What's it worth? Exploring value uncertainty using interval questions in Contingent Valuation[1]

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Running title: What's it worth? Value Uncertainty in CV.

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ABSTRACT

In this paper we explore the idea that people only know the value they place on a given environmental change as a range, rather than as a singleton. We use the payment ladder design of contingent valuation, and take as a case study the value of coastal water quality improvements in Scotland. Kaplan-Meier survival curves, Tobit analysis and a modified Turnbull algorithm are used to explore the data. We find that most people state their values as a range, and investigate empirically the determinants of this range. The paper concludes with some thoughts concerning possible links between value ranges, context-dependence and uncertainty.

Keywords: contingent valuation, preference uncertainty, payment ladders, context dependence, coastal water quality, survival analysis.

1. Introduction

In this paper, we investigate empirically the notion that most people only know their Willingness-to-pay (WTP) or Willingness-to-Accept-Compensation (WTAC) for a given environmental change within a variable range [4, 19, 23]. We do not address ourselves at present to the rather different notion of preference construction associated with authors such as Gregory [10]and Payne [18], which states that individuals construct their preferences in a context-dependent matter, based on certain fundamental attitudes and beliefs. Rather, we take it as possible that, although people have a set of preferences which is not primarily determined by a valuation context/exercise, they find it hard to express these preferences or the values derived from them as single, precise values. Indeed, in our sample of 783 individuals, individuals invariably (i.e. 781) report an interval WTP rather than a single number.

One possible way of explaining why people find it difficult to state a single, "crystallized" value of WTP (or WTAC) is uncertainty over preferences. For example, Ready, Navrud and Dubourg [20] conditioned responses to both dichotomous choice and payment card designs using statements concerning how sure respondents were about whether they would really pay the amount in question (see also [11]). They found that the dichotomous choice design led to greater preference uncertainty, measured in this way, than the payment card design. They also found that allowing for uncertainty reduced the difference between sample mean WTP in the two designs. Li and Mattsson [16] and Champ et al [3] have also studied this type of uncertainty within a Dichotomous Choice format.

Our approach to capturing valuation uncertainty relies on a different type of CV design, the payment ladder. A payment ladder lists a series of money values, starting at low numbers and ending in reasonably high numbers (see annex one for the ladder used in our case study).

Starting with the smallest value on the card, respondents are asked to consider each value in turn, ticking amounts they would definitely pay, crossing amounts they would definitely not pay, and leaving blank amounts for which they could not say one way or the other. An individual's maximum WTP, it is assumed, is at least as great as the amount against which they placed their highest tick but is less than the amount against which they placed their lowest cross. Payment ladders have been used before in a value uncertainty context, by Jones-Lee et al [14] in a study of the benefits of reductions in non-fatal accidents. However, these authors asked respondents to pick a value between their highest tick and lowest cross as the amount they "had most difficulty in deciding over" and this amount was then used as a "best point estimate" of WTP, and the data then treated as a continuous variable. In this paper, we wish to explore rather less restrictive ways of handling this type of response, which may be ultimately more informative. We do this in the context of a study which tries to measure the benefits of improving coastal water quality in Scotland.

2. The policy context

Attention within the European Union has recently been focussed on the costs and benefits of improving coastal water quality. This has come about both though moves to strengthen the existing Bathing Waters Directive (76/160), but also due to the continued failure of many waters to reach the standards set out in the current directive, and the perceived high costs of meeting even these standards. In the UK, a House of Lords committee questioned whether the benefits of water quality improvements mandated by the Bathing Waters Directive were large enough to justify the cost [13]. The UK government has more recently commissioned work looking at the costs and benefits of strengthening the current directive, in order to inform the UK's negotiating stance.

Our case study focusses on bathing water quality in South-West Scotland. Water quality along this coast has been problematic for many years, due mainly to bacteriological contamination as measured by faecal coliform counts. As Table 1 shows, all the major bathing beaches along this coast have failed the Bathing Waters Directive mandatory and guideline standards on frequent occasions over the last 10 years[2]. In 1998, only one out of the seven coastal areas passed EU mandatory standards although this picture improved in 1999 due partly to a dryer summer. By 2000, four out of seven beaches passed the mandatory standard. Whilst the EU test is rather strict in the sense that for a beach to "fail" in a given year, only 2 out of 20 samples taken through the summer need to be above statutory levels, the data nevertheless suggests that a problem exists[3]. Under the existing Bathing Waters Directive, responsible authorities (Scottish Water, in this case) are required to take action to bring water quality up to mandatory standards for total and faecal coliforms. Water quality has been improving over time as increasing investment in municiple sewage treatment takes effect, and continued failures at some sites has now focussed attention on non-point sources of pollution, running off of farmland into rivers and thus the sea [21].

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The benefits of improving UK coastal water quality have been the subject of a number of studies. A contingent valuation study by Georgiou et al [8] estimated Willingness to Pay for day trippers, holiday makers and residents in two East Anglian coastal resorts (Great Yarmouth and Lowestoft) for improvements in water quality up to EU mandatory levels. For residents, the mean value found was £9.33-£13.50/year. A second contingent valuation survey by Georgiou et al [9] gave estimates of £20.17-£37.41/household/year in Great Yarmouth and Lowestoft, for a toughening of the Bathing Waters Directive. A combined stated -revealed preference study by Hanley, Bell and Alvarez-Farizo [2] estimated gains to beach visitors in SW Scotland from improvements in coastal water quality, along with predicted changes in visit rates: the increase in aggregate recreation benefits was estimated at around £1.25million

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[2] The mandatory standards are: for total coliforms, 95% of samples must contain less than 10,000 coliforms per 100ml water, whilst for faecal coliforms 95% of samples must contain less than 2,000 coliforms per 100ml. The guideline standards require 80% of samples to have less than 500 total coliforms and 100 faecal coliforms per 100ml.

[3] The Directive sets out a compulsory sampling programme in this context, which for Scotland implies that 20 samples must be collected between June 1st and mid-September.

per annum. Finally, Eftec [5] used a choice experiment approach to value improvements in four attributes of beach recreation (including bathing water quality) to the UK general public.

3. Survey design

In our case study, an in-house contingent valuation survey of local residents in two of the largest towns on the South-Western Scottish coastline (Ayr and Irvine) was carried out in the winter of 1999/2000. We focussed on these two towns since they are major population centres within easy reach of the beaches listed in Table 1. Design of the questionnaire followed usual CV procedures of focus group work and pre-testing. Increases in local water and sewerage rates were used as the payment vehicle. The final sample contained 351 useable responses from the Ayr survey, and 432 from the Irvine survey.

The contingent valuation section of the questionnaire explained to respondents that water quality could only be improved to EU guideline standards at a cost, and that this would mean an increase in local water rates. People in the Ayr sample were asked their WTP in order to improve water quality at Ayr beach, and people in the Irvine sample asked their WTP in order to improve quality at Irvine beach. We collected data on respondents' current rating of local water quality, the number of trips they made to the beach per year, and how long they had lived in the area. This was in addition to the usual socio-economic information such as age, educational achievements and household income.

4. Results

Descriptive statistics

The two samples (Ayr and Irvine) differ in terms of several of the variables which might be assumed, a priori, to be important in explaining the value of local water quality improvements, although these differences were not statistically significant at the 90% level of confidence. These variables included length of residence in the area, rating of local water quality and household income. Let us define SIMPLE = (UPPER+LOWER)/2, the half-way distance between the UPPER and LOWER willingness-to-pay. Table 2 gives some results based on this procedure. The mean lower value of WTP (highest tick) was greater for Ayr (£8.84) than at Irvine (£5.26); this was also true of the upper bound on WTP (Ayr £15.64, Irvine £9.21). In both cases these differences are not significant .For Irvine, 90% of the observations lie in the range 0-£20; for Ayr, 90% lie in the range 0-£50. In both locations, there appear to be two separate populations of value, namely WTP = 0 and WTP > 0. In the sample, about 36% stated an upper WTP of zero (37.7% and 34.7% in the Irvine and Ayr samples, respectively).

In order to obtain some insights into how the respondents replied to the valuation questions, it is useful to inspect the Kaplan-Meier survival curve. The Kaplan-Meier estimate of the survival distribution is often used in survival analysis to obtain a non-parametric estimate of the underlying distribution function. It is simply obtained as the product of “survival” probabilities. Thus, let WTP[i], i=1..n denote the ordered set of responses to a WTP question in a sample of n individuals (ignore ties, for simplicity). The unconditional probability Pr(WTP ≥WTP[i]) is equal to Pr(WTP ≥ WTP[i] | WTP[i] ≥ WTP[i-1])*Pr(WTP ≥ WTP[i-1]). Using the expression for conditional probability repeatedly, one obtains the result that the unconditional probability of Pr(WTP ≥WTP[i]) is the product of conditional probabilities. The final result is Pr(WTP ≥WTP[i]) = $\prod^{i}_{j}$(1-d(j)/n(j)), where d(j) is the number of respondents with WTP less than WTP[i] and n(i) =n(i-1)-d(i-1)-c(i-1), with c(i) being the number of censored observations. Note that n(0) is the number of respondents in the survey. The Kaplan-Meier estimates are non-parametric maximum likelihood estimates of the underlying distribution. Figures 1 and 2 show the Kaplan-Meier curves for the two samples for both UPPER and LOWER values. These estimates of the survival curves conveniently summarize a number of pertinent facts about WTP in the sample. As noted, there is a substantial fraction of zero WTP responses for both the lower and upper estimates of WTP. Furthermore, the distributions are concentrated in the range £0-£20.

Estimation of the WTP distribution

We use a fairly standard approach in the biometrics literature to estimate the WTP distribution for each sample, using a slight modification of the Turnbull algorithm [24]. A useful extension of the Turnbull (1976) algorithm is provided by An and Ayala [1], who apply the extension to contingent valuation with double-bounded data. A crucial advantage of the Turnbull approach is that no particular distribution is assumed.

Our problem is slightly different from that Haab and McConnell [12] and others have looked at when analyzing binary valuation questions. In these cases, the intervals that bound WTP are fixed exogenously; in our application, however, the bounds are provided by the individual. In a large enough sample, and given an optimal design of the bid-vector and a correct distributional assumption, this difference might be of less importance from a statistical point of view. However, because the valuation questions may be interpreted differently by different respondents one may well obtain quite different results in practice. For example, in the double-bounded set-up, the individual is asked two questions, the first being whether or not he would accept to pay X for an environmental improvement. Depending on the answer, a follow-up amount is then used to bound the individual's WTP into 4 possible intervals (represented by the four possible outcomes, "no-no"," no-yes", yes-no", “yes-yes"). This set-up is potentially vulnerable to an unintended impact on WTP. For example, a follow-up question given that the respondent first said “yes” may be awkward to formulate (“why pay more if delivery is already promised?”). This potential problem has been analyzed in [11]. The payment ladder approach is not sensitive to this particular problem, although starting point bias (untestable in our set-up) could be an issue. Furthermore, the double-bounded approach is typically based on the assumption that the individual know her WTP exactly, although this is not necessary, as discussed above (additional assumptions are, however, needed; see e.g. [17]).

We focus on individuals with positive WTP. The zeroes will be handed separately. It is assumed that the individual's WTP is somewhere in a self-reported interval $I_i = (L_i,U_i)$. In order to obtain the non-parametric maximum likelihood estimate (NPMLE) of the underlying distribution of WTP, several approaches can be used. Following [22] , let s(j), j=1..m+1 be the unique ordered elements of the set $\{0, L_i,U_i ,\infty\}$ and α_{ij} an indicator of the event that the individual's WTP is in the interval (s_{j-1} , s_j). Define $p_j = F(s_j)-F(s_{j-1})$, where F is the c.d.f of the underlying random variable WTP. The relevant log-likelihood function can be written as:

$$l(p) \quad = \quad \sum_{i=1}^{n} \log\left[F(U_i) - F(L_i)\right] \quad = \quad \sum_{i=1}^{n} \log\left(\sum_{j=1}^{m+1} a_{ij}\, p_j\right) \ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

where $p = (p_1,p_2\ldots p_{m+1})$. This likelihood is maximized subject to $\sum_{j=1}^{m+1} p_j = 1$ and $p_j \geq 0$ (j = 1,....,m+1). For details, see [7]. There are several algorithms available for solving this problem. We use an algorithm publicly available for the R-program at http://cran.r-project.org/. Our algorithm is reproduced in Appendix 2, and results are shown in Figure 3.

First, note that the curves in Figure 3 may usefully be interpreted as demand curves, because they display the proportion that would be willing to pay a particular price for a unit of the public good. Second, the curves are constructed conditional on WTP being positive. It is straightforward to add the proportion of zeroes to the picture, by simply adding the spikes at zero. As can be seen, the Ayr sample seems to generate higher WTP, and that WTP decreases in this sample more quickly (most of the action is in the interval £0-£20, as noted above). Indeed, the probability that WTP > £50 is virtually zero. The median WTP is about £15 in the Ayr sample and about £7.50 in the Irvine sample, according to the model. This can be compared with the corresponding raw-data, in which the median for the Irvine sample is £5 and £13 for LOWER and UPPER, respectively. The corresponding medians for the Ayr sample is £10 and £20. The naive estimate of taking the midpoint works fairly well here; the median of the midpoints is £9 and £17.5 (conditional on WTP > 0), respectively. Mean WTP cannot be calculated without further assumptions on tail behaviour. A rough indication is given by the area bounded by the estimated survival curves.

A log-rank type of test described in Fay [6] was used to test the hypothesis that the survival curves in the two locations Irvine and Ayr originate from the same distribution. The test rejected this hypothesis. Benefits transfer between the two sites based on the transfer of value functions is therefore also rejected. Finally, we note that deriving aggregate benefit estimates from this type of data may be problematic. This is because each individual may have a unique subjective probability distribution concentrated on their self-reported interval.

Exploring the valuation gap

To explore the data further, we carried out some simple regression experiments. Because of the significant fraction of zeroes, we used the Tobit model; OLS-results are rather similar. We have also used variations of the Tobit model, including a Weibull model allowing for heterogeneity ([15]). Results are rather similar, so we discuss the simple Tobit results only (Table 3).

Perhaps the most interesting result is the parameter estimate for the variable YEARS, which is significant at the 10% level in both models and negative. Thus, the longer the respondent has lived in the area, the smaller is the difference between LOWER and UPPER WTP. A possible interpretation is that uncertainty about preferences is reduced over time. The location dummy (LOCATION) is coded such that Ayr = 1; thus Ayr respondents display a higher uncertainty, in the sense of displaying a larger difference between UPPER and LOWER WTP. Income is positive and significant, perhaps indicating the fact that a higher income allows a higher WTP and potentially a higher difference. A closer look at the income variable suggests that LOWER is less responsive to income compared to UPPER. The variable INTEREST is coded such that a lower value indicates higher interest. This thus shows that if the respondent takes a greater interest in the interview, she displays lower value uncertainty. The variable SCOPE allowed a simple test for test for part-whole bias, since it is composed of answers to the de-briefing question: "When you gave your maximum sure willingness to pay value, what was this for?" The frequency table of this variable (Table 4) suggest a potential part-whole bias problem in the data. There is some indication that individuals who paid only for the improvement of the relevant beach (that is, those people responding to the valuation scenario which the researchers intended to frame) display a lower gap between UPPER and LOWER. However, these interpretations are not based on an underlying conceptual model, which at the current stage of our research is lacking.

5. Discussion and Conclusions

In this paper, we use a payment ladder approach to contingent valuation, thereby revisiting some of the earliest approaches to eliciting WTP. There is strong evidence that most respondents are uncertain over the value they place on a given environmental improvement (in our case, an improvement in coastal water quality. The payment ladder approach allows respondents to quantify this valuation uncertainty, which emerges as a gap between the highest amount people say they are sure they would pay, and the lowest amount they say they are sure they would not pay. This uncertainty may have many roots, and we have not offered any conceptual model to delineate it in detail. Preference uncertainty, uncertainty about the environmental good and incentives to mask true WTP are all possible ways to model this gap.

However, one interesting possible line of enquiry is as follows. We stated at the outset of this paper that we would not go down the road of constructed preferences in thinking about value uncertainty. However, it is possible that our survey design is picking up preferences which are both context dependent *and* context independent. Stated preference methods such as contingent valuation deal in hypothetical bargains at some future time period, when the individual hypothetically hands over dollars in exchange for a specified environmental improvement. For low prices on a payment ladder, an individual who chooses the "yes, I would definitely pay this" option by ticking yes is revealing that they would pay this amount irrespective of the payment context that emerges on this future occasion, that is regardless of the actual availability of substitutes/complements or their prices at this future time. The deal is agreed to in a context-independent manner. When the same respondent checks the "no" option to a higher price, then she is revealing that she would not accept this deal at the future time, again regardless of the actual availability of substitutes/complements or their prices at this future time. Again, this decision on the deal at higher prices is context-independent. However, when the respondent says neither definitely yes or no to intermediate prices on the ladder for the public good, they may be signaling that their preferences in this range *are* context dependent. In other words, that they reserve judgement on the deal until exact future circumstances are revealed (which, of course, will never happen since the deal is entirely hypothetical).

This mix of context dependent and context independent preferences for the same individual for the same good seems intuitively plausible, and also offers a way of thinking about the size of the valuation gap. Context-dependence is implied by a non-zero gap. As uncertainty of any type increases, then if people value flexibility when the hypothetical future deal is concluded, greater uncertainty will result in a bigger gap, whatever the source of this uncertainty. The determinants of the demand for flexibility would then turn out, empirically, to be joint determinants of the valuation gap size along with the degree of uncertainty. Separating out these two effects would likely best be done in a future experimental study.

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Table 1 Water quality over time at main south-west beaches, 1989-2000

	1989	*1990*	*1991*	*1992*	*1993*	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*	*2000*
Ard.	F	F	PM	F	F	F	F	PM	F	F	PM	F
Ayr	F	F	F	F	F	F	PM	PM	PM	F	F	F
Girv.	PM	F	PM	F	PM	F	F	F	F	F	PM	PM
Irv.	F	F	F	F	F	F	PM	PM	F	F	F	PM
Prest	F	F	F	F	F	F	PM	PM	PM	F	PM	PM
Trn	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	PM	F
Turn	F	F	F	F	F	F	F	F	PM	F	F	PM

F = fail mandatory standard; **PM** = pass mandatory standard

Key to beach names: Ard = Ardrossan; Girv. = Girvan; Irv. = Irvine; Prest. = Prestwick;

Trn. = Troon; Turn = Turnberry;

Note: no beaches passed the higher Guideline sample during any year in the time series.

Table 2. Mean WTP (£) in the overall sample and the Irvine and Ayr samples respectively, where SIMPLE=(UPPER-LOWER)/2.

	Pooled Sample Mean	Std.Dev.	N	Mean (Irvine sample, N=432)	Mean (Ayr sample, N=351)
SIMPLE	9.48	13.24	783	7.23	12.24
LOWER	6.86	10.5	783	5.26	8.84
UPPER	12.6605	17.06	783	9.21	15.64

Table 3. Tobit regression results explaining the valuation gap. Dependent variable = DIFF=UPPER-LOWER.

Variable	Coefficient	Standard error	T stat	prob	Mean of variable
constant	-5.01	3.68	-1.36	0.17	
Years	-0.07	-0.03	-2.05	0.04	27.7
Location	5.90	1.19	4.92	0.00	1.48
HHincome	2.42	0.46	5.21	0.00	2.10
Interest	-2.99	0.85	-3.49	0.00	2.03
Scope	-0.89	0.52	-1.71	0.08	2.21
Age	0.79	0.65	1.22	0.22	3.09
sigma	13.49	0.65	29.09	0.00	

Where:

Years	How long have you lived here? (in years)
Location	1= Irvine 2 = Ayr
Hhincome	Household income after tax; from 1 = lowest to 15 highest. 0 = not given
Interest	How interesting did you find this interview? 1 - very interesting, 2=somewhat, 3=not interesting, 4 = don’t know
Scope	Test for part-whole bias: "When you gave your max wtp, what was this for?" 1 = improvements at this beach only (the right answer!) 2= improvement at all scottish beaches 3= general environmental improvement 4= not sure
Age	Categorical variable for age from 1 = youngest to 5= oldest

and "sigma" is the disturbance standard deviation

Table 4: results for "scope" variable

SCOPE	IRVINE (# respondents)	AYR (# respondents)
1	184	92
2	81	106
3	116	72
4	51	81

Note: Values generated in response to de-briefing question: "When you gave your maximum sure willingness to pay value (highest tick on the ladder), what was this for?". Responses coded as 1 = improvements at this beach only (the right answer!), 2 = improvements at all Scottish beaches 3 = general environmental improvement, 4= not sure.

Appendix One: payment ladder

"Read out column A from lowest to highest: read out column B from highest to lowest"

£ per annum increase	A: I would definitely pay per year (tick)	B: I would definitely NOT pay per year (cross)
1		
2		
3		
5		
7.5		
10		
13		
15		
20		
26		
34		
40		
52		
60		
65		
70		
93		
104		
125		

Instructions to interviewers:

"Ask people if they would definitely pay £1 per year extra for improving water quality. If yes, tick the first cell in column A, then ask if they would definitely pay £2. Keep going until the respondent says "no". Then ask them if they are sure £125 is too much for them. If yes, place a cross in the lowest cell of column B, and ask them if £104 is too much. Keep going up column B until they say that they are not sure if £x is too much."

Figure 1a. Kaplan-Meier survival curve for the Irvine sample; LOWER.

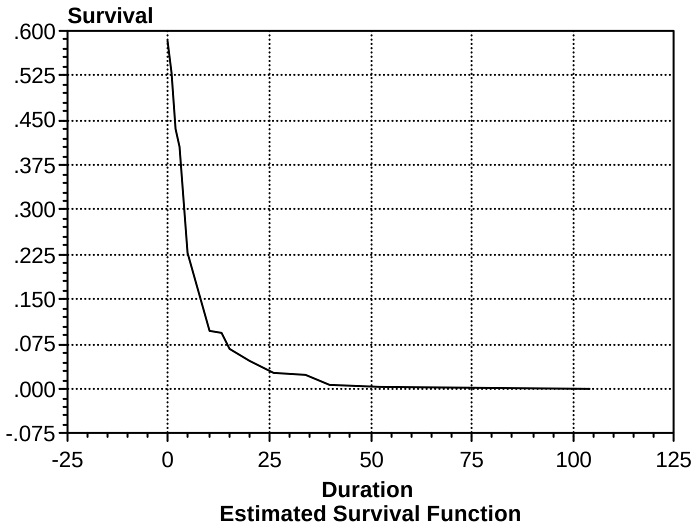

Figure 1b. Kaplan-Meier survival curve for the Irvine sample; UPPER

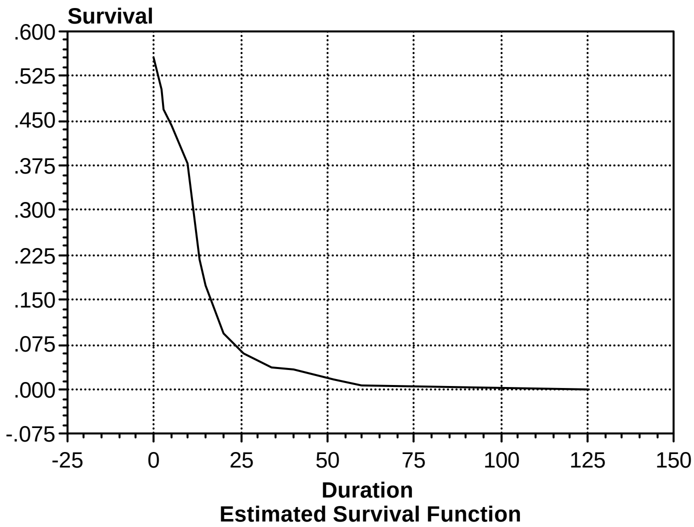

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Figure 2a. Kaplan-Meier survival curve for the Ayr sample; LOWER.

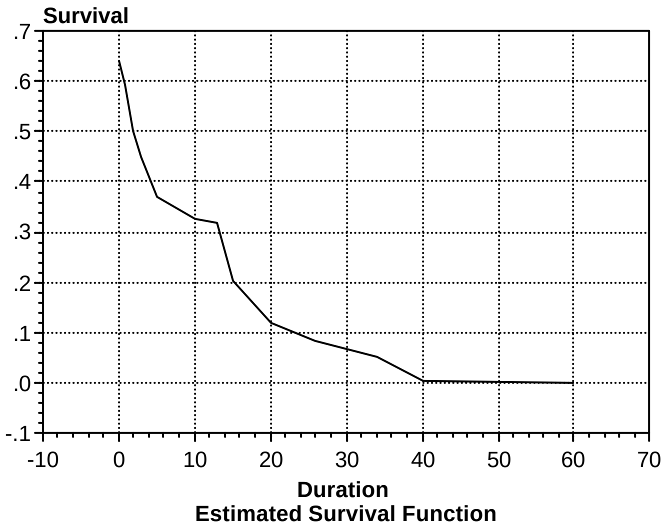
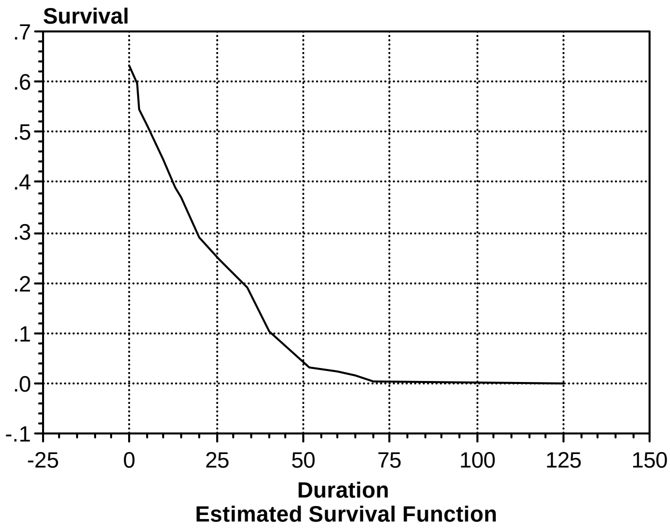


Figure 2b. Kaplan-Meier survival curve for the Ayr sample; UPPER



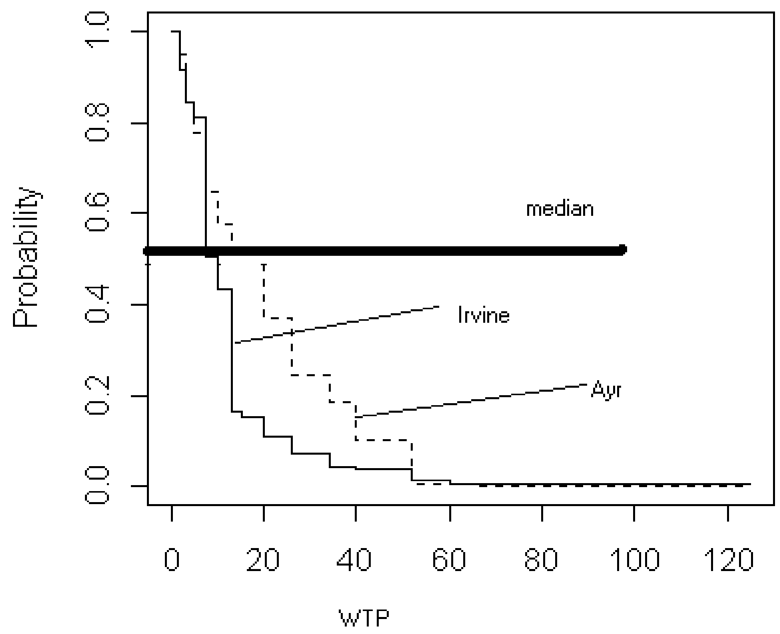


Figure 3. Estimated distribution of WTP using NMPLE.

Appendix Two

Computer program for estimating the NPMLE using R. R can be downloaded from http://cran.r-project.org/. The program is written by Michael P. Fay.

```
"icfit"<-
function(L = left, R = right, initp = NA, minerror = 1e-006, maxcount
= 10000)
{
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
 for discussion of algorithm and theory
see Gentleman and Geyer (1994) Biometrika 81:618-623.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        n <- length(L)
        if(n != length(R))
                stop("length of the two interval vectors must be the
same")
        theta <- sort(unique(c(L, R, 0, Inf)))
        k <- length(theta)
        %% allow L[i]==R[i], but must adjust it so that L[i] equals
the
%% next smaller value of theta
        if(any(L == R)) {
                exacts <- sort(unique(R[R == L]))
                if(exacts[1] == 0)
                        stop("L[i]==R[i]=0 for some i")
                for(j in 1:length(exacts))
                        L[R == L & L == exacts[j]] <-
theta[(1:k)[theta ==
                                exacts[j]] - 1]
        }
        A <- matrix(0, n, k)
        for(i in 1:n) {
                A[i, L[i] < theta & theta <= R[i]] <- 1
        }
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
 perform primary reductions on A
 see Aragon and Eberly (1992) J of Computational and Graphical
     Statistics 1:129-140 for discussion of primary reduction
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
        colsums <- apply(A, 2, sum)
        pairmult <- rep(0, k - 1)
        mark.to.keep <- rep(T, k)
        for(i in 1:(k - 1)) {
                pairmult[i] <- sum(A[, i] * A[, i + 1])
                if(pairmult[i] == colsums[i]) {
                        if(colsums[i] < colsums[i + 1]) {
                                mark.to.keep[i] <- F
                        }
                }
                if(pairmult[i] == colsums[i + 1]) {
                        if(colsums[i] >= colsums[i + 1]) {
                                mark.to.keep[i + 1] <- F
                        }
                }
```

```
        }
        A <- A[, mark.to.keep]  %%% come up with the initial
estimates
%% Replace inefficient code for more efficient code
% p <- matrix(1, n, k)
        if(any(is.na(initp))) {
%% Replace inefficient code for more efficient code
%  for(i in 1:n) {
%   p[i,  ] <- A[i,  ]/sum(A[i,  ])
%  }
%  pbar <- apply(p, 2, mean)
                pbar <- apply(A/apply(A, 1, sum), 2, mean)
        }
        else {
                if(length(initp) != k)
                        stop("initp not of proper length")
                if(sum(initp[mark.to.keep]) != 1) {
                        warning("after primary reduction, sum of
initp !=1")
                        initp <- initp/sum(initp[mark.to.keep])
                }
                pbar <- initp[mark.to.keep]
        }
        error <- 1
        count <- 1
        u <- -1
        while(error > minerror & count < maxcount) {
%%% algorithm to improve initial estimates
                pbar[pbar < minerror] <- 0
        %% Replace inefficient code for more efficient code
%  for(i in 1:n) {
%   p[i,  ] <- A[i,  ] * (pbar/sum(pbar * A[i,  ]))
% }
%  pbar <- apply(p, 2, mean)
                temp <- A/as.vector(A %*% pbar)
                pbar <- apply(t(temp) * pbar, 1, mean)
                count <- count + 1
                d <- apply(temp, 2, sum)
                u <-  - d + n
                u[pbar > 0] <- 0
                error <- max(d + u - n)
        }
%%%% test the Kuhn-Tucker conditions
        if(any(u < 0))
                warning("problem with convergence, decrease
minerror")
        if(count == maxcount)
                warning("problem with convergence, increase
maxcount")
        temppbar <- rep(0, k)
        temppbar[mark.to.keep] <- pbar
        surv <- rep(0, k)
        for(i in 1:(k - 1)) {
                surv[i] <- sum(temppbar[(i + 1):k])
        }
        names(temppbar) <- as.character(theta)
        names(surv) <- as.character(theta)
        %% Since theta[k]==Inf, take off those values
        theta <- theta[ - k]
        surv <- surv[ - k]
        %% but leave it on the density so it sums to 1, and it may
```

```
%% be reentered in as initp if needed
        out <- list(u = u, error = error, count = count, p =
tempppbar, time =
                theta, surv = surv)
        out
}
"icplot"<-
function(surv, time = as.numeric(names(surv)), xrange = NA,
lines.only = F,
        XLAB = "Time", YLAB = "Probability", LTY = 1, ...)
{
        k <- length(surv)
        if(length(time) != k)
                stop("length of surv and time must be the\n\tsame")
        if(time[k] == Inf)
                stop("time value = Inf, cannot plot it")
        if(lines.only == F) {
                if(is.na(xrange)) {
                        xrange <- range(c(time, 0))
                }
                plot(xrange, c(0, 1), type = "n", xlab = XLAB, ylab =
YLAB, ...
                        )
        }
        x <- rep(0, 2 * k + 1)
        y <- rep(1, 2 * k + 1)
        for(j in 1:(k - 1)) {
                y[(2 * j + 1):(2 * j + 2)] <- surv[j]
                x[(2 * j):(2 * j + 1)] <- time[j]
        }
        y[2 * k + 1] <- surv[k]
        x[(2 * k):(2 * k + 1)] <- time[k]
        lines(x, y, lty = LTY)
}
```