**Dealing with Preference Uncertainty with Mixture Models**

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**Abstract:** In the current paper, we compare alternative approaches to incorporating uncertainty into the statistical analysis of dichotomous choice responses. In doing so, first we employ previous modelling techniques that included uncertainty of preferences, and secondly we compare the obtained results with those coming from a novel approach here developed, a finite mixture model. The finite mixture model is a very flexible framework used to deal with preference uncertainty. Our case study uses data gathered in the Prestige oil spill valuation study from Spain.

## 1. Introduction

Dichotomous choice (DC) questions are very popular in the context of valuation of natural resources and public policies. The NOAA panel recommendations (Arrow *et al.*, 1993) as well as their easy econometric handling favoured their use during many years in the contingent valuation (CV) literature. However, a clear shortcoming of single DC questions is that they offer a very limited amount of information regarding the individual's underlying preferences. Because of this limitation, it became common practice to include a series of follow up questions in order to increase the knowledge about the underlying preferences, so that more efficient welfare estimates can be computed. In the recent years, follow up questions related to the certainty level of the DC response are popular instruments.

Preference uncertainty may be motivated by several reasons, including the lack of previous thought about the valuation question (Loomis and Ekstrand, 1998), the need of more knowledge about the good or service being valued, or the lack of understanding about the future consequences derived from the committed payment. Previous studies have dealt with preference uncertainty in different ways, some being more ad-hoc than others. In the current paper, we compare alternative approaches to incorporating uncertainty into the statistical analysis of DC data in terms of statistical performance of the WTP function and WTP magnitudes. In doing so, first we employ previous modelling techniques that included uncertainty of preferences, and secondly we compare the obtained results with those coming from a novel approach here developed, a finite mixture model. The finite mixture model is a very flexible framework used to deal with preference uncertainty. Our case study uses data gathered in the Prestige oil spill valuation study in Spain.

This paper is organized as follows. Section 2 presents a review of studies dealing with uncertainty in the context of CV. Section 3 presents the theoretical foundations of the empirical mixture model. Section 4 presents the description of the data set used, and section 5 outlines the results. The last section presents a summary of concluding remarks.

**2. Literature Review**

One of the first attempts to include uncertainty in CV studies was the work by Champ et al. (1997). They investigate how the follow-up certainty question helps differentiating between respondents who would actually donate an amount in a real setting from those who would not. They conclude that the certainty scale is a promising approach to estimating a lower bound to Hicksian surplus measures.

Several studies, such as those by Ready, Whitehead and Blomquist (1995) use a new polychotomous valuation (PC) question, and compare the obtained results via a traditional DC with those from a PC framework. In the DC question, respondents are given the options to respond with a “yes” or “no” to the valuation question, while in the PC question, respondents are presented with six responses to choose from, “definitely yes,” “probably yes,” “maybe yes,” “maybe no,” “probably no,” and “definitely no.” The results obtained by Ready, Whitehad and Blomquist (1995) reveal that PC questions generate higher rates of “yes” responses because the respondent can give an affirmative response, without making an strong commitment. However, the authors state that this greater easy in giving an affirmative response may also give the respondent less inducement to consider the question carefully before answering. Unfortunately, their PC data are not reliable enough to estimate welfare estimates. Welsh and Poe (1998) employ a multiple bounded uncertainty model (MBUM) with 13 bids, combining that with uncertain response options. Their results are compared from those coming from a DC question format. They show that this multiple bounded question format reduces the confidence bounds around the WTP estimates by over 60% relative to a single-bounded question with the same bid design, showing that this format may provide a valid approach to model uncertainty levels. Evans, Flores and Boyle (2003) used also a sort of multiple-bounded uncertainty valuation model, allowing respondents to indicate qualitative levels of uncertainty. Their particular modelling framework allows the inclusion of uncertainty motivated by the respondent or researcher, being named the dual-uncertainty decision estimator (DUDE). It relies on assigning finite probabilities to each WTP certainty level, where a response indicating a certainty level of "definitely yes" implies a probability equal to 1, and "not sure" a probability equal to 0.5. The results provided by this model are compared with other Welsh and Poe (1998) type of MBUM. Their results suggest that the DUDE model is relatively insensitive to changes in the research-imposed information.

Loomis and Ekstrand (1998) present different approaches to model the 10 point follow-up certainty scale to "calibrate" the positive responses to the WTP question. They compare results with different recoding levels of the certainty scale question with those coming from an "asymmetric uncertainty model," which multiplies the "Yes" response by the certainty score. In this model, an individual denoting a 10 score in the certainty scale will be assigned a 1 probability of paying the given amount, whereas an individual selecting a 1 will be assigned a 0.1 probability to its response. These direct weights have the advantages of not relying on the researcher's arbitrary interpretation. Their results suggest that incorporating the degree of uncertainty into the WTP analysis produces results with the highest goodness of fit and the smallest variability of the mean WTP among the various models utilized.

Different approaches to those outlined above have been used by Li and Mattson (1995) and Alberini, Boyle and Welsh (2003). Li and Mattson (1995) develop a structural model to include preference uncertainty into the modelling framework, modelling WTP responses with a composite error statistical framework. Alberini, Boyle and Welsh (2003) extend the analysis previously done by Welsh and Poe (2003), estimating a random effects probit model to estimate the coefficients of correlation between responses from the same individual to different bids. Their results suggest that the correlation coefficient among responses is close enough to zero that warrant treating the responses from the same individual as independent. These results have been later refused by Vossler and Poe (2005).

In the current work, we first follow some DC recoding options similar to those presented by Champ et al. (1997), and compare them with those developed by Loomis and Ekstrand (1998). The results coming from these popular DC recoding approaches will be compared with those from a finite mixture model developed to deal with the uncertainty bias. In the next section, we present the theoretical underpinnings of this finite mixture model, as well as its advantages over previously employed techniques when dealing with uncertainty in the context of preference analysis.

## 3. Finite Mixture Models

Mixture models have multiple applications. In environmental valuation they have been used to incorporate heterogeneous preferences towards the good or program being valued (Hilger and Hanemann, 2006). In the current application, we use a mixture model approach to better account for the uncertainty bias of respondents coming from a CV exercise. The goal in our estimation is to “unmix” the sample and identify the explicit stochastic structure underneath the unique behaviour of each certainty level (or segment).

Latent class mixture models attempt to simultaneously organize observations into component distributions (certainty segments) and characterize each component density function along with the relationship between components. This methodology is very flexible and allows us to understand factors affecting the classification of individuals in different certainty segments, as well as the possibility to compute the respective WTP estimates for each segment. Comparison of model fitting results from different population groups (individuals who are certain and uncertain (or hesitant) about their response to the WTP question) can offer some valid insights.

The probability density function for a finite mixture model distribution can be represented in general terms as:

(1) $$p\left(\mathbf{x}\middle|\mathbf{\Psi}\right)=\sum_{s=1}^{S}\pi_s f\left(\mathbf{x}\middle|\boldsymbol{\theta}_s\right)=\int_{\Theta} f\left(\mathbf{x}\middle|\boldsymbol{\theta}\right)dG_{\pi}\left(\boldsymbol{\theta}\right)$$

Where $\mathbf{\Psi}=\{\boldsymbol{\theta},\boldsymbol{\pi}\}$, $\boldsymbol{\theta}=\{\boldsymbol{\theta}_1,...,\boldsymbol{\theta}_s\}\in\Theta,\boldsymbol{\pi}=(\pi_1,...,\pi_s)$ define a probability distribution over $\Theta$, $f\left(\mathbf{x}\middle|\boldsymbol{\theta}\right)$ denotes a generic member of a parametric family of probability densities, and $G_{\pi}\left(\boldsymbol{\theta}\right)$ denotes the probability measure over $\Theta$ defined by $\boldsymbol{\pi}$. In our empirical exercise it is assumed that there are S certainty levels into which the individual can be classified, s=0,1,2,..$S$ where $S$ is generally unobservable. The probabilities to belonging to a given certainty level are denoted by $\pi_s$, while the $f\left(\mathbf{x}\middle|\boldsymbol{\theta}_\mathbf{s}\right)$ component models the within market behavior. As previously stated, a DC valuation question is used to recovery WTP estimates for a given public program. In this case, the participant may respond Yes or No to the DC WTP question. When using a DC valuation question, the within market segment behavior is described by the following probabilities:

(2) $\Pr(No) = P(V_i^* < B_i) = G(B_i \,|\boldsymbol{\theta}_s)$

(3) $\Pr(Yes) = P(V^* \geq B_i) = 1 - G\left(B_i \,\middle|\boldsymbol{\theta}_s\right)$,

Where $G(B_i \,|\boldsymbol{\theta}_\mathbf{s})$ is a cumulative distribution function (such as the logistic) and $V_i^*$ is the individual indirect utility received from contributing to a public program.

Let the probability of respondent *i* choosing a certainty level j (j=1, 2,3…J), conditional on belonging to a market segment *s* be $P_i(j\,|s)$, so that the probability density function within a certainty segment is defined as:

(4) $f(\mathbf{x}|\boldsymbol{\theta}) = \prod_{j=1}^{J} P_i\left(j\,\middle|\boldsymbol{\theta}_\mathbf{s}\right)^{I_j(x)}, x = 1,\ldots,J$

with j=1 indicating a No, and j=2 indicating a Yes, and $\sum_{j=1}^{J} P_i\left(j\,\middle|\boldsymbol{\theta}_s\right) = 1$. The indicator function $I_j(x)$ is equal to 1 if the response is $x$=$j$ and 0 otherwise.

For each respondent *i* let $\mathbf{x}_\mathbf{i}$ be a row vector containing the price as well as other factors affecting the decision to pay for the program, with the corresponding vector of estimable parameters $\boldsymbol{\theta}_\mathbf{s}$ Assuming that the willingness to pay function can be modeled with a logistic distribution function, the within market segment (2-3) can be completed by specifying the cumulative distribution function:

$$(5)\quad G\left(\mathbf{x_i}\,|\,\boldsymbol{\theta}_\mathbf{s}\right) = \frac{\exp(\mathbf{x_i}\boldsymbol{\theta}_\mathbf{s})}{1+\exp(\mathbf{x_i}\boldsymbol{\theta}_\mathbf{s})} \quad \text{for } s = 1,\ldots,S.$$

Without loss of generality it is necessary to normalize the parameter vector for one of the segments to zero for identification purposes. Assuming a linear index structure, the segmentation probabilities $\pi_s$ can be modeled by an unordered multinomial logit specification so that the probability that the consumer *i* belongs to certainty segment *s* is:

$$(6)\quad P_i\left(x \cap s\right) = P_i(s)\prod_{j=1}^{J} P_i\left(j\,|\,s\right)^{I_j(x)}$$

The total probability of belonging to an individual choosing a response $x = j \in \{1,\ldots,J\}$ and belonging to any of the certainty levels (segments) in the market is:

$$(7)\quad \sum_{s=1}^{S} P_i\left(x \cap s\right) = \sum_{s=1}^{S} P_i(s)\prod_{j=1}^{J} P_i(j\,|\,s)^{I_j(x)}.$$

Based on (7) the likelihood function across all sample observations can be expressed as:

$$(8)\quad L\left(\boldsymbol{\theta},\boldsymbol{\gamma}\,|\,\mathbf{x},\mathbf{z}\right) = \prod_{i=1}^{n}\sum_{s=1}^{S} P_i(s)\prod_{j=1}^{J} P_j(j\,|\,s)^{Ij(x)},$$

Where n denotes the sample size. The log-likelihood function is then:

$$(9)\quad LL(\boldsymbol{\theta},\boldsymbol{\gamma}\,|\,\mathbf{x},\mathbf{z}) = \sum_{i=1}^{n}\ln\left(\sum_{s=1}^{S} P_i(s)\prod_{j=1}^{J} P_i\left(j\,|\,s\right)^{I_j(x)}\right),$$

Where the estimates of $\boldsymbol{\theta}$ and $\boldsymbol{\gamma}$ can be obtained by maximizing (9) for a given S.

In the empirical analysis that follows we compare the results provided with this mixture model, by which we classify individuals into different certainty levels, and estimate their respective WTP estimates, with those results coming from previous DC recoding options. Note that we are mainly concerned with the uncertainty levels associated with the affirmative responses since the general concern regarding reliance on hypothetical WTP.

## 4. Empirical Application: The Prestige Oil Spill Valuation Study

The data used in this application come from a recent CV survey developed in Spain. Our study was developed in mainland Spain and in the Balearic and Canary Islands. We excluded the Spanish colonies of Ceuta and Melilla located in Northern Africa due to the serious difficulties of setting a reliable survey mechanism in these two cities.

The distribution of observations per Autonomous Communities matches quite well the total Spanish population per Autonomous Community. The CV survey was carried out in a representative sample of the Spanish population during the spring and early summer 2006. In total, about 1140 completed surveys were collected, and the response rate was about 44.4%. The main socio-economic characteristics of the sample are presented in Table 1.

The main objectives of the present survey were: a) to assess the total passive value lost in the Prestige oil spill, as it has been done in previous oil spills, such as in the Exxon Valdez oil spill (Carson et al.,2003 ); and b) to assess the sensitivity of WTP estimates under different scenarios.

Surveys were administered at private homes at different hours during the week days and weekends. This survey had different sections. The section of analysis in the present paper is the economic questions in which individuals were interviewed about their WTP for the described prevention program. Right after the WTP question, a follow-up certainty scale from 1-10 was presented. Finally, the last section contained the socio-economic questions. In particular, the WTP question was:

*It is expected that this program is in full operation in 2010. If the implementation of the escort ship and rapid response program described above will cost your household* **€--,** *would you vote to pay this amount just* *one single time (say in the next tax declaration)* *to reduce the damages described from the oil spill to the nature and fauna by oil spills?*

YES …..1 NO …..2

*.We do know there are many factors beyond your control that may affect the level of probability that you may vote as you stated above. Please circle the level of certainty you have regarding your previous response, meaning how sure you are about casting your vote in this way in a future referendum, given that 1=not certain at all, and 10=absolutely certain.*

*Not sure* *Hesitant* *Totally sure*

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| *1* | *2* | *3* | *4* | *5* | *6* | *7* | *8* | *9* | *10* |

**5. Preliminary Results**

Table 2 presents the distribution of responses per certainty level. As it turns out, 31.94% of the respondents indicated a certainty level of 10 points and 66.25% of the respondents stated a certainty level of 8 points or above. A preliminary analysis of the distribution of affirmative responses per certainty level denotes that in a large number of occasions (140), affirmative responses received a certainty score of 10.

Our results show considerable differences between the estimates obtained from logit models with different recoding of the certainty scale. Table 3 presents the coefficient estimates obtained with a DC logit model (without applying any recoding to the certainty levels), as well as a logit model with a certainty level of 9 and 10 recoded as 1 and the rest of responses as 0 (the Champ *et al.* , 1997 recoding), and the asymmetric recoding applied by Loomis and Ekstrand, 1998.

Empirical estimates show expected results. Respondents facing higher bids and older are less likely to pay for the prevention program. However, individuals with education levels corresponding with High school and University degrees are more likely to pay for the described prevention program. Other variables such as the familiarity with the affected area also increase the WTP estimate. These results are consistent across the different specifications and recoding formats.

Mean WTP estimates and 95% confidence intervals from these logit models are presented in Table 4. WTP results show a considerable difference between WTP logit estimates coming from the DC logit (baseline model) with those from the recoded affirmative responses. These results will be compared with those from the finite mixture model. A major advantage of the mixture model here presented is that it would allow for the consideration of the differential socioeconomic effects across the sample groups. Other results and further implications will be also presented.

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**Table 1: Main Socio-Economic Characteristics of the Sample**

| Variable | Mean or % | Census Comparison (INE, 2005) |
|---|---|---|
| ***Gender*** | 48.95 (% male) | |
| ***Age*** | 44.75 (mean) | |
| ***Education %*** | | |
| No formal education | 7.81 | |
| Primary school | 28.16 | 37.4 (primary school and below) |
| High School | 29.39 | 40.5 (high school and professional school) |
| Professional School | 13.95 | |
| University Degree 3 years | 8.51 | 21.8 (university degree and more) |
| University Degree 5 years | 8.68 | |
| Post-graduated Studies and PhD | 1.40 | |
| No response | 2.11 | |
| ***Yearly Income (2005) %*** | | |
| Less than €5,999 | 3.07 | |
| €6,000-€11,999 | 13.68 | |
| €12,000-€17,999 | 16.67 | |
| €18,000-€23,999 | 13.07 | |
| €24,000-€29,999 | 8.68 | |
| €30,000-€35,999 | 3.60 | |
| €36,000-€59,999 | 3.51 | |
| €60,001-€70,000 | 0.35 | |
| €70,001-€80,000 | 0.18 | |
| More than €80,001 | 0.18 | |
| No response | 37.02 | |
| ***Civil Status %*** | | |
| Single | 27.54 | |
| No partner-living with parents | 7.46 | |
| Married | 51.32 | |
| Separated | 2.89 | |
| Divorced | 1.67 | |
| Widowed | 7.98 | |
| No response | 1.14 | |
| ***Employment %*** | | |
| Self-employed | 10.70 | |
| Full-time employed | 35.88 | |
| Part-time employed | 8.60 | |
| Unemployed | 5.09 | |
| Student | 8.33 | |
| Looking after the home | 10.53 | |
| Retired | 18.42 | |
| Other | 2.46 | |

**Table 2: Results for levels of certainty**

Level of certainty

| Scale | Responses | % |
|---|---|---|
| 1 | 17 | 1.52 |
| 2 | 8 | 0.72 |
| 3 | 17 | 1.52 |
| 4 | 25 | 2.24 |
| 5 | 82 | 7.34 |
| 6 | 76 | 6.80 |
| 7 | 152 | 13.61 |
| 8 | 210 | 18.80 |
| 9 | 173 | 15.49 |
| 10 | 357 | 31.96 |
| **Total** | **1117** | **100.00** |

**Graph 1: Distribution of WTP Responses Per Certainty Level**

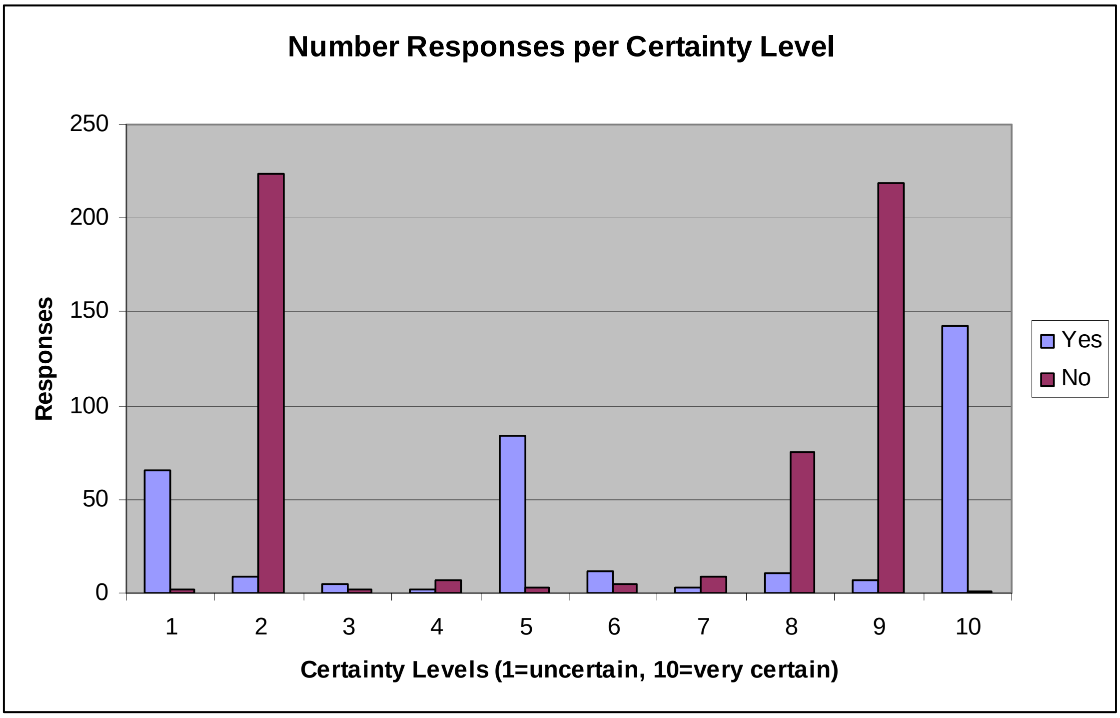

**Table 3: Empirical Results**

| | DC | Logit | | Champ & Bishop,1997 | | | Loomis & Ekstrand, 1998 | | |
|---|---|---|---|---|---|---|---|---|---|
| WTP | Coef. | Std. Err. | T-value | Coef. | Std. Err. | T-value | Coef. | Std. Err. | T-value |
| Bid | -0.007 | 0.001 | -7.89 | -0.007 | 0.001 | -5.47 | -0.001 | 0.000 | -5.97 |
| Age | -0.012 | 0.005 | -2.51 | -0.008 | 0.008 | -1.09 | -0.0001 | 0.001 | -0.05 |
| IncomeSources | 0.022 | 0.104 | 0.21 | 0.181 | 0.168 | 1.08 | 0.0001 | 0.026 | 0 |
| PrimarySchool | 0.185 | 0.183 | 1.01 | 0.089 | 0.283 | 0.32 | 0.033 | 0.045 | 0.72 |
| Highschool | 0.686 | 0.256 | 2.68 | 0.373 | 0.399 | 0.94 | 0.115 | 0.066 | 1.75 |
| UniversityDegree | 1.407 | 0.648 | 2.17 | 0.395 | 0.889 | 0.44 | 0.308 | 0.160 | 1.93 |
| UncertaintyScale | 0.092 | 0.025 | 3.73 | | | | | | |
| KnowAffectedPeople | 0.177 | 0.185 | 0.96 | 1.008 | 0.558 | 1.81 | 0.019 | 0.048 | 0.4 |
| VisitedAffectedArea | 0.612 | 0.174 | 3.51 | 0.730 | 0.277 | 2.63 | 0.082 | 0.045 | 1.84 |
| Male | -0.114 | 0.164 | -0.69 | -0.440 | 0.257 | -1.71 | -0.037 | 0.041 | -0.9 |
| Constant | 0.122 | 0.348 | 0.35 | 0.847 | 0.498 | 1.7 | 0.270 | 0.081 | 3.32 |
| Log-likelihood | -437.64 | | | -181.81 | | | | | |

**Table 4: Mean WTP Estimates**

| **WTP=** $\frac{-\hat{\alpha}}{\hat{\beta}}$ | **Mean WTP** | **95 % C.I.*** |
|---|---|---|
| DC Model | 72.59 | (66.51,78.66) |
| Loomis &Ekstrand, 1998 | 110.24 | (100.30, 120.18) |
| Champ & Bishop Recoding, 1997 | 259.15 | (254.62, 263.68) |

* C.I. were estimated with the Jacknife technique.