Dealing with Preference Uncertainty in Contingent Valuation: A Mixture Model Approach

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Abstract: 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 used to deal with uncertainty, a finite mixture model. The finite mixture model is a very flexible framework used in this case to deal with latent clustering of observations. Our case study uses data gathered in the Prestige oil spill valuation study from Spain. Those certain of their CVM responses would pay a one time WTP of 82 Euro, while those less certain would only pay 54 Euro. Results provided by the finite mixture model show promising signs of incorporating preference uncertainty without researcher judgements regarding recoding or reinterpretation of respondent´s answers.

Keywords: bias, contingent valuation, finite mixture models, uncertainty

JEL Classification: H43, D8

Acknowledgements

The authors wish to thank, without implicating, *Fundación Arao* for funding of the project. They also thank Carlos Cigarrán and Lucia Sixto from the research company Sondaxe.

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 true preferences. Because of this limitation, it became common practice to include a series of follow up questions after the valuation scenario, increasing the knowledge about the underlying preferences for the good or program being valued, while allowing for the computation of more efficient welfare estimates. In the literature, follow up questions related to the certainty level of the DC response are popular instruments to assess the uncertainty bias.

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 functions and estimated welfare 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 applied, a finite mixture model. The finite mixture model is a very flexible framework used in this case 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 preference uncertainty in the context of valuation of environmental resources. 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 obtained with the different methods. 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 Ready, Whitehead and Blomquist (1995). They use a 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 with 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 a variant of the 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). Their model 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´s MBUM model. Their results suggest that a main difference between both approaches is that the DUDE model is relatively insensitive to changes in the research-imposed information.

Another line of studies has incorporated uncertainty using a 10 point follow-up certainty scale. Champ et al. (1997) 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. In their study, all "yes" respondents were recoded as a "no" if the respondent was not completely certain, i.e. providing a certainty score below 10. They conclude that the certainty scale is a promising approach to estimating a lower bound to Hicksian surplus measures. In a similar fashion, Ready, Navrud, and Dubourg (2001) use a WTP question posed using the following choices: a) almost certain yes (95% sure yes), b) most likely yes, c) equally likely yes or no, d) more likely no, and e) almost certain no. Using the same recoding approach as in Champ et al.

(1997), only the almost certain yes responses were recoded as affirmative responses. As a result, Loomis and Ekstrand (1998) named these previous recoding methods as "asymmetric uncertainty models (ASUM)." Their ASUM model multiplies the affirmative responses by the certainty score. Therefore, in this model, an individual responding in a affirmative way to the WTP question and 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 affirmative response. These direct weights have the advantages of not relying on the researcher's arbitrary interpretation of respondent's certainty levels. 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 these previously outlined above have been also 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 conducted 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 refuted by Vossler and Poe (2005).

Another approach to the study of uncertain preferences is the work by van Kooten, Krcmar, and Bulte (2000). They propose the use of fuzzy contingent valuation, especially useful to deal with cases in which respondents are *never* fully knowledgeable about their preferences with respect to the good being valued. In this sense, fuzzy contingent valuation may deal with cases which have been previously ignored in the literature. According to Shaikh, Sun and van Kooten (2007) a respondent only knows the level above which she will certainly reject the requested bid or payment, and the level below which she will certainly accept the proposed payment. In between these two levels, the preferences are ambiguous, so that respondent's WTP and willingness not to pay (WNTP) are best viewed as fuzzy sets. Shaikh, Sun and van Kooten (2007) compare fuzzy model with the traditional random utility model (RUM), the Champ et al. model (1997), and the Loomis and Ekstrand (1998) ASUM recoding methods, among others, concluding that the performance of the fuzzy models is quite satisfactory.

In the current work, we first follow some DC recoding options similar to those outlined above, mainly the RUM, and both ASUMs methods. The results coming from these popular DC recoding approaches will be compared with those from a finite mixture model here 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 many uses in economics. In environmental valuation they have been used to incorporate heterogeneous preferences towards the good or program being valued (Grimsrud, Mittelhammer, and Berrens, 2006). For example, Boxall and Adamowicz (2002) use finite mixture models to model the systematic heterogeneity of recreationists; Nonetheless, the potential of mixture models is just being tapped and the number of empirical applications is still fairly limited at this time. 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 segment or cluster.

Latent class mixture models attempt to simultaneously organize observations into component distributions, 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. This opportunity is farther exploited by computing the respective WTP estimates for each certainty segment. A clear advantaged of the proposed method with respect to other prior recoding applications of the certainty scale is that it does not rely on any arbitrary interpretation of the certainty scale. Furthermore, comparison of model fitting results from different classes or segments can offer some valid insights in terms of policy analysis.

Theory of Finite Mixture Models

The probability density function for a finite mixture model distribution can be represented in general terms as (Titterington, Smith, and Makov, 1985):

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

Where $\boldsymbol{\Psi} = \{\boldsymbol{\theta}, \boldsymbol{\pi}\}, \boldsymbol{\theta} = \{\boldsymbol{\theta}_1, ..., \boldsymbol{\theta}_s\} \in \Theta, \boldsymbol{\pi} = (\pi_1, ..., \pi_s)$ define a probability distribution over Θ, $f(\mathbf{x}|\boldsymbol{\theta})$ denotes a generic member of a parametric family of probability densities, and $G_{\pi}(\boldsymbol{\theta})$ denotes the probability measure over Θ defined by $\boldsymbol{\pi}$. In our empirical exercise it is assumed that there are S certainty segments 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 segment are denoted by π_s, while the $f(\mathbf{x}|\boldsymbol{\theta}_s)$ 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) $\Pr(Yes) = P(V^* \geq B_i) = 1 - G(B_i|\boldsymbol{\theta}_s)$,

Where $G(B_i|\boldsymbol{\theta}_s)$ is a cumulative distribution function (such as the logistic), and Bi is the bid amount respondents are asked to pay, and V_i^* is the individual indirect utility received from contributing to a public program.

Let the probability of respondent *i* choosing to pay or not to pay (j=1, 2), 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) $f(\mathbf{x}|\boldsymbol{\theta}) = \prod_{j=1}^{J} P_i\left(j|\boldsymbol{\theta}_\mathbf{s}\right)^{I_j(x)}, x = 1, 2.$

with j=1 indicating a No, and j=2 indicating a Yes, and $\sum_{j=1}^{J} P_i\left(j|\boldsymbol{\theta}_s\right) = 1$. 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) $G\left(\mathbf{x}_\mathbf{i}|\boldsymbol{\theta}_\mathbf{s}\right) = \frac{\exp(\mathbf{x}_\mathbf{i}\boldsymbol{\theta}_\mathbf{s})}{1 + \exp(\mathbf{x}_\mathbf{i}\boldsymbol{\theta}_\mathbf{s})}$ for $s = 1, ..., S$.

Assuming a linear index structure, the segmentation probabilities π_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) $P_i\left(x \cap s\right) = P_i(s)\prod_{j=1}^{J} P_i\left(j|s\right)^{I_j(x)}$

The total probability of an individual choosing a response $x = j \in \{1, 2\}$ and belonging to any of the certainty levels (segments) in the market is:

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

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

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

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

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

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 compute the optimal number of certainty segments or clusters, based on the responses given to the 10 point certainty scale. Furthermore, we characterize the different clusters based on the individuals´ characteristics, and compute WTP estimates for each of the corresponding clusters or classes of individuals. These WTP estimates are then compared to several of the past valuation models that incorporate uncertainty as well as the standard binary logit model. We also compare the different WTP and assess whether they are different in a significant way.

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 conducted with a representative sample of Spanish residents in mainland Spain and in the Balearic and Canary Islands. The main objective of the survey was to assess the total passive value lost in the Prestige oil spill. Surveys were administered at private homes at different hours during the week days and weekends. The CV survey was carried out in the spring and early summer 2006. In total, about 1140 surveys were collected; being the response rate was about 44.4%[1]. The main socio-economic characteristics of the sample are presented in Table 1.

[1] In this current application, we use the subset of data without any missing value in the explanatory variables.

The survey instrument had different sections. The survey followed closely the structure of other previous work done by Carson *et al.* (2003) in the valuation of the Exxon Valdez oil spill. The section of analysis in the present paper contains the economic questions in which individuals were interviewed about their WTP for the described oil spill 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 verbatim employed in the WTP question was:

> *If the implementation of the escort ship and rapid response program described above will cost your household* **€--,** *would you vote in favor of paying this amount just <u>one single time (say in the next tax declaration)</u> to reduce the damages described to the nature and fauna by oil spills?*
>
> YES …..1 NO …..2

We are aware that there are many factors beyond your control that may affect the level of certainty of the response that you just 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. Empirical Results

Graph 1 presents the distribution of yes/no responses to the DC valuation question per certainty level. As it turns out, 31.94% of the respondents indicated a certainty level of 10 points, while in total, about 66.25% of the respondents stated a certainty level of 8 points or above. The proportion of individuals who are less certain is smaller, with a 13.34% of survey respondents stating certainty levels of 5 points or below. Graph 2 presents a representation of the non-parametric distribution of the total number of responses per certainty level. Visually, the distribution of responses per certainty levels has two local maxima, with the most prominent located at the 10 point scale of the certainty scale, and the second in the neighbourhood of the second point scale.

As stated earlier, we first employ previous recoding models developed to deal with uncertainty in CV studies, such as the ASUM models. Our results show considerable differences between the estimates obtained from these models. Table 3 presents the results obtained with a DC logit model based (the classical RUM, without applying any recoding to the certainty levels); and the Champ *et al*. (1997) and the Loomis and Ekstrand (1998) ASUM model.

Empirical estimates presented in Table 3 show expected results throughout the estimated equations. Respondents facing higher bids are less likely to pay for the described prevention program, as microeconomic theory would predict. In addition, those who visited the affected area are more likely to pay for the escort ships and rapid response program. Education plays also a statistically significant role on explaining WTP for the rapid response and escort ship program. In this sense, in two out of the three logit empirical specifications, the coefficients denoting that the respondent has completed High school or a University degree are positive and statistically significant.

With the implementation of the finite mixture model, we are able to separate responses according to their certainty levels. The log-likelihood function presented in (9) has been maximized with the Expectation-Maximization (EM) algorithm, until the log-likelihood falls under a pre-specified threshold or a maximum number of iterations were reached. In general terms, the EM algorithm is very suitable for fitting models to incomplete data. There are two main ways to assign data into the latent classes, the hard assignment via the specification of the maximum posterior probability, and a random assignment (similar to Bayesian methods), which has been employed here. The estimation has been conducted with the open source R computing and statistical environment, version 2.5.0, using the *FLEXMIX* package.

In this application, two major classes or segments of respondents are distinguished, denoted as the "uncertain" and the "certain" class, respectively. Graph 3 shows the rootogram of posterior probabilities of belonging to both classes (where Class 1 =Uncertain, and Class 2=Certain). Rootograms are very similar to histograms; the only difference is that the height of the bars corresponds to square roots of counts, rather than the counts themselves. In this way, the low counts are more visible and the peaks less emphasized. According to this graphical display, we observe that observations belonging to the second class are well identified, and as a consequence, the peak at probability 1 indicates that a mixture component is well separated from the other components. This is also reflected on the ratio between the size of the cluster and the number of non-vanishing posterior probabilities reported on the bottom of Table 4. In this regard, for well-separated components, it is expected to obtain ratios closer to 1, being for this Certain cluster of respondents .96. On the other hand, observations classified into the Uncertain cluster are more difficult to classify, and in addition to the mixture component, there remain other components to be identified, as the heights of the rootograms show, while the ratio between the size of the cluster and the non-vanishing posterior probabilities is about .53. Hence, we can conclude that the components of the Certain class are better separated than the components of the Uncertain one.

Table 4 presents the analysis of the socio-economic determinants of the clusters. Individuals belonging to the Certain cluster are characterized by being more likely to have a higher educational attainment and being male. Furthermore, those respondents who receive a higher bid are also more likely to belong to the certain class. In this regard, our results seem to follow previous findings encountered by Loomis and Gonzalez-Cabán (1997). In the Uncertain cluster, the effects of the cited explanatory variables are just the opposite. Furthermore, individuals classified as members of the uncertain cluster are less likely to be older, and to have visited the affected coast.

Table 5 shows the WTP results per class of respondents or cluster. WTP of individuals, conditional on being classified as uncertain respondents is affected in a negative and statistically significant way by the bid offered, and their age. Other explanatory variables, such as education (High School and University levels) and whether the individual visited the affected area carry a positive and statistically significant effect on WTP responses. WTP of the individuals, condition on being classified as certain respondents, seems to be mainly affected by the bid amount, and whether the individual visited the affected area, while the rest of the explanatory variables are not statistically significant. This is the reason that justifies the exclusion of the rest of the explanatory variables in the restricted WTP logit model also presented in Table 5.

Mean WTP estimates and their respective 95% confidence intervals coming from all the estimated models are presented in Table 6. WTP results show a considerable difference between estimates derived from previous recoding formats, and those obtained from the mixture classes. In this sense, it is interesting to highlight the fact that the magnitude of the WTP estimate from the cluster of certain respondents is fairly higher than the corresponding estimate from the uncertain cluster. In particular, the mean WTP of individuals classified as belonging to the certain cluster is estimated as €82.14, while the corresponding estimate for the individuals belonging to the uncertain class is €54.08. For comparison purposes, these welfare estimates differ from all previously computed. WTP obtained from a regular RUM DC (which included the certainty scale as an explanatory variable) provides a WTP estimate of €72.59, being in between the WTP estimates obtained from both clusters. The WTP results coming from the ASUM recoding frameworks developed by Loomis and Ekstrand (1998) and Champ and Bishop (1997) are well above the dichotomous choice and mixture model estimates.

6. Conclusions

In the current paper, we compare alternative approaches to incorporating uncertainty into the statistical analysis of DC responses. In doing so, first we employ previous modelling techniques that dealt with different types of recoding of the uncertainty scale. Then, we compare the obtained results with those coming from a finite mixture model. As stated earlier, the finite mixture model is a very flexible framework. In this particular case it has been used to create clusters of respondents with respect to their certainty levels, as expressed in the follow-up certainty scales. Our case study uses data gathered in the recent Prestige oil spill valuation study in Spain.

We conclude that latent class models may be very suitable alternatives to cluster individuals according to their certainty levels when responding to WTP questions. This is a technique with numerous advantages with respect to previously developed recoding methods. The main reason is that WTP magnitudes obtained with recoding rely on subjective interpretations of the probability of paying for a given good or service, while in general, the welfare estimates are very sensitive to the recoding format. Furthermore, the identification of explanatory variables affecting the inclusion of each observation in each cluster or latent class provides interesting insights about the effects of explanatory variables, such as formal education and direct experience with the area object of study in the valuation process. Future work may validate whether latent clustering may be such a valid tool for environmental economics as is becoming for marketing studies.

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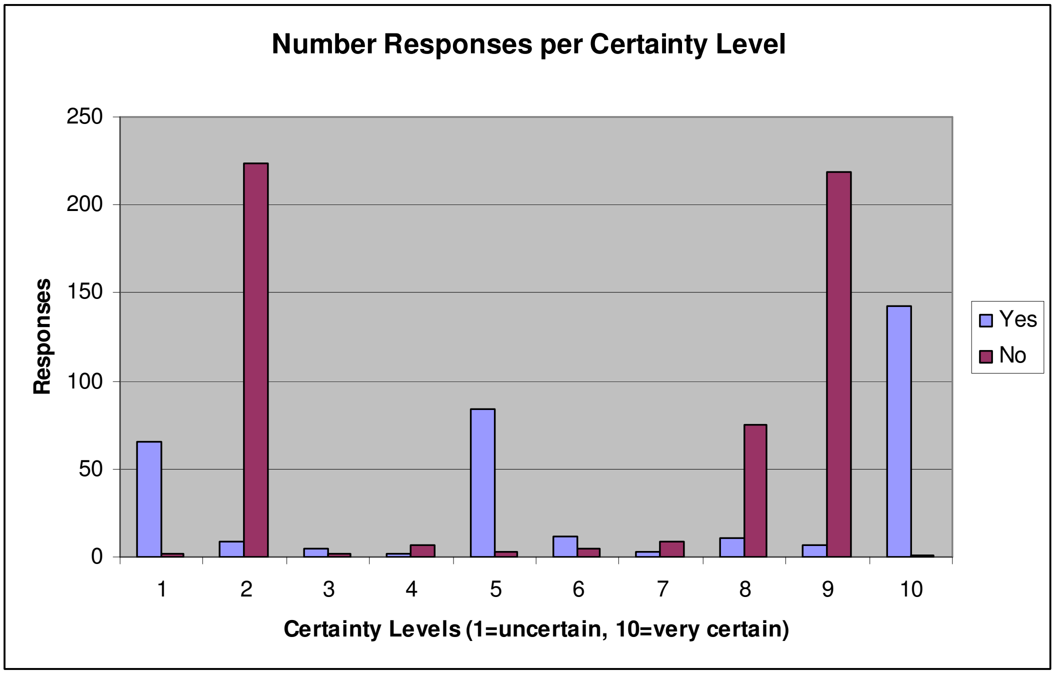
Table 1: Main Socio-Economic Characteristics of the Sample

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	7.64
€6,000-€11,999	13.68	20.72
€12,000-€17,999	16.67	25.06
€18,000-€23,999	13.07	19.89
€24,000-€29,999	8.68	13.00
€30,000-€35,999	3.60	6.31
€36,000-€59,999	3.51	6.12
€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	58.20
Separated	2.89	
Divorced	1.67	
Widowed	7.98	7.67
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	

Graph 1: Number of Positive and Negative Responses per Certainty Level



MARIA: CAN YOU USE PERCENTAGE OF RESPONSES INSTEAD OF # OF RESPONSES AS YOU REFER TO PERCENTAGES IN THE TEXT

Graph 2: Non-Parametric Distribution of Responses Per Certainty Level

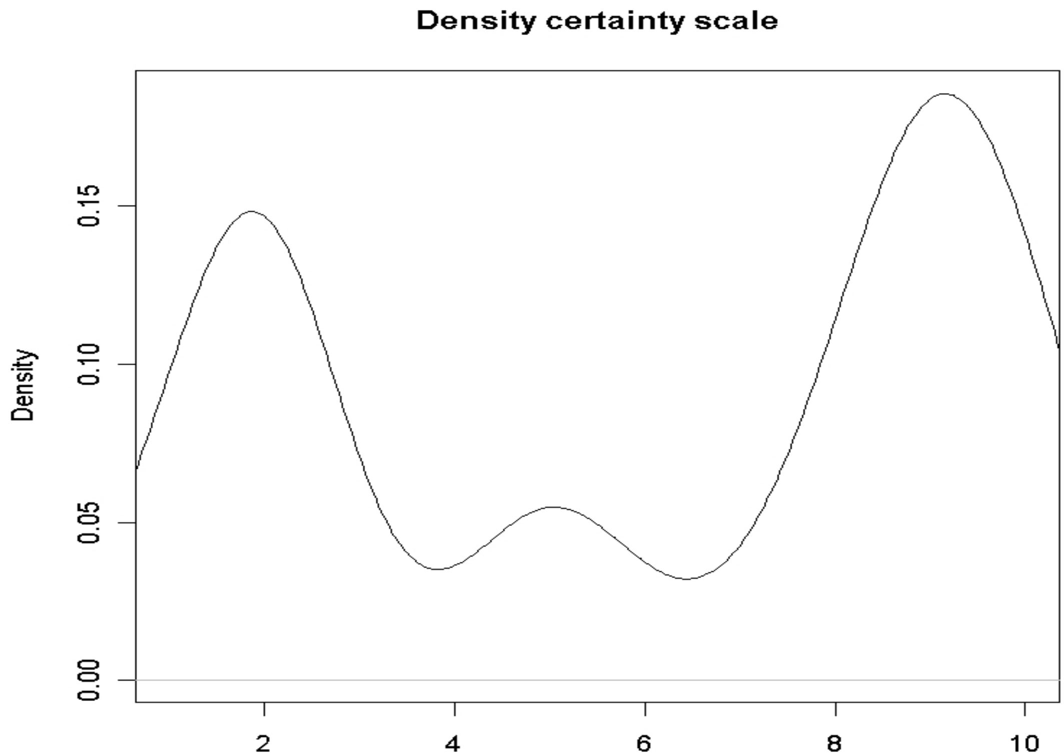


Table 2: Summary Statistics of Explanatory Variables

Name	Definition	Mean	Std. Dev.
WTPbid	Bid offered	158.481	113.203
Age	Respondent's Age	44.913	17.874
Income-sources	Whether respondent is income earner	0.494	0.810
Primary-School	=1 if respondent completed primary school, 0 otherwise	0.421	0.494
High-School	=1, if respondent completed high school, 0 otherwise	0.132	0.339
University	=1 if individual completed a College Degree	0.017	0.129
Certainty-scale	=1, not certain at all, 10=totally certain about response	6.070	3.385
Know- People	=1, if individual knew people affected by the Prestige oil spill, 0=otherwise	0.122	0.456
Visited-Area	=1, if individual have visited affected area, 0 otherwise	0.305	0.461
Male	=1 if respondent is a male, 0 otherwise	0.484	0.499

Table 3: Empirical Results-Previous Modeling Formats in the Literature

	Standard Binary Logit			Champ et al. ,1997 RECODING			ASUM (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
Income Sources	0.022	0.104	0.21	0.181	0.168	1.08	0.0001	0.026	0
Primary School	0.185	0.183	1.01	0.089	0.283	0.32	0.033	0.045	0.72
High School	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
Certainty Scale	0.092	0.025	3.73						
KnowPeople	0.177	0.185	0.96	1.008	0.558	1.81	0.019	0.048	0.4
Visited Area	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: Mixture Modeling Results for Class Assignment

	Estimate	Std. Error	T-value	Pr (>│t│)
Certain Class				
Constant	2.1467	0.2435	8.8158	0.0000
Bid	0.0026	0.0006	4.1298	0.0000
Coast	-0.0472	0.1229	-0.3842	0.7010
Know People	-0.2850	0.1183	-2.4086	0.0163
Income Sources	0.0102	0.0752	0.1362	0.8917
Age	-0.0012	0.0035	-0.3519	0.7250
Male	0.2061	0.1192	1.7289	0.0843
Visited Affected Area	0.5862	0.1288	4.5507	0.0000
Primary School	0.2705	0.1354	1.9973	0.0461
High School	-0.0449	0.1852	-0.2423	0.8086
University Degree	5.6460	0.4067	13.8813	0.0000
Uncertain Class				
Constant	9.4160	0.1120	84.0588	0.0000
Bid	-0.0007	0.0002	-3.2047	0.0014
Coast	-0.1066	0.0559	-1.9058	0.0570
Know People	0.2122	0.0699	3.0357	0.0025
Income Sources	-0.0005	0.0356	-0.0129	0.9897
Age	-0.0035	0.0016	-2.1431	0.0324
Male	-0.0636	0.0534	-1.1913	0.2339
Visited Affected Area	0.1725	0.0588	2.9320	0.0035
Primary School	-0.0677	0.0587	-1.1523	0.2496
High School	0.1039	0.0861	1.2067	0.2280
University Degree	-7.3962	0.2372	-31.1752	0.0000
Log Likelihood	-1597.209			

	Prior	Size	Post>0	Ratio
Certain Class	0.467	348	361	0.964
Not Certain Class	0.533	392	736	0.533

Graph 3: Rootogram of Posterior Probabilities

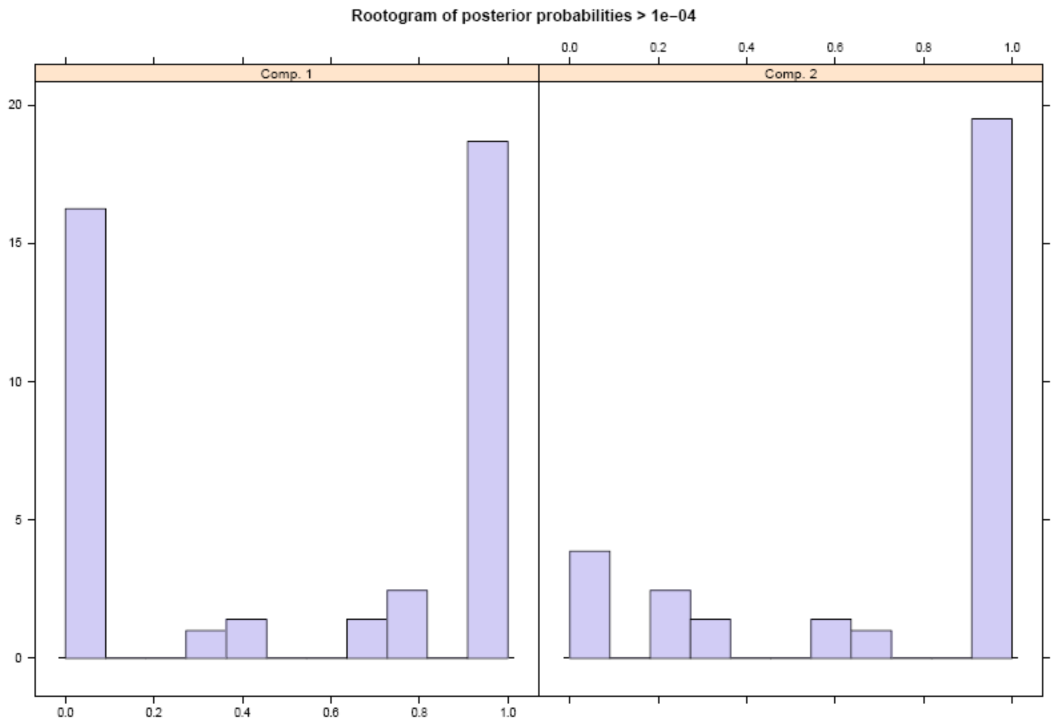


Table 5: Logit WTP Models: Uncertain and Certain Class

Uncertain Class	Restricted Model				Unrestricted Model			
	Estimate	**Std. Error**	**T-value**	**Pr (>lzl)**	**Estimate**	**Std. Error**	**T-value**	**Pr (>lzl)**
Constant	0.6084	0.2726	2.232	0.0256	-0.6436	0.4612	1.40	0.163
Bid	-0.0166	0.0028	-5.991	0.0000	-0.0057	0.0012	-4.88	0.000
Coast					0.0487	0.2332	0.21	0.835
Know-people					0.2471	0.2340	1.06	0.291
Income Sources					0.0416	0.1560	0.27	0.790
Age					-0.1901	0.0068	-2.78	0.005
Male					-0.1131	0.2236	-0.51	0.613
VisitedArea					0.4380	0.2339	1.87	0.061
Primary school					0.3865	0.2492	1.55	0.121
Highschool					0.9227	0.3540	2.61	0.009
University					2.6451	1.1061	2.39	0.017
Log-likelihood	-115.73				-241.441			

Certain Class	Restricted Model				Unrestricted Model			
	Estimate	**Std. Error**	**T-value**	**Pr (>lzl)**	**Estimate**	**Std. Error**	**T-value**	**Pr (>lzl)**
Constant	0.4323	0.2190	1.974	0.0484	0.5952	0.4856	1.23	0.220
Bid	-0.0082	0.0015	-5.322	0.0000	-0.0074	0.0013	-5.54	0.000
Coast					0.1344	0.2554	0.53	0.599
Know people					-0.1361	0.2928	-0.46	0.642
Income Sources					-0.0389	0.1435	-0.27	0.787
Age					-0.0051	0.0073	-0.70	0.481
Male					-0.1495	0.2449	-0.61	0.542
VisitedArea					0.7493	0.2759	2.72	0.007
Primaryschool					-0.0003	0.2692	-0.00	0.999
Hightschool					0.4163	0.3712	1.12	0.262
University					-0.2589	1.2189	-0.21	0.832
Log-likelihood	-143.55				-197.48			

Table 6: Mean WTP Estimates

WTP= $\frac{-\hat{\alpha}}{\hat{\beta}}$	**Mean WTP**	**95 % C.I.***
DC Standard Logit Model	72.59	(66.57, 78.66)
ASUM (Loomis& Ekstrand, 1998)	110.34	(110.30, 120.18)
Champ et al. Recoding, 1997	-439.05	(-432.46, -445.65)
Mixture-Model, **Uncertain Class**	54.08	(42.01, 66.15)
Mixture-Model, **Certain Class**	82.14	(76.07, 88.22)

C.I. were estimated with the Jacknife technique

Table 6: (Cont.)

WTP= $\frac{1}{-\hat{\beta}}\ln(1+\exp^{\alpha})$	**Mean WTP**
DC Standard Logit Model	141.18
ASUM (Loomis& Ekstrand, 1998)	502.95
Champ et al. Recoding, 1997	88.81
Mixture-Model, **Uncertain Class**	62.82
Mixture-Model, **Certain Class**	113.69

C.I. were estimated with the Jacknife technique