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Disentangling the Influence of Knowledge on Processing Strategies in Choice Modelling.

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Abstract:

This paper seeks to disentangle the effect of knowledge on processing strategies using data from a discrete choice experiment on cold-water corals in Norway. Cold-water corals are a deep-sea ecosystem for which we have limited scientific knowledge and for which public awareness is low, and consequently is likely to be an unfamiliar good to many members of the public. One simplifying strategy often employed by respondents in a choice experiment is to simply ignore some of the attributes, i.e. attribute non-attendance. After the initial presentation of the good, before answering the choice cards, the respondents were given a quiz over the material covered in the presentation. This provides us with an *ex ante* measure of their knowledge. We use a combination of discrete and continuous mixture models to disentangle the effects of variations in knowledge about the good. We use a respondent's quiz score as covariates in the probability function of attending to an attribute. Our results show that knowledge, as measured by the quiz score, has a significant effect on the probability of attending to the attribute for three out of four attributes. This has direct implication for practitioners in that proper information may help avoid the use of simplifying strategies.

Introduction

Within environmental economics, it is common to elicit preferences for environmental goods for which scientific knowledge is limited and public awareness is low. This poses a problem for the use of stated preferences as part of a cost-benefit analysis of public policy choice, since it implies making policy recommendations based on the preferences of "uninformed respondents". For "goods" such as biodiversity conservation, it is therefore important to provide information about relevant aspects of the environmental good prior to the valuation task in a way that is meaningful to respondents. One way to achieve this is to use "valuation workshops" (Alvarez-Farizo et al., 2007, MacMillan et al., 2002). In a valuation workshop, respondents are presented with relevant information and have the option of asking clarifying questions before answering a stated preference questionnaire. Another advantage of the valuation workshop is the possibility of quizzing and questioning the respondents on the material described to them, so that their knowledge can be determined. This provides a way of measuring *ex ante* knowledge of respondents before their choices are made, and of comparing information provided with the knowledge acquired (La Riviere et al., 2014).

This paper investigates the connections between three important strands of the choice modeling literature. The first concerns the effects of information and knowledge on stated preferences. This issue has been of interest to practitioners since the first applications of contingent valuation to environmental goods for which respondents often have no direct experience in consuming. The second concerns the way in which respondents make choices under complexity, and the extent to which they fall back on heuristics to simplify their decisions. This has led to a focus on attribute non-attendance as one such heuristic (see e.g. Hensher et al., 2005, Scarpa et al., 2009, Campbell et al., 2011). Attribute non-attendance in turn is related to the third strand of the choice modeling literature, which is concerned with the nature of the utility function and whether people are indeed willing to make trade-offs between all attributes which are used to describe their choices.

The effort required by a respondent in a discrete choice experiment is increasing in choice task complexity (e.g. number of attributes, levels, alternatives, tasks and complexity of the good) (Caussade et al., 2005, Blamey et al., 2002). The more effort that is required on part of the respondent in a discrete choice experiment, the more likely it is that he or she will use a simplifying strategy and heuristic. One such strategy, which is the focus of this paper, is simply to ignore one or more of the attributes when choosing between alternatives in the choice task, also called attribute non-attendance.

We argue that the respondent's knowledge about the environmental good under evaluation influences perceived choice task difficulty, in that more knowledge reduces the effort required through reduced perceived difficulty of the choice task. We hypothesize that the degree to which respondents simplify by ignoring attributes is influenced by their knowledge of the environmental good. Specifically, the hypothesis to be tested is that the more knowledge one has about the environmental good, i.e. the higher one's quiz score, the less likely an attribute is to be ignored in making choices.

There is some evidence suggesting that prior knowledge of the good (Kosenius, 2013) and the relevancy of the information provided prior to the discrete choice experiment (Hensher, 2006) may avoid the tendency to ignore attributes. Kosenius (2013) looks at stated non-attendance in a discrete choice experiment on water quality in Finland and finds that a respondent's proximity to the water body is related to lower levels of attribute non-attendance. The author argues that this proximity is an indication of their familiarity with and knowledge of the good, which suggests that there is a link between the level of familiarity and knowledge of the issue and the use of simplifying heuristics. Hensher (2006) defines the amount of information received as the number of attributes associated with each choice set and finds evidence suggesting the processing strategy adopted by a respondent is dependent on the nature of the attribute information and not strictly the quantity (p. 820).

In this paper, we carry out a choice experiment on the preferences of citizens for a very unfamiliar good, namely cold water corals. Such corals are found in deep waters around many coastlines worldwide, and are valued as biodiversity hotspots in the deep sea. However, their condition world-wide is threatened by deep sea trawling, oil and gas exploration, and deep water mining (Fosså et al., 2002). Using a series of valuation workshops, we explore the link between the answers respondents gave to a quiz about cold water corals, yielding a measure of their knowledge, and their choices in a discrete choice experiment. More specifically, we implement a discrete and continuous mixture model to disentangle the influence of knowledge on processing strategies. Using the quiz scores, first, we classify individuals into high and low knowledge groups based on whether or not they scored above the median on the quiz. Second, we classify respondents based on quartiles and include this as dummies in the probability functions of attending to different attributes, i.e. as covariates to explain membership to different latent classes.

Our results suggests that there is a link between how much the respondent knows about the good and the probability of attending to an attribute, i.e. respondents with a high quiz score are more likely to be predicted as having attended to an attribute. This effect is measurable and significant for three out of the four attributes used in the discrete choice experiment when we classify a respondent's knowledge by in which quartile their quiz score was. This result has direct implications for stated preference practitioners in that it is important to provide good and relevant information prior to conducting stated preference surveys. This may be particularly important when the good is unknown.

The rest of the paper has the following outline. Section two presents the data, section three presents the methodology and the theoretical model, section four discusses the results and section five concludes the paper.

Data

We use data from a discrete choice experiment aimed at eliciting the Norwegian population's willingness-to-pay for protection of cold-water coral sites off the coast of Norway. Cold-water coral is a good for which scientific knowledge is scarce and public awareness is low. For respondents to make informed decisions we need to provide them with information in a manner that is conducive to understanding. This is the main reason why valuation workshops were used to gather the data. We gathered the data using 24 valuation workshops in 22 municipalities in Norway in the spring of 2013. A professional survey company recruited participants to the valuation workshops. The interested reader can find the main results and a more detailed discussion of the data in Aanesen et al. (2014). In the valuation workshop, the respondents received a presentation about cold-water corals during which they had the opportunity to ask clarifying questions before filling out the first part of the questionnaire. The first part of the questionnaire included a quiz with eight questions about cold-water corals related to the material covered in the presentation. This provides us with an *ex ante* measure of their knowledge about the good that they are evaluating and explicitly allows us to examine how knowledge influences the use of attribute processing strategies. After the quiz, the respondents received a second presentation, this time concerned with explaining how the discrete choice experiment worked, before filling in their choice cards. In the choice experiment, we asked the respondents to choose between two alternatives for cold-water coral protection and the situation today (the status quo). Four attributes described each alternative: the size of the proposed area, the importance of the area for industry (fisheries and oil/gas), the importance of the area as habitat for fish and other marine life, and the cost of each management scenario measured as a lump sum increase in annual federal taxes. The attributes relating to size and habitat took on three levels each, and the attributes related to industry and cost took on five levels each, including the status quo levels. We show a sample choice card in Figure 1 (translated into English).

[Insert Figure 1 about here]

Method

Here we outline the discrete mixture random parameters logit model (DM-RPL). We use a discrete mixture to classify respondents into classes and combine this with a random parameters logit model to uncover preference heterogeneity among respondents. There are two main reasons for this. One, it is computationally simpler to estimate four probability functions, i.e. the probability of attending to each of the attributes, and then construct the discrete mixing distribution as opposed to estimating a class probability function for each class, and two, it makes the interpretation of the coefficients pertaining to our hypothesis easier.

To introduce the notation we start by specifying a linear utility function that is separable in cost and other attributes, and we assume that respondent *i*'s utility from choosing alternative *j* in choice situation *t* can be expressed as:

$$U_{ijt} = \beta_i' x_{ijt} + \varepsilon_{ijt} \tag{1}$$

where β are parameters to be estimated and ε is an *i.i.d.* type I extreme value distributed error term with constant variance $\pi^2/6$. Given these assumptions, the probability of the sequence of choices made by respondent *i* is given by the multinomial logit model depicted in equation (2).

$$\Pr\left(U_{ijt} > U_{iqt}\right) = \prod_{t=1}^{T} \frac{\exp(\beta_i' x_{ijt})}{\sum_{q=1}^{Q} \exp(\beta_i' x_{iqt})} \tag{2}$$

Respondents may use a number of different attribute processing strategies, but in this paper, we focus on one: attribute non-attendance. For simplicity, we assume that an attribute is either fully attended to or not (Colombo et al., 2013). With four attributes, we end up with 16 possible combinations of attributes being attended to or not, i.e. 16 different attribute processing strategies[1]. We take these attribute processing strategies into account by assuming that we can classify each respondent into one of sixteen latent classes, each class corresponding to one attribute processing strategy. Instead of specifying and estimating the membership for each individual class, we use a discrete mixture. In a discrete mixture model, the parameters can only take on a finite number of values (see e.g. Hess et al., 2007). In our case, we use it to estimate the share of respondents who attend to or ignore each attribute. The (unconditional) probability that a specific attribute is attended to can be estimated using a simple logistic regression, where we allow attendance to be a function of a constant and dummy variables indicating the level of knowledge (as measured by the quiz score). The probability that respondent *i* attends to attribute *k* is denoted by π_{ik}^1 and shown in Equation 3.

$$\pi_{ik}^1 = \frac{1}{1+\exp(-(C + \alpha_i score))} \tag{3}$$

where $\alpha_i score$ is the score that respondent *i* received in the quiz. The probability that respondent *i* ignores the attribute, denoted by π_{ik}^0, is therefore $\pi_{ik}^0 = 1 - \pi_{ik}^1$. Next, we use these probabilities to create the discrete mixing distribution. Let $s = 1, \dots, S$ be an index over all possible

[1] With *k* number of attributes taking on *n* outcomes (here dichotomous), we get n^k number of classes. In our case $2^4 = 16$.

combinations of the probabilities π_{ik}^{1} and π_{ik}^{0} and represents the discrete mixing distribution for the sixteen different attribute processing strategies.

$$S = \begin{cases} s = 1 \rightarrow \ \omega_{i1} = \pi_{i\,size}^{0} \times \pi_{i\,commercial}^{0} \times \pi_{i\,habitat}^{0} \times \pi_{i\,cost}^{0} \\ s = 2 \rightarrow \ \omega_{i2} = \pi_{i\,size}^{0} \times \pi_{i\,commercial}^{0} \times \pi_{i\,habitat}^{0} \times \pi_{i\,cost}^{1} \\ s = 3 \rightarrow \ \omega_{i2} = \pi_{i\,size}^{0} \times \pi_{i\,commercial}^{0} \times \pi_{i\,habitat}^{1} \times \pi_{i\,cost}^{0} \\ s = 4 \rightarrow \ \omega_{i3} = \pi_{i\,size}^{0} \times \pi_{i\,commercial}^{0} \times \pi_{i\,habitat}^{1} \times \pi_{i\,cost}^{1} \\ \vdots \\ s = 16 \rightarrow \ \omega_{i16} = \pi_{i\,size}^{1} \times \pi_{i\,commercial}^{1} \times \pi_{i\,habitat}^{1} \times \pi_{i\,cost}^{1} \end{cases} \tag{4}$$

We consider attribute non-attendance by restricting the parameter on the ignored attribute to zero in the likelihood function (Hensher et al., 2005). We accommodate this by introducing a dummy variable δ_{ik} that takes on the value zero if respondent *i* ignores attribute *k* and one otherwise.

$$\Pr(U_{ijt} > U_{iqt}) = \sum_{s=1}^{S} \omega_{is} \ \prod_{t=1}^{T} \frac{\exp(\delta_{ik}\, \beta_i' x_{ijt})}{\sum_{q=1}^{Q} \exp(\delta_{ik} \beta_i' x_{iqt})} \tag{5}$$

So far, we have assumed that all respondents have the same marginal utility of each attribute. However, this is unlikely. We allow for heterogeneous preferences, i.e. different marginal utilities of attributes across respondents, by allowing for random variations in the parameters. Let Θ_i represent the vector of random parameters and Ω denote the mean and variance of these parameter distributions, then we can denote the joint density of the parameters $\beta_{ik}$by $f(\Theta_i|\Omega)$. The unconditional probability becomes the weighted integral over the logit formula over all possible values of the parameters as seen in Equation 6. This integral does not have an analytical solution, but is approximated through simulation.

$$\Pr(U_{ijt} > U_{iqt}) = \sum_{s=1}^{S} \omega_{is} \ \int \prod_{t=1}^{T} \frac{\exp(\delta_{ik}\, \beta_i' x_{ijt})}{\sum_{q=1}^{Q} \exp(\delta_{ik} \beta_i' x_{iqt})} f(\Theta_i|\Omega) d(\Theta_i) \tag{6}$$

Thus, our model represents a combination of a discrete and a continuous mixing model. Such models have previously been applied by e.g. Campbell et al. (2010) or Doherty et al. (2013).

Results

Sample description and Quiz score responses

Table 1 shows the demographic composition in the sample and compares it to the Norwegian population. Respondents were sampled to be representative with respect to gender, age and geographic location. We see that in terms of these three characteristics the sample matches the population fairly well. The sample is more skewed in terms of education and income. We acknowledge the potential link between education and knowledge acquisition skills and that this might influence the quiz scores. Although, as we shall see we still get decent variation in the number of correct answers.

[Insert Table 1 about here]

After the presentation about cold-water corals in the valuation workshop, the respondents received a quiz over the material covered. The maximum attainable score was eight correct answers. We show the percentage distribution of quiz scores in Table 2. The median score is seven correct answers. The quartiles are less than six (19.5 percent of respondents), six (24.5 percent of respondents), seven (27.5 percent of respondents) and eight correct answers (28.5 percent of respondents).

[Insert Table 2 about here]

In addition, we asked respondents after completing all the choice tasks to state which attributes were not important when making their choices. 4 percent stated that the size attribute was not important, 6 percent stated that the industry attribute was not important, 2 percent stated that the habitat attribute was not important and 12 percent stated that the cost attribute was not important.

Estimation results

In this section, we report the results from the estimation of the models. We consider three models. Model 1 is the random parameters logit model, which serves as a reference for comparison, and Model 2 and Model 3 are combinations of discrete and continuous mixture models to test our hypothesis. The latter two differ in how we specify the influence of knowledge (median/quartiles) in the probability function of attending to an attribute. In Model 1, the probability of attending to an attribute is a function whether a respondent scored above the median and in Model 2, the probability is function of which quartile the respondent's score is in. We assume that the parameters on the non-cost attributes follow a normal distribution and that the cost parameter follows a lognormal distribution. All three models are estimated using 1000 Halton draws. Specifying the cost parameter to follow a log-normal distribution implies all respondents have the same sign and the willingness-to-pay distributions have defined moments (Daly et al., 2012).

Let us take a closer look at Model 1, which is the random parameters logit model. In the random parameters logit model it is assumed that all attributes are attended to. The results show that the parameter estimates on the size, industry – fisheries and habitat attributes are significant at the one percent level, and the parameter estimates on industry – oil/gas and cost are insignificant. We see that a large increase in the protected area is preferred to a small as evident by the larger estimate. Examining the industry attribute more closely, whether or not the area is important for the oil- and gas industry does not influence utility, but we have a positive influence on utility if the protected area is important for the fisheries. One explanation for this could be that deep sea trawling is the biggest threat to the corals and that protecting the area means that fishing will be reduced in the area and hence damage to the reefs are reduced. Furthermore, people have a strong preference for protecting an area that is important habitat for fish. The standard deviations of the parameter distributions are all highly significant and for all attributes, except for habitat, larger than the mean, indicating strong preference heterogeneity. Remember, cost is lognormal distributed and the estimated mean and standard deviation are of the underlying normal distribution.

Now we turn our attention to Model 2. We see that the parameter estimates on size, habitat and cost are significant at the one percent level; the estimate on industry – oil/gas at the ten percent level and on industry – fisheries is insignificant. We see that in this model the preferences regarding the levels of the industry attributes are opposite.

The estimates of interest regarding our hypothesis are in the probability function of attending to the attributes, specifically does scoring above the median influence the probability of attending to a given attribute. Our *a priori* expectation is that these should be positive, i.e. the probability of attending to an attribute is increasing in knowledge with the corollary being the probability of ignoring an attribute is increasing with decreasing level of knowledge. The parameters on how the level of knowledge impacts the probability of attending to size, industry and habitat are of the expected sign, but insignificant. The probability of attending to cost, on the other hand, is lower if you score above the median. This is contrary to our expectations. However, there might be two reasons for why this is the case. First, the respondents have firsthand experience with money and, as such, are familiar with it. It is possible that they understand the cost attribute better and consequently the knowledge of the good might influence the probability of attendance differently. Second, the fact that they receive information and we are asking about cold-water corals might give the impression that they are important and that we need to protect them. Thus, we observe the tendency that increased knowledge reduces the probability of attending to an attribute. This is likely to be a case-specific effect.

[Insert Table 3 about here]

Lastly, we take a closer look at Model 3. The parameter estimates in Model 3 are similar to those obtained in Model 2. We see that the parameter estimates for size, habitat and cost are significant at the one percent level; the estimates on industry – fisheries is significant at the ten percent level and on industry – oil/gas is insignificant. Compared to Model 2, the significance of the estimates on the levels of the industry attribute are opposite.

Again, we are interested in the estimates in the probability function of attending to the attributes. Now, we are no longer classifying individuals by whether they scored above the median, but to which quartile they belong. Looking back at Table 1, the quartiles are less than six, six, seven and eight correct answers on the quiz. We have the same *a priori* expectation of the sign of the parameter estimates, and based on the results from Model 2 we have an indication as to which parameters are significant. We see that the signs on the estimates in the probability of attending to the size, industry and habitat attributes are positive and the sign on the estimates are negative for scoring in the third and fourth quartile for the cost attribute. This corresponds well to the results obtained in Model 2.

As expected, scoring in the second, third or fourth quartile does not influence the probability of attending to the size attribute, as evident by the insignificant parameter estimates. Turning attention to the industry attribute, we see that scoring in the second, third or fourth quartile does influence the probability of attending to the attribute in the expected direction. The estimates are significant at the five percent level for second and third, and significant at the ten percent level for scoring in the fourth. This implies that a significantly higher share of respondents who attained a high score on the quiz are more likely to attend to the attribute. Looking at the probability of attending to the habitat attribute, we observe something interesting. From Model 2 we have that scoring above the median does not affect the probability, however, results from Model 3 suggests that scoring in the third quartile increase the probability of attending to the attribute and implies a link between knowledge and attribute attendance. The sheer magnitude of the estimate on scoring in the fourth quartile is interesting, although it is insignificant. It is conceivable that "everybody" having eight correct answers on the quiz attended to this attribute[2]. Lastly, we examine the probability of attending to the cost attribute. Scoring in the third or fourth quartile has the same negative sign as scoring above the median in Model 2, however, only the estimate on scoring in the third quartile is significant at the five percent level.

The results as presented here, with significant effects in the probability function of attending to an attribute for three out of four attributes implies that there is a link between knowledge and attendance (non-attendance), i.e. respondents with a high quiz score are more likely to be predicted as having attended to the attribute. Moving from classifying based on above/below the median to quartiles does provide additional insight, but it comes at a cost of slightly worse model fit as evident by the Adj. pseudo R-squared and the AIC/N statistic. The changes are small, but arises from the penalty of estimating an additional 8 parameters.

In addition to this, we report descriptive statistics of the means of the conditional (i.e., individual-specific) willingness-to-pay estimates derived from the three models. Table 3 shows the mean, median and 2.5 and 97.5 quantiles of this distribution. The willingness-to-pay estimates are

[2] During the different runs of the model, this parameter estimate varied widely but the change in the log likelihood value was less than 0.00025, which could mean that the log-likelihood function is very flat for this parameter.

conditional on the respondent's choices, the distribution parameters and attribute levels. We only calculate the willingness-to-pay for the classes in which both the non-monetary and monetary attribute was considered. Note that in the case where either cost or the non-monetary attribute was ignored, we have no information on the marginal utility of either attribute, and consequently WTP is undefined.

First, we look at the willingness-to-pay estimates from the random parameters logit model and we observe that they are unreasonably high. This is possibly the result of respondents not taking the cost attribute into consideration, i.e. attribute non-attendance. Note also that the estimate on cost for the underlying normal distribution in Model 1 is insignificant, but becomes highly significant in Model 2 and Model 3 when attribute non-attendance is considered. In fact, 12 percent of the respondents stated that the cost attribute was not important when making choices between alternatives. Furthermore, the average probability of being in a class where the cost attribute is ignored is 47.48 percent in Model 2 and 44.68 percent in Model 3. Not surprisingly, a large share of respondents are predicted as having extremely small marginal utility of money under the first model. For this dataset, the implications of overlooking non-attendance of cost are clear to see, since we get unreasonably high willingness-to-pay estimates (because the denominator is very close to zero). When we look at the willingness-to-pay estimates derived from Model 2 and Model 3, we see that they are substantially and significantly lower. This result is in line with the majority of studies looking at AN-A (see e.g. Colombo et al., 2013, Campbell and Lorimer, 2009, Hensher et al., 2005).

[Insert Table 4 about here]

Conclusions

We set out to disentangle the effect of knowledge on processing strategies using data from a discrete choice experiment on cold-water coral protection in Norway. Specifically we tested the hypothesis that the more you know about the environmental good the less likely you are to use simplifying heuristics, in our case: ignoring one or more of the attributes on the choice card. We achieved this by estimating a combination of discrete and continuous mixture models, where we probabilistically classified respondents into 16 classes, each describing one attribute processing strategy.

Our results are mixed, but they show that knowledge, measured by the quiz score, influences the probability of attending to an attribute. This implies that respondents with a high quiz score are more likely to be predicted as attending to the attribute. Four attributes described each alternative in the discrete choice experiment: the size of the area, the importance for industry, the importance as habitat and the cost.

We find that the respondent's knowledge about cold-water corals does not influence the probability of attending to (ignoring) the size attribute, but it does influence the probability of attending to the industry attribute in the expected direction, i.e. the more one knows the more likely one is to attend to that attribute. One possible explanation for this result is that in the presentation, before answering the quiz, respondents learned that the largest threats to cold-water coral habitats were deep sea trawling and oil and gas activities. This might cause respondents to be more aware of this issue and potentially move them from a "do not care"-position, i.e. ignore the attribute, to a "do care"-position, i.e. attend to the attribute.

When we look at the probability of attending to the habitat attribute, we observe differences based on how we classify respondents with respect to knowledge. When we estimate the probability of attendance based on the median score, there is no significant effect. Moving on to classify by quartiles, we see that respondents scoring in the third quartile have increased probability of attending to the attribute, as expected. The sheer magnitude of the estimate on scoring in the fourth quartile suggests that it might influence the probability of attendance, but it is insignificant. It is possible that respondents who scored in the fourth quartile all attended to the attribute.

The level of knowledge does affect the probability of attending to cost, but the direction of the effect is in the opposite direction to what we expected. We believe that this may be because respondents are familiar with money and thus it might affect the probability of attendance differently than the non-monetary attributes.

This paper shows that knowledge about the good may in fact influence whether a respondent uses attribute processing strategies and simplifying heuristics. I.e. the more you know (higher quiz score) the more likely you are to attend to an attribute. The implication for practitioners is that providing good and correct information prior to a choice experiment is important in that it may avoid, to some extent, the use of heuristics, which in theory should give more precise welfare estimates. Seeing as the goal of many valuation studies is as input in cost-benefit analysis and as policy, it is crucial that we get the most precise estimates.

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Table 1

		Valuation Workshop	Norwegian Population
Gender	*Male*	53.60 %	50.25 %
	Female	46.40 %	49.75 %
Age	*18 - 25*	11.40 %	13.65 %
	26 - 35	16.70 %	17.10 %
	36 - 45	19.50 %	18.26 %
	46 - 55	19.70 %	17.22 %
	56 - 65	14.40 %	14.80 %
	66+	18.20 %	18.98 %
Geographic location	Oslo and Akershus	20.40 %	23.69 %
	Hedemark and Oppland	8.40 %	7.48 %
	South-East Norway	14.30 %	18.98 %
	Agder and Rogaland	14.60 %	14.72 %
	Western - Norway	19.40 %	17.14 %
	Trøndelag	9.60 %	8.64 %
	Northern Norway	13.30 %	9.36 %
Education	*Middle School or less*	6.90 %	27.90 %
	3 year high school	35.50 %	41.70 %
	More than high school	57.30 %	30.40 %
Personal Income	*Less than NOK 200.000*	16.20 %	25.26 %
	200.000 - 300.000	16.80 %	17.49 %
	301.000 - 400.000	22.70 %	18.01 %
	401.000 - 500.000	20.90 %	15.31 %
	501.000 - 600.000	10.30 %	9.11 %
	601.000 - 700.000	5.90 %	5.02 %
	701.000 - 800.000	2.30 %	2.99 %
	801.000 - 900.000	1.80 %	1.91 %
	901.000 - 1.000.000	1.30 %	1.28 %
	More than NOK 1.000.000	1.80 %	3.62 %

N = 397

Table 2

Distribution of respondents by quiz score								
Score	1	2	3	4	5	6	7	8
Percent	0.00 %	1.50 %	1.80 %	3.30 %	12.90 %	24.50 %	27.50 %	28.50 %

Parameters of the Utility function												
	Model 1				Model 2				Model 3			
Attribute					Mean (s.e.)		SD (s.e.)		Mean (s.e.)		SD (s.e.)	
Size - Small	0.7889	***	1.4425	***	3.996	***	0.4703	***	4.1780	***	0.3917	
	(0.1239)		(0.1183)		(0.3442)		(0.5420)		(0.3550)		(0.7495)	
Size - Large	1.0829	***	1.7453	***	4.7677	***	1.8913	***	4.9893	***	-1.9611	***
	(0.1394)		(0.1315)		(0.3996)		(0.2209)		(0.4181)		(0.2452)	
Industry - Oil/Gas	0.0276		1.3906	***	-0.3338	*	2.4597	***	-0.2229		-2.3271	***
	(0.0939)		(0.1044)		(0.2356)		(0.3598)		(0.2180)		(0.3017)	
Industry - Fisheries	0.3443	***	1.3760	***	0.2724		-2.2267	***	0.3339	*	-2.1849	***
	(0.0956)		(0.1014)		(0.2205)		(0.2907)		(0.2159)		(0.2748)	
Habitat	2.1458	***	1.9249	***	2.1804	***	1.8038	***	2.1923	***	1.7937	***
	(0.1363)		(0.1318)		(0.2539)		(0.1570)		(0.1850)		(0.1469)	
Cost	-0.2039		2.7736	***	1.9577	***	-1.4960	***	1.7805	***	-1.5863	***
	(0.2066)		(0.1814)		(0.3024)		(0.2111)		(0.2348)		(0.1922)	
Constant_Size	-				-0.2504				-0.2969			
					(0.2066)				(0.2981)			
Constant_Commercial	-				-0.3034				-0.8203	**		
					(0.3266)				(0.4569)			
Constant_Habitat	-				1.0194	**			0.6553	*		
					(0.4710)				(0.4768)			
Constant_Cost	-				0.4491	*			0.6608	*		
					(0.3046)				(0.4134)			
AboveMedianSize	-				0.3021				-			
					(0.2608)							
AboveMedianCommercial	-				0.2877				-			
					(0.3501)							
AboveMedianHabitat	-				2.8685				-			
					(4.010)							
AboveMedianCost	-				-0.6173	**			-			
					(0.2753)							
ScoreSixSize	-				-				-0.0096			
									(0.3912)			
ScoreSevenSize	-				-				0.2159			
									(0.3902)			
ScoreEightSize	-				-				0.4060			
									(0.3729)			
ScoreSixCommercial	-				-				1.0410	**		
									(0.5656)			
ScoreSevenCommercial	-				-				1.007	**		
									(0.5459)			
ScoreEightCommercial	-				-				0.7774	*		
									(0.5303)			
ScoreSixHabitat	-				-				0.7262			
									(0.7580)			
ScoreSevenHabitat	-				-				1.8063	*		
									(1.2423)			
ScoreEightHabitat	-				-				9.6770			
									(63.239)			
ScoreSixCost	-				-				-0.1163			
									(0.4510)			
ScoreSevenCost	-				-				-0.9967	**		
									(0.4391)			
ScoreEightCost	-				-				-0.4885			
									(0.4346)			

Model Characteristics			
Adj. Pseudo R-Squared	0.334	0.355	0.355
LL(0)	-5144.8	-5144.8	-5144.8
Log Likelihood Value	-3414.6	-3297.8	-3292.4
AIC/N	1.4634	1.4169	1.4181
K	12	20	28
N	4683	4683	4683

*** Significant at 1 % level
** Significant at the 5 % level
* Significant at the 10 % level

Table 3.ble 3

Table 4

Willingness-to-pay (NOK)					
		2.5 %	**Median**	**Mean**	**97.5 %**
Size - Small	Model 1	-60380.00	1113.00	37850.00	244408.68
	Model 2	0.00	0.33	24.31	261.23
	Model 3	0.00	0.10	44.99	537.64
Size - Large	Model 1	-66980.00	1686.00	75100.00	541547.25
	Model 2	0.00	0.32	29.82	292.20
	Model 3	0.00	0.14	54.21	531.68
Commercial - Oil/Gas	Model 1	-128000.00	-59.69	18290.00	342927.71
	Model 2	-34.72	0.00	-1.90	29.96
	Model 3	-61.90	0.00	0.40	58.52
Commercial - Fisheries	Model 1	-152300.00	99.43	33150.00	285497.79
	Model 2	-22.45	0.00	3.36	105.98
	Model 3	-27.11	0.00	7.91	131.62
Habitat	Model 1	-23090.00	25850.00	126200.00	673536.72
	Model 2	-12.07	8.80	129.80	1000.67
	Model 3	-15.80	10.17	173.70	1391.63

*1 NOK = € 0.12

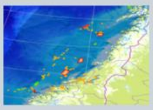
Attribute		Alternative 1	Alternative 2	Alternative 3 (Status Quo/Situation today)
Size of protected area		5.000 km^2	10.000 km^2	2.445 km^2
Is the area attracive for commercial activities?	 	Attractive for oil and gas	Attractive to the fisheries	To some extent for both
Is the area important habitat for fish		Not important	Important	To some extent
Cost per household per year		100 kr/year	1000 kr/year	0
I prefer				

Figure 1