\theta)$, such as the median WTP for the utility theoretic model, $(g(\theta) = \alpha(s)/\beta)$, and that the squared error loss is appropriate. Under the squared error loss function, a design is chosen to maximize the following expected utility:

$$\Psi_2(B) = -\int_{Y}\int_{\Theta}\left[g(\theta) - \hat{g}(\theta)\right]^2 p(y,\theta \mid B) d\theta dy. \tag{11}$$

The criterion function in equation (11) is a complex function of the bid design and, for a given bid design, typically requires numerical integration techniques to evaluate. Fortunately, two approximations to $\Psi_2(B)$ have been developed in the literature based on normal approximations to the posterior distribution for θ. Chaloner and Larntz (1989) use

$$\theta \mid y, B \sim N(\hat{\theta}, H_0 \equiv [N \cdot I(\hat{\theta}, B)]^{-1}), \tag{12}$$

whereas Kanninen (1991) and Tsutakawa (1980) use

$$\theta \mid y, B \sim N(\hat{\theta}, H_1 \equiv [N \cdot I(\hat{\theta}, B) + V^{-1}]^{-1}), \tag{13}$$

where I is the Fisher information matrix per observation, N is total number of observations in the sample, and V is variance-covariance matrix of the prior distribution for the parameter vector θ. The advantage of the specification in (13) is that the inclusion of V not only keeps the elements of H_1 in equation (13) bounded, but also is consistent with the idea that, when the sample size is small, the posterior covariance matrix is not likely to differ greatly from V. The posterior variance $V[g(\theta) \mid y]$ is then approximated by the delta method using

$$V[g(\theta)\mid y] \approx c(\theta)^T H_k\, c(\theta), \tag{14}$$

where

$$c(\theta) = \frac{\partial g(\theta)}{\partial \theta}. \tag{15}$$

Under the normal approximation in equation (12), $\Psi_2(\theta)$ can be approximated by

$$\phi_0(B) = -\int c(\theta)^T \{N \cdot I(\theta, B)\}^{-1} c(\theta) p(\theta) d\theta. \tag{16}$$

Similarly, under the normal approximation in equation (13), the approximation to the objective function becomes:

$$\phi_1(B) = -\int c(\theta)^T \{N \cdot I(\theta, B) + V^{-1}\}^{-1} c(\theta) p(\theta) d\theta. \tag{17}$$

That is, the squared error loss criterion yields a Bayesian version of C-Optimality, minimizing the expected posterior variance of the function of interest. Both Chaloner and Larntz (1989) and Tsutakawa (1980) adopted this criterion.

2. Optimization of the Criteria Functions

In general, choosing the optimal bid design based upon the criteria function in either equations (16) or (17) requires selecting the number of design levels, *K*, the levels themselves (i.e., B_k, $k = 1, \cdots, K$), and the number of sample points per design level n_k, with $\sum_{k=1}^{K} n_k = N$.[3] This is a complicated numerical optimization problem. In order to simplify the problem, Tsutakawa (1980) restricted the designs he considered to ones that assigned the same number of observations to each design point (i.e., $n_k = N / K$), with design points

[3] The sample size, *N*, is assumed fixed.

spaced equally around the midpoint of the distribution being estimated; i.e.,

$$B_k = z + \{k - (K+1)/2\} \cdot w, \tag{18}$$

where z is the midpoint and w is the interval width. Under these restrictions, criterion function (17) is optimized, for given K, with respect to z and w, yielding $z^*(K)$ and $w^*(K)$. Tsutakawa (1980) used a normal-gamma prior for parameters α and β in equation (2) and approximated the integrals in equation (17) by combining Gauss-Hermite and Gauss-Laguerre quadrature methods. The optimal design was then determined by examining the expected posterior variance values for various triplets $(K, z^*(K), w^*(K))$.

Chaloner and Larntz (1989) relaxed Tsutakawa's (1980) equally spaced design restriction. Instead of taking the derivative approach, Chaloner and Larntz adopted the Nelder-Mead simplex algorithm that does not require derivatives and directly obtains n_k and B_k ($k = 1, \cdots, K$) for a given K. The design is then chosen that optimize the criterion on the smallest number of design points. In the last step, authors verified global optimality with directional derivative over possible value of B.

Tsutakawa (1980) and Chaloner and Larntz (1989) both show that optimal design gets wider and number of design point K increases with parameter uncertainty. Chaloner and Larntz show that, while Tsutakawa's equally spaced design is 94% as efficient as non-equally spaced design, the number of observations per design level is not necessarily same over design point with uniform prior on parameters.

3. Recent developments in Bayesian Design.

There have been a number of recent developments in the Bayesian design literature that are relevant to my dissertation. First, there are a number of papers that consider alternatives to the normal approximation in equation (12) and (13). Sun, Tsutakawa and Lu (1996) and Müller and Parmigiani (1995) propose the Monte Carlo simulation approach to obtaining an exact evaluation of expected utility in optimal design. Sun, Tsutakawa and Lu (1996) compare the performance of approximation to expected utility with that of exact expected utility approach. They show, even though the solution to the design problem based on the normal approximation is generally quite accurate, the approximation to the expected posterior variance itself may be substantially understated. They also show that the error in the asymptotic expected posterior variance relative to the exact expected posterior variance 1) increases with parameter uncertainty, 2) decreases with the number of design point and 3) decreases with the number of observations.

Müller and Parmigiani (1995) rely on smoothness of expected utility with respect to the design attributes to simplify the search for the optimal design. Specifically, they simulate expected utilities for a series of design points, estimate a smoothed representation of the expected utilities as a function of design characteristics, and then analytically derive the optimal design. They show that design points obtained by the smoothing method provides a consistent estimate of optimal design and suggest that curve-fitting method would be appropriate for sequential design because computation is less costly. The basic steps are as follows:

Step 1: A set of mid point and width values $(z_i(K), w_i(K)), i = 1,\cdots,M$ are selected from the set of possible designs $\mathbf{D}$ and design points $B_i(K)$ are obtained from equation (18) for given K.

Step 2: $\phi_1(B_i)$, or $\Psi(B_i)$, is obtained by Monte Carlo integration of the approximate posterior variance over $\theta_j(z_i, w_i), j = 1,\cdots,M_S$,where M_S is the number of Monte Carlo simulation, drawn from prior distribution $p(\theta \mid z_i, w_i)$. The approximated posterior variance can be obtained by either Tierney and Kadane (1986)'s method or the normal approximations in equation (12) or equation (13).

Step 3: A smoothed expected utility $\phi_1^*(z_i, w_i \mid K)$ is obtained by fitting $\phi_1(B_i)$ with respect to $(z_i(K), w_i(K)), i = 1,\cdots,M$ using a locally weighted running line smoother.

Step 4: The optimal design $B^* = (z^*(K), w^*(K))$ is determined by evaluating deterministically the maximum of $\phi_1^*(z_i, w_i \mid K)$, i.e.,

$$(z^*(K), w^*(K)) = Max_{z,w}\phi_1^*(z, w \mid K).$$

IV. Single Stage Design

In this section, I focus my attention on the single-stage design in which the CVM survey is implemented without a pre-test phase. This is similar to what Kanninen (1991) considered. The two-stage design with a pre-test is considered in section **V**. I begin by reviewing and replicating the basic results obtained by Kanninen (1991) in the third chapter of her dissertation. Specifically, optimal classical and Bayesian bid designs are obtained using the utility difference model proposed by Hanemann (1984). The performance of each design is then compared using the expected posterior variance criterion. I then propose an optimal bid design approach based on Cameron's (1988) bid function representation of DCR responses and I use both the Müller and Parmigiani (1995) curve-fitting approach to bid design and alternative approximations to the expected posterior variance.

A. Kanninen's Bayesian Designs

Kanninen (1991) adapts Tsutakawa's (1980) two-parameter (α, β) logit model of response, the normal approximation to the expected posterior variance in equation (17) above, and assumes a normal prior distribution for the parameter vector $\theta = (\alpha, \beta)$. She advocates using a normal prior because maximum likelihood estimates of the parameter vector are typically available for contingent valuation based on pre-test data. That is, the prior distribution of the two parameters could be assumed to be distributed bivariate normal based on the asymptotically normal pre-test estimates. Using this set-up, she obtains the same results as Tsutakawa (1980) and Chaloner and Larntz (1989); i.e., that the optimal number of design points and their spread increases with the prior uncertainty about the parameter vector

θ. However, if the prior uncertainty is low, she finds the optimal design reduces to the standard result of a single bid point. She also develops an optimal Bayesian design for double-bound model to enhance parameter estimate efficiency. In the remainder of this section I describe the results from replicating her single-bounded design efforts.

Kanninen maximized equation (17) for given number of design points *K*, ranging from 1 to 7 for the single-bound model with sample size $N = 500$. The prior means for α and β are set to 2.5 and 0.01, respectively. This yields a modal WTP of 250. In one set of examples, the prior variance of α is allowed to range from 0.1 to 2.1, while the variance of β is fixed to 1e-6. The prior modal WTP thus has a variance ranging from 10 to 210. In a second set of examples, the prior variance of α is held constant at 0.1 while the prior variance of β ranges from 1.e-6 to 1.3e-5. The prior covariance is always set to 0. One reason why Kanninen sets the prior variance β so low (relative to its prior mean) is to reduce the prior odds that β is close to zero (and hence WTP goes to infinity).

I replicate Kanninen's optimal bid design results when *K*=2, allowing the prior variance of α to vary while fixing the prior variance of β. I then compare the performance of Bayesian design with that of classical design. Expected utility (in this case the expected posterior variance of WTP) is evaluated at the C-, D-Optimality and Fiducial method design points shown at Table 1.

Figure 1 plots the square root of the expected posterior variance $s_i = \sqrt{\phi_i}$ for the various classical criteria, i.e., i = C for C-optimal, = D for D-optimal, and = F for fiducial and = B for Bayesian optimal designs. The prior variance of α was allowed to range from 0.1 to 2.1. In Figure 1, the horizontal axis is the implied prior standard deviation of WTP (σ_{WTP}), which ranges from 40 to 150. Figure 2 provides essentially the same information, but in terms of the cost of using the various classical designs (relative to the optimal Bayesian design)

As anticipated, the expected posterior standard deviations (s_i) are lowest for the optimal Bayesian designs. At σ_{WTP}=40.31, s_i evaluated using the C-and D-Optimality, and Fiducial designs is 9.43, 11.44, and 9.63, respectively, while s_i for the Bayesian design is 9.34. The C-Optimality criterion dominates the Fiducial method until σ_{WTP} reaches 50. The D-Optimality criterion is inferior to the C-Optimality until σ_{WTP} reaches approximately 100 and is inferior to the Fiducial method until σ_{WTP} exceeds 125.

The results in Figures 1 and 2 make sense intuitively. The Bayesian and C-Optimal designs employ similar objective functions both related to the variance in the estimated mean WTP. The difference is that the Bayesian design takes into account prior uncertainty regarding the mean WTP. When this uncertainty is low, the C-Optimal design does relatively well. However, when this prior uncertainty is high, the classical design placing all bids at a single point does poorly. In contrast, the classical Fiducial method uses two bids (at $(\alpha \pm 0.61)/\beta)$). At low levels of prior uncertainty, the C-Optimal design dominates. As this uncertainty increases, however, having some spread in the bids becomes preferable and the Fiducial design yields a lower value in s_i. Similarly, the D-Optimal design, with the bids spread even further (at $(\alpha \pm 1.54)/\beta)$, becomes preferable only at higher levels of prior uncertainty.

So far, the results that we have seen are for when the prior standard deviation of α varies while the prior standard deviation of β is held fixed. On the other hand, the results when the prior standard deviation of β varies and the prior standard deviation of α remains fixed highlights the drawback of the utility difference approach noted above. Specifically, if the prior uncertainty about β increases to the extent that the value of β is likely to be close to zero, it is then likely that the corresponding WTP becomes very large (since WTP=α / β). Indeed, the moments for the prior on WTP do not exist (See e.g., Fieller, 1932; Curtiss, 1941; Marsaglia, 1965; Hinkley, 1969). One approach is to limit the range of prior uncertainty regarding the marginal utility of income (e.g., using a truncated normal prior on β) in order to get bid values for a given *K*. However, such limit on the variance of the parameter would not fully reflect the uncertainty of WTP.

B. Bid Function Approach to Optimal Design

In contrast to the utility difference approach, the mean WTP derived from the bid function approach is typically linear in the unknown parameters. In the remainder of this section, I consider the simplest version of equation (8) in which $\delta(s) = \delta$. I derive optimal design points using the asymptotic approximation method and the equally spaced design assumption in equation (18) for $N = 500$. The prior distributions for δ and κ are assumed to be independent. The prior distribution of δ is assumed to follow normal distribution with mean μ_δ and variance τ^2, while the prior distribution for κ is assumed to be triangular distribution with mean m_κ and spread s_κ. The density of a triangular distribution with mean m_κ and spread s_κ is zero beyond the range ($\kappa_{\text{Min}}, \kappa_{\text{Max}}$), where $\kappa_{\text{Min}} \equiv m_\kappa - s_\kappa$ and $\kappa_{\text{Max}} \equiv m_\kappa + s_\kappa$, rises linearly from κ_{Min} to m_κ, and drops linearly to κ_{Max}. While the uniform distribution is sometimes used to model the uncertainty of a parameter (e.g., κ), it assumes that the parameter κ is equally likely to take the values between κ_{Min} and κ_{Max}. In contrast, the triangular distribution describes the situation where the parameter κ is most likely to take the value of m_κ, with diminishing probability for regions away from m_κ.

The prior density of (δ, κ) is then given by the pdf for $\delta \in R, \kappa \in [\kappa_{Min}, \kappa_{Max}]$,

$$p(\delta, \kappa) \propto \exp\{-(\delta - \mu_\delta)^2 / 2\tau^2\}\{[\kappa - \kappa_{\text{Min}}]d + [\kappa_{\text{Max}} - \kappa](1-d)\}, \tag{19}$$

where $d = 1$ if $\kappa \in (\kappa_{\text{Min}}, m_\kappa)$ and $d = 0$ otherwise.

The H_1 matrix in equation (13) is then

$$H_1 = (I + V^{-1})^{-1}, \text{where } V = \begin{bmatrix} \tau^2 & 0 \\ 0 & s_\kappa^2 / 6 \end{bmatrix}. \tag{20}$$

Using $c(\theta) = (1, 0)'$, the expected utility in equation (17) is maximized with respect to (z, w) as in Tsutakawa (1980). The model has four parameters defining prior distributions, $(\mu_\delta, \tau, m_\kappa, s_\kappa)$. The value of μ_δ is assumed to be equal to 250. I consider values for τ taken from the set {1, 10, 20, 30, 40, 50, 60, 70, 80, 90}, values of m_κ taken from the set {20, 30, 40, 50, 60, 70, 80} and values of s_κ from the set {5, 10, 15, 20, 30} in order to examine how the optimal Bayesian bid design responds to:

- changes in the prior uncertainty about the mean WTP (i.e., changes in τ)
- changes in the mean dispersion of WTP (m_κ); and
- changes in the prior uncertainty about the dispersion of WTP in the population (i.e., changes in s_κ).

Numerical integration of equation (17) over δ and κ is performed and the optimal values for (z, w) are obtained by Nelder-Mead algorithm. I also restrict my attention to a sample of $N = 500$ and designs that are symmetric about the mean WTP.

The results show how optimal design points respond to uncertainty in terms of the mean and dispersion of WTP. First, consider the case when $m_\kappa = 20$ and $s_\kappa = 5$. Figure 3 illustrates how the optimal two point design changes for the bid function approach as the prior standard deviation of δ (i.e., τ) is varied. When τ is equal to 1 and the analyst is relatively certain about the mean WTP, the optimal design degenerates to a one point design with all the bids placed at 250. However, as τ increases above 1, the Bayesian optimal design points diverge away from the single-point design placing the two bids further from the mean WTP of 250. For example, the two-point design (common in a classical setting) puts the bids at 161 and 340 when τ =90.

Of course, two bids need not be optimal. Figure 4 illustrates what happens to the optimal bid design if we allow the number of bid points to increase up to an eight-point design. As the prior uncertainty regarding the mean WTP increases, it becomes optimal to increase both the spread of the bids and the number of bids used. With τ =30, three bids becomes optimal. By the time τ doubles to 60, an eight point design dominates. Figure 5 illustrates the performance of the Bayesian designs for various values of *K*. The corresponding eight-point provides an efficiency gain over a two-point design of about a factor of three (see Table 2). However, although placing multiple bids ($K > 3$) yields the apparent efficiency gain compared to two-point design when τ is big, placing more than four-bid points yields little efficiency gain. Therefore, placing more bids might not be optimal in practice when an analyst considers the cost of the contingent valuation survey design (e.g., cost of printing the survey with more than four-bid points). This suggests that a two-or three-point design may often be sufficient in practice.

More generally, we might want to consider how the optimal design responds to changes in τ, s_κ and m_κ. Since κ measures the population dispersion in WTP, a large m_κ corresponds to a large prior mean in the dispersion of WTP in the population, whereas a large s_κ implies the uncertainty about this dispersion. For ease of exposition, I consider only the two-point design case and fix the midpoint of the design at the prior median WTP (μ). In this case, the only design decision is the width of the design interval, *w*.

Figure 6 presents the surface of optimal width *w* as a function of τ and m_κ at s_κ equal to 5. The figure suggests that, for a given value of m_κ, the optimal design width is increasing with the prior uncertainty about the mean WTP (i.e., τ). However, for a given τ, the optimal width decreases with the mean dispersion in WTP (i.e., m_κ). When $\tau = 20$, the optimal bid width is 49. This width drops to 33 when $m_\kappa = 30$. For m_κ bigger than 30, the optimal width is zero. In general, the point at which the optimal bid width drops to zero appears to be a function of τ and m_κ. In particular, if the ratio of τ to m_κ ($v_r \equiv \tau / m_\kappa$) is less than one, the optimal width becomes to zero. However, as optimal width contour plots in Figures 7 to 9 illustrate, the region in the optimal width remains zero disappears as the uncertainty of the dispersion of WTP distribution (s_κ) increases. It also appears that the optimal bid width has a convex relationship with respect to m_κ; i.e., the optimal width increases up to some m'_κ and decreases thereafter.

What does this suggest? For simplicity, suppose there is no uncertainty about the dispersion of WTP distribution; i.e., $s_\kappa = 0$. For the ratio v_r to be equal to one implies that the prior mean in the dispersion of WTP (m_κ) is equal to the uncertainty of mean WTP (τ) so that the WTP in the population has the same distribution as the mean WTP (δ) with the same mean 250 and variance $\tau^2 = m_\kappa^2$. Therefore, the posterior variance of mean WTP (δ) becomes the variance of WTP and the Bayesian design points becomes the C-Optimality design placing one bid point at the mean WTP (μ_δ) 250. For the region where v_r is less than one, the Bayesian bid design becomes the C-Optimal design. On the other hand, when the uncertainty about the dispersion of WTP distribution becomes significant, posterior variance of mean WTP (δ) diverges away from the variance of WTP. Therefore, there is less chance for the optimal bid width to become zero.

Finally, the cost of using classical design (i.e., ignoring parameter uncertainty) is shown in Figure 10 for $m_\kappa = 50$. This cost is defined to be ratio of expected posterior variance of the C-Optimal design to that of Bayesian design. Expected posterior variance of C-Optimal design is obtained by evaluating equation (11) at C-Optimal design points (i.e., B_1=B_2=250). As expected, the ratio is bigger than 1 over the entire region of (τ, s_κ) because Bayesian design minimizes the expected posterior variance. For $s_\kappa = 5$ (i.e., when the prior uncertainty on the dispersion of WTP distribution is low) the performances of C-Optimal and optimal Bayesian designs are close for all τ. However, as this prior uncertainty grows, the Bayesian design performs substantially better than classical design. Likewise, for given s_κ, the cost of using the classical design generally increases with uncertainty about the mean WTP (i.e., τ). The cost of using the C-Optimal design peak at $s_\kappa = 25$ and $\tau = 70$. The cost of ignoring the prior uncertainty is generally substantial.

C. The Curve-Fitting Method Result

In this section, I illustrate the Bayesian optimal design obtained using the curve-fitting method recently suggested by Müller and Parmigiani (1995).[4] The point of this exercise is to see whether the resulting optimal designs are similar to those obtained using the asymptotic expected utility approach and standard optimization technique.[5] In addition, I compare optimal designs obtained by approximating the expected posterior variance using Tierney and Kadane's (1986) method versus using the traditional normal approximation. As Sun, Tsutakawa, and Lu (1996) show, even though the solution to the design problem based on the normal approximation is generally quite accurate, the error in the normal approximation relative to the exact posterior variance is substantial when parameter uncertainty is high. Therefore, using more accurate approximation to posterior variance might be crucial.[6] In conducting these comparisons, I consider nine prior specifications, varying the uncertainty regarding the prior mean with $\tau = \{20, 50, 80\}$ and the mean population dispersion in WTP with $m_\kappa = \{20, 30, 40\}$. In all the comparisons μ_δ is fixed at 250, the uncertainty regarding the population dispersion of WTP is fixed at $s_\kappa = 5$, and the sample size per bid is fixed at $n_k = 250$.

As described above, step 1 of the curve fitting approach requires the selection of a set of bid designs, **D**, to use in simulating points along the expected posterior variance function $\phi(B)$. In the case of symmetric two-point designs, this corresponds to specifying the set of possible bid widths, w_i. Müller and Parmigiani (1995) recommend picking w_i, $i = 1,\cdots,M$, randomly over a range of reasonable designs. I set this range to be $(0,200)$.

Step 2 in the curve fitting approach requires the calculation of the approximated

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[4] Müller and Parmigiani (1995) note that it is not possible to make any universal recommendations between the curve-fitting and standard optimization method. The choice depends heavily on specifics of the problem, such as computational effort involved in evaluating the utility function, required accuracy, and smoothness of expected utility.

[5] I will refer to the latter approach as the "standard method" in the remainder of this chapter.

[6] Tierney and Kadane (1986)'s posterior variance approximation has an absolute error of order $O(n^{-3})$ or a relative error of order $O(n^{-2})$.

posterior variance for each design point. Specifically, for each bid width, w_i, $j = 1,\cdots,M_s$ pairs ($\theta_{i,j}, y_{i,j}$) are drawn from the independent prior distribution (i.e., equation 19) and the binomial distribution with probability of yes in equation (9). These simulated pairs are in turn used to compute $\Psi_2(w_i)$ in equation (11).

Step 3 in the curve fitting approach requires fitting a curve to the set of observations on $\Psi_2(w_i)$. Following Müller and Parmigiani (1995), I use the locally quadratic regression surface. Since this scatter plot smoothing uses the l nearest points for each data point, $\Psi_2(w_i)$, $i = 1,\cdots,M$, it requires the specification of how many data points are used as the nearest neighbor around each of the point $\Psi_2(w_i)$ to fit a quadratic regression. This is called the "span". A larger span (e.g., 0.75) includes a 75% of the sample size around the point in quadratic fit $\Psi_2^*(w_i)$ and generally results in a smoother curve. In contrast, a smaller span (e.g., 0.25) uses a 25% of the sample size around each data point to fit $\Psi_2^*(w_i)$, allowing for greater curvature in the approximating function $\Psi_2^*(w_i)$. I consider span widths of 0.25, 0.50, and 0.75.

Finally, in step 4 of the curve fitting approach, the optimal bid width (w^*) can then be selected by finding the minimum of $\Psi_2^*(w_i)$. That is, one can simply sort the pair of ($w_i, \Psi_2^*(w_i)$) in ascending order with respect to $\Psi_2^*(w_i)$, yielding the minimum $\Psi_2^*(w_i)$ and corresponding optimal width w^*, as I do in this analysis.

Table 3 contains the optimal bid widths (i.e., w) using three methods: M1) the standard method, M2) the curve-fitting method using the normal approximation to the posterior variance in equation (13), and M3) the curve-fitting using Tierny's approximation to the posterior variance. Both curve fitting approaches use a span of 0.75.

There are two comparisons of interest here. First, consider the comparison between methods M1 and M2; i.e., comparing the standard and curve fitting methods, both using the normal approximation to the posterior variance in equation (13). In this comparison, the only difference lies in the use of curve fitting to find the optimal bid width. As Table 3 indicates, the resulting bid width values for the two methods are very similar to each other, except for $\tau = 20$, $m_\kappa = 40$. Thus, in terms of optimization method, the curve-fitting method performs well relative to the standard method.

The second consideration of interest is between methods M2 and M3; i.e., comparing the two curve fitting methods, one using the normal approximation to the posterior variance and the other using Tierny-Kadane's approximation to the posterior variance. In general, we would expect the Tierny-Kadane approximation to be more accurate than the normal approximation. The bid width values at the second and the third three columns of Table 3 are almost same as well. This result shows that, in terms of the approximation to posterior variance, and given the same optimization method (i.e., curve-fitting), the normal approximation to posterior variance yields similar bid width values, compared to Tierny-Kadane's approximation method. This is consistent with earlier findings in the literature.

One thing to note is that the variation of bid values with m_κ is small for three methods while the variation of bid values with τ is large. This is due to the relative flat curvature of expected posterior variance (EPV) surface with respect to m_κ. Figure 11 to 14 show the four EPV scatter plots from curve-fitting with normal and Tierny-Kadane approximation, respectively. Figure 11 and Figure 13 show EPV scatter plots with $m_\kappa = \{20, 30, 40\}$ and $\tau = 50$ while Figure 12 and Figure 14 show EPV scatter plots with $\tau = \{20, 50, 80\}$ and $m_\kappa = 20$. Figure 11 and Figure 13 show that as the mean dispersion of the population WTP distribution increases, EPV scatter plots get flatter but essentially achieve their minima at the same point. This results in less variation of bid values with m_κ. On the other hand, Figure 12 and Figure 14 show that as the uncertainty of mean WTP distribution increases, the minima of the EPV scatter plot increases resulting in large variation of optimal width with τ. The EPV scatter plots in Figure 11 through 14 also suggest that, in some settings, precisely identifying the optimal bid width is not crucial. For example, with $\tau = 50$ and $m_\kappa = 20$, bid widths ranging from 10 to 120 yields similar EPV values (ranging from 20 to 40). Thus placing two bids at 240 and 260 (i.e., w=20) yields a similar expected posterior variance to placing two bids at 190 and 310 (i.e., w=120). In these settings, the precise selection of the optimal bid width is less important. It also suggests that, rather than using the optimal width of 102, there is little cost to using a round number, say 100.

Finally, the curve fitting approach requires the choice of the span used to fit $\Psi_2^*(w)$. Table 4 shows the sensitivity of the optimal width to the choice of the span. The Tierny-Kadane approximation results appear to be somewhat less sensitive to the span choice for all three spans used, the optimal widths increasing with respect to both τ and m_κ. On the other hand, the optimal width from normal approximation appears to be more sensitive to the choice of the span. For example, optimal width is not monotonically increasing with respect to m_κ for each of three spans and this becomes apparent as span is at 0.25. When span is set at 0.25, 25 percent of M observations around for each data point are used to fit the curve. Therefore, the local variation for each observation will be kept. On the other hand, when span is set at 0.75, there is less variation for each observation because the variation is averaged out. In general, a lower span seems preferable so as to not lose the variation of expected posterior variance surface.

V. Two Stage Design

A. Solution to Sequential Design

The results from the previous section indicate that Bayesian design techniques can provide substantial improvements in the expected posterior variance of the mean WTP obtained from dichotomous choice surveys. The standard optimization and curve fitting approaches yield similar results. However, one reason for introducing curve fitting techniques is that they can be particularly useful in a sequential design setting; i.e., when a survey (or experiment) is to be conducted in waves. This is commonly done in contingent valuation studies in which a pre-test version of the survey is administered so as to better choose the bids used in the final survey mailing.[7]

When an experiment is to be performed sequentially in two stages, the design for the second stage, upon completion of the first stage, is just a one-stage problem with the posterior distribution after the first stage being used as the prior for the second. The problem in sequential design is to choose the first stage design that will optimize the overall experiment in some sense. However, direct implementation of dynamic programming solutions are extremely computation intensive. As Müller and Parmigiani (1995) suggest, the curve-fitting method can be used to reduce computation time in a sequential design structure. In this section, I develop an optimal sequential design in which the bid design considers both the optimal sample distribution between a survey pre-test and formal survey administration and the optimal bid design for each stage under the assumption that a balanced two point design (K=2) is used with mid point known to be 250. The asymptotic normal approximation is used in computing the expected posterior variance.

Sequentially, suppose we are conducting a contingent valuation survey with a fixed sample size of N. The goal is to design optimal bids for pretest and complete survey to estimate mean WTP, δ. In order to do this, the researcher must specify the fraction of the overall sample (λ) to allocate to the pre-test sample size. Thus, the sample size for the pre-test becomes $N_1 = \lambda N$ and the sample for the final implementation becomes $N_2 = (1-\lambda)N$. The tradeoff here is that by allocating more of the sample to the pre-test, the uncertainty regarding the WTP distribution shrinks and one can better design the bids for the final implementation. However, in doing so, there are fewer observations left for the final implementation and it becomes less informative itself.

Given λ, the next stage in the design problem is to choose optimal widths w_1 and w_2 for each stage. Similar to previous sections, I assume equally spaced design framework.

[7] The last thing a surveyor wants is to have set the bids so huge that everyone says "no" or so low that everyone says "yes".

Usually, the solution cannot be obtained in closed form. One solution to get around this problem is to ignore the sequential nature of the problem. However, this would be ineffective in that it would ignore information obtained in stage 1 in setting the bid levels in stage 2, which was the very reason for conducting the pre-test. Instead, in this section I use a simulation based design yields to determine optimal design, conveying its inherently sequential nature.

The curve-fitting based implementation of a sequential design algorithm is as follows:

Step 1: A set of sample portion and width values for each stage $(\lambda_i, w_i^1, w_i^2), i = 1,\cdots,M$ are selected from the set of possible designs $\mathbf{D^1}$ and $\mathbf{D^2}$ and design points $B_i^1(K)$ and $B_i^2(K)$ are obtained from the equation (18) for given design point, $K = 2$.

Step 2: For each design point (λ_i, $B_i^1(K)$, $B_i^2(K)$) draw θ, y_1, and y_2 from the prior and likelihood functions respectively. Compute the approximate posterior variance $I^2(\theta, \lambda, B^2(K), y_2) + (I^1(\theta, \lambda, B^1(K), y_1) + V^{-1})^{-1}$, where I^s is the Fisher information matrix at the stage s and V is prior covariance matrix.

Step 3: The second stage EPV, $\Psi^2(\lambda_i, B_i^1, B_i^2, y_{1i})$ in equation (10) is obtained by Monte Carlo integration of the $I^2(\theta_i, \lambda_i, B_i^2(K), y_{2i}) + (I^1(\theta_i, \lambda_i, B_i^1(K), y_{1i}) + V^{-1})^{-1}$ over θ_i, $y_{1i}(B^1(K), B^2(K))$, and $y_{2i}(B^1(K), B^2(K))$, where M is the number of Monte Carlo simulations, drawn from prior distribution and likelihood functions for given design points.

Step 4: A smoothed expected utility for the second stage $\Psi^{2*}(\lambda_i, B_i^1, B_i^2, y_{1i})$ is obtained by fitting $\Psi^2(\lambda_i, B_i^1, B_i^2, y_{1i})$ with respect to $(\lambda_i, B_i^1(K), B_i^2(K))$ and y_{1i}, using a locally weighted running line smoother.

Step 5: The second stage optimal design B^{2*} is determined by evaluating deterministically the maximum of $\Psi^{2*}(B_i^1, B_i^2, y_{1i})$ over $\mathbf{D^2}$.

Step 6: The first stage optimal design B^{1*} is determined by evaluating deterministically $\Psi^{1*}(\lambda_i, B_i^1) = \Psi(\lambda_i, B_i^1, B_i^{2*}(\lambda_i, B_i^1(K), y_{1i}), y_{1i})$, which is obtained using a locally weighted running line smoother. Ψ^{1*} is then analytically optimized with respect to B_i^1.

Step 7: The optimal sample portion λ^* is determined by optimizing deterministically $\Psi^{0*}(\lambda_i, B_i^{1*}) = \Psi(\lambda_i, B_i^{1*}, B_i^{2*}(\lambda_i, B_i^{1*}(K), y_{1i}), y_{1i})$ over λ_i, which is obtained using a locally weighted running line smoother.

B. Implementation Result

Sequential design is implemented for τ = {20, 30, 40, 50, 60, 70, 80, 90} with $m_k = 20$, $s_k = 15$, and the number of Monte Carlo simulation M = 3,000. Scatter plot smoothing is conducted with the span equal to 0.75.

Table 5 shows the optimal sample allocation (λ) and optimal widths for the pre-test survey and complete survey, respectively, at the number of Monte Carlo simulation (M) equal to 3,000. Several results emerge. First, for low levels of initial (prior) uncertainty regarding the mean WTP ($\tau \leq 60$), a relatively small proportion of the sample is allocated to the pre-test (typically less than 25%). However, when this prior uncertainty becomes large, (e.g., $\tau > 70$) a much larger proportion of the sample is allocated to the pre-test. However, it should be noted that the trade off between a small or large pre-test is a relatively close one. Figure 15 provides a graph of $\Psi^{0*}(\lambda_j, B_j^{1*}, B_j^{2*})$ for the case $\tau = 80$. While λ^* = 73% is optimum, it is not much preferred to λ^* close to 30%. Second, optimal width at the pre-test survey is wider than the complete survey except for τ =20.[8] This makes intuitive sense as the pre-test is being used to provide information for the second stage. The second stage, on the other hand is better informed and, hence, can use a narrower bid design. As the uncertainty of mean WTP increases, the pre-test optimal width increases with the prior uncertainty which is similar result to the single stage design. On the other hand, the complete survey optimal

[8] As shown in the single stage design, the ratio of v_r is equal to one so that the Bayesian optimal design becomes C-Optimal design.

width narrows down to 50 or less for $\tau > 70$.

The sequential design illustrated above fixed the design mid points for both the pre-test and complete survey stage at 250 (i.e., $\mu_\delta = 250$). It is natural to do this at the pre-test stage, since our prior mean WTP is 250. However, in some sense, it is unrealistic to fix the complete survey mid point at 250 because the very reason why the researcher relies on the sequential design is to collect information about the population mean WTP. An extension of the above analysis would be to optimally choose the mid point of the complete survey stage as a choice variable in the steps described in the previous section. For example, at step 1, one could also randomly draw the mid point for the complete survey from the region (e.g., $z_i^2 \in (0, 300)$), with the design choice set then being $(\lambda_i, w_i^1, z_i^2, w_i^2)$, $i = 1, \cdots, M$. The bid points B_i^1 and B_i^2 would obtained from the equation (8) and the rest of the steps conducted as described in the previous section. The implementation of the modified steps remains as one for further study.

VI. Conclusion

Optimal design in contingent valuation is a crucial step in the efficient estimation of the WTP for environmental goods and services. The efficient estimation of WTP is important, in turn, in developing environmental policies. The purpose of this chapter in my dissertation was to illustrate the benefits and consequences of including prior information (and prior uncertainty) in the design process. Both the Classical and Bayesian design approaches were applied to the bid function approach to modeling WTP responses from a dichotomous choice referendum survey. As noted above, using the bid function approach, rather than Hanemann's (1982) utility difference approach (as in Kanninen, 1982), avoids problems associated with the moments of the ratio of two normal variables. In the case of a single stage design, the chapter also illustrates the use of alternative approximations to the expected posterior WTP (i.e., the normal approximation versus the Tierny-Kadane method) and alternative optimization technique (i.e., direct optimization versus curve fitting). In general the results indicate that 1) optimal spread in the bids increases with the parameter uncertainties; 2) the optimal number of bid points (K) increases with the parameter uncertainties; and 3) the cost of ignoring the uncertainty about the parameters of WTP distribution can be substantial. These results are similar to those obtained using the utility difference approach. In addition, curve-fitting method is shown to be a usable alternative to direct optimization routine; i.e., Bayesian optimal bids using the standard method are similar to those obtained using the curve-fitting method. In terms of posterior variance approximation methods, the normal approximation to posterior variance results are similar to those obtained using Tierny-Kadane's method. The curve fitting section also illustrates a number of important points regarding the optimal bid design. First, the expected posterior variance (EPV) surfaces depends all of the attributes of the prior distribution; i.e., on the prior distribution of the mean WTP and on the prior distribution for the dispersion of WTP in the population. Second, the impact of the uncertainty regarding the mean WTP (τ) appears to be larger than that of mean dispersion in the population WTP (m_{κ}). Third, the EPV is relatively flat over a wide range of optimal width values. This suggests that while it is important to incorporate prior information in designing the optimal bid values, identifying precisely the optimal bids is not crucial.

Finally, curve-fitting method makes it easier to implement the sequential design. I find that the number of sample size for the pre-test survey and the pre-test stage optimal bids increase with the parameter uncertainty and they are wider than those of the final survey stage. The width between the optimal bids at the complete survey stage shrinks as the sample size at the pre-test stage increases.

Finally, the results of this chapter provide some practical guidelines to the optimal bid design for researchers conducting contingent valuation surveys:

- Even when there is substantial uncertainty about the distribution of WTP, placing two or three point design provides most of the gains from optimal Bayesian design.

- Since the impact of the uncertainty about mean WTP on the optimal bids is bigger than that of the mean dispersion of WTP, placing wider bids is recommended when the uncertainty about mean WTP is huge.
- Due to the flat curvature of EPV surface, precise selection of optimal bids is less important, for example, placing two bids at 240 and 260 yields similar performance as placing two bids at 190 and 310. This suggests that there is room for rounding in specifying the final bids.
- The sequential design suggests that there is a tradeoff in the allocation of the sample between the pre-test and final survey and the optimal bids at the final stage depends on this allocation.

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Appendix: Tables and Figures

Table 1. Optimal Design Points for Classical Approach

	D-Optimality	C-Optimality	Fiducial Method
x_1	$(1.5434 + \alpha)/\beta$	α/β	$(0.6105 + \alpha)/\beta$
x_2	$(-1.5434 + \alpha)/\beta$	α/β	$(-0.6105 + \alpha)/\beta$

Table 2. Expected Posterior Variance – Bid function approach

τ	K=2	K=3	K=4	K=5	K=6	K=7	K=8	Optimal K
1	0.009	0.009	0.009	0.009	0.009	0.009	0.009	1.000
10	0.049	0.050	0.050	0.050	0.050	0.050	0.050	2.000
20	0.066	0.067	0.067	0.067	0.067	0.068	0.068	2.000
30	0.087	0.084	0.084	0.084	0.084	0.085	0.085	3.000
40	0.117	0.104	0.103	0.103	0.103	0.104	0.104	6.000
50	0.162	0.128	0.124	0.124	0.123	0.124	0.124	6.000
60	0.230	0.159	0.148	0.145	0.145	0.145	0.145	8.000
70	0.333	0.198	0.174	0.169	0.167	0.167	0.167	8.000
80	0.492	0.251	0.206	0.194	0.191	0.190	0.190	8.000
90	0.741	0.324	0.244	0.223	0.216	0.214	0.213	8.000

Table 3. Curve-Fitting method results

	τ								
	Standard Method			Curve fitting					
				Normal Approximation[a]			Tierny-Kadane Approximation[a]		
m_{κ}	20	50	80	20	50	80	20	50	80
20	49	102	157	56	100	122	59	88	101
30	33	101	155	58	105	135	63	109	135
40	0	91	152	62	95	139	77	115	144

[a] Scatter plot smoothing is obtained using a span of 0.75.

Table 4. Impact of the choice of span on optimal width

	τ					
	Normal Approximation			Tierny-Kadane Approximation		
	Span = 0.50					
m_{κ}	20	50	80	20	50	80
20	42	94	133	44	90	99
30	43	103	131	56	110	127
40	55	91	144	56	114	153
	Span = 0.25					
20	51	88	146	58	88	94
30	41	103	118	67	104	135
40	48	96	141	71	122	159

Table 5. Sequential Design Implementation Result[a]

		τ							
M		20	30	40	50	60	70	80	90
3,000	λ^*	0.30	0.14	0.16	0.19	0.23	0.72	0.73	0.73
	w_1^*	2	223	257	256	266	264	269	273
	w_2^*	83	83	124	124	124	50	35	35

[a] m_κ and s_κ are fixed at 20 and 15, respectively.

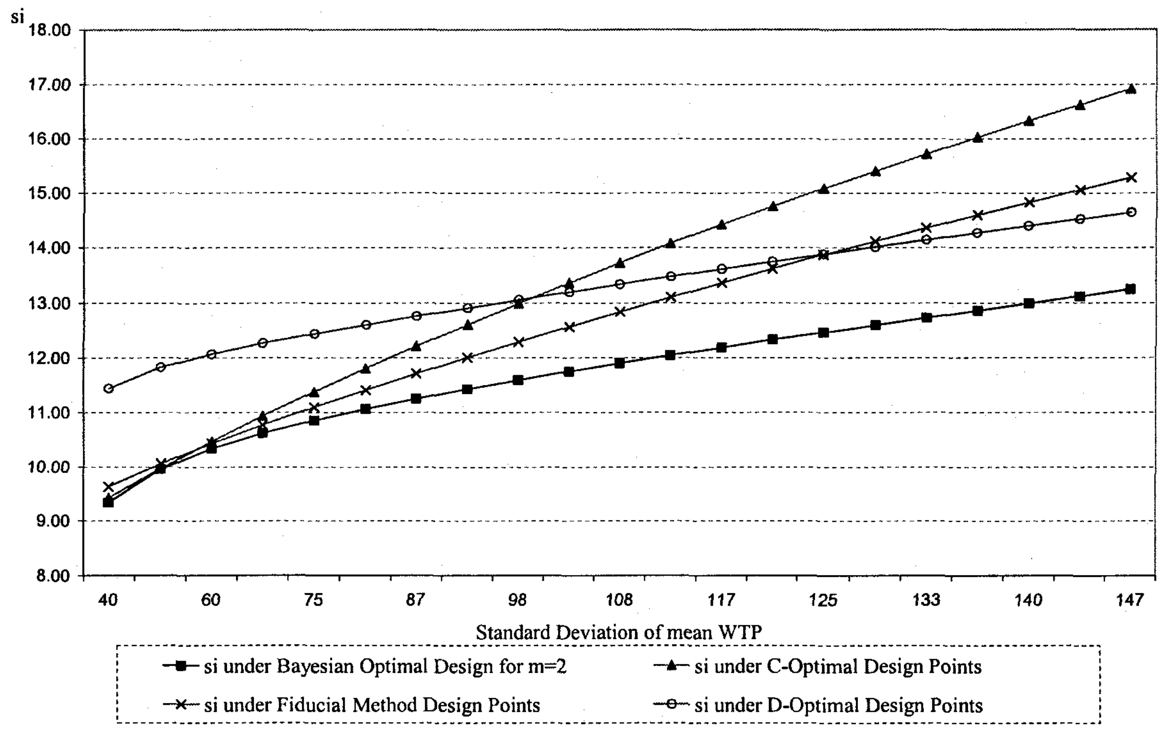

Figure 1. Comparison of s_i Evaluated at Classical Approach Bid Points

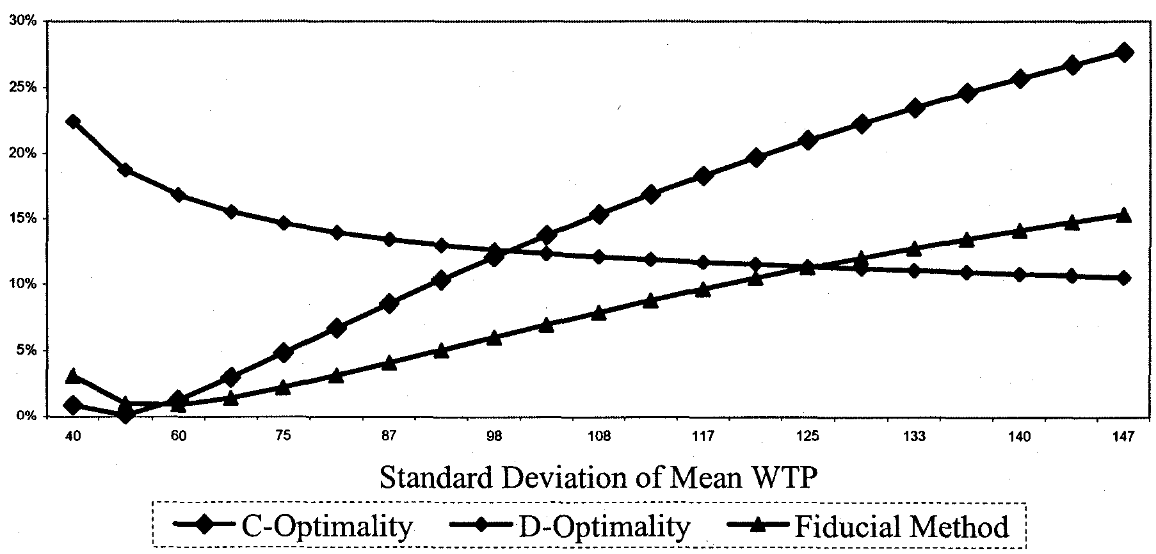

Figure 2. Relative Errors of Classical Design

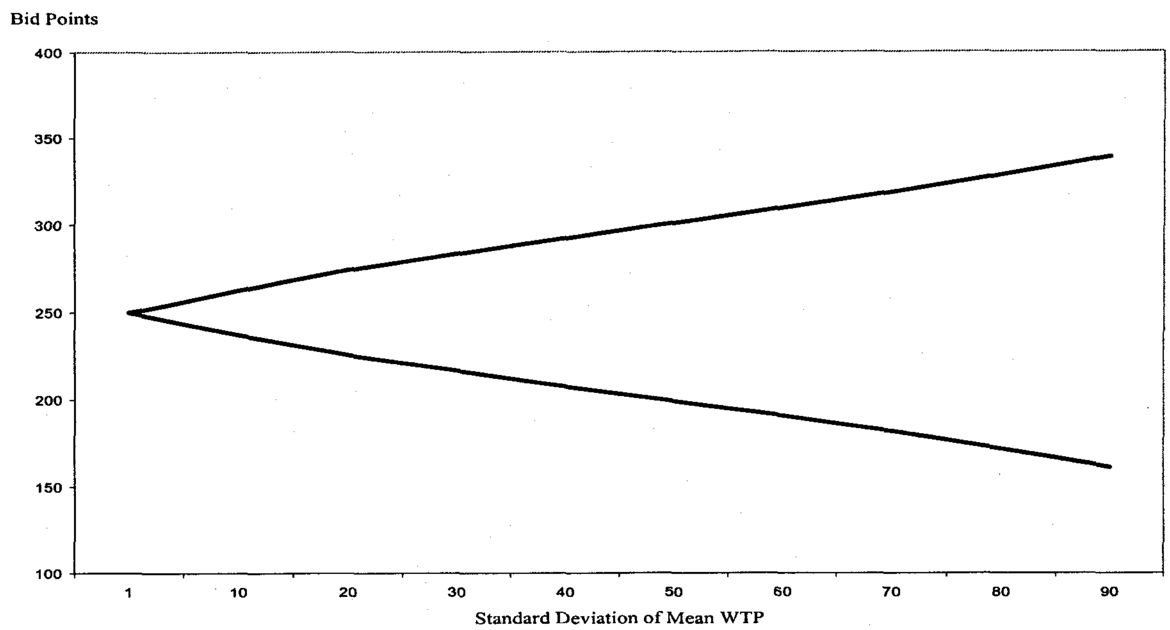

Figure 3. Bid Function Approach – Two Point Design

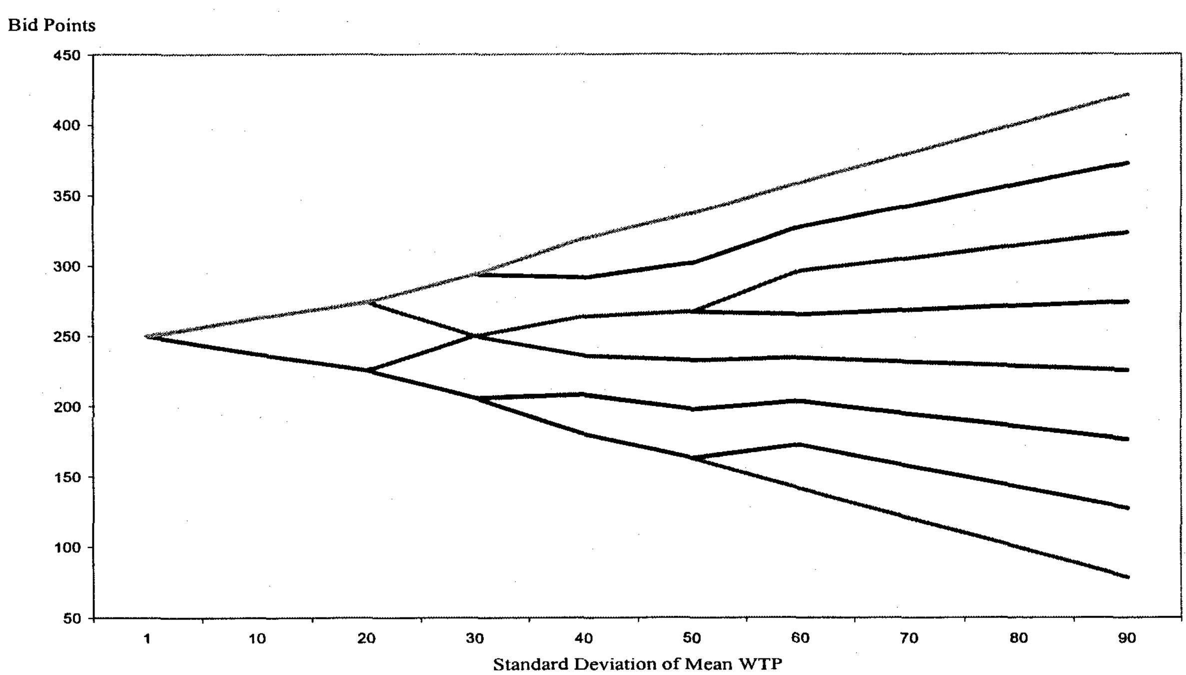

Figure 4. Bid Function Approach – Eight Point Design

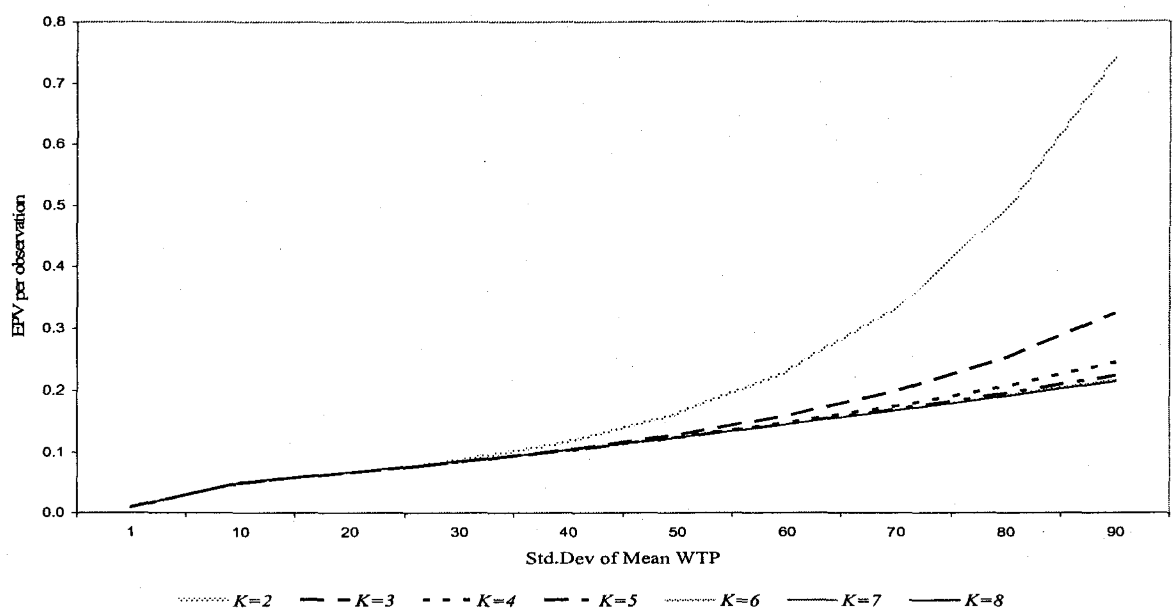

Figure 5. Expected Posterior Variance for Each Design Point (*K*)

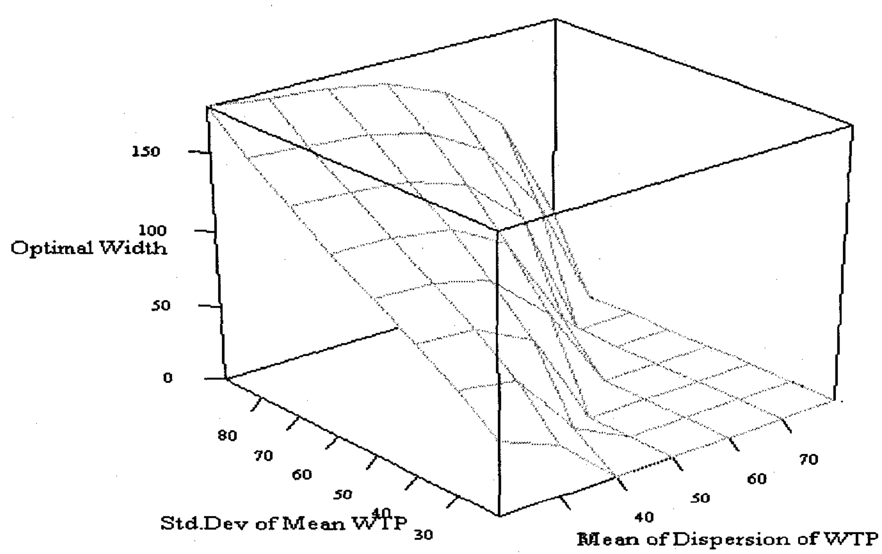

Figure 6. Optimal Bid Width as a Function of τ and m_{K} ($s_{K} = 5$)

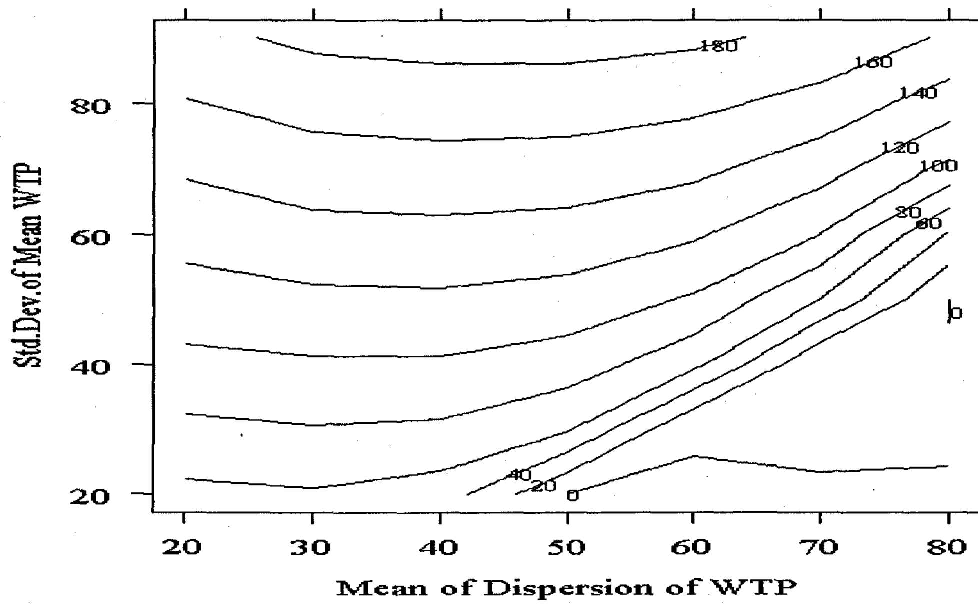

Figure 7. Optimal Width Contour Plots ($s_\kappa = 10$)

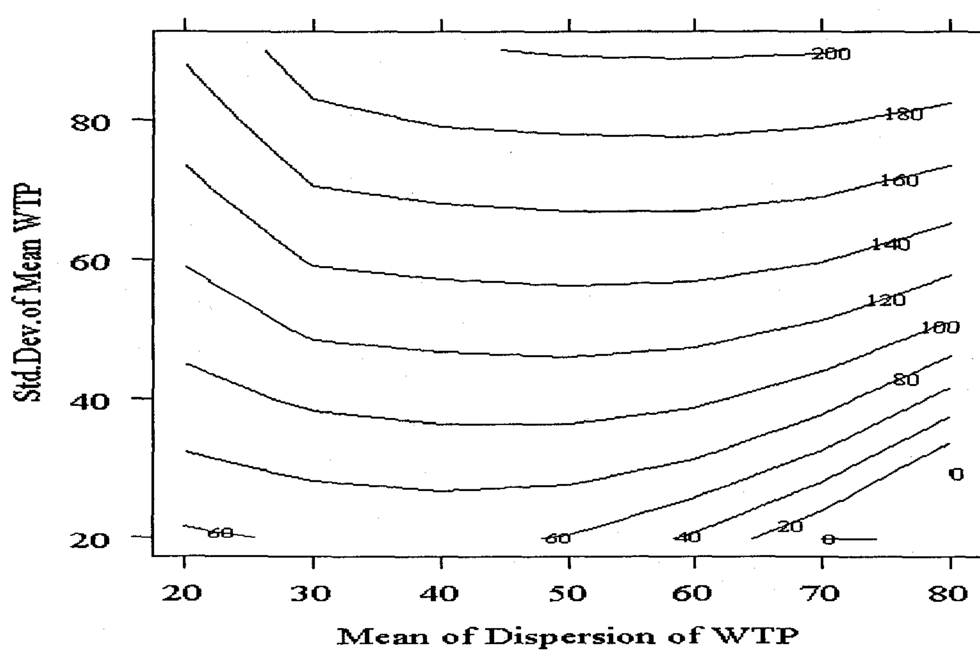

Figure 8. Optimal Width Contour Plots ($s_\kappa = 15$)

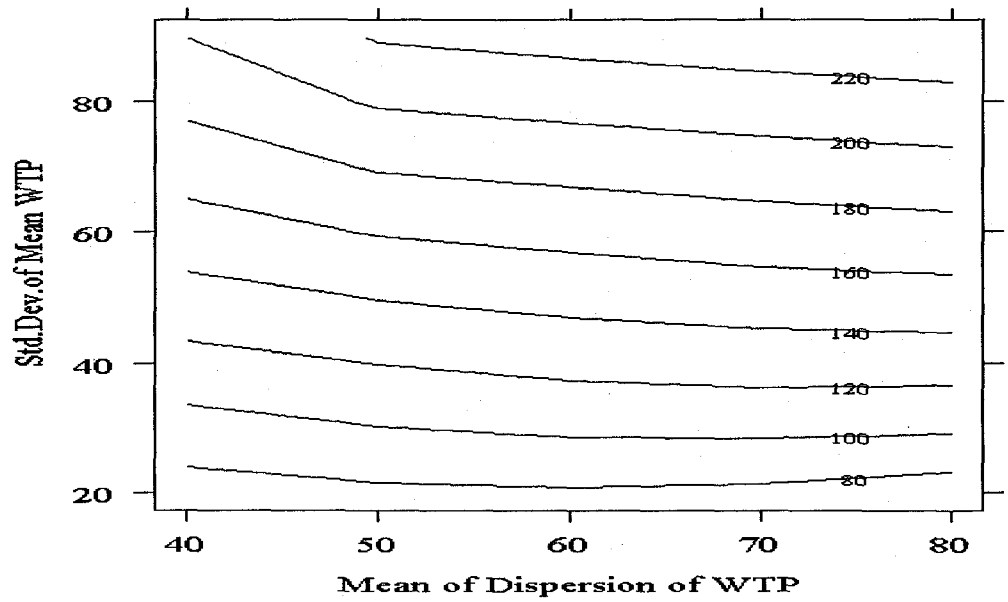

Figure 9. Optimal Width Contour Plots when s_κ is 30

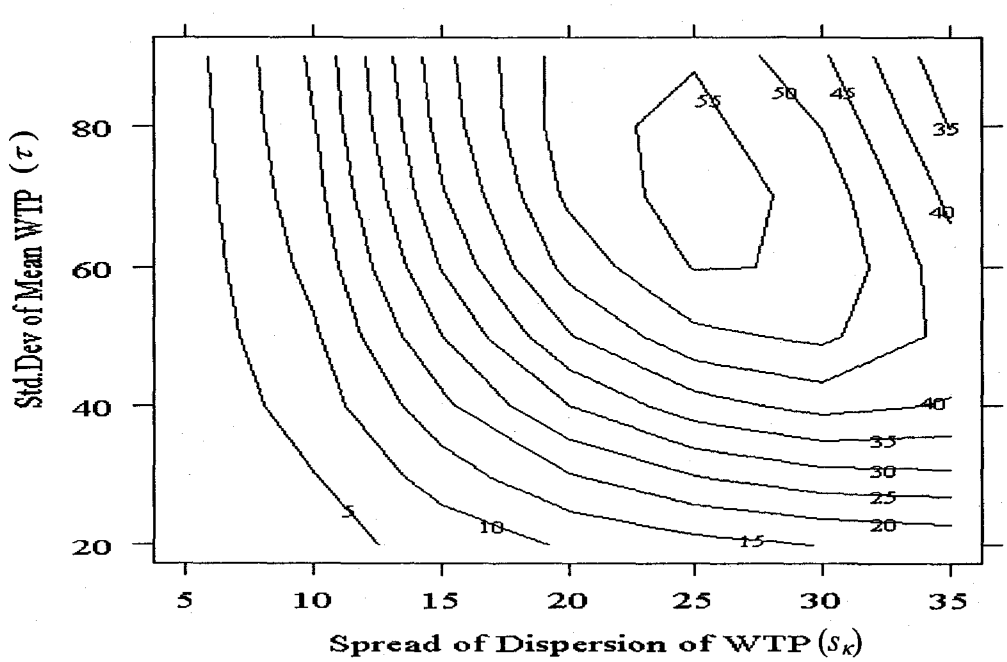

Figure 10. Cost Contours From Using C-Optimal Design

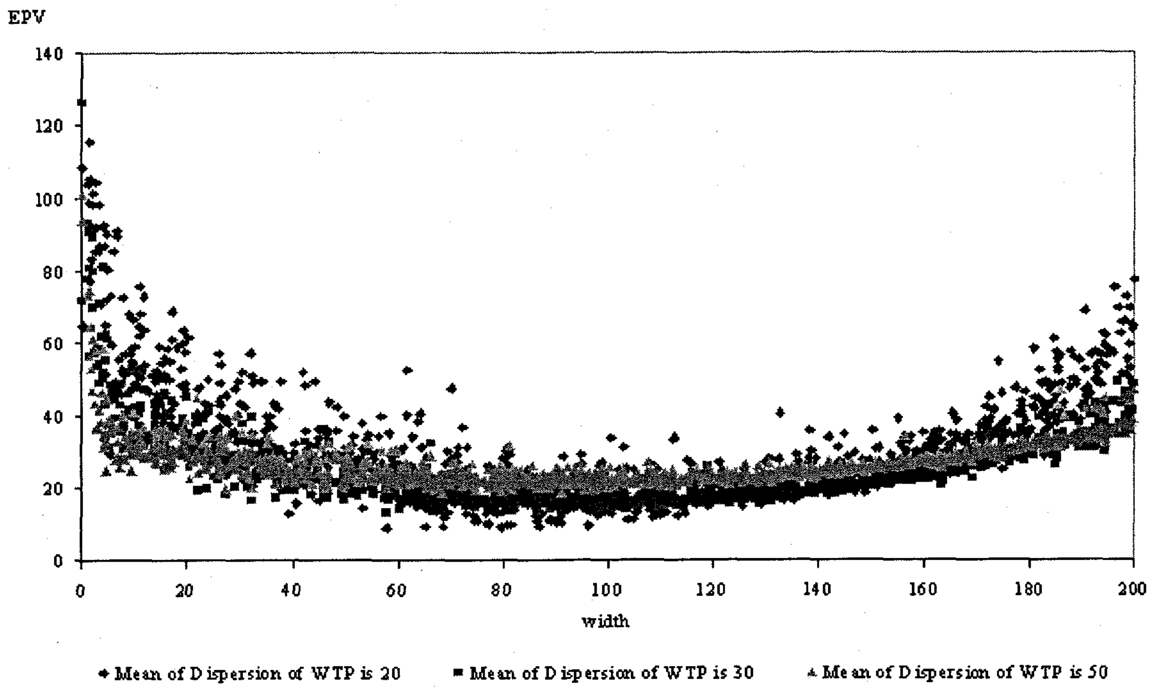

Figure 11. EPV scatter plots from Normal approximation with each of m_κ at $\tau = 50$

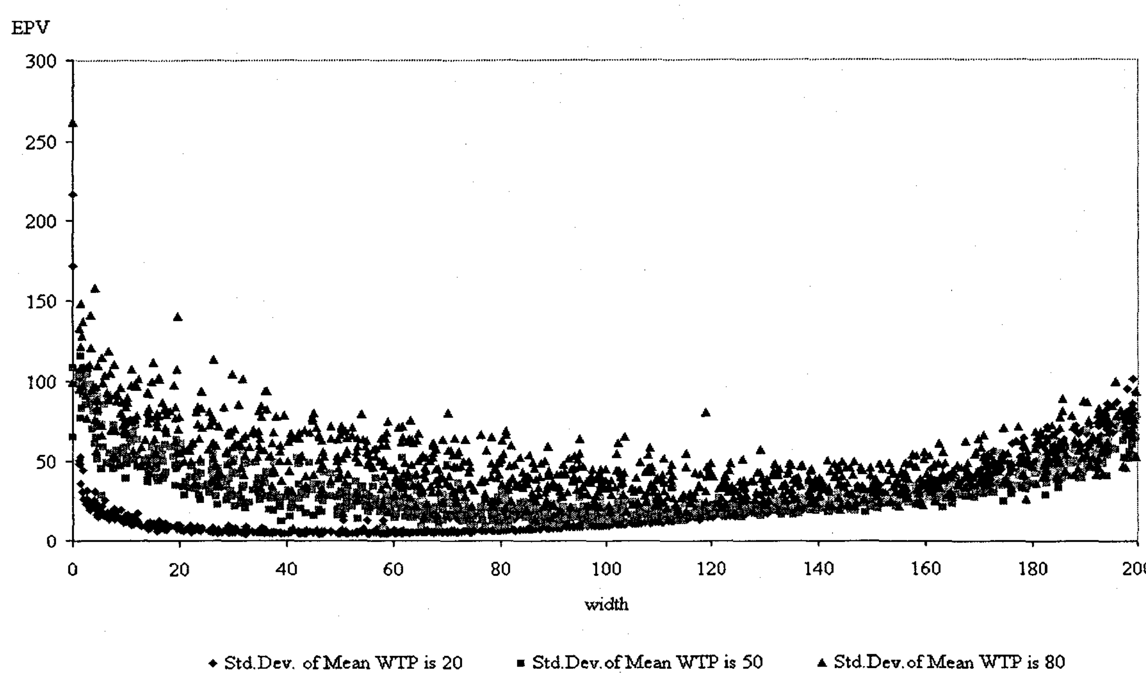

Figure 12. EPV scatter plots from Normal approximation with each of τ at $m_\kappa = 20$

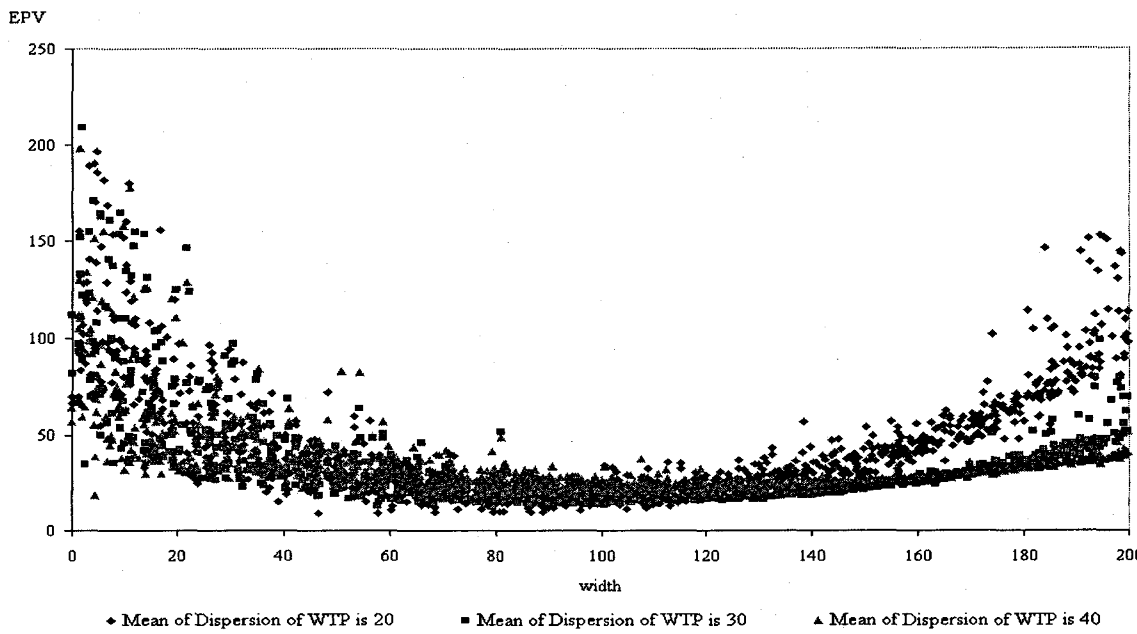

Figure 13. EPV scatter plots from Tierny-Kadane approximation with each of m_κ at $\tau = 50$

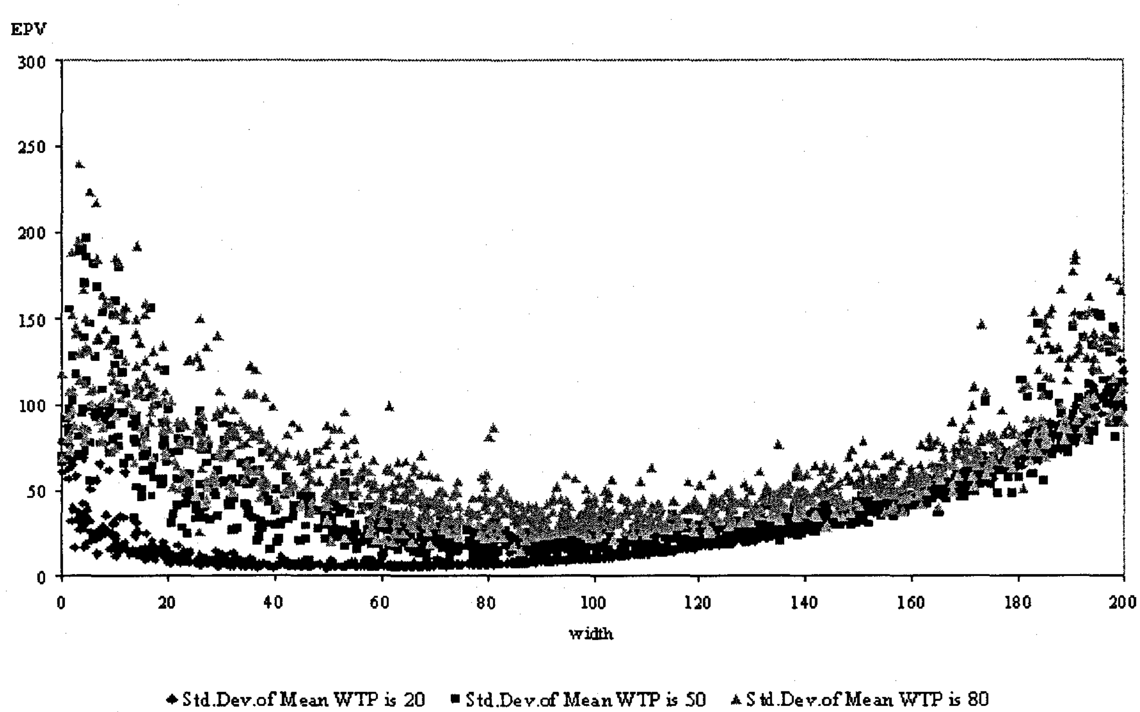

Figure 14. EPV scatter plots from Tierny-Kadane approximation with each of τ at $m_\kappa = 20$

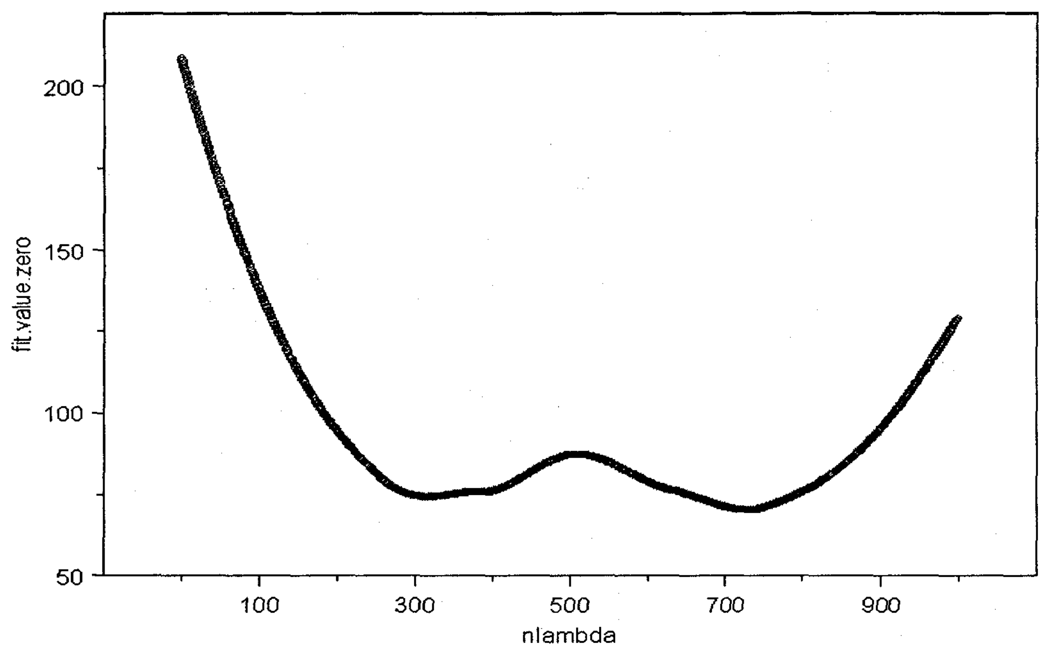

Figure 15. Plot of $\Psi^{0*}(\lambda_j, B_j^{1*}, B_j^{2*})$ and λ_j

Chapter 3. Water Quality Perceptions and Site Choice Decisions

I. Introduction

According to the U.S. Environmental Protection Agency's most recent national water quality inventory (Nutrient Criteria Technical Guidance Manual: Lakes and Reservoirs, 2000), 45% of the lake acres in the nation are impaired. This assessment is based on physical water quality measures. In Iowa, the problem is no better. Indeed, over half of the 131 lakes included in the Iowa Lake Valuation project are on the U.S. EPA's impaired list (EPA water quality inventory for the state of Iowa, 2003).

Despite the fact that physical measures indicate water quality impairments in the state, these same lakes are used extensively by Iowans for recreational boating, fishing, swimming, etc. According to the summary report of Iowa Lake Valuation project (Azevedo *et al.* 2003), approximately 62% of all Iowa households visited one of the 131 lakes in 2002, with an average of about eight day-trips per year. Yet these same respondents indicated that water quality was the most important factor they consider when choosing a lake for recreation. Clear Lake in north-central Iowa is the center of many activities and is especially lively in the summer months despite being on the lists of impaired lakes. Fishermen, recreational boaters, swimmers and beach users all frequent the lake. As Ditton and Goodale (1973) suggests, physical water quality is not necessarily the quality that attract or deter recreation users.

The question is what form of quality attributes drives individual's site choice decision: physical measures or quality perceptions? How do these affect trip behavior? This chapter of my dissertation utilizes detailed data on trip behavior and water quality perceptions collected from Iowa Lake Survey 2003 and physical quality measures collected by the Iowa State University Limnology laboratory to investigate which measures have the greatest impact on the site choice decision.

A related issue of interest is whether individual water quality perceptions are correlated with the available physical measures, i.e., to what extent do individual perceptions align with physical measures of quality? Biases in quality perceptions are of interest to policy makers from the standpoint of welfare analysis. If perceptions do influence recreation trip behavior, but these perceptions differ from the corresponding physical measures (or the U.S. EPA's categorization of them), the changes to the physical water quality of a lake may have unintended impacts of lake usage and the corresponding welfare calculations may be problematic.

The remainder of this chapter is divided into six sections. Section II provides a review of the existing literature on water quality perceptions. Section III describes the trip behavior and quality assessments data collected in the Iowa Lake Survey 2003 and physical measures of 131 Iowa lakes collected from Dr. John Downing and his team. The repeated mixed logit model (RXL) to be used in the analysis is described in Section IV. Model and welfare estimation results are discussed in Section V and Section VI. Section VII provides conclusions and an outline of the remaining research associated with this essay.

II. Literature Review

Recent studies of recreation demand show that physical water quality measures significantly impact the site choice decision. Phaneuf, Herriges, and Kling (2000) estimated a Kuhn-Tucker model analyzing angler behavior in the Great Lakes. They include catch rates for particular fish species of interest as well as a toxin measure derived from the average toxin levels given in a study by De Vault *et al.* (1989). The authors find that the toxin level, a measure of the presence of environmental contaminants, significantly influences the recreation decision.

Egan (2003) estimates the demand for day-trips to 129 Iowa lakes using data from the first year of the Iowa Lakes valuation project. Included in his analysis are 11 physical quality measures (secchi depth, chlorophyll, nitrogen, total phosphorus, etc.) and a series of other lake specific characteristics (ramp, wake, facilities, state park designation etc). His results show that individuals do respond to physical quality characteristics in choosing where to recreate. Egan (2003) goes on to estimate the willingness of Iowans to pay to improve the physical water quality levels in the state.

The Egan (2003) analysis, however, does not explore the crucial link between the physical water quality measures and individual perceptions of them. Researchers often argue that choices are made on the basis of perceptions. Yet, there has been relatively little use of perceptions of quality attributes in recreation demand modeling in the past due to the cost of collecting individual perception information. One of the few exceptions is Adamowicz *et al.* (1997), which examines perceptual and objective quality attribute measures in discrete choice models of moose hunting site choice behavior. They employed data collected from recreational moose hunters in Alberta, Canada including actual and perceived hunting site attributes (access, moose population and congestion) of hunters. Their analysis shows that the model with perceptual attributes of a hunting site outperforms that of an objective quality attribute, though only modestly. Two scenarios are considered for welfare estimation: one involving closure of a site and the other involving a change in perceptions to the agency's objective measure for those individuals who have perceptions that are lower than the target level. The authors find that welfare estimates obtained using the "perception" model are less than that from the "objective quality" model for both scenarios. This is because individuals are assumed to experience a welfare gain only when their perception of the site quality is below the agency target.

III. Data and Survey Results

Two sources of data will be used in this chapter: results from the 2003 Iowa Lakes Survey and physical water quality measures collected by the ISU Limnology Lab. These data sources are described in turn in the following two subsections.

A. The 2003 Iowa Lakes Survey

The 2003 Iowa Lakes Survey is the second year survey in a four year study, jointly funded by the Iowa Department of Natural Resources and the USEPA, aimed at understanding recreational lake usage in Iowa and the value placed on water quality in the state. The survey was sent by direct mail in January of 2004 to a random sample 8,000 Iowans, collecting information on their recreation behavior as well as their assessment of Iowa's 131 principal lakes. Standard follow-up procedures were used to encourage a high response rate to the survey (see, e.g., Dillman, 1978, 2000), including a postcard reminder mailed two weeks after the initial mailing and a second copy of the survey mailed one month later. In addition, survey respondents were provided with a $10 incentive for completing the survey. A copy of Iowa Lake Survey 2003 is included as an appendix to this chapter (Appendix A).

The survey itself has three major sections. The first section (pp. 3-7) asks respondents to report both how frequently they visited each of 131 lakes in the state during 2003 and to rate those lakes they are familiar with in terms of water quality. The 10-point water quality ladder (Figure 1) employed by EPA is used in this water quality assessment.[9] The water quality ladder has been used in the past both to categorize lakes in terms of quality and in

[9] All figures and tables are in Appendix B.

communicating potential water quality improvements (e.g., from "boatable" to "fishable" or "drinkable"). The second section of the survey (pp. 8-9) consists of dichotomous choice referendum questions and is not used in this essay. Section three, (pp. 10-11) collects socio-demographic information, including age, gender, education, etc.

A total of 5,281 surveys have been returned. Allowing for the fact that 219 surveys were undeliverable and 61 individuals were deceased, this corresponds to a 68% response rate. From the 5,281 completed surveys, the final sample of 5,052 individuals was obtained as follows. Non-Iowans were excluded (47 observations) based on zip code. Anyone reporting more than 52 total single day trips to the 131 lakes were excluded as well (182 observations). The analysis below focuses on single day trips only in order to avoid the complexity of modeling multiple day visits. Defining the number of choice occasions as 52 trips per year allows one trip to one of the 131 Iowa lakes per week. While the choice of 52 is arbitrary, it seems a reasonable cut-off for the total number of allowable single day trips for the season. Invariably some of the respondents who recorded trips greater 52 did in fact take this number of trips. However, since this survey was randomly sent out to Iowan, some of the recipients live on a lake and it may be those individuals who record hundreds of "trips" are simply returning to their sleep of residence.

Table 1 lists the summary statistics for trips and the socio-demographic data. The average number of total single day trips to all 131 lakes is 6.97, ranging from zero to 52 trips per year. The survey respondents are more likely to be older, male, have a higher income, and be more educated than the general Iowa population. Schooling is entered as a dummy variable equaling one if the individual has attended or completed some level of post high school education.

As indicated above, water quality assessment data were collected by directly asking the respondents to assign a number between 0 and 10 based on the water quality ladder (Figure 1) for the lakes they visited in 2003 or considered visiting recently. The water quality ladder, proposed by Carson and Mitchell (1983), was pictured page by page on the survey with verbal descriptions. The top of the water quality ladder stands for the best possible quality of water, while the bottom of the ladder stands for the worst. The lowest level is so polluted that contact with it is dangerous to human health. Water quality that is "boatable" would not harm an individual if they happened to fall into it for a short time while boating or sailing. Water quality that is "fishable" is a higher level of quality than "boatable". Although some kinds of fish can live in boatable water, it is only when water is "fishable" that game fish like bass can live in it. Finally, "swimmable" water is of a high enough quality that it is safe to swim in and ingest in small amounts.

The summary statistics for day trips (per capita) and median, mean, and standard deviation of the water quality perception for the lakes are listed in Table 2. The sample size is 131 lakes. Total day trips per lake is divided by the total number of surveys sent out to the local zone where a lake is located in order to standardize population size effect on trips. On average, Iowans took 0.36 trips per capita to each lake last year.

Although some individuals perceived that some of lakes were polluted dangerously, most respondents perceived the 131 lakes to be safe for swimming and boating on average. The mean water quality assessment ranges across lakes from 4.11 to 6.81. The standard deviation of the water quality assessment of a lake measured across individuals who rated the lake ranges from 1.06 to 2.42. This suggests that for some lakes, individuals share very similar perceptions regarding the lake's quality. For example, for Green Castle Lake (Marshall County), the standard deviation of water quality perceptions is 1.07 across 35 respondents. For other lakes, such West Lake (Osceola) with a standard deviation of 2.63

across 62 respondents, the water quality perceptions are wide ranging.

An initial question regarding the lake perceptions data is whether or not it influenced which lakes Iowan visited in 2003. To investigate this, Table 3 lists the number of day trips per capita to the 20 best and 20 worst lakes sorted by their mean water quality assessments. Although some lakes had few respondents assessing their water quality, the mean number of day trips to the "best" lakes (with a mean assessment of 6.46) is roughly two and a half times the mean number of trips to the "worst" lakes (which had a mean assessment of 4.89). The best lakes, of course, do not have uniformly higher visitation rates. Ottumwa Lagoon (Wapello), Lake Macbride (Johnson), Swan Lake (Carroll) and George Wyth Lake (Black Hawk) in the "worst" lakes category all have higher visitation rates than Lake Wapello and Little River Watershed Lake included in the "best" lakes category. More detailed analysis will be required to tease out other factors influencing recreational site choices, such as proximity to population centers. However, these aggregate data do suggest that water quality perception likely influences the site choice decision.

It should also be noted that high quality assessments do not necessarily imply that the lake is less contaminated (based on actual physical water quality measures). According to the list of impaired lakes of Iowa, Lake Meyer, Lake Keomah, Lake Smith, and Lake Icaria are impaired, even though they have high mean quality assessments. Moreover, four lakes among the worst assessed lakes, including Mitchell Lake, Meyers Lake, Briggs Woods Lake and George Wyth Lake are not on the list. This implies that individual's perceptions may not agree with either EPA or physical water quality assessments.[10] Correlation coefficients of mean water quality assessment with the number of day trips and physical water quality

[10] Of course, factors other than physical water quality conditions may play a role in listing a lake on the impaired water quality list.

measures are calculated in the following subsection.

B. Physical Quality Measures

Table 4 lists the summary statistics of physical water quality measures. Secchi depth is a measure for clarity of water surface indicating how far down into the water an object remains visible. Chlorophyll is an indicator of plant biomass or algae and leads to greenness in the water. Total phosphorus is usually the principal limiting nutrient in Iowa lakes, meaning its levels most likely determines algae growth. Three nitrogen levels are provided, including NH_3+NH_4 (measuring particular types of nitrogen such as ammonia which can be toxic), NO_3+NO_2 (measuring the nitrates in the water), and total nitrogen. Silicon is important to diatoms which extract it from the water to use as a component of their cell walls. Diatoms, in turn, are a key food source for marine organisms. The acidity of the water is measured by "pH" with levels below 6 or above 8 indicating unhealthy lakes. Alkalinity is the concentration of calcium or calcium carbonate in the water. Plants need carbon to grow and all carbon comes from alkalinity, therefore alkalinity is an indication of the abundance of plant life. ISS is the inorganic suspended solids, basically soil and silt in the water due to erosion. VSS is volatile or organic suspended solids, both measures that will decrease clarity in the water.

It is evident that considerable variation in physical water quality characteristics is present across the lakes in Iowa. For example, Secchi depth varies from a low of 0.17 meters to a high of 8.10 meters and total phosphorus varies from 17 to 384 μg/L, some of the highest concentrations in the world. All of the physical measures are the average values for the 2003 season. Samples were taken from each lake three times throughout the year, in spring/early summer, mid-summer, and late summer/fall, to include seasonal variation (for more detail on this data collection procedures see http://limnology.eeob.iastate.edu).

According to EPA's "Nutrient Criteria Technical Guidance Manual (2000)", the four paramount variables for nutrient criteria are total phosphorus, total nitrogen, chlorophyll, and Secchi depth. Scientists consider inorganic suspended solids and organic suspended solids to be crucial indicators as well. The question is, how close are the perceptions of individuals and physical measures of EPA's and/or scientists? Further, do EPA's water quality index and/or scientist's water quality index explain water quality perception?

EPA's water quality index used in the water quality ladder is a weighted average of up to nine quality indices based on physical quality measures including total phosphates (PO_4), total nitrates (NO_3), total suspended solids, dissolved oxygen and pH. A water quality index using the latter five variables is constructed using data from the ISU limnology lab.[11] In addition, Carson's Trophic State Indices (CSTI) for lakes based on Secchi depth (CTSI_SEC), chlorophyll (CTSI_Chla), total phosphorus (CTSI_TP) are provided from the ISU Limnology Lab.[12] As described in Appendix D, a trophic state index is an objective standard of the trophic state of any body of water whereas the water quality ladder index represents a subjective judgment by a group of scientist.

Table 5 lists correlation coefficient of quality assessment with several physical measures, EPA's water quality index and Trophic State Indices. The correlations are provided for the sample as a whole and for two subsamples: those reporting that they engaged in water contact activities (e.g., swimming and jet skiing) and those who did not (e.g., nature appreciation and picnicking). One might expect those engaged in water contact activities might be more aware of and/or affected by the physical water quality conditions.

For the sample as a whole, day trips were found to be positively correlated with the

[11] Appendix C provides details regarding the construction of these water quality indices.
[12] For details about Carson's Trophic State Index, see Appendix D.

corresponding water quality perception measure. This suggests, as indicated by Table 3, that overall quality perceptions do influence trip behavior. The overall water quality assessments also are generally consistent with the actually physical water quality measures. Specifically, all of the physical measures are negatively correlated with the mean water quality assessment except for secchi depth; clarity of the water has a positive relationship with the water quality ladder assessment (0.351). However, the degree of correlation varies by the physical water quality measure. For example, there is relatively little correlation between the water quality assessment and nitrates, chlorophyll or pH. Water quality perceptions also appear to be correlated with a number of existing water quality indices based on physical water quality measures. EPA's water quality index is positively correlated with water quality perceptions. The various CTSI, as expected, consistently have negative correlations with water quality perceptions, since lower CTSI's correspond to higher levels of water quality. This indicates that EPA's and scientists' measures of water quality are at least partly consistent with individuals' water quality assessments. At the same time, it is important to note that these correlations are by no means perfect. The correlation between the water quality perceptions and the water quality index (both of which use the water quality ladder) is just over 0.21. A number of single water quality measures have higher correlations with the water quality perceptions, including secchi depth, ISS, and VSS. The CTSI_SEC index fairs somewhat better, but still has a simple correlation coefficient of only -0.357.

The relationship between the physical measures and the overall water quality perceptions also appears to vary by the type of activity engaged in at the lakes. About one third of the households in the sample did not participate in water body contact recreation. As Ditton and Goodale (1973) suggested, water quality perceptions might be not the same over all respondents. Most recreation users participate in boating (43%), fishing (52%) and swimming (40%). Non-participants in water contact recreation enjoy camping (30%), picnicking (43%), and nature appreciation and viewing wildlife (42%). Overall, 3,619 visitors participated in water contact recreation, whereas 1,433 did not.

The mean assessment of the water contact group is more highly correlated with day trips (0.257) than for the non-contact group (0.047). Because they are more likely to participate in boating, swimming, and fishing activity on the lake, higher quality assessment would lead to more trips to lake. They are apparently aware of the levels of total nitrogen, phosphorus and suspended solids, or at least their visible impacts. All of the correlation coefficients are statistically different from zero at a 10% level except for the nitrates, chlorophyll, and pH. On the other hand, for individuals who want to take a walk along the beach at a lake, ride a bike or simply appreciate the lake's natural surroundings, the water quality itself may not impact them as much or they may have less direct contact with the water in constructing an overall water quality prerception. For these households, the correlation coefficient of day trips and most of physical quality measure (except for total phosphorus, nitrogen, silica and inorganic suspended solids) are not statistically different from zero.[13]

These simple summary statistics concerning water quality assessments and physical quality measures data again suggest that there is a linkage, though imperfect, between individual water quality perceptions and the actual physical measures collected by scientists. However, the linkage also appears to depend upon the recreator's activities. Recreators' activities influence on their site choice decision and their types of activities might in turn impact their water quality perceptions. For example, if individuals prefer jet skiing or boating

[13] Of course, the sample size is also smaller for this group, which will impact the precision with which the correlation coefficients are estimated.

to walking around the lake, they may choose a lake where motorized vessels are allowed or one with a boat ramp, regardless of the water's visibility. The question is whether or not these facilities characteristics in turn end up impacting the individual's water quality assessment. To investigate this, the lake site characteristics were obtained from the Iowa Department of Natural Resources. Table 6 provides a summary of these site characteristics. As Table 6 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-seven percent of the lakes allow wakes, whereas thirty-three 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 39 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.

The correlation coefficient of the boat ramp dummy variable with mean water quality perceptions is positive and significant for water contact group whereas it is insignificant for the non-water contact group. The disability facilities and state park dummy variables both have positive correlation coefficients with water quality perceptions. However, these correlations are insignificant at a 5 percent critical level with *p*-values ranging from 7 to 10 percent. Acreage of a lake has a positive correlation with the water quality perception, although it is not significant. These results suggests that individual's water quality perceptions are somewhat correlated with the lake site characteristics, with the boat ramp characteristic having the clearest effect.[14]

In order to investigate the linkage between water quality perceptions and physical water quality measures and/or site characteristics, I ran a simple linear regression of mean perceptions on physical measures and site characteristics. Some physical measures are logarithmically transformed (e.g., Chlorophyll, total phosphorus, total nitrogen, total and cyano-bacteria), whereas others (Secchi depth, the nitrogen, silica and alkalinity) are entered linearly according to Egan *et al.* (2004). Dissolved oxygen, total nitrates, pH, suspended solid and turbidity are transformed to quality indices according to McClelland (1974) on which EPA's water quality index is based.[15] Finally, five lake-characteristic variables (log transformed acres and the ramp, wake, state park and wake dummy variables) are entered. All variables are normalized using their respective standard errors in order to compare the size of the impact. The estimated coefficients are listed in Table 7. Overall, these physical measures and lake characteristic variables explain about 39% (adjusted R^2) of the variation in water quality perception's and the model appears to be significantly explaining the perceptions (the *F*-value of the null hypothesis of all coefficients are zero is 3.93 with a p-value of less than 0.01). Secchi depth, log transformed chlorophyll and total phosphorus, alkalinity and square and linear terms of dissolved oxygen quality index and the square term of total suspended solid quality index are significant at the 10% level. The signs of these terms are generally as one would expect except for the turbidity quality index. Also, the boat

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[14] It should be noted that the causation may run in the other direction in the case of lake attributes. For example, boat ramps and lake facilities may be constructed at a lake site because they are generally of high quality and the demand for such facilities is there.
[15] See Appendix C.

ramp and wake dummy variables appear to be significant and have a positive effect on water quality perception. The result supports the evidence of a relationship between water quality perception and the physical measures and site characteristics.

IV. Model

There are two competing hypotheses regarding the role of perceptions and physical water quality measures in determining recreation demand. The first assumes that physical measures influence site choices indirectly by influencing an individual's overall perception of each lake, whereas the second suggests the physical attributes influence behavior in a complex fashion that cannot be captured by a single index or water quality ladder. Of course, there is also the possibility that neither have a significant impact on lake usage, which may be driven instead by other site characteristics such as facilities and proximity to population centers. To investigate these alternatives, I consider a model of the utility derived from visiting site j on choice occasion t that nests both of these alternatives. Specifically, suppose that the utility of individual i associated with visiting site j visit on choice occasion t is given by

$$\begin{aligned} U_{ijt} &= V(P_{ij}, Z_j, Q_j, X_j, s_i) + \varepsilon_{ijt} \\ &= \begin{cases} \kappa' s_i + \varepsilon_{i0t} \\ \alpha_i - \lambda P_{ij} + \beta' Z_j + \delta' Q_j + \gamma_i' X_j + \varepsilon_{ijt}, \quad i = 1, \cdots, I, j = 1, \cdots, J, t = 1, \cdots, T \end{cases} \end{aligned} \tag{1}$$

where V is the deterministic component of utility and ε_{ijt} is an error component which is an *iid* extreme value random variable. The vector s_i consists of socio-demographic characteristics, while P_{ij} is the travel cost from each Iowan's residency to each of the 131 lakes as calculated using PCMiler. Z_j represents observable water quality attributes for lake

j. Q_j denotes the overall water quality perception regarding lake j and X_j denotes other site characteristics (including lake facilities and state park designation). Notice that the parameters on the lake attributes (γ_i) and α_i are allowed to vary across individuals, allowing for heterogeneity of preferences. Specifically, these parameters are assumed to be distributed randomly across individuals in the population. The random parameter α_i was introduced by including a dummy variable D_j which equals one for all of the recreation alternatives $(j = 1, \cdots, J)$ and equals zero for the stay at home option $(j = 0)$, following Herriges and Phaneuf (2002).

The random coefficient vectors for each individual, γ_i and α_i can be expressed as the sum of population means $\bar{\gamma}$ and $\bar{\alpha}$, and individual deviations from the means, τ_i and ϕ_i, which represents the individual's tastes relative to the average tastes in the population (Train, 1998).[16] Therefore, we can redefine

$$\begin{aligned} \gamma_i &= \bar{\gamma} + \tau_i \text{ and} \\ \alpha_i &= \bar{\alpha} + \phi_i. \end{aligned} \tag{2}$$

The partitioned utility function in (1) is then

$$U_{ijt} = \begin{cases} \kappa' z_i + \eta_{i0t}, & j = 0 \\ \bar{\alpha} - \lambda' P_{ij} + \beta' Z_j + \delta' Q_j + \bar{\gamma} X_j + \eta_{ijt}, & j = 1, \cdots, J, \end{cases} \tag{3}$$

where

$$\eta_{ijt} = \begin{cases} \varepsilon_{i0t}, & j = 0 \\ \tau_i X_j + \phi_i + \varepsilon_{ijt}, & j = 1, \cdots, J \end{cases} \tag{4}$$

[16] Specifically, I assume that $\gamma_i \sim N(\bar{\gamma}, \Sigma)$ where Σ is a (k x k) diagonal variance covariance matrix with diagonal element $\sigma^2_{\gamma k}$ for the k^{th} site characteristic. Similarly, $\alpha_i \sim N(\bar{\alpha}, \sigma^2_{\alpha})$.

is the unobserved portion of utility. This unobserved portion is correlated over sites and trips because of the common influence of the terms τ_i and ϕ_i, which vary over individuals. For example, an individual with a large negative deviation from the mean of α_i will be more likely to choose the stay-at-home option on each choice occasion, the ϕ_i capturing in this case some unobserved attribute of the individual causing them to prefer staying at home (e.g., they cannot swim or do not like fishing). On the other hand, someone with a large positive deviation ϕ_i will tend to take many trips. The variation in the γ_i's allows the marginal effects of site characteristics to vary across individuals. The random parameters γ_i and α_i do not vary over sites or choice occasions. Thus, the same preferences are used by the individual to evaluate each site across time periods. Since the unobserved portion of utility is correlated over sites and trip choice occasions the familiar IIA assumption does not apply.

Given that the ε_{ijt}'s are assumed to be *iid* extreme value, the resulting model corresponds to McFadden and Train's (2000) mixed logit framework. A mixed logit model is defined as the integration of the logit formula over the distribution of unobserved random parameters (Revelt and Train, 1998). Let the vector of random parameters in the model defined above be denoted by $\omega_i = (\alpha_i, \gamma_i)$ and let $\xi = (\beta, \delta, \lambda, \kappa)$ denote the fixed parameters. If the random parameters, ω_i, were known then the probability of observing individual i choosing alternative j on choice occasion t would follow the standard logit form

$$L_{ijt}(\omega_i, \xi) = \frac{\exp[V_{ijt}(\omega_i, \xi)]}{\sum_{k=0}^{J} \exp[V_{ikt}(\omega_i, \xi)]}. \tag{5}$$

Since the ω_i are unknown, the corresponding unconditional probability, $P_{ijt}(\theta, \xi)$ is obtained by integrating over an assumed probability density function for the ω_i's. The unconditional probability is now a function of θ, where θ represents the estimated moments of the random parameters.[17] This repeated Mixed Logit model assumes the random parameters are *iid* distributed over the individuals with

$$P_{ijt}(\theta,\xi) = \int L_{ijt}(\omega_i,\xi) f(\omega_i \mid \theta) d\omega, \qquad (6)$$

where $f(\omega_i \mid \theta)$ is the assumed distribution for the random parameters. No closed form solution exists for this unconditional probability and therefore simulation is required for the maximum likelihood estimates of θ.[18]

Two hypotheses are of interest. The first hypothesis of interest is $H_0^1 : \beta = 0$, i.e., whether or not physical quality measures directly impact the utility of visiting a given site (beyond what is captured by the perceptions variable). The second hypothesis of interest is $H_0^2 : \delta = 0$; i.e., whether or not the perceptions regarding water quality at the lake, based on USEPA's water quality ladder, influence individual household behavior (beyond what is captured by direct physical water quality variables). Egan (2003)'s model is the restricted one based on this second hypothesis. Adamowicz *et al.* (1997) compared two restricted models and estimated WTPs: one is the model under the hypothesis 1 (using perceptual data only) and the other one is under hypothesis 2 (using physical quality data only). The advantage of the current work is that we have a much more extensive list of physical water quality measures and perceptions data for a larger set of site alternatives.

One issue in using the water quality perceptions data in modeling site choice is that we do not have data on this water quality perception for each individual and lake

[17] In the current model, $\theta = (\bar{\gamma}, \bar{\alpha}, \sigma_{\gamma 1}, \cdots, \sigma_{\gamma k}, \sigma_{\alpha})$

[18] Train (2003) describes simulation methods for use with mixed logit models, in particular maximum simulated likelihood which I employ. Software written in GAUSS to estimate mixed logit models is available from Train's home page at http://elsa.berkeley.edu/~train.

combination. This is similar to the problem associated with catch rate data in standard recreation demand models; i.e., because a household only visits a limited number of lakes, individual catch rate information is typically only available for these visited lakes. Moreover, the catch rates information itself is endogenous. Following the standard procedure used in case of catch rate, the mean water quality assessment of a lake is used as a proxy variable for water quality perception in this model because some lakes have a few visitors and respondents providing water quality assessments.

V. Estimation Result

A. Specification

Although the model for testing the null hypothesis and welfare estimation is set in equation (1), the functional forms to be useful for the physical water quality measures, lake characteristics and socio-demographic variables are unknown. Economic theory provides little or no guidance in terms of these choices. Egan *et al.* (2004), however, provides an extensive investigation into the choice of functional form for water quality measures, lake characteristics and socio-economic variables in their model of recreation demand. Specifically, using data from the first year of the Iowa Lakes survey, they split the available sample into 3 subsamples, using the first for specification search, the second for estimation and the third for investigating out-of-sample predictions. They focused 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. The specification search process involved comparing numerous combinations of linear and logarithmic forms for the water quality measures. In the analysis below, I follow

Egan *et al.*'s (2004) final specification for the physical measures, lake characteristics and socio-demographic variables.

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. A quadratic age term is included in the model to allow for nonlinearities in the impact of age. Site characteristic are included with random coefficients. This is to allow for heterogeneity in individual preferences regarding site characteristics, such as wake restrictions and site facilities. 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 γ_i are each normally distributed with the mean ($\bar{\gamma}_k$) and dispersion ($\sigma_{\gamma k}$) for each parameter. Physical water measures (Z_j) are categorized into five groups 1) Secchi depth, 2) Chlorophyll, 3) Nutrients (Total nitrogen and Total phosphorus), 4) Suspended solids (Inorganic and Organic) and 5) 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 (Azevedo *et al.*, 2003). Egan *et al.*'s (2004) specification search results suggested bacteria, Chlorophyll, and nutrients enter logarithmically and the remaining variables enter linearly. This model is referred to as Model A. A more complex model, including pH, alkalinity, silicon, nitrates, and ammonium nitrogen is referred to Model B. These additional variables are entered in a linear form, except for pH for which is a quadratic term is also included.

A total of seven models are considered. The first four represent variations on models A and B in Egan *et al.* (2004):

Model A_1: Model A as estimated in Egan *et al.* (2004)

Model A_2: A_1 plus the water quality perceptions variable

Model B_1: Model B as estimated in Egan *et al.* (2004)

Model B_2: B_1 plus the water quality perceptions variable.

In terms of equation (3), the difference between models A_1 and A_2 (B_1 and B_2) is that A_1 (B_1) constrains $\delta = 0$, allowing a test of hypothesis H_0^2. I include also three models to illustrate the consequences of relying on a single measure of water quality, in this case one that is widely used by the U.S. Environmental Protection Agency:

Model C_1: Model A_1, but replacing all physical water quality measures with the single water quality ladder index.

Model C_2: Model A_2, but replacing all physical water quality measures with a single water quality ladder index.

Model C_3: Model A_2 with the physical water quality attributes constrained to have no impact (i.e., $\beta = 0$ in equation 3).

Note that it is the comparison of models A_1 and C_3 that provides the basis for testing hypothesis H_0^1 (i.e., that only the perceptions index matters).

B. Estimation Result

The resulting parameter estimates are presented in two Tables, 8a and 8b. Table 8a lists parameter estimates for socio-demographic variables and mean and dispersion parameters for random coefficients for lake amenities data. Most of the coefficients are significant at the 5 percent level, except for inorganic suspended solids for Model B_1 and B_2 and some of the socio-demographic data including age, age square and school dummy variables. The age variable is not significant for Model A_1, B_1, B_2, and C_1, while the age square variable is not significant for Model A_2. The school variable is insignificant in Model A_1, but significant in the others. Note that the socio-demographic data are included in the conditional indirect utility for the stay-at-home option. Therefore, 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 C_2 and C_3, the peak occurs at about age 48, which is consistent with the estimate of larger households taking more trips, as at this age the household is more likely to include children. Higher-educated individuals appear to be more likely to stay-at-home, with corresponding positive coefficients on the school variable. The price coefficient is negative as expected and virtually identical in all seven models.

Turning to the site amenities, 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_1 the dispersion on the size of the lake indicates almost all people prefer bigger lakes. 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 roughly split, with 62 percent preferring a lake that allows wakes and 38 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 7 out of a possible 52 choice occasions.

The physical water qualities and mean perception coefficients are reported in Table 8b. For four models, the effect of Secchi depth is positive, while inorganic (volatile) suspended solid have a negative impact, indicating that respondents strongly value water clarity. However, the coefficients on chlorophyll and volatile suspended solids are 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 that higher algae growth leads to fewer recreational trips. Total nitrogen having a positive coefficient is consistent with expectations given the negative sign on total phosphorus. With such large amounts of phosphorus in the water, more nitrogen can actually be beneficial by allowing a more normal phosphorus-to-nitrogen ratio. Two other forms of nitrogen, NO_3+NO_2 and NH_3+NH_4, are negative. 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. 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 8.3) to trips, indicating that as the pH level rises above 8.3, trips are predicted to increase. This is the opposite of what I expected.

The water quality perception has a positive and statistically significant impact in both models A_2 and B_2. Entering the mean perception to models A_1 and B_1 does not change the signs or general size of the physical water quality measures. The coefficients on water quality perceptions indicate that lakes which have higher mean perception are more likely to be places where individuals want to visit, as expected. Clearly, the hypothesis H_0^2 that the physical water quality measures above capture the full impact of water quality on the household's trip patterns can be rejected. Water quality perceptions, as captured by Q_j, also significantly affect where people choose to recreate. However, it is also clear that the perceptions index is an incomplete measure of how water quality affects household behavior. Comparing models A_1 or B_1 to model C_3, we clearly reject the restriction $\beta = 0$ (H_0^1).[19]

VI. Welfare Estimation

The results of the previous section indicate that water quality impacts individual recreation decisions in a complex fashion and that individual perception measures may be useful in explaining such site choice decisions. The question then is whether excluding such perceptions information significantly biases the estimated welfare implications of water quality improvements. To simplify the discussion, I focus my attention on the results of model C_1 and C_2 in which the physical water quality measures are summarized using the water quality ladder index used by the USEPA, which ranges from 1 to 10. The problem from a policy point of view is that a proposed water quality improvement may move a lake from "boatable" (with an index of 3.5) to "swimmable" (with an index of 7) based on the physical attributes of the lake, but not be perceived by individuals as being as big of a change, perhaps moving the lake from "boatable" to only "fishable" (with an index of 5). Welfare calculations based only on the direct physical measures may miss how individuals perceive such water quality changes.[20] In some sense, the model employing only the water

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[19] The corresponding likelihood ratio test statistics is $\chi^2 = 82$ (p-value < 0.001) for model A whereas $\chi^2 = 50$ (p-value < 0.001) for model B.

[20] The bias could, of course, move in the other directions, with households perceiving bigger changes than actually occur based on the physical water quality measures.

quality index (Model C_1) is from the physical scientist's (and typically the policymaker's) perspective. Model C_2, on the other hand, by incorporating individual perceptions data, takes into account how individuals translate the physical water quality measures into the attributes of the lake that matter to them directly.

Three water quality improvement scenarios, measured by a water quality index and/or water quality perception, are considered with the results from Model C_1 and C_2 used for all the scenarios. The first scenario improves all 130 lakes to the water quality of West Okoboji Lake, the clearest, least impacted lake in the state. Table 9 compares the water quality perception and water quality index of West Okoboji Lake with the average of the other 130 lakes. Both as measured by the water quality index and the mean perceptions variable, West Okoboji represents a substantial improvement over the other 130 lakes in the state. Both the water quality index and water quality perception are second highest (9.08 and 6.81 respectively) among 130 lakes. The second scenario is a less ambitious, more realistic, plan of improving nine lakes to the water quality of West Okoboji Lake (see Table 9 for comparison). The state is divided into nine zones with one lake in each zone being considered for improvement, 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 as possible candidates for a clean-up project. The last scenario is also a policy-oriented improvement. Currently of the 131 lakes, 65 are officially listed on the EPA's impaired water list. TMDLs are being developed for these lakes and by 2009 plans must be in place to improve the water quality at these lakes enough to remove them from the list. Therefore, in this third scenario, the 65 impaired lakes would be improved to the median mean water quality perception and/or water quality index level of the 66 non-impaired lakes. Table 10 compares the median values for the non-impaired lakes to the averages of the impaired lakes. Notice that there is not much of a movement in either water quality measure under this last scenario.

Based on the test results in Section V and the random parameter vector estimates, $\theta_i = (\gamma_i, \alpha_i)'$, the conditional compensating variation associated with a change in water, water quality perceptions from Q to Q' and physical water quality from Z to Z' for individual i on choice occasion t is given by

$$CV_{it}(\theta_i) = \frac{1}{\lambda}\left\{ \ln[\sum_{j=0}^{J} \exp(V_{ijt}[Q', Z'; \theta_i])] - \ln[\sum_{j=0}^{J} \exp(V_{ijt}[Q, Z; \theta_i])] \right\}, \tag{7}$$

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

$$CV_{it}(\theta_i) = \frac{1}{R}\sum_{r=1}^{R}\frac{1}{\lambda}\left\{ \ln[\sum_{j=0}^{J} \exp(V_{ijt}[Q', Z'; \theta_i^r])] - \ln[\sum_{j=0}^{J} \exp(V_{ijt}[Q, Z; \theta_i^r])] \right\}, \tag{8}$$

where R is the number of draws and r represents a particular draw from its distribution. The simulation process involves drawing values of $\theta_i = (\gamma_i, \alpha_i)'$ and then calculating the resulting compensating variation for each vector of draws, and finally averaging over the results for many draws. Following Von Haefen (2003), 2,500 draws were used in the simulation.

The resulting welfare estimates are provided in Table 11, along with the predicted number of trips under all scenarios. Improving all 130 lakes to both the water quality perceptions and water quality index of West Okoboji Lake (using Model C_2) leads to 17 percent increase in average trips. In contrast, improving to the water quality index of West Okoboji Lakes alone (using Model C_1) leads to only a 3 percent increase in average trips. The annual compensating variation (CV) estimate when ignoring water quality perceptions

(Model C_1) is \$12.39, versus a CV of \$68.35 when considering both water quality index and perceptions (Model C_2) for every Iowa household. Aggregating to the annual value for all Iowans simply involves multiplying by the number of households in Iowa, which is 1,153,205.[21] Thus, ignoring the perception information leads to a substantially smaller estimate in the overall impact of the first policy scenario.

Under the second scenario, the annual compensating variation per household estimate is \$0.90 when water quality improvement measured by water quality index (Model C_1) and \$7.87 when quality improvement measured by both the water quality ladder and perception (Model C_2). This estimate is 7 percent and 11 percent of the values obtained in scenario one; i.e., in which all lakes were improved. As with the first scenario, the welfare estimates are substantially smaller when individual perceptions information is ignored.

The third scenario is also valued considerably lower than the first water quality improvement scenario. The estimated compensating variation per Iowa household is \$3.06 when only water quality index is used (Model C_1) and \$6.23 when both measures are used (Model C_2). Also, the predicted trips only increase 1.24 percent for water quality index improvement (Model C_1) and 1.90 percent for both water quality perception and water quality ladder index improvements (Model C_2).

As discussed above, there is a big margin between compensating variations, one ignoring water quality perceptions information and the other including it. There is also a reduction in terms of predicted trip change, 28, 15, and 14 percent for the three scenarios, respectively. Further, the evidence that compensating variation calculated using both water quality measures is bigger than that calculated using water quality index suggests that agent's

[21] Number of Iowa households as reported by Survey Sampling, Inc., 2003.

cost-benefit analysis of improving water quality ignoring lake visitor's perception could be biased. In the current setting, the bias is downward.

VII. Conclusion

Individual day trip data collected from the Iowa Lake Survey 2003 shows that subjective quality assessment may influence individual's site choice decision. In addition, individuals appear to have somewhat different views of water quality than is captured by the objective water quality ladder measures used by the EPA and/or scientist. Correlation coefficients show that this disparity is different for two recreation groups: water body contact group and non-water body contact group. The fact that water quality perceptions do not perfectly align with either the physical measures or the corresponding water quality index suggests that such perception may provide useful additional information in explaining individual behavior.

Repeated mixed logit model estimation result indicates that individuals' site choice decisions depend significantly on physical water quality, the water quality index and water quality perception. As was the case in Adamowitcz *et al.* (1997), the models with perceptions included outperform the models without such perception information.

Compensating variation estimates in the last section of the chapter illustrate the importance of incorporating perceptions in terms of both estimating the welfare and trip impacts of proposed policy initiatives. Annual compensating variation ignoring individual's water quality perceptions is reduced by as much 90% of what is estimated using water quality perceptions. In terms of the annual predicted trips, ignoring individual's water quality perceptions reduces the change in predicted trips by as much as 28%. Therefore, in order to get accurate welfare measure, quality perceptions should be considered.

In this chapter, mean water quality assessment of a lake is used in the same way catch rate data has traditionally been used recreation demand analysis in part, because the water quality assessment is endogenous. In addition, individual's water quality assessments for all the 131 lakes are not available because survey respondents only reported the water quality assessments over lakes they were familiar with. However, as described in the previous section, water quality perception of each individual is linked with the physical water quality measures through individual's activities at the lakes where they visited. One refinement to the current analysis would be to replace the mean water quality assessment with a fitted assessment, derived, for example, from a regression of water quality perceptions on individual's socio-demographic variables, physical water quality measures, and the characteristics of the lakes. Although the variation of the water quality perceptions is small, making use of the predicted water quality assessments over the 131 lakes (i.e., in an instrumental variable approach) would avoid the endogeneity problem and would potentially improve both the explanatory power of the recreation demand and welfare estimation.

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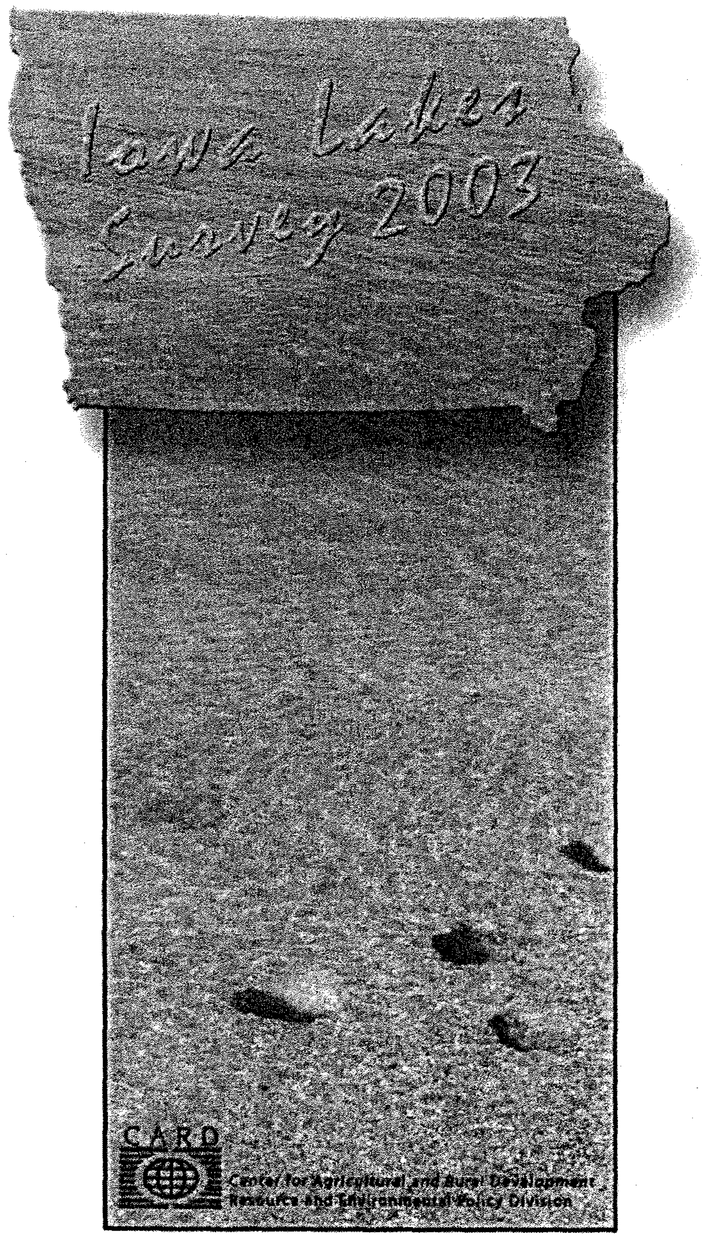
Appendix A. 2003 Iowa Lakes Survey



IOWA STATE UNIVERSITY
DEPARTMENT OF ECONOMICS

In order to make sound decisions concerning the future of Iowa lakes, it is important to understand how the lakes are used, as well as what factors influence your selection of lakes to visit. The answers you give to the questions in this survey are very important. Even if you have not visited any lakes in Iowa, please complete and return the questionnaire. It is critical to understand the characteristics and views of both those who use and those who do not use the lakes.

In this first section, we would like to find out which of the lakes on the enclosed map you visited and what you did there.

1. Please indicate how often you or other members of your household visited each of the following lakes in the current year. If you have not visited any lakes in Iowa this year please check this box.

   ❑ I have not visited any lakes in Iowa this year.

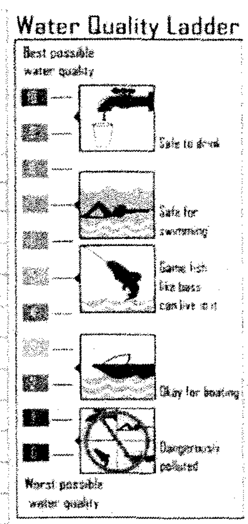
   In addition to recording the number of visits you took to each lake, if any, please indicate which of the lakes you *considered* visiting this year by marking the box in the second column.

   We are very interested in your view of the water quality of Iowa's lakes. One way of thinking about water quality is to use a ladder like the one shown to the right of the list of lakes. The top of the water quality ladder stands for the best possible quality of water, while the bottom of the ladder stands for the worst. On the ladder you can see the different levels of water quality.

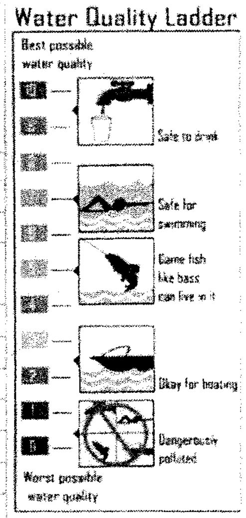
   For example: the lowest level is so polluted that it has oil, raw sewage, and/or other things in it like trash; it has almost no plant or animal life, smells bad, and contact with it is dangerous to human health. Water quality that is "boatable" would not harm you if you happened to fall into it for a short time while boating or sailing. Water quality that is "fishable" is a higher level of quality than "boatable." Although some kinds of fish can live in boatable water, it is only when water is "fishable" that game fish like bass can live in it. Finally, "swimmable" water is of a high enough quality that it is safe to swim in and ingest in small amounts.

   For any lake with which you are familiar, please indicate your assessment of the level of water quality associated with that lake by assigning a number between 0 and 10 that is based on the water quality ladder pictured. Familiar lakes include both those that you have visited this year as well as those you have visited in the recent past.

Name of Lake (County)	Check if you have ever considered visiting this lake	Number of visits (January-December) in 2003		Water Quality Assessment
		Single-day	Over-night	
Arbor Lake (Poweshiek)		#____(trips)	#____(trips)	#____
Arrowhead Lake (Pottawattamie)		#____(trips)	#____(trips)	#____
Arrowhead Pond (Sac)		#____(trips)	#____(trips)	#____
Avenue of the Saints Lake (Bremer)		#____(trips)	#____(trips)	#____
Badger Creek Lake (Madison)		#____(trips)	#____(trips)	#____
Badger Lake (Webster)		#____(trips)	#____(trips)	#____
Beaver Lake (Dallas)		#____(trips)	#____(trips)	#____
Beeds Lake (Franklin)		#____(trips)	#____(trips)	#____
Big Creek Lake (Polk)		#____(trips)	#____(trips)	#____
Big Spirit Lake (Dickinson)		#____(trips)	#____(trips)	#____
Black Hawk Lake (Sac)		#____(trips)	#____(trips)	#____
Blue Lake (Monona)		#____(trips)	#____(trips)	#____
Bob White Lake (Wayne)		#____(trips)	#____(trips)	#____
Briggs Woods Lake (Hamilton)		#____(trips)	#____(trips)	#____

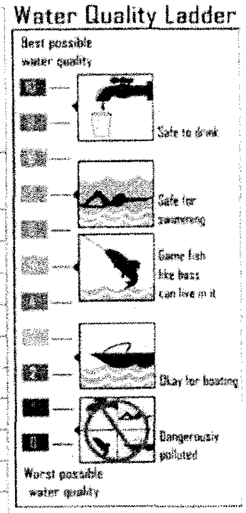


Name of Lake (County)	Check if you have ever considered visiting this lake	Number of visits (January-December) in 2003		Water Quality Assessment
		Single-day	Over-night	
Browns Lake (Woodbury)		#____(trips)	#____(trips)	#____
Brushy Creek Lake (Webster)		#____(trips)	#____(trips)	#____
Carter Lake (Pottawattamie)		#____(trips)	#____(trips)	#____
Casey Lake (aka Hickory Hills) (Tama)		#____(trips)	#____(trips)	#____
Center Lake (Dickinson)		#____(trips)	#____(trips)	#____
Central Park Lake (Jones)		#____(trips)	#____(trips)	#____
Clear Lake (Cerro Gordo)		#____(trips)	#____(trips)	#____
Cold Springs Lake (Cass)		#____(trips)	#____(trips)	#____
Coralville Lake (Johnson)		#____(trips)	#____(trips)	#____
Crawford Creek Impoundment (Ida)		#____(trips)	#____(trips)	#____
Crystal Lake (Hancock)		#____(trips)	#____(trips)	#____
Dale Maffitt Lake (Madison)		#____(trips)	#____(trips)	#____
DeSoto Bend Lake (Harrison)		#____(trips)	#____(trips)	#____
Diamond Lake (Poweshiek)		#____(trips)	#____(trips)	#____
Dog Creek (Lake) (O'Brien)		#____(trips)	#____(trips)	#____
Don Williams Lake (Boone)		#____(trips)	#____(trips)	#____
East Lake (Osceola) (Clarke)		#____(trips)	#____(trips)	#____
East Okoboji Lake (Dickinson)		#____(trips)	#____(trips)	#____
Easter Lake (Polk)		#____(trips)	#____(trips)	#____
Eldred Sherwood Lake (Hancock)		#____(trips)	#____(trips)	#____
Five Island Lake (Palo Alto)		#____(trips)	#____(trips)	#____
Fogle Lake (Ringgold)		#____(trips)	#____(trips)	#____
George Wyth Lake (Black Hawk)		#____(trips)	#____(trips)	#____
Green Belt Lake (Black Hawk)		#____(trips)	#____(trips)	#____
Green Castle Lake (Marshall)		#____(trips)	#____(trips)	#____
Green Valley Lake (Union)		#____(trips)	#____(trips)	#____
Greenfield Lake (Adair)		#____(trips)	#____(trips)	#____
Hannen Lake (Benton)		#____(trips)	#____(trips)	#____
Hawthorn Lake (aka Barnes City) (Mahaska)		#____(trips)	#____(trips)	#____
Hickory Grove Lake (Story)		#____(trips)	#____(trips)	#____
Hooper Area Pond (Warren)		#____(trips)	#____(trips)	#____
Indian Lake (Van Buren)		#____(trips)	#____(trips)	#____
Ingham Lake (Emmet)		#____(trips)	#____(trips)	#____
Kent Park Lake (Johnson)		#____(trips)	#____(trips)	#____

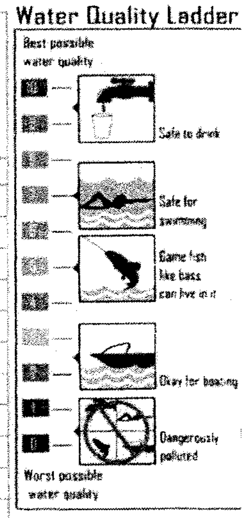


Name of Lake (County)	Check if you have ever considered visiting this lake	Number of visits (January-December) in 2003		Water Quality Assessment
		Single-day	Over-night	
Lacey-Keosauqua Park Lake (VanBuren)		#____(trips)	#____(trips)	#____
Lake Ahquabi (Warren)		#____(trips)	#____(trips)	#____
Lake Anita (Cass)		#____(trips)	#____(trips)	#____
Lake Cornelia (Wright)		#____(trips)	#____(trips)	#____
Lake Darling (Washington)		#____(trips)	#____(trips)	#____
Lake Geode (Henry)		#____(trips)	#____(trips)	#____
Lake Hendricks (Howard)		#____(trips)	#____(trips)	#____
Lake Icaria (Adams)		#____(trips)	#____(trips)	#____
Lake of the Hills (Scott)		#____(trips)	#____(trips)	#____
Lake Iowa (Iowa)		#____(trips)	#____(trips)	#____
Lake Keomah (Mahaska)		#____(trips)	#____(trips)	#____
Lake Manawa (Pottawattamie)		#____(trips)	#____(trips)	#____
Lake McBride (Johnson)		#____(trips)	#____(trips)	#____
Lake Meyer (Winneshiek)		#____(trips)	#____(trips)	#____
Lake Miami (Monroe)		#____(trips)	#____(trips)	#____
Lake Minnewashta (Dickinson)		#____(trips)	#____(trips)	#____
Lake Orient (Adair)		#____(trips)	#____(trips)	#____
Lake Pahoja (Lyon)		#____(trips)	#____(trips)	#____
Lake Smith (Kossuth)		#____(trips)	#____(trips)	#____
Lake Sugema (Van Buren)		#____(trips)	#____(trips)	#____
Lake of Three Fires (Taylor)		#____(trips)	#____(trips)	#____
Lake Wapello (Davis)		#____(trips)	#____(trips)	#____
Little River (Decatur)		#____(trips)	#____(trips)	#____
Little Sioux Park Lake (Woodbury)		#____(trips)	#____(trips)	#____
Little Spirit Lake (Dickinson)		#____(trips)	#____(trips)	#____
Little Wall Lake (Hamilton)		#____(trips)	#____(trips)	#____
Littlefield Lake (Audubon)		#____(trips)	#____(trips)	#____
Lost Island Lake (Palo Alto)		#____(trips)	#____(trips)	#____
Lower Gar Lake (Dickinson)		#____(trips)	#____(trips)	#____
Lower Pine Lake (Hardin)		#____(trips)	#____(trips)	#____
Manteno Lake (Shelby)		#____(trips)	#____(trips)	#____
Mariposa Lake (Jasper)		#____(trips)	#____(trips)	#____
Meadow Lake (Adair)		#____(trips)	#____(trips)	#____

Water Quality Ladder

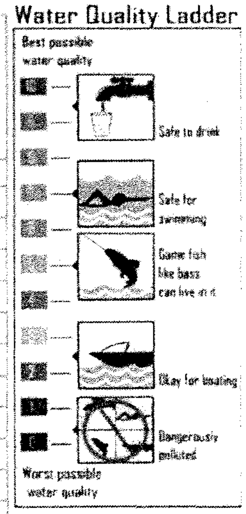


Name of Lake (County)	Check if you have ever considered visiting this lake	Number of visits (January-December) in 2003		Water Quality Assessment
		Single-day	Over-night	
Meyers Lake (Black Hawk)		#____(trips)	#____(trips)	#____
Mill Creek (Lake) (O'Brien)		#____(trips)	#____(trips)	#____
Mitchell Lake (Black Hawk)		#____(trips)	#____(trips)	#____
Moorhead Lake (Ida)		#____(trips)	#____(trips)	#____
Mormon Trail Lake (Adair)		#____(trips)	#____(trips)	#____
Nelson Park Lake (Crawford)		#____(trips)	#____(trips)	#____
Nine Eagles Lake (Decatur)		#____(trips)	#____(trips)	#____
North Twin Lake (Calhoun)		#____(trips)	#____(trips)	#____
Oldham Lake (Monona)		#____(trips)	#____(trips)	#____
Otter Creek Lake (Tama)		#____(trips)	#____(trips)	#____
Ottumwa Lagoon (Wapello)		#____(trips)	#____(trips)	#____
Pierce Creek Lake (Page)		#____(trips)	#____(trips)	#____
Pleasant Creek Lake (Linn		#____(trips)	#____(trips)	#____
Pollmiller Park Lake (Lee)		#____(trips)	#____(trips)	#____
Prairie Rose Lake (Shelby)		#____(trips)	#____(trips)	#____
Rathbun Lake (Appanoose)		#____(trips)	#____(trips)	#____
Red Haw Lake (Lucas)		#____(trips)	#____(trips)	#____
Red Rock Lake (Marion)		#____(trips)	#____(trips)	#____
Roberts Creek Lake (Marion)		#____(trips)	#____(trips)	#____
Rock Creek Lake (Jasper)		#____(trips)	#____(trips)	#____
Rodgers Park Lake (Benton)		#____(trips)	#____(trips)	#____
Saylorville Lake (Polk)		#____(trips)	#____(trips)	#____
Silver Lake (Delaware)		#____(trips)	#____(trips)	#____
Silver Lake (Dickinson)		#____(trips)	#____(trips)	#____
Silver Lake (Palo Alto)		#____(trips)	#____(trips)	#____
Silver Lake (Worth)		#____(trips)	#____(trips)	#____
Slip Bluff Lake (Decatur)		#____(trips)	#____(trips)	#____
South Prairie Lake (Black Hawk)		#____(trips)	#____(trips)	#____
Spring Lake (Greene)		#____(trips)	#____(trips)	#____
Springbrook Lake (Guthrie)		#____(trips)	#____(trips)	#____
Storm Lake including Little Storm Lake (Buena Vista)		#____(trips)	#____(trips)	#____
Swan Lake (Carroll)		#____(trips)	#____(trips)	#____
Thayer Lake (Union)		#____(trips)	#____(trips)	#____
Three Mile Lake (Union)		#____(trips)	#____(trips)	#____



Name of Lake (County)	Check if you have ever considered visiting this lake	Number of visits (January-December) in 2003 Single-day	Over-night	Water Quality Assessment
Trumbull Lake (Clay)		#____(trips)	#____(trips)	#____
Tuttle Lake (Emmet)		#____(trips)	#____(trips)	#____
Twelve Mile Creek Lake (Union)		#____(trips)	#____(trips)	#____
Union Grove Lake (Tama)		#____(trips)	#____(trips)	#____
Upper Gar Lake (Dickinson)		#____(trips)	#____(trips)	#____
Upper Pine Lake (Hardin)		#____(trips)	#____(trips)	#____
Viking Lake (Montgomery)		#____(trips)	#____(trips)	#____
Volga Lake (Fayette)		#____(trips)	#____(trips)	#____
West Okoboji Lake (Dickinson)		#____(trips)	#____(trips)	#____
West Osceola (Clarke)		#____(trips)	#____(trips)	#____
White Oak Lake (Mahaska)		#____(trips)	#____(trips)	#____
Williamson Pond (Lucas)		#____(trips)	#____(trips)	#____
Willow Lake (Harrison)		#____(trips)	#____(trips)	#____
Wilson Park Lake (Taylor)		#____(trips)	#____(trips)	#____
Windmill Lake (Taylor)		#____(trips)	#____(trips)	#____
Yellow Smoke Park Lake (Crawford)		#____(trips)	#____(trips)	#____
Other Lakes in Iowa		#____(trips)	#____(trips)	#____

Water Quality Ladder



2. Please indicate how often you or other members of your household visited lakes or rivers in each of the following locations this year.

	Single-day	Over-night
Lakes in Illinois		
Lakes in Minnesota		
Lakes in Missouri		
Lakes in Nebraska		
Lakes in South Dakota		

	Single-day	Over-night
Lakes in Wisconsin		
The Missouri River		
The Mississippi River		
Other Lakes and Rivers		

3. What activities do you or members of your household typically participate in during your lake visits? Check all that apply.

❑Boating ❑Jet skiing ❑Nature Appreciation/wildlife viewing
❑Camping ❑Sailing ❑Snowmobiling and other winter recreation
❑Fishing ❑Canoeing ❑Swimming and beach use
❑Hunting ❑Picnicking ❑ Other________________

In the following sections we will ask you some questions about potential changes to the water quality of Rathbun Lake located in Appanoose County. First, however, we will give you some information on the current condition of the lake. Please read this information carefully before answering the questions that follow.

Rathbun Lake's Current Condition

The quality of a lake can be described in many ways. One measure of water quality is the clarity of the lake water. Water clarity is usually described in terms of how far down into the water an object remains visible. The clarity of Rathbun Lake is currently between 2 to 4 feet. This means that objects are visible down to about 2 to 4 feet under the surface of the water.

Current conditions of Rathbun Lake can be summarized as:	
Water Clarity:	Objects distinghishable 2 to 4 feet under water
Algae blooms:	1 to 3 per year
Water color:	blue to greenish brown
Water odor:	mild to occasionally strong
Bacteria:	occasional short-term swim advisories possible
Fish:	good crappie and walleye

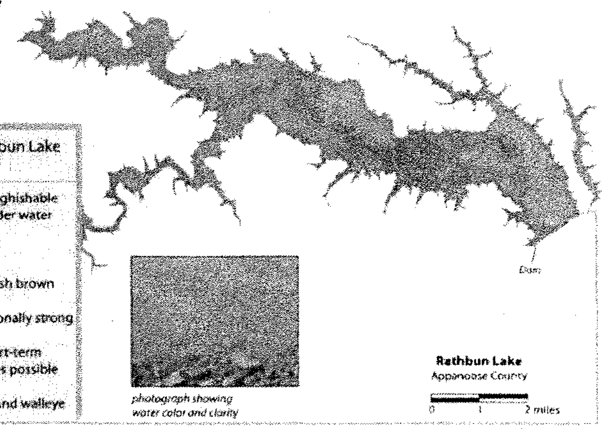


Figure 1. Current conditions of Rathbun Lake

Another measure of water quality is the amount of nutrients and other contaminants contained in the water. Water degradation can result from a number of sources, including urban runoff, fertilizers used in agriculture, motor vehicles, and others. Currently nutrients contribute to the occurrence of algae blooms in the lake, usually 1 to 3 times per year. Under some circumstances these blooms can be a health concern, causing skin rashes and allergic reactions. While Rathbun Lake is currently not regularly monitored, lakes with water quality measurements similar to those of Rathbun Lake had "Swimming is Not Recommended" signs posted by the Iowa Department of Natural Resources for anywhere from 6 to 8 weeks during a typical summer.

The overall quality of the water can affect other conditions of the lake. Poor water quality can result in an undesirable color and odor to the lake water. Currently, the color of Rathbun Lake varies between blue and greenish brown. The water usually has a mild to occasionally strong odor that many describe as "fishy."

Finally, the quality of the water affects the variety and quantity of fish in the lake. Rathbun Lake is a popular fishing lake for crappie and walleye. Catch rates for crappies are typically very good (about 120,000 annually) while walleye catches are more variable, but Rathbun Lake is the best walleye fishery in southern Iowa (about 2,000 annually). Large mouth bass and bluegill are not important sportfish species at Rathbun Lake.

4. During the course of the next year (2004), how many trips do you expect to take to Rathbun Lake?
   ______trips in 2004.

In the next question, we will be asking you how you would vote on a special ballot regarding the water quality of Rathbun Lake. While there is currently no such ballot initiative, we would like you to respond as if you were actually voting on the initiative and as if this were the only alternative available for improving water quality in the lake. (In particular, assume that no state action will be undertaken unless the referendum passes.)

When you think about your answer, it is important to keep in mind that people may indicate that they would be willing to pay more money when payment is hypothetical than when they are immediately expected to pay. It may be easy for people to say that they support a project when they are not sure they will ever have to pay any money based on their response. However, if the proposed payments are real and immediate, people may be more inclined to think about other options and what things they would have to give up to make this payment. So in answering the following questions, please keep in mind both the benefits of the water quality improvement and the impact that passage of such a referendum would have on your finances. In other words, **please answer as if this were a real referendum.**

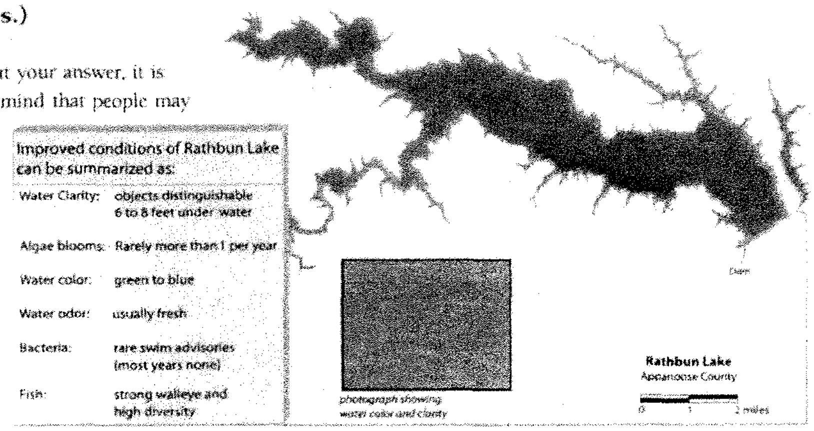


Figure 2. Conditions of Rathbun Lake following an improvement

Suppose that investments could be made to actually improve the quality of Rathbun Lake. These investments might include dredging, building protection strips along the edge of the lake to reduce runoff from the surrounding watershed or other structural changes to the lake and watershed. These changes would improve the lake over the next 5 years to the conditions described in Figure 2.

5. Would you vote "yes" on a referendum to improve the water quality in Rathbun Lake to the level described here? The proposed project would cost you $«CV BID» (payable in five $«Bid div 5» installments over a five year period.)

   ❑no ❑yes

6. How sure are you of this answer?

   1 (not sure at all) 2 3 4 5 (certain)

7. To help us better understand your answer, please indicate the **single** most important reason for your response to the preceding question:
   - ❑In general, the project is not a good use of my money
   - ❑In general, the project is a good use of my money
   - ❑The project is not realistic or unclear
   - ❑The costs of the project should be paid for by those damaging the lake, not by me
   - ❑I already contribute to environmental causes as much as I can afford
   - ❑No one should have the right to damage the lake in the first place
   - ❑ Other____

8. How many trips to Rathbun Lake would you make next year (2004) if the water quality at Rathbun Lake was improved by the amount described in Figure 2?
   ____________trips in 2004.

Information on you and other members of your household will help us better understand how household characteristics affect an individual's use of Iowa lakes and attitudes towards changes in them. It will also help us to determine how representative our sample is of the state of Iowa. All of your answers are strictly confidential. The information will only be used to report comparisons among groups of people. We will never identify individuals or households with their responses. Please be as complete in your answers as possible. Thank you.

9. What is your age?
   ❑Under 18 ❑26 – 34 ❑50 - 59 ❑76 +
   ❑18 – 25 ❑35 – 49 ❑60 - 75

10. Are you
    ❑male ❑female

11. What is the highest level of schooling that you have completed? (Please check only one)
    ❑Some high school or less ❑Some college or trade/vocational school ❑Advanced degree
    ❑High school graduate ❑College graduate

12. How many adults (including yourself) live in your household? ________

13. How many children live in your household (18 or under)?________

14. What is your current employment status?
    ❑full time ❑part time ❑student ❑unemployed ❑retired

15. If you are currently employed, how many hours a week do you typically work? ________

16. If you are currently employed, do you have the option of working additional hours to increase your total income?

☐no ☐yes—if so, what would your hourly wage be? $_______ per hour

17. If you answered "no" to question 16, and you could have the option of working more or less hours, which would you prefer?

☐Work more hours ☐Work the same number of hours ☐Work fewer hours

18. What is your total household income (before taxes) for 2003?

☐Under $10,000	☐$25,000-$29,999	☐$50,000-$59,999	☐$125,000-$149,999
☐$10,000-$14,999	☐$30,000-$34,999	☐$60,000-$74,999	☐Over $150,000
☐$15,000-$19,999	☐$35,000-$39,999	☐$75,000-$99,999	
☐$20,000-$24,999	☐$40,000-$49,999	☐$100,000-$124,999	

19. Do you own a boat? ☐yes ☐no

Finally, we would appreciate a little more information on your reaction to this survey.

20. How likely do you think it is that the results of surveys such as this one will affect decisions about water quality in Iowa lakes?

1 (no effect at all) 2 3 4 5 (definite effects)

21. If a water quality project such as the one described on page 9 were initiated but later information suggested that it would be ineffective, how likely is it that the project would be scrapped?

1 (impossible) 2 3 4 5 (certainly)

22. If a project such as the one described on page 9 failed to pass in a referendum, what do you think is the likelihood that another, similar project would be considered within the next few years?

1 (impossible) 2 3 4 5 (certainly)

23. What do you think is the likelihood that you will get additional information about the effectiveness of water quality improvement projects in the next few years?

1 (impossible) 2 3 4 5 (certainly)

Thank you for your participation in this survey. After completion, surveys should be returned to:

Catherine Kling
568 Heady Hall, Mailstop «Mailstop»
Iowa State University
Ames, IA 50011-1070

Appendix B. Figure and Tables

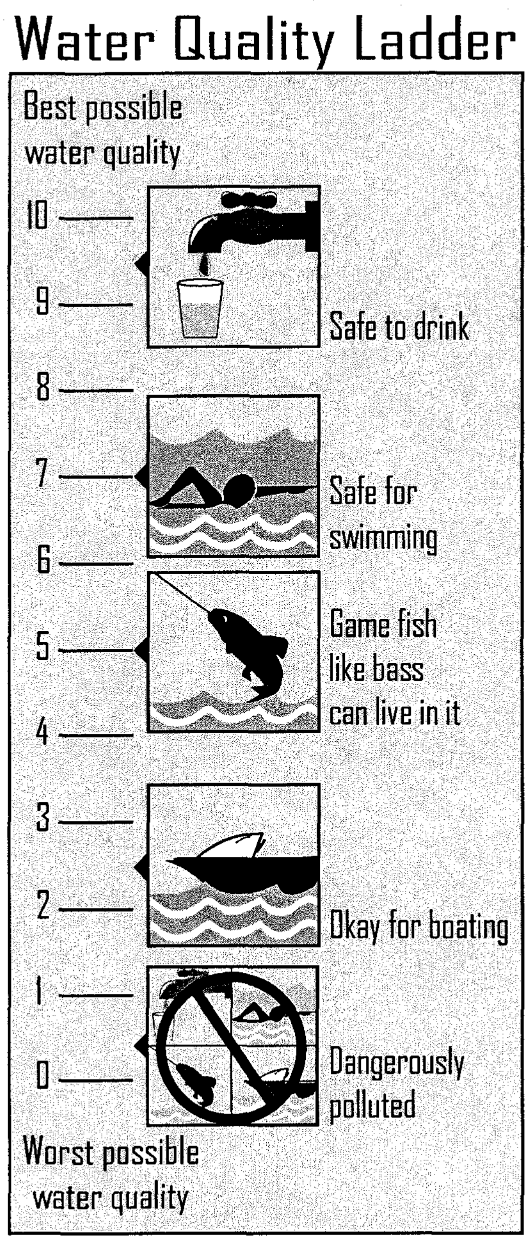


Figure 1. Water Quality Ladder

Table 1. Socio-Demographics Summary Statistics[a]

	Mean	Std. Dev.	Minimum	Maximum
Total Day Trips	6.97	10.19	0	52
Income	$55,697	$36,444	$7,500	$200,000
Male	0.67	0.46	0	1
Age	54.21	15.89	15	82
School	0.67	0.46	0	1
Household size	2.54	1.31	1	21

[a] Sample Size=5,052 individuals

Table 2. Summary Statistics of Water Quality (WQ) Perception[a]

	Mean	Std. Dev.	Minimum	Maximum
Median WQ Perception	5.81	0.66	4.00	7.00
Mean WQ Perception	5.75	0.51	4.11	6.81
Standard deviation of WQ Perception	1.66	0.28	1.06	2.42
Day Trips per capita	0.36	0.50	0.02	4.26

[a] Sample Size = 131 Lakes

Table 3. Water Quality Perception (WQP) and Total Day trip per Capita

	County	Impaired	Day-trip [a]	WQP [b]	N [c]
Best 20 Water Quality Perception Lakes and Day Trips					
West Okoboji Lake	Dickinson	0	1.46	6.81	571
Dale Maffitt Reservoir	Madison	0	0.11	6.68	93
Fogle Lake	Ringgold	0	0.09	6.67	12
Three Mile Lake	Union	0	1.37	6.67	156
Pleasant Creek Lake	Linn	0	0.39	6.61	204
Poll Miller Park Lake	Lee	0	0.18	6.59	27
Rathbun Reservoir	Appanoose	0	4.26	6.54	387
Lake Wapello	Davis	0	0.48	6.46	106
Big Spirit Lake	Dickinson	0	0.92	6.44	369
Lake Meyer	Winneshiek	1	0.71	6.43	473
Mill Creek Lake	O'Brien	0	0.12	6.42	31
Twelve Mile Creek Lake	Union	0	0.83	6.37	110
Lake Keomah	Mahaska	1	0.11	6.37	90
Little River Watershed Lake	Decatur	0	0.49	6.36	45
Lake Iowa	Iowa	0	0.17	6.34	86
Lake Smith	Kossuth	1	0.30	6.33	88
Kent Park Lake	Johnson	0	0.20	6.32	165
Lake Icaria	Adams	1	1.12	6.31	101
Lake Ahquabi	Warren	0	0.24	6.31	200
Greenfield Lake	Adair	0	0.16	6.26	34
Average		0.2	0.69	6.46	167

[a] Day Trip Per Capita
[b] Mean Water Quality Perception
[c] Number of respondents to assess the lake

Table 3. (continued)

	County	Impaired	Day trip [a]	WQP [b]	N [c]
Worst 20 Water Quality Perception Lakes and Day Trips					
George Wyth Lake	Black Hawk	0	0.69	5.25	224
Mariposa Lake	Jasper	1	0.04	5.24	42
Williamson Pond	Lucas	1	0.05	5.22	9
Briggs Woods Lake	Hamilton	0	0.31	5.18	88
Tuttle Lake	Emmet	1	0.08	5.14	22
Ingham Lake	Emmet	1	0.10	5.07	45
Lake Macbride	Johnson	1	1.20	5.06	160
Mitchell Lake	Black Hawk	0	0.05	5.04	26
Meyers Lake	Black Hawk	0	0.12	5.00	49
Lower Gar Lake	Dickinson	1	0.20	4.97	99
Swan Lake	Carroll	1	0.54	4.96	108
Lake Darling	Washington	1	0.43	4.95	148
Little Wall Lake	Hamilton	1	0.25	4.89	111
Silver Lake (Palo Alto)	Palo Alto	1	0.05	4.83	18
Arbor Lake	Poweshiek	1	0.08	4.70	44
Silver Lake (Delaware)	Delaware	1	0.07	4.69	39
Trumbull Lake	Clay	1	0.05	4.59	22
Carter Lake	Pottawattamie	1	0.39	4.53	98
Manteno Park Pond	Shelby	1	0.04	4.30	10
Ottumwa Central Park Ponds	Wapello	1	0.59	4.11	89
Average		0.8	0.27	4.89	73

Table 4. Water Quality Variables and 2003 Summary Statistics

	Mean	Std. Dev	Min	Max
Secchi Depth (m)	1.44	1.12	0.17	8.10
Chlorophyll (ug/l)	20.12	7.71	2.09	37.62
Nitrogen (ug/l)	294.64	168.69	52.04	1278.84
Nitrates (mg/l)	1.54	3.13	0.02	14.79
Total Nitrogen (mg/l)	2.72	3.19	0.49	15.66
Total Phosphorus (ug/l)	93.93	65.62	16.87	383.77
Silicon (mg/l)	4.01	2.49	0.88	11.22
pH	8.48	0.27	7.95	9.49
Alkalinity (mg/l)	107.90	33.64	56.33	201.00
Inorganic SS (mg/l)	8.08	7.27	0.60	49.54
Volatile SS (mg/l)	8.40	6.38	0.85	38.55
Cyanobacteria (mg/l)	293.63	827.09	0.01	7178.13
Total Bacteria (mg/l)	302.60	829.14	3.99	7178.60

Table 5. Correlation Coefficient of Quality Assessment with Several Physical Measures

Variables	All Sample (5052)			Water Contact Group (3619)			Non-Water Contact Group (1433)		
	correlation	statistic	pvalue	correlation	statistic	pvalue	correlation	statistic	pvalue
Day Trip per Capita	0.252	2.963	0.004	0.257	3.019	0.003	0.047	0.536	0.593
Secchi Depth	0.351	4.260	<0.001	0.365	4.455	<0.001	0.132	1.517	0.132
Chlorophyll	-0.072	-0.823	0.412	-0.087	-0.987	0.325	0.009	0.106	0.916
Total Phosphorus	-0.330	-3.977	<0.001	-0.331	-3.987	<0.001	-0.209	-2.424	0.017
Total Nitrogen	-0.191	-2.216	0.028	-0.196	-2.275	0.025	-0.136	-1.564	0.120
Nitrogen	-0.352	-4.268	<0.001	-0.362	-4.415	<0.001	-0.241	-2.817	0.006
Nitrates	-0.029	-0.327	0.744	-0.031	-0.351	0.726	-0.041	-0.465	0.643
pH	<0.001	0.002	0.998	-0.006	-0.065	0.949	-0.001	-0.013	0.990
Alkalinity	-0.145	-1.661	0.099	-0.145	-1.664	0.099	-0.146	-1.675	0.096
Silica	-0.307	-3.664	<0.001	-0.311	-3.720	<0.001	-0.184	-2.123	0.036
ISS	-0.334	-4.025	<0.001	-0.338	-4.081	<0.001	-0.166	-1.917	0.057
VSS	-0.321	-3.844	<0.001	-0.336	-4.054	<0.001	-0.082	-0.937	0.350
TSS	-0.339	-4.095	<0.001	-0.349	-4.235	<0.001	-0.129	-1.483	0.141
CTSI_SEC	-0.357	-4.344	<0.001	-0.369	-4.516	<0.001	-0.139	-1.595	0.113
CTSI_Chla	-0.065	-0.743	0.459	-0.079	-0.905	0.367	0.009	0.100	0.921
CTSI_TP	-0.306	-3.654	<0.001	-0.307	-3.663	<0.001	-0.196	-2.267	0.025
WQI	0.214	2.484	0.014	0.218	2.541	0.012	0.144	1.654	0.101
BOAT RAMP	0.257	3.024	0.003	0.253	2.973	0.004	0.138	1.585	0.115
Wake	0.015	0.169	0.866	0.017	0.189	0.851	-0.058	-0.663	0.508
Facilities	0.151	1.732	0.086	0.158	1.821	0.071	0.055	0.626	0.533
State Park	0.143	1.640	0.103	0.145	1.662	0.099	0.099	1.127	0.262
Log (Acreage Use)	0.135	1.542	0.125	0.118	1.354	0.178	0.111	1.272	0.206

Table 6. Summary Statistics for Lake Site Characteristics

	Mean	Std. Dev	Min	Max
Acres	662.41	2105.41	10	19,000
Ramp	0.86	0.35	0	1
Wake	0.67	0.47	0	1
State Park	0.39	0.49	0	1
Handicap Facility	0.38	0.49	0	1

Table 7. Regression of Mean Perceptions on Physical Measures and Lake Characteristics

	Estimate	Std. Err	*p*-value
Constant	-0.093	0.132	0.479
Secchi Depth	0.296	0.154	0.056
Log (Chlorophyll)	0.346	0.123	0.006
Nitrogen (NH3+NH4)	-0.021	0.119	0.859
Log (Total Phosphorus)	-0.322	0.139	0.022
Log (Total Nitrogen)	-0.244	0.302	0.422
Silika	-0.107	0.103	0.303
Alkalinity	-0.191	0.089	0.035
Log (total bacteria)	-0.117	0.190	0.541
Log (cyanobacteria)	0.018	0.193	0.925
Quality Index of dissolved Oxygen	0.513	0.163	0.002
Square of Quality Index of dissolved Oxygen	0.168	0.081	0.042
Quality Index of Total Nitrates	-0.353	0.287	0.222
Quality Index of pH	-0.112	0.135	0.408
Square of Quality Index of pH	0.068	0.063	0.281
Quality Index of total suspended solids	-0.113	0.214	0.598
Square of Quality index of suspended solids	-0.142	0.072	0.052
Quality Index of turbidity	-0.224	0.128	0.083
Boat Ramp dummy	0.162	0.083	0.054
Wake dummy	0.208	0.083	0.013
Handicap facilities dummy	-0.004	0.081	0.965
Log (Acreage Use)	0.156	0.096	0.106
State Park dummy	0.038	0.089	0.673

Table 8a. Repeated Mixed Logit Model Parameter Estimates[a]

	Model A		Model B		Model C		
Male	-9.11 (0.429)	-7.55 (0.428)	-11.92 (0.475)	-11.91 (0.473)	-5.83 (0.432)	-14.89 (0.487)	-14.85 (0.484)
Age	-0.12 (0.074)	0.20 (0.078)	0.07 (0.081)	0.09 (0.081)	0.002 (0.078)	-1.26 (0.095)	-1.27 (0.095)
Age2	0.005 (0.001)	0.001 (0.001)	0.002 (0.001)	0.002 (0.001)	0.003 (0.001)	0.013 (0.001)	0.014 (0.001)
School	-0.26 (0.387)	3.67 (0.422)	1.37 (0.524)	1.25 (0.527)	4.88 (0.433)	0.95 (0.542)	0.90 (0.540)
Household Size	-0.49 (0.167)	-0.98 (0.163)	-1.10 (0.185)	-1.06 (0.185)	-1.25 (0.168)	-1.65 (0.191)	-1.66 (0.189)
Price	-0.331 (0.001)	-0.332 (0.001)	-0.334 (0.001)	-0.334 (0.001)	-0.330 (0.001)	-0.334 (0.001)	-0.335 (0.001)
Mean Estimate for Random Coefficient							
Log(Acres)	3.45 (0.063)	3.38 (0.066)	3.71 (0.069)	3.56 (0.069)	3.11 (0.065)	3.20 (0.066)	3.21 (0.066)
Ramp	14.46 (0.828)	14.49 (0.833)	13.69 (0.843)	13.11 (0.851)	14.39 (0.826)	10.79 (0.719)	10.74 (0.719)
Facilities	1.42 (0.235)	1.29 (0.247)	0.96 (0.241)	1.13 (0.242)	0.90 (0.234)	1.00 (0.241)	0.96 (0.242)
State Park	2.99 (0.260)	3.59 (0.267)	3.43 (0.307)	3.59 (0.305)	4.23 (0.252)	3.82 (0.254)	3.86 (0.254)
Wake	4.10 (0.258)	3.54 (0.260)	2.13 (0.320)	1.58 (0.323)	3.43 (0.255)	4.27 (0.297)	4.33 (0.297)
α	-8.91 (0.214)	-10.09 (0.229)	-10.29 (0.040)	-10.28 (0.040)	-10.42 (0.039)	-10.28 (0.040)	-10.37 (0.040)
Dispersion Estimate for Random Coefficients							
Log(Acres)	0.35 (0.01)	0.35 (0.01)	0.33 (0.01)	0.33 (0.01)	0.34 (0.01)	0.32 (0.05)	0.32 (0.01)
Ramp	19.92 (0.62)	21.05 (0.71)	18.01 (0.63)	18.09 (0.63)	21.99 (0.58)	18.69 (0.58)	18.72 (0.57)
Facilities	13.13 (0.26)	13.38 (0.27)	12.68 (0.24)	12.54 (0.24)	13.24 (0.26)	13.20 (0.26)	13.25 (0.27)
State Park	11.75 (0.26)	12.26 (0.27)	14.29 (0.28)	14.27 (0.28)	12.54 (0.26)	12.77 (0.27)	12.75 (0.27)
Wake	13.38 (0.25)	13.28 (0.27)	15.79 (0.32)	15.70 (0.32)	13.63 (0.27)	16.30 (0.33)	16.34 (0.33)
α	2.38 (0.03)	2.50 (0.03)	2.46 (0.03)	2.46 (0.03)	2.51 (0.03)	2.47 (0.03)	2.47 (0.03)

Parentheses are standard errors.

[a] All of the parameters are scaled by 10, except α (which is unscaled)

Table 8b. Repeated Mixed Logit Model Parameter Estimates[a] .

Variable	Model A		Model B		Model C		
Secchi	2.51 (0.096)	2.28 (0.098)	2.59 (0.100)	2.36 (0.100)			
Log(Chlorophyll)	2.50 (0.223)	2.21 (0.224)	3.01 (0.234)	2.63 (0.234)			
NH3+NH4			-0.01 (0.001)	-0.01 (0.001)			
NO3+NO2			-1.59 (0.071)	-1.71 (0.072)			
Log(Total Nitrogen)	0.32 (0.068)	0.41 (0.068)	4.87 (0.283)	5.48 (0.284)			
Log (Total Phosphorus)	-1.38 (0.135)	-1.12 (0.141)	-4.03 (0.160)	-3.90 (0.164)			
Silicon			1.10 (0.035)	1.08 (0.035)			
pH			-69.89 (10.836)	-64.04 (11.099)			
pH2			4.25 (0.627)	3.88 (0.643)			
Alkalinity			0.04 (0.003)	0.05 (0.003)			
Inorganic SS	-0.083 (0.009)	-0.079 (0.009)	-0.008 (0.010)	-0.009 (0.010)			
Volatile SS	0.24 (0.014)	0.26 (0.014)	0.03 (0.019)	0.08 (0.019)			
Log (Cyanobacteria)	-1.64 (0.079)	-1.71 (0.085)	-1.36 (0.091)	-1.41 (0.091)			
Log (Total Bacteria)	1.82 (0.099)	1.97 (0.109)	0.87 (0.116)	1.01 (0.120)			
Mean Perception (δ)		1.47 (0.127)		2.22 (0.141)		3.50 (0.100)	3.40 (0.096)
Water Quality Index					0.40 (0.057)	-0.02 (0.006)	
Log-Likelihood	-59319	-59278	-59096	-59071	-59614	-59502	-59503

Parentheses are standard errors.

[a] All of the parameters are scaled by 10, except for α (which is unscaled)

Table 9. West Okoboji Lake vs. the other 130 Lakes

	West Okoboji Lake	Average of the other 130 Lakes	Average of the 9 Zone Lakes
Mean Perception	6.81	5.74	5.67
Water Quality Index	9.08	7.79	7.90

Table 10. 65 Non-Impaired Lakes vs. the 66 Impaired Lakes

	Median of the 65 Non-Impaired Lakes	Averages of the 66 Impaired Lakes
Mean Perception	5.94	5.60
Water Quality Index	8.17	7.45

Table 11. Annual Compensating Variation Estimates

Average CV	All 130 Lakes Improved to West Okoboji.		9 Zone Lakes Improved to West Okoboji.		65 Impaired Lakes Improved to Median	
	Model C_1	Model C_2	Model C_1	Model C_2	Model C_1	Model C_2
Per Choice Occasion	\$0.24	\$1.31	\$0.02	\$0.15	\$0.05	\$0.12
Per Iowa Household	\$12.39	\$68.35	\$0.90	\$7.87	\$3.06	\$6.23
For all Iowa Households[a]	\$14.29	\$78.82	\$1.03	\$9.08	\$3.53	\$7.18
Predicted Trips[b]	6.68	8.53	6.47	7.45	6.53	7.42

[a] Units are million dollars.
[b] Predicted Trips are 6.45 using Model C_1 with current water quality index and 7.28 using Model C_2 with current water quality perceptions.

Appendix C. Water Quality Index

According to McClelland (1974), water quality index (WQI) is a continuous scale from 0 to 100 which reflects the composite influence of nine significant physical, chemical, and microbiological parameters of water quality. It was developed and field evaluated by the National Sanitation Foundation (NSF) to provide a uniform method for indicating and reporting the benefits – or lack of benefits – realized from billions of dollars invested in stream quality improvement program.

It was developed based on an opinion research technique. A panel of 142 persons with expertise in water quality management was carefully selected and they received a series of mailed questionnaire. In the first questionnaire, they were asked to rate the 35 parameters for possible inclusion in a water quality index on a scale of "1" (highest relative significance) to "5" (lowest relative significance). In the second mailing, respondents were asked to review their original judgments and modify them if they wished. In addition, panelists were asked to designate not more than 15 parameters, which they considered to be the "most important" for inclusion in a water quality index. Utilizing expert opinion derived from first two rounds of the study, 11 parameters, or groups of parameters, were listed. In the third mailing, respondents were asked to assign values and draw graphs for the variation in level of water quality produced by different levels of the nine individual parameters: dissolved oxygen, fecal coliform density, pH, biochemical oxygen demand (5-days), nitrates, phosphates, temperature, turbidity, and total solids. Also, respondents were asked to compare relative overall water quality, using a scale of "1" (highest relative value) to "5" (lowest relative value) to obtain the parameter weightings. Finally, "Judgments" of all panelists were then combined to produce a set of "average curve" scaled between 0 and 100 – one for each parameter.

The WQI is derived by converting concentrations of each water quality characteristic into a corresponding index, q_i which is read from the quality curve. Weight for each of the corresponding index, w_i were derived based on the summary judgments of the expert panel. These weights were designed to sum to 1 for the nine water quality characteristics. The q_i

and w_i values were combined into a composite multiplicative index of the following form:

$$\prod_{i=1}^{n} q_i^{w_i}$$

The subscript refers to the i-th parameter, and n is the number of parameters (in this case, n=9). By design, WQI varies between and is bounded by 0 and 100.

To construct water quality index, it must be modified to account for the four characteristics (i.e., temperature, fecal coliform, phosphates, and biochemical oxygen demand for 5-days) that are not modeled. Temperature and fecal coliform were not available from the ISU Limnology lab and units of biochemical oxygen demand and phosphates were not consistent with McClelland (1974). To accomplish this, new weights are calculated for the remaining five parameters so that the ratios of the five weights are retained and the weights sum to 1. Table B.1 below presents the original and revised parameter weights for the nine pollutants. Each of the five quality curve are duplicated by linear interpolation method. Although it is impossible to get the same value with respect to the parameter level, linear interpolation method gives the value of quality curves as close as McClelland's.

Table C.1. Original and Revised Weights for WQI parameters

Parameters	Original Weights	Revised Weights
Dissolved Oxygen	0.17	0.32
Total Suspended Solid	0.07	0.13
Nitrates	0.10	0.19
Turbidity	0.08	0.15
pH	0.11	0.21
Fecal Coliform Density	0.16	0.00
Biochemical Oxygen Demand (5-day)	0.11	0.00
Temperature	0.10	0.00
Phosphates	0.10	0.00
Total	1.00	1.00

The categories of Water Quality Ladder are defined according to a corresponding WQI values, i.e., boatable if WQI value is 25, fishable if WQI value is 50, and swimmable if WQI value is 70.

Reference

McClelland, N. I., "Water Quality Index Application in the Kansas River Basin," EPA-907/9-74-001, 1974.

Appendix D. Carson's Trophic State Index (CTSI)

Carson and Simpson (1996) defined trophic state as the total weight of living biological material (biomass) in a waterbody like a lake, a river, and a stream at a specific location and time. In accordance with the definition of trophic state, the trophic state index (TSI) of Carlson (1977) uses algal biomass as the basis for trophic state classification.[22] Because of the reciprocal relationship between biomass concentration and Secchi depth (SD) transparency, each doubling in biomass would result in halving transparency. By transforming SD values to the logarithm to the base 2, each biomass doubling would be represented by a whole integer at SD value of 1m, 2m, 4m, 8m, etc. Based on this relation, some algebra gives a trophic state index based on SD ranges from 0 to 100 as following:

$$CTSI\_SEC = 10\,(6 - \ln SD / \ln 2),$$

where ln is a natural log transformation and SD measured in meter. The advantage of using the SD is that it is an extremely simple and cheap measurement and usually provides a TSI value similar to that obtained for chlorophyll.

In addition, utilizing the relationship between SD and chlorophyll pigment (Chla) and total phosphorus (TP), trophic indices based on chlorophyll and total phosphorous are defined as

$$CTSI\_Chla = 10\,\{6 - (2.04 - 0.68 \ln Chla) / \ln 2\}$$

$$CTSI\_TP = 10\,\{6 - (\ln(48/TP) / \ln 2\}.$$

The number derived from chlorophyll is best for estimating algal biomass in most lakes and priority should be given for its use as a TSI. The advantage of phosphorous index is that it is relatively stable throughout the year and, because of this, can supply a meaningful value during seasons when algal biomass is far below its potential maximum.

The CTSI reflects a continuum of "states." The range of the index is from approximately zero to 100, although the index theoretically has no lower or upper bounds. The index has the advantage over the use of the raw variables in that it is easier to memorize units of 10 rather than the decimal fractions of raw phosphorus or chlorophyll values.

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[22] Details can be found on the website at http://dipin.kent.edu/tsi.htm#A%20Trophic%20State%20Index.

A trophic state index is not the same as a water quality index. Since eutrophic is often equated with poor water quality, TSI and water quality index are confused with each other. Water quality index depends on the use of that water and the local attitudes of the people, which is a subjective judgment. On the other hand, the TSI is an objective standard of trophic state of any body of water.

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Chapter 4. Estimation of the Impact of Water Quality Improvement

I. Introduction

The recreation demand model provides one approach to estimating the benefits of quality improvement. However, this approach is often limited by range of the observed variation of the quality change. To address this limitation, the recreation demand literature increasingly makes use of contingent behavior (CB) data. In the CB framework, respondents are asked how their pattern of trips to a set of sites would change given a proposed water quality change.[23] Thus, combining observed data with CB data allows the analyst to estimate the impact of water quality improvement on the trip behavior beyond the observed variation. Further, even when quality variations already exist, the additional variation provided by CB data will generally yield more precise recreation demand parameter estimates. However, relatively little is known as to whether the stated responses to these hypothetical quality changes are consistent with how households respond to actual quality changes. The question is: Do individuals respond to hypothetical water quality changes in the same as way as they respond as actual water quality changes? Do they respond more to hypothetical water quality changes (e.g., with the hope of influencing policy change or because they ignore their budget constraint)? Alternatively, do they respond less because they do not believe the changes will actually occur?

The purpose of this chapter is to investigate individual's response to a hypothetical water quality improvement. Toward this end, I jointly model the recreation demand model using observed and CB trip data collected from the 2004 Iowa Lakes Survey. The Iowa lakes survey collected three sets of trip data for 131 lakes in Iowa: a) actual trips in 2004, b) anticipated trips in 2005 to the same lakes given current lake conditions and c) anticipated trips in 2005 given a hypothetical improvement to the lakes. The hypothetical water quality improvement was described in terms of the water quality ladder index detailed in the

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[23] Sometimes it is referred as "stated preference", SP, data.

previous chapter. Specifically, the hypothetical water scenario proposed improving all lakes in the state to be at least safe for swimming, with a water quality index of 7. The three types of recreation data provide a unique opportunity to investigate the consistency of individual responses to actual versus hypothetical environmental conditions.

The remainder of this chapter is divided into six sections. Section II provides a review of the existing literature on the estimation of the recreation demand using CB data. Section III describes the observed and CB trip pattern under the current water quality and the hypothetically improved water quality level collected in the 2004 Iowa Lakes Survey. The repeated mixed logit model (RXL) to be used in the analysis is described in Section IV. The estimation results are then discussed on Section V. Section VI provides welfare measure estimate based on the estimated model and conclusions follow in Section VII.

II. Literature

A number of recent recreation demand studies have combined observed and contingent behavior data in order to better estimate household response to environmental quality changes. Adamowicz *et al.* (1994) compare site selection choices estimated from actual data versus under hypothetical scenarios. Adamowicz *et al.* (1997) compare the choice of moose hunting sites using observed (i.e., revealed preference, RP) and stated preference (SP) data and investigate the effect of perceptions versus objective measures of environmental quality on site demand. Both Englin and Cameron (1996) and Azevedo, Herriges and Kling (2003) combined data on the number of trips actually taken with intended number of trips given alternative trip costs. Layman, Boyce, and Criddle (1996) combine observed travel cost data and hypothetical travel cost data to estimate the value of three alternative recreational fishing management proposals. Loomis (1997) uses information on actual trips at current trip costs, intended visitation at higher trip costs, and intended visitation with two proposed quality levels of the resource. Grijalva *et al.* (2002) use three types of mountain climbing data: the first one is prepolicy observed climbing trip data, the second one is CB climbing trip data given hypothetical changes in site access, and the final one is postpolicy observed climbing trip data. The CB trip data consisted of two hypothetical policy scenarios. One is the closure of one site and the other is the closure of two sites. They show that policy change causes significant changes in consumer surplus.

The primary point of most of the above studies is to illustrate the benefits of combining observed and contingent behavior trip data for the valuation of environmental quality changes. One such advantage is the ability to evaluate policies beyond the realm of observable levels of a given resource before it is effectively lost, or over quality and price changes that are policy relevant but historically unobservable (Adamowicz *et al.*, 1994; Englin and Cameron, 1996; Grijalva *et al.*, 2002). Adamowicz *et al.* (1994) also state that the multicollinearity between quality characteristics that is often present in observed data may be reduced through the strategic design of quality levels in the intended behavior portion of the survey. In addition, Ben-Akiva and Morikawa (1990) show that combining these two data sets increases the accuracy of parameter estimation over models using either type of data alone.

Considerably less attention has been paid in the literature to testing the validity of individual responses to contingent behavior scenarios; i.e., whether observed and contingent behavior data are consistent with the same underlying preference structure.[24] Ideally, testing the "consistency" of the two data sets would take the form of tests for the equality of parameters estimated separately for the two types of data. The problem is that most data sets

[24] This issue is analogous to concern in the contingent valuation literature regarding the incentive compatibility of CV referendum questions.

lack sufficient variation in both price and quality to fully test for consistency in the responses of participants. Azevedo, Herriges and Kling (2003) test for the consistency of RP and CB trips to wetlands, but are limited to investigating travel cost responses (real and hypothetical). Their data lacked sufficient variation in wetland quality attributes. Adamowicz *et al.* (1997) also test for consistency between observed and contingent behavior data. They compare the choice of moose hunting sites using observed (RP) trips to and stated preferences (SP) in the form of conjoint data.[25] They also investigate the effect of perceptions versus objective measures of environmental quality on site demand. The subjective perceptions of quality are then used as explanatory variables in an $RP_{perceptions}$ model. An $RP_{objective}$ model is also developed using objective perceptions of quality as explanatory variables. Both models are pooled in order to test for consistency between actual and CB responses. For each of these pooling models they fail to reject the null hypothesis of parameter equality. However, the consistency test for a third model, which pools all three data sets, results in the rejection of parameter equality.

There are two limitations to the Adamowicz *et al.* (1997) study. First, limitations in the actual site quality attributes preclude them from estimating a full set of quality effects for the revealed preference data alone. Second, the contingent behavior data is based on hypothetical sites and attributes. The hypothetical nature of the sites makes the direct comparison (and modeling) of the RP and CB data less straightforward. The advantage of the Iowa Lakes data, in contrast, is that there is ample variation in the water quality attributes and the RP and CB trip information concerns the same set of actual sites.

[25] Conjoint CB surveys ask respondents to choose among pairs (or sets) of hypothetical sites, rather than reporting visits to actual sites under hypothetical quality changes.

III. Data and Survey Results

The 2004 Iowa Lakes Survey is the third year survey in a four year study, jointly funded by the Iowa Department of Natural Resources and the USEPA, aimed at understanding recreational lake usage in Iowa and the value placed on water quality in the state. The survey was sent by direct mail in February of 2005 to the 5,206 Iowans who completed the 2003 survey.[26] The survey collected information on a household's past trip behavior in 2004 and anticipated trips in 2005 under both current and hypothetically improved water quality levels.

Similar to the 2003 Iowa Lakes Survey, standard follow-up procedures were used to encourage a high response rate to the survey, including a postcard reminder mailed two weeks after the initial mailing and a second copy of the survey mailed one month later. In addition, survey respondents were provided with a $10 incentive for completing the survey. A copy of Iowa Lakes Survey 2004 is included as an appendix to this chapter (Appendix A).

The survey itself has two major sections. The first section (pp 3-7) asks respondents to report how frequently they visited each of 131 lakes in the state during 2004 and how frequently they intend to visit in 2005 under both current conditions and a proposed water quality improvement. In describing both current and hypothetical water quality conditions, the water quality ladder index described in the chapter 3 was used. The proposed water quality improvement scenario would move all the lakes to at least the swimmable level (7). If current water quality index of a lake is below 7 (swimmable) then the improved water quality is 7. If current water quality of a lake is above or at 7, then water quality is unchanged under the scenario. Under this scenario, the water quality of fifty-two lakes in Iowa would be

[26] The 2003 Iowa Lakes survey was mailed to 8,000 Iowa residents selected randomly from among households living in the state.

improved, while seventy-nine lakes are remained unchanged. Color coded numbers, along with the water quality ladder, were used to convey the water quality conditions.

In order to collect information about each household's single day trips for each of the lakes in the survey, three columns were provided in which to indicate actual single day trips in 2004 and anticipated trips in 2005 under current and proposed water quality levels. The first column is for the actual number of past trips in 2004 (i.e., "observed trips") and the second column is for the anticipated number of trips in 2005 under the current water quality (i.e., "next year trips"). The third and fourth columns show the current water quality conditions and proposed water quality improvement in terms of the water quality ladder. Given the water quality improvement scenario, respondents are asked to indicate how many single day trips they would take to each of the lakes in the last column (i.e., "CB trip").

The second section of the survey (pp 7-10) collects socio-demographic information, including age, gender, education, etc. Further, the second section of the questionnaire asks for details of a household's employment status including the number of work weeks, paid vacations, work hours per week, either hourly wage or salary, and the work options (e.g., whether individual is free to choose their number of hours to work). These latter data are not used for the current analysis.

A total of 4,310 surveys have been returned to date. Allowing for 65 undeliverable surveys and 14 deceased individuals in the original sample this corresponds to an 84% response rate. The high response rate is a result, in part, from the fact that the sample used for the survey is a subset of the last year's respondents. From the 4,310 completed surveys, 1,223 surveys were available in time for this analysis.[27] A portion of the respondents, however, did not complete the survey sections on 2004 and 2005 trips: 41 for observed trips,

[27] The remainder of the surveys are still in the process of being entered and checked for coding errors.

100 for next year trips, and 362 for CB trips. In order to maintain a balanced panel, the union of these three non-responses was deleted, from the sample, leaving the 838 respondents who had provided information on all three types of day trips.

Finally, similar to the previous chapter, anyone reporting more than 52 total single day trips to the 131 lakes in any of the three types of trips was excluded. This reduced the sample to 782 observations. Defining the number of choice occasions as 52 trips per year allows one trip to one of the 131 Iowa Lakes per week. While the choice of 52 is arbitrary, it seems a reasonable cut-off for the total number of allowable single day trips for the season. Invariably some of the respondents who recorded trips greater 52 did in fact take this number of trips. However, since this survey was randomly sent out to Iowan, some of the recipients live on a lake and it may be those individuals who record hundreds of "trips" are simply returning to their place of residence.

The initial question on the individual's trip behavior in next year is whether or not he/she takes more trips to the improved lake. Table 1 lists the summary statistics for the three types of trips and for several key socio-economic variables.[28] The average number of observed single day trips in 2004 to all 131 lakes is 6.65, ranging from zero to 50 trips per year. The average number of trips anticipated in 2005 under current conditions is 9.11 and 9.26 under hypothetically improved water quality. Thus, survey respondents expect to take more trips in 2005 regardless of whether the water quality will be improved or not. The survey respondents are more likely to be older, male, have a higher income, and be more educated than the general Iowa population. Schooling is entered as a dummy variable equaling one if the individual has attended or completed some level of post high school education.

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[28] All of the tables are in Appendix B.

Table 2 summarizes the average of differences between the total numbers of trips to a lake under the hypothetical water quality improvements and the anticipated numbers of day trips under current conditions, both for 2005. As expected, the average number of day trips increases for those lakes with initial water quality is below 7 (i.e., for the lakes that are improving). The lake whose water quality improved from 3 to 7 is the Lake of Three Fires, in Taylor County, and its day trips increases by 12 under the proposed water quality improvements. Day trips to lakes whose initial water quality is 6, increased by 6.5 over the 21 lakes. On the other hand, day trips to lakes whose initial water quality is at or above 7 decrease. Table 2 suggests that proposed water quality improvement generally increase an individual's anticipated trips to the improved lakes and that they, on average, substitute trips to non-improved lakes with trips to improved lakes. For example, suppose there are three lakes, A, B, and C, around individual i and travel costs to each of three lakes are \$10, \$14, and \$20 respectively. Suppose water quality of three lakes are rated as 5 (A), 6 (B), and 7(C) on the water quality ladder and individual i took trips to the one lake whose water quality is at 7 (Lake C) because water quality is the most important factor to his/her site choice decision. Now, suppose water quality of the lake A and B is improved to the swimmable level (7). Then the hypothetical water quality improvement changes the individual i's intended trips such that he/she decreases trips to lake C while increasing trip to lake A or B. A more detailed analysis will be required to measure the specific impact of hypothetical water quality improvement. However, these aggregate data do suggest that individuals respond to the hypothetical water quality improvement in the manner we would expect.

IV. Model

Three types of data (observed trips in year 2004, next year trip under current water quality, and contingent behavior trip under hypothetically improved water quality) are used to jointly estimate the recreation demand and to test the hypotheses regarding contingent behavior responses. Two hypotheses are of interest: one is whether individual anticipate changes for their day trips next year and the other is whether individuals respond to hypothetical water quality improvements in the same way they responded to actual water quality different across lakes in 2004.

The model begins by specifying the utility that individual i associates with visiting site j on choice occasion t under scenario s, where s = 04 (for 2004 RP data), 05 (for 2005 anticipated trips), and 05H (for 2005 trips under hypothetical conditions). Specifically, I assume that

$$\begin{aligned} U_{ijts} &= V(P_{ij}, Z_j, X_j, s_i) + \varepsilon_{ijts} \\ &= \begin{cases} \kappa' s_i + \varepsilon_{i0ts} \\ \alpha_i + \beta_i D_s - \lambda P_{ij} + (\delta + \delta^{05} D_s) Z_{js} + \delta^H Z_{js}^H + \gamma_i' X_j + \varepsilon_{ijts} \end{cases} \\ & i = 1, \cdots, I, j = 1, \cdots, J, t = 1, \cdots, 52 \ . \end{aligned} \tag{1}$$

The notation is similar to the model in chapter 3. Each data set has 52 choice occasions. V is the deterministic component of utility and ε_{ijts} is an error component which is assumed to be an *iid* extreme value random variable. The vector s_i consists of socio-demographic characteristics. P_{ij} is the travel cost from each Iowan's residence to each of the 131 lakes as calculated with PCMiler. Z_{js} represents water quality ladder index for lake j under scenario s. D_s is the dummy variable that = 1 for s = 05 and 05H, and = 0 otherwise. Thus, β_i captures shifts in the intercept of V between 2004 and 2005, while δ^{05} captures shifts in the marginal response to water quality. Z_{js}^{H} denotes the hypothetical difference between baseline water quality and the water quality under scenario s. Thus $Z_{js}^{H} = 0$ for s = 04 and 05, while taking nonnegative values for the contingent behavior trip (s = 05*H*). The parameter δ^{H} then captures shifts in the marginal response to a hypothetical improvement of water quality. X_j denotes other site characteristics (including lake facilities and state park designation).

Notice that the parameters α_i, β_i, and γ_i are allowed to vary across individuals, allowing for heterogeneity of preferences and correlation in the utilities of individuals across choice occasions. Specifically, these parameters are assumed to be distributed randomly across individuals in the population. The random parameter α_i was introduced by including dummy variable R_j which equals one for all of the recreation alternatives $(j = 1, \cdots, J)$ and equals zero for the stay at home option $(j = 0)$, following Herriges and Phaneuf (2002). Similarly, β_i was introduced by including $R_j \times D_s$, which equals zero for the actual trips in 2004 and stay at home option while it equals one for all of the recreation sites for anticipated trips in 2005.

The random parameters α_i, β_i, and γ_i can be viewed as sum of their respective means ($\overline{\alpha}$, $\overline{\beta}$, and $\overline{\gamma}$) and individual deviations from these means (ϕ_i, ρ_i, and τ_i), allowing for variation in an individual's tastes relative to the average tastes in the population (Train, 1998). Therefore, we can rewrite the utility function in (1) as

$$U_{ijts} = \begin{cases} \kappa' s_i + \eta_{i0ts}, & j = 0 \\ \overline{\alpha} + \overline{\beta} D_s - \lambda' P_{ij} + (\delta + \delta^{05} D_s) Z_{js} + \delta^{H} Z_{js}^{H} + \overline{\gamma}' X_j + \eta_{ijts}, & j = 1, \cdots, J, \end{cases} \tag{2}$$

where the unobservable portion of utility is given by

$$\eta_{ijts} = \begin{cases} \varepsilon_{i0ts}, & i = 1,\cdots,N \\ \phi_i + \rho_i D_s + \tau_i' X_j + \varepsilon_{ijts}, j = 1,\cdots,J, i = 1,\cdots,N, t = 1,\cdots 52. \end{cases} \tag{3}$$

This unobservable portion of utility is correlated over sites and trips because of the common influence of the deviation terms which vary over individuals. For example, an individual with a large negative deviation from the mean of α_i will be more likely to choose the stay-at-home option on each choice occasion, the ϕ_i capturing in this case some unobserved attribute of the individual causing them to prefer staying at home (e.g., they cannot swim or do not like fishing). On the other hand, someone with a large positive deviation ϕ_i will tend to take many trips. In addition, by introducing dummy variable D_s, the error correlation due to "repeated choices" is addressed. Thus, the error correlation across repeated choices increases as the variance of the random coefficients increase. Random parameter interpretation is useful because error correlation due to repeated choices and preference heterogeneity can be addressed. Further, since the unobserved portion of utility is correlated over sites and trips choice occasions, concern about the familiar IIA assumption does not apply.

Given that the ε_{ijts} 's are assumed to be *iid* extreme value, the resulting model corresponds to McFadden and Train's (2000) mixed logit framework. A mixed logit model is defined as the integration of the logit formula over the distribution of unobserved random parameters (Revelt and Train, 1998). Let the vector of random parameters in the model defined above denoted by $\omega_i = (\alpha_i, \beta_i, \gamma_i)$ and let $\xi = (\lambda, \kappa, \delta, \delta^{05}, \delta^{H})$ denote the fixed parameters. If the random parameters, ω_i, were known then the probability of observing individual i choosing alternative j on choice occasion t for scenario s would follow the standard logit form

$$L_{ijts}(\omega_i,\xi)=\frac{\exp(V_{ijts}(\omega_i,\xi))}{\sum_{k=0}^{J}\exp[V_{ikts}(\omega_i,\xi)]}. \qquad (4)$$

Since V_{ijts} is not a function of t, the overall contribution of individual i to the likelihood function would be

$$L_i(\omega_i,\xi)=\prod_s\prod_j L_{ijs}(\omega_i,\xi)^{n_{ijs}},$$

where n_{ijs} denotes the number of trips by individual i to site j under scenario s and $L_{ijs}(\omega_i,\xi)$ denotes the common value of $L_{ijts}(\omega_i,\xi)$ across at t. Since the ω_i is unknown, the corresponding unconditional probability, $P_i(\theta,\xi)$ is obtained by integrating over an assumed probability density function for the ω_i's. The unconditional probability is now a function of θ, where θ represents the estimated moments of the random parameters.[29] This repeated Mixed Logit model assumes the random parameters are *iid* distributed over the individuals so that

$$P_i(\theta,\xi)=\int L_i(\omega_i,\xi)f(\omega_i\,|\,\theta)d\omega_i\,. \qquad (5)$$

No closed form solution exists for this unconditional probability and therefore simulation is required for the maximum likelihood estimates of θ and ξ.[30] One thing to note is that since individual i appears three times in the model, the same draws of the random parameter vector are used for three repeated choices. This specification does not lead to perfect error

[29] In the current model, $\theta=(\bar{\gamma},\bar{\alpha},\bar{\beta},\sigma_{\gamma 1},\cdots,\sigma_{\gamma k},\sigma_\alpha)$

[30] Train (2003) describes simulation methods for use with mixed logit models, in particular maximum simulated likelihood which I employ. Software written in GAUSS to estimate mixed logit models is available from Train's home page at http://elsa.berkeley.edu/~train.

correlations because the independent extreme value term ε_{ijts} still enters the utilities for each choice.

Again, there are two variations which might impact the individual's trip behavior in the model. One is year-to-year fluctuation (from year 2004 to year 2005) given current water quality and the other is hypothetical water quality improvement in year 2005. The parameters β_i and δ^{05} capture changes in behavior due to year-to-year fluctuation where β_i captures mean shift in total trips and δ^{05} reflects changes in response to water quality between years. In contrast, the parameter δ^{H} captures differences in the response to hypothetical water quality improvements in 2005.

Three hypotheses are of interest. The first hypothesis of interest is whether or not individuals respond differently to hypothetical water quality improvement than they do to actual water quality differences across lakes, i.e., $H_0^1 : \delta^H = 0$. The second hypothesis of interest is whether or not individuals anticipate changes in their overall trips between 2004 and 2005. This hypothesis can be written as $H_0^2 : \beta_i = 0, \delta^{05} = 0$. The last hypothesis is the joint hypothesis; i.e., $H_0^3 : \beta_i = \delta^{05} = \delta^H = 0$.

V. Estimation Result

A. Specification

The model in equation (1) uses the same functional forms as in the chapter 3 for the lake characteristics and socio-demographic variables. The water quality index is entered linearly. 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. A quadratic age term is included in the model to allow for nonlinearities in the impact of age. Site characteristics are included with random coefficients.

This is to allow for heterogeneity in individual preferences regarding site characteristics, such as wake restrictions and site facilities. 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 skies, etc. It is assumed that the random parameters γ_i are each normally distributed with the mean ($\bar{\gamma}_k$) and dispersion ($\sigma_{\gamma k}$) for each parameter. Three models are estimated: the full model and two reduced models with hypothesis 2 (Model R_1) and hypothesis 3 (Model R_2) respectively.

B. Estimation Result

The resulting parameter estimates of three models are presented in two Tables, 3a and 3b. Table 3a lists parameter estimates for socio-demographic variables and mean and dispersion parameters for random coefficients for lake amenity variables. Except for age and household size variable in full model, all the coefficients are significant at 1% level while age square variables in three models are significant and positive. In general, these variables do not vary substantially across the three models. Note that the socio-demographic data are included in the conditional indirect utility for the stay-at-home option. Therefore, male individuals are 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. Higher-educated individuals appear to be more likely to stay-at-home, with corresponding positive coefficients on the school variable. The price coefficients are all negative and significant and virtually identical in three models.

Turning to the site amenities, 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, the dispersion on the size of the lake indicates almost all people prefer bigger lakes. 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 prefer lakes that allow wakes. It seems the population is roughly split, with slightly more than a half of the visitors preferring a lake that allows wakes and the rest of visitors 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 7 out of a possible 52 choice occasions. On the other hand, the mean of β_i is positive, indicating that on average respondents anticipate receiving higher utility from taking the trips in 2005 regardless of water quality. The dispersion on β_i is relatively small, though statistically significant, indicating the most individuals have $\beta_i > 0$.

The three parameter estimates regarding individual's water quality responses are reported in Table 3b. Beginning with the full (unconstrained) version of the model, all three of the water quality related parameters are statistically significant. As was the case in chapter 3, the parameter δ indicates that individuals do respond positively to water quality conditions. There also appears to be a statistically significant, though small, increase in this response between 2004 and 2005, with $\delta^{05} = 0.021$. Finally, the response to the increased (hypothetical) water quality is little bit smaller than the response observed to actual water quality for s = 04 and 05, with δ^{H} slightly decreasing the marginal impact of a water quality change.

Therefore, hypothesis that individuals do not respond differently to hypothetical water quality improvements H_0^1 is rejected. It is also the case that individuals have a somewhat larger response to water quality in terms of their 2005 trip plans. The likelihood ratio test statistic comparing the full model versus R_1 is $\chi^2 = 55.4$ with 2 degree of freedom so that H_0^2 is rejected with p-value is less than 0.001. Similarly, the joint hypothesis $H_0^3 : \beta_i = \delta^{05} = \delta^H = 0$ is rejected at 1% critical level, with a likelihood ratio test statistic of $\chi^2 = 63.8$ with 3 degree of freedom. The individual marginal responses to water quality conditions in 2004 and 2005 and hypothetically improved water quality are significantly different with a marginal effects of 0.15, 0.17, and 0.13, respectively.

VI. Welfare Estimation

The results of the previous section indicate that individuals respond less to the hypothetical water quality improvement than they do to actual water conditions. In this section, the impacts of year-to-year variation and the hypothetical water quality improvement are investigated in terms of the predicted trips and annual compensating variation (CV) under a water quality improvement to Storm Lake. The current water quality of Storm Lake is rated as a 5, which is "fishable" according to EPA's water quality ladder. The proposed change is to improve water quality of this lake up to 7, which is "swimmable". The question is: while the CB data yield a statistically significant different marginal response to water quality, are the predicted trips and welfare implications substantially different?

The full (unconstrained) model is used for welfare estimate in order to capture the three responses of individuals to actual water conditions in 2004 and 2005 and to hypothetical water quality improvements. Based on the test results in Section V and the random parameter vector estimates, $\theta_i = (\alpha_i, \beta_i, \gamma_i)'$, the conditional compensating variation associated with a change in water quality index from Z_s to Z_s' for individual i on site choice occasion t under scenario s is given by

$$CV_{its}(\theta_i) = \frac{1}{\lambda}\left\{\ln[\sum_{j=0}^{J}\exp(V_{ijts}[Z_s';\theta_i])] - \ln[\sum_{j=0}^{J}\exp(V_{ijts}[Z_s;\theta_i])]\right\}, \tag{6}$$

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

$$CV_{its}(\theta_i) = \frac{1}{R}\sum_{r=1}^{R}\frac{1}{\lambda}\left\{\ln[\sum_{j=0}^{J}\exp(V_{ijts}[Z_s';\theta_i^r])] - \ln[\sum_{j=0}^{J}\exp(V_{ijts}[Z_s;\theta_i^r])]\right\}, \tag{7}$$

where R is the number of draws and r represents a particular draw from its distribution. The simulation process involves drawing values of $\theta_i = (\alpha_i, \beta_i, \gamma_i)'$ and then calculating the resulting compensating variation for each vector of draws, and finally averaging over the results for many draws. A total of 2,500 draws were used in the simulation. One thing to note is that, although indirect utility function depends on scenario s, summation in the bracket should be over the sites j only. Since indirect utility function takes three different forms with respect to three scenarios, three compensating variations are estimated.

The resulting welfare estimates are provided in Table 4, along with the predicted number of trips under each of three models (s = 04, s = 05, and s = 05H). Mean predicted trips and after improvement predicted trips do not vary much across three scenarios. After improving Storm Lake's water quality up to "swimmable" predicted trips to Storm Lake water condition scenarios increases up to 33% (from 0.12 to 0.16). In contrast, predicted trips to Storm Lake under hypothetical water quality scenario are little changed.

The annual compensating variation (CV) estimates per Iowa household under actual water conditions are somewhat larger based on the s = 05 versus the s = 04 responses ($1.24 and $1.11 respectively). In contrast, the annual compensating variation per Iowa household based on the hypothetical water quality improvement scenario (s = 05H) is reduced to $1.01.

This is the lowest compensating variation among those obtained under the three scenarios. One possibility is that individuals do not believe the hypothetical water quality improvement. Aggregating to the annual value for all Iowans simply involves multiplying by the number of households in Iowa, which is 1,153,205.[31]

VII. Conclusion

Individual's response to hypothetical water quality improvement is measured and tested whether it is significantly or not using three sets of trip data for 131 lakes in Iowa: actual trips in 2004, anticipated trips in 2005, and anticipated trips in 2005 given a hypothetical improvement to the lakes. The trip data sets are collected from the 2004 Iowa Lakes Survey. The hypothetical water quality scenario is to improve all lakes in the state to be at least safe for swimming. Survey respondents appear to increase their anticipated trip to the improved lakes. A Repeated mixed logit model estimation result shows that individuals respond less to the hypothetical water quality improvement than they do to actual water quality. One explanation may be that individuals do not believe hypothetical water quality improvements will indeed occur.

The results in this chapter should be of some comfort to policymakers and practitioners. While the marginal response to hypothetical water quality changes are smaller than observed responses, and the difference is statistically significant, the differences are small. Moreover, at least for the Storm Lake water quality scenario, the implications in terms of trips and welfare measures are also small. Whether these results hold up in other settings is an empirical question.

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[31] Number of Iowa households as reported by Survey Sampling, Inc., 2003.

One issue in jointly estimating the model using the three data sets is scale parameter estimation although this is not investigated in the analysis. Although the error generation process for a collection of next year trip and contingent behavior trip might be expected to be the same, it may be different from the process producing the actual trip data. In particular, the effect of unobserved variables may produce different variances for the ε_{ijts} terms in the three data sets. In this case the variance of one data set must still be normalized to unity, but the relative variance for the remaining data set is identified and can be estimated. By convention, the actual trip data are assumed to reflect the baseline scale associated with the "observed behavior". Anticipated trip data sets scale coefficients are then defined as the multiplicative factor applied to all of the two data sets to equalize the variances of the stochastic portion of the utility function. Because scale and variance have a reciprocal relationship, values less than one imply that the next year and contingent behavior data sets variance is larger than the observed trip data variance component. Thus, one refinement of the current analysis would be to allow for different variance scales between the RP and CB data.

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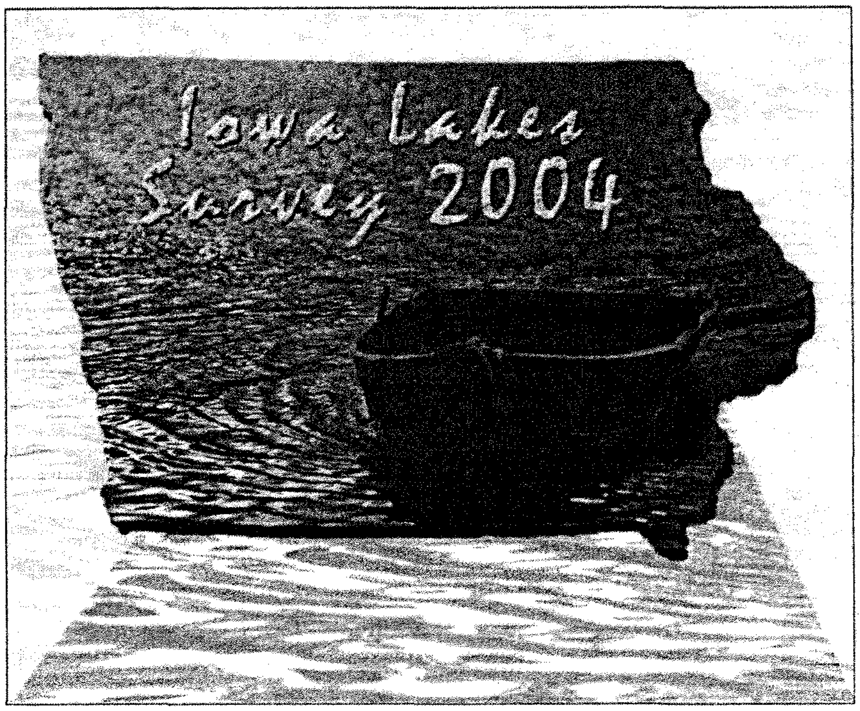
Appendix A. The Iowa Lakes Survey 2004



CARD
Center for Agricultural and Rural Development
Resource and Environmental Policy Division

IOWA STATE UNIVERSITY
DEPARTMENT OF ECONOMICS

In order to make sound decisions concerning the future of Iowa lakes, it is important to understand how the lakes are used, as well as what factors influence your selection of lakes to visit. The answers you give to the questions in this survey are very important. Even if you have not visited any lakes in Iowa, please complete and return the questionnaire. It is critical to understand the characteristics and views of both those who use and those who do not use the lakes.

In this first section, we would like to find out which of the lakes in the enclosed map you visited in 2004 and how your lake visits might change in the future with changes in lake water quality.

1. Please indicate in the first column how often in 2004 you or other members of your household visited each of the lakes listed on the following pages for a single day trip. In this questionnaire, we will be asking you detailed information only about your single day trips (and not overnight trips). If you did not visit any lake in Iowa in 2004, please check this box.

   ☐ **I did not visit any lakes in Iowa in 2004.**

   If you took overnight trips to Iowa lakes in 2004 please check this box

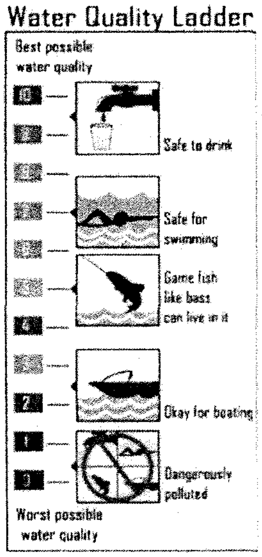
   ☐ **I took one or more overnight trips to lakes in Iowa in 2004.**

2. Please indicate in the second column how many single day trips you plan to make to each of the lakes in 2005. If you do not plan to visit any lakes in Iowa in 2005, please check this box.

   ☐ **I do not plan to visit any lakes in Iowa in 2005.**

3. There are currently efforts underway to improve the water quality of Iowa's lakes. We are interested in knowing how these changes might impact your single day trips to lakes. One way of thinking about water quality is to use a ladder like the one shown below. The top of the water quality ladder stands for the best possible quality of water, and the bottom of the ladder stands for the worst. On the ladder you can see the different levels of water quality.

Water Quality Ladder

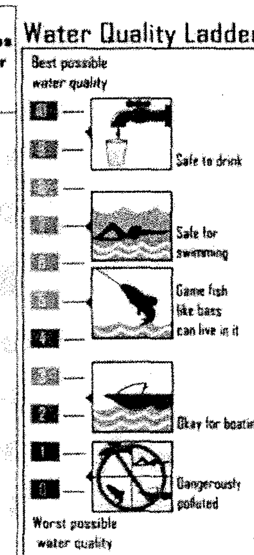


For example: The lowest level is so polluted that it has oil, raw sewage, and/or other things in it like trash; it has almost no plant or animal life, smells bad, and contact with it is dangerous to human health. Water quality that is "boatable" would not harm you if you happened to fall into it for a short time while boating or sailing. Water quality that is "fishable" is a higher level of quality than "boatable." Although some kinds of fish can live in boatable water, it is only when water is "fishable" that game fish like bass can live in it. Finally, "swimmable" water is of a high enough quality that it is safe to swim in and ingest in small amounts.

For each of the lakes below, we have indicated the current water quality conditions in terms of the water quality ladder. For example, Arbor Lake in Powershiek County is currently rated as a 6 on the water quality ladder. This is above the minimum for fishable, but below the swimmable level. Badger Creek Lake in Madison county, on the other hand, has a current water quality level of 4, which is okay for boating, but not fishable. In the last column of the table, we would like you to indicate how many single day trips you would make to each of the lakes given all of the lakes were improved to at least swimmable (7). Notice that many lakes are already at or above the swimmable level. Please keep in mind that you may choose to take fewer trips to some lakes, while taking more trips to others. If you would not plan to take any trips to Iowa lakes, even given the water quality improvements, please check the following box:

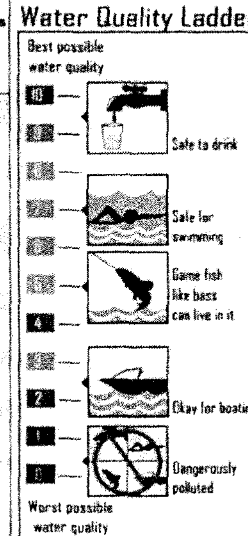
☐ **I would not plan to visit any lakes in Iowa in 2005 even if the water quality improved as indicated.**

Name of Lake (County)	Number of Visits: Actual 2004	Number of Visits: Anticipated 2005	Water Quality: Current	Water Quality: Proposed	Anticipated Single Day Trips with the higher Proposed Water Quality
Lake Ahquabi (Warren)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Lake Anita (Cass)	#____(trips)	#____(trips)	8	8	#____(trips)
Arbor Lake (Poweshiek)	#____(trips)	#____(trips)	6	7	#____(trips)
Arrowhead Lake (Pottawattamie)	#____(trips)	#____(trips)	5	7	#____(trips)
Arrowhead Pond (Sac)	#____(trips)	#____(trips)	9	9	#____(trips)
Avenue of the Saints Lake (Bremer)	#____(trips)	#____(trips)	5	7	#____(trips)
Badger Creek Lake (Madison)	#____(trips)	#____(trips)	4	7	#____(trips)
Badger Lake (Webster)	#____(trips)	#____(trips)	6	7	#____(trips)
Beaver Lake (Dallas)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Beed's Lake (Franklin)	#____(trips)	#____(trips)	5	7	#____(trips)
Big Creek Lake (Polk)	#____(trips)	#____(trips)	7	7	#____(trips)
Big Spirit Lake (Dickinson)	#____(trips)	#____(trips)	8	8	#____(trips)
Black Hawk Lake (Sac)	#____(trips)	#____(trips)	7	7	#____(trips)
Blue Lake (Monona)	#____(trips)	#____(trips)	7	7	#____(trips)
Bob White Lake (Wayne)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Briggs Woods Lake (Hamilton)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Brown's Lake (Woodbury)	#____(trips)	#____(trips)	8	8	#____(trips)
Brushy Creek Lake (Webster)	#____(trips)	#____(trips)	7	7	#____(trips)
Carter Lake (Pottawattamie)	#____(trips)	#____(trips)	7	7	#____(trips)
Casey Lake (aka Hickory Hills) (Tama)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Center Lake (Dickinson)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Central Park Lake (Jones)	#____(trips)	#____(trips)	6	6	#____(trips)
Clear Lake (Cerro Gordo)	#____(trips)	#____(trips)	6	7	#____(trips)
Cold Springs Lake (Cass)	#____(trips)	#____(trips)	8	8	#____(trips)
Coralville Lake (Johnson)	#____(trips)	#____(trips)	6	7	#____(trips)
Lake Cornelia (Wright)	#____(trips)	#____(trips)	7	7	#____(trips)
Crawford Creek Impoundment (Ida)	#____(trips)	#____(trips)	8	8	#____(trips)
Crystal Lake (Hancock)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Dale Maffitt Lake (Madison)	#____(trips)	#____(trips)	9	9	#____(trips)
Lake Darling (Washington)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
DeSoto Bend Lake (Harrison)	#____(trips)	#____(trips)	8	8	#____(trips)
Diamond Lake (Poweshiek)	#____(trips)	#____(trips)	4	7	#____(trips)
Dog Creek (Lake) (O'Brien)	#____(trips)	#____(trips)	7	7	#____(trips)
Don Williams Lake (Boone)	#____(trips)	#____(trips)	7	7	#____(trips)
East Lake (Osceola) (Clarke)	#____(trips)	#____(trips)	6	7	#____(trips)
East Okoboji Lake (Dickinson)	#____(trips)	#____(trips)	8	8	#____(trips)
Easter Lake (Polk)	#____(trips)	#____(trips)	6	8	#____(trips)
Eldred Sherwood Lake (Hancock)	#____(trips)	#____(trips)	6	7	#____(trips)
Five Island Lake (Palo Alto)	#____(trips)	#____(trips)	7	7	#____(trips)
Fogle Lake (Ringgold)	#____(trips)	#____(trips)	8	8	#____(trips)
Lake Geode (Henry)	#____(trips)	#____(trips)	7	7	#____(trips)
George Wyth Lake (Black Hawk)	#____(trips)	#____(trips)	8	8	#____(trips)
Green Belt Lake (Black Hawk)	#____(trips)	#____(trips)	8	6	#____(trips)

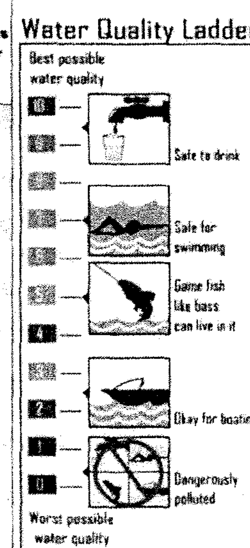


Name of Lake (County)	Number of Visits: Actual 2004	Number of Visits: Anticipated 2005	Water Quality: Current	Water Quality: Proposed	Anticipated Single Day Trips with the higher Proposed Water Quality
Green Castle Lake (Marshall)	#____(trips)	#____(trips)	7	7	#____(trips)
Green Valley Lake (Union)	#____(trips)	#____(trips)	8	8	#____(trips)
Greenfield Lake (Adair)	#____(trips)	#____(trips)	6	8	#____(trips)
Hannen Lake (Benton)	#____(trips)	#____(trips)	8	8	#____(trips)
Hawthorn Lake (aka Barnes City) (Mahaska)	#____(trips)	#____(trips)	9	9	#____(trips)
Lake Hendricks (Howard)	#____(trips)	#____(trips)	5	7	#____(trips)
Hickory Grove Lake (Story)	#____(trips)	#____(trips)	7	7	#____(trips)
Hooper Area Pond (Warren)	#____(trips)	#____(trips)	8	8	#____(trips)
Lake Icaria (Adams)	#____(trips)	#____(trips)	7	7	#____(trips)
Indian Lake (Van Buren)	#____(trips)	#____(trips)	7	7	#____(trips)
Ingham Lake (Emmet)	#____(trips)	#____(trips)	6	7	#____(trips)
Lake Iowa (Iowa)	#____(trips)	#____(trips)	8	8	#____(trips)
Kent Park Lake (Johnson)	#____(trips)	#____(trips)	8	8	#____(trips)
Lake Keomah (Mahaska)	#____(trips)	#____(trips)	5	7	#____(trips)
Lacey Keosauqua Park Lake (VanBuren)	#____(trips)	#____(trips)	9	9	#____(trips)
Lake of the Hills (Scott)	#____(trips)	#____(trips)	7	7	#____(trips)
Lake of Three Fires (Taylor)	#____(trips)	#____(trips)	5	7	#____(trips)
Little River (Decatur)	#____(trips)	#____(trips)	8	8	#____(trips)
Little Sioux Park Lake (Woodbury)	#____(trips)	#____(trips)	8	8	#____(trips)
Little Spirit Lake (Dickinson)	#____(trips)	#____(trips)	6	7	#____(trips)
Little Wall Lake (Hamilton)	#____(trips)	#____(trips)	4	7	#____(trips)
Littlefield Lake (Audubon)	#____(trips)	#____(trips)	5	7	#____(trips)
Lost Island Lake (Palo Alto)	#____(trips)	#____(trips)	7	7	#____(trips)
Lower Gar Lake (Dickinson)	#____(trips)	#____(trips)	5	7	#____(trips)
Lower Pine Lake (Hardin)	#____(trips)	#____(trips)	5	7	#____(trips)
Lake Manawa (Pottawattamie)	#____(trips)	#____(trips)	6	7	#____(trips)
Manteno Lake (Shelby)	#____(trips)	#____(trips)	7	7	#____(trips)
Lake Macbride (Johnson)	#____(trips)	#____(trips)	8	8	#____(trips)
Mariposa Lake (Jasper)	#____(trips)	#____(trips)	5	7	#____(trips)
Meadow Lake (Adair)	#____(trips)	#____(trips)	7	7	#____(trips)
Lake Meyer (Winneshiek)	#____(trips)	#____(trips)	7	7	#____(trips)
Meyers Lake (Black Hawk)	#____(trips)	#____(trips)	8	8	#____(trips)
Lake Miami (Monroe)	#____(trips)	#____(trips)	7	7	#____(trips)
Mill Creek (Lake) (O'Brien)	#____(trips)	#____(trips)	8	8	#____(trips)
Lake Minnewashta (Dickinson)	#____(trips)	#____(trips)	7	7	#____(trips)
Mitchell Lake (Black Hawk)	#____(trips)	#____(trips)	7	7	#____(trips)
Moorhead Lake (Ida)	#____(trips)	#____(trips)	8	8	#____(trips)
Mormon Trail Lake (Adair)	#____(trips)	#____(trips)	8	8	#____(trips)
Nelson Park Lake (Crawford)	#____(trips)	#____(trips)	8	8	#____(trips)
Nine Eagles Lake (Decatur)	#____(trips)	#____(trips)	8	8	#____(trips)
North Twin Lake (Calhoun)	#____(trips)	#____(trips)	7	7	#____(trips)
Oldham Lake (Monona)	#____(trips)	#____(trips)	8	8	#____(trips)
Lake Orient (Adair)	#____(trips)	#____(trips)	5	7	#____(trips)

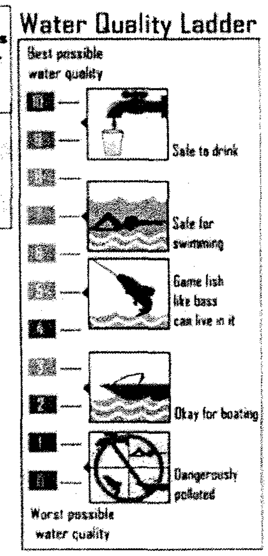
Water Quality Ladder



Name of Lake (County)	Number of Visits: Actual 2004	Number of Visits: Anticipated 2005	Water Quality: Current	Water Quality: Proposed	Anticipated Single Day Trips with the higher Proposed Water Quality
Otter Creek Lake (Tama)	#____(trips)	#____(trips)	7	7	#____(trips)
Ottumwa Lagoon (Wapello)	#____(trips)	#____(trips)	5	7	#____(trips)
Lake Pahoja (Lyon)	#____(trips)	#____(trips)	6	7	#____(trips)
Pierce Creek Lake (Page)	#____(trips)	#____(trips)	5	7	#____(trips)
Pleasant Creek Lake (Linn)	#____(trips)	#____(trips)	8	8	#____(trips)
Polmiller Park Lake (Lee)	#____(trips)	#____(trips)	8	8	#____(trips)
Prairie Rose Lake (Shelby)	#____(trips)	#____(trips)	7	7	#____(trips)
Rathbun Lake (Appanoose)	#____(trips)	#____(trips)	7	7	#____(trips)
Red Haw Lake (Lucas)	#____(trips)	#____(trips)	9	9	#____(trips)
Red Rock Lake (Marion)	#____(trips)	#____(trips)	6	7	#____(trips)
Roberts Creek Lake (Marion)	#____(trips)	#____(trips)	7	7	#____(trips)
Rock Creek Lake (Jasper)	#____(trips)	#____(trips)	7	7	#____(trips)
Rodgers Park Lake (Benton)	#____(trips)	#____(trips)	6	7	#____(trips)
Saylorville Lake (Polk)	#____(trips)	#____(trips)	5	7	#____(trips)
Silver Lake (Delaware)	#____(trips)	#____(trips)	4	7	#____(trips)
Silver Lake (Dickinson)	#____(trips)	#____(trips)	6	7	#____(trips)
Silver Lake (Palo Alto)	#____(trips)	#____(trips)	6	7	#____(trips)
Silver Lake (Worth)	#____(trips)	#____(trips)	4	7	#____(trips)
Slip Bluff Lake (Decatur)	#____(trips)	#____(trips)	8	8	#____(trips)
Lake Smith (Kossuth)	#____(trips)	#____(trips)	8	8	#____(trips)
South Prairie Lake (Black Hawk)	#____(trips)	#____(trips)	7	7	#____(trips)
Spring Lake (Greene)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Springbrook Lake (Guthrie)	#____(trips)	#____(trips)	5	7	#____(trips)
Storm Lake including Little Storm Lake (Buena Vista)	#____(trips)	#____(trips)	5	7	#____(trips)
Lake Sugema (Van Buren)	#____(trips)	#____(trips)	8	8	#____(trips)
Swan Lake (Carroll)	#____(trips)	#____(trips)	5	7	#____(trips)
Thayer Lake (Union)	#____(trips)	#____(trips)	5	7	#____(trips)
Three Mile Lake (Union)	#____(trips)	#____(trips)	8	8	#____(trips)
Trumbull Lake (Clay)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Tuttle Lake (Emmet)	#____(trips)	#____(trips)	6	7	#____(trips)
Twelve Mile Creek Lake (Union)	#____(trips)	#____(trips)	8	8	#____(trips)
Union Grove Lake (Tama)	#____(trips)	#____(trips)	5	7	#____(trips)
Upper Gar Lake (Dickinson)	#____(trips)	#____(trips)	7	7	#____(trips)
Upper Pine Lake (Hardin)	#____(trips)	#____(trips)	6	7	#____(trips)
Viking Lake (Montgomery)	#____(trips)	#____(trips)	7	7	#____(trips)
Volga Lake (Fayette)	#____(trips)	#____(trips)	6	7	#____(trips)
Lake Wapello (Davis)	#____(trips)	#____(trips)	8	8	#____(trips)
West Okoboji Lake (Dickinson)	#____(trips)	#____(trips)	8	8	#____(trips)
West Osceola Lake (Clarke)	#____(trips)	#____(trips)	8	8	#____(trips)
White Oak Lake (Mahaska)	#____(trips)	#____(trips)	8	8	#____(trips)
Williamson Pond (Lucas)	#____(trips)	#____(trips)	6	7	#____(trips)
Willow Lake (Harrison)	#____(trips)	#____(trips)	8	8	#____(trips)



Name of Lake (County)	Number of Visits: Actual 2004	Number of Visits: Anticipated 2005	Water Quality: Current	Water Quality: Proposed	Anticipated Single Day Trips with the higher Proposed Water Quality
Wilson Park Lake (Taylor)	#____(trips)	#____(trips)	[illegible]	[illegible]	#____(trips)
Windmill Lake (Taylor)	#____(trips)	#____(trips)	[illegible]	7	#____(trips)
Yellow Smoke Park Lake (Crawford)	#____(trips)	#____(trips)	[illegible]	[illegible]	#____(trips)
Other Lakes in Iowa________	#____(trips)	#____(trips)	No Change		#____(trips)



4. Of the trips you've reported on the preceding pages what percentage of these were
   a) alone or only with members of your immediate household _____%
   b) with friends or members of another household _____%
   c) trips members of your household took but you did not + _____%
   100 %

Information on you and other members of your household will help us better understand how household characteristics affect an individual's use of Iowa lakes and attitudes towards changes in them. It will also help us to determine how representative our sample is of the state of Iowa. All of your answers are strictly confidential. The information will only be used to report comparisons among groups of people. We will never identify individuals or households with their responses. Please be as complete in your answers as possible. Thank you.

5. What is your age?

☐ Under 18 ☐26-34 ☐50-59 ☐76+

☐18-25 ☐35-49 ☐60-75

6. You are

☐Male ☐Female

7. What is the highest level of schooling that you have completed? (Please check only one)

☐Some high school or less ☐Some college or trade/vocational school ☐Advanced degree

☐High school graduate ☐College graduate

8. How many children live in your household (18 or under)? ___________

9. How many adults (including yourself) live in your household? ___________

10. What is your total household income before taxes for 2004?

☐Under $10,000	☐$25,000-$29,999	☐$50,000-$59,000	☐$125,000-$149,000
☐ $10,000-$14,900	☐ $30,000-$34,999	☐$60,000-$74,999	☐over $150,000
☐$15,000-$19,900	☐$35,000-$39,999	☐$75,000-$99,999	☐ $20,000-$24,999
☐$40,000-$49,999	☐$100,000-$124,000		

11. How many of the adults you reported in question 9 contribute to your reported household income? ______

Information on employment helps us better understand how time spent working affects an individual's or household's use of Iowa lakes since time spent at a recreational spot is time that cannot be spent at work. Again, all of your answers are strictly confidential. The information will only be used to report comparisons among groups of people. We will never identify individuals or households with their responses. Please be as complete in your answers as possible. Thank you.

12. What is your current employment status?

☐Full time ☐part time ☐self-employed ☐student ☐unemployed ☐retired

13. If you are currently employed, how many weeks per year do you work? ______

  13a. Of these weeks, how many are paid vacation? ______

14. If you are currently employed, how many hours per week do you typically work? ____

15. If you are currently employed, are the number of hours you work per week scheduled for you (for example, your employer requires a 40 hour work week, or schedules hours in advance), or are you free to choose when and how long you work?

☐Fixed/scheduled hours ☐Free to choose

16. If you had the opportunity to work fewer hours and receive less income, or work more hours and receive more income, would you change your weekly work hours, and if so by how much?

☐No, I would not change my weekly work hours

☐Yes, I would change to working fewer hours and receive less income

16a. How many less hours would you work per week, if you could work as many hours as you wanted? ________

☐Yes, I would change to working more hours and receive more income

16b. How many more hours would you work per week, if you could work as many hours as you wanted? ________

17. If you are currently employed, are you paid an hourly wage, or do you receive a salary?

☐I am paid an hourly wage

Wage per hour is approximately:

☐Under $5.00	☐$11.00-$12.99	☐$19.00-$20.99	☐$27.00-$28.99
☐$5.00-$6.99	☐$13.00-$14.99	☐$21.00-$22.99	☐over $29.00
☐$7.00-$8.99	☐$15.00-$16.99	☐$23.00-$24.99	
☐$9.00-$10.99	☐$17.00-$18.99	☐$25.00-$26.99	

☐I am paid a salary

Yearly salary is approximately:

☐Under $10,000	☐$25,000-$29,999	☐$50,000-$59,000	☐$125,000-$149,000
☐$10,000-$14,900	☐$30,000-$34,999	☐$60,000-$74,999	☐over $150,000
☐$15,000-$19,900	☐$35,000-$39,999	☐$75,000-$99,999	
☐$20,000-$24,999	☐$40,000-$49,999	☐$100,000-$124,000	

If there is a second adult in your household, please answer the same set of questions for that person.

18. What is the other adult's current employment status?

☐Full time ☐part time ☐self-employed ☐student

☐unemployed ☐retired

19. If the other adult is currently employed, how many weeks per year does he/she work? ____

19a. Of these weeks, how many are paid vacation? ____

20. If the other adult is currently employed, how many hours per week does he/she typically work? ____

21. If the other adult is currently employed, are the number of hours he or she works per week scheduled for him or her (for example, his or her employer requires a 40 hour work week, or schedules hours in advance), or is he or she free to choose when and how long he or she works?

☐Fixed/scheduled hours ☐Free to choose

22. If the other adult had the opportunity to work fewer hours and receive less income, or work more hours and receive more income, would he/she change his/her weekly work hours, and if so by how much?

☐No, the other adult would not change his/her weekly work hours

☐Yes, the other adult would change to working fewer hours and receive less income

21a. How many less hours would the other adult work per week, if he/she could work as many hours as he/she wanted? ______

☐Yes, the other adult would change to working more hours and receive more income

21b. How many more hours would he/she work per week, if he/she could work as many hours as he/she wanted? _______

23. If the other adult is currently employed, is he/she paid an hourly wage, or does he/she receive a salary?

☐The other adult is paid an hourly wage

Wage per hour is approximately:

☐Under \$5.00	☐\$11.00-\$12.99	☐\$19.00-\$20.99	☐\$27.00-\$28.99
☐\$5.00-\$6.99	☐\$13.00-\$14.99	☐\$21.00-\$22.99	☐over \$29.00
☐\$7.00-\$8.99	☐\$15.00-\$16.99	☐\$23.00-\$24.99	
☐\$9.00-\$10.99	☐\$17.00-\$18.99	☐\$25.00-\$26.99	

☐The other adult is paid a salary

Yearly salary is approximately:

☐Under \$10,000	☐\$25,000-\$29,999	☐\$50,000-\$59,000	☐\$125,000-\$149,000
☐\$10,000-\$14,900	☐\$30,000-\$34,999	☐\$60,000-\$74,999	☐over \$150,000
☐\$15,000-\$19,900	☐\$35,000-\$39,999	☐\$75,000-\$99,999	
☐\$20,000-\$24,999	☐\$40,000-\$49,999	☐\$100,000-\$124,000	

Thank you for your participation in this survey. After completion, surveys should be returned to:
Catherine Kling
568 Heady Hall, Mailstop <<Mailstop>>
Iowa State University
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Appendix B. Tables

Table 1. Summary Statistics of total number of trips and socio-demographic variables[a]

	Mean	Std. Dev	Minimum	Maximum
2004 (Observed) Day Trips	6.65	8.88	0	50
2005 Anticipated Day Trips	9.11	10.88	0	52
2005 CB Day Trips	9.26	11.35	0	52
Income	$58,608	$37,160	$7,500	$200,000
Male	0.65	0.47	0	1
Age	54.46	15.57	15	82
School	0.70	0.46	0	1
Household Size	2.45	1.23	1	10

[a] Sample Size = 782 individuals

Table 2. Average Number of Trip Changes[a]

	Proposed Water Quality		
Initial Water Quality	7	8	9
3	12.0		
	(1)		
4	14.4		
	(5)		
5	4.4		
	(25)		
6	6.5		
	(21)		
7	-3.7		
	(32)		
8		-2.0	
		(43)	
9			-1.8
			(4)

[a] Sample Size = 131 Lakes and parentheses are number of lakes

Table 3a. Parameter Estimates[a]

	Full Model	Model R_1	Model R_2
Price	-0.381 (<0.001)	-0.382 (<0.001)	-0.382 (<0.001)
Male	-9.137 (0.265)	-3.624 (0.264)	-3.673 (0.264)
Age	-0.534 (0.495)	-4.889 (0.451)	-4.831 (0.453)
Age2	0.451 (0.044)	0.929 (0.041)	0.921 (0.041)
School	2.852 (0.289)	5.276 (0.293)	5.271 (0.293)
Household Size	-0.082 (0.122)	0.957 (0.113)	0.941 (0.113)
Mean Estimate for Random Coefficient			
Log (Acre)	0.411 (0.005)	0.397 (0.005)	0.397 (0.005)
Ramp	13.189 (0.577)	13.059 (0.574)	13.001 (0.570)
Wake	0.307 (0.143)	0.542 (0.147)	0.514 (0.146)
Facility	7.245 (0.183)	6.672 (0.174)	6.655 (0.174)
State Park	1.645 (0.183)	1.543 (0.187)	1.448 (0.185)
α_i	-10.693 (0.034)	-10.071 (0.024)	-10.069 (0.024)
β_i	0.835 (0.027)		
Dispersion Estimate for Random Coefficient			
Log (Acre)	0.310 (0.004)	0.309 (0.004)	0.308 (0.004)
Ramp	17.321 (0.421)	16.907 (0.405)	16.793 (0.401)
Wake	11.439 (0.136)	11.385 (0.136)	11.398 (0.135)
Facility	12.481 (0.160)	11.258 (0.156)	11.278 (0.156)
State Park	9.903 (0.178)	10.248 (0.170)	10.262 (0.169)
α_i	2.531 (0.021)	2.599 (0.021)	2.599 (0.021)
β_i	0.202 (0.017)		

Parentheses are standard errors

Table 3b. Parameter Estimates

	Full Model	Model R_1	Model R_2
Z_s (δ)	0.151	0.163	0.167
	(0.008)	(0.005)	(0.005)
Z_s x D05 (δ^{05})	0.021		
	(0.009)		
Z_H (δ^{H})	-0.042	-0.048	
	(0.008)	(0.008)	
Likelihood Value	-99,008.3	-99,036.0	-99,040.2

Parentheses are standard errors

Table 4. Welfare Estimates

	$S = 04$	$S = 05$	$S = 05H$
Mean Predicted Trip	10.58	10.59	10.52
Mean Predicted Storm Lake Trip	0.12	0.12	0.14
After Improvement			
Predicted Trip	10.60	10.61	10.61
Predicted Trip to Storm Lake	0.16	0.16	0.15
Average CV			
Per Choice Occasion	\$0.02	\$0.02	\$0.02
Per Iowa Household	\$1.11	\$1.24	\$1.01
For all Iowa Household[a]	\$1.27	\$1.43	\$1.17

[a] Units are million dollars.

Chapter 5. Conclusions

The purpose of this dissertation was to improve on existing nonmarket valuation techniques by incorporating three sources of information rarely used in the literature. Two approaches to nonmarket valuation techniques were considered: one is dichotomous choice referendum (DCR) format in contingent valuation studies and the other is recreation demand model. The former is a stated preference approach and the latter is a revealed preference approach. Prior information on (and uncertainty about) the distribution of willingness to pay (WTP) was incorporated in chapter 2 when designing DCR surveys. Individual perceptions regarding on environmental quality were considered (in chapter 3) and contingent behavior data based on hypothetical environmental quality improvement was utilized (in chapter 4) in order to investigate the impact of hypothetical water quality improvement on the recreational demand pattern.

Chapter 2 illustrated the benefits and consequences of including prior information (and prior uncertainty) in the design process. In general, in the case of single stage design, the results indicate that optimal spread in the bids and the optimal number of bids points increase with the parameter uncertainties. In addition, cost of ignoring prior uncertainty about the parameters of WTP distribution appears to be substantial when using both the bid function approach and utility difference approach. Using the Cameron's (1988) bid function approach, rather than Hanemann's (1982) utility difference approach avoids problems associated with the moments of the ratio of two normal variables. The use of alternative approximations to the expected posterior WTP and alternative optimization technique are illustrated. The normal approximation to posterior variance results are similar to those obtained using Tierny-Kadane's method. In addition, curve-fitting method is shown to be a usable alternative to direct optimization routine. The curve-fitting method results illustrate a number of important points regarding the optimal bid design. First, the expected posterior variance (EPV) surfaces depends all of the attributes of the prior distribution; i.e., on prior distribution of the mean WTP and on the prior distribution for the dispersion of WTP in the population. Second, the impact of the uncertainty regarding the mean WTP appears to be larger than that of mean dispersion in the population WTP. Third, the EPV is relatively flat over a wide range of optimal width values. This suggests that while it is important to incorporate prior information in designing the optimal bid values, identifying precisely the optimal bids is not crucial. In the case of a sequential design, utilizing curve-fitting method is shown to be alternative way to implement the sequential design. I find that the number of sample size for the pre-test survey and the pre-test stage optimal bids increases with the parameter uncertainty and they are wider than those of the final survey stage. The optimal bids at the complete survey stage shrinks as the number of sample size at the pre-test stage increases.

The results of chapter 2 answer the frequent questions about the bid design for researchers conducting contingent valuation surveys. The frequent questions in the single stage design would be: 1) how many bid points should be placed; 2) how wide the spread of bid points should be; 3) how precisely the bids should be selected; in the sequential design case, 4) what is the optimal allocation of the sample between the pre-test and final survey? The answers which I find in chapter 2 are: 1) a two or three point design usually suffices even when there is substantial uncertainty about the distribution of WTP, 2) placing wider bids is recommended when the uncertainty about mean WTP is huge, 3) due to the flat curvature of EPV surface, precise selection of optimal bids is less important, 4) when the uncertainty about mean WTP is huge, one third up to two third of total samples is recommended for the pre-test survey and the optimal bids at the final stage depends on this allocation.

In chapter 3, I find the importance of incorporating individual perceptions regarding water quality. Individual's day trip data collected from Iowa Lakes Survey 2003 shows that perceptions regarding water quality appears to influence individual's site choice decision and their perceptions on water quality do not perfectly align with scientist and/or EPA's view to water quality. Correlation coefficients of mean water quality perceptions with physical water quality measures (including EPA's water quality index) indicates that this disparity depends on what activities an individual participates in at the lakes where he/she visits; i.e., water quality perception of each individual is linked with the physical water quality measures through individual's activities at the lakes where they visited. Regression analysis shows that physical water quality measures partly explain individual water quality perceptions. Repeated mixed logit model estimation results illustrate that individual site choice decision depends significantly on physical water quality, the water quality index and water quality perceptions. The estimation models with perceptions included outperform the models without such perception information. Both annual compensating variation and annual predicted trips ignoring individual's water quality perceptions are reduced substantially when compared to models including water quality perception information.

The benefits of combining contingent behavior (CB) data based on hypothetical environmental quality improvement and revealed preference (RP) data are illustrated using the data collected from the Iowa Lakes Survey 2004 in chapter 4. Three types of day trips are jointly modeled: actual trips in 2004, anticipated trips in 2005 under current conditions, and contingent behavior trips in 2005 under hypothetically improved water quality. The results from both simple summary statistics and a Repeated Mixed logit (RXL) model indicate that survey respondents anticipate increasing their trips in response to the hypothetically improved lakes, with a corresponding decrease in their trips to those lakes that are not improved. While the RXL model does indicate that survey participants were less responsive to the hypothetical water quality changes than they were to actual difference currently existing across lakes, the differences in response were small and the implications in terms of estimated welfare changes was small.