The Value of Familiarity: Effects of Knowledge and Objective Signals on Willingness to Pay for a Public Good

Jacob LaRiviere\textsuperscript{1}, Mikołaj Czajkowski\textsuperscript{2}, Nick Hanley\textsuperscript{3}, Margrethe Aanesen\textsuperscript{4}, Jannike Falk-Petersen\textsuperscript{5} and Dugald Tinch\textsuperscript{6}

Abstract

We design and conduct a field experiment in which treated subjects receive a precise and objective signal regarding their knowledge about a public good before estimating their WTP for it. We find that the causal effect of objective signals about the accuracy of a subject’s knowledge for a public good can dramatically affect their valuation for it: treatment caused a significant increase of $85-$129 in WTP for well-informed individuals. We find no such effect for less informed subjects. Our results imply that WTP estimates for public goods are not only a function of true information states of the respondents but beliefs about those information states.

Keywords: Information, Beliefs, Field Experiment, Valuation, Uncertainty, Choice Experiment

JEL Codes: C93, Q51, D83

June 2014

Acknowledgements: The data from the cold water coral survey was collected as part of the project "Habitat-Fisheries interactions - Valuation and bio-economic modeling of Cold Water Coral", funded by the Norwegian Research Council (grant no 216485). DT’s inputs were funded by MASTS, the Marine Alliance Science and Technology Scotland (www.masts.ac.uk). We thank three referees and former JEEM editor Daniel Phaneuf for comments on an earlier version of this paper. David Eil, Bill Neilson, Justin Rao, and Christian Vossler all provided helpful feedback during this research project. MC gratefully acknowledges the support of the Polish Ministry of Science and Higher Education and the Foundation for Polish Science. NH thanks the University of Waikato for their support during the writing of this paper.

\textsuperscript{1}Corresponding author. Department of Economics and Baker Center for Public Policy, University of Tennessee, Knoxville, TN 37996-0550. (865) 974-8114. Jlarivi1@utk.edu
\textsuperscript{2}Department of Economic Sciences, University of Warsaw. miq@wne.uw.edu.pl
\textsuperscript{3}Division of Economics, University of Stirling. n.d.hanley@stir.ac.uk
\textsuperscript{4}Faculty of Biosciences, Fisheries and Economics, University of Tromso. margrethe.aanesen@uit.no
\textsuperscript{5}Faculty of Biosciences, Fisheries and Economics, University of Tromso. jannike.falk-petersen@uit.no
\textsuperscript{6}Division of Economics, University of Stirling. dugald.tinch@stir.ac.uk
1. Introduction

Familiarity with economic decisions can significantly influence how those economic decisions are made. For example, direct experience with a good can influence an economic agent’s valuation for that good (Nelson 1970, Erdem and Keane 1996, and Ackerberg 2003). Even in the absence of direct personal experience, additional information in the form of expert advice or objective information about a good or economic game can affect economic decision making (Schotter 2003, Eil and Rao 2011, Grossman and Owens 2012). To this end, there is a growing literature highlighting how economic agents alter their behavior when they have better information (Duflo and Saez 2003, Jensen 2007, Bhargava and Manoli 2013, and Jessoe and Rapson 2014). In other words, not only does direct experience matter for economic decision making, but so do other measures of familiarity such as objective information about the attributes, benefits and costs of a good.

While economic research shows that better information can affect important economic decisions, like willingness to pay (WTP) for a good, one under-studied characteristic of information is a consumer’s belief about the quality of their information set. An intrinsic characteristic of a consumer’s information set is that, unless the consumer is an expert in the area, they are likely to be uncertain about their information set’s accuracy. While not adequately accounting for this uncertainty can lead to negative economic consequences, a growing body of work in behavioral economics finds that in many circumstances, economic agents exhibit overconfidence (Camerer and Lovallo 1999). Further, recent work shows that economic agents are also likely to underweight new objective information that is at

---

7 In order to address endogeneity of experience, empirical literature attempting to identify the effect of experience on demand often use structural Bayesian learning demand models.

8 A referee and our editor noted that information about a good and experience with a good are related but also quite different. For example, experience with a good could change a consumer’s preferences for it via providing additional information about the good or directly influencing preferences through experience. To our knowledge, parsing out precisely how these two channels are similar, different and how they could affect important economic choices like valuation of a good is an open question in the literature.

9 Indeed, this is the cause of great stress for many college students during tests.
odds with their priors and overweight information in line with their priors, especially if that information reflects poorly on their self-image (Eil and Rao 2011 and Grossman and Owens 2012).

In stated preference valuations of public goods, how a consumer’s existing information about a good interacts with new information plays a crucial role. In such surveys, the researcher provides the subject with a large amount of information about a public good (e.g., a new flood defense system, provision of a public green space, etc...) before eliciting willingness to pay (WTP). If subjects are uncertain about their preferences, information provided by the surveyor could interact with the ex-ante information endogenously acquired by the subject before the survey to affect WTP estimates (Ready, Whitehead and Blomquist, 1995). As a result, understanding the characteristics of subjects’ information updating process is vital for stated preference WTP elicitation.

The literature unclear as to the nature of information updating used by subjects in stated preference valuation. Evidence suggests subjects in stated preference surveys update their information sets in certain ways consistent with Bayesian updating with respect to endogenously acquired information like previous experience with a public good (Czajkowski, Hanley, and LaRiviere 2014a and Czajkowski, Hanley, and LaRiviere 2014b). However, evidence from laboratory experiments suggests that subjects do not always exhibit strictly Bayesian updating when exogenously provided with new information in new situations (Eil and Rao 2011 and Grossman and Owens 2012). Indeed, there is no widely accepted theoretical model for how subject’s priors about their preferences for a good interact with information

---

10 Although beyond the scope of the current paper, information can also change the context or framing of a valuation decision, and thus change people’s responses to the valuation question (Cookson, 2000).

11 We wish to clearly distinguish our approach to the “preference refinement” literature (Swait and Adamowicz, 2001, Holmes and Boyle 2005, Brown et. al. 2008 and Kingsley and Brown 2010). In that literature, subjects are asked to perform repeated choice experiments for the same public good with the same information set. That literature finds subjects refine their preferences for goods in a stated preference setting as their have more experience making choices, asymptoting to some set value. We are concerned with a different question: how information provided to a subject in a stated preference survey and how signals about the accuracy of a subject’s information set affect WTP for the good for a single choice experiment. The interaction of these two lines of research would be a very fruitful area for future research.
provided in a survey. The mixture of endogenously-acquired and exogenously-provided information with an environmental good must be accounted for in trying to correctly model the effects of knowledge on the mean and the variance of willingness to pay (Cameron and Englin 1997).

One overlooked area lying at the intersection of valuation and behavioral economics concerns how preferences and WTP for a public good could be affected by exogenously varying an agent’s certainty about the “quality” of their information set. This paper develops and tests hypotheses addressing this unresolved issue. We embed a field experiment within a choice experiment designed to elicit WTP for policies intended to preserve cold water coral (CWC) sites off the coast of Norway. We measure subjects’ knowledge about CWCs by giving them a quiz on scientific information about the public good. The main hypothesis then uses a purely experimental design embedded in the choice experiment to test the causal effect of providing objective signals about subjects’ knowledge about CWC on the level and predictability of their stated WTP by randomizing which subjects receive their test score.

The experiment is constructed as follows: at the beginning of the stated preference survey we provided basic information about CWCs in the context of development pressures around the coast of Norway. Next, all subjects take a short quiz that asks brief scientific questions which probe their understanding of CWCs (e.g., CWC depth, if CWC is a living organism, etc...). Next, subjects are randomly assigned to a treatment or control group. In the treatment group, subjects are informed of their test scores immediately after completing the quiz. In the control group, subjects are not informed of their test scores. This allows us to identify the causal effect of objective signals of a consumer’s knowledge about a public good on the mean and precision of willingness to pay estimates.

We find a surprising main result: informing a subject of their test score when they are well-informed caused a significant increase in stated WTP of between $85-$129 for establishing a large marine

---

12 Treated subjects are not, though, told how their score relates to other individuals’ scores.
protected area. Further, the channel for this treatment effect occurs only for the size of the preserve itself. We find no effect of treatment on preferences for indirect use values the quiz did not cover like potential harm to industry. We do not find this effect for individuals who are not well-informed. Better-informed subjects had a higher WTP and higher scale (lower variance) than less well-informed subjects, although no causal effects can be established here. Finally, we find that well-informed subjects in the treatment group do not have significantly more predictable WTP estimates (as measured through the scale term in our econometric model). That is, receiving the external signal about how well informed you are does not seem to affect the scale of the utility function for our respondents.

Our main experimental result is different from previous work which shows that objective signals about an economic agent’s subjective beliefs about themselves (e.g., their attractiveness to the opposite sex) affects economic decision making (Eil and Rao 2011) or that agents don’t update negative signals in the same way as positive signals (Grossman and Owens 2012). We instead find that objective signals conveying positive information (e.g., subjects have a more complete information set) significantly affect stated willingness to pay estimates. In a stated preference context, the implication is that an external signal of the extent of people’s knowledge about a public good can be expected to produce different effects on estimated willingness to pay depending on the level of knowledge.\(^\text{13}\)

How levels and certainty over a subject’s information set affects consumer WTP is particularly important in the context of stated preference valuation for public goods. First, in stated preference valuation subjects are given a large amount of new information that they may or may not already know. Thus, in stated preference valuation, how information provided to the subject interacts with the subject’s ex ante information set matters. Second, if the information provided to a subject implicitly reinforces what they already know about a good, providing that information could act as a positive objective signal.

\(^\text{13}\) If these results carry over to private goods, the implication for firms is to send well-informed consumers signals confirming that they are indeed well-informed before offering them the product. Similarly, it is optimal to not send uninformed consumers signals telling them that they are poorly informed.
about the subject’s information set. Third, if in the design of a survey there is positive reinforcement to subjects about their information set, we find evidence that it will significantly increase estimated WTP for the good. Lastly, we find a similar result from the lab that transfers to field experiments in CV studies. This provides motivation for further investigating the link between results from experimental economics and stated preference methods.

The remainder of this paper is organized as follows: section two discusses a conceptual framework for interpreting the role of objective signals on willingness to pay. Section three discusses our case study, experimental design and empirical strategy. Section four presents results and a discussion. Section five offers concluding remarks.

2. Conceptual Framework

The main hypotheses we test in this paper are 1) what is the causal effect of objective signals of knowledge on WTP for a public good and 2) how the effect of objective signals could vary over different levels of knowledge. The motivation for our experiment is recent work in experimental economics which shows that there is a causal effect of information on economic decision making and that this effect varies according to whether the information reflects positively or negatively on the individual (Eil and Rao 2011 and Grossman and Owens 2012). Importantly, though, these earlier experimental studies do not develop any theoretical model of how information could affect economic decision making. While fully developing an overarching theoretical model is beyond the scope of this paper, we present a conceptual framework for how objective signals could affect WTP for a public good.

The most natural framework for processing new information is Bayesian updating. In Bayesian updating new information (the signal) is weighted against previously existing information (the prior) to form an
updated posterior distribution about the state of the world (e.g., a subject’s valuation for the good). In Bayesian updating, the amount of weight given to new information relative to existing information is well-defined.

One form of new information is an objective signal about the quality of an information set. If a subject receives an objective signal that their information or knowledge about a topic is high quality, then it should decrease the relative weight the subject gives to new information. Specifically, the subject would be more likely to interpret new information at odds with their prior information as noise. The converse is also true: if a subject receives an objective signal that their information or knowledge about a topic is low quality, it should increase the weight the subject gives to new information.

Recent behavioral and experimental research shows that agents might give less weight to objective signals that are not flattering to the subject, such as poor performance on a test (Eil and Rao 2011 and Grossman and Owens 2012). In our setting, we exogenously provide treated individuals with their test score on a quiz about objective characteristics of a public good. To the extent that a low score is unflattering, this previous literature suggests that there might be no influence of being treated and having a low score on our outcome of interest: WTP. Conversely, since a high score is flattering, it is feasible that agents would incorporate this signal in forming their WTP for a public good. Theoretical models of “confirmatory bias” in which agents don’t update if a signal is at odds with their priors have a flavor of this empirical finding (Rabin and Schrag 2002).

One important caveat is how subjects’ beliefs about the accuracy of their information set could be correlated with the level of knowledge a subject has about a particular topic. For example, if low scoring people on average know they have poor quality information sets, then the objective signal doesn’t

---

14 Czajkowski, Hanley, and LaRiviere (2014a) and Czajkowski, Hanley, and LaRiviere (2014b) offer two specific models of Bayesian updating in the context of how additional experience or information about a good could affect the ability of the econometrician to predict WTP. They find that differing levels of experience and differing information sets provided to subjects can affect WTP is ways consistent with Bayesian updating.
convey new information. Similarly, high scoring people could systematically believe they have accurate information. In that case, we would expect treatment to have no effect for either high or low quality information set subjects.

Lastly, there is a related literature in psychology on the role of confidence, for example with regard to accuracy in recall (de Soto et al, 2014), judgement (Aly et al, 2013), willingness to revise beliefs (Sitzman et al 2014), social achievement (Kennedy et al, 2013) and decision making (Bang et al, 2014). We add to this literature by designing an experiment which can exogenously varies confidence in the quality of a subject’s information set through objective signals about the quality of a subject’s information set. From an economics perspective, much of this work on confidence can be handled in a model of Bayesian updating. For example, increased confidence is synonymous with increasing precision of posterior distributions. To that end, over-confidence in the behavioral literature relates to the relative weight given to priors relative to objective signals.

3. Case study, experimental design and Econometric Strategy

3.1 Case Study

A large number of cold-water coral sites have recently been discovered off the coast of Norway. They represent high biodiversity ecosystems, but are threatened by a number of pressures including deep-water fishing, mineral extraction and pipeline laying. Deep-water fishing using trawls is a particularly important cause of degradation. Since growth rates are slow, cold water corals (CWC) have very long recovery times once damaged, and can therefore be regarded as a non-renewable resource within a time frame relevant for humans. Although CWC reefs are protected from bottom trawling and other types of destructive activity, the Norwegian government is considering extensions of this protection.

---

15 Cold-water corals are slow-growing organisms, growing less than 25mm annually (UNEP, 2007). They are generally found at depths between 100 – 2000 meters, with the deepest reef recorded at 3000m (Fossa et. al. 2002). They are found world-wide and can form large reefs and mounds. The largest cold water coral reef known today is Røstrevet, outside the coast of Northern Norway. It is 35 km long and 3 km wide.
This means extending the size of protected areas from just the reef to a larger area encompassing the reef and its surroundings.

A choice experiment was designed to collect information about peoples’ valuation for such extended protection. The results are intended as an input to the actual decision-making process on site selection: our choice experiment was thus “consequential” (Vossler et al, 2012). Based on focus groups and scientific inputs, four attributes were used in the design. These were 1) the total size of area to be protected, 2) whether future protected areas would be located in areas important for commercial activities (fisheries and/or the oil/gas industry), 3) how important the CWC is as nursery and habitat for fish, and 4) costs. The size of protected area attribute consisted of 3 levels:

- No increase in protected area, but keep the current 2,445 km² of protected area (reference level only used in the Business As Usual alternative)
- A moderate increase to 5,000 km² (SIZE₅)
- A large increase to 10,000 km² (SIZE₁₀)

With regard to commercially-important areas, respondents were told protected area status could in some areas involve either prohibiting or limiting commercial activities such as fishing or oil and gas exploration. Other areas, however, are not attractive for such activities. The levels this attribute took were thus:

- Attractive for fisheries (FISH)
- Attractive for oil and gas industry (OIL/GAS)
- Attractive to both fisheries and the oil/gas industry
- Attractive to neither fisheries nor the oil/gas industry
For the attribute *important to fish*, respondents were told that the amount of fish can vary from one reef to another, thus one can assume that some coral reefs may either be an important habitat for many fish species – both commercial and non-commercial - *(HAB)* or may not. As of today, among the protected reef areas there are some which are very important as habitat for fish and some that are not so important. Finally, respondents were told that whether the Norwegian authorities would increase the amount of protected CWC areas depends on support in the population. The willingness to pay in the form of increased taxes per household to secure larger areas of CWC protection is used as a signal to the authorities of the strength of this support. The tax would be ear-marked with all revenues going to a CWC fund *(FEE)*. Five non-discretionary amounts were used: 0, 100, 200, 500 and 1000 NOK ($0, $17, $34, $83, and $165) per year.

Choice cards were then designed based on these four attributes, using two options which increased CWC protection at a cost, and one no increase, no cost alternative. Figure 1 gives an example. The choice tasks were designed using a Bayesian efficient design procedure based on the pilot data. After an introduction to CWC and the management issue to be considered to make the respondents familiar with the topic, each respondent was given the survey which included 12 choice cards. Data were collected from a large stratified sample of randomly-chosen Norwegian households using a face-to-face interview format. In all, 397 responses were used in the analysis below.

3.2 Experimental Design

As part of this experiment, we are able to test for how different knowledge levels about CWCs affect WTP and scale estimates. The main contribution of the paper, however, is that we design an experiment to test how objective signals of knowledge about the CWC affect WTP and scale estimates. To do so, we developed a novel technique to create a score which informs the econometrician about the level of familiarity each participant has for CWCs. After the presentation of preliminary information
about the CWC survey, each respondent completed a short 8-question multiple choice quiz on cold-water corals (see Table 5). Each question had 4 possible answers of which only one was correct. We take a participant’s score (0-8) and use it as a measure of their knowledge of CWCs. This score acts as a metric for information set quality and familiarity with the good.

We integrated a field experiment into the CWC survey to identify the causal effect of an objective signal of a participants’ knowledge about a public good- CWC in this case- on WTP and scale estimates. Respondents were randomly allocated into two groups of equal size. Group 1 were told how well they had performed in the quiz (number of correct answers) before they started the choice experiment. Group 2 were not told their score. Group 1, then, is the treatment group and group 2 is the control group. Because assignment into groups was random, the interpretation of the estimated coefficient on the binary treatment variable is causal.

Importantly, the quiz is entirely designed around objective information about CWCs in and of themselves. Not a single question deals with the oil/gas or fishing industries, nor the effect of CWC on habitat for juvenile fish. The quiz was directly about characteristics of the public good (e.g., cold water coral or “CWC”) in and of itself. At no point in the survey scientific information about the interaction of CWC and fish presented. Presumably, whatever the subject knew before about the interaction of fish/oil/habitat and CWC is what they knew after. As a result, the only relevant information for which a subject received a signal if treated was over the CWC in and of itself. As a result, we expected the strongest effect of treatment for treated subjects is size of the CWC preserve since the signal did not give any information whatsoever about oil/gas or fish.

3.3 Econometric Strategy

The most versatile methods in which consumers’ preferences for public goods can be modelled and quantitatively described are based on their stated choices, i.e. choices which they make in a carefully
designed, hypothetical situations. Stated preference methods, and the discrete choice experiment (DCE) elicitation format in particular, are of importance for researchers and policy-makers because they allow for modelling of consumers’ preferences for goods (or changes of their characteristics) which are not yet available in markets (Hanley and Barbier, 2009). They allow for estimating welfare changes resulting from the provision of environmental public goods, public health or transport infrastructure improvements into a common framework.

We model respondents’ stated choices using random utility theory (McFadden 1974). We assume that the utility associated with any choice alternative can be divided into a sum of contributions that can be observed by a researcher, and a component that cannot, and hence is assumed random. Formalizing, let individual $i$ choose among $J$ alternatives, each characterized by a vector of observed attributes $\mathbf{x}_{ij}$. The utility associated with alternative $j$ is then given by:

$$U_i(\text{Alternative} = j) = U_{ij} = \mathbf{\beta}' \mathbf{x}_{ij} + \epsilon_{ij},$$

(1)

where $\mathbf{\beta}$ is a parameter vector of marginal utilities of the attributes. Assumptions with respect to the random term $\epsilon$ variance may be expressed by scaling the utility function in the following way:

$$U_{ij} = \sigma \mathbf{\beta}' \mathbf{x}_{ij} + \epsilon_{ij},$$

(2)

$\sigma$ is a variance parameter.

---

16 These situations can be described to respondents by the means of attributes of a good. The choice alternatives are then defined in terms of attribute levels – a respondent is asked to select an alternative which would provide him with the highest utility. As long as these choice situations are framed in such a way that they pose some characteristics of consequentiality (e.g., a survey is said to inform policy-makers so that they can design a new policy which would be most preferred by the public), respondents’ choices are believed to reveal their underlying preferences (Carson, R. T. and M. Czajkowski 2014).
Where the random component of the utility function is typically assumed to be independently and identically (iid) Extreme Value Type 1 distributed across individuals and alternatives, while ‘scaling’ the deterministic parameters of the utility function by $\sigma$ introduces the proper amount of randomness in the respondents’ observed choices.\footnote{This randomness is necessary since it is otherwise impossible to explain why respondents who are identical with respect to all observable characteristics may make different choices.} Since the utility function is ordinal, arbitrary scaling of the model parameters does not alter the preference structure. The coefficients $\sigma$ and $\beta$ cannot both be identified and are reported as a product which can only be interpreted relative to the other model parameters.\footnote{The ratio of the coefficient of a characteristic-related attribute to the coefficient of a monetary attribute becomes a marginal rate of substitution, i.e. in this case the implicit price (WTP) for the particular characteristic. Note that in this case the scale parameter cancels out.}

The focus of this paper makes it interesting to test how observed scale, $\sigma$, and WTP estimates change with respect to respondents’ information (knowledge) levels. The interpretation of some respondents having a higher scale parameter is that their choices are less random from the perspective of the analyst. In our econometric framework, this means that the ratio of the deterministic component of their utility function to the random component is higher. This can be introduced by making the scale parameter dependent on respondents’ characteristics, which in our case will be related to their test score. Since scale is strictly positive, it is possible to introduce scale-related covariates in the following way:

$$U_j = \sigma \exp(\theta'k_j)\beta'x_{ij} + \epsilon_{ij}. \quad (3)$$

As a result, the ‘effective’ scale is a function of $k_i$, a vector of respondent-specific variables.

The above specification leads to the Heteroskedastic Multinomial Logit (H-MNL) model, with the following closed-form expression of the probability of choosing alternative $j$ from a set of $J$ available alternatives:
We choose this model because it allows us to simply and transparently highlight the effect of respondents’ prior information (knowledge or experience) and the effect of signals about knowledge on scale and WTP estimates. A similar specification, which allows for a systematic investigation of differences in scale between respondents, choice tasks or alternatives was earlier used by Dellaert, Brazell et al. (1999) and Swait and Adamowicz (2001).

The goal of this paper is to test two hypotheses. First, we test for how knowledge about the public good (e.g., CWCs) is related to WTP and scale estimates for increased provision of the good. To test for increases in WTP, we include the knowledge score as a covariate in the vector $x$ and test for the sign of the coefficient for WTP for increased provision of the public good. To test for increases in scale we include the knowledge score as a covariate in the vector $k$ and test for the sign and significance of the estimated coefficient. Because quiz scores are not exogenous at the participant level, these estimates are not causal. Second, we test for the causal effect for how objective signals of a survey participant’s knowledge about a public good affects their WTP and scale estimates. We test for the signal’s effect on WTP and scale estimates in the exact same way as above. Since we randomly assign subjects to treatment and control groups which determine whether or not they receive a signal, our estimates for this variable are causal.

4. Results

In what follows we present the results from estimating the H-MNL model described above using the data collected from the CWC survey. The goal of this section is twofold. First, we would like to investigate how knowledge correlates with WTP and the scale parameter for the public good. Second,
we would like to test whether objective signals of respondent’s knowledge about a public good cause changes in their WTP and scale. Attribute levels of choice alternatives for each study were coded in the way described in section 3. We present results in the following order: 1) effects of more knowledge on scale, 2) effects of more knowledge on WTP, 3) effects of signals of knowledge on scale and 4) effects of signals of knowledge on WTP.\(^{19}\) These first two results are descriptive while the last two are causal.

4.1 Familiarity and Scale

In this section, we define our familiarity measures (knowledge in the CWC study) in the following way. We used a knowledge-related binary variable (\(KNL\)) which is based on respondent’s score on the CWC quiz. \(KNL\) is an indicator variable which takes the value of one is the subject scored better than the mean score (6.5) on the quiz.\(^{20}\) We also estimated the model using other thresholds and measures. All qualitative results are similar throughout the paper. We principally chose to focus on above and below the mean measures to more closely follow the work of Eil and Rao (2011) and Grossman and Owens (2012). We maintain this binary distinction for high and low knowledge for WTP estimates throughout the paper.\(^{21}\) We include the \(KNL\) as a covariate of scale as explained by equation 3 – to investigate if better informed subjects are more predictable, on average, in their choices (Table 1).

Table 1 shows the results from using each measure of familiarity as a covariate of scale. The coefficient of interest in table 1 is on \(KNL\). Respondents with higher quiz scores had a higher scale coefficient, i.e. the magnitude of the deterministic component of their utility functions relative to the random component was higher than for respondents with lower quiz scores. Put another way, more knowledge

\(^{19}\) A model which simultaneously includes respondent-specific characteristics as interactions of choice attributes and covariates of scale cannot be identified. For this reason we estimate the effects of familiarity on scale and the effects of familiarity on WTP separately. This specification allows us to investigate if respondent preferences, and so WTPs, vary with each kind of familiarity in the same way.

\(^{20}\) Other summary statistics were: standard deviation = 1.33, median = 6, min = 2, max = 8.

\(^{21}\) We have also have run the regressions using the continuous measure of knowledge scores and varied the cutoff in constructing the binary variable. The same qualitative results hold. Those results are available from the authors upon request.
about CWC contributes to respondents being more consistent, conditional on covariates in their stated choices about the public good. As shown in Czajkowski et. al. (2014b), this result is consistent with respondents using Bayesian updating to refine their preferences for existence values.

4.2 Familiarity and WTP

We also estimate the model in which the familiarity-related variable is interacted with the choice attributes. It is important to note, before proceeding, that these estimates are not causal. They are only presented to see how familiarity obtained via knowledge is correlated with WTP estimates. Any causality for knowledge on WTP estimates can in no way be inferred in this section.

Table 2 shows WTP estimates. In addition to the coefficients associated with each choice attribute (main effects), we also provide interactions of each attribute-specific coefficient with the binary indicator of familiarity level (\( KNL \)). Finally, the labels ‘low knowledge’ represents respondents below the mean level of knowledge in the sample, while ‘high knowledge’ refers to respondents above the mean.

The results in Table 2 indicate that participants who scored above the mean (seven or eight correct answers) were willing to pay significantly more for larger CWC protection. They were also more sensitive to whether the sites would be in conflict with oil and gas operations. Respondents with higher knowledge had significantly lower marginal dis-utility associated with costs (in absolute terms), and therefore were willing to pay significantly more for individual attributes as well as the best overall improvement scenario (1,109 vs. 3,121 NOK or $188 vs. $530). Agents with more familiarity with the public good are thus willing to pay more for it. In sum, then, for our non-causal results we find that higher levels of knowledge, as measured by quiz score, significantly increase scale (reduce the randomness of choice from the econometrician’s perspective) and increases WTP estimates for the conservation of CWC.
4.3 Objective signals and scale

We next test whether objective signals about an agent’s knowledge about a public good cause differences in her scale (and stated WTP – but the WTP is not the issue in this section) for the public good. This is made possible by the experimental treatment we incorporated in the cold water corals study: half of respondents were in a treatment group and were told their test scores before they completed the choice cards, while the other half were in a control group and not told their test scores.  

To test for the effect of objective signals on scale, we estimate the H-MNL model using score and treatment-related covariates. Again, we parse the subjects into two groups: those that score above the mean on the quiz (KNL) and those that score below the mean (baseline). In addition, we interact it with a dummy variable (Treatment) which takes the value one if a respondent was told his or her score. All these 3 covariates enter the scale coefficient, so that equation (3) now takes the following form:

$$ U_i = \sigma \exp(\theta_1 KNL + \theta_2 Treatment + \theta_3 KNL \cdot Treatment) \beta' x_{ij} + \epsilon_{ij}. $$

This specification allows the influence of the signal to vary across the subjects as a function of their score. This specification, motivated by the findings in Grossman and Owens (2012) and Eil and Rao (2011), allows for the possibility of asymmetric effects of treatment on high and low scorers.

The effects of being in the treatment group on choice uncertainty are illustrated with the results presented in Table 3. The baseline is low knowledge and in the control group. The binary variable KNL indicates whether a subject is in the high scoring group. For those in a treatment group, the shift in their scale is reflected by (Treatment). Finally, for those who both had a high knowledge score and were in a control group an additional interaction is introduced (KNL * Treatment). This specification allows us to test the following hypotheses:

---

22 A table showing scores and demographic characteristics by treatment status is available from the authors upon request. We find no significant differences in observables by treatment status.
(i) higher knowledge score changes the scale parameter \( \theta_1 = 0 \)

(ii) being told one's quiz score changes the scale parameter \( \theta_2 = 0 \)

(iii) being told one's quiz score changes the scale parameter differently for respondents with higher knowledge \( \theta_3 = 0 \)

A significant coefficient on \( \theta_2 \) indicates that receiving any test score systematically affects the scale. A positive and significant coefficient implies being in the treatment group significantly increases the relative importance of the deterministic portion of the random utility model. In other words, consumers' valuation for the good becomes less random from the econometrician's perspective. A significant coefficient on \( \theta_3 \) indicates that the marginal effect for a subject receiving an objective signal about their quiz score and being in the high knowledge group systematically affects the scale parameter. A positive and significant coefficient implies that well-informed subjects receiving a signal that they are indeed well-informed causes them to have significantly less dispersion in their WTP as derived from the DCE for the good.

Table 3 shows that respondents with higher knowledge scores have overall higher scale parameters, which is in line with the findings presented in Table 1. The treatment, however, does not seem to significantly affect the scale for respondents with low knowledge; the estimated standard error is almost twice as large as the point estimate. Finally, although we find that treatment does increase the scale parameter for respondents with high knowledge score, this effect is not statistically significant. Overall, we take this as evidence that objective signals of knowledge do not affect the scale (e.g., the precision) of the utility function for public goods.

4.4 Objective signals and WTP
While the above results show that signals do not have an effect on the scale of the utility function (i.e. an effect on its error term variance), it is entirely possible that there could still be an asymmetric effect on the individual preference parameters, and hence on respondents’ WTP. To test for an effect of signals on WTP, we estimate a MNL model where for each choice attribute we include interactions with knowledge levels and treatment-related indicator variables. As before, we split the sample into 4 different groups of CWC respondents: high quiz scorers and low quiz scorers and treatment and control group. Higher scorers are defined as individuals scoring above the mean (7 or 8) and low scorers are individuals scoring below the mean (0-6).\textsuperscript{23} We allow a subject’s preference for each attribute of the public good to vary by their knowledge group and treatment status in the following way:

$$x_{ij} = (\theta_1 KNL_i + \theta_2 \text{Treatment}_i + \theta_3 KNL_i \cdot \text{Treatment}_i)x_j$$

A significant coefficient on $\theta_2$ indicates that receiving any test score significantly affects subject $i$’s preference for attribute $j$. A positive and significant coefficient implies being in the treatment group significantly increases the preference for that attribute. A significant coefficient on $\theta_3$ indicates a marginal effect for treatment on the high knowledge group for attribute $j$. A positive and significant coefficient implies that well-informed subjects receiving a signal that they are indeed well-informed causes them to have significantly greater preference for attribute $j$.

Table 4 shows effects on both preference parameters (left hand panel) and WTP estimates for each attribute (right-hand panel). For preferences, well-informed subjects were willing to pay significantly more in fees for the public good than less-informed subjects (although the total effect of fees was still negative). The main finding of the experiment, though, is that subjects with high scores who received the treatment had significant increase in their stated preference for a larger CWC reserve relative to

\textsuperscript{23} Recall that the median test score was 7.
high scoring individuals who did not receive treatment. Put another way, for well-informed individuals, treatment caused a significant increase in the preference for more provision of the public good. Treatment had no such significant effect on the preferences of the low scoring group. The effect was significant and positive for both a doubling and a quadrupling of the size of the protected area at the 5% level.

There was no other observed significant effect of treatment, nor the interaction of high knowledge and treatment, for any characteristic. Specifically, treatment had no significant effect at the 5% level for either high or low scoring groups on preferences for CWC reserve if subjects were told the reserve would affect commercial interests or non-commercial fish stocks. The interaction of being well-informed and treated caused a marginally significant decrease at the 10% level in preferences for CWC protection if informed that the area was important to fisheries. Given the lack of statistical evidence, we attribute this marginally significant coefficient to noise. No other interactions were significant. In sum, then, we find strong and consistent evidence that treatment increased the preference for more of the public good (e.g., a larger reserve). We find no other convincing evidence of significant treatment effects. These results are consistent with the nature of the informative signal for the treated group: the only information for which a subject received a signal is over the CWC in and of itself. Not a single question dealt with fisheries, oil/gas or habitat.

The significant effect of treatment on preferences for high scorers acts to increase estimated WTP for the amount of the public good (e.g., CWC preserve size) for that group. The effects are substantial on both coefficient levels and standard errors. For moderate (large) increases in the reserve size, treatment led to a statistically significant increase on willingness to pay of $85 ($129). In both cases,
there is a very significant reduction in the standard errors of WTP estimates for the treated group: the simulated standard error on WTP decreases by roughly 50% for nearly every attribute including size.\textsuperscript{24} 

The magnitude of these results is somewhat surprising: high scorers being informed of their level of knowledge declare significantly higher WTP for the level of provision of the public good. This effect was significant for preferences at the 5% level for both moderate and large increases in reserve size. There were no other significant effects at the 5% level. As a result, signals affected preferences to provide an increased quantity of the public good for the high scoring group. We find no convincing evidence that signals caused a change in preferences for the public good when informed it could affect other industries or non-commercial fish habitat. In sum, then, treatment causes an increase in demand for the public good for high scorers. It causes no change in the interaction of demand for the public good and any other form of demand which was part of the survey (e.g., commercial or habitat effects).

As in many laboratory and field experiments with similar designs, we can only suggest possible mechanisms for this result. First, we can note that the result is only present for high scorers. Consequently, we can infer that the mechanism is related to the level of knowledge of the individual in addition to uncertainty over the accuracy of their knowledge. Further, the effect was only present for preferences directly related to the informative nature of the signal (e.g., demand for the public good rather than interactions of the public good with other industries). This result is largely consistent with other behavioral literature on asymmetric updating (Eil and Rao 2011 and Grossman and Owens 2012).

Indeed, a main contribution of our paper is finding this kind of asymmetric updating result in a stated preference survey. However, like that earlier work we cannot precisely determine how a subject’s beliefs about the accuracy of their knowledge interact with the objective signal. To do inform a theoretical model that does so, the experimental design would need to vary priors and signal strength.

\textsuperscript{24} Although the high scoring control group had a negative mean WTP for increasing the reserve’s size, the estimate was not at the 5% level.
One appealing strictly neoclassical explanation is that uncertainty about the accuracy of a consumer’s information matters for stated WTP for public good provision. There is evidence for this type of an explanation since only preferences related to the informative signal (e.g., size of CWC preserve) were affected by receiving that signal. Appendix A outlines a strictly Bayesian model in which objective signals about knowledge affect WTP for well-informed risk averse agents more than less-informed risk averse agents. In the model, uncertainty over knowledge leads to uncertainty over valuation for the public good. The uncertainty manifests as uncertainty over expected utility with respect to a numeraire good. Risk aversion leads to greater increases in WTP for the public good for well-informed agents relative to less informed agents upon receiving an objective signal about the quality of one’s information set under certain assumptions about preferences in the fully informed state. An important feature of this model is that the consumer must budget a set amount of resources to providing public goods so that curvature of the utility function over the private good is sufficiently pronounced. This sort of model is essentially a model of confidence: increased peakedness of posterior distributions due to objective signals amount to increases in confidence about the information set.25

There are of course other behavioral explanations like a connoisseur effect for the public good or an intrinsic social responsibility prompted by the objective signal informing individuals they are indeed well-informed.26 There is suggestive evidence for this latter explanation since the treated high scoring group was willing to pay more for increased size of the protected CWC area but their preferences for the interaction of demand for the public good and all private benefit attributes for the oil, gas and fishing industries were unaffected. We are not aware of any work which evaluates how objective signals about a particular public good affect altruistic or impurely altruistic motives for giving. Alternatively, it could

25 Note that this is not the same thing as overconfidence. Overconfidence involves overweighting priors relative to signals. Confidence involves priors or posteriors being more peaked.
26 By connoisseur effect, we mean that being informed that one knows more about a good than others directly increases an agent’s valuation for a good.
be that high scoring types thought they were less informed than they actually were and subsequently increased their WTP on hearing this “good news”. This type of behavioral updating explanation where not only signals matter, but also the way in which the signal differs from the prior, has support in recent experimental work (Eil and Rao 2011 and Grossman and Owens 2012). While we sketch of Bayesian updating model which is consistent with our results, more theoretical work which can parse between such a behavioral updating and a Bayesian updating procedure is needed. Lastly, it could be that temporary positive objective signals – whether related to a good or not – lead to general changes in observed behavior, like increases in demand for a related (or potentially any) good. There is some evidence of this behavior in the experimental literature (Bernheim and Rangel 2004) and testing such a model in this context would be straightforward.

An even larger question is what this result implies for choice experiments in general. If actual WTP for a public good is so intimately tied to knowing the accuracy of one’s information state, this is surprising. Clearly, we do not imply that the optimal stated preference protocol should include objective signals of respondents’ information states, but we do acknowledge that these results have implications for both the robustness of WTP estimates and the proper interpretation of WTP estimates. Our results imply that WTP estimates are not only a function of true information states of the respondents but also their beliefs about those information states. As a result, one possible line of inquiry for future academic research would be to identify the percentage of estimated WTP due to how information provided during a survey acts as an objective signal.

5. Conclusions

We also note, that since the increase was the highest (and was the only significant effect) for the two size-related attributes, this corresponds to respondents who had high knowledge score and being told about it to be less likely to choose the SQ alternative (which was the baseline for the two size-related attributes).

More informed WTP estimates are desirable since stated preference WTP estimates are often used to inform the design of a subsequent ballot initiative and voters often acquire information on political issues before casting ballots.
In this paper, we investigate the effects of objective signals of knowledge on willingness to pay for a public good. We find that objective signals of a participants’ knowledge about a good cause an increase in agents’ willingness to pay for provision of that good. The marginal effect of additional knowledge on WTP is significant and large for well-informed subjects who are randomly assigned treatment in which they receive an objective signal about the accuracy of their knowledge. In effect, then, well-informed subjects are willing to pay significantly more for the good when subjects receive objective signals about the quality of their information set. We find no such effect for relatively poorly informed subjects.

We are not able to determine the precise mechanism for how objective signals about knowledge affect WTP. There are several possible explanations which we are not able to reject as possible explanations: good news/bad news, risk aversion and neoclassical Bayesian updating, a connoisseur effect, etc... Our main result, then, prompts further questions for additional research both in the behavioral literature and insofar as this result has implications for demand estimation for public goods.
References


Table 1 – The effects of information on choice uncertainty

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Coefficient (s.e.)</th>
<th>WTP [NOK] (s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE₅</td>
<td>-0.0398 (0.0432)</td>
<td>-87.71 (97.2214)</td>
</tr>
<tr>
<td>SIZE₁₀</td>
<td>0.1096** (0.0437)</td>
<td>241.78*** (91.1841)</td>
</tr>
<tr>
<td>OIL/GAS</td>
<td>0.0587** (0.0437)</td>
<td>129.55** (91.1841)</td>
</tr>
<tr>
<td>FISH</td>
<td>0.1099*** (0.0288)</td>
<td>242.51*** (64.1483)</td>
</tr>
<tr>
<td>HAB</td>
<td>0.7123*** (0.0544)</td>
<td>1571.55*** (143.0891)</td>
</tr>
<tr>
<td>FEE</td>
<td>-0.4533*** (0.0496)</td>
<td>–</td>
</tr>
</tbody>
</table>

Covariates of Scale

| KNL | 0.4356*** (0.0827) | – |

Model Characteristics

| LL          | -4759.73            |
| McFadden's pseudo R² | 0.0626             |
| AIC/n       | 2.0358              |
| n (observations) | 4683              |
| k (parameters) | 7                 |
Table 2 – The effects of information on taste parameters and WTP

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Coefficient (s.e.)</th>
<th>WTP [NOK] (s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Main effects</td>
<td>Interactions (KNL)</td>
</tr>
<tr>
<td>SIZE₅</td>
<td>-0.1382* (0.083)</td>
<td>0.1569 (0.1139)</td>
</tr>
<tr>
<td>SIZE₁₀</td>
<td>-0.0792 (0.0867)</td>
<td>0.3685*** (0.1165)</td>
</tr>
<tr>
<td>OIL/GAS</td>
<td>-0.0304 (0.0566)</td>
<td>0.1596** (0.074)</td>
</tr>
<tr>
<td>FISH</td>
<td>0.1948*** (0.0589)</td>
<td>-0.0658 (0.0768)</td>
</tr>
<tr>
<td>HAB</td>
<td>0.8478*** (0.0642)</td>
<td>0.1795** (0.085)</td>
</tr>
<tr>
<td>FEE</td>
<td>-0.8412*** (0.0865)</td>
<td>0.3366*** (0.1125)</td>
</tr>
</tbody>
</table>

Model Characteristics

- LL: -4708.69
- McFadden’s pseudo R²: 0.0727
- AIC/n: 2.0161
- n (observations): 4683
- k (parameters): 12
Table 3 – The effects of objective signals on choice uncertainty

Cold water corals study

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Coefficient (s.e.)</th>
<th>WTP [NOK] (s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIZE\textsubscript{5}</td>
<td>-0.0314 (0.0448)</td>
<td>-66.39 (96.2244)</td>
</tr>
<tr>
<td>SIZE\textsubscript{10}</td>
<td>0.123*** (0.0463)</td>
<td>260.33*** (90.6029)</td>
</tr>
<tr>
<td>OIL/GAS</td>
<td>0.0606** (0.0284)</td>
<td>128.19** (59.1948)</td>
</tr>
<tr>
<td>FISH</td>
<td>0.1103*** (0.0307)</td>
<td>233.42*** (63.5447)</td>
</tr>
<tr>
<td>HAB</td>
<td>0.7366*** (0.0755)</td>
<td>1558.48*** (140.951)</td>
</tr>
<tr>
<td>FEE</td>
<td>-0.4726*** (0.0609)</td>
<td>–</td>
</tr>
</tbody>
</table>

Covariates of scale

| KNL        | 0.3252*** (0.1179) | – |
| Treatment  | -0.0792 (0.1427)   | – |
| KNL*Treatment | 0.2153 (0.1659)   | – |

Model characteristics

| LL          | -4743.60 |
| McFadden's pseudo R\textsuperscript{2} | 0.0658 |
| AIC/\textit{n} | 2.0297 |
| \textit{n} (observations) | 4683 |
| \textit{k} (parameters) | 9 |
Table 4 – The effects of objective signals on taste parameters and WTP

Cold water corals study

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Interactions (KNL)</th>
<th>Interactions (Treatment)</th>
<th>Interactions (KNL*Treatment)</th>
<th>Low knowledge and no treatment</th>
<th>High knowledge and no treatment</th>
<th>Low knowledge and treatment</th>
<th>High knowledge and treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>SIZE₅</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.1717</td>
<td>-0.1371</td>
<td>0.063</td>
<td>0.5668**</td>
<td>-236.06</td>
<td>-854.05*</td>
<td>-114.18</td>
<td>507.88***</td>
</tr>
<tr>
<td>(0.1184)</td>
<td>(0.1641)</td>
<td>(0.1644)</td>
<td>(0.2277)</td>
<td>(179.705)</td>
<td>(451.095)</td>
<td>(125.384)</td>
<td>(169.578)</td>
</tr>
<tr>
<td><strong>SIZE₁₀</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.0891</td>
<td>0.0767</td>
<td>0.0185</td>
<td>0.5669**</td>
<td>-122.52</td>
<td>-262.63</td>
<td>-160.90</td>
<td>775.90***</td>
</tr>
<tr>
<td>(0.1261)</td>
<td>(0.1693)</td>
<td>(0.1741)</td>
<td>(0.2345)</td>
<td>(180.175)</td>
<td>(412.617)</td>
<td>(159.158)</td>
<td>(221.207)</td>
</tr>
<tr>
<td><strong>OIL/GA</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.0122</td>
<td>0.1567</td>
<td>-0.0352</td>
<td>0.0076</td>
<td>-16.76</td>
<td>-41.39</td>
<td>-217.32</td>
<td>-67.37</td>
</tr>
<tr>
<td>(0.0813)</td>
<td>(0.1076)</td>
<td>(0.1135)</td>
<td>(0.1485)</td>
<td>(112.068)</td>
<td>(501.353)</td>
<td>(196.383)</td>
<td>(283.822)</td>
</tr>
<tr>
<td><strong>FISH</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.1195</td>
<td>0.0914</td>
<td>0.1460</td>
<td>-0.2993*</td>
<td>164.35</td>
<td>-221.94</td>
<td>-27.03</td>
<td>-369.6</td>
</tr>
<tr>
<td>(0.0852)</td>
<td>(0.1119)</td>
<td>(0.1185)</td>
<td>(0.1543)</td>
<td>(118.124)</td>
<td>(518.48)</td>
<td>(199.154)</td>
<td>(296.607)</td>
</tr>
<tr>
<td><strong>HAB</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.8948***</td>
<td>0.1736</td>
<td>-0.0906</td>
<td>0.0199</td>
<td>1230.24***</td>
<td>5.32</td>
<td>-275.56</td>
<td>-108.89</td>
</tr>
<tr>
<td>(0.0913)</td>
<td>(0.1222)</td>
<td>(0.1276)</td>
<td>(0.1688)</td>
<td>(216.962)</td>
<td>(552.397)</td>
<td>(219.509)</td>
<td>(314.365)</td>
</tr>
<tr>
<td><strong>FEE</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.7273***</td>
<td>0.3657**</td>
<td>-0.2246</td>
<td>-0.0459</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>(0.1226)</td>
<td>(0.1607)</td>
<td>(0.1726)</td>
<td>(0.2242)</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
</tbody>
</table>

Model characteristics

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>LL</strong></td>
<td>-4695.99</td>
</tr>
<tr>
<td>McFadden’s pseudo $R^2$</td>
<td>0.0752</td>
</tr>
<tr>
<td>AIC/n</td>
<td>2.0158</td>
</tr>
<tr>
<td>n (observations)</td>
<td>4683</td>
</tr>
<tr>
<td>k (parameters)</td>
<td>24</td>
</tr>
</tbody>
</table>
**Figure 1. Example choice card**

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>Alternative 1</th>
<th>Alternative 2</th>
<th>Alternative 3 (status quo)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Size of protected area</strong></td>
<td><img src="image1" alt="" /></td>
<td>5.000 km²</td>
<td>10.000 km²</td>
</tr>
<tr>
<td><strong>Attractive for industry</strong></td>
<td><img src="image2" alt="" /></td>
<td>Attractive for both oil/gas and the fisheries</td>
<td>No, not attractive for any industry</td>
</tr>
<tr>
<td><strong>Importance as nursery- and hiding area for fish</strong></td>
<td><img src="image3" alt="" /></td>
<td>Not important</td>
<td>Important</td>
</tr>
<tr>
<td><strong>Cost per household per year</strong></td>
<td><img src="image4" alt="" /></td>
<td>100 NOK/year</td>
<td>1000 NOK/year</td>
</tr>
<tr>
<td><strong>I prefer</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 5. Questions from CWC quiz (correct answers in italics)

Question 1: What is a coral?

1. an animal
2. a plant
3. a fungus
4. don’t know

Question 2: At which depths do we find most cold water coral reefs?

1. < 30 meters
2. 30-100 meters
3. > 100 meters
4. don’t know

Question 3: How much do cold water corals grow annually?

1. 4-25 mm
2. 25-100 mm
3. >100mm
4. don’t know

Question 4: What do cold water corals eat?

1. They emit secretions that attract fish that they catch and eat
2. They filter small organisms and suspended matter that happens to pass by
3. They photosynthesise with the help of a symbiotic algae
4. Don’t know

Question 5: What is the main threat to cold water coral reefs?

1. Predation by fish
2. Destruction by wave action
3. Bottom trawling
4. don’t know

Question 6: At what temperature range do cold water corals grow?

1. 0°C to 4°C
2. 4°C to 13°C
3. 13°C to 18°C
4. don’t know
Question 7: How do cold water corals reproduce?

1. Asexually through budding where a polyp divides into two genetically identical pieces
2. Sexually where a sperm fertilizes an egg that develops into a larva
3. Both sexually and asexually
4. don’t know

Question 8: How old is the oldest cold water coral reef found off the Norwegian coast?

1. Less than 1000 years old
2. Between 1000 and 8000 years old
3. Between 8000 to 10 000 years old
4. don’t know
Appendix A: Bayesian Model of WTP as a Function of Objective Signals.

Assume that a consumer is allocating money over privately providing a public good, \( G \), and a numeraire private good, \( c \), to maximize utility subject to a budget constraint normalized to the price of the private good:

\[
\max_{c,G} \quad U(c, G) \quad s.t. \; c + pG = w
\]

Assume that utility is concave in the private good \( c \) but linear in private provision of the public good \( G \).

Substituting in for the private good the first order condition is \( h^*(c^*) = 1/p \).

Consider a risk averse Bayesian updater with an uncertain measure of knowledge \( k \) and a prior distribution \( f(k) \) over their true knowledge state. The prior represents uncertainty over the accuracy of their knowledge. A consumer \( i \) has a mapping from knowledge to utility given by \( v_i(k) \). This valuation function can vary across consumers and need not be monotonic. The valuation of the good for consumer \( i \) is:

\[
E[V_i] = \int v_i(k) f(k) dk.
\]

Assume that the government’s payment mechanism for the public good \( G \) can extract true valuation. In this case, the consumer’s problem is reduced to maximizing expected utility over the valuation of the public good:

\[
\max_v \quad E[U(w - v_i, v_i)] = \int U(w - v_i(k), v_i(k)) f(k) dk.
\]

By definition, increases in expenditures on the public good must decrease consumption of the numeraire good since \( c = w - v_i(k) \). Therefore, if uncertainty over the knowledge of the public good influences valuation of the public good then it also affects optimal private consumption and expected
utility. As a result, even if utility is linear in private provision of the public good, uncertainty over valuation of the public good can interact with risk aversion for the private good.

Now take two consumers with the same budget constraint and uncertainty over the accuracy of their knowledge described by priors. Assume that full information consumer (a) has a low valuation for the public good and consumer (b) has a high valuation for the public good. If \( f(k) \) is sufficiently wide then both consumers may not be WTP a positive amount of the public good. If she is sufficiently risk averse then consumer (b) may not want to commit herself to a lower level of consumption of the numeraire good for the chance of earning large returns from providing the public good.

Now consider consumption dynamics for a mean preserving change in \( f(k) \). For example, a mean preserving decrease in the variance of \( f(k) \) would result from an objective signal of the consumer’s knowledge level \( k \).\(^{29}\) A signal of low quality information doesn’t affect variance of the prior distribution. Conversely, a signal of high quality information would either not affect stated WTP for consumer (a) or increase it in the case of consumer (b) as she is now willing to commit herself to lower consumption of the numeraire good. This situation would be consistent with the results from our field experiment. We leave a more detailed formation of this model to future research.

\(^{29}\) Implicitly we assume here that priors are centered around the true knowledge state on average.