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Valuing environmental amenities with nonparametric and semiparametric methods

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Valuing environmental amenities with nonparametric and semiparametric methods

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CHAPTER I

INTRODUCTION

The dissertation consists of three essays. Each essay is presented in its own chapter beginning with chapter II. While each chapter is written as a standalone document, the essays complement each other in subject matter, methodology and relevance to the econometrics and natural resource economics literature. In particular, the most fundamental problem investigated is how can we, as precisely as possible, value non-market goods without making parametric assumptions that may influence welfare estimates.

In an effort to do just that, I begin in Chapter II by exploring the available methodologies that researchers have used in the past. It is apparent that there has been concern regarding the bias of parametric estimators. In fact, significant effort has gone into devising semi-nonparametric estimators to avoid the pitfalls of parametric models. However, to this point there has been no direct comparison of standard parametric models to some of the more recent flexible semi-nonparametric models. Moreover, the semi-nonparametric estimators have not been established to be the best technique in a non-market valuations setting, although claims of that nature have been made. One contribution of chapter II is thus to rigorously compare the standard valuation models to the semi-nonparametric models.

In addition, the generalized maximum entropy estimator is introduced. This estimator has an appealing interpretation in information theory and is considered to be a non-parametric estimator. I adapt the generalized maximum entropy estimator to the valuation framework and compare the performance of this estimator (based on mean-squared error) against the parametric and semi-nonparametric estimators. The goal is to determine which estimators we should be using in applied settings.

The focus of chapter III is to estimate the value placed on wetlands in Iowa's prairie pothole region by Iowa households using the semi-nonparametric and nonparametric estimators developed in chapter II. The data to estimate these models comes from a survey sent to Iowa residents in the spring of 1998. The details of the data and the survey methodology are described in chapter III. The results indicate that typical Iowa households are willing to pay about $1.06 annually to preserve or restore wetlands. The results also provide an empirical framework to compare the semi-nonparametric and nonparametric methods.

Chapters II and III explore semi-nonparametric and nonparametric methods when using contingent valuation data. In chapter IV, I turn to potentially observed data on usage patterns of recreation (often called travel cost data) and consider nonparametric approaches to estimate value in this case. I start by appealing to the general axiom of revealed preference pioneered by Varian [56] and consider the welfare bounds he proposes. Unfortunately, the bounds on welfare measures with this information alone do not provide bounds that are tight enough to provide useful policy information in most settings. To improve upon these bounds, I consider possible contingent behavior that the applied researcher may have. Armed with this stated preference data, I use standard Hicksian welfare theory to develop tighter bounds on value. The exciting aspect of this methodology is that the bounds thus derived are guaranteed to be accurate so long as preferences are consistent with standard neoclassical utility theory. The remaining question is, are the bounds tight enough to meaningfully measure value for goods? To answer this question, a Monte Carlo experiment is undertaken that compares traditional parametric approaches to the non-parametric bounds generated by this theory. As this chapter demonstrates, the Monte Carlo results suggest that there are situations in which the nonparametric bounds will be quite informative. It is worth emphasizing again that, in all instances, due to the lack of restrictions on preferences, the nonparametric bounds are always true bounds. This chapter suggests that future research efforts designed to value environmental amenities should seriously consider the use of nonparametric bounds to avoid the potential pitfalls of the parametric estimators.

The three essays comprising this dissertation contribute to the knowledge of the economics valuation literature in several important ways. First, semi-nonparametric and nonparametric estimators are rigorously assessed in a Monte Carlo study to determine if a methodology exists that does not rely upon the accuracy of parametric statements. The generalized maximum entropy framework is adapted to the discrete choice contingent valuation method. In addition, we investigate semi-nonparametric models in order to evaluate their fitting ability in this discrete choice setting. The estimators are applied to an important policy setting; namely, the valuation of wetlands in Iowa's prairie pothole region. Finally, the nonparametric method of Varian is adapted and extended to provide meaningful lower and upper bounds on welfare measures.

CHAPTER II

ROBUST ESTIMATORS OF WILLINGNESS TO PAY IN THE DICHOTOMOUS CHOICE CONTINGENT VALUATION FRAMEWORK

Introduction

Welfare analysis in the environmental arena is often complicated by absence of observable market transactions (i.e., revealed preferences) from which to infer the value placed in an environmental good or service. To fill this void, many researchers have turned to the stated preference methods of Contingent Valuation (CV). Dichotomous choice CV, in particular, has come to dominate much of this literature. Within this framework, survey respondents are presented with a hypothetical change in environmental quality and, in the case of a quality improvement, a proposed cost of acquiring the change. The individual's willingness to incur the proposed costs reveals information about the value placed in the environmental improvements. Unfortunately, the standard procedures for extracting the implied willingness-to-pay (WTP) of an individual, as well as the distribution of WTP in a target population, rely heavily upon parametric assumptions regarding the nature of consumer preferences. For example, Cameron's [8] bid function approach begins by segmenting the individual's WTP into two components: (1) a nonstochastic bid function that is assumed to depend upon observed characteristics of the individual and the environmental attributes being valued and (2) a stochastic component or residual used to capture variations in preferences. Typically, researchers then make parametric assumptions regarding both the functional form of the WTP and the distribution of the error term, estimating the model via maximum likelihood techniques. Theory, however, provides us with little guidance regarding the appropriate parametric specifications to use and the resulting WTP estimates can be quite sensitive to the selections made.[1]

The possible bias of parametric estimators has received considerable attention in the general discrete choice literature (e.g., Manski [42], Cosslett [14], Stoker [55], and Matzkin [44]), with studies appearing directly in the CV literature only more recently (e.g., Kriström [39], Chen and Randall [11], and Creel and Loomis [17]). Yet, while a variety of nonparametric and semi-parametric estimators have been proposed, only limited information exists on the gains (or losses) of these estimators relative to the standard parametric procedures, or of the factors that are likely to influence these gains.[2] The purpose of this paper is to partially fill this gap. We contrast the performance of several parametric and nonparametric estimators that have been proposed in the literature

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[1] It should be noted that valuation efforts based upon revealed preferences (e.g., recreation demand models) are also not immune to the problems of model specification. See, for example, Creel [15], Kling [37], Herriges and Kling [29], and Ziemer et al. [62].

[2] Three notable exceptions are Manksi and Thompson [43]; Horowitz [30]; and Huang, Nychka and Smith [32]. The current paper differs from the first two studies in that [43] and [30] investigate the operational characteristics of the maximum score estimator, which has received little attention in the valuation literature because its implementation can be difficult. In contrast, both of the semi-nonparametric estimators considered in this paper can be implemented using readily available optimization routines. The third study, [32], focuses on the relative performance of the nonparametric cubic smoothing spline, which does not allow for the conditioning of willingness-to-pay on individual characteristics, such as age or income. Both of the semi-nonparametric methods investigated here allow for conditioning variables. Furthermore, Huang, Nychka and Smith start with the specification of an individual's indirect utility function, as in Hanemann [27], whereas we begin by identifying the bid function, as in Cameron [8]. A comparison of results is provided in the Monte Carlo Section below.

using a Monte Carlo framework, examining the sensitivity of the resulting WTP estimates to the underlying distribution of preferences and the estimation procedure employed. In process, we provide an adaptation of the Generalized Maximum Entropy (GME) estimator introduced by Golan, Judge and Perloff [25] to the contingent valuation problem.

The remainder of the paper is divided into six sections. Section II provides a brief overview of the dichotomous choice contingent valuation method and sets up much of the paper's notation. We then describe in Section III the four estimators to be contrasted in our Monte Carlo analysis. These include the parametric probit and log-probit models used extensively in the CV literature, Chen and Randall's [11] semi-nonparametric (SNP) estimator, and an adaptation of the GME estimator of Golan, Judge, and Perloff [25]. The structure of the Monte Carlo exercise is detailed in Section IV, with the results presented in Section V. An application of all four estimators is then presented in Section VI using the same data on water quality valuation employed by Chen and Randall [11]. The final Section provides the conclusions from our analysis.

Dichotomous Choice Contingent Valuation

The contingent valuation method relies upon survey questionnaires to elicit information about an individual's evaluation of a nonmarket good or service. While a variety of survey formats have been proposed, the referendum or dichotomous choice format currently dominates the literature. In this setting, survey respondents are presented with hypothetical changes to both an environmental amenity and their level of income. The individual's willingness to accept the income change reveals information about the compensating variation that they associate with the proposed environmental change. This information can in turn be used to conduct welfare analysis.

In order to fix ideas, consider a proposed environmental improvement. Let[3]

$$WTP_i = W(X_i, \varepsilon_i; \beta) \tag{2.1}$$

denote the i^{th} individual's underlying willingness-to-pay for the environmental improvement, where X_i is a vector of socio-demographic characteristics and β is a vector of unknown coefficients. The disturbance term ε_i is assumed to capture variations in preferences within the population including unobserved individual characteristics. Let B_i denote the corresponding income reduction, or bid, posed in the CV question. One of the advantages of the dichotomous choice format touted in the literature is that it parallels the type of decisions typically made by consumers in the marketplace; i.e., accepting or rejecting a good or service at a fixed price (B_i). The key disadvantage of the format is that the survey response reveals only limited information about the consumer's underlying WTP, bounding above or below the proposed bid. Thus, rather than observing the consumer's WTP, the analyst observes only the latent variable no_i, where

$$no_i = \begin{cases} 1 & W(X_i, \varepsilon_i; \beta) < B_i \\ 0 & W(X_i, \varepsilon_i; \beta) \geq B_i . \end{cases} \tag{2.2}$$

Discrete choice econometric methods are then brought to bear on the problem in order to characterize the distribution of WTP in the population, rather than the WTP of a given

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[3] While we will be employing Cameron's [8] bid function approach to analyzing dichotomous choice CV question, parallel results can be obtain when starting with a specification of the individual's indirect utility function, as in Hanemann [27].

individual. In particular, it is common practice to assume that the ε_i enters the bid function W in an additive fashion, so that

$$W(X_i, \varepsilon_i; \beta) = w(X_i; \beta) + \varepsilon_i, \tag{2.3}$$

where $w(X_i;\beta)$ denotes the nonstochastic portion of WTP. The analyst then postulates a specific form for the cumulative distribution of ε_i, $\Lambda(\varepsilon_i)$, so that:

$$\begin{aligned} \Pr(no_i = 1) &= \Pr[W(X_i, \varepsilon_i; \beta) < B_i] \\ &= \Pr[\varepsilon_i < B_i - w(X_i; \beta_i)] \\ &= \Lambda[B_i - w(X_i; \beta)]. \end{aligned} \tag{2.4}$$

The resulting log-likelihood function is given by

$$L = \sum_{i=1}^{n} no_i \ln\{\Lambda[B_i - w(X_i;\beta)]\} + \sum_{i=1}^{n} (1 - no_i) \ln\{1 - \Lambda[B_i - w(X_i;\beta)]\}. \tag{2.5}$$

Maximum likelihood techniques can then applied to estimate the parameters of the model. The problem with the standard parametric approach is that it is not clear what functional forms should be used in specifying either $w(X_i;\beta)$ or $\Lambda(\varepsilon_i)$.

Alternative Estimators

A variety of functional forms and estimators have been proposed in the literature for estimating the distribution of WTP from dichotomous choice CV surveys. In this section, we review two parametric and two semi-nonparametric approaches.

Parametric Estimators

Among the most common parametric model employed in the CV literature is the linear probit model. This specification assumes that[4]

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[4] The linear logit model is similarly obtained by specifying Λ to be an extreme value distribution. In this case, we would simply replace Φ in the likelihood with the logistic cdf.

$$W(X_i, \varepsilon_{Ni}; \beta_N) = \beta'_N X_i + \varepsilon_{Ni} \tag{2.6}$$

where $\varepsilon_{Ni} \sim i.i.d.N(0, \sigma_N^2)$ and $w(X_i;\beta) \equiv \beta'_N X_i$. Thus, the probability of a "no" response is:

$$\begin{aligned}\Pr(no_i = 1) &= \Lambda[B_i - \beta'_N X_i] \\ &= \Phi\left[\frac{B_i - \beta'_N X_i}{\sigma_N}\right] \\ &= \Phi[\delta'_N Z_i],\end{aligned} \tag{2.7}$$

where $\Phi(\cdot)$ denotes the standard normal cdf; $\delta_N = (\delta_{N0}, \delta_{N1}, \ldots, \delta_{Nk})' \equiv (\sigma_N^{-1}, -\sigma_N^{-1}\beta'_N)'$; and $Z_i = (B_i, X'_i)'$ The corresponding log-likelihood is given by:

$$\mathsf{L}_N = \sum_{i=1}^{n} no_i \ln[\Phi(\delta'_N Z_i)] + \sum_{i=1}^{n}(1 - no_i)\ln[1 - \Phi(\delta'_N Z_i)]. \tag{2.8}$$

An important attribute of the linear probit model in the CV setting is that, unlike most probit applications, the dispersion of WTP in the population (captured by σ_N) can be separately identified (Cameron [8]). This is accomplished by varying the bids (i.e., the B_i's) across observations. In particular, if $\hat{\delta}_{Nk}$ denotes the k^{th} element of the maximum likelihood estimate of δ_N, then $\hat{\sigma}_N = \hat{\delta}_{N0}^{-1}$. The original parameter vector can likewise be recovered using $\hat{\beta}_{Nk} = \hat{\delta}_{Nk} / \hat{\delta}_{N0}$. Finally, we note that in the probit framework both the conditional mean WTP ($\mu_X \equiv E(WTP|X)$) and the conditional median WTP ($m_X \equiv Median(WTP|X)$) are given by

$$\mu_X = m_X = \beta'_N X_i. \tag{2.9}$$

The conditional dispersion of WTP in the population is given by

$$d_X \equiv StdDev(WTP|X) = \sigma_N \tag{2.10}$$

Another commonly employed parametric estimator is the linear log-probit model. Here, it is assumed that the bid function takes the form

$$W(X_i, \varepsilon_{Li}; \beta_L) = \exp(\beta_L' X_i + \varepsilon_{Li}) \tag{2.11}$$

where $\varepsilon_{Li} \sim i.i.d.N(0, \sigma_L^2)$, or equivalently

$$\ln[W(X_i, \varepsilon_{Li}; \beta_L)] = \beta_L' X_i + \varepsilon_{Li}. \tag{2.12}$$

The corresponding likelihood is

$$\mathsf{L}_L = \sum_{i=1}^{n} no_i \ln[\Phi(\delta_L' Z_i)] + \sum_{i=1}^{n} (1 - no_i) \ln[1 - \Phi(\delta_L' Z_i)], \tag{2.13}$$

where $Z_i = [\ln(B_i), X_i']'$. Again, $\hat{\sigma}_L = \hat{\delta}_{L0}^{-1}$ and $\hat{\beta}_{Lk} = \hat{\delta}_{Lk} / \hat{\delta}_{L0}$. In the case of the lognormal specification, the conditional mean WTP is given by:

$$\mu_X = E[\exp(\beta_L' X_i + \varepsilon_{Li})] = \exp\left(\beta_L' X_i + \frac{\sigma_L^2}{2}\right). \tag{2.14}$$

whereas the conditional median WTP corresponds to $m_X = \exp(\beta_L' X_i)$. Finally, the conditional dispersion of WTP in the population is given by:

$$d_X = \exp(\beta_L' X) \sqrt{\exp(2\sigma_L^2) - \exp(\sigma_L^2)} \tag{2.15}$$

A Semi-Nonparametric Estimator

A number of authors have recently proposed relaxing the restrictions of the standard parametric models, relying instead on flexible approximations to the unknown distribution preferences. In particular, Chen and Randall [11] have proposed a semi-nonparametric (SNP) estimator for WTP.[5] The authors begin by assuming that the bid function has the structure:

$$W(X_i, \varepsilon_{Si}; \beta_S) = \exp[w(X_i; \beta_S)]\varepsilon_{Si} \equiv G(X_i; \beta_S)\varepsilon_{Si} \tag{2.16}$$

where $G(X_i; \beta_S)$ is an unknown function characterizing the nonstochastic portion of willingness-to-pay and ε_{Si} is an unknown disturbance term with an unknown distribution. Chen and Randall [11] use the exponential form for $G(X_i; \beta_S)$, together with the restriction that ε_{Si} has support only for nonnegative values, to ensure that willingness-to-pay is nonnegative, i.e. $WTP_i \geq 0$. This structure for the bid function then implies that:

$$\begin{aligned} \Pr[no_i = 1] &= \Pr[G(X_i; \beta_S)\varepsilon_{Si} < B_i] \\ &= \Pr\left[\varepsilon_i < \frac{B_i}{G(X_i; \beta_S)}\right] \\ &= \Lambda\left[\frac{B_i}{G(X_i; \beta_S)}\right] \\ &= \Lambda[u_i] \end{aligned} \tag{2.17}$$

where

$$u_i \equiv \frac{B_i}{G(X_i; \beta_S)}. \tag{2.18}$$

In order to reduce the reliance on a specific model parameterization, the authors use flexible approximations to the two unknown functions of the model: $G(\cdot)$ and $\Lambda(\cdot)$.

Gallant's [21] Fourier Flexible Form (FFF) is used to model the nonstochastic portion of the individual's bid function. That is, $w(X; \beta_S)$ is approximated by:[6]

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[5] Creel and Loomis [17] develop a similar estimator, beginning from a specification of the consumer's indirect utility function (as in Hanemann [27]), rather that starting with bid function.

$$\begin{aligned} w_{JA}(X_i;\delta_{JA}) &= \mu_0 + b'x_i + \tfrac{1}{2}x_i'Cx_i + \sum_{\alpha=1}^{A}\left(\mu_{0\alpha} + 2\sum_{j=1}^{J}\left\{\mu_{j\alpha}\cos(j\kappa_\alpha' x_i) - v_{j\alpha}\sin(j\kappa_\alpha' x_i)\right\}\right) \\ &= \delta_{JA}'\phi_{JA}(X_i) \end{aligned} \quad (2.19)$$

where x_i is the $K \times 1$ vector consisting of the elements of X_t *excluding* any constant term,

$$C = -\sum_{\alpha=1}^{A}\mu_{0\alpha}\kappa_\alpha\kappa_\alpha' , \quad (2.20)$$

$$\delta_{JA} = (\mu_0, \mu_{01}, \ldots, \mu_{0A}, b_1, \ldots, b_K, \mu_{11}, \ldots, \mu_{JA}, v_{11}, \ldots, v_{JA}), \quad (2.21)$$

denotes the parameters of the Fourier approximation, and $\phi_{JA}(X_t)$ denotes the vector of corresponding transformations of X_i, including linear and quadratic terms in x_i and the $\cos(j\kappa_\alpha' x_i)$ and $\sin(j\kappa_\alpha' x_i)$ transformations. The κ_α's are $K \times 1$ multiple index vectors used to construct all possible elementary combinations of the explanatory variables (i.e., the x_i) and their multiples. For example, as Chen and Randall [11] note, the typical κ_α's when $K = 3$ would include (1,0,0), (0,1,0), (0,0,1), (1,1,0), (1,0,1), (0,1,1), (1,-1,0), (1,0,-1), etc. The number of these multiple indices (*A*) and the number of multiples (*J*) determines the degree of truncation being used in the Fourier series to approximate $w(X;\beta_S)$. Both *A* and *J*, along with the specific κ_α's to be used, must be selected by the analyst. Some guidance regarding these choices is provided in the literature. For example, Chen and Randall [11] indicate that, in practice, analysts rely on only a subset of the

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[6] The notation used in this section is similar to Chen and Randall [11]. Additional details regarding the Fourier form and its characteristics can be found in Chen and Randall [11], Creel [16], and Gallant [21,22].

possible multiple indices, excluding those indices that do not "...provide further statistical improvements" [11, p. 331]. As a guide to specific choice of specific indices, Gallant [21] notes that the length of the κ_α's is typically no more than 2 or 3.[7] This would rule out, for example, the multiple index $\kappa_\alpha = (1,-2,1)'$. Finally, Creel [16] observes that, in practice, J is usually only 1 or 2. In Chen and Randall's [11] original application, the authors chose $J=A=1$, with $\kappa_1 = (1,0,0)$. They note that adding multi-indices or increasing J did not significantly increase the likelihood function.

Given the Fourier form approximation to $w(X_i;\beta_S)$, the nonstochastic function $G(X_i;\beta_S)$ in equation (2.16) is then approximated by:

$$G_{JA}(X_i;\delta_{JA}) = \exp[w_{JA}(X_i;\delta_{JA})]. \tag{2.22}$$

The second unknown function in modeling CV bid responses is the distribution $\Lambda(\cdot)$. Here the authors rely upon a variant of Gallant and Nychka's [23] semi-nonparametric estimation procedure. The heart of this procedure is the specification of a monotonic transformation of the error term ε_{Si} such that

$$\Gamma[h(u_i)] = \Lambda[u_i]. \tag{2.23}$$

where $\Gamma(\cdot)$ is a known distribution (e.g. the exponential distribution). While the appropriate monotonic transformation function is unknown, Chen and Randall approximate $h(\cdot)$ using the polynomial series:

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[7] The length of a κ_α vector in the case of elementary multiple indices corresponds to the sum of the absolute value of its components.

$$h_r(u) = \gamma_0 + \int_0^u (\gamma_1 + \gamma_2 \eta + \cdots \gamma_r \eta^{r-1})^2 d\eta. \tag{2.24}$$

This structure ensures that the transformation is indeed monotonic.

Substituting the approximations to $G(X_i;\beta_S)$ and $\Lambda(\cdot)$, the log-likelihood function corresponding to the model in equation (2.5) becomes:

$$\mathrm{L}_S = \sum_{i=1}^{n} no_i \ln\left\{\Gamma\left[h_r\left(\frac{B_i}{G_{JA}(X_i;\delta_{JA})}\right)\right]\right\} + \sum_{i=1}^{n}(1-no_i)\ln\left\{1-\Gamma\left[h_r\left(\frac{B_i}{G_{JA}(X_i;\delta_{JA})}\right)\right]\right\}. \tag{2.25}$$

One of the advantages of the Chen and Randall [11] estimator is that is can be implemented using standard maximum likelihood routines. Furthermore, the authors prove that if the truncation points used in the two approximations (*JA* and *r*) are increased as the sample size *n* increases, the maximum likelihood estimates of both $\hat{w}_{JA}(X_i;\delta_{JA})$ and $\hat{\Lambda}_r(u_i) \equiv \Gamma\left[\hat{h}_r(u_i)\right]$ will converge uniformly and almost surely to the underlying functions $w(X_i;\beta_S)$ and $\Lambda(u_i)$.

The conditional mean WTP is obtained by taking the expected value of equation (2.16), yielding

$$\mu_X = G_{JA}\left(X_i;\hat{\delta}_{JA}\right)\int_0^\infty \tau \hat{h}_r'(\tau) e^{-\hat{h}_r(\tau)} d\tau. \tag{2.26}$$

This calculation is performed using numerical integration. The semi-nonparametric model's estimated of the conditional median WTP solves

$$\hat{h}_r\left[\frac{m_X}{G_{JA}\left(X;\hat{\delta}_{JA}\right)}\right] = \ln(2). \tag{2.27}$$

Due to the nonlinear nature of the problem, a closed form solution for m_X is not readily available. Hence, we solve for median WTP via numerical bisection. In general, the estimated median WTP will not be equivalent to mean WTP. Finally, the conditional dispersion of WTP in the population is given by

$$d_X = \sqrt{G_{JA}\left(X_i;\hat{\delta}_{JA}\right)\int_0^{\infty}\tau^2\hat{h}_r'(\tau)e^{-\hat{h}_r(\tau)}d\tau - \mu_X^2} \qquad (2.28)$$

A Generalized Maximum Entropy Estimator

Another alternative to standard parametric estimators can be constructed using maximum entropy econometrics.[8] The entropy framework has its roots in information theory and the physical sciences, with Boltzman suggesting as early as the 1870's that *entropy* be used to measure the information content of a distribution. Formally, the entropy index for a discrete distribution is given by:

$$H(p) = -\sum_{j=1}^{m} p_j \ln(p_j)\,. \qquad (2.29)$$

where p_j denotes the probability that the j^{th} event occurs and m denotes the total number of possible events. Shannon [53] employed entropy as a measure of uncertainty in communications signals. It was Jaynes [33,34], however, that pioneered the use of the entropy metric as the basis for estimation and inference, particularly for problems that are ill defined or intractable using standard statistical procedures. His *maximum entropy principle* argued for selection of the choice probabilities so as to minimize the information structure imposed on the distribution (i.e., maximize the distribution's

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[8] The generalized maximum entropy approach is a relatively recent addition to the econometrics literature. For the sake of brevity, however, this section provides only a brief review of maximum entropy paradigm. A more comprehensive treatment can be found in Golan, Judge and Miller's [24] monograph on entropy econometrics.

entropy) and yet remained consistent with the observed data. Golan, Judge and Miller [24] later generalized the maximum entropy approach to allow for noise in the data, with Golan, Judge, and Perloff [25] adapting the approach to the analysis multinomial response data. It is the Generalized Maximum Entropy (or GME) estimator of Golan, Judge, and Perloff [25] that we adapt to the dichotomous choice CV problem.

In the bivariate discrete choice framework, where the analyst observes either $no_i = 1$ or $no_i = 0$, the maximum entropy (ME) estimator is obtained by solving the problem:

$$\underset{p}{Max}\, H(p) = \sum_{i=1}^{N}\left[p_i \ln(p_i) + (1-p_i)\ln(1-p_i)\right] \tag{2.30}$$

subject to the K moment conditions:

$$Z'no = Z'p \tag{2.31}$$

where no is the $N \times 1$ vector whose i^{th} element is no_i, $p_i \equiv \Pr[no_i = 1] = \Lambda(\delta_G' Z_i)$, and Z is the $N \times K$ matrix of covariates assumed to influence the choice probabilities. As several authors note (e.g., [24], [25], and [54]), an interesting feature of the ME estimator is that the resulting first order conditions are *identical* to those obtained when $\Lambda(\cdot)$ is assumed to be the logistic cdf and maximum likelihood procedures are used. Thus, the fitted choice probabilities obtain from the commonly used linear logit model are the same as those obtained using the ME estimator.

The problem with the ME estimator is that it assumes that the moment conditions in equation (2.31) are non-stochastic. The generalized maximum entropy estimator relaxes this assumption, allowing for an unobserved source of noise and replacing equation (2.31) with

$$Z'no = Z'p + Z'e = Z'(p+e) \tag{2.32}$$

where e is the $N \times 1$ unobserved disturbance vector. Following Golan, Judge and Perloff [25], the random disturbance is assumed to have a finite number of support points ($v_t, t = 1,\dots,T$) in the interval [-1,1]. Letting $q_{it} = \Pr(e_i = v_t)$, the noise term can be written in matrix notation as

$$e = Vq = \begin{bmatrix} v' & & & \\ & v' & & \\ & & \ddots & \\ & & & v' \end{bmatrix} \begin{bmatrix} (q_{11},\dots,q_{1M})' \\ (q_{21},\dots,q_{2M})' \\ \vdots \\ (q_{n1},\dots,q_{nM})' \end{bmatrix}. \tag{2.33}$$

The generalized maximum entropy problem becomes one of choosing both the choice probabilities (i.e., the p_i's) and noise probabilities (i.e., the q_{it}'s) optimally. Formally, this involves solving:

$$\underset{p,q}{Max}\, H(p,q) = -\sum_{i=1}^{n}(p_i \ln(p_i) + (1-p_i)\ln(1-p_i)) - \sum_{i=1}^{n}\sum_{t=1}^{T}[q_{it}\ln(q_{it})], \tag{2.34}$$

subject to

$$Z'no_i = Z'p + Z'Vq \tag{2.35}$$

and

$$\sum_{t=1}^{T} q_{it} = 1 \quad \forall i = 1,\dots,N. \tag{2.36}$$

The above problem involves solving for n unknown probabilities (i.e., the p_i's) and nT error weights (i.e., the q_{it}'s) using the $K+1$ data constraints in equation (2.35) and the N adding-up constraints in equation (2.36). While the above problem can be solved using standard numerical procedures, Golan, Judge and Miller [24] argue that it is typically easier to solve the equivalent dual problem

$$\underset{\lambda}{Max}\, C = \sum_{i=1}^{n} no_i \lambda' Z_i + \sum_{i=1}^{n} \ln(\Omega_i) + \sum_{i=1}^{n} \ln(\Psi_i) - n\ln(T), \tag{2.37}$$

where

$$\Omega_i \equiv 1 + e^{-\lambda' Z_i} \tag{2.38}$$

$$\Psi_i \equiv \sum_{t=1}^{T} e^{-v_t \lambda' Z_i} \tag{2.39}$$

and λ is a $(K+1)\times 1$ vector of parameters. The resulting choice probabilities become

$$p_i = \frac{e^{-\lambda' Z_i}}{1+e^{-\lambda' Z_i}} \tag{2.40}$$

Equation (2.40) makes clear the similarity between the GME estimator and the standard linear logit model. In general, the GME estimator is a shrinkage estimator. The structure of the error support (v) will imply how "close" the GME estimator is to the logit estimator asymptotically. As the error support vector widens in coverage of the interval [-1,1], the GME estimates collapse to the origin. As the error support vector narrows around zero, the estimates converge to the ML logit estimates. Allowing v to be wide imposes the most shrinkage on the estimates, which includes the benefit of smaller variance properties. Setting v to be narrow permits the most freedom for the estimates to deviate from zero, however, the cost is less flexibility in the stochastic characterization of the model.

Golan, Judge and Perloff [25] take v to be symmetric about zero with endpoints $\left[-N^{-1/2}, N^{-1/2}\right]$. As the sample size gets large, the GME estimator converges to the ML logit estimator. Interestingly, altering the error support vector to be symmetric about zero with endpoints $\left[-N^{-1/2}, N^{-1/2}\right]$ implies the GME estimator outperforms the probit model even when the true model is probit (this is shown for a standard normal error distribution by Golan, Judge and Miller [24]). When the true error distribution is not standard and we are forced to estimate the variance, the dominance of the GME estimator wanes. In this case, the GME estimator only marginally outperforms the probit model.

Up until this point, we have reviewed the GME estimator for the bivariate discrete choice problem in general terms. Adapting it to the dichotomous choice CV problem is straightforward. We have that

$$\begin{aligned} p_i &= \Pr[no_i = 1] \\ &= \Lambda(\delta'_G Z). \end{aligned} \tag{2.41}$$

A comparison to equation (2.7), suggests that the analogue to the linear probit model emerges if we set $Z_i = [B_i, -X'_i]'$ and $\delta_G = (\xi^{-1}, -\xi^{-1}\beta'_G)'$. Using the fact that the choice probabilities in equation (2.40) have a logistic form, both the conditional mean and median WTP are given by

$$\mu_X = m_X = \beta'_G X_i, \tag{2.42}$$

with the conditional dispersion of WTP in the targeted population given by

$$d_X = \frac{\pi\xi}{\sqrt{3}}. \tag{2.43}$$

Design of the Monte Carlo Study

The estimators detailed in the previous section provide alternative approaches to analyzing consumer responses to dichotomous choice CV questionnaires. In this section, we describe a Monte Carlo experiment designed to investigate and contrast the performance of these approaches in estimating the characteristics of WTP in a target population, including the mean and median WTP and its dispersion in the population.

The Monte Carlo experiment centers around the construction of an underlying "true" distribution of WTP. We consider four basic distributions: normal, lognormal, uniform and a bimodal distribution. The first two distributions provide settings in which the two parametric approaches (probit and log-probit respectively) provide the correct specifications. The uniform and bimodal distributions were chosen to test more extreme departures from the standard parametric assumptions. The bimodal distribution is constructed as a combination of two standard normal populations, displace from each other by a fixed constant in terms of WTP. This might arise in practice if a significant discrete characteristic of the population (e.g., gender) were excluded from the specification of the nonstochastic portion of the bid function (i.e., $w(X_i;\beta)$).

Table 2.1 summarizes the four basic distributions considered. The second column provides the equations used to generate observations on WTP_i for each of the "true" distributions. A simple linear form was used for the nonstochastic portion of the bid function. In particular, it was assumed that

$$\begin{aligned} w(X_i;\beta) &= \beta' X_i \\ &= \beta_0 + \beta_1 X_i \end{aligned} \qquad (2.44)$$

where $\beta_1 = 2$ and X_i is a single covariate distributed uniformly on the interval [-30,30]. β_0 was selected for each distribution to insure that the mean WTP was equal to 100. The stochastic component for each of the true distributions was then generated according to the specification in the last column of Table 2.1. The parameter σ_W^2 measures the dispersion of WTP_i for the typical consumer (i.e., $X_i = 0$) in the population. Formally,

$$\sigma_W^2 = Var(WTP_i | X_i = 0) \qquad (2.45)$$

Four dispersion levels were investigated in the Monte Carlo analysis, with σ_W = 5, 10, 25 and 50. Finally, given observations on WTP_i, simulated survey responses to bid values in a dichotomous choice CV questionnaire (i.e., no_i's) were constructed. In all of the Monte Carlo experiments, we employed a bid design in which the sample was evenly divided into five group, facing bids (i.e., B_i's) of 25, 50, 75, 125 or 175 respectively.

For each of the sixteen possible true distributions (i.e., four distribution types and four dispersion levels), $T=500$ samples of size $N=300$ were drawn. The four estimators described in the previous section were then applied each sample to estimate the mean, median, and dispersion of WTP in the population. The probit, log-probit, and GME estimators assumed the simple linear form in equation (2.3) for the bid function. For the Chen and Randall [11] semi-nonparametric estimator, we used the Fourier form:

$$w_1(X_i;\delta) = \delta_0 + \delta_1 \cos(\tilde{X}_i) + \delta_2 \sin(\tilde{X}_i) \tag{2.46}$$

where $\tilde{X}_i \equiv 2\pi(X_i + 30)/60$, transforming the covariate X_i to lie in the interval $[0,2\pi]$.

Monte Carlo Results

The primary purpose of CV analysis is typically to characterize the distribution of *WTP* for a specific environmental amenity. Thus, we do not report individual parameters, restricting our attention instead to the performance of the models in terms of estimating the conditional mean and median WTP of the typical observation (i.e., μ_0 and m_0, respectively) and the dispersion of WTP in the sample population (i.e., d_0). Starting with the conditional mean, Table 2.2 provides a summary of the root mean squared error (RMSE) in estimating μ_0 using the four estimators for each of the sixteen assumed *true* distributions. Bold numbers are used for the lowest RMSE within each distribution.

Table 2.1: Monte Carlo Distributions

Distribution	WTP_i	Error Generation
Normal	$WTP_i = \beta_{N0} + \beta_1 X_i + \varepsilon_{Ni}$ $\beta_{N0} = 100$	$\varepsilon_{Ni} \sim N(0, \sigma_W^2)$
Log-normal	$WTP_i = \exp(\beta_{L0} + \beta_1 X_i + \varepsilon_{Li})$ $\beta_{L0} = \ln(100) - \frac{1}{2}\ln\left[1 + (\sigma_W/100)^2\right]$	$\varepsilon_{Li} \sim N\left(0, \ln\left[1 + (\sigma_W/100)^2\right]\right)$
Bimodal	$WTP_i = \beta_{B0} + \beta_1 X_i + \varepsilon_{1i} + \tau_i \Delta$ $\beta_{B0} = 100$ $\tau_i = \begin{cases} 1 & \rho_i > 0.5 \\ -1 & \rho_i \leq 0.5 \end{cases}$	$\varepsilon_{1i} \sim N(0,1)$ $\Delta = \sqrt{\sigma_W^2 - 1}$ $\rho_i \sim Uniform[0,1]$
Uniform	$WTP_i = \beta_{U0} + \beta_1 X_i + \varepsilon_{Ui}$ $\beta_{U0} = 100$	$d_i \sim Uniform[-a, a]$ $a = \frac{1}{2}\sigma_W \sqrt{12}$

A number of patterns emerge from Table 2.2. First, as one might expect, the probit model has the lowest RMSE when the underlying distribution is normal and the log-probit model typically performs best when the underlying distribution is lognormal. What is perhaps more surprising is the generally strong performance of probit for all of the assumed distributions. The probit estimator yields the lowest RMSE for 12 of the 16 specifications. Furthermore, even when probit is outperformed by one of the other estimators, the difference is not substantial. The largest difference emerges when the true distribution is lognormal and $\sigma_{w} = 25$, with the probit model having a RMSE only 16 percentage points higher than the log-probit model. The GME estimator yields generally similar RMSE's, outperforming probit in one case.[9] The same cannot be said for the log-Probit's model. The log-probit model's performance is often substantially worse than that of the simple probit model, particularly when there is sizable dispersion in WTP. When $\sigma_{w} = 50$, the RMSE for the log-probit model is between 2.5 and 3 times the RMSE for probit. Finally, we note that the semi-nonparametric (SNP) estimator generally does well when the underlying true distribution is relatively smooth. However,when there is a high degree of curvature in the underlying density function (as there is with the bimodal

[9] This should not be too surprising, given the good fit of the probit model, the well known similarity between the linear probit and linear logit estimators, and the relationship between the GME and logit estimators asymptotically.

Table 2.2: RMSE in Estimating the Conditional Mean WTP (μ_0)

	a. Normal Distribution			
Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.5**	**2.0**	3.1	**4.6**
Log-Probit	3.7	5.0	8.4	13.4
SNP	3.3	3.1	5.3	13.8
GME	1.7	2.2	**3.0**	4.7

	b. Lognormal Distribution			
Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	3.2	3.4	5.0	**4.4**
Log-Probit	**1.3**	**2.1**	**4.3**	11.3
SNP	4.1	3.0	5.4	8.1
GME	4.2	4.1	4.6	4.5

	c. Bimodal Distribution			
Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.7**	**2.6**	**3.9**	**6.4**
Log-Probit	3.9	5.9	11.3	16.3
SNP	3.2	3.8	13.0	56.5
GME	2.0	2.7	7.6	6.5

	d. Uniform Distribution			
Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.4**	**2.1**	**3.2**	**5.2**
Log-Probit	3.6	4.4	8.3	15.0
SNP	3.3	2.9	5.5	18.4
GME	1.7	2.5	3.3	5.4

model when $\sigma_w = 50$), the quadratic approximation to $\Lambda(\cdot)$ appears to be insufficient, with a RMSE of nearly nine times that of the simple probit specification.[10]

Table 2.3 provides a parallel set of results when the focus in on characterizing the condition median WTP (i.e., m_0). The findings here basically mirror those in Table 2.2. Again, all of the estimators perform well when there is little variability in the underlying population. However, when level of dispersion is high, as is typically the case in actual CV work, the RMSE of the estimated m_0 varies substantially from estimator to estimator. While the performance of the simple probit model is not quite as strong as when we focus on the mean, it still yields the lowest RMSE in 11 of the 16 cases. Again, the gains are the greatest when there is considerable dispersion in the WTP within the targeted population.

Finally, policy makers are often concerned not only with the central tendencies of WTP, but also with its variability or dispersion within a targeted population. Table 2.4 reports on the ability of the four estimators to characterize the conditional dispersion of WTP (d_0). Surprisingly, the simple probit model excels in this arena as well. Again, in 12 of the 16 specifications, the probit model outperforms both log-probit and the two semi-nonparametric approaches, with a substantially higher RMSE (42% higher) only in the

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[10] This suggests the need for a higher order approximation may be necessary in the case to capture the form of the transformation function $h(\cdot)$. Alternatively, an alternative to the exponential kernal $\Gamma(\cdot)$ may improve the overall fit of the model. However, preliminary investigations along this line did not yield substantial improvements in the RMSE for the SNP estimator.

case of the lognormal distribution when $\sigma_w = 50$. The probit model substantially outperforms the other three approaches when the underlying distribution of preferences has a substantial dispersion and is either bimodal or uniform. The RSME of the probit specification is typically 30 to 40 percent of the RMSE obtained by either the log-probit or SNP estimators. While the GME estimator sometimes matches the performance of the probit model, particularly when the level of dispersion is high, the RMSE in estimating d_0 is substantial when the degree of dispersion is small.

The strong performance of the probit specification highlighted in Table 2.3 through 5 is consistent with earlier comparisons of parametric and nonparametric estimators. Both Horowitz [30] and Manski and Thompson [43] found that the logit model, similar in nature to probit, typically dominated the more flexible maximum score estimators. Similarly, Huang, Nychka, and Smith [32] found that conventional probit and logit models outperformed cubic smoothing splines. One explanation for the relatively poor performance of the semi-nonparametric estimators is that, by their nature, they rely more heavily upon the data to reveal the shape of the underlying WTP distribution, rather than assumed distributional structures. As Creel and Loomis [17] note, this suggests that they may require both a greater number and range of bid values in order to capture the shape of the underlying WTP distribution. While a full-scale investigation into bid design is beyond the scope of the current paper, Table 2.5 reports on a simple investigation into the performance of the SNP estimator given a range of bid designs, increasing in complexity from four bid levels to 79 bid levels. The five designs considered place an equal number of bids at various percentiles of the underlying true distribution, with each subsequent bid

Table 2.3: RMSE in Estimating the Conditional Median WTP (m_0)

	a. Normal Distribution			
Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.5**	**2.0**	3.1	**4.6**
Log-Probit	3.6	4.4	4.9	10.8
SNP	2.6	3.2	4.2	5.9
GME	1.7	2.2	**3.0**	4.7

	b. Lognormal Distribution			
Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	3.4	3.8	7.5	11.9
Log-Probit	**1.3**	2.0	**4.3**	11.8
SNP	1.6	**2.0**	5.1	**10.4**
GME	4.4	4.5	7.1	11.1

	c. Bimodal Distribution			
Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.7**	**2.6**	**3.9**	**6.4**
Log-Probit	3.7	4.8	4.8	47.7
SNP	2.7	3.9	21.8	17.0
GME	2.0	2.7	7.6	6.5

	d. Uniform Distribution			
Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.4**	**2.1**	**3.2**	**5.2**
Log-Probit	3.5	3.9	5.4	12.2
SNP	2.6	2.9	4.9	8.0
GME	1.7	2.5	3.3	5.4

Table 2.4: RMSE in Estimating the Conditional Dispersion of WTP (d_0)

a. Normal Distribution

Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.7**	**1.9**	**2.9**	**4.9**
Log-Probit	1.8	2.4	4.7	15.3
SNP	23.8	19.1	6.1	12.6
GME	13.5	10.1	4.4	6.9

b. Lognormal Distribution

Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	1.5	2.3	**3.3**	8.5
Log-Probit	**1.5**	**2.2**	3.4	7.8
SNP	23.6	19.2	5.9	8.4
GME	14.1	10.2	3.5	**6.0**

c. Bimodal Distribution

Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.9**	**4.1**	**10.2**	**27.2**
Log-Probit	2.5	5.6	16.2	67.1
SNP	23.9	19.5	43.3	67.9
GME	14.0	11.9	80.2	35.5

d. Uniform Distribution

Estimator	$\sigma_W = 5$	$\sigma_W = 10$	$\sigma_W = 25$	$\sigma_W = 50$
Probit	**1.7**	**1.8**	3.1	**6.0**
Log-Probit	1.7	2.2	**2.9**	18.7
SNP	23.8	19.2	6.0	19.5
GME	13.5	10.1	3.5	10.8

Table 2.5: Sensitivity of SNP Approach to Bid Design

Design		RMSE	
Number of Bids	Percentiles at which bids were evenly spaced	μ_0	d_0
4	20%,40%,60%,80%	60.2	190.0
9	10%,20%,...,90%	26.3	80.3
19	5%,10%,15%,...,95%	30.3	65.6
39	2.5%,5%,7.5%,...,97.5%	37.8	75.9
79	1.25%,2.5%,3.75%,...,98.75%	33.4	43.9

design essentially doubling the number of bids.[11] As expected, increasing the number and range of the bids does alter the performance of the SNP estimator. However, as in the parametric bid design literature (e.g. Kanninen [36]), the best design for estimating μ_0 differs from the best design for estimating d_0. Estimating the dispersion of WTP benefits substantially from a finer and wider range of bids, whereas estimates of the mean WTP are best with relatively few bid levels.

Empirical Application

A common criticism of Monte Carlo studies is that they lack a basis in the real world. Analysts must specify the underlying distributions and functions and choose which characteristics to vary in their experiment. While the hope is always that the choices made bound what one would find in practice, there is always the concern that

[11] For this example, we assumed that WTP was normally distributed, with a mean WTP of 250 and a dispersion level of $\sigma_w = 100$.

some critical dimension of the problem has been missed.[12] In order to provide additional insight, it is helpful to provide an empirical example. Here, we use the same data base as Chen and Randall [11] employed as an application. The data were obtained from a dichotomous choice CV study design to value improvements to environmental quality of Big Darby Creek in Ohio. The survey was conducted in 1989, yielding information on 274 Ohio residents visiting Battelle-Darby Creek Park. Table 2.6 provides a summary of the individual characteristics, while Table 2.7 provides the pattern of responses obtained in the dichotomous choice CV question. Notice that the survey responses suggest a median WTP of roughly $75, given that 50.9% percent of the population was willing to pay this amount for the water quality improvements. Less than forty percent of the sample was willing to pay $150.

Table 2.8 provides the mean WTP for the water quality improvements using the four estimators. The probit, log-probit, and GME approaches all yield estimates of the mean *WTP* that lie in the range from $80 to $100. The SNP approach, however, yields a WTP estimate that is roughly four times as large as any of the other approaches. These findings are consistent with the results of the Monte Carlo analysis. In particular, the performance of the SNP estimator is at its worst when there is high level of variability in the underlying distribution of WTP and when the distribution is bimodal, as Chen and Randall [11, p. 334] in their application. The general consistency of the mean WTP

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[12] Analysts will often attempt to minimize this problem by basing the basic model on results obtained previously in the literature. In this case, for example, a mean *WTP* of 100 was chosen to mimic the empirical results obtained in Chen and Randall [11].

Table 2.6: Survey Respondent Characteristics

Variable	Mean	Standard Deviation
Price (B_i)	55.9	50.6
Age	41.4	14.3
Gender	0.50	0.50
Schooling	0.34	0.47

Table 2.7: Survey Response Patterns

Bid	Percent "No"
$10	28.3
$20	17.6
$30	44.8
$75	49.1
$150	61.5

Table 2.8: Estimated Mean WTP for Ohio River

Estimator	Estimated Mean WTP
Probit	86.51 (51.15)
Log-Probit	97.66 (91.22)
SNP	391.75 (407.75)
GME	86.44 (52.15)

estimates when the other three estimators provides some reassurance that the true mean WTP is on the order of $90, it is not precisely measured with any of the models given the limited sample size.

Conclusions

The purpose of this paper was two-fold, providing an adaptation of the GME estimator to the problem of estimating WTP given dichotomous choice CV data and investigating the relative performance of both parametric and semi-nonparametric estimators using Monte Carlo analysis. One reason for developing and using less parametric approaches is that they, hopefully, limit the role and impact of model specification on the resulting estimates of *WTP*. Our results, however, suggest that nonparametric and semi-nonparametric approaches are not, as yet, a panacea for the problems encountered in using parametric estimators. In fact, the simple linear probit model typically provided the best in estimating the conditional mean and median WTP and its dispersion in the sample, regardless of whether the true distribution of WTP was normal, log-normal, uniform, or bimodal. The GME approach also performed well. However, the log-probit specification, used extensively in the literature to impose non-negativity on the distribution of WTP, did not perform nearly as well. Finally, the SNP estimator did not perform as well when there was substantial curvature in the underlying distribution of WTP. Additional research is needed into this estimator in order to determine how its performance can be enhanced using alternative degrees of truncation in the approximating functions and alternative bid designs.

CHAPTER III

ESTIMATING VALUE FOR WETLANDS IN IOWA

Introduction

In the past century, we have witnessed the formation of private organizations whose sole purpose is to preserve or restore wetlands (e.g., Nature Conservancy, Ducks Unlimited). Recent projects, such as the North American Waterfowl Management Plan, have returned 27,000 acres in Iowa to their original wetland state. This has led to a dramatic recovery for many species of birds and plants. The associated gains from flood control, water quality improvement, and wildlife habitat have received considerable coverage in the media. It is natural to then ask whether there is a role for Iowa's state government in assisting these efforts or whether past efforts have brought about the optimal level of wetlands in the state as a whole or particular regions. An economic benefits and cost analysis could determine if additional restoration efforts to augment Iowa's wetlands would be efficient. Unfortunately, policymakers have little information regarding the value society associates with wetlands. These values include both recreational and non-use values. Many activities are centered in and around wetlands, including hiking, biking, bird watching, wildlife viewing, hunting and fishing. Also, individuals may value wetland restoration projects because they provide for the option to visit them in the future or because they simply value their existence.

The purpose of this study is to estimate the value Iowa households place on restoring wetlands in Iowa's Prairie Pothole Region. The prairie potholes of Iowa are a portion of a larger collection of wetlands in the U.S. and Canada known as the Prairie Pothole

Region. This region has lost over half of its original wetland acreage. Iowa, in particular, has lost over 98% of its pothole acreage. Given the diverse characteristics and benefits of wetlands, additional restoration projects are a relevant and a practical policy consideration.

The difficulty in deriving recreational value for wetlands is the problem inherent to all public goods. As we discussed in Chapter II, the lack of market-clearing transactions implies that economists must rely upon other methods to derive value. Wetlands provide habitat for many wildlife species. Thus, the entire area enjoys the benefits provided by wetlands. Also, the fact that someone else has visited the site does not prevent others from doing the same. These aspects of a public good often mean that the good is under-produced as individuals lack the incentive to maintain it. Furthermore, there is no market clearing mechanism economists can refer to in order to measure value of the good in question. However, there are implied markets for wetland visitation. With travel cost models (see Freeman [20], chapter 8 for a review), the researcher can estimate use values, but this would be an incomplete valuation method as it captures only use values and ignores non-use values.

A common alternative methodology is the contingent valuation method (CVM). Under this approach researchers elicit values for the good by surveying the target population and asking them if they are willing to pay a hypothetical bid amount. These are known as dichotomous choice questions. Their advantage is that they are relatively easy for individuals to respond to, similar to everyday take-it or leave-it buying decisions. To obtain this information, the target population is surveyed.

On the other hand, the resulting survey responses are discrete and at most provide bounds on each individual's value for the good. That is, the researcher only knows whether the subject says "yes" or "no" to any specific bid value. The information content of these discrete responses is much less than if the full willingness to pay were observed. To estimate WTP values with the discrete data, the typical approach requires making parametric assumptions regarding a bid function and stochastic disturbance term. However, researchers have pointed out that estimated values from these models are sensitive to the parametric specifications (Hanemann [28], Herriges and Kling [29], Kling [37], and Ziemer et al. [62]). That is, it is crucial that the researcher know the precise parametric family that generates the data or the resulting estimates will be inconsistent. To avoid these influences on estimated values, researchers have suggested more flexible methods, such as semi-nonparametric and nonparametric estimators (Cosslett [14], Chen and Randall [11], Creel [16], Creel and Loomis [17], Kristrom [39], Manski [42], Manski and Thompson [43] and Matzkin [44]). The appealing aspect of these estimators is that they do not force the researcher to make parametric specifications and the resulting welfare measures will be more robust to various data generating mechanisms.

The remaining portions of this chapter describe the contingent valuation method, alternative parametric and semi-nonparametric dichotomous choice model estimators, the design and implementation of the survey instrument used to elicit values associated with Iowa's prairie pothole wetlands, the results of the estimation techniques, and conclusions.

Contingent Valuation Method

As stated above, the goal of this study is to estimate WTP for restoring wetlands to Iowa's prairie pothole region among Iowa households. The CV question in the survey asks for individuals willingness-to-contribute to a fund that intends to add 2,500 acres of land annually over the next 15 years to wetlands in this region. Thus, the value we are estimating is Iowa households' WTP for the restoration program. This information can in turn be used to conduct welfare analysis and design policies regarding future wetland programs.

In order to fix ideas, let

$$WTP_i = W(X_i, \varepsilon_i; \beta) \tag{3.1}$$

denote the i^{th} individual's underlying willingness-to-pay for the augmentation to Iowa's wetlands, where X_i is a vector of socio-demographic characteristics and β is a vector of unknown coefficients. The disturbance term ε_i is assumed to capture variations in preferences within the population including unobserved individual characteristics. Let B_i denote the corresponding income reduction, or bid, posed in the CV question. One of the advantages of the dichotomous choice format is that it parallels the type of decisions typically made by consumers in the marketplace; i.e., accepting or rejecting a good or service at a fixed price (B_i). As noted above, the key disadvantage of the format is that the survey response reveals only limited information about the consumer's underlying WTP, bounding above or below the proposed bid. Thus, rather than observing the consumer's WTP, the analyst observes only the latent variable no_i, where

$$no_i = \begin{cases} 1 & W(X_i, \varepsilon_i; \beta) < B_i \\ 0 & W(X_i, \varepsilon_i; \beta) \geq B_i. \end{cases} \tag{3.2}$$

We will estimate this bid function with a variety of alternative WTP estimators. Specifically, the estimators are the probit, log-probit, semi-nonparametric (SNP) and generalized maximum entropy estimator (GME). A more developed discussion of these estimators was presented in chapter II of this dissertation.

The reason for considering the various estimation techniques is twofold. First, we explore the possible divergence in values of the estimation techniques. Second, as we want to arrive at an accurate estimate for Iowa household's value for this restoration program, we should consider how sensitive the estimates are to the model assumptions. We will now layout the formalities of each estimator.

Parametric Estimators

The probit specification assumes:

$$W(X_i, \varepsilon_{Ni}; \beta_N) = \beta'_N X_i + \varepsilon_{Ni} \tag{3.3}$$

where $\varepsilon_{Ni} \sim i.i.d.N(0, \sigma_N^2)$ and $w(X_i; \beta) \equiv \beta'_N X_i$. Thus, the probability of a "no" response is:

$$\begin{aligned} \Pr(no_i = 1) &= \Lambda[B_i - \beta'_N X_i] \\ &= \Phi\left[\frac{B_i - \beta'_N X_i}{\sigma_N}\right] \\ &= \Phi[\delta'_N Z_i], \end{aligned} \tag{3.4}$$

where $\Phi(\cdot)$ denotes the standard normal cdf; $\delta_N = (\delta_{N0}, \delta_{N1}, \ldots, \delta_{Nk})' \equiv (\sigma_N^{-1}, -\sigma_N^{-1}\beta'_N)'$; and $Z_i = (B_i, X_i')$. The corresponding log-likelihood is given by:

$$\mathsf{L}_N = \sum_{i=1}^{n} no_i \ln[\Phi(\delta'_N Z_i)] + \sum_{i=1}^{n} (1 - no_i) \ln[1 - \Phi(\delta'_N Z_i)]. \tag{3.5}$$

We can then use maximum likelihood techniques to estimate the unknown parameters. This allows us to state the bid function for the wetlands restoration program among Iowa households as:

$$\hat{W}(X_i, \varepsilon_{Ni}; \hat{\beta}_N) = \hat{\beta}'_N X_i. \tag{3.6}$$

Another commonly employed parametric estimator is the linear log-probit model. Here, it is assumed that the bid function takes the form

$$W(X_i, \varepsilon_{Li}; \beta_L) = \exp(\beta'_L X_i + \varepsilon_{Li}) \tag{3.7}$$

where $\varepsilon_{Li} \sim i.i.d. N(0, \sigma_L^2)$, or equivalently

$$\ln[W(X_i, \varepsilon_{Li}; \beta_L)] = \beta'_L X_i + \varepsilon_{Li}. \tag{3.8}$$

The corresponding likelihood is

$$\mathsf{L}_L = \sum_{i=1}^{n} no_i \ln[\Phi(\delta'_L Z_i)] + \sum_{i=1}^{n} (1 - no_i) \ln[1 - \Phi(\delta'_L Z_i)], \tag{3.9}$$

where $Z_i = [\ln(B_i), X'_i]'$. The corresponding estimate of an individual's bid function for the wetlands restoration program among Iowa households is:

$$\hat{W}(X_i, \varepsilon_{Li}; \hat{\beta}_L) = e^{\hat{\beta}_L X_i + \hat{\sigma}_L^2}. \tag{3.10}$$

A Semi-nonparametric Estimator

Chen and Randall's [11] semi-nonparametric approach begins by assuming that the bid function takes the form:

$$W(X_i, \varepsilon_{Si}; \beta_S) = \exp[w(X_i; \beta_S)]\varepsilon_{Si} \equiv G(X_i; \beta_S)\varepsilon_{Si} \tag{3.11}$$

where $G(X_i; \beta_S)$ is an unknown function characterizing the nonstochastic portion of WTP and ε_{Si} comes from an unknown distribution. They use the exponential form for $G(X_i; \beta_S)$, together with the restriction that ε_{Si} has support only for nonnegative values to ensure that willingness-to-pay is nonnegative, i.e. $WTP_i \geq 0$. This structure for the bid function then implies that:

$$\begin{aligned} \Pr[no_i = 1] &= \Pr[G(X_i; \beta_S)\varepsilon_{Si} < B_i] \\ &= \Pr\left[\varepsilon_i < \frac{B_i}{G(X_i; \beta_S)}\right] \\ &= \Lambda\left[\frac{B_i}{G(X_i; \beta_S)}\right] \\ &= \Lambda[u_i] \end{aligned} \tag{3.12}$$

where

$$u_i \equiv \frac{B_i}{G(X_i; \beta_S)}. \tag{3.13}$$

In order to reduce the reliance on a specific model parameterization, the researcher can use the flexible approximations to the two unknown functions of the model: $G(\cdot)$ and $\Lambda(\cdot)$. Chen and Randall [11] suggest the use of a flexible fourier form for $G(\cdot)$, with

$$G_{JA}(X_i; \delta_{JA}) = \exp[w_{JA}(X_i; \delta_{JA})]. \tag{3.14}$$

We define:

$$\begin{aligned} w_{JA}(X_i; \delta_{JA}) &= \mu_0 + b'x_i + \tfrac{1}{2}x_i'Cx_i + \sum_{\alpha=1}^{A}\left(\mu_{0\alpha} + 2\sum_{j=1}^{J}\{\mu_{j\alpha}\cos(j\kappa'_\alpha x_i) - v_{j\alpha}\sin(j\kappa'_\alpha x_i)\}\right) \\ &= \delta'_{JA}\phi_{JA}(X_i) \end{aligned} \tag{3.15}$$

where x_i is the $K\times 1$ vector consisting of the elements of X_i *excluding* any constant term,

$$C=-\sum_{\alpha=1}^{A}\mu_{0\alpha}\kappa_\alpha\kappa'_\alpha, \tag{3.16}$$

$$\delta_{\mathcal{A}}=(\mu_0,\mu_{01},\dots,\mu_{0A},b_1,\dots,b_K,\mu_{11},\dots,\mu_{\mathcal{J}A},v_{11},\dots,v_{\mathcal{J}A}), \tag{3.17}$$

denotes the parameters of the Fourier approximation, and $\phi_{\mathcal{A}}(X_i)$ denotes the vector of corresponding transformations of X_i, including linear and quadratic terms in x_i and the $\cos(j\kappa'_\alpha x_i)$ and $\sin(j\kappa'_\alpha x_i)$ transformations. The κ_α's are $K\times 1$ multiple index vectors used to construct all possible elementary combinations of the explanatory variables (i.e., the x_i) and their multiples.

The second unknown function in modeling CV bid responses is the distribution $\Lambda(\cdot)$. Here the authors rely upon a variant of Gallant and Nychka's [23] semi-nonparametric estimation procedure. The heart of this procedure is the specification of a monotonic transformation of the error term ε_{Si} such that

$$\Gamma[h(u_i)]=\Lambda[u_i]. \tag{3.18}$$

where $\Gamma(\cdot)$ is a known distribution (e.g. the exponential distribution). While the appropriate monotonic transformation function is unknown, Chen and Randall approximate $h(\cdot)$ using the polynomial series:

$$h_r(u)=\gamma_0+\int_0^u(\gamma_1+\gamma_2\eta+\cdots\gamma_r\eta^{r-1})^2d\eta. \tag{3.19}$$

This structure ensures that the transformation is indeed monotonic.

For the sake of brevity, we will not motivate these approximations here.[1] However, approximating $G(\cdot)$ and $\Lambda(\cdot)$ with $G_{JA}(\cdot)$ and $\Gamma[h_r(\cdot)]$ (respectively) will allow us to specify the following likelihood:

$$\mathsf{L}_S = \sum_{i=1}^{n} no_i \ln\left\{\Gamma\left[h_r\left(\frac{B_i}{G_{JA}(X_i;\delta_{JA})}\right)\right]\right\} + \sum_{i=1}^{n}(1-no_i)\ln\left\{1-\Gamma\left[h_r\left(\frac{B_i}{G_{JA}(X_i;\delta_{JA})}\right)\right]\right\}. \quad (3.20)$$

Upon estimating equation (3.20) above, the estimate of an individuals' bid function for the wetlands restoration program among Iowa households is:

$$\hat{W}(X_i, \varepsilon_{Si}; \hat{\beta}_S) = \hat{G}_{JA}\left(X_i; \hat{\beta}_S\right)\hat{\mu}_S, \quad (3.21)$$

where $\hat{\mu}_S$ is the expected value of the estimated density for ε_{Si}. That is, with this SNP methodology, the distribution of ε_{Si} can be estimated. Thus, we can use the estimated density of ε_{Si} to approximate the true expected value by $\hat{\mu}_S$.

An advantage of the above procedure is that the researcher is not forced to make assumptions regarding the functional form of the bid function nor the stochastic disturbance term. Instead, using flexible approximations with good convergence properties, the researcher can get useful estimates for the model parameters. Obviously, this development is very appealing. However, as demonstrated in chapter II of this dissertation, the Monte Carlo results indicate the technique is not completely free of parameterization decisions made by the researcher. For example, model estimates are sensitive to the specification of the known cdf $\Gamma(\cdot)$. In an applied framework, it is not

[1] This development is provided in greater detail in Chapter II of this dissertation.

clear what choice of $\Gamma(\cdot)$ one should employ. Again, this is why we choose to use a variety of WTP estimators in this setting.

A Generalized Maximum Entropy Estimator

The final estimator we consider is the generalized maximum entropy estimator. An appealing aspect of this estimator is that it minimizes the information structure imposed on the distribution while being consistent with the observed data (Golan, Judge, and Miller [24]). The objective function is[2]:

$$\underset{\lambda}{Max}\, C = \sum_{i=1}^{n} no_i \lambda' Z_i + \sum_{i=1}^{n} \ln(\Omega_i) + \sum_{i=1}^{n} \ln(\Psi_i) - n\ln(T), \tag{3.22}$$

where

$$\Omega_i \equiv 1 + e^{-\lambda' Z_i} \tag{3.23}$$

$$\Psi_i \equiv \sum_{t=1}^{T} e^{-v_t \lambda' Z_i} \tag{3.24}$$

and λ is a $(K+1)\times 1$ vector of parameters and Z is the $N \times K$ matrix of explanatory variables. Adapting the GME specification to the dichotomous choice CV problem is straightforward if we set $Z_i = [B_i, -X_i']'$ and $\delta_G = (\xi^{-1}, -\xi^{-1}\beta_G')'$.[3] Estimated WTP for an individual is then given by

$$\hat{W}\left(X_i, \varepsilon_{Gi}; \hat{\beta}_G\right) = \hat{\beta}_G' X_i. \tag{3.25}$$

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[2] The motivation and derivation of this objective function is presented in Chapter II of this dissertation.

[3] The term ξ is $\frac{\pi}{\sqrt{3}}$. This derivation is related to the link between the GME and the logit model.

Survey Design and Implementation

A blue ribbon panel of economists commissioned by the National Ocean and Atmospheric Administration (NOAA) established a set of guidelines concerning survey design and implementation for eliciting value. Highlights of the NOAA panel guidelines include (NOAA, [47]):

- a CV study should describe the population for which the study is attempting to value;
- careful pretesting and focus group sessions should be administered;
- the survey instrument should provide an accurate description of the program;
- referendum questions should be used in resource valuation;
- respondents should be reminded of substitutes;
- the referendum question should be followed up to determine why they answered the way they did;
- the survey should collect information on respondents socio-demographic data and prior knowledge;
- while eliciting these values, the survey instrument should remind respondents of their budget constraint; and
- the respondents should be debriefed regarding their beliefs in the scenarios posed.

In our survey effort, we closely follow the recommendations of the NOAA panel. This survey effort itself was funded by the U.S. Environmental Protection Agency.

The Targeted Good—Iowa Prairie Potholes

In Iowa, the prairie pothole region historically included 7.6 million acres of wetlands. By 1980, the wetland composition of the region fell below 30,000 acres (Bishop et al. [6]). Private interests controlled only 5,000 acres of this area. Largely, this trend reflected the value of land in agricultural production. Private individuals had the incentive to install tile drainage systems to prevent water saturation. This was necessary to make the land more conducive for agricultural purposes. Bishop et al. [6] suggest:

> The primary reason for these wetland losses can be traced directly to federal, state and local government programs which were enacted for the purpose of draining wetlands. These programs, such as the Swamp Land Acts of the 1850s, the Reclamation Act of the early 1900s and several USDA programs offered cost-sharing or financial incentives to convert wetlands to productive agricultural land. The Flood Control Act of the 1940s authorized the U.S. Army Corps of Engineers to construct major drainage outlets and flood control channels which impacted riparian wetlands.

There were some efforts to conserve wetlands during the late 1920s and early 1930s. Primarily, these efforts were motivated by waterfowl hunters who were concerned about decreasing waterfowl populations. These concerns were reflected in the Migratory Bird Conservation Act of 1929 and the Migratory Bird Hunting Stamp Act of 1934. Both of these policies enacted by Congress established funds for the purpose of acquiring wetlands for their preservation. Despite these early efforts, the trend would be towards rapid losses in wetland acreage until the mid-1980s.

Due to increased knowledge regarding the benefits of wetlands, such as pollution mitigation, wildlife habitat, and flood control, several efforts have been aimed at protecting or restoring wetlands. Some of these programs include the North American Waterfowl Management Plan, North American Wetland Conservation Act, Wetland Reserve Program and the Emergency Wetland Reserve Program. As of 1997, total acreage restored or protected by these recent programs amount to 84,209 acres (Bishop et al, [6]). At least partially due to these gains, populations of many species of birds and plants have shown notable increases. Waterfowl populations, which had hit a low during the mid-1980s, are now recovering. Populations of mallard and blue-winged teal ducks have shown promising increases. Although biologists do not know exactly how populations of birds and other species will respond as more wetlands are restored, it is likely that these gains will be maintained or even improved. Likewise, it is expected that significant additional gains in flood control and water quality will occur if more wetland acres are restored.

The ability to restore additional wetlands in the Iowa prairie pothole region hinges on funding. As part of the North American Wetland Conservation Act, restoration projects may receive up to 50% of cost if the state meets the other portion. Given that the per acre cost of recent restoration projects was $936, the state needs to provide approximately $468 per acre at a minimum to gain the National funding. Thus, estimating an empirical value will aid in determining the appropriateness of applying for additional funds through the North American Wetland Conservation Act.

Survey Design

The final survey instrument was the result of a sequence of design phases, including an initial design developed in consultation with wetland experts here at Iowa State University and throughout the state. The survey was then subjected to a series of focus groups.

The focus group sessions were used to gauge the respondents understanding of the instrument and find any other problems with the survey. The sessions were productive in learning how the respondents were interpreting the instrument. Individuals who participated in the focus group sessions consisted of a group of wildlife and conservation enthusiasts, a group of elementary school parents, and a church group. For participating in the focus group the individuals received $10.00. This payment was made to encourage the individuals to review and complete the survey instrument as well as attend the 1-1.5 hour focus group session. Each focus group had an individual session time and meeting place. Comments from all individuals in the focus groups were encouraged. Finally, a pre-test of the survey instrument was conducted using 400 Iowa households. Details of the pre-test are described below. The final survey design benefited at each of these test phases and includes five sections.

The first section is the introduction of the survey, providing a definition and description of wetlands. In this section respondents are asked to report wetland visitation frequency by region and to indicate what types of activities they participated in at the wetland sites. Households were also posed with a contingent behavior question that asked how they would change their visitation patterns under a hypothetical increase in visitation costs. In the second section, we ask the individuals to identify the benefits and costs they associate with wetlands as well as indicate the importance of various characteristics when choosing to visit wetlands. We also ask them to characterize the current state of wetlands in Iowa as well as recent trends. The fourth section is the heart of the wetland survey from the point of view of this chapter. Here we describe a program designed to augment Iowa's prairie pothole wetlands annually over the next 15 years. Then we pose a CV question asking for their willingness to contribute to such a program. The text of the CV question is:

> One objective of this survey is to determine how valuable the Prairie Pothole Wetland Restoration Project is to Iowans. In the next question, we will be asking you about how much you would be willing to contribute to such a project. While you will not actually be contributing to the program at this time, we would like you to respond as if you were pledging to contribute to the project. In particular,

please keep in mind any limits your budget would place on such contributions, as well as what you would have to give up to contribute.

16. Would you be willing to contribute an additional $B on a one time basis (payable in annual installments of $B/5 over five years) to an Iowa Prairie Pothole Management trust fund? This fund would be used to acquire about 2,500 acres of land annually for the next 15 years from willing landowners that would then be restored to prairie potholes.

B represents the bid amount of the dichotomous choice CV question and was varied across survey instruments according to the bid design described below. The fifth and final section of the survey collects socio-demographic data from the individual, which we use as explanatory variables in the analysis presented below.

Sample Design and Selection

The survey was administered to 4,000 Iowa households in early 1998. Of these, 1,600 went to individuals who had purchased a Hunting or Fishing License in Iowa during 1996. The remaining 2,400 of the surveys went to residents of Iowa selected randomly from the general population.[4] The 2,400 households from the general population were selected randomly from phone directories in Iowa by Survey Sampling, Inc. Selection of the 1,600 individuals from the hunting or fishing license holders was more difficult. This is because the license holder data is not computerized. Instead, a copy from each license sold is kept on file in an Iowa Department of Natural Resources warehouse in Des Moines, Iowa. The licenses are filed by the county of purchase. To ensure that our selection technique generated a random sample, we needed an algorithm for selecting individuals from the files.

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[4] This sampling technique effectively forms a stratification of Iowa residents. The goal of the stratification was to ensure that wetland users were well represented in the sample. We present a statistical method to explore the consequences of this stratification on our sample estimates in a later section.

To ensure regional representation, we divided the state of Iowa into ten regions (we made these divisions by crop reporting districts). The weight placed on each crop reporting district was the regions proportion of total licenses sold. Within each crop reporting district, the weight placed on a county was the county's proportion of licenses sold in the crop reporting district. The county weights within a crop reporting district sum to one by definition.

With these weights, we randomly selected an individual by first randomly drawing a crop reporting district. Next, we selected a county randomly. Once the county was selected, we pulled the warehouse box containing a copy of all licenses sold in that county. The licenses sold to Iowa residents were then stacked and the height measured. Drawing a random number from the uniform distribution identified a license from the stack. This algorithm was then be repeated 1,600 times to construct a random sample from the population of license holders.

Bid Design

The dichotomous choice CV question in section four of the survey asks the respondent if they are willing to pay a specific dollar amount B in support of the Prairie Pothole Restoration Project in Iowa. As Cameron [8] has noted, it is the variation of B across the individual surveys that allows the analyst to identify both the parameters of the underlying bid function and the dispersion parameter, σ. The task of selecting both the bid levels and their distribution among the survey sample is one of optimal bid design. By varying the number and dispersion of bids across the surveys, one can alter the precision with which individual parameters of the model are estimated and, hence, the precision with which the bid function itself is estimated.

There exists a substantial literature on optimal bid design, both in the general discrete choice setting (Abdelbasit and Plackett [1], and Minkin [45]) and as it applies to CV analysis (Kanninen [35], [36] and Cooper [13]). The standard bid design approach selects the bids so as to maximize the Fisher information matrix (D-optimality) or to minimize the variance of some function of the parameters (C-optimality), such as the bid function. The problem with these classical approaches, however, is that they require knowledge of the parameter that one is trying to estimate in order to construct the optimal design. Typically, researchers will use their prior beliefs in order to construct the optimal design. This suggests a Bayesian framework might be appropriate (e.g., Chaloner and Larntz [10]), using prior information from focus groups and pre-tests in developing an optimal bid design. While such an effort is beyond the scope of the current paper, we have employed a pseudo-Bayesian approach to the bid design in the wetlands survey. In particular, the following four step-procedure was used in the bid design.

<u>Step 1: Pre-test</u>. During the pre-test phase, a wide variety of annual bid values were employed, ranging from \$5 to \$250. This was done so as to ensure that we covered the likely range of underlying bid values in the population. A total of 228 useable responses were obtained (for roughly a 57% response rate).

<u>Step 2: Initial Estimates of the Mean WTP</u>. Using the survey responses from the pre-test, a simple log-probit model was estimated, including only an intercept term ($\alpha = 2.43$, with a standard error of 0.88) and a dispersion coefficient

($\sigma = 2.81$, with a standard error of 1.06). The estimated median value for the bid function is then 11.36 per year.

Step 3: A Pseudo-Bayesian Design. While we could have applied classical bid design techniques at this stage, using the point estimates from the log-probit model, we chose instead to employ a pseudo-Bayesian approach. In particular,

- Using the asymptotic normal distribution of the pre-test parameters, T parameter simulations were drawn, yielding parameter pairs of (α_t, σ_t), t=1...T.
- For each simulated parameter pair, a sample of N simulated households was constructed, with implied WTP levels of W_{it}, i=1...N.
- For each simulated sample, the pseudo-households were randomly assigned a bid (b_{is}) for each of s trial bid design, s=1...S.[5] The household's implied response to these bids yielded N bid-response pairs for each trial bid design; i.e., (b_{its}, D_{its}), where $D_{its} = 1$ if $W_{it} > b_{its}; = 0$.
- Finally, using the N bid-response pairs, a mean WTP ($\overline{W}_{ts}$) and its estimated standard deviation ($\hat{\sigma}_{ts}$) can be constructed for each bid design (s=1...S) and each simulated pair of parameters (t=1...T). The selected final survey design

[5] A bid design corresponds to designing the number of bid levels to be used, the bid levels themselves, and the proportion of the sample assigned to each bid level. In order to limit the possible number of bid designs, we required that (a) bid levels be in increments of five dollars, (b) at most six bid level be used, and (c) the sample be allocated in 5 percent blocks.

- minimized the mean value of $\hat{\sigma}_u$ across the parameter simulations; i.e., we chose $s^* = \underset{s}{ArgMin} \frac{1}{T}\sum_{t=1}^{T} \hat{\sigma}_{tt}$.

Table 3.1 provides the final bid design. It is worth noting that the resulting mean value of $\hat{\sigma}_u$ was 1.86 for the optimal bid design, compared to 16.83 when we used the D-optimal design suggested by Kanninen [36].

Table 3.1: Final Bid Design

Bid level (*B*)	Proportion of Sample
25	50
50	5
75	5
100	15
250	15
500	10

Survey Implementation

A pre-test sample of 400 was selected from the population. After amending the survey to accommodate the concerns from the focus group sessions, we printed surveys for the pre-test sample. The pre-test surveys were mailed by the middle of November, 1997. We received 174 completed surveys from the pre-test and 39 surveys were undeliverable (48% response rate). For completing the pre-test survey, respondents were promised $4.00. Finally, after receiving the pre-test survey results, we made minor changes to the survey before sending them out to our full sample in early 1998.

In an effort to maximize the response rate to the survey, surveys were administered according to Dillman's [19] methods. A postcard was mailed out to the households who failed to respond to the survey after two weeks. If the individual failed to respond in the next two weeks, a duplicate survey was mailed with another reminder. As a final incentive to reduce non-responses, the households were promised $10.00 for completion of the survey.

We received 2,026 surveys out of 3,557 that were deliverable. This implies that the response rate was approximately 57%. Of the 1,600 directed to individuals who had purchased a hunting or fishing license in 1996, 1,330 were deliverable and 776 were completed. Of the 2,400 directed to the general population, 2,227 were deliverable and 1,250 were completed. Given the length of the survey, this response rate is reasonably reflective of all Iowa households' attitudes towards wetlands. A breakdown of the sample appears in Table 3.2 below.

Table 3.2: Sample breakdown by strata

	Hunters and Fishers	**General Population**	**Total**
Initial Sample	1,600	2,400	4,000
Deliverable	1,330	2,227	3,557
Responses	776	1,250	2,026
Response Rates	58.3%	56.1%	57.0%

The Model

The explanatory variables come from the socio-demographic variables obtained from the last section of the survey. The variables included are: age; sex; education; ownership of a fishing license; and ownership of a duck stamp. Each of these variables takes on a discrete value. We have three classifications for age (which implies two dummy variables). The classifications were young age (less than 34), prime age (between 35 and 59), and golden age (greater than 59). Education was classified into two groups. The groups were individuals with some college experience versus those without any college. Summary data for these variables appear in Table 3.3. One of the first points of interest is the representation of fishing license holders in the sample. Clearly, license holder's are over represented in the sample. As mentioned previously, 40% of all surveys were directed to individuals who had purchased a hunting or fishing license in Iowa during 1996. Effectively, we can think of Iowa as consisting of individuals from two strata (license holders and non-license holders). However, if we believe the effect of holding a license in 1996 can be captured by a discrete variable and we include this variable as an explanatory variable in our model of the bid function, it is reasonable to expect that no further modeling is required (Lerman and Manski, [41]). That is, we may write:

$$f\left(no_i, z_i \mid \hat{\beta}\right) = P\left(no_i \mid \hat{\beta}, z_i\right) f(z_i) \tag{3.26}$$

where z_i is a dummy variable that indicates strata. Note that the probability of an observation being drawn from a particular stratum is unaffected by the model parameters. As equation (3.26) indicates, incorporating the stratification into the likelihood statement is insignificant as the term is a constant and has no impact on the maximization process.

Incorporating equation (3.26) into a general expression for our maximum likelihood statement gives us:

$$\underset{\hat{\beta}}{Max}\sum_{i=1}^{n}\ln\left(P\left(no_i|\hat{\beta},z_i\right)f(z_i)\right)=\underset{\hat{\beta}}{Max}\sum_{i=1}^{n}\left[\ln\left(P\left(no_i|\hat{\beta},z_i\right)+\ln\left(f(z_i)\right)\right)\right]. \quad (3.27)$$

As long as we include the stratification as conditionally influencing the probability of the discrete response, no further weighting is required.

The coefficient for each remaining explanatory variable is assumed to be constant across strata. Thus, we may apply the estimators discussed above to the dataset, where the variables are defined as follows:

$x_{1i} \equiv$ 1 if the individual falls into the young age category; and 0 otherwise
$x_{2i} \equiv$ 1 if the individual falls into the golden age category; and 0 otherwise
$x_{3i} \equiv$ 1 if the individual falls into the female category; and 0 otherwise
$x_{4i} \equiv$ 1 if the individual falls into the some college category; and 0 otherwise
$x_{5i} \equiv$ 1 if the individual falls into the fishing license owner category; and 0 otherwise
$x_{6i} \equiv$ 1 if the individual falls into the duck stamp owner category; and 0 otherwise.
(3.28)

Each variable is then mean differenced, with $\tilde{x}_{ji} \equiv x_{ji} - \bar{x}_{j\cdot}$. The values of the mean differenced variables are reported in Table 3.4. Note that the mean for each variable is simply the negative of the value reported in the "If false" column in Table 3.4. This is because the discrete variable takes on a zero when the variable is false. Thus, the mean-differenced value is simply the negative of the mean.

Table 3.3: Data Summary

Variable	Percent in Sample
Young Age	20.9
Prime Age	56.2
Golden Age	22.9
Female	24.2
Some College	42.3
Fishing License Holder	67.8
Duck Stamp Holder	15.1

Table 3.4: Mean-differenced data summary

Variable	If true	If false
Young Age	0.791	-0.209
Golden Age	0.771	-0.229
Female	0.758	-0.242
Some College	0.577	-0.423
Fishing License	0.322	-0.678
Duck Stamp	0.849	-0.151

Estimation Results

The coefficient estimates that result from applying each of the estimation techniques to the Iowa wetlands dataset are provided in Tables 3.5-3.8. Coefficients that are estimated to be significantly different from zero at the 5% level and 1% level are indicated by the * and **, respectively. The estimation techniques consistently identify the coefficient on golden age, female, some college and duck stamp ownership variables to be significant. The exception is that the SNP model did not find the golden age variable to be statistically different from zero at any reasonable level of significance. The signs indicate that individuals characterized by being either in the golden age or female category had smaller bid amounts for the restoration program. Further, individuals that had some college or owned a duck stamp were willing to contribute more to the restoration program. The models that included a coefficient on the bid amount and an intercept term found (all but the SNP model) the estimated coefficients to be significantly different from zero.

Tables 3.9 and 3.10 present the marginal dollar effects on the bid function of various household characteristic. As the variables were mean differenced, the intercept term is also the mean WTP value for the sample. To obtain the estimated value for a prime age male with no college who owns both a fishing license and a duck stamp, one need only sum the corresponding cells of Table 3.9 by characteristic and the mean value for the sample. That is,

$$\hat{W} = 6.09 + 3.38 + 3.26 - 8.86 + 2.12 + 21.83 = \$27.82\,. \qquad (3.29)$$

Table 3.5: Probit Model results

Variable	Coefficient	t-stat
Bid Amount	0.0172	13.61**
Intercept	0.1050	2.77**
Young Age	-0.0470	-0.62
Golden Age	-0.2121	-2.69**
Female	-0.2318	-3.21**
Some College	0.3606	5.83**
Fishing License	0.1183	1.81*
Duck Stamp	0.4432	5.09**

Table 3.6: Generalized Maximum Entropy Model results

Variables	Coefficient	t-stat
Bid Amount	0.0303	12.10**
Intercept	0.1980	3.01**
Young Age	-0.0862	-0.72
Golden Age	-0.3472	-2.65**
Female	-0.3655	-2.92**
Some College	0.5862	5.81**
Fishing License	0.1896	1.52
Duck Stamp	0.7284	4.71**

Table 3.7: Log-probit Model results

Variables	Coefficient	t-stat
Bid Amount	0.4617	15.32**
Intercept	0.8713	11.21**
Young Age	-0.0462	-0.50
Golden Age	-0.2229	-2.74**
Female	-0.2303	-3.12**
Some College	0.3704	5.92**
Fishing License	0.1120	1.64
Duck Stamp	0.4508	5.26**

Table 3.8: Semi-Nonparametric Model Results

Variables	Coefficient	t-stat
Young Age	0.0348	0.28
Golden Age	-0.3334	-1.37
Female	-0.6264	-3.45**
Some College	0.8763	5.71**
Fishing License	0.3361	2.04**
Duck Stamp	0.9264	3.98**
γ_0	0.5445	12.58**
γ_1	0.2380	13.50**
γ_2	0.0027	-3.21**

Table 3.9 demonstrates that the results for the GME model are similar to the probit model. This result stems from the relationship between the entropy formulation of the problem and the logit framework[6]. As the logit model generates results close to probit, so does the GME model.

Table 3.10 compares the SNP model to the log-probit. The effects by classification of the explanatory variables are given in percent terms. Thus, to derive an estimate of an individual's WTP for the restoration program who is a prime age male with no college and owns both a fishing license and a duck stamp, we compute:

$$\hat{W} = \$8.43(1+.1403)(1+.1285)(1-.2881)(1+.0814)(1+1.2906) = \$19.13 \qquad (3.30)$$

A similar calculation would be performed for the SNP model.

Table 3.11 compares the estimated results for a series of stylized individuals. We consider stylized individuals rather than covering the complete space of possible characteristic combinations as there are 48 possible combinations. The stylized individuals are:

- a prime age male with some college who is an outdoor enthusiast;
- a prime age male with some college who is a fishing enthusiast;
- a prime age female with some college who is an outdoor enthusiast;
- a prime age female with some college who is a non-enthusiast;
- a golden age female with no college who is a non-enthusiast; and
- a young male with no college who is a non-enthusiast.

[6] This feature of the GME model is discussed in chapter II.

Table 3.9: Probit and GME Model Results in Dollars

Characteristic	**Probit**	**GME**
Mean WTP for the sample	$6.09	$6.53
Young Age	-$2.38	-$2.48
Prime Age	$3.38	$3.21
Golden Age	-$8.92	-$8.24
Female	-$10.19	-$9.13
Male	$3.26	$2.92
Some College	$12.06	$11.14
No College	-$8.86	-$8.19
Fishing License	$2.12	$2.01
No Fishing License	-$4.65	-$4.24
Duck Stamp	$21.83	$20.39
No Duck Stamp	-$3.88	-$3.63

Table 3.10: Log-probit and SNP Model Results

Characteristic	**Log-Probit**	**SNP**
Mean WTP for the sample	$8.43	$15.75
Young Age	-26.48%	-18.21%
Prime Age	14.03%	7.13%
Golden Age	-29.64%	-23.23%
Female	-31.47%	-37.79%
Male	12.85%	16.40%
Some College	58.81%	65.73%
No College	-28.81%	-31.00%
Fishing License	8.14%	11.44%
No Fishing License	-15.16%	-20.37%
Duck Stamp	129.06%	117.57%
No Duck Stamp	-13.71%	-13.06%

Table 3.11: Stylized individual results in Dollars

Stylized Characteristics	**Probit**	**Log-probit**	**SNP**	**GME**
Prime age male with some college and an outdoor enthusiast	\$48.74	\$42.67	\$78.92	\$46.20
Prime age male with some college and a fishing enthusiast	\$23.03	\$16.08	\$31.54	\$22.18
Prime age female with some college and an outdoor enthusiast	\$35.29	\$25.91	\$42.18	\$34.15
Prime age female with some college who is a non-enthusiast	\$2.81	\$7.66	\$12.04	\$3.88
Golden age female with no college and a non-enthusiast	-\$30.41	\$2.12	\$3.59	-\$26.90
Young male with no college and is a non-enthusiast	-\$10.42	\$3.65	\$7.16	-\$9.09

For this analysis, we define an outdoor enthusiast to be an individual that possesses both a fishing license and a duck stamp. An individual classified as a non-enthusiast has neither a fishing license nor a duck stamp. A fishing enthusiast would hold only a fishing license while a waterfowl enthusiast would hold only a duck stamp. With these definitions in mind, we can compare the results across models. For the prime age stylized individuals, the model estimates are quite similar with the possible exception being the SNP model, which tends to estimate a high value for WTP for the restoration program (nearly double the values from the other methods). The table also illustrates why the log-probit model is a favorite among researchers with applied datasets as it does not produce any negative WTP for a good by construction for any individual in the population. However, if we are interested strictly in an estimate of mean WTP, the probit model is likely to be a more reliable estimator.[7]

To accomplish our goal, we need to arrive at an estimate of mean WTP for the restoration program for all Iowa households. As briefly mentioned above, the stratification issue is critical in this analysis. That is, our survey was sent out to two different strata in the Iowa population. The first strata consists of households who held a hunting or fishing license in Iowa during the last three years. We will denote the number of individuals in Iowa in this strata as N_1 and n_1 will represent the number of individuals from this strata in our sample. The second strata consists of households who held neither a hunting license nor a fishing license during the past three years. We will denote the number of these individuals in the Iowa population as N_2 while n_2 represents the number

[7] This assertion is due to the Monte Carlo results presented in chapter II of this dissertation.

of individuals from this strata in our sample. Note that $N_1 + N_2 = N$, where N is the total number of Iowa households. Thus,

$$w_1 = \frac{N_1}{N} \text{ and } w_2 = \frac{N_2}{N} \tag{3.31}$$

represents the proportions of Iowa households from strata 1 and strata 2, respectively. Notice that for our sample,

$$w_1 < \frac{n_1}{n_1 + n_2} \text{ and } w_2 > \frac{n_2}{n_1 + n_2}. \tag{3.32}$$

This implies that the number of individuals who are not outdoor enthusiasts are underrepresented in the sample. Thus, the mean from the sample is biased towards the value that enthusiast households place on wetlands. In order to get an unbiased estimate of the population mean WTP for the restoration program, we need to weight the observations by strata (Cochran, [12]). That is, note the following:

$$\hat{W}_{1\cdot} = \frac{1}{n_1}\sum_{i=1}^{n_1} \hat{W}_{1i}\left(X_{1i}, \varepsilon_{1i}; \hat{\beta}\right) \to \frac{1}{N_1}\sum_{i=1}^{N_1} W_{1i}\left(X_{1i}, \varepsilon_{1i}; \beta\right) = W_{1\cdot} \text{ as } n_1 \to N_1$$

and (3.33)

$$\hat{W}_{2\cdot} = \frac{1}{n_2}\sum_{i=1}^{n_2} \hat{W}_{2i}\left(X_{2i}, \varepsilon_{2i}; \hat{\beta}\right) \to \frac{1}{N_2}\sum_{i=1}^{N_2} W_{2i}\left(X_{2i}, \varepsilon_{2i}; \beta\right) = W_{2\cdot} \text{ as } n_2 \to N_2 .$$

Further, we can write:

$$\begin{aligned} W_{\cdot} &= \frac{1}{N}\sum_{j=1}^{2}\sum_{i=1}^{N_j} W_{ji} \\ &= \frac{1}{N}\sum_{i=1}^{N_1} W_{1i} + \frac{1}{N}\sum_{i=1}^{N_2} W_{2i} = \frac{N_1}{N}\left(\sum_{i=1}^{N_1}\frac{W_{1i}}{N_1}\right) + \frac{N_2}{N}\left(\sum_{i=1}^{N_2}\frac{W_{2i}}{N_2}\right) \\ &= w_1 W_{1\cdot} + w_2 W_{2\cdot} \end{aligned} \tag{3.34}$$

Given equation (3.33), then

$$w_1\hat{W}_{1\cdot} + w_2\hat{W}_{2\cdot} \xrightarrow{j=1,2;n_j \to N_j} w_1 W_{1\cdot} + w_2 W_{2\cdot} \tag{3.35}$$

In order to get an unbiased estimate of the population mean, we multiply the mean WTP estimate of license holders by the proportion of license holders in the Iowa population. According to the 1990 Census, there were 1,064,325 Iowa households. Also, 57% of the responses from the surveys sent to the general population indicated that someone in the household had purchased a hunting or fishing license in the last three years. We used this fraction as the proportion of Iowa households with at least one member of the household owning a hunting or fishing license (thus, we estimate the number of hunting or fishing license holding households to be 606,665). Similarly for non-license holders, we multiply the mean WTP estimate of non-license holders by the proportion of non-license holders in the Iowa population (457,660 Iowa households are estimated to be non-license holders or 43% of all Iowa households). The estimate of the population mean is the sum of these two weighted stratum means. The mean WTP according to the probit model for license holders in the sample is $9.72 while the mean WTP for non-license holders is -$3.94.

After making the weighting adjustment described above and applying it to the Iowa wetlands sample, we get the estimates for the mean value of Iowa households WTP for the restoration program. These results are presented in Table 3.12 by models. Tables 3.9 and 3.10 above reported the mean WTP of the sample for each estimator. Consistent with intuition, the estimated population mean is below the sample mean for each estimation technique. This is the result we expected as the license holders were over represented in the sample. Moreover, the estimation results suggest individuals with a hunting or fishing license had a higher value for wetlands. Thus, the estimated population mean is less than the estimated sample mean. In general, the probit, log-probit and GME yield similar values for prairie pothole restoration while the SNP values are nearly three times the probit results.

Table 3.12: Population mean values by model

Models	Population mean	Per Acre Value
Probit	$3.85	$109.27
Log-probit	$7.75	$219.96
GME	$7.53	$213.72
SNP	$14.33	$406.71

Investigating the Effects of Stratification

As noted in the sample selection section above, a stratified sampling scheme was used in the survey implementation. In this section, we investigate the effects of that stratification on the welfare estimates.

Data stratification may, in general, cause sample estimates to be biased estimators of the population parameters. This can be illustrated as follows. There exists a population likelihood function that can be expressed as follows:

$$L = \prod_{i=1}^{N_1} P_{1i}^{no_{1i}} (1 - P_{1i})^{1-no_{1i}} \prod_{i=1}^{N_2} P_{2i}^{no_{2i}} (1 - P_{2i})^{1-no_{2i}} . \qquad (3.36)$$

This allows us to express the log-likelihood function as:

$$\ln L = \sum_{i=1}^{N_1}\left\{no_{1i}\ln P_{1i} + (1-no_{1i})\ln(1-P_{1i})\right\} + \sum_{i=1}^{N_2}\left\{no_{2i}\ln P_{2i} + (1-no_{2i})\ln(1-P_{2i})\right\}$$

$$= N_1\left(\frac{\sum_{i=1}^{N_1}\left\{no_{1i}\ln P_{1i} + (1-no_{1i})\ln(1-P_{1i})\right\}}{N_1}\right) + N_2\left(\frac{\sum_{i=1}^{N_2}\left\{no_{2i}\ln P_{2i} + (1-no_{2i})\ln(1-P_{2i})\right\}}{N_2}\right)$$

$$= N_1A_1 + N_2A_2,$$

where

$$A_j \equiv \frac{\sum_{i=1}^{N_j}\left\{no_{ji}\ln P_{ji} + (1-no_{ji})\ln(1-P_{ji})\right\}}{N_j} \quad \text{for } j = 1,2. \tag{3.37}$$

Similarly, the likelihood function for the sample can be expressed as:

$$\hat{L} = \prod_{i=1}^{n_1} P_{1i}^{no_{1i}}(1-P_{1i})^{1-no_{1i}} \prod_{i=1}^{n_2} P_{2i}^{no_{2i}}(1-P_{2i})^{1-no_{2i}} \tag{3.38}$$

This allows us to express the log-likelihood function as:

$$\ln \hat{L} = \sum_{i=1}^{n_1}\left\{no_{1i}\ln P_{1i} + (1-no_{1i})\ln(1-P_{1i})\right\} + \sum_{i=1}^{n_2}\left\{no_{2i}\ln P_{2i} + (1-no_{2i})\ln(1-P_{2i})\right\}$$

$$= n_1\left(\frac{\sum_{i=1}^{n_1}\left\{no_{1i}\ln P_{1i} + (1-no_{1i})\ln(1-P_{1i})\right\}}{n_1}\right) + n_2\left(\frac{\sum_{i=1}^{n_2}\left\{no_{2i}\ln P_{2i} + (1-no_{2i})\ln(1-P_{2i})\right\}}{n_2}\right). \tag{3.39}$$

The properties of the maximum likelihood estimator give us:

$$\frac{\sum_{i=1}^{n_j}\left\{no_{ji}\ln P_{ji} + (1-no_{ji})\ln(1-P_{ji})\right\}}{n_j} \to A_j. \tag{3.40}$$

If we make use of this fact with our sample log-likelihood function, we have:

$$\ln \hat{L} \to n_1A_1 + n_2A_2 \neq N_1A_1 + N_2A_2 = \ln L. \tag{3.41}$$

For all cases where $n_1<N_1$ and $n_2<N_2$, we see that $\ln \hat{L}$ will not converge to $\ln L$.

To correct for this, we can think of using the following weighted log-likelihood function.

$$\begin{aligned}\ln \hat{L}_w &= \sum_{i=1}^{n_1} \frac{N_1}{n_1}\{no_{1i}\ln P_{1i} + (1-no_{1i})\ln(1-P_{1i})\} + \sum_{i=1}^{n_2} \frac{N_2}{n_2}\{no_{2i}\ln P_{2i} + (1-no_{2i})\ln(1-P_{2i})\} \\ &= N_1\left(\frac{\sum_{i=1}^{n_1}\{no_{1i}\ln P_{1i} + (1-no_{1i})\ln(1-P_{1i})\}}{n_1}\right) + N_2\left(\frac{\sum_{i=1}^{n_2}\{no_{2i}\ln P_{2i} + (1-no_{2i})\ln(1-P_{2i})\}}{n_2}\right) \\ &\rightarrow N_1A_1 + N_2A_2 = \ln L.\end{aligned} \tag{3.42}$$

By the properties of our maximum likelihood techniques, the weighted sample log-likelihood converges to the population log-likelihood. Thus, the weighting scheme gives us the desirable convergence property.

The weighting scheme implies the sample likelihood has the form:

$$\hat{L}_w = \prod_{i=1}^{n_1}\left\{P_{1i}^{no_{1i}}(1-P_{1i})^{1-no_{1i}}\right\}^{\frac{N_1}{n_1}} \prod_{i=1}^{n_2}\left\{P_{2i}^{no_{2i}}(1-P_{2i})^{1-no_{2i}}\right\}^{\frac{N_2}{n_2}}. \tag{3.43}$$

If the sample was conducted proportionally to the population (i.e., $w_1 = \frac{n_1}{n_1+n_2}$), then $\frac{N_1}{n_1} = \frac{N_2}{n_2}$. This implies the weighting method is inconsequential. That is, maximizing the straightforward sample likelihood function is equivalent to maximizing the weighted maximum likelihood function as the weights drop out.

For the wetlands survey we analyzed in this chapter, $w_1 \neq \frac{n_1}{n_1+n_2}$. Thus, the optimization of the simple sample likelihood could potentially lead to biased estimates if our concern is making inferences on the population. However, as we constructed the WTP function, the estimated probability of a "no" response is a function of the individual's strata. Thus, as Lerman and Manski [41] point-out, the weighting scheme will not be a factor.

To demonstrate this result, we maximize the weighted likelihood problem for the probit model with the wetlands dataset according to equation (3.42). The results are presented in Table3.13. Upon inspection of Table 3.13, we see a high degree of congruence between the two methodologies. That is, the parameters are of similar magnitude and in all cases they are of the same sign. The estimated model parameters for the weighted probit model are presented in Table 3.14. Comparing Table 3.14 to Table 3.5 (the probit model results), we see that the t-statistics give us the same conclusions in regards to significance of variables. In fact, the t-statistics are also close in magnitude. This suggests that the weighting scheme is not necessary as the estimated parameters are invariant.

Conclusions

The estimates presented in Table 3.12 are largely consistent across model parameterizations with the lone exception being the SNP estimator, which estimates a much larger value than the other models. This result is not surprising given the work presented in chapter II of this dissertation. In fact, taking Chapter II as the guide, the results from the probit and GME estimation techniques are likely to be our best guess as to the true mean value for the Iowa population.

The average aggregate amount that Iowa households are willing to commit to wetland restorations that take place in the next 15 years is $109.27 per acre. When individuals responded to the CV question in our analysis, they were aware of the benefits and costs associated with wetlands. This includes the gain in flood control, water quality improvement, and wildlife habitat. The value we estimated then reflects both use and nonuse values for wetlands. Given the current land prices in Iowa, it is doubtful the value reported here could buy land already in a wetland state from private individuals for the purpose of maintaining the wetland indefinitely. Again, this value is based upon the estimated average per Iowa household.

It is interesting to note that individuals with the highest use values, such as outdoor, fishing and waterfowl enthusiasts, account for a high percent of the total value for the population. The values these enthusiasts place on wetlands are reported in Table 3.15. If we consider the aggregate value that Iowa's enthusiast households place on the restoration program, we get $157.25 per acre or 144% of the total value of the Iowa population. While these values ignore the discounting that is necessary due to spreading the payments out over 5 years, we see that these households have much larger value for wetland restoration efforts. Given that establishing these collaboratives are costly for private individuals, perhaps the role for policymakers is to shift this burden from the private individuals to government agencies. That is, government resources could be allocated for the purpose of developing wetland management plans. This stops short of suggesting public funds be spent for acquiring wetlands. In fact, this analysis suggests that this should not be done based on average Iowa household's valuation of wetlands.

Table 3.13: Weighted Probit comparison to Probit

Characteristic	Probit	Weighted Probit
Mean WTP for the sample	6.09	6.04
Young Age	-2.38	-2.23
Prime Age	3.38	3.63
Golden Age	-8.92	-9.92
Female	-10.19	-11.03
Male	3.26	3.53
Some College	12.06	11.95
No College	-8.86	-8.78
Fishing License	2.12	2.28
No Fishing License	-4.65	-4.80
Duck Stamp	21 83	21.35
No Duck Stamp	-3.88	-3.80

Table 3.14: Weighted probit model results

Variable	Coefficient	t-stat
Bid Amount	0.0175	13.29**
Intercept	0.1055	2.60**
Young Age	-0.0442	-0.47
Golden Age	-0.2367	-2.90**
Female	-0.2544	-3.59**
Some College	0.3620	5.66**
Fishing License	0.1238	1.87*
Duck Stamp	0.4392	4.39**

Table 3.15: Enthusiast's mean values by model

Models	Enthusiast's mean	Per Acre Value
Probit	$9.72	$157.25
Log-probit	$9.54	$154.34
GME	$9.82	$158.87
SNP	$18.03	$291.68

CHAPTER IV

NONPARAMETRIC BOUNDS ON WELFARE MEASURES FOR NONMARKET GOODS

Introduction

In a series of influential papers, Varian ([56], [60]) extended and refined the work of Afriat [4],[5], Samuelson [52], Houthakker [31], and Richter [50], among others, to form the basis for a series of empirically testable hypotheses known generally as the theory of revealed preference. This work demonstrates how observed demand behavior can be used to recover information about an individual's preference ordering without resorting to parametric assumptions regarding the form of the consumer's underlying demand or utility function. Revealed preference theory has been influential in developing empirical tests of utility theory (Varian [57],[58]), investigating issues of changes in consumer's tastes (Chalfant and Alston [9]), testing whether firms behave as profit maximizers (Varian [59]), etc. The general framework has also been extended to account for stochastic elements (Varian [60]), Sakong and Hayes [51]). The ability to characterize information about consumer's preferences without imposing a specific functional form for utility or demand is intuitively appealing and has provided a rich base for empirical research in consumer and firm theory.

The issue of parametric specification has been of widespread concern in nonmarket valuation. Most nonmarket valuation methods require the analyst to specify a particular functional form for an estimating equation. It may be a demand, bid, or utility function (or hedonic price function). Although the analyst may perform goodness of fit tests or use other tools to choose among functional forms, there remains a great deal of arbitrariness and researcher judgment in the choice of functional form.

In the travel cost model, it has long been understood that the choice of functional form for either the demand function or the indirect utility function can have significant consequences for the magnitude of the resulting welfare estimates (Ziemer, Musser, and Hill [62], Kling [37], Ozuna [48]). The same has been found in random utility models of recreation demand with respect to the choice of functional form and the assumed error structure (Morey, Rowe, and Watson [46], Kling and Thomson [38], Herriges and Kling [29]). Hedonic housing models used to value air quality are subject to similar concerns (Cropper, Deck, and McConnell [18]). Finally, the contingent valuation literature has found that changes in either the error structure or the assumed bid function's form can yield large differences in valuation estimates from discrete choice formats (Hanemann [28]).

Given the empirically observed sensitivity of welfare estimates to functional form, it is natural to consider whether nonparametric methods such as those refined and developed by Varian might be of value in nonmarket welfare analysis. In this research, we first adopt Varian's [56] work on bounding welfare measures to the task of valuing nonmarket commodities. Next, we demonstrate how the bounds can be narrowed with appropriate data on optimal market bundles at new prices. The exciting aspect of this work is that these bounds are derived using only quantity and prices of visits to a recreation area without resorting to any parametric assumption on demand or utility.

To accomplish this objective, we first demonstrate how bounds on compensating variation for a price change can be constructed when the analyst has a single data point (one price/quantity combination) for each individual in the sample. Next, we show how the addition of a second such point can narrow these bounds. Finally we show how these bounds can be further tightened with the addition of a third and more observations for each individual. To derive these bounds, we make use of the relationship between compensating variation and equivalent variation.

The nonparametric bounds thus developed will only prove useful if they are fairly tight. To investigate their potential empirical value, we conduct a Monte Carlo experiment. In this experiment, the nonparametric lower and upper bounds are compared to computed "true" values of WTP using simulated data sets. Additionally, a natural comparison is to consider how well the bounds perform in estimating welfare relative to traditional parametric approaches. To consider this, traditional travel cost type models are estimated on the simulated data sets and point estimates and confidence intervals are constructed from these models which are then compared to the nonparametric bounds.

In the recreation demand literature, Adamowicz, Fletcher, and Graham-Tomasi, [2] and Larson et al [40] have used Varian's methodology to test for consistency between contingent valuation (stated preference) models and recreation demand (revealed preference) models. The approach we develop differs significantly from these previous applications: here, we take the methodology further by developing bounds on welfare measures for nonmarket goods.

A caveat on the nonparametric bounds described below is that, because they use the theoretical relationship between compensating and equivalent variation, and because this relationship itself reverses depending on if the good is a normal or inferior good, the methodology applies only for a normal good. Thus, an analyst using these bounds m ust be sure that the good is not inferior. We comment further on this issue in the theoretical section of the paper.

Using Observed Data to Compute Bounds on the WTP for Price Changes

Bounds Based on One Data Point for Each Individual

The following development of the bounds with a single data point draw heavily on Varian's [56] seminal work. To begin the discussion of welfare bounds, consider a simple budget constraint for an individual choosing between recreation visits (v) and a composite commodity (z). In Figure 4.1, $X_0 \equiv (v_0, z_0)$ denotes the chosen commodity bundle at the initial price vector (denoted P_0 in the figure) and M is the consumer's income. Let $X \equiv \{(v,z): v,z \in R_+\}$ is the set of all possible bundles.

In order to calculate the exact compensating variation (CV) associated with a particular price change, we would need to determine the amount of money the individual is willing to give up to receive the price change. Formally,

$$\begin{aligned} CV &= e(P_0,U_0) - e(P_N,U_0) \\ &= M - e(P_N,U_0), \end{aligned} \tag{4.1}$$

where $e(P,U)$ denotes the individual's expenditure function, $U_0 \equiv U(v_0,z_0)$ denotes the level of utility at X_0, and P_0 and P_N are the prices before and after the price change. The first term $e(P_0,U_0)$ is exactly the initial income of the consumer (M). If we can provide bounds on the second term, $e(P_N,U_0)$, we can also bound CV. Thus, we seek to compute lower and upper bounds on the expenditure that would be necessary for the consumer after the price change to obtain the original utility level.

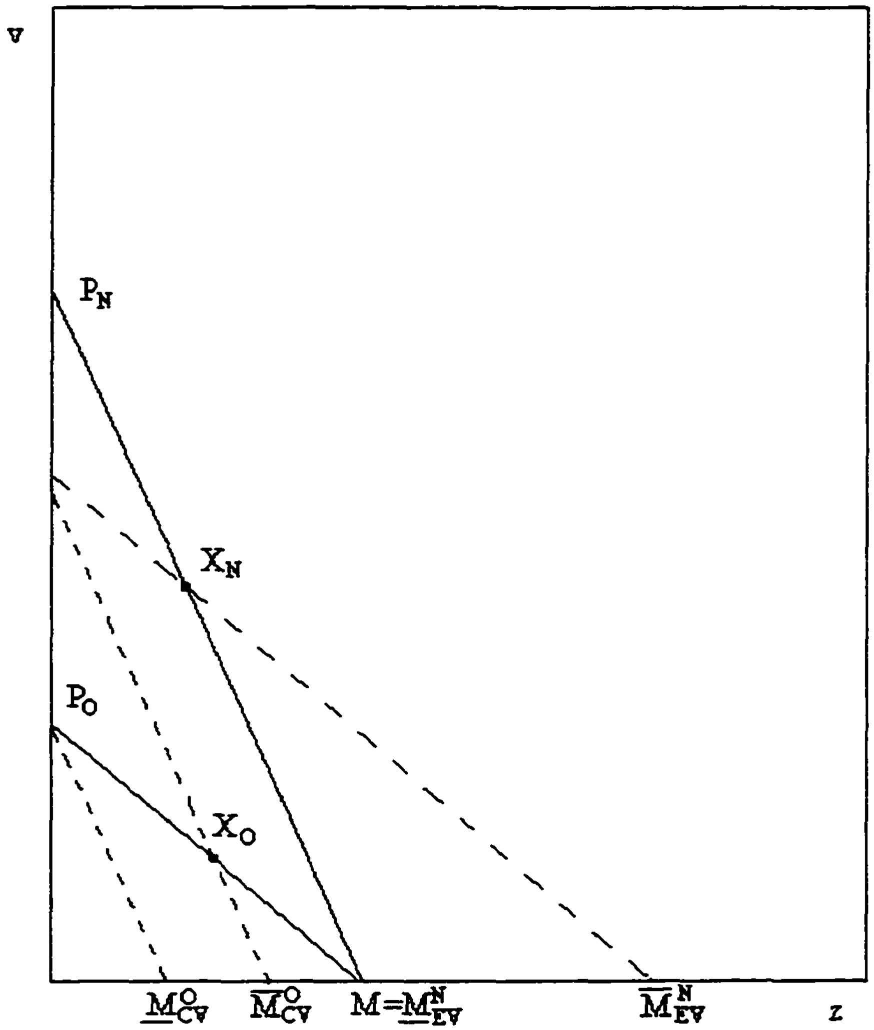

Figure 4.1: Expenditure Bounds

We now ask the question: What is the most amount of income we can take away from or give to this individual after a price change to be sure that he or she can attain the original level of utility? Suppose, as depicted in Figure 4.1, we are interested in the CV for a price decrease from P_0 to P_N where P_0 represents the budget constraint at the initial prices and P_N represents the new budget constraint.

We know the individual can at least attain his initial level of utility if he can afford his initial bundle. Thus, that amount of expenditure is the most he would ever need after the price change. In Figure 4.1, this upper-bound on expenditure is:

$$\overline{M}_{CV}^{O} = P_N X_O . \tag{4.2}$$

Graphically, $\overline{M}_{CV}^{O}$ can be identified as the vertical intercept of a straight line parallel to P_N that intersects X_0 (the dashed line through X_0 in Figure 4.1). If the consumer views v and z as perfect complements, $\overline{M}_{CV}^{O}$ is exactly equal to the expenditure necessary to attain the original level of utility at the new prices. However, if there is at least some substitution possible between v and z, the consumer could attain his initial utility level with less income than $P_N X_0$, thus $\overline{M}_{CV}^{O}$ represents an upper bound on necessary expenditure.

Following this logic, the least expenditure that could possibly be required to keep the consumer at the original level of utility after the price change would occur if the goods were perfect substitutes (i.e., straight line indifference curves). In this case, income can be taken away from or given to the consumer until he would pick the corner solution that minimizes expenditures. Graphically, the lower bound on expenditure can be identified by drawing a straight line parallel to P_N that intersects the vertical intercept of P_0, denoted $\underline{M}_{CV}^{O}$ in Figure 4.1.

Combining the upper and lower bounds on expenditure, we get bounds on CV:

$$B_{CV}^{O} \equiv \left\{ M - \overline{M}_{CV}^{O}, M - \underline{M}_{CV}^{O} \right\} \tag{4.3}$$

The superscript in the LHS and the expenditure bounds reflects the fact that these bounds are constructed knowing only a single data point (the original commodity bundle) Thus, the compensating variation for a price change can be bounded by the original expenditure minus $\overline{M}_{CV}^{O}$ and $\underline{M}_{CV}^{O}$. Note that the lower bound on expenditures determines the upper bound on CV and vice versa.

The proximity of CV to the bounds depends upon the degree of substitutability between the goods. If the goods are perfect substitutes, CV will exactly equal the upper bound. Conversely, if the goods are perfect complements, CV is exactly the lower bound.

Although it is clear that this procedure can be used to compute bounds on individual CV, such bounds will only be of interest if they are fairly narrow. Unfortunately, the bounds identified in equation (4.3) are unlikely to be tight. The next section describes how the addition of a second data point (price/quantity observation) can narrow these bounds.

Bounds Based on Two Data Points for Each Individual

In this section, we demonstrate how the bounds based on Varian's General Axiom of Revealed Preference can be improved by appealing to the properties of Hicksian welfare measures. Now suppose that in addition to knowing the optimal bundle chosen by the consumer at the original prices, the analyst also knows the optimal bundle chosen by the individual at the new prices. A second price/quantity vector might be obtained for an actual sample in at least two different ways. First, analysts might collect data on use over two seasons or time periods. In this case, the analyst would have two consumption bundles at two sets of prices based on revealed preference data. Alternatively, contingent behavior (stated preference) data could be combined with the revealed preference data to generate the second data point. In fact, a series of price/quantity combinations could be collected in a survey where respondents are asked how many visits they would take under a range of different prices of access to the good.

Regardless of the source of this second data point, the question of interest is: does the addition of this information help us tighten the bounds on CV for a price change from P_0 to P_N? The answer is yes, but the link is indirect and requires us to consider the equivalent variation (EV) for the price decrease. In particular, suppose that the consumer reveals to the researcher that X_N is (or would be) his chosen commodity bundle at prices P_N. This information allows us to compute bounds on the EV for the price change from P_0 to P_N. By appealing to the fact that the equivalent variation for a price decrease is greater than or equal to the compensating variation for the same price decrease, we can potentially tighten the upper bound on CV by using the upper bound on EV in its place.

Equivalent variation for the price decrease is defined as

$$\begin{aligned} EV &= e(P_0, U_N) - e(P_N, U_N) \\ &= e(P_0, U_N) - M. \end{aligned} \tag{4.4}$$

The second term on the RHS of (4.4) equals the consumers income so, again, if we can bound the first term, we can bound the equivalent variation.

To do so, again consider Figure 4.1. The exact EV could be obtained if we knew exactly how much money we would need to give the consumer at the initial prices (P_0) to achieve the utility at X_N. Now, the most that would be required to achieve this utility level is if the consumer could obtain bundle X_N at the original prices. Thus, if the consumer were given $\overline{M}_{EV}^{N} - M$ instead of the price change, we can be certain that he could achieve at least the same level utility as if the price change had occurred. Thus, $\overline{M}_{EV}^{N} - M$ provides an upper bound on the necessary compensation.

However, unless the consumer is unwilling to substitute any z for v, the consumer will be able to achieve the same level of utility as X_N provides at less than this level of compensation. What is the least amount of compensation that might allow the consumer to obtain the same utility as provide by X_N? If z and v are perfect substitutes and an interior solution is observed, the indifference curve between them would be a straight line and would be identical to the budget line defined by P_N. In this case, the consumer would need only his original income to achieve the new utility level. Thus, the lower bound on EV is simply $\underline{M}_{EV}^{N} - M = 0$. Unfortunately, a lower bound of zero is not particularly informative. Nevertheless, we can now bound EV as follows:

$$B_{EV}^{N} \equiv \left\{ \underline{M}_{EV}^{N} - M, \overline{M}_{EV}^{N} - M \right\} = \left\{ 0, \overline{M}_{EV}^{N} - M \right\}, \tag{4.5}$$

where the superscript "N" indicates that only the second data point is used to construct these bounds. We now use the bounds on EV to potentially help tighten the bounds on CV. Since EV for a price decline is greater than CV, we know that an upper bound on EV must also be an upper bound on the CV. Thus, we can use the lower of the two upper bounds derived via nonparametric methods to provide an upper bound on CV. The bounds on CV derived using information from both data points can be written

$$B_{CV}^{ON} \equiv \left\{ M - \overline{M}_{CV}^{O}, Min(M - \underline{M}_{CV}^{O}, \overline{M}_{EV}^{N} - M) \right\}. \tag{4.6}$$

The superscripts on B indicate that both points are used in inferring the bounds.

As something of an aside, note that bounds on EV can be similarly constructed and tightened by using information about CV. Specifically,

$$B_{EV}^{ON} \equiv \left\{ Max(\underline{M}_{EV}^{N} - M, M - \overline{M}_{CV}^{O}), \overline{M}_{EV}^{N} - M \right\}. \tag{4.7}$$

The improvement of the lower bound in this case also follows from the fact that the EV for a price decrease equals or exceeds the CV. Clearly this might tighten the bounds significantly as the lower bound of $\underline{M}_{EV}^{N} - M = 0$ is uninformative.

Both commodity bundles considered thus far have been located on one of the budget constraints corresponding to the two price vectors for which the welfare change is being assessed. In the next section, we consider whether further tightening of the bounds is possible if the analyst also knows what choices the consumer would make at intermediate price ratios.

Bounds Based on Three or More Data Points for Each Individual

Now suppose that the analyst knows yet a third price-quantity combination for each individual and suppose that that combination corresponds to a price ratio that lies between the initial and proposed price change. Can information about the commodity bundle that the consumer chooses at such a price ratio be used to narrow the bounds on CV (or EV)? The answer is yes: it can raise the lower bound under some circumstances and lower the upper bound in all cases.

To see how this point may raise the lower bound, turn to Figure 4.2 where we have depicted the original and new budget constraints (P_0 and P_N) and the corresponding optimal commodity bundles (X_0 and X_N). We have also drawn an intermediate budget constraint and an optimal bundle labeled X_1. Recall that to provide a lower bound on CV, we want to know what amount of income we can take away from the consumer and be sure that he can still attain the same level of utility with the new prices as at the original commodity bundle.

As drawn, knowledge that X_1 is the optimal commodity bundle at prices P_1 allows us to increase the amount of income that can be taken away from the consumer and still be sure that the original utility level is obtained, thus increasing the lower bound on CV. To see this, note that since X_1 is chosen at P_1 when X_0 was affordable, we know that X_1 represents a higher level of utility than X_0 and lies on a higher indifference curve than X_0. This, in turn, implies that if income were taken away from the consumer at the new set of prices (P_N) until the consumer could afford X_1, they would still be obtaining at least as much utility as at X_0. Thus, an expenditure level of $\overline{M}^{1}_{CV}$ is sufficient to ensure that the consumer is no worse off than the original utility level. Thus, we have an improved lower bound on CV and we can write our newly formulated lower bounds that are based on information from three data points as

$$LB^{ON1}_{CV} \equiv \left\{ Max(M - \overline{M}^{O}_{CV}, M - \overline{M}^{1}_{CV}) \right\} \tag{4.8}$$

Thus, we have succeeded in further decreasing the interval over which the true CV is contained. In like manner, lower bounds on the EV can be written

$$LB^{ON1}_{EV} \equiv \left\{ Max(\underline{M}^{N}_{EV} - M, M - \overline{M}^{O}_{CV}, M - \overline{M}^{1}_{CV}) \right\} \tag{4.9}$$

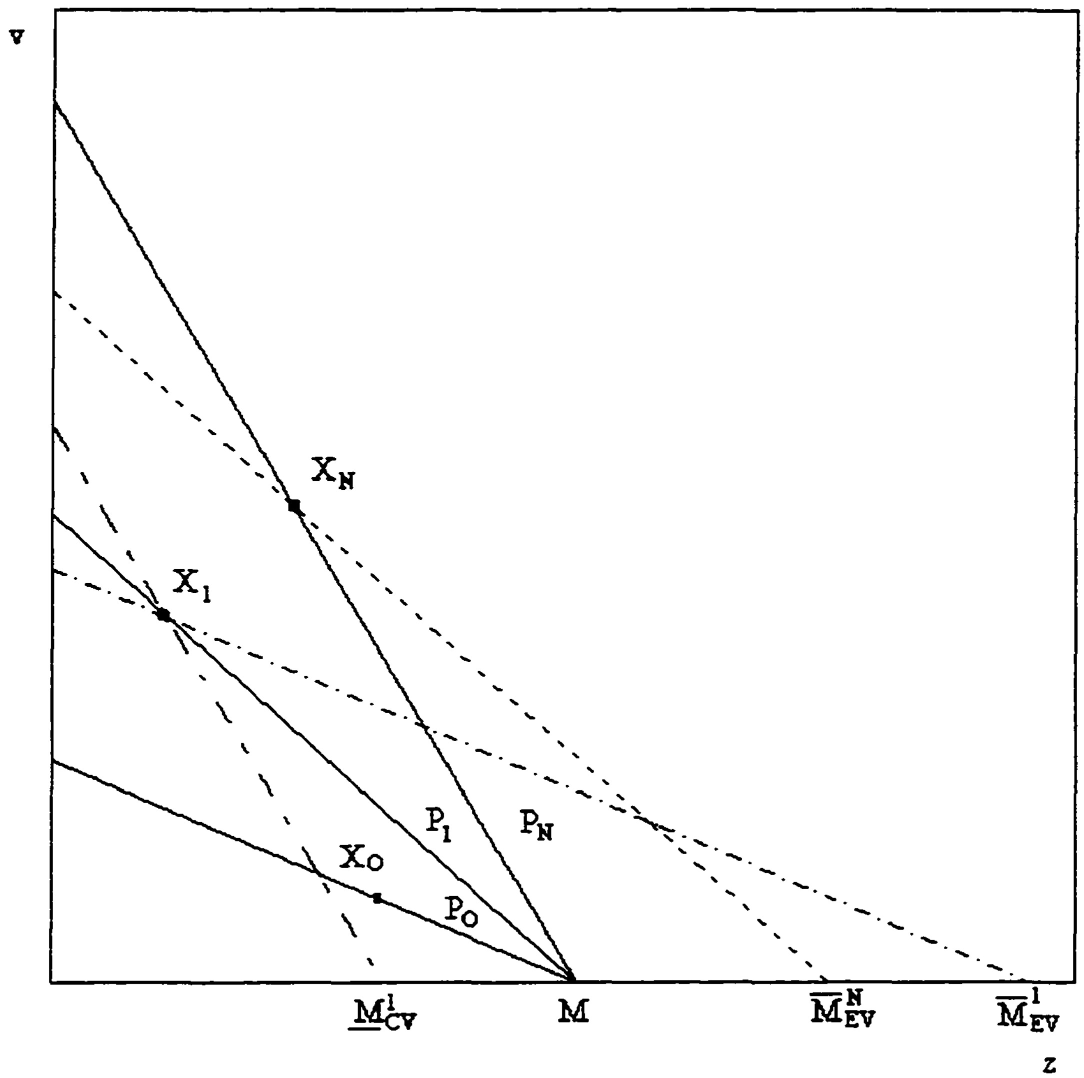

Figure 4.2: Expenditure Bounds with Multiple Data Points

At this point, it is important to point out that not all intermediate price ratios will provide information that can be used to raise the lower bounds. Graphically, the optimal commodity bundle associated with P_1 (X_1) must lie to the left of the line through X_0 with a price ratio of P_N. Otherwise, no improvement on the bound generated by $\overline{M}_{CV}^{O}$ can be computed. Consumption bundles that will tighten the welfare bounds will be generated only when the consumer's preferences generate backward bending offer curves such that the new consumption bundle is cheaper than the original bundle at the new prices.

The addition of this third data point can also lower the upper bound on CV. Specifically, with a third data point, the new upper bound can be written

$$(P_O - P_1)v_1 + (P_1 - P_N)v_N. \tag{4.10}$$

To demonstrate that (4.10) constitutes an upper bound, appeal again to the fact that the EV for a price decrease is greater than the CV for the same price decrease. From this fact follows the first inequality in (4.11)

$$\begin{aligned} e(P_0,U_0) - e(P_1,U_0) &\le e(P_0,U_1) - e(P_1,U_1) \\ &\le P_0 v_1 + z_1 - M \\ &= P_0 v_1 + z_1 - (P_1 v_1 + z_1) \\ &= (P_0 - P_1)v_1. \end{aligned} \tag{4.11}$$

The second inequality in (4.11) follows from the fact that the expenditure necessary to achieve U_1 at the initial prices (P_0) must be less than or equal to the expenditure that would be required to allow the consumer to purchase the commodity bundle that achieves U_1 at prices P_1. Based on identical reasoning, the following inequalities hold

$$
\begin{aligned}
e(P_1,U_0)-e(P_N,U_0) &\le e(P_1,U_N)-e(P_N,U_N) \\
&\le P_1 v_N + z_N - M \\
&= P_1 v_N + z_N - (P_N v_N + z_N) \\
&= (P_1 - P_N) v_N .
\end{aligned} \tag{4.12}
$$

Summing (4.11) and (4.12) yields

$$e(P_0,U_0)-e(P_N,U_0) \le (P_0 - P_1)v_1 + (P_1 - P_N)v_N , \tag{4.13}$$

which establishes the new upper bound. The reasoning can be extended indefinitely so that all additional data points will also lower this upper bound.

This new upper bound is strictly less than the potential upper bound determined by EV i.e.,

$$(P_O - P_1)v_1 + (P_1 - P_N)v_N < (P_O - P_1)v_N = P_O v_N - P_1 v_N + z_N - z_N = \overline{M}_{EV}^{N} - M. \tag{4.14}$$

It is now possible to write lower and upper bounds on CV associated with three data points

$$B_{CV}^{ON1} \equiv \left\{ Max(M - \overline{M}_{CV}^{O}, M - \overline{M}_{CV}^{1}), Min(M - \underline{M}_{CV}^{O}, (P_O - P_1)v_1 + (P_1 - P_N)v_N \right\} . \tag{4.15}$$

Adding information on individual's optimal commodity bundles at a variety of price ratios can tighten the nonparametric bounds on CV or EV for a price change. It is worth reemphasizing that these bounds assume no parametric assumption: regardless of the preferences of the individual, as long as they conform to the basic postulates of neo-classical consumer theory, the bounds provided must be accurate.[1]

Although their accuracy is certain, the ultimate value of these bounds depends on their width. Bounds that are very wide will provide too little information for a policy

---

[1] When working with real data, it will be necessary to worry about the implications of errors in consumer's optimization behavior or other reasons why the reported prices and/or quantities may contain random components.

analyst and will likely be passed over in favor of parametric estimates that provide at least the appearance of precision to those who use this information.

Next, we investigate the situations under which these bounds may generate relatively tight bounds on welfare change. In the next section, we focus on the effects of the degree of substitutability on the magnitude of the bounds. In the following section, we examine the improvement that additional data points generate for the bounds and the magnitude of the bounds relative to the point estimates and confidence intervals generated by parametric approaches to welfare estimation.

The Implications of Substitutability on the Magnitude of the Bounds

In the previous section, the lower bound on CV was seen to exactly equal the true CV when the two goods are perfect complements and the upper bound was exactly the true CV when the two goods are perfect substitutes. These results make clear that the accuracy of the bounds are affected by the degree of substitutability between the good whose price change is being evaluated and the numeraire. To further investigate the consequences of substitutability on the bounds, we consider a simple numerical example using a CES utility function where a range of substitutability conditions can be examined by varying the magnitude of a single parameter.

Consider the Constant Elasticity of Substitution (CES) utility framework

$$U(v,z)=\left(\alpha z^{\rho}+(1-\alpha)v^{\rho}\right)^{1/\rho},\ s\equiv\frac{1}{1-\rho}, \tag{4.16}$$

where, as before, z is the numeraire, v is the quantity of the environmental good, and s, ρ, and α are parameters.The CES is a convenient utility function to work with since the single parameter, s, determines the degree of substitutability between the goods.

Figure 4.3 plots the CV for a price decrease from \$30 to \$6 for a hypothetical individual using the CES utility function over a wide range of s. The parameter α is set to 0.75; thus, the individual has a relatively lower preference for the environmental good relative to the numeraire. The substitutability parameter, s, ranges from one to infinity and is plotted on the horizontal axis (when s=1 the CES framework generalizes to the Cobb-Douglas framework). The yellow line (starting just under \$20,000) plots the true WTP value given by the CES specification. The light blue and dark blue line (the dark blue is overlapped by the LB2 line) are the upper and lower bounds (respectively) on WTP when only the original consumption bundle is known.

If the analyst observes the consumption bundle at the proposed price change, the upperbound becomes the lesser of the light blue line and the dark purple line. Also, the additional data point gives us the light purple line as the new lowerbound. Clearly, this additional datapoint in the CES framework will not always tighten the nonparametric bounds. However, there is substantial potential. Adding the third datapoint (a consumption bundle at some intermediate price) does not raise the lowerbound in this example (recall that not all such intermediate points do so). Yet it does further reduce the upperbound (given by the brown line).

In figure 4.4, the parameter α is set to 0.25 to represent a situation where the individual highly desires the environmental good. This is evidenced by the higher value of WTP for the price decrease in the environmental good. Notice in this case that the additional datapoints help only for relatively high levels of substitutability. Further, in both figures WTP is shrinking as the substitutability parameter is increasing. This is due

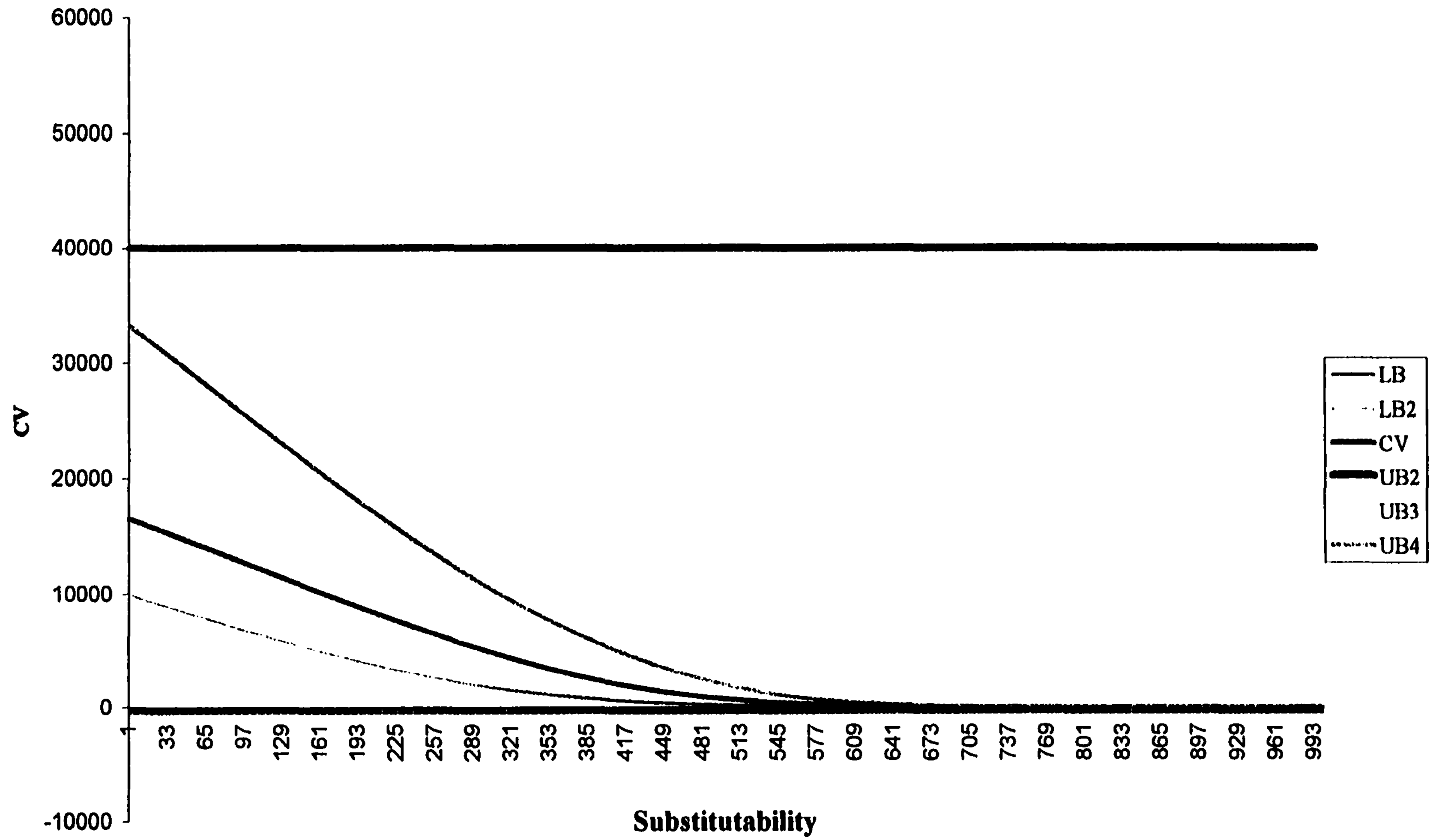

Figure 4.3: Nonparametric Bounds as a function of substitutability in a CES Framework
(LB and LB2 overlap for much of the range of substitutability)

to the fact that the initial commodity bundle changes at different values of s. In particular, as s gets larger the individual moves towards the corner solution that provides more of the cheaper good, in this case the numeraire good. However, by varying the parameter α, we can influence which corner solution they choose for the given price change.

Consider figure 4.5. In this diagram α=0.0025. As the substitutability parameter increases here, the individual moves towards the corner solution of all environmental goods. Thus, in this deterministic setting, we see that there is a threshold in the parameter settings that influence whether WTP will be rising or falling as the substitutability parameter increases. This threshold will be met for some value of α between (0.0025, 0.25).

In figure 4.3, the nonparametric bounds are strictly tightening as the substitutability parameter is increasing. This is not the case in figure 4.4. Instead the nonparametric bounds initially begin widening as the substitutability parameter begins increasing to some level. Then, as s becomes quite large the bounds begin shrinking.

Clearly, the deterministic experiment suggests that WTP for the price decrease depends largely upon the parameter values. From previous studies, we know that WTP differs greatly across utility specifications. However, we have also learned from this deterministic setting that the nonparametric bounds to have the potential to provide useful information on the magnitude of WTP despite being ignorant of the true utility framework at the individual specific level.

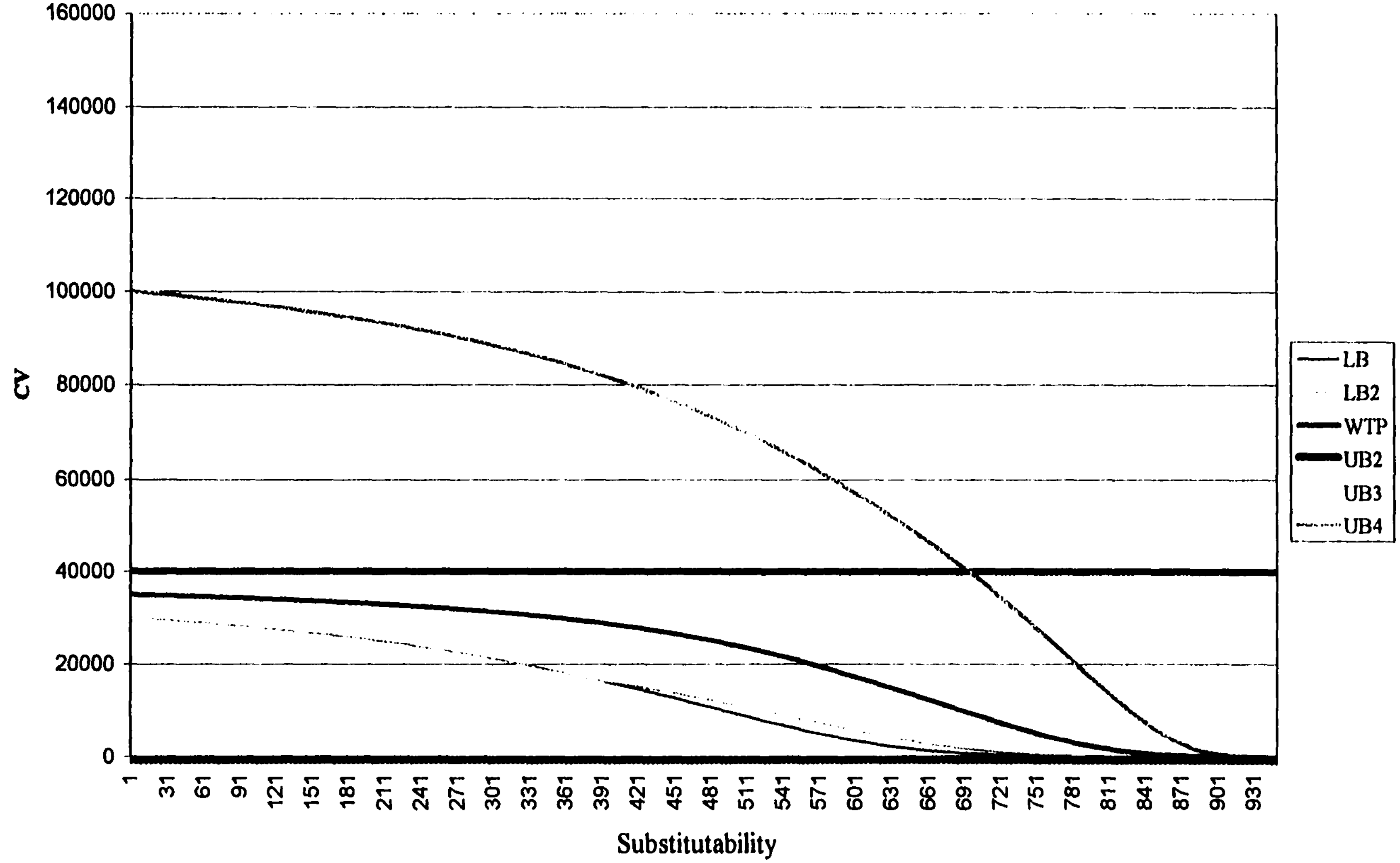

Figure 4.4: Nonparametric Bounds as a function of substitutability in a CES Framework

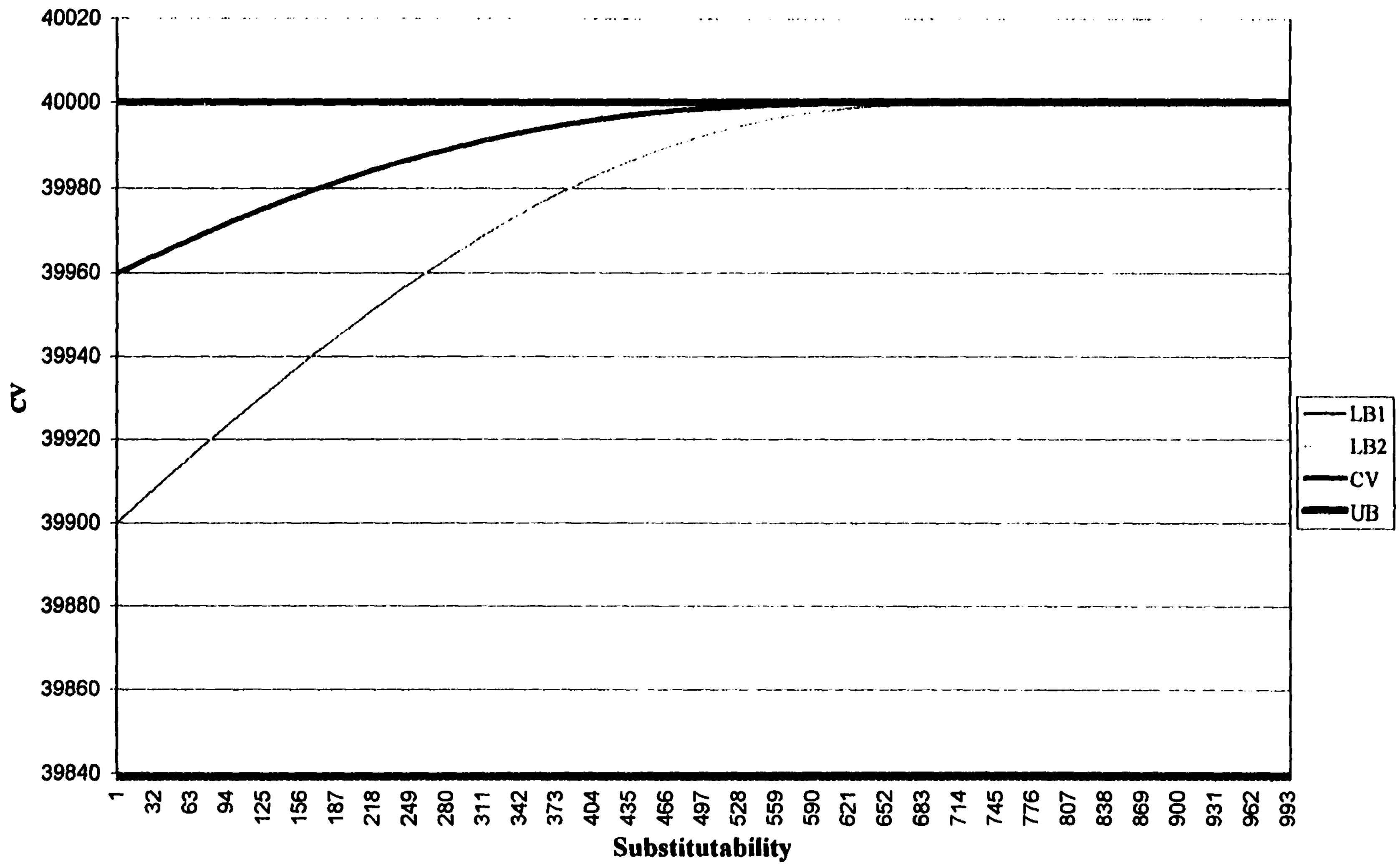

Figure 4.5: Nonparametric Bounds as a function of substitutability in a CES framework (LB1 and LB2 overlap)

The deterministic CES framework outlined above gives us insight into the potential of the bounds by allowing us to investigate the characteristics of utility that narrow or widen the bounds. However, this simple numerical exercise does not shed any light on the value of the nonparametric bounds relative to point estimates of welfare generated by parametric methods. If parametric methods can be accurately estimated and/or if the nonparametric bounds are quite wide, there is little reason to pursue research employing the nonparametric bounds. Alternatively, if nonparametric bounds are found to have the potential to be relatively narrow in practice and/or if parametric methods generate significant error in welfare measurement then nonparametric bounds may have an important role to play in welfare analysis

A Monte Carlo Study

Design of the Study

The purpose of the Monte Carlo experiment is to explore the feasibility of the nonparametric method, to gauge the performance of the nonparametric bounds, and to compare them to welfare estimates generated by traditional parametric methods. Thus, the Monte Carlo experiment is designed with these three questions in mind:

- How narrow can we expect the nonparametric bounds to be?
- How much does the addition of data points improve (tighten) the bounds?
- How do the nonparametric bounds compare to welfare estimates generated by parametric estimators?

To shed light on the answers to these questions, simulated data is generated by using two different utility functions. First, we employ a utility function that generates semi-log demands of the following form:

$$U=\frac{\beta+\gamma v}{-\gamma\beta}\exp\left[\frac{(\gamma(\alpha+\varepsilon)v-\beta z-R\ln(v))}{\beta+\gamma v}\right], \tag{4.17}$$

where, greek letters indicate parameters and v is the environmental good (for concreteness we now consider it to be recreation visits) and z is again the numeraire. The corresponding expression for the CV for a price change of the recreation good is

$$CV=-\frac{1}{\gamma}\left[\ln\left(-\gamma U^{0}-\frac{\gamma}{\beta}e^{\beta P+\alpha+\varepsilon}\right)\right]+\frac{1}{\gamma}\left[\ln\left(-\gamma U^{0}-\frac{\gamma}{\beta}e^{\beta P'+\alpha+\varepsilon}\right)\right]. \tag{4.18}$$

For the Monte Carlo experiment, the parameter values in the semilog utility function are set at $\alpha=2$, $\beta=-0.04$, and $\gamma=-0.00002$.[2] The stochastic error component is distributed $N(0,\sigma_{\varepsilon}^{2})$ and four different dispersion levels are examined: $\sigma_{\varepsilon}=0.25$, 0.50, 0.75 and 1.00.

The second utility framework employed in the Monte Carlo data construction is the CES function used in the numerical example above (equation (4.16)). An error term is introduced into the CES additively via the "α" parameter:

$$U=\left[(1-\alpha-\eta)v^{\rho}+(\alpha+\eta)z^{\rho}\right]^{1/\rho}, \tag{4.19}$$

where η~Uniform(-0.25,0.25). Then, the true form of recreation demand is given by

$$v=\frac{(1-\alpha-\eta)^{s}M}{(\alpha+\eta)^{s}P^{s}+(1-\alpha-\eta)^{s}P}. \tag{4.20}$$

We set the parameter $\alpha=0.75$. To examine the sensitivity of the results to the degree of substitution, we investigate four different values of s: s=0.5,2, 5, and 20. Finally, the expression for CV for a price change is

---

[2] These parameter values were chosen because they were employed in a previous Monte Carlo study (Kling, 1997) of recreation demand and they produce "sensible" looking numbers of visits.

$$CV = U^{*}\left\{P\left[(\alpha+\eta)^{s}P^{s-1}+(1-\alpha-\eta)^{s}\right]^{\frac{1}{1-s}} - P'\left[(\alpha+\eta)^{s}P'^{s-1}+(1-\alpha-\eta)^{s}\right]^{\frac{1}{1-s}}\right\}. \quad (4.21)$$

For each of the utility functions and parameter values, we generate 1,000 samples of 300 observations each. For each observation, the simulated price is randomly drawn from the uniform distribution on the interval (5,55). Also, income is randomly drawn from the uniform distribution on the interval (5000, 85000). Note that in the semilog monte carlo experiment our focus is on various dispersion levels whereas in the CES case we focus on alternative degrees of substitutability.

How Tight Are the Nonparametric Bounds and How Much Do Additional Data Points Improve the Bounds?

As demonstrated in the theoretical sections above, bounds on welfare measures can be constructed with a single data point, two data points, and three or more points for each individual. In the first part of the Monte Carlo experiment, we investigate how the addition of data points (observations) for each individual in the sample can narrow the bounds. Although the previous numerical exercise also shed light on this question, in the Monte Carlo setting, we can investigate the more typical situation of a complete sample of differing individuals. As mentioned earlier, one possible source for such additional observations is via contingent behavior. Although those who are suspicious of contingent valuation as a reliable valuation method may discount such data, some analysts may be more comfortable with behavioral contingent data than willingness to pay questions. For example, Bockstael and McConnell [7] have recently argued that:

> Such contingent behavior studies might not suffer from many of the problems encountered when asking values and they would be targeted towards people who "behave" in the context of the problem and who would presumably not find it

> difficult to imagine the behavioral changes they would make when faced with different prices, different qualities, different alternatives. (p. 29)

If contingent behavior is viewed as a reliable source of data and if nonparametric bounds can be constructed from this data that are sufficiently narrow to be of practical use, there might be a potentially compelling case for their use in place of parametric estimates. A Monte Carlo experiment where there is assumed to be no measurement error associated with the data is an ideal environment to shed light on this question. For, if the nonparametric bounds are too wide to be of policy interest in this setting, they can almost certainly be ruled out as a viable valuation strategy when the vagaries of real data are considered.

To assess the gains from adding contingent behavior data to a single observed data point for each observation (such as might be collected in a typical recreation demand study), we compute the nonparametric bounds for each Monte Carlo sample and average the lower and upper bounds. This process is repeated for each of the samples.

First, the upper and lower bound on CV for a price decrease associated with a single data point is computed.[3] This is equivalent to using the information an analyst might typically have from a travel cost type recreation demand study. For each individual in the sample, the analyst would know only how many trips the individual took during the time period and at what price. In the rows marked "Point O" of Tables 4.1 and 4.2, we report the bounds generated by such a procedure for both the CES and Semi-log utility functions. Results are presented for two different price changes: a 25%

[3] Since the CV for a price decrease is identical to the EV for the inverse price increase, the values in the tables can be interpreted as bounds on either measure; however, we will refer to it as a bound on CV for simplicity.

decrease and a 80% decrease. For the Semi-log demand function we report these bounds for four different values of σ_ε. For the CES, we report the bounds for four different values of s (the substitutability parameter).

As can quickly be seen, the range between the lower and upper bound is enormous in all cases and thus of no real value from an applied policy perspective. This is not surprising as a single data point per individual provides little information. In the rows marked "Point N", a second data point for each individual is used (along with the first) to form the bounds. This point corresponds to the quantity chosen by the individual at the "new" price, i.e., it corresponds to point "N" in Figures 4.1 and 4.2 from the theoretical discussion. With the introduction of this second point, the upper bound on the compensating variation drops dramatically in all cases.

In the rows marked "Point 1", the third data point is used to raise the lower bound and lower the upper bound as described in the theoretical section above. The third data point is generated by determining the quantity consumed at the midpoint price between the initial and final price in the welfare change. Although the gains in tightening the interval are not nearly as large as the addition of the second point, it is clear that valuable gains are possible. In the case of the semi-log utility function, the addition of the third data point never raises the lower bound. This occurs because the two goods (v and x) are not close enough substitutes to generate the necessary conditions for the tightening of the lower bound (see page 6). In contrast, for the CES utility function, the necessary conditions are satisfied in a number of instances, thus the addition of the third data point

Table 4.1: Semi-Log Utility

a. WTP for 25% reduction in price

Theoretical Bounds	σ=0.25		σ=0.50		σ=0.75		σ=1	
	I_L	I_H	I_L	I_H	I_L	I_H	I_L	I_H
Point O	128.94	11305	135.65	11305	153.17	11305	179.0	11305
Point N	128.94	142.86	135.65	163.07	153.17	199.69	179.0	265.00
Point 1	128.94	141.90	135.65	161.96	153.17	198.30	179.0	263.09
Point 2	128.94	141.27	135.65	161.23	153.17	197.39	179.0	261.83
Point 3	128.94	140.96	135.65	160.86	153.17	196.94	179.0	261.21

b. WTP for 80% reduction in price

Theoretical Bounds	σ=0.25		σ=0.50		σ=0.75		σ=1	
	I_L	I_H	I_L	I_H	I_L	I_H	I_L	I_H
Point O	432.47	37131	460.66	37131	507.31	37131	598.0	37131
Point N	432.47	521.72	460.66	594.44	507.31	729.52	598.0	959.33
Point 1	432.47	510.22	460.66	581.39	507.31	713.74	598.0	937.76
Point 2	432.47	502.80	460.66	572.73	507.31	703.28	598.0	923.90
Point 3	432.47	499.21	460.66	568.54	507.31	698.16	598.0	917.19

Table 4.2: Constant Elasticity of Substitution

a. WTP for a 25% reduction in price

Theoretical Bounds	**s=0.5**		**s=2**		**s=5**		**S=20**	
	I_L	I_H	I_L	I_H	I_L	I_H	I_L	I_H
Point O	7882	11450	98	11450	0.02	11450	0	11450
Point N	7882	10563	98	251	0.02	0.54	0	0
Point 1	7882	10035	98	224	0.02	0.41	0	0
Point 2	7882	9730	98	210	0.02	0.35	0	0
Point 3	7882	9581	98	204	0.02	0.33	0	0
True	8040	8389	130	188	0.04	0.28	0	0

b. WTP for a 80% reduction in price

Theoretical Bounds	**s=0.5**		**s=2**		**s=5**		**s=20**	
	I_L	I_H	I_L	I_H	I_L	I_H	I_L	I_H
Point O	25408	36882	313	36882	0.05	36882	0	36882
Point N	25408	36882	313	9569	0.05	627	0	90
Point 1	25408	36882	468	4330	1.26	174	0	23
Point 2	25408	36882	468	3628	1.26	164	0	23
Point 3	25408	36379	468	3500	1.26	163	0	23
True	28115	29205	1408	1914	9.96	42	0	1.37

both raises the lower bound and lowers the upper bound. However, even when the lower bound remains unchanged, the range between the lower and upper bound is small enough to be of use in certain policy situations.

In the rows marked "Point 2" and "Point 3", two additional price/quantity combinations are used to tighten the bounds. These combinations are determined by computing the midpoints between the point 1 price and the initial price and the final price, respectively. Again, the nonparametric bounds are potentially tightened by this additional information. The gains come primarily from lowering the upperbound on WTP. Essentially, each new data point will necessarily lower the upperbound as we are able to trace out the individuals demand function. If we learn of every commodity bundle the individual would choose for all intermediate prices, our upperbound on WTP would be precisely the individual's Marshallian consumer surplus. The individual's consumer surplus is the best we can do in deriving an upperbound on WTP for the price decrease in the nonparametric setting.

Our ability to raise the lowerbound hinges on the shape of the individual's offer-curve. Specifically, if the offer curve is backward bending for some intermediate price changes and we learn of commodity bundles chosen at these prices, then we may raise the lowerbound on WTP. A backward bending offer curve is a necessary but not sufficient condition for raising the lowerbound on WTP for a given price change. Unlike the case for lowering the upperbound, simply having additional intermediate commodity bundles will not necessarily raise the lowerbound. This is one reason we chose to examine the CES framework: we were assured of backward bending offer-curves. Recall that a backward bending offer curve implies that the substitution effect dominates the income effect.

These Monte Carlo results strongly suggest that with the addition of at least one more, and possibly several, data points, nonparametric bounds can be constructed that are narrow enough to be truly informative to a policy maker. Next, we consider how these bounds compare to parametric estimates generated by the same amount of information.

How Do the Nonparametric Bounds Compare to Standard Parametric Estimates?

For purposes of this portion of the Monte Carlo study, we assume that the researcher has access to a data set with three data points for each individual in the sample, corresponding to points O, N, and 1 from the previous section. Again, we have in mind that the researcher may have undertaken a contingent behavior survey to collect such data and we will again abstract from measurement error or other problems potentially associated with such data. Here we ask how well the researcher could do with such a data set in estimating CV using the nonparametric bounds relative to employing a parametric demand model (such as a typical travel cost type model).

For each sample, we estimate each of three parametric demand functions:

$$
\begin{aligned}
&\text{Log-linear:} && \ln(v) = \alpha + \beta \ln(P) + \gamma \ln(M) + \varepsilon, \\
&\text{Semi-log:} && \ln(v) = \alpha + \beta P + \gamma M + \varepsilon, \text{ and} \qquad (4.22) \\
&\text{Linear:} && v = \alpha + \beta P + \gamma M + \varepsilon,
\end{aligned}
$$

Where the greek letters again correspond to parameters. These demand functions were chosen due to their common use in recreation demand modeling. To estimate the models, we include all three data points for each individual that are used in constructing the nonparametric bounds. Thus, the original point plus the "contingent behavior" data are used in constructing both the nonparametric bounds and the parametric estimates. In this way, the parametric and nonparametric methods are both confronted with the same amount of information. To incorporate the fact that the three observations for each individual are not independent[4] (that is, $E(\varepsilon_{ij}\varepsilon_{ij}) \neq 0,\ j = 1,2,3$ where i indexes individuals and j indexes observations), we estimate the models in (4.22) using a standard Feasible Generalized Least Square Estimators to capture this correlation.[5]

After estimating each model, we calculate the average estimated CV for each functional form and do so for each of the 1000 repetitions. Next, we order the respective averages from smallest to largest and construct empirical 95% confidence intervals for each method.

To provide a benchmark against which to compare both the nonparametric bounds and the parametric estimates, we compute the true compensating variation for a proposed price decrease and average these over all individuals in the simulated samples and over the 1000 Monte Carlo trials. We also order the distribution of the 1000 sample average true CV's from highest to lowest and identify the fifth and ninety-fifth percentile of that distribution. This provides the 95% confidence interval for the true distribution against which the parametric confidence intervals and the nonparametric bounds can be assessed.

Table 4.3 contains the point estimates, confidence intervals, nonparametric bounds and true CV and bounds for the Semi-log utility function. Again, four different

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[4] In real data, the correlation across individuals may arise from omitted variables specific to individuals or any number of measurement problems. In our simulated data, correlation across individuals arises from the fact that individuals have different true parameters values from one another.
[5] Appendix 1 contains the derivation and explanation of the estimator.

standard deviations of the error are considered. We also report the average R^2's for the parametric estimates to provide a sense of the goodness-of-fit of the parametric models to the data (and thus how "typical" these scenarios might be).

First note that the nonparametric bounds are always (by construction) true bounds on the true intervals. In contrast, the parametric bounds are not. Interestingly, even the bounds generating the correct functional form (the semi-log reported in line three) often generate confidence bounds that are not true bounds in that estimated confidence intervals lie within the true intervals.[6]

It is perhaps most constructive to compare the nonparametric bounds with the semi-log demand function bounds. Using a parametric method, an applied researcher could expect to do no better than if he were using the correct functional form. As one might expect, the semi-log demand confidence intervals are tighter than the nonparametric bounds (although in a number of cases they are too tight!). However, even for relatively large price changes (80% decrease), the nonparametric bounds are relatively close generating intervals that are only about 33% wider than the semi-log demand intervals and 42% wider than the true intervals.

Table 4.4 provides the results for the CES utility function. In this case, there is no parametric demand function that is an exact match for the true demand function, although the log-linear represents a special case of the CES demand. In fact, this situation strikes us as the most accurate representation of the typical study.

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[6] This occurs because the semi-log model is misspecified in that the error enters additively in the demand function.

Table 4.3: Semi-Log Utility

a. WTP for a 25% reduction in price

Models	**σ=0.25**				**σ=0.50**			
	I_L	**AVG**	**I_H**	**R^2**	**I_L**	**AVG**	**I_H**	**R^2**
Linear TCM	136.0	140.2	144.5	0.70	143.7	153.5	164.4	0.37
Log-Linear TCM	135.1	139.3	143.6	0.70	142.2	152.6	163.3	0.42
Semi-Log TCM	135.6	139.9	144.2	0.78	142.9	153.1	164.3	0.47
Nonparametric	133.1		146.1		140.1		166.7	
True	135.2	139.9	144.4		142.3	153.1	164.6	

b. WTP for a 25% reduction in price

Models	**σ=0.75**				**σ=1**			
	I_L	**AVG**	**I_H**	**R^2**	**I_L**	**AVG**	**I_H**	**R^2**
Linear TCM	162.2	180.0	201.5	0.19	190.2	223.0	263.8	0.10
Log-Linear TCM	159.7	178.8	201.6	0.26	186.9	221.0	261.2	0.17
Semi-Log TCM	160.6	179.2	201.3	0.29	188.2	221.2	259.4	0.19
Nonparametric	158.1		205.7		184.4		268.6	
True	160.4	179.4	202.8		186.7	221.5	262.5	

Table 4.3: (Continued)

c. WTP for a 80% reduction in price

Models	σ=0.25				σ=0.50			
	I_L	AVG	I_H	R^2	I_L	AVG	I_H	R^2
Linear TCM	429.5	445.8	462.1	0.71	453.8	489.8	526.7	0.37
Log-Linear TCM	430.2	445.3	461.8	0.71	453.3	489.0	526.6	0.43
Semi-Log TCM	426.6	441.6	457.7	0.78	449.6	484.5	522.6	0.48
Nonparametric	405.6		474.6		429.2		541.8	
True	426.9	441.5	457.1		451.0	484.8	520.1	

d. WTP for a 80% reduction in price

Models	σ=0.75				σ=1			
	I_L	AVG	I_H	R^2	I_L	AVG	I_H	R^2
Linear TCM	502.9	572.9	643.8	0.19	589.8	707.1	851.7	0.10
Log-Linear TCM	504.2	571.5	642.4	0.26	591.0	700.6	827.2	0.17
Semi-Log TCM	494.4	565.2	633.6	0.29	584.8	690.5	809.9	0.19
Nonparametric	479.4		664.2		557.4		871.4	
True	502.0	564.9	631.8		581.3	690.6	813.1	

Again, there are a number of estimated confidence intervals that lie within the true intervals. Even more strikingly, in some cases (identified in the table in italics) the point estimates themselves lie outside of the true interval. Thus, by using a parametric point estimate an analyst might actually be reporting a welfare measure that is not even within the true 95% confidence interval. This of course is not news to applied researchers: incorrect functional forms are well known to potentially generate welfare measures with large error. More to the point is that an alternative that does not require the assumption of a particular functional form exists and generates ranges that, at least in some cases, are likely to be narrow enough for policy making.

As a final measure of the value of the nonparametric bounds, we compute the mean percent error associated with using the midpoint of the nonparametric bounds as an estimate of the average CV and compare these to the mean percent errors associated with the point estimates from the parametric models. Table 4.5 contains these results. Strikingly, the midpoint of the nonparametric bounds provides a mean percent error of the same order of magnitude as the parametric estimators. And, in two out of the three cases examined the midpoint generates the lowest mean percent error!

Nonparametric Bounds and Standard Parametric Estimators When the Population Preference Structure is Heterogeneous

An even more realistic situation than one in which recreationists have random parameters is one in which the population consists of individuals with different utility structures. To consider this situation, we allow the population we are sampling from to consist of individuals with both semilog utility and CES utility. Each type comprises

Table 4.4: Constant Elasticity of Substitution

a. WTP for a 25% reduction in price

Models	s=0.5				s=2			
	I_L	AVG	I_H	R^2	I_L	AVG	I_H	R^2
Linear TCM	6347	6519	6674	0.67	121	160	204	0.18
Log-Linear TCM	3786	5109	6981	0.92	70	101	160	0.25
Semi-Log TCM	5791	5924	6038	0.82	81	99	117	0.23
Nonparametric	7687		9352		89		181	
True	7839	8021	8183		118	142	167	

b. WTP for a 25% reduction in price

Models	s=5				s=20			
	I_L	AVG	I_H	R^2	I_L	AVG	I_H	R^2
Linear TCM	0.06	0.21	0.41	0.04	-85634	10965	146801	0
Log-Linear TCM	0.02	0.06	0.11	0.21	0	0	0	0.21
Semi-Log TCM	0.01	0.04	0.08	0.19	0	0	0	0.19
Nonparametric	0.02		0.22		0	0	0	
True	0.03	0.10	0.19		0	0	0	

Table 4.4: (Continued)

c. WTP for a 80% reduction in price

Models	**s=0.5**				**s=2**			
	I_L	**AVG**	I_H	R^2	I_L	**AVG**	I_H	R^2
Linear TCM	25864	26686	27469	0.48	2697	3640	4655	0.07
Log-Linear TCM	15183	16601	18086	0.92	538	633	747	0.37
Semi-Log TCM	19754	20214	20672	0.80	632	771	912	0.31
Nonparametric	23845		34185		450		3437	
True	26406	26936	27453		1355	1613	1872	

d. WTP for a 80% reduction in price

Models	**s=5**				**s=20**			
	I_L	**AVG**	I_H	R^2	I_L	**AVG**	I_H	R^2
Linear TCM	111	490	998	0.01	0.01	50.77	291	0
Log-Linear TCM	0.74	2.74	5.58	0.34	0	0	0	0.34
Semi-Log TCM	0.22	0.47	0.82	0.28	0	0	0	0.29
Nonparametric	1.48		289		0		72.94	
True	11.57	39.64	76.20		0	0.76	4.68	

50% of the population. The parameter values for the semi-log specification are as given above with σ_ε being 0.015625; 0.0625; and 0.125. For the CES framework the parameters are α=0.55, s=2.5 and η~U[-0.00125,0.00125].

Table 4.6 contains the results of this simulation experiment. Note in particular that despite the relatively high values of R^2, the parametric model's confidence intervals do not contain any of the true mean values of WTP. In contrast, the nonparametric bounds are true bounds and for this particular parametrization, the width of the nonparametric bounds are quite tight. We think these results provide a compelling case for further investigation of nonparametric methods.

Final Remarks on the Value of Nonparametric Bounds on Welfare

In this paper, we have presented simple methods for constructing nonparametric bounds on compensating or equivalent variation for price changes based on nonparametric methods. We began by adopting the methods developed by Varian and derived additional results allowing significant tightening of the bounds. These bounds have the potential to provide an alternative valuation method to standard parametric estimation of recreation demand. We also investigate the possible magnitude of these bounds using numerical examples and simulated data.

The ultimate usefulness of the bounds derived here will depend upon how tight the bounds can be constructed for real data and on whether the data necessary to compute such bounds can be obtained and deemed reliable. In our Monte Carlo analysis, we have demonstrated that there are situations under which the first of these conditions will hold:

Table 4.5: Mean Percent Error in Parametric Average Point Estimates and the Midpoint of the Nonparametric Bounds in the CES framework

Model	**Mean Percent Error**		
	s=2	s=2.5	s=5
Linear TCM	4.3%	17.5%	69.3%
Log-Linear TCM	-28.4%	-29.7%	-38.7%
Semi-Log TCM	-31.9%	-36.9%	-58.5%
Nonparametric Bounds	-8.0%	-10.2%	-16.0%

bounds constructed without reference to parametric demand specifications can yield intervals that are narrow enough for policy purposes. However, questions concerning the reliability of contingent behavior data or the possibilities of collecting time series data must await the confrontation of a real data set.

In addition, as we pointed out initially, the above prescribed methodology is valid only for a non-inferior good. That is, the income effect must be non-negative. In some cases, this may be problematic as empirical research on recreation goods has found evidence of negative income effects for certain resources. However, a closely related methodology can be developed that provides a tightening of the Varian bounds in this case. The difference stems from the reversal of the inequality between CV and EV for a price change in the case of an inferior good. Using this relationship, we could narrow the

Table 4.6: Model Performance with Heterogeneous Population Preferences

a. WTP for a 20% reduction in price

Models	**σ_ε=0.015625**				**σ_ε=0.0625**			
	I_L	**AVG**	**I_H**	**R^2**	**I_L**	**AVG**	**I_H**	**R^2**
Linear TCM	170.3	170.7	171.1	0.11	181.2	182.0	182.8	0.19
Log-Linear TCM	-1049	-823	-648	0.50	77.27	80.0	82.78	0.54
Semi-Log TCM	130.3	130.6	130.8	0.49	130.9	131.2	132.9	0.49
Theoretical Bounds	108.7	120.1	131.5		107.0	119.5	132.1	
True	125.4	125.7	125.9		124.5	125.4	126.2	

b. WTP for a 20% reduction in price

Models	**σ_ε=0.125**			
	I_L	**AVG**	**I_H**	**R^2**
Linear TCM	171.1	172.5	173.9	0.20
Log-Linear TCM	151.4	159.7	168.6	0.56
Semi-Log TCM	127.9	129.8	131.6	0.54
Theoretical Bounds	104.2	119.3	134.4	
True	124.6	126.2	127.6	

nonparametric bounds on WTP by considering the additional datapoints. The key difficulty with this divergence of methodology is that the analyst would need to make a decision regarding the income effect on an observation-by-observation level. A misclassification of one observation may cause the constructed nonparametric bounds to be incorrect for that observation. Propogating this dilemma throughout the dataset may leave the analyst with incorrect bounds on true WTP. However, this conflict is no less troublesome for parametric models, which impose a single parameter value for the income effect on the entire sample.

Nonparametric bounds on welfare measures for the case of non-inferior goods are appealing in that they require absolutely no assumptions about utility functions or error structures. They also do not require assuming that all individuals in a sample have the same preference structures or parameter values. Such liberty is heartening, but comes at a cost. Rather than being able to report precise-sounding estimates of welfare, bounds convey uncertainty. However, as the results of these Monte Carlo experiments suggest, the "certainty" conveyed by point estimates from traditional parametric estimators may be misleading.

The results using nonparametric bounds developed here constitute a first look at applying nonparametric methods to bound welfare measures for nonmarket goods. Based on the theoretical and simulated results presented here, we are optimistic that additional work in this area will yield large returns. The ability to provide policy makers with tight bounds on welfare measures for nonmarket goods that are free of functional form assumptions is an appealing proposition.

APPENDIX

FEASIBLE GENERALIZED LEAST SQUARES ESTIMATOR

Theoretically, it is likely that an individual's noise terms are correlated as we observe her chosen commodity bundles at various prices. Consider the individual's stated demand at prices P_1.

$$R(M,P_1) = X\beta + \varepsilon_1 \qquad \text{(A.1)}$$

While the individual has precise information concerning the number of trips she will take at price P_1, the researcher does not observe this information. Now, consider her demand at prices P_2.

$$R(M,P_2) = X\beta + \varepsilon_2 \qquad \text{(A.2)}$$

For this individual, it is reasonable to expect that:

$$E(\varepsilon_1\varepsilon_2) \neq 0. \qquad \text{(A.3)}$$

Thus, when we estimate the TCM, we should allow for this correlation. Note, it is still the case that individual t's error term is independent of individual j's error term. Also, it is reasonable to assume that each individual comes from the identical distribution. This implies that the correlation parameter is constant across the population. With these assumptions in place, we may now consider a Feasible Generalized Least Squares approach to estimating the TCM.

Formally, the previous remarks can be expressed as:

$\forall t \neq s, E(\varepsilon_{it}\varepsilon_{is}) = 0.$ and $\forall i, j; E(\varepsilon_{it}\varepsilon_{jt}) = \sigma_{ij}$ and

$$\Omega = E(\varepsilon\varepsilon') = \begin{bmatrix} \sigma_\varepsilon^2 I_n & \sigma_{12} I_n & \sigma_{13} I_n \\ \sigma_{12} I_n & \sigma_\varepsilon^2 I_n & \sigma_{23} I_n \\ \sigma_{13} I_n & \sigma_{23} I_n & \sigma_\varepsilon^2 I_n \end{bmatrix}. \tag{A.4}$$

The first subscript indicates which subsample the observation is from while the second subscript indicates the individual. As we can directly see in Eq. (A.4), each individual's decisions are correlated. The formulation of the TCM (for the case of a Linear Model) allows us to perform the following stacked-regression (Seemingly Unrelated Regression):

$$\begin{pmatrix} Y_1^* \\ Y_2^* \\ Y_3^* \end{pmatrix} = \begin{bmatrix} 1 & P_1 & M \\ 1 & P_2 & M \\ 1 & P_3 & M \end{bmatrix} \begin{pmatrix} \alpha \\ \beta \\ \gamma \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \varepsilon_3 \end{pmatrix}. \tag{A.5}$$

Step 1: Estimate $\hat{\beta} = (X'X)^{-1} X'Y$ and obtain $\hat{\varepsilon}_1, \hat{\varepsilon}_2, \hat{\varepsilon}_3$. (A.6)

Step 2: Construct: $\hat{\Omega} = \begin{bmatrix} \hat{\sigma}_\varepsilon^2 I_n & \hat{\sigma}_{12} I_n & \hat{\sigma}_{13} I_n \\ \hat{\sigma}_{12} I_n & \hat{\sigma}_\varepsilon^2 I_n & \hat{\sigma}_{23} I_n \\ \hat{\sigma}_{13} I_n & \hat{\sigma}_{23} I_n & \hat{\sigma}_\varepsilon^2 I_n \end{bmatrix}$, (A.7)

where

$$\hat{\sigma}_{ij} = \frac{\sum_{t=1}^{n} \left\{ \left(\hat{\varepsilon}_{it} - \frac{1}{n} \sum_{s=1}^{n} \hat{\varepsilon}_{is} \right) \left(\hat{\varepsilon}_{jt} - \frac{1}{n} \sum_{s=1}^{n} \hat{\varepsilon}_{js} \right) \right\}}{n-1} \tag{A.8}$$

Step 3: Estimate: $\hat{\beta}_{FGLS} = \left(X'\hat{\Omega}^{-1}X\right)^{-1} X'\hat{\Omega}^{-1}Y$. (A.9)

Step 4: Estimate CV using the parameter estimates from Step (3).

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IMAGE EVALUATION TEST TARGET (QA-3)

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