



# Modeling Uncertain Preferences in Contingent Valuation with a Mixture Model Approach

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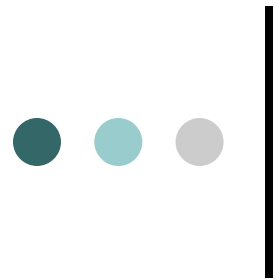
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Envecon conference



# Uncertainty in CVM

- Uncertainty of respondents may be caused by multiple reasons, among them:
  - Lack of knowledge or experience with the good or program being valued
  - Truly uncertain preferences: Not much thought about how much they value the good in monetary terms
  - Non stable preferences: Due to a single payment without repetition or chance to experience



# Approaches to deal with Uncertainty

- Polychotomous questions

- Ready, Whitehead and Blomquist (1995) present respondents with six responses to choose from, “definitely yes,” “probably yes,” “maybe yes,” “maybe no,” “probably no,” and “definitely no.”



# Approaches to deal with Uncertainty

## ○ Polychotomous questions

- Ready, Whitehead and Blomquist (1995) present respondents with six responses to choose from, “definitely yes,” “probably yes,” “maybe yes,” “maybe no,” “probably no,” and “definitely no.”
- **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.**
- **Welsh and Poe (1998) employ a multiple bounded uncertainty model (MBUM) with 13 bids, combining that with uncertain response options.**



# Approaches to deal with Uncertainty

- 10 point follow-up certainty scale
  - Champ et al. (1997) all “yes” respondents were recoded as a “no” if the respondent was not completely certain, i.e. providing a certainty score below 10.



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- **Loomis and Ekstrand (1998) “asymmetric uncertainty models (ASUM): multiplies the Yes responses by the certainty score: Yes response with a 10 score assigned a 1 probability of paying the given amount; whereas an individual selecting a 1 will be assigned a 0.1 probability to its Yes response.**



# Research Objectives

- Results coming from these popular DC recoding approaches outlined earlier will be compared with those from a finite mixture model developed here to deal with the uncertainty bias.
  - Advantage of proposed methodology: No recoding or interpretation of the certainty scale is needed



# Finite Mixture Models

- Commonly used in the marketing literature
- Not too many applications in environmental economics (Boxall and Adamowicz, 2002)
  - Advantages:
    - clustering individuals with respect to a latent or non-observable variable
    - Clusters or classes of individuals are modeled as a function of explanatory variables
    - No need of scaling of variables
    - Great flexibility with respect to possible selection of empirical forms



# Finite Mixture Model

- Finite mixture model with  $K$  components of form:

$$h(y|x, w) = \sum_{k=1}^K \pi_k f(y|x, \theta_k)$$

$$\pi \geq 0, \quad \sum_{k=1}^K \pi_k = 1$$

- Where  $y$ =dependent variable, with conditional density  $h$ ,  $x$  is a vector of explanatory variables, and  $\theta_k$  is the component specific parameter vector for the density function  $f$ , and  $w$  is the vector for all parameters

# ● ● ● | Data

- CVM survey conducted to quantify the passive use value lost in the Prestige oil spill
- Survey structure followed previous surveys developed by Carson *et al.* (2003) for central California Oil Spills and Exxon Valdez Oil spill.
- Representative sample of Spanish households



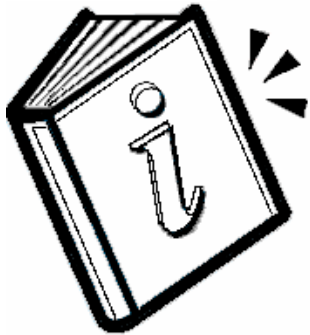
# Rapid Response and Clean Up Program

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Training of personnel

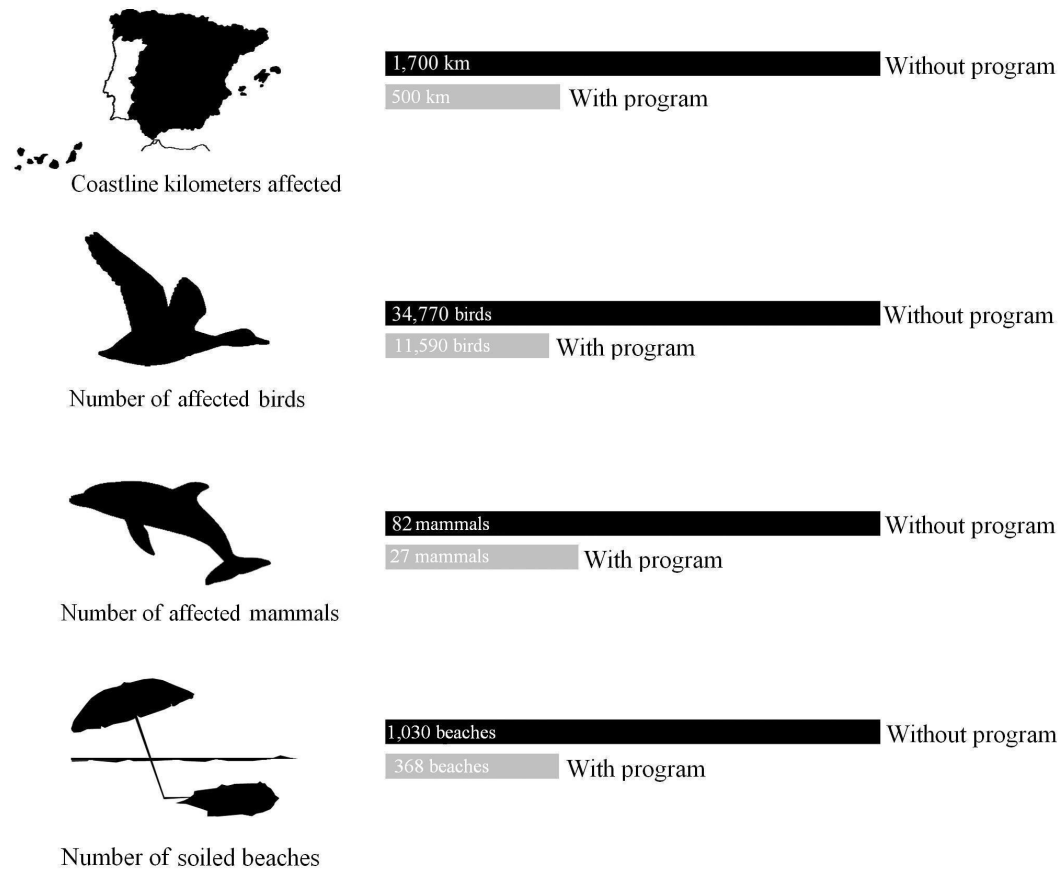
Surveillance

Rapid and qualified  
response





## Expected Damages every 7 years caused by oil spills





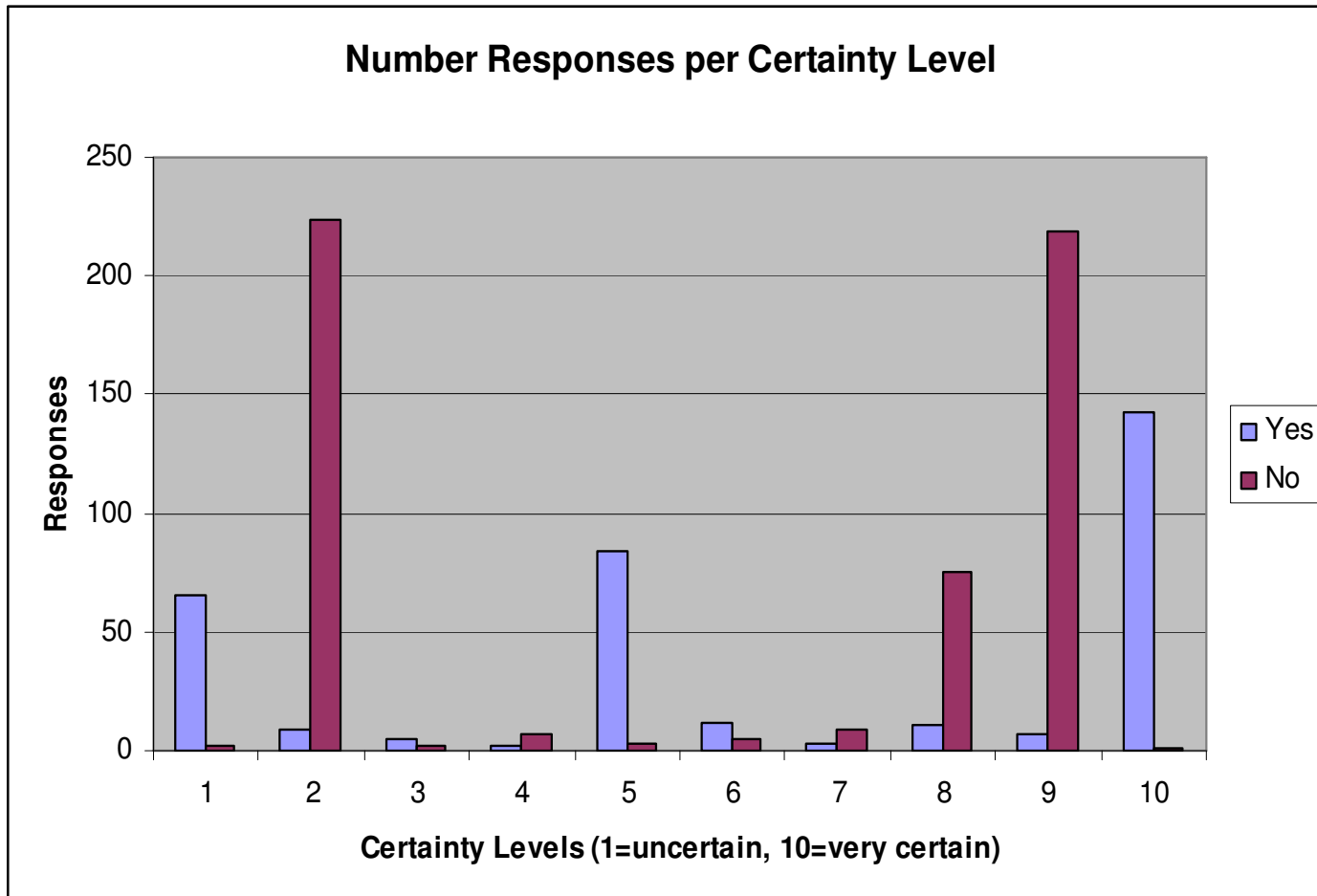


# Results

- 1140 surveys were collected in representative sample
- Multi-stage sampling procedure
- Surveys conducted during spring and early summer 2006
- 44.4 % response rate
- First approximation to uncertainty in responses employing and comparing:
  - RUM
  - Champ et al.(1997) recoding
  - ASUM model (Loomis and Ekstrand,1998)



# Distribution of Responses





# Explanatory Variables

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



# Logit Results

	Standard Binary Logit		Champ et al. ,1997 RECODING		ASUM (Loomis & Ekstrand, 1998)	
WTP	Coef.	T-value	Coef.	T-value	Coef.	T-value
Bid	-0.007	-7.89	-0.007	-5.47	-0.001	-5.97
Age	-0.012	-2.51	-0.008	-1.09	-.0001	-0.05
Income Sources	0.022	0.21	0.181	1.08	.0001	0
Primary School	0.185	1.01	0.089	0.32	0.033	0.72
High School	0.686	2.68	0.373	0.94	0.115	1.75
UniversityDegree	1.407	2.17	0.395	0.44	0.308	1.93
Certainty Scale	0.092	3.73				
KnowA People	0.177	0.96	1.008	1.81	0.019	0.4
Visited Area	0.612	3.51	0.730	2.63	0.082	1.84
Male	-0.114	-0.69	-0.440	-1.71	-0.037	-0.9
Constant	0.122	0.35	0.847	1.7	0.270	3.32
Log-likelihood	-437.64		-181.81			



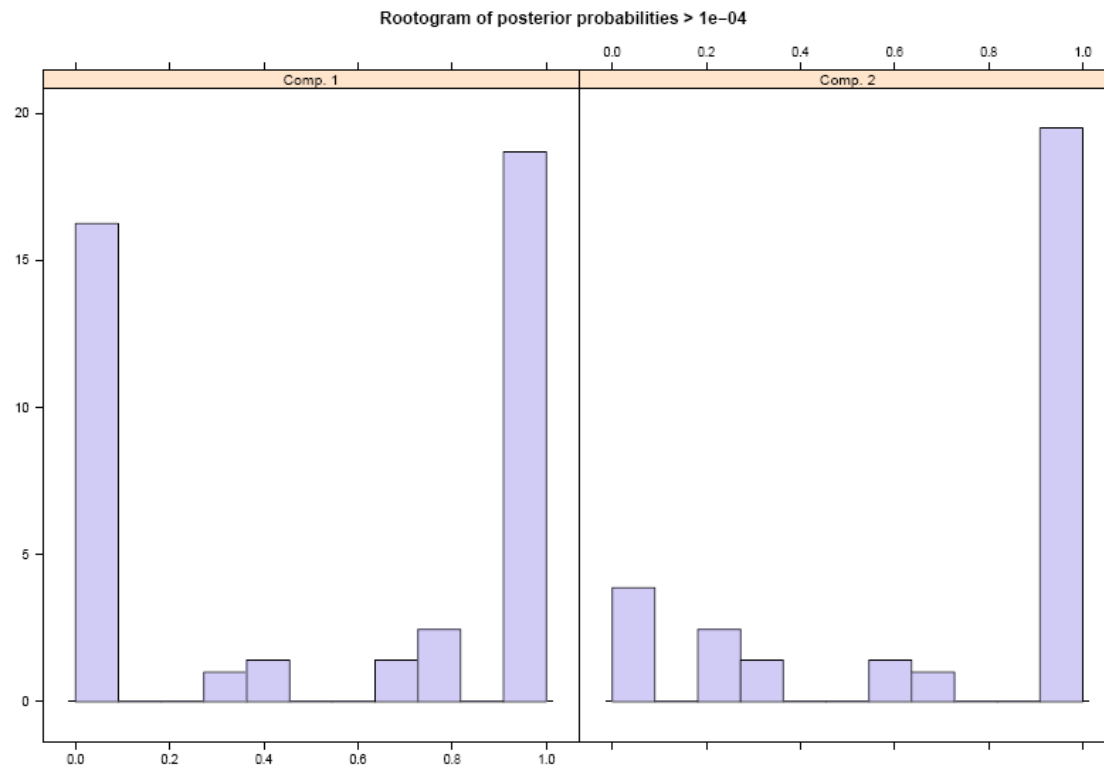
# Mixture Model: Latent Class Results

Table 4: Mixture Modeling Results for Class Assignment

	Estimate	T-value		
<b>Certain Class</b>				
Constant	2.1467	8.8158		
Bid	0.0026	4.1298		
Coast	-0.0472	-0.3842		
Know People	-0.2850	-2.4086		
Income Sources	0.0102	0.1362		
Age	-0.0012	-0.3519		
Male	0.2061	1.7289		
Visited Affected Area	0.5862	4.5507		
Primary School	0.2705	1.9973		
High School	-0.0449	-0.2423		
University Degree	5.6460	13.8813		
<b>Uncertain Class</b>				
Constant	9.4160	84.0588		
Bid	-0.0007	-3.2047		
Coast	-0.1066	-1.9058		
Know People	0.2122	3.0357		
Income Sources	-0.0005	-0.0129		
Age	-0.0035	-2.1431		
Male	-0.0636	-1.1913		
Visited Affected Area	0.1725	2.9320		
Primary School	-0.0677	-1.1523		
High School	0.1039	1.2067		
University Degree	-7.3962	-31.1752		
Log Likelihood	-1597.209			
	<b>Prior</b>	<b>Size</b>	<b>Post&gt;0</b>	<b>Ratio</b>
Certain Class	0.467	348	361	0.964
Not Certain Class	0.533	392	736	0.533

# Rootgram of Posterior Probabilities

Graph 3: Rootogram of Posterior Probabilities

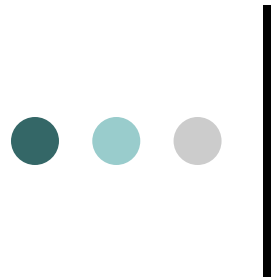




For  $K=3$

	Prior	Size	Post	Ratio
Component 1	0.456	367	401	0.915
Component 2	0.218	125	734	0.170
Component 3	0.326	248	255	0.973

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# More evidence about the K-size

	Log-lik.	AIC	BIC
Cluster 1 (df=12)	-1938.82	3901.64	3956.92
Cluster 2 (df=25)	-1587.113	3224.226	3339.39
Cluster 3 (df=35)	-1436.989	2949.979	3125.032
Cluster 4 (df=51)	-1332.040	2766.080	3001.020

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# WTP Estimates in Euro's

$WTP = \frac{-\hat{\alpha}}{\hat{\beta}}$	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, <b>Uncertain Class</b>	54.08	(42.01, 66.15)
Mixture-Model, <b>Certain Class</b>	82.14	(76.07, 88.22)

C.I. were estimated with the Jackknife technique



# WTP Estimates in Euro's

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



# Conclusions

- Mixture models may be suitable to cluster individuals and within clusters may allow to model WTP for the public good or program
- Advantages over previous methods: non-recoding or interpretation of responses
- Clustering may be used to compute reliable WTP estimates
  - Ignoring non certain classes, given that certain respondents are more likely to behave as stated (Champ et al.)
  - Computing the social WTP, weighting each WTP estimate by the relative importance of each class