The use of economic analysis for water quality improvement investments

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Chapter 5:
Parametric and Non Parametric Approaches to Contingent Valuation Methods

5.1. Introduction

In Chapter 4 we illustrated an array of valuation methods being used to estimate benefits from non-marketed goods. One of those methods, CVM, is an increasingly respectable and common way of estimating the benefits of environmental projects. CVM involved directly asking people about their willingness to pay (WTP) for the environmental effects to be provided by the project. Since it may include nonuse values, it may be one's only alternative method for estimating use and nonuse values, especially for goods not traded in markets. Also, CVM is the only technique that measures Hicksian surplus directly, without requiring additional manipulation.

Two broad alternative ways of asking the valuation question are available: "open-ended," in which the respondent can name any amount s/he wishes when asked some version of "What are you WTP?", and "dichotomous choice" (referendum or yes/no) in which the respondent is asked: "Are you willing to pay (at least) $ (per period)?" There is a vast and rapidly growing literature on these methods, especially the problems that arise in creating successful survey instruments, obtaining satisfactory response rates, and interpreting responses (See Chapter 4).

An ambitious attempt to assess the usefulness of the method and to suggest ground rules for future application was made by the National Oceanic and Atmospheric Agency (NOAA) in the U.S. in the early 1990s. This effort involved a panel of distinguished economists, and the panel's report (NOAA 1993) has been very influential. In particular, and most relevant to this study, the panel recommended that CV studies be done using yes/no referendum format questions. This recommendation has been adopted by many practitioners who deal with real world program or project evaluation.

The referendum CV approach opens a new and substantial source of uncertainty in benefit estimation. That source is the choice of econometric technique and subsequent calculation rules used to translate yes/no responses (referendum format) into mean or median WTP numbers. In project analysis this source of uncertainty is easily overlooked. Under the referendum format it is not possible to know the true WTP of any individual directly. Because those who answer in the affirmative might actually be willing to pay even more, and those who answer in the negative might be willing to pay something less, econometric techniques have to be brought to bear to somehow interpolate and infer an expected value or other central tendency measure from the dichotomous choice information. Simplicity of data analysis was sacrificed in the referendum method in order to construct what many felt was a more realistic choice game.

In consequence, the notion that contingent valuation experiments of the referendum type can reveal a unique number which accurately and unambiguously represents individual willingness to pay for water quality improvement is unrealistic. Rather, there are several possible numbers, each dependent upon the way the initial survey was designed and administered and the way the resulting raw data was passed through the summarizing econometric sieve and reconstituted in the form of a central tendency measure. In short, such estimates are always uncertain when we acknowledge the existence of many routes that potentially can be taken to get at them and the several decision alternatives present at each step along the way. This is not a counsel of doom, or a suggestion that Cost-Benefit (CB) analysis based on referendum CV not be undertaken. But it is a fact that any benefit estimate to a greater or lesser degree is always a product of the analyst's protocol and judgment, something respectable analysts recognize and communicate to the users of their results.

There are basically two routes to analyzing referendum data[105] (Carson and Hanemann 2005). The one most frequently pursued by project economists which relies on economic theory involves several steps, beginning with the specification and statistical estimation of one or more probability models of individual choice, employing prior assumptions about the form of the inverse distribution (parametric methods), and the covariates belonging in the distribution which serve to change its location and shape across respondents. This is followed by the evaluation of conditional mean or median formulas derived from the choice model, which depend on its estimated parameters. For the parametric methods the maximum likelihood is emphasized as applied to referendum data associated with qualitative dependent variable models. After calculating individual specific means or medians, averages are taken over the entire sample to produce global central tendency measures. A less frequently

105 Other forms such as semi-nonparametric, in which the restrictions of the standard parametric models are relaxed, relying instead on flexible approximations to the unknown distribution of preferences, or semi-parametric, which imposes restrictions on the model, not on the form of the estimator, have been proposed (for semi-nonparametric see Crooker and Herriger 2004; Creel and Loomis 1997; Chen and Randall 1997.For semi-parametric see Belluzo 2004a and 2004b; Sanz et al. 2003; An 2000; Horowitz 1998; Powell 1994). Since the purpose of this study is to elucidate the uncertainty in expected willingness-to-pay from a battery and fairly robust methods and the numbers of estimates that can be derived from parametric and nonparametric are substantial and substantiated by many authors, we will not discuss semi-nonparametrics or semi-parametrics here.

traveled but much easier route ignores covariates and does not specify any particular inverse distribution. Instead it uses all the data in pooled form (i.e. the marginal distribution) to produce nonparametric measures of central tendency. Nonparametric approaches let the data speak for itself without imposing any assumptions about the data (Haab and McConnell 2002).

Carson and Hanemann (2005) identify several issues that arise with both methods (parametric and nonparametric) for which the research will have to make a decision on: (a) allowing (or not) for negative WTP amounts; (b) allowing (or not) zero WTP for the good; (c) ensuring that the WTP distribution exhibits weak monotonicity as the monetary value increases; (d) determining how smooth the WTP distribution has to be away from zero; and (e) how to deal with the right-hand tail of the response probability distribution (truncation as monetary value approaches income).

The remainder of this chapter is organized as follows. Section 5.2 will provide the mechanics with referendum data and Random Utility Models (RUMs) (parametric approaches). The advantages and limitations of this method will then be depicted. Section 5.3 will introduce the nonparametric approaches in CVM. The final section will provide some concluding remarks prior to implementing these methods in an applied case (Chapter 6).

5.2: Mechanics with Referendum Data and Random Utility Models (Parametric Approaches)

Consider an individual who must decide whether to answer yes or no to the following: *Would you vote for a program to increase environmental quality from q0 to q1 if it would decrease your annual income by $?*

Let the indirect utility function be u(Y,q,X) where Y represents income, X is a vector of individual characteristics and the vector of market prices P is omitted since prices are assumed to be constant.

The individual responds yes if:

$u(Y\ B, q^1, X) \quad u(Y, q^0, X) \geq 0$ (5.1)

and no otherwise.

Let h(•) be the observable component of utility. Here h represents and indirect utility function which in statistical estimation is often called the index function or utility index, denoted as the summed product of the parameter estimates and the explanatory variables, Xβ (Greene 1997). The probability of a "yes" response is given by:

$$P_1 = P[h(Y – B, q^1, X) + \varepsilon_1 > h(Y, q^0 , X) + \varepsilon_0] \quad (5.2)$$

Where εi(i= 0,1) are independent, identically distributed random variables with zero means and the error term represents influences on utility not observed by the analyst, or just random error in the choice process itself[106]. Equation (5.2) is the point of departure for all random utility described below. Given that the error term posses these characteristics, two widely used distributions are the normal and logistic[107]. Assuming the error difference follows a Logistic distribution[108], the probability of a "yes" response can be expressed as an estimable random utility (difference) model, or RUM:

$$P_1 = e^{\Delta h} / (1+ e^{\Delta h}) = (1 + e^{-\Delta h})^{-1} \quad (5.3)$$

Where $\Delta h = h^1 – h^0$ and h^0 represents the initial indirect utility function and h1 is the indirect utility function reflecting the decrease in Y by B and the increase in environmental quality from q^0 to q^1. The linear utility difference index Δh in the "no income effects" RUM is usually specified as a function of the bid level, B, and a set of socioeconomic variables, S, including a constant term (α_1-α_0) but not including income as an argument (i.e. $\Delta h = (\alpha_1-\alpha_0)+ \beta B + \zeta S$). This most basic of specifications imposes the assumption of a constant marginal utility of income, which simplifies recovery of an expected value for WTP.

106 This assumption describes most distributions used (Haab and McConnell 2002).

107 In this study we will discuss the logistic distribution; the distribution used in the case study. The primary reason for this is that the use of the normal distribution (untruncated) allows for the possibility of negative values of expected willingness to pay, invalidating the conventional welfare definition of compensating variation in utility theory, which is linked to willingness to pay. There is a vast literature on whether we could accept negative willingness to pay, for a change in the quality of a good and for ways of dealing with the issue. See Hanley (2009), Haab and McConnell (2002 and 1997), Bohara (2001); Hanemann and Kriström (1995), and Hanemann (1991). "For most problems addressed by contingent valuation, negative willingness to pay is simply wrong. Contingent valuation typically deals with public goods or public dimensions of private goods. For most public goods, negative willingness to pay is not correct because the good can simple be ignored if it does not provide utlity to the respondent. Frequently, negative estimates of willingness to pay are a consequence of statistical fit and functional form, not true preferences." (Haab and McConnell p. 253, 1997b). Some authors advise the use of distributional assumptions that rule out negative WTP by bounded or truncating it at some level (zero at the left of the tail and some upper limit, usually the largest bid amount used in the study or income level amount at the right tail (see Carson and Hanemann 2005; Carson et al. 2003; Bateman et al. 2003; Buckland et al. 1999; Ekstrand and Loomis 1998; Duffield and Patterson 1991).

108 The logistic regression is the natural way to analyze dichotomous choice data (Carson and Hanemann 2005; Haab and McConnell 2002; Buckland et al. 1999; Ready and Hu 1995; Bishop and Heberlein 1979).

By reversing the sign on the probability difference, we get the expression for the probability of rejecting the offer:

$P_0 = (1 + e^{\Delta h})^{-1}$ (5.4)

We define the willingness to pay for q^1 (WTP) by the amount of money that must be taken away from the individual enjoying an improved amenity level, q^1, that leaves he/she as well off as the initial amenity and income situation. This is the Hicksian Equivalent variation measure.

$u(Y\ WTP, q^1) = u(Y, q^0)$ (5.5)

and

$h(Y – WTP, q^1) + \varepsilon_1\ \ \varepsilon_0 = h(Y, q^0)$ (5.6)

Because of the term $\varepsilon^1\ \varepsilon^0$, WTP is a random variable. Then, the probability of accepting the offer is also the probability that WTP ≥ B, and the probability of rejecting the offer is the probability that WTP < B. This is a cumulative distribution function and can be denoted as F(WTP). As pointed out by Hanemann (1984), the truncated expected value of the random variable (WTP) can be found from the cumulative density function as follows:

$$E[WTP] = \int_0^{\infty} [1 - F(WTP)]dWTP \quad (5.7)$$

Here, the integration is only over positive values of WTP, because if there is utility improvement, WTP theoretically cannot be negative (although it can depend on who you ask and how the question is phrased) (Carson et al. 2003; Bateman et al. 2003). Similarly, the untruncated expected value of the random variable (WTP) can be found from the cumulative density function:

$$E[WTP] = \int_0^{\infty} [1 - F(WTP)dWTP - \int_{-\infty}^{0} [F(WTP)]dWTP \quad (5.8)$$

The latter, treating the negative domain of WTP as admissible, will generally be less than or equal to the truncated WTP represented by the first term in the above expression (Johansson et al. 1989).

Table 5.1. Formulae for Central Tendencies from the Probability Model

Description	Symbol	Equation
Mean, E(WTP), ∞ < WTP < ∞	C+	α/β
Median WTP	C*	α/β
Truncated Mean, E(WTP), 0 < WTP < ∞	C'	ln (1+exp (α))/β
Truncated Mean, E(WTP), 0<WTP<B_{max} where B_{max} is the maximum bid	C~	1/β ln[(1+exp(α))/(1+exp(α βB_{max}))]
Truncated Mean, Log Transform, E($exp^{ln(WTP)}$), ∞ < lnWTP <∞ (utility difference logit, log of bid, 0 Lower Limit, No Upper Limit)	C^{+}_{ln}	exp(α/β) [(π/β)/(sin(π/β))] (Only applies if 0 <1/β<1, otherwise numerical approximation required)
Truncated Mean, Log Transform, E($exp^{ln(WTP)}$), ∞ < lnWTP <ln Income (utility difference logit, log of bid, 0 Lower Limit, Income Upper Limit)	$C^{\sim}_{ln}$	No Analytic Expression–Requires Numerical Approximation
Truncated Median, Log Transform	C^{*}_{ln}	exp(α/β)

For the logit probability model[109], Hanemann (1984, 1989) and Ardila (1993) provide the WTP formulas shown in Table 5.1 for the unrestricted expected value, the median, and the truncated expected value that restricts WTP to be positive. The α term in the table is shorthand for an augmented intercept absorbing the estimated constant and the socioeconomic variable influences on Δh (α equals (α_1 α_0)+ ÇS). The letter C in the table is shorthand for the central tendency measure of WTP, following the notation of Hanneman (1984), the original source. In models with several explanatory variables, the parameter α can be replaced by an augmented intercept, using the coefficient estimates evaluated at the means of the independent variables, except of course, the bid price, β[110].

The parametric route can quickly become quite complex, producing a wide array of central tendency estimates. It is not uncommon to find instances where predicted WTP can vary from low to high by a factor of two, five or ten with the same data (see Chapter 6), depending on the analyst's choice of density function, the specification of the functional form of the indirect utility index and its arguments, and whether a mean, a truncated mean, or a median is

109 The most widely used parametric distribution is the logistic function (in linear and log form). Other distributions used but less popular are the normal, Haneamann's (1984) variant of the logistic model, which includes income effects, McFadden's (1994) flexible model, the Gamma, and the Weibull (for additional details on these distributions see Carson forthcoming, 2007, and 1997; Carson and Hanemann 2005; Carson et al. 1995; Kerr 2000; Hazilla 1997; McFadden 1994; Hanemann 1984)

110 The augmented intercept, α, referred to in Table 5.1 is simply the original intercept (for purposes of this note call it β_0) plus the rest of the i=1...n 1 parameter estimates other than the bid parameter estimate multiplied by the respective sample means of the explanatory variables X_i. The β attached to bid in Table 5.1 is, in this notation, equivalent to βn.

used. In short, with referendum data there are a host of possible measures of central tendency of willingness to pay.

In order to estimate WTP we have to estimate the probability of accepting or rejecting the offered price as a function of the price itself and some socioeconomic variables that shift the indirect utility function (Δh above). As stated above, when using parametric approaches, economists have preferred the use of Logit and/or Probit models.

Once the parameter estimates have been obtained, a WTP compensating variation measure that conforms to demand theory can be derived (Hanely et al 2001). For the Logit probability model, Hanemann (1984) and Ardila (1993) provide the WTP formulas shown in Table 5.1 for the unrestricted expected value, the median, and the truncated expected value that restricts WTP to be positive.

Given the theoretical underpinnings of the conventional random utility model (RUM) sketched above, it is necessary to recognize that when the RUM is specified as a Logit model with a linear utility difference index specification, a fundamental contradiction arises because the Logit potentially allows predicted willingness to pay to fall between minus and plus infinity, admitting the possibility of negative values (Haab and McConnell 2002; 1998a; 1998b; 1997a; 1997b). Negative WTP should be ruled out for well conceived environmental improvements, as should expected payments exceeding actual income[111]. The expedients for guaranteeing satisfaction of one or both of these limits by evaluating the linear utility index model estimated with Logit or Probit from zero bid to either plus infinity or income (truncated means), or by forcing the estimated density to lie in the positive region by using the logarithm of bid rather than the untransformed bid in estimation, leave a great deal to be desired. They are just ad hoc fixes to the conventional random utility model's fundamental specification error of an unrestricted error term.

111 This is strictly true only if the answer supplied reflects an understanding that payments for the good offered are to be taken out of current income without drawing down savings or liquidating other forms of wealth. It is unlikely that low income survey respondents (who usually dominate CV surveys taken in developing countries), would either have assets to pledge or be willing to pledge them in excess of current income when valuing a non unique environmental good like water quality improvement. However, the preservation of unique natural assets may evoke contributions in excess of income, especially among the upper strata, and especially if the question is posed as a one time payment rather than a series of payments strung out over several years

Although it was originally discussed in the late 1980s (Johansson et al. 1989; Hannemann 1989) the issue was brought more fully to light by Haab and McConnell (1998a and 1998b). The latter suggest employing a beta distribution for the density of willingness to pay to consistently hold WTP between zero and some upper bound such as income. The same authors, in 2002 proposed an alternative way to achieve a similar restriction by bounded Probit (or Logit) estimation (Haab and McConnell 2002).

Rather than starting from a RUM model specification, Haab and McConnell (2002) start at the other end with an expression for WTP that represents the amount of income the individual is willing to pay, expressed as the product of income and a proportion of income lying between zero and one. Somewhat analogous to the conventional RUM, the proportion is estimated as a function of the bid amount and other socioeconomic variables but the bid-related variables disappears when predicting the median proportions[112].

While this approach makes no claim to being consistent with any theoretical indirect utility function, it solves the practical problem of finding a non-zero WTP that at the same time will not exceed income. Haab and McConnell suppose the WTP lies between zero and some upper bound, A, such that:

$$Median(WTP_i) = \frac{A_i}{1+e^{-Xi\beta-\varepsilon i}} = p(\varepsilon_i)A_i \qquad (5.9)$$

where $p(\varepsilon i) = 1/(1+e^{-X(i)\beta-\varepsilon(i)})$ falls in the (0,1) interval, $\varepsilon_i \sim N(0, \sigma^2)$, $X_i\beta$ is the inner product of the J covariates ($X_i = X_{i1}......X_{iJ}$) and a vector of coefficients β and Ai is a known constant for individual I, such as income, which is assumed to be a reasonable upper bound on willingness to pay. When Ai is interpreted as income, equation (5.9) shows that WTP goes to zero for very large negative errors of $X_i\beta$ and to income with very large positive errors of $X_i\beta$.

If the ith respondent is asked "Would you pay 'B_i' for a proposed water quality improvement?" the probability of a no response is the probability that willingness to pay would be less than Bi, Haab and McConnell write this as:

$$VTP_i < B_i) = P\left(\frac{A_i}{1+e^{-X_i\beta-\varepsilon_i}} < B_i\right) = P\left(\frac{\varepsilon_i}{\sigma} < \frac{-\ln\left(\frac{A_i-B_i}{B_i}\right) - X_{i}}{\sigma}\right. \qquad (5.10)$$

112 The remainder of this section is drawn directly from parts of Haab and McConnell's papers and book.

when εi is distributed N(0,1), the last expression on the right hand side is the contribution to the likelihood function for a standard probit model where the probability of a 'no' response is modeled with the covariates X_i and ln $[(A_i-B_i)/Bi]$. Similarly, the probability of a 'yes' response becomes:

$$P(WTP < B_i) = P\left(\frac{\varepsilon_i}{\sigma} < \frac{\ln\left(\frac{A_i - B_i}{B_i}\right) + X_i\beta}{\sigma} \right) \quad (5.11)$$

Combining (5.10) and (5.11) results in a standard probit model with Xi (including a constant) and ln $[(A_i-B_i)/B_i]$ as covariates. The estimated coefficient on X_i will be an estimate of β/σ and the estimated coefficient for ln $[(A_i-B_i)/B_i]$ will be an estimate of 1/σ. The unscaled βs can be recovered by dividing the estimates of β/σ by the estimated parameters 1/σ attached to the construction variable ln $[(A_i-B_i)/B_i]$. The median WTP for each individual is then obtained by setting εi in (5.9) to zero because that is the value that splits the symmetric error distribution in half.

(17) $$Median(WTP_i) = \frac{A_i}{1+e^{-X_i\beta}} = p(\varepsilon_i)A_i \quad (5.12)$$

There is no closed form analytical solution for the expected value of WTP (mean) in the bounded probit or logit formulation so it must be found by numerical integration (Haab and McConnell 1997a). The general form of expected willingness to pay is given by:

$$E(WTP_i) = \int_{-\infty}^{\infty} WTP(X_i\beta, \varepsilon) f(\varepsilon) d\varepsilon \quad (5.13)$$

The integral in (5.13) ca be approximated by:

$$E(WTP) \approx \sum_{k=1}^{n} (1/\sigma)\phi \frac{\varepsilon_k}{\sigma} WTP(X_i\beta, \varepsilon_k)(\varepsilon_k - \varepsilon_{k-1}) \quad (5.14)$$

where Φ(·) is the standard normal pdf, εk are points on the distribution support of ε and n is large enough so that the approximation is smooth.

The technique for this numerical integration as it applies to mean estimates from CV studies is now described.

The mean E(x) of a continuous random variable x with a cumulative distribution function F(x)[113] and probability density function f(x) –which is the first derivative of F(x) w.r.t. x- is given by:

$$E(x) = \int_{-\infty}^{+\infty} xf(x)dx \quad (5.15)$$

The problem is to use a discrete approximation to (21) above to compute:

$$E(x) = \sum_x xf(x) \quad (5.16)$$

where the range of x is approximately minus to plus infinity for the untrancated mean and zero to some upper limit xmax for the truncated mean.

The fundamental theorem of the calculus tells us that the area under a curve f(x) between the limits x_1 and x_2 is (i) the sum of a number of infinitesimally small subdivisions in x of length n; (ii) the definite integral of f(x) between the limits; or the difference between the integral F(x) evaluated at x_1 and x_2:

$$\lim_{n\to\infty}\sum_{i=1}^{n} f(x_i)\Delta x_i = \int_{x_1}^{x_2} f(x)dx = F(x_2) - F(x_1) \quad (5.17)$$

We know the value of F(x) for any bid x from the bid group proportions. Therefore, we can split the x range into "small" intervals and sum the means from each small interval to get the grand mean. That is, the contribution to the overall mean from the approximate mean within any bid group interval is the product of some x within the interval (i.e. the lower limit, x_1, the upper limit, x_2, or some arbitrary value of x in between) times the probability that x lies between x_1 and x_2:

E(x) in interval x_1-x_2 = $\int_{x_1}^{x_2} xf(x)dx = x[F(x_2) - F(x_1)] for (x_1 \le x \le x_2)$ (5.18)

Generalizing, then, then grand mean is the sum of the interval sub-means. That is, symbolically, using the lower limit of each interval for each xi and then repeated applying (5.18) above:

$$[F(x_2) - F(x_1)] + x_2[F(x_3) - F(x_2)] + x_3[F(x_4) - F(x_3)] .... + x_{n-1}[F(x_n) \cdot \quad (5.19)$$

113 To obtain the mean from the survivial function, 1-F(x), the same reasoning developed below also applies.

where x1= a large negative number for the unrestricted mean or 0 for the truncated mean and xn equals a large positive number for the unrestricted mean and the truncated mean bounded at zero but unbounded from above, or xmax when bounding from above at average income or some fraction thereof.

In addition, the density (a.k.a. pdf and f(x)), at some point in any interval given ascending values for x (i.e. $x_1<x_2<x_3<\ldots..x_n$) is approximately by–and proportional to-the difference between adjacent CDF values (Freund and Walpole, Theorem 3.3, p.80), where the factor of proportionality is the sum of f(x) over the sampled points to normalize to one (Pollard 1977):

$$f(x_i)(1/\sum f(x)) \approx \left[F(x_i) - F(x_{i-1})\right] \quad (5.20)$$

The above relationships can be used to compute the mean by numerical integration for any formulas in Table 5.1, even without access to specialized software. While admittedly crude, with a sufficient number of points it is possible to come very close to the analytical results in a simple spreadsheet setup by computing the sum of the products of the interval mid-points (or lower-bounds) times the difference in adjacent CDF values, ΔF(x). Equivalently, f(x) values can be multiplied by the successive values of x and summed, but the result has to be divided by the normalizing factor ∑f(x) to get the mean.

Applications of the bounded Probit estimator for mean and median will be depicted in Chapter 6 of this dissertation.

5.2.1. Advantages and Limitations of Parametric Approaches

The first models developed by researchers to derive WTP estimates from CVM where the parametric approaches. One salient feature of these models is that in addition to calculate WTP, they allow incorporating respondent characteristics into the willingness to pay function, which provides additional information to the researcher on the validity and reliability of the CV method, they are suitable for model testing, and allow to extrapolated sample responses to more general populations (Carson and Hanemann 2005; Haab and McConnell 2002 and 1997). But the respondent characteristics are also extremely valuable for the policymaker who needs to make informed decisions on public spending. The additional information will assist the decision-maker in identifying who are the winners and losers of different programs or projects.

> *CV can help decision makers to identify the public's interest. It is particularly useful in two cases. One is where the benefits of providing an environmental good are large but diffuse and its provision is opposed by a powerful special interest group. In this case a countervailing interest group pushing for the good's provision in unlikely to spring up. The other is where there is a strong lobby in favor of providing an environmental good, with the public as a whole footing the bill and their aggregate willingness to pay for it being much smaller than its cost. The nature of the political process will often be to supply the good to the determinant of the public's welfare as long as there is not a strong group opposing it. In both cases, an estimate of the public's WTP for the good can help illumination the nature of the decision at hand (Carson and Hanemann 2005, pp. 920).*

On the downside, the estimation of parametric models requires three major assumptions taken by the researcher: a) know the appropriate set of exogenous variables, b) the signs to expect on these variables, and c) which functional forms are acceptable[114] (Cooper 2002; Boyle 1990; McConnell 1990). In addition, when the pattern of responses is well behaved, the WTP estimates will not be especially sensitive to the choice of distribution. However, in many cases, these patterns are not well behaved resulting in the distribution or the functional form having substantial effect on the estimates of WTP (Bengoechea

114 In the words of Boyle (1990): "Economic theory helps guide such decisions, but an empirical investigator is still left with substantial latitude as to actual choices." (pp. 126). "…….a large number of functional forms can be consistent with economic theory." (pp. 126). "Economic theory allows the formation of hypotheses about relevant variables for inclusion, relationships among included variables, expected signs of estimated coefficients, and possibly even statements regarding relative magnitudes of estimated coefficients. However, intuition must also play a role." (pp. 129)

et al 2005; Crooker and Herriges 2004; see Chapter 4 in Haab and McConnell 2002 for several case studies illustrating this last point). Bengoechea et al. (2005) summarize the effect of the assumptions quite clearly. They compare the results of five empirical models (parametric and nonparametric) used in recent investigations to estimate the existence value of a protected natural area in Spain. On the use of parametric approaches they conclude: "The WTP estimators obtained are strongly dependent of the assumptions made about the underlying consumer preferences structure and the empirical models used in the WTP inference process." (pp. 243). Another factor is influencing the difficulties of parametric approaches is the fact that theory provides little guidance regarding the appropriate parametric specifications (Carson and Hanemann 2005; Crooker and Herriges 2004).

Therefore, the major downside then of parametric models lies in the risk of misspecification resulting in parameter and welfare biases (Haab and McConnell 2002; Hutchinson et al. 2001; Kerr 2000; Boyle 1990). These potential biases and sensitivities have opened the field in applied welfare to incorporate non-parametric methods of central tendency measures to fit the response distributions that rely only on the notion that when the respondent answers "yes" to a CV question, his/her WTP is not less than the offered prices.

5.3. Non-Parametric Approaches to CVM

The section will present the theoretical underpinnings for non-parametric approaches and for the three most widely used approaches (and cover three different ranges or bounds): a) a lower bound estimator also known as the Turnbull estimate; b) an intermediate measure known as Kriström's nonparametric measure; and c) an upper bound known as the Paasche Mean. The mean and variances formulas for these approaches will be presented. We will conclude with an analysis of the main benefits and constraints of non-parametric approaches in CVM.

5.3.1. Theoretical Underpinnings

The non-parametric approach invokes the Sample Mean Theorem[115], which from an operational point of view involves the computation of sample statistics. This Theorem provides the basis for the most elementary nonparametric estimation method (Hazilla 1999). The sample mean, $\bar{x}$ from a group of observations is an estimate of the population mean, μ. Given a sample of size n, based on an open-ended survey, consider n independent random variables X_1, X_2, X_3…..X_n, each corresponding to one randomly selected observation. Each of these variables has the distribution of the population, with mean μ and standard deviation, σ. The sample mean is defined as: $\bar{X} = \frac{1}{n}(X_1 + X_2 + X_3 + ... + X_n)$. By the properties of means and variances of random variables, the mean and variance of the sample mean are the following: $\mu_{\bar{x}} = \mu$ and $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$. For large sample sizes, the variance is much smaller. When the distribution of the population is normal, then the distribution of the sample mean is also normal (Goldberger 1991).

5.3.2. Logic of Nonparametrics

The logic behind all three nonparametric estimators is the same. The proportion of "no" answers at each bid level x provides a discrete stepwise approximation to the cumulative distribution function. The mean E(x) of a continuous random variable x with a cumulative distribution function F(x) and probability density function f(x), which is the first derivative of F(x) with respect to x, is given by

$$E(x) = \int_{-\infty}^{+\infty} xf(x)dx \quad (5.21)$$

The issue is to use a discrete approximation to (5.21) to compute

$$E(x) \approx \sum_X xf(x) \quad (5.22)$$

where the range of x is from 0 to some upper limit xmax that forces F(x) close to 1.0 because the bid is so high that almost all respondents would be unwilling to pay that amount for the environmental improvement.

The fundamental theorem of the calculus tells us that the area under the curve f(x) between the limits x_1 and x_2 is (a) the sum of a number of infinitesimally small subdivisions in x of length n, (b) the definite integral of f(x) between the limits, or (c) the difference between the integral F(x) evaluated at x1 and x2:

115 The general method for constructing non-parametric tests for models of consumer behavior was discovered by Afriat (1967) (Varian 1983).

$$\lim_{n\to\infty}\sum_{i=1}^{n} f(x_i)\Delta x_i = \int_{x_1}^{x_2} f(x)dx = F(x_2) - F(x_1) \quad (5.23)$$

We know the value of F(x) for any bid x from the bid group proportions. Therefore, the bid or x range can be split into intervals and the means from each small interval summed to get the grand mean. That is, the contribution to the overall mean from the approximate mean within any bid group interval is the product of some x within the interval (i.e., the lower limit, x_1, the upper limit, x_2, or some value of x in between, which Kriström's (1990) method sets at the group midpoint) times the probability that x lies between x_1 and x_2:

$$\text{E(x) in interval x2} - \text{x1} = \int_{x_1}^{x_2} xf(x)dx = x[F(x_2) - F(x_1)] \text{ for } (x_1 \le x \le x_2) \quad (5.24)$$

Generalizing, then the grand mean is the sum of the interval submeans. Symbolically, using the lower limit of each interval for each xi and repeatedly applying (5.24):

$$E(x) \approx x_1[F(x_2) - F(x_1)] + x_2[F(x_3) - F(x_2)] + x_3[F(x_4) - F(x_3)] \ldots + x_{n-1}[F(x_n) - F(x_{n-1})] \quad (5.25)$$

where $x_1 = 0$ and xn equals a large positive number xmax when bounding from above at average income or some assumed fraction of average income. Notice that the (unobserved) value of x_n, which represents the bid driving the probability of acceptance to 0 and the probability of rejection to 1, does not figure in the calculation.

Equation (5.25) is Haab and McConnell's (1997a; 1997b; 1998a; 1998b) lower bound Turnbull mean. The intermediate and upper bound means are obtained by simply redefining the point of evaluation, x, in each interval to ½ of the lower plus upper bounds of the interval, or just the upper bound.

While Boman et al. (1999) try to put all three measures on a consistent symbolic footing, there are errors in their notation for the means, and unfortunately their variance formulas are conceptually incorrect[116]. In the next section, all three measures are recast in the Haab and McConnell (1997a; 1997b; 1998a; 1998b) notational framework, which is conceptually correct.

116 The Boman et al. (1999) variance formulas incorrectly treat the bid, not the cell proportions, as a random variable and are inconsistent with the respective expected-value formulas because they were not derived from them using the fundamental rules pertaining to the variance of a sum of random variables. Instead, an inappropriate textbook formula was forced to stand in. The discrepancy was discovered by comparing the variances of the lower bound means produced using the Haab and McConnell formula and the Boman formula. The variance from the latter was roughly double the former. See Vaughan and Rodriguez (2000) for further elaboration.

5.3.3. Three Non-parametric Approaches

In this section, three nonparametric measures will be introduced: a) a lower bound estimator also known as the Turnbull estimate; b) an intermediate measure known as Kriström's nonparametric measure; and c) an upper bound known as the Paasche Mean[117].

5.3.3.1. A Lower Bound: Haab and McConnell's Turnbull Estimate

Consider a stylized contingent valuation question. Respondents are asked: "Would you be willing to pay an amount b_j?" The bj are indexed j= 0,1….M+1 and bj>bk for j>k, and b_0=0. Let pj be the probability that the respondent's WTP is in the bid interval b_{j-1} to b_j. This can be written as[118]:

$p_j = P(b_{j-1} < w \leq b_j)$ for j=1,….., M+1…. (5.26)

Alternatively, the cumulative distribution function is written

$F_j = P(w \leq b_j)$ for j=1,…., M+1 where F_{M+1}=1 (5.27)

For reasons already discussed, one aims to have b_{M+1} high enough that F_{M+1} = 1. That is, b_{M+1} is effectively infinite in the problem setting. Then

$p_j = F_j + F_{j-1}$ (5.28)

and $F_0 \equiv 0$. The Turnbull can be estimated by treating either the F_j, j=1 → M or p_j, j=1 → M as parameters.

The p's can be estimated quite simply. Let N_j represent the number of "no" responses registered in each bid group j. If $[N_j /(N_j+Y_j)] > [N_{j-1}/(N_{j-1}+Y_{j-1})]$ for all j between 1 and M, then $p_j = [N_j /(N_j+Y_j)] - [N_{j-1}/(N_{j-1}+Y_{j-1})]$. The probability $N_j /(N_j+Y_j)$ represents the proportion of respondents who say "no" to b_j. As such, it is a natural estimator of F_j[119] Hence, the estimator of pj could be written:

$p_j = F_j + F_{j-1}$ where $F_j = N_j /(N_j+Y_j)$ (5.29)

117 For additional nonparametric methods and detailed theoretical framework see Bengoechea-Monrancho (2005); Carson and Hanemann (2005); Chapter 3 of Haab and McConnell (2002); An and Ayala (1997); Harrison and Kriström (1995); Carson et al. (1994); Duffield and Patterson (1991).

118 This section is an abridged version of the presentation in McConnell (1995). A complete treatment is available in Haab and McConnell (1998a; 1998b; 1997a; 1997b).

119 The estimate of Fj assumes that the proportion of "no" responses increases as the bid increases across all bid classes.

Expected willingness to pay can be written as

$$E(WTP) = \int_0^\infty WTPdF(WTP) = \sum_{j=1}^{M+1} \int_{b_{j-1}}^{b_j} WTPdF(WTP) \quad (5.30)$$

Replacing willingness to pay by the lower bound of each interval produces a lower-bound estimate of the expected value of willingness to pay:

$$E(LB_{WTP}) = 0xP(0 \le w < b_1) + b_1 P(b_1 \le w < b_2) + \ldots + b_M P(b_M \le w < b_{M+1}) = \sum_{j=1}^{M+1} b_{j-1} P_j \quad (5.31)$$

where pm+1 = 1 + FM.

One important aspect to note is that bM is the is the highest bid actually offered to respondents and is the lower bound of the final interval running from bM to infinity. This lower bound distinguishes the Turnbull approach from Kriström's method (section 5.3.3.2 below).

The variance of the lower bound mean is

$$V\left(\sum_{j=1}^{M+1} p_j b_{j-1}\right) = \sum_{j=1}^{M+1} b_{j-1}^2 \left[V(F_j) + V(F_{j-1})\right] - 2\sum_{j=1}^{M} b_j b_{j-1} V(F_j) \quad (5.32)$$

where the variance of each proportion $V(F_j)$ is equal to $F_j(1-F_j)/(N_j+Y_j)$. This variance is inversely related to the sample size.

This too can be calculated rather easily from a simple table of proportion of yes's or no's and the total number of respondents in each grouping.

The Turnbull estimator has been widely used to provide the "preferred" lower bound estimate of means WTP in several environmental damage assessment studies (Hutchinson et al. 2001). This is the theoretical bases of the Turnbull estimator. The results of applying these formulas will be displayed in Chapter 6.

5.3.3.2. An Intermediate Measure: Kriström's Nonparametric Mean

The Turnbull lower bound estimator assumes that the mass of the distribution function falls at the lower bound of the range of prices for each mass point[120] (Haab and McConnell 2002). Kriström's (1990) nonparametric method interpolated between price points to describe the distribution between prices.

120 For example, using the notation used for the Turnbull estimator, if the probability that the willingness to pay is between b1 and b2 is estimated to be 30%, then the full 30% of the distribution masses at b1.

This non-parametric approach is based on a theorem developed by Ayer et al. (1955) (Bengoechea-Morancho et al. 2005).

Kriström originally suggested arraying the frequency of affirmative responses in each bid class in monotonically descending order with ascending bids, connecting the points by linear interpolation, and approximating the integral under the resultant empirical cumulative density to get the mean. In this method it is assumed that the distribution function is piece-wise linear between prices. Formalizing and using the distribution function rather than the survivor function, the intermediate mean is

$$E(INT_{WTP}) = \sum_{j=1}^{M+1} bmid_j p_j \quad (5.33)$$

where bmidj is the midpoint in each bid interval, or ½ ($b_j - b_{j-1}$).

The variance of the intermediate mean is

$$V\left(\sum_{j=1}^{M+1} p_j bmid_j\right) = \sum_{j=1}^{M+1} bmid_j^2 \left[V(F_j) + V(F_{j-1})\right] - 2\sum_{j=1}^{M} bmid_j bmid_{j+1} V(F_j) \quad (5.34)$$

There are two main simplifying assumptions needed: First, unlike the Turnbull, the bid that drives the probability of acceptance to 0 must be specified by the analyst if the survey does not reveal it, so Kriström's mean depend in part to this arbitrary value of b_{m+1}. To construct the empirical cumulative densities a conservative upper limit for bm+1 must be assumed[121]. Second, the approach considers linear interpolation to as valid to obtain the survival function intermediate points. The expected WTP is provided by the area limited under the empirical survival function and the value of the median is obtained by finding the amount whose acceptation probability equals 0.5 (Bengoechea-Morancho et al. 2005).

5.3.3.3. An Upper Bound: The Paasche Mean of Boman et al.

The upper bound mean, presented by Boman et al. (1999) involves straightforward reindexing of the bid in the lower bound formulas and is given by

$$E(UB_{WTP}) = \sum_{j=1}^{M+1} b_j p_j \quad (5.35)$$

121 For the case study in Chapter 6 the upper limit (bm+1) was set at approximately 3 percent of average household income which is consistent with the literature. The sensitivity to this assumption has to be noted: in the case study in question and for the 'close-to-river case', the upper limit is set to R$40 (3 percent of income). If the upper limit is set to R$30 rather than R$40, the mean would fall by about R$0.50. The nonparametric estimates of a location would probably be better if the sample had included more bid intervals spanning a wider bid range.

Again, like the intermediate mean, an arbitrary value of b_{M+1} must be specified by the analyst. The variance of the upper bound mean is

$$V\left(\sum_{j=1}^{M+1} p_j b_j\right) = \sum_{j=1}^{M+1} b_j^2 \left[V(F_j) + V(F_{j-1})\right] - 2\sum_{j=1}^{M} b_j b_{j+1} V(F_j) \quad (5.36)$$

5.4. Summary of the Nonparametric Means and their Variances

To summarize, Haab and McConnell's (1998a; 1998b; 1997a; 1997b) lower bound Turnbull mean sets each b_j to the lower bound of the bid interval (i.e., the first interval runs from 0 to the lowest bid offered, so b_j at j equals 0 is set to 0, etc.). The intermediate and upper bound means are obtained by simply redefining the point of evaluation, b, in each interval to some fraction ķ times the lower bound plus (1-ķ) times the upper bound of the interval, where $0 \leq \kappa \leq 1$. Kriström's (1990) intermediate mean sets ķ to ½ (the midpoint of the interval), while the upper bound mean sets ķ to 0. While Boman et al. (1999) try to put all three measures on a consistent symbolic footing, there are errors in the notation for the means and, unfortunately, their variance formulas are incorrect. The table below summarizes the formulas for nonparametric means and their variances, utilizing Haab and McConnell's notation, which is conceptually correct.

Table 5.2. Summary of Nonparametric Means and Variances Formulas

Measure	Mean	Variance of Mean*
Lower bound	$\sum_{j=1}^{M+1} b_{j-1} p_j$	$\sum_{j=1}^{M+1} (b_{j-1})^2 \left[V(F_j) + V(F_{j-1})\right] - 2\sum_{j=1}^{M} (b_j b_{j-1}) V(F_j)$
Intermediate	$\sum_{j=1}^{M+1} \left[\kappa b_{j-1} + (1-\kappa) b_j\right] p_j$	$\sum_{j=1}^{M+1} \left[\kappa b_{j-1} + (1-\kappa) b_j\right]^2 \left[V(F_j) + V(F_{j-1})\right] - 2\sum_{j=1}^{M} \left[\kappa b_{j-1} + (1-\kappa) b_j\right]\left[\kappa b_j + (1-\kappa) b_{j+1}\right] V(F_j)$
Upper bound	$\sum_{j=1}^{M+1} b_j p_j$	$\sum_{j=1}^{M+1} (b_j)^2 \left[V(F_j) + V(F_{j-1})\right] - 2\sum_{j=1}^{M} (b_j b_{j+1}) V(F_j)$

**The parameter ķ is assumed by the researcher to form a weighted average of the lower and upper bound bids in any interval. Kriström's mean uses ķ=0.5, but any value of ķ between 0 and 1 is admissible. If ķ = 0, the Turnbull lower bound means results, and ķ = 1 returns the Paasche upper bound mean of Boman et al. (1999).*

5.5. Advantages and Limitations of Nonparametric Approaches

There are several advantages of using non-parametric approaches. First, nonparametric statistics require no explicit assumption about the form of the population distribution from which the sample is drawn (Haab and McConnell 2002). Second, it is a fairly simple and straightforward method to implement. Third, in the context of repeated sampling, this method is correct on average. Lastly, it avoids a possible specification error associated with parametric estimators that rely on strong distribution assumptions (Hazilla 1999).

One of the main disadvantages of this approach is that if the specific form of the data generation process is known, then not using this information is inefficient. Another disadvantage is that, given its simplicity, nonparametric approaches allow limited exploration of the effect of the covariates (Haab and McConnell 2002). Bengoechea et al. (2005), Bohara et al. (2001), Hutchinson et al. (2001), Haab and McConnell (1997), and Creel and Loomis (1997) point out the fact that even if these estimators perform adequately in estimating WTP, they are inferior to parametrics methods.

5.6. Conclusions and Recommendations

In this chapter we presented the two most widely used and accepted routes to analyzing referendum data: parametric and nonparametric approaches.

Referendum-type questions are thought to be easier to answer than the open-ended variety. But there is a downside: econometric techniques must be applied to the referendum data in order to infer the mean or median willingness to pay of the sample and, thus, of the population of potential beneficiaries.

The use of parametric techniques, although favored by most economists, forces the data to a specific distribution, constricting CV data to a limited form of the underlying distribution function. This risks misspecification (Cooper 2002). If the model is different than the real but not observed model then the covariate effects can be wrong in magnitude and size, and hypothetical tests will not be valid (Carson and Hanemann 2005; Haab and McConnell 2002).

Theory provides limited guidance on which parametric specifications to use and the resulting WTP estimates can be sensitive to the selections made (Carson and Hanemann 2005; Crooker and Herriges 2000). As described in this chapter, there is a vast array of central tendency formulas that can be applied with parametric techniques and the range in the results (which will be demonstrated in Chapter 6), with the same data, can also be considerable.

McFadden and Leonard (1993, pp. 167-168) provide an interesting summary of the advantages and disadvantages of parametric approaches:

> *The advantages of parametric methods are that they make it relatively easy to impose preference axioms, pool data across experiments, and extrapolate the calculations of value to different populations than the sampled population. Their primary limitation is that, if the parametrization is not flexible enough to describe behavior, then the misspecification will usually cause the mean WTP calculated from the estimated model to be a biased estimate of true WTP.*

On the other hand, nonparametric statistics require no explicit assumption about the form of the population distribution from which the sample is drawn and it if fairly simple to implement. But nonparametrics allow limited exploration of the effect of the covariates.

Carson and Hanemann (2005) summarize with clarity the advantages of the two approaches (parametric and nonparametric):

> *For the simple purpose of describing the WTP distribution, an unconditional approach may work fine and avoids a number of modeling issues related to correctly specifying the conditional WTP distribution. However, policymakers generally want to see the conditional estimates as they care who the gains and losses accrue to (pp. 888, footnote 114).*

Before becoming completely and inextricably caught in selecting the "most appropriate" approach the analyst must pause to consider the options available at the point of the exercise. If the primary goal is to explain and understand respondent behavior[122], verify whether CV survey responses are consistent with economic theory, or estimate WTP for a population other than the one sampled, parametric choices must be estimated. But if all one needs is a benefit measure for Cost-Benefit analysis, on the other hand, nonparametric estimates of WTP may have the edge. This last approach may be preferred especially in the context of analysis in developing countries where financial resources are limited. The most recommended strategy however is to present results using a variety of estimators. This is especially relevant in the context of large-scale investments that support public policy decisions.

122 Parametric models allow for the incorporation of respondent characteristics into the function.

PART III

Case Study Application