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**Incorporating issues of risk and uncertainty
into Choice Modelling experiments**

Xuehong Wang and John Rolfe

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About the authors

John Rolfe is a Professor in Regional Development Economics in the Faculty of Business and Informatics at CQ University.

Dr Xuehong Wang is a research officer with the Centre for Environmental Management at CQ University

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Abstract

Many policy issues, and the choice of management and funding options to address them, have elements of risk and uncertainty associated with them. Choice experiments, such as those conducted in choice modelling (CM), may need to frame tradeoffs in light of this information. The goal of the research reported in this paper is to explore some methodological issues for identifying and treating uncertainty in the application of CM experiments. A review of theoretical models and one case study application in the CM technique reported by Roberts et al (2008) suggests that inclusion of uncertainty information in the choice sets should influence responses significantly. However, key challenges that remain are to define and describe the elements of risk and uncertainty that are to be included in a choice experiment, to communicate the issues to respondents, and to develop appropriate forms of analysis.

1. Introduction

Choice modelling¹ (CM) is a stated preference non-market valuation technique typically used to estimate values for improvements or losses in environmental condition where data are not available from markets (Louviere et al. 2000; Bennett and Blamey 2001). While it shares some similarities with the contingent valuation method (CVM), with both techniques capable of assessing non-use values, CM involves the use of multiple choice sets that are distinguished by variations in the levels of underlying attributes. A key advantage of the CM technique over the CVM is the ability to frame complex tradeoffs to respondents, with a rich set of subsequent data that allow better understanding and prediction of respondent behaviour (Rolfe et al. 2000).

A key challenge in designing a CM experiment is to limit the complexity of the choice options so that they can be feasibly completed in a survey format by respondents (Carson et al. 1994). This is typically done by condensing key issues into a small set of attributes varying over a discrete number of levels and minimizing the number of choice alternatives (Louviere et al. 2000, Bennett and Blamey 2001). An additional way of reducing complexity has been to minimize issues of risk and uncertainty associated with choice outcomes, even though uncertainty is a key feature of many environmental systems (Roberts et al 2008). In this paper the potential for including risk and uncertainty aspects more directly in CM experiments is reviewed.

There is an extensive literature in economics on risk and uncertainty, including applications in environmental economics. However, there has been very limited direct application of the CM technique to issues involving risk and uncertainty of outcomes. In part, this is because some consideration of risk and uncertainty is built into the framework of non-market valuation. The assessment of non-market values can include option values and quasi-option values in a total value framework, where the choices that people make to protect environmental assets may be driven by a complex group of reasons, including attitudes to risk and uncertainty of environmental outcomes. As well, the inclusion of non-market values into an evaluation framework such as cost-benefit analysis often is combined with some assessment of the likelihood of occurrence of different scenarios.

While some aspects of risk and uncertainty around environmental outcomes can be handled in a broader economic framework, other issues around risk and uncertainty may be integral to the performance of a CM experiment. In most non-market CVM and CM studies, researchers assume that the different scenarios presented to respondents can be achieved, and that respondents are certain about their underlying preferences. While researchers do not know the underlying preferences of respondents with certainty, the Random Utility Theory (RUT) underpinning both CM and CVM

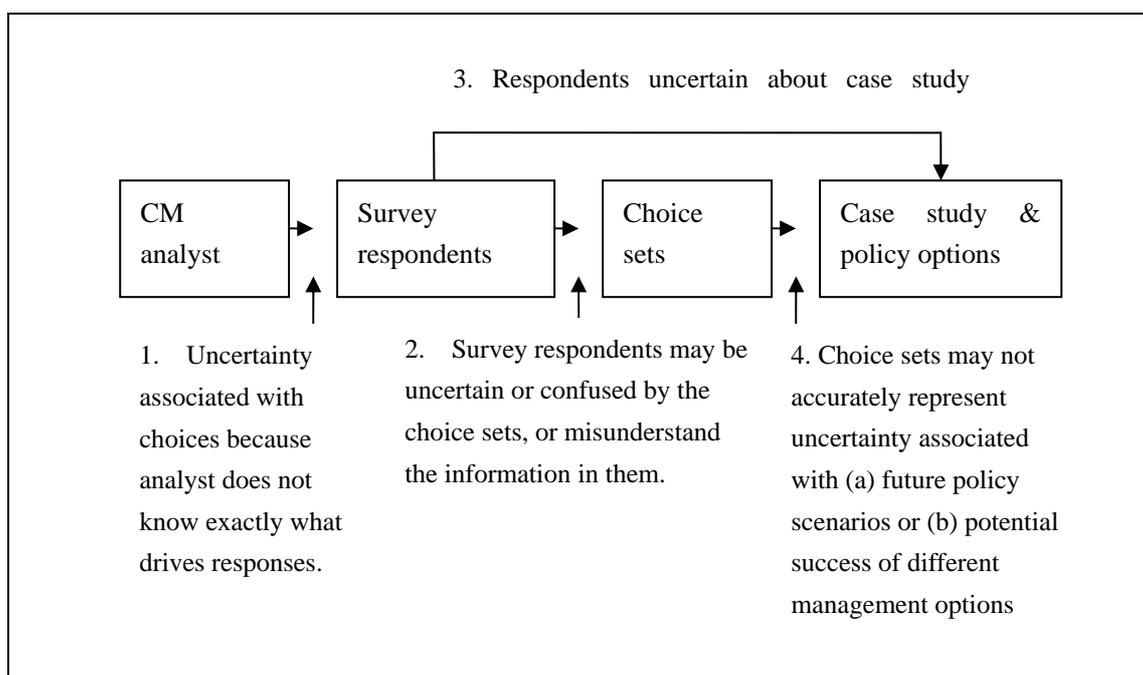
¹ These are also known as discrete-choice experiments or choice-based conjoint analysis.

frameworks provides a mechanism for distinguishing between the deterministic and random error components of choices (McFadden 1973).

The conduct of a CM (or CVM) experiment may involve different layers of uncertainty ranging from the analyst through to the environmental issue being addressed (Figure 1). Issues around risk and uncertainty with stated preference experiments can be distinguished into four key groups:

1. Analysts do not know exactly what drives choice responses,
2. Respondents may be uncertain or confused about the choice sets, or misunderstand the information presented,
3. Respondents may be uncertain about the case study issues,
4. Choice profile(s) do not accurately reflect the uncertainty that future outcomes that are depicted will occur, and how this uncertainty may vary with different management and policy options.

Figure 1. Uncertainty in key assessment stages in CM experiments



Researchers have focused most attention on issue 1, with the development of the RUT and the associated Random Utility Model to underpin the application of both CM and CVM techniques. There has also been some attention devoted to issue 2, with data routinely collected in most CM experiments about respondent experiences in completing choice tasks, and this information sometimes being used in the modelling stages. Issue 3, where respondents may not have accurate or realistic views of risks and uncertainties, has been explored in the context of information disclosure such as the presentation and communication of risk scenarios and how respondents' risk perceptions are updated with more information. Issue 4 has typically been downplayed in CM experiments, with choice sets normally described in ways that

suggests that outcomes and potential improvements could occur with certainty.

Standard utility theory would suggest that higher values are associated with policy options that have lower risks and uncertainty of adverse impacts. This suggests that stated preference studies which include risk and uncertainty information more explicitly into the choice alternatives may provide more accurate feedback about community preferences. Some CM applications (e.g. Roberts 2008) are moving from a simple focus on potential outcomes to also consider preferences for the management options and policy pathways used to achieve the outcomes. In these cases, there is an increased need to distinguish differences between the management options and policy pathways, with varying levels of risk and uncertainty a key factor.

The goal of the research reported in this paper is to explore some methodological issues for identifying and treating uncertainty in the application of CM experiments. The sensitivity of CM value estimates to varying levels and representations of risk and uncertainty information will be a key issue around this research. This research also aims to develop a way to communicate risk and uncertainty information to CM respondents in an effective manner to derive ex ante value estimates that can better predict behaviour. The aim of this research report is to scope the issues around incorporating risk and uncertainty in economic analysis that are of relevance to CM applications. This is done through a comprehensive literature review.

This report is structured as follows. In the next section, a historical overview of the treatment of risk and uncertainty in the literature is outlined. Definitions of risk and uncertainty and economic theories are discussed in this context. Section 3 details the economic models and methods used in previous studies to incorporate risk and uncertainty, with an emphasis on the CV studies. In Section 4, a discussion of the implications of risk and uncertainty issue in the GBR resource management is provided. The potential research issues/ research design in the CM context is also briefly explored in this section.

2. An Overview of Risk and Uncertainty

The terminology used and the definitions of risk and uncertainty are often overlapping. Knight (1921) was among the first to distinguish between risk and uncertainty through the concepts of known and unknown probabilities. According to Knight, risk is characterised by the presence of a unique, additive and fully reliable probability distribution. In other words, risk is present if a probability can be assigned to future events. In contrast, uncertainty is present if the likelihood of future events is indefinite or incalculable (Knight 1921). The distinction between whether probability is known or unknown has also been discussed in other formats such as ambiguous vs. unambiguous probability (Ellsberg 1961) and precise or sharp vs. vague probability

(Savage 1954).

Most environmental and health risks are made up of both exogenous and endogenous components. The traditional approach was to assume that risks faced by an individual were exogenous. More recently several authors have argued that many risks can be controlled by an individual or household through self-protection, making the risks endogenous (Bateman et al 2005; Shogren 1990; Shogren and Crocker 1991; Agee and Crocker 1994). For instance, morbidity and mortality risks associated with drinking contained with arsenic can be reduced through actions the household might take, including drinking bottled water, installing filters or moving away from an area with high arsenic concentration in the drinking water source (Shaw et al 2005). Both exogenous and endogenous risk can vary across individuals.

Environmental policy and economic issues can involve uncertainty in a number of ways. The most important aspect of uncertainty arises when the probability of an environmental outcome is unknown. This 'technical' uncertainty characterises a number of environmental issues such as climate change and biodiversity loss where it is often difficult to assess the precise factors that cause damage, the likelihood of future losses occurring and the effectiveness of potential management actions.

There are a number of other types of uncertainty to consider in an economic analysis of environmental issues, particularly for a stated preference experiment. As summarised in Figure 1, it is difficult to frame the actual levels of risk and uncertainty into choice tradeoffs, respondents may be uncertain about the case study of interest or about how to answer the choices in an experiment, and the analyst may be uncertain about the reasons why respondents have made different choices.

Second, response uncertainty in stated preference experiments may be caused by conflicting information. This can happen when experts themselves are not clear about the risk magnitude (Fox and Tversky 1991). Third, because in many cases outcomes are stochastically related to actions, uncertainty can arise when the policy outcome is unknown or when respondents have varying views (subjective risk perception) on how effective the proposed actions will be. Finally, there are also cases when respondents are not sure about their preferences, commonly referred to as preference uncertainty. The difficulties that people have to assess quantitative information accurately and the uncertainty that this may induce has been previously noted by Ellsberg (1961) and Tversky et al (1988).

Different aspects of uncertainty can also be self-reinforcing. Uncertainty about the probability of environmental risks and about the effectiveness of policy intervention may have an impact on respondents' preference uncertainty. Studies show that the framing and the amount of information about the process causing the risk can influence both perceptions and behaviour. In their contingent behaviour studies, Viscusi et al (1987) and Weinstein et al (1989) found a link between risk perceptions

and behaviour. On the other hand, people's perceptions of risk and uncertainty depend in part on their preferences (Smith 1992). As Smith (1992) argued, people's preferences influence how they acquire this information, form risk perceptions, and value actions intended to reduce the perceived risk. Studies have also found that cognitive factors influence respondent's understanding of risk information, especially when the experimental situations introduced multiple-risk sources (Viscusi et al 1987; Magat et al 1988).

In the literature, attempts have been made to establish the connection between risk perceptions and values. The expected utility (EU) theory (von Neuman and Morgensern 1947) and the subjective expected utility (SEU) theory (Savage 1954) are the central framework for the economist's analysis of choice under risk and uncertainty. In both the EU and SEU models, choices are made so as to maximise the expected value of an individual's utility. This can be illustrated in the following equation:

$$V(\{x, p\}) = \sum_{i=1}^n U(x_i)p_i \quad (1)$$

where $V(\cdot)$ is the individual's ex ante welfare, $U(\cdot)$ is the individual's ex post utility function, x_i is a vector of goods and services in the i th state of the world, and p_i is the probability that the i th state of the world will actually occur (Shaw and Woodward 2008).

In EU theory, the utilities of outcomes are weighted by their probabilities. While an underlying assumption of EU theory is that the probabilities of outcomes are known, SEU theory is used when probabilities are not known by the decision maker. In other words, application of the SEU theory recognises the importance of subjective or perceived risks. With SEU theory, preferences can be represented by a numerical expected utility that uses subjective probabilities of states (which may differ across people) to weight consequence utilities (Camerer and Weber 1992). A key challenge then is to define and determine the subjective probabilities. Options range from using some 'objective' assessment that might be provided by experts through to respondent perceptions, even though the latter may not correspond well to reality (Slovic 1987). Bateman et al (2005) argued that in terms of WTP for a risk reduction, the relevant measurement of risk is people's subjective assessment of risk, rather than a scientifically observed measure.

As can be seen in Equation (1), the EU and SEU are linear in the probabilities that characterise risks, with an underlying assumption that individuals do not have preferences over probabilities. However, some research suggests individuals often do not behave in a manner consistent with the EU/ SEU framework. There are two main reasons for this. First, decision makers often do not treat probabilistic outcomes or events in the standard additive manner as required in the EU and SEU models. Instead,

disproportionately more weight is given to low probability and high consequence events (Shaw and Woodward 2008). Second, people regularly demonstrate an aversion to ambiguity, preferring situations with clear probabilities to those in which the probabilities are uncertain (Ellsberg 1961).

To address the limitations of the EU and SEU models, alternative risk models have been explored and tested in the experimental settings. These include prospect theory (Kahneman and Tversky 1979), the rank dependent expected utility theory (Quiggin 1982), and the prospective reference theory (Viscusi 1989). The prospect theory and the rank dependent expected utility theory assume that people transform expected probabilities into decision weights, but there is not a direct mapping process. Instead, people tend to underweigh outcomes that are considered highly probable, and to overweigh outcomes that have low probability of occurrence.

The prospective reference theory recognises that individual's risk perceptions reflect each individual's prior beliefs, the information they receive about the process, and the relative degree of confidence they assign to each decision (Viscusi 1989). According to the theory, respondents combine personal prior estimates of the effectiveness of the stated intervention with the effectiveness stated in CV instruments to obtain a posterior estimates of the risk reduction for which they report willingness to pay (WTP). Specifically, Viscusi (1989) suggested that prior beliefs about the good may influence respondents' WTP in stated preference experiments, thereby providing an explanation for observed non-linearity between WTP and reduction in mortality risks. Similar results were reported by Corso et al (2001) who found in a study about travel risks that perceptions about the effectiveness of airbags positively affects WTP for risk reductions. Using data about individuals' preferences among health insurance plans, Marquis and Holmer (1996) found that the model which assumes people evaluate gains and losses relative to a reference rather than final outcomes, treat gains and losses asymmetrically, and process certain and uncertain outcomes separately provides a better fit than the standard utility model.

3. Methodologies to Incorporate Risk and Uncertainty in stated preference techniques

Incorporating risk and uncertainty in respondent decision processes in CV studies has been explored in the context of both actual risks and the effects of different information programs. In this section, methods used to incorporate risk and uncertainty is reviewed in detail, with an emphasis on those used in CV studies. Following the information summarised in Figure 1, these include the use of RUT to address uncertainty from the analyst's perspective (issue 1), modelling respondent uncertainty about the choice profiles (issue 2), minimising respondent uncertainty

through information disclosure (issue 2 and 3), and incorporating uncertainty information explicitly in choice questions (issue 4).

3.1 Uncertainty from Analyst's Perspective

As the key theoretical underpinning of CV and CM studies, the RUT addresses issues of randomness and uncertainty from the analyst's perspective (McFadden 1973). The RUT postulates that, from the point of view of the analyst, an individual's utility consists of a deterministic component plus an unobservable random error term. This can be expressed as:

$$U_i = V_i + \varepsilon_i \quad (2)$$

where U_i is the latent, unobserved utility for choice alternative i ; V_i is the systematic, observable or "explainable" component of the latent utility for option i ; and ε_i is the random or "unexplained" component of the latent utility associated with option i (Bennett and Blamey 2001). Because of the random component, the researcher can never expect to predict preferences perfectly. This leads to expressions for the probability of choice:

$$P(i) = P[(V_i + \varepsilon_i) > (V_j + \varepsilon_j)] \quad (3)$$

for all j options in the choice set.

The random component arises either because of randomness in the preferences of the individual or the fact that the analyst does not have the complete set of information available to the individual. While RUT recognises that there is uncertainty in the observation of preferences, it does not distinguish among potential sources of the random component (Figure 1). Only one element of random effects may derive from the analyst not having complete knowledge of an individual's preferences. Randomness in the preferences of an individual may be due to the individual's uncertainty or confusion about the choice sets and misunderstanding of the information in the choice sets (issue 2, see Figure 1), or individual's uncertainty about the case study (issue 3). In other cases, respondents are not provided with full information in relation to uncertainty associated with future policy scenarios or potential success of different management options in the choice profiles (issue 4).

3.2 Modelling Respondent Uncertainty

Respondent uncertainty about preferences and choices has been noted in many CV

studies (Ready et al 1995; Blamey et al 1999). Suggested reasons include unfamiliarity with the public good that is to be valued, the hypothetical nature of CV, being unable to make tradeoffs between the environmental amenity and the monetary good, and a lack of understanding of the contingency in question and the policy instrument proposed for addressing the environmental spill over (Shaikh et al 2007). Low credibility of sources of information can also create an important kind of ambiguity (Einhorn and Hogarth 1985) leading to respondent's preference uncertainty.

A number of methods have been developed in CV studies to identify and model respondent uncertainty. Some researchers have embedded information about respondent uncertainty directly in the response options to the valuation question (Ready et al 1995; Blamey et al 1999; Wang 1997; Welsh and Poe 1998; Alberini et al 2003). For example, Ready et al (1995) developed a polychotomous choice question format where the respondent can answer one of six responses to a CVM trade-off: definitely yes, probably yes, maybe yes, maybe no, probably no and definitely no. They found that allowing for respondent ambivalence increased estimated WTP relative to forcing respondents to answer yes or no in a standard dichotomous choice question. Blamey et al (1999) used a dissonance-minimising format which allowed respondents to express multiple attitudes in the CV questions in order to reduce the occurrence of yea-saying. Results suggest that when respondents are ambivalent or uncertain, allowing for this to be expressed has a significant impact on value estimation.

Respondent uncertainty can also be identified in the data analysis stage. In a number of CV studies follow-up" questions were asked of respondents about how certain or confident they were of their previous "yes"/"no" answers (Li and Mattson 1995; Champ et al 1997; Johannesson et al 1998; Loomis and Ekstrand 1998; van Kooten et al 2001). In these studies, the degree of confidence of respondents has been elicited either through descriptive word scales (e.g. definitely yes, probably yes, probably no, definitely no) or through numerical certainty categories. The certainty scale can then be directly used as an estimate of the probability of paying their bid amount (Li and Mattson 1995; Loomis and Ekstrand 1998). These studies found that incorporating uncertainty in the analysis generated more consistent predictions for respondents who reported greater confidence in their answers.

Even though the numerical certainty categories appear to have the potential to improve the estimation efficiency, certain conditions must hold (Loomis and Ekstrand 1998). First, respondents must be able to assess the certainty of their valuation with some degree of accuracy. Second, they must also interpret the certainty scale equivalently. However, both these two conditions do not necessarily hold. For some of their models, Loomis and Ekstrand (1998) found the explicit incorporation of the certainty variable may introduce additional variance into analysis.

Follow-up questions have also been asked in CM studies about the level of confidence

or certainty that respondents hold when answering the choice questions. This can be used to help explain decision pathways. For instance, Blamey et al (2000) used nested logit models to show that decision pathways can be explained by the level of confusion/ understanding of respondents about the choice sets. In that study, respondents were more likely to choose the Status Quo option over an improvement option if they identified that the choice sets were confusing.

3.3 Information Disclosure

Efforts have been made in stated preference experiments to reduce or minimise the uncertainty of respondents about choice profiles (issue 2) or about case study issues (issue 3) through information disclosure. Some studies focus on the presentation and communication of risk scenarios and how this affects stated behaviour and real behaviour. It has been argued that people have limited appreciation for small probabilities (Frederick and Fischhoff 1998; Viscusi 1998), and this will affect their understanding of the magnitude of risk reduction and hence their WTP. A number of risk communication tools such as tables, graphs, risk ladders and pie charts have been developed to convey information about probabilities and risks. In a study conducted by Corso et al (2001), respondents in each sub sample were presented with one of three visual aids (a logarithmic scale, a linear scale and an array of dots) or no visual aid. The visual aids were used to describe an annual risk reduction of 1/10000 or 0.5/10000. Results showed that WTP was sensitive to the magnitude of risk reductions for the subgroups exposed to the dots and the logarithmic risk ladder, but not sensitive for the group that received no visual aid.

Smith et al (1995) investigated the effects of different risk information booklets on households' decisions to undertake mitigation from the lifetime risks of lung cancer from radon. Two features of risk information were identified. The first involved quantitative information about the lifetime risks of lung cancer from radon, and the second emphasised government action guidelines and instructions for protection versus one that encouraged personal judgment and evaluation. By comparing these quantitative and qualitative approaches, the effects of different risk information treatments on mitigation behaviour were then examined through multinomial logit model specifications.

Bateman et al (2005) examined how WTP for Ultra Violet Radiation health risk reduction varied according to an exogenous element of realised risk after controlling for the endogenous behaviour which affects the realised level of risk. Risk was reflected in the actual behaviour of individuals and variations in risk levels were provided through design of the sampling frame. Survey respondents in four countries with significant differences in scientifically established risk levels were provided with both a private and public good scenario for risk reductions. Results showed that

variation in WTP across these countries is entirely consistent with changes in exogenous risk levels.

Other studies have explored how respondents' risk perceptions can be influenced by information disclosure. These studies have focused on risk communication through eliciting information about individual subjective distribution of risks and exploring how these subjective distributions change in the face of new information. In their experimental studies, Shaw et al (2006) used four treatments with varying presentations of the health risk information to examine the effects of risk presentation on auction bids for a healthy product. While one of the treatments did not have any information on risk, the second presented conflicting risk information with ambiguity in the form of a conflicting second "expert" opinion. The other two treatments had "clear" risk information about health risk reductions. Results show that the subjects' maximum WTP for a product varies depending on the amount of information about the product's health risk reductions that they are given, which influence their risk perceptions (subjective risks). Ambiguity in these risks led to a lower WTP.

Cameron (2005a) explored how people update their beliefs in the face of new and sometimes conflicting information on climate change risks. In her experimental design, information on both the mean and dispersion of the individual's subjective distribution for future annual average temperature was elicited. The dispersion of distribution (variance) was approximated through elicitation of "high" and "low guesses" to capture individual's uncertainty about future conditions. Individual updated subjective risks were explored as a function of individual priors, the nature of external information, and individual attributes. Weights that individuals place on the opinions of government scientists and environmental groups were estimated. Results showed that people may update their expectations for annual temperatures in an approximately Bayesian fashion, but variances change in other ways. In addition, the source and nature of external information, as well as its collective ambiguity, can have varying effects across the population.

In another paper, Cameron (2005b) showed how people's updated perceptions about climate change affect their willingness to support climate change mitigation programs. In particular, individual posterior subjective distributions for future climate conditions are combined with stated choices over alternative climate policies to estimate individual option prices for climate change mitigation. Using a small convenience sample, the desired welfare measures were calculated based on the expected indirect utility-difference function. It was found that individuals' WTP for climate change mitigation is sensitive to both expected future conditions and uncertainty about future conditions.

Aadland et al (2007) developed a Bayesian approach to model the elicitation of WTP for public goods within the context of a CV survey. WTP was elicited in the presence of agent uncertainty and other information signals such as referendum prices and

cheap-talk scripts. The model was further tested and proved in an experimental setting which showed that the interaction between anchoring (prior distribution over uncertain WTP) and the information prompt (in the form of cheap-talk scripts) creates a systematic bias in WTP. The direction and magnitude of the bias in dichotomous choice formats depends on the distribution of initial WTP (subjects' priors) relative to the announced opening price in the questionnaire.

3.4 Explicit Incorporation of Uncertainty in Choice Questions

In previous CM studies, choice sets are normally described in ways that suggest that outcomes could occur with certainty. As shown in Figure 1, these choice profiles may not reflect uncertainty associated with future policy scenarios or potential success of different management options (issue 4). Roberts et al (2008) are among the first to introduce probabilistic outcomes explicitly into the CM survey design and to examine how this uncertainty affects the preferences of respondents for environmental improvements. They used a split-sample design where one group of respondents was asked to choose among environmental outcomes with certainty while the other group was presented with choice questions in which the levels of attributes were associated with some probability. There were substantial differences in the value estimates generated from these two survey formats, confirming that including risk and uncertainty in CM significantly affects people's preferences for environmental goods.

In contrast to the predictions of prospect theory (Kahneman and Tversky 1979) and the rank dependent expected utility theory (Quiggin 1982), the results of Roberts et al. (2008) showed that respondents overweighted the probabilities of likely events and underweighted the probabilities of unlikely events. This had implications for the WTP to reduce the probability of algal blooms in their study, with respondents having higher WTP for scenarios that reduced the uncertainty of outcomes. Among the reasons suggested for differences in WTP between certainty and uncertainty states were (a) increased complexity inducing more critical analysis, (b) respondents may be uncomfortable with some perceptions about risky outcomes, and (c) uncertain outcomes may appear more realistic than ones presented with certainty.

4. Implications for GBR and CM Design

The GBR is under mounting pressure due to increasing human activities such as recreation, fishing, shipping, and agricultural and urban development. There are concerns about impacts in the GBR area, the effects of poor water quality entering the region and the potential for adverse climate change pressures (Rolfe et al 2008). The

government has already taken actions to help reduce the pressures impacting on the condition of the GBR. Current activities include improving water quality through better management of land-based activities, increasing the area of green zones and controls on recreation and fishing activities, and plans to mitigate climate change impacts through carbon emission reductions (Rolfe et al 2008).

A non-market valuation case study of improved protection for GBR resources can illustrate a number of uncertainty issues. First, natural variability and its potential impacts on the natural resources in the GBR are not well understood even within the scientific community. Second, the interactions between the natural processes (e.g. global climate change) and human activities are unclear. Third, the effectiveness of policy intervention or management options is uncertain. These uncertainties will have an impact on the risk perceptions of people, and the ambiguity around risk perceptions thus derived will lead to preference uncertainty. In other words, the uncertainty attached to the potential environmental and policy outcomes can be expected to play a large role in value estimates.

There are several possible ways to test for the impacts of information about uncertainty on value estimation in CM experiments. The most direct method would be to include the probability of environmental outcomes occurring in the choice alternatives. This approach could treat the likelihood of an outcome occurring as another attribute within the choice profiles. A split-sample format can be used with one version including the probability information and the other version excluding it. By comparing the WTP derived from the two survey formats, the effect of uncertainty on elicited preferences can be investigated.

The second main option is to provide information about the likelihood of outcomes occurring in the framing statements for an experiment. This has the disadvantage of being uniform, as the likelihood of outcomes is not specific to each choice alternative.

The third main option is to collect information about the level of uncertainty that respondents have in their choices after the choice sets have been completed. Again, it would be difficult to distinguish how perceptions vary across choice sets or between choice profiles, limiting the usefulness of this approach.

A number of other methodological issues around uncertainty can also be tested in experimental settings. One key area is to identify the most appropriate communication tools and visual aids to present information about risk and uncertainty issues for environmental issues. A second issue is to identify how perceptions of risk and uncertainty may vary across different environmental issues, thresholds and pressures. A third is to identify how perceptions about risk and uncertainty may change with information presented in a survey format.

5. Conclusions

Stated choice experiments typically frame choice scenarios with complete certainty, even though case study situations can rarely be defined so precisely. A key question therefore is whether the responses to choice scenarios will be different when information about the levels of risk and uncertainty associated with the different options is included in the choice task. There are a number of theoretical models about decision processes which suggest that results should differ. One case study application in the CM technique reported by Roberts et al (2008) confirms that inclusion of uncertainty information in the choice sets does influence responses significantly.

Significant challenges remain. A key difficulty is to define and describe the elements of risk and uncertainty that are to be included in a choice experiment, as these are likely to extend over a number of elements of the selected case study and the associated management options. A second challenge is to include risk and uncertainty issues within choice experiments in ways that are understandable to respondents, while a third is to analyse the results where various elements of uncertainty in the responses given need to be identified separately.

For the GBR case study of interest, the consideration of risk and uncertainty will focus on the relationship expected between the types of management actions and certainty with which outcomes are achieved in the GBR (Rolfe et al 2008). In the policy context, this approach has relevance because some policy options have high levels of certainty of outcomes but be expensive to implement in both financial and political terms, while other options may be much cheaper but have less certain outcomes. In this project, CM experiments will be conducted to explore how levels of risk and uncertainty can be incorporated into choice sets and whether inclusion of this information has an impact on value estimates.

References

Aadland, D.M., Caplan, A.J. and Phillips, 2007. 'A Bayesian examination of information and uncertainty in contingent valuation', *Journal of Risk and Uncertainty*, 35: 149-78.

Agee, M.D. and Crocker, T.D., 1994. 'Parental and social valuations of child health information', *Journal of Public Economics*, 55 (1): 89-105.

Alberini, A., Boyle, K. and Welsh, M., 2003. 'Analysis of contingent valuation data with multiple bids and response options allowing respondents to express uncertainty', *Journal of Environmental Economics and Management*, 45: 40-62.

Bateman, I.J., Brouwer, R., Georgiou, S., Hanley, N., Machado, F., Mourato, S. and Saunders, C., 2005. 'A "natural experiment" approach to contingent valuation of private and public UV health risk reduction strategies in low and high risk countries', *Environmental and Resource Economics*, 31: 47-72.

Bennett, J. and Blamey, R. (eds), 2001. *The Choice Modelling Approach to Environmental Valuation*, Edward Elgar, Cheltenham.

Blamey, R. K., Bennett, J.W., Morrison, M.D., 1999. 'Yea-saying in contingent valuation surveys', *Land Economics*, 75(1):126-141.

Blamey, R.K., Bennett, J.W., Louviere, J.J., Morrison, M.D. and Rolfe, J.C., 2000. 'A test of policy labels in environmental choice modelling studies', *Ecological Economics*, 32:269-286.

Camerer, C. and Weber, M., 1992. 'Recent developments in modelling preferences: uncertainty and ambiguity', *Journal of Risk and Uncertainty*, 5: 325-70.

Cameron, T.A., 2005a. 'Updating subjective risks in the presence of conflicting information: an application to climate change', *Journal of Risk and Uncertainty*, 30 (1): 63-97.

Cameron, T.A., 2005b. 'Individual option prices for climate change mitigation', *Journal of Public Economics*, 89: 283-301.

Carson, R.T., Louviere, J., Anderson, D., Arabie, P., Bunch, D., Hensher, D., Johnson, R., Kuhfeld, S., Steinberg, D., Swait, J., Timmermans, H., Wiley, J., 1994. 'Experimental analysis of choice', *Marketing Letters*, 5(4):351-368.

Champ, P.A., Bishop, R.C., Brown, T.C. and McCollum, D.W., 1997. 'Using donation mechanisms to value nonuse benefits from public goods', *Journal of Environmental Economics and Management*, 33: 151-62.

Corso, P.S., Hammitt, J.K. and Graham, J.D., 2001. 'Valuing mortality-risk reduction: using visual aids to improve the validity of contingent valuation', *Journal of Risk and Uncertainty*, 23 (2): 165-84.

Ellsberg, D., 1961. 'Risk, Ambiguity, and the Savage Axioms', *Quarterly Journal of Economics*, 75: 643-69.

Einhorn, H. and Hogarth, R.M., 1985. 'Ambiguity and uncertainty in probabilistic inference', *Psychology Review*, 92: 433-61.

Fox, C.R. and Tversky, A., 1991. 'Preference and belief: ambiguity and competence in choice under uncertainty', *Quarterly Journal of Economics*, 110: 585-603.

Frederick, S. and Fischhoff, B., 1998. 'Scope sensitivity in elicited valuations', *Risk Decision and Policy*, 3: 109-24.

Johannesson, M., Liljas, B. and Johansson, P., 1998. 'An experimental comparison of dichotomous choice contingent valuation questions and real purchase decisions', *Applied Economics*, 30: 643-47.

Kahneman, D. and Tversky, A., 1979. 'Prospect theory: an analysis of decision under risk', *Econometrica*, 47 (2): 263-92.

Knight, F.H., 1921. *Risk, Uncertainty and Profit*, Houghton, Mifflin C., Boston.

Li, C.Z. and Mattsson, L., 1995. 'Discrete choice under preference uncertainty: an improved structural model for contingent valuation', *Journal of Environmental Economics and Management*, 28: 256-69.

Loomes, G. and Sugden, R., 1982. 'Regret theory: an alternative theory of rational choice under uncertainty', *The Economic Journal*, 92: 805-24.

Loomis, J. and Ekstrand, E., 1998. 'Alternative approaches for incorporating respondent uncertainty when estimating willingness to pay: the case of the Mexican Spotted Owl', *Ecological Economics*, 27: 29-41.

Louviere, J., Hensher, D., Swait, J., 2000. *Stated Choice Models - Analysis and Application*, Cambridge University Press, Cambridge. U.K.

Magat, W.A., Viscusi, W.K. and Huber, J., 1988. 'Consumer processing of hazard

warning information', *Journal of Risk and Uncertainty*, 1: 201-23.

Marquis, M.S. and Holmer, M.R., 1996. 'Alternative models of choice under uncertainty and demand for health insurance', *The Review of Economics and Statistics*, 78 (3): 421-7.

McFadden, D., 1973. 'Conditional logit analysis of qualitative choice behavior', in Zarembka, P. (ed) *Frontiers in Econometrics*, Academic Press, New York.

Quiggin, J., 1982. 'A theory of anticipated utility', *Journal of Economic Behaviour and Organisation*, 3 (4): 323-43.

Ready, R., Whitehead, J. and Blomquist, G., 1995. 'Contingent valuation when respondents are ambivalent', *Journal of Environmental Economics and Management*, 29: 181-97.

Roberts, D.C., Boyer, T.A. and Lusk, J.L., 2008. 'Preferences for environmental quality under uncertainty', *Ecological Economics*, 66: 584-93.

Rolfe, J., Bennett, J. and Louviere, J. 2000 "Choice Modelling and its Potential Application to Tropical Rainforest Preservation", *Ecological Economics*, 35:289-302.

Rolfe, J., Windle, J. and Bennett, J., 2008. 'Designing choice experiments to incorporate tests for geographic scale and scope differences', Research Report 1, *Assessing Protection Values for the Great Barrier Reef Research Reports Series*, University of Central Queensland, Rockhampton.

Savage, L.J., 1954. *The Foundations of Statistics*, Wiley, New York.

Shaikh, S.L., Sun, L. and van Kooten, G.C., 2007. 'Treating respondent uncertainty in contingent valuation: a comparison of empirical treatments', *Ecological Economics*, 62: 115-25.

Shaw, W.D., Riddel, M. and Jakus, P.M., 2005. 'Valuing environmental changes in the presence of risk: an update and discussion of some empirical issues', in Folmer, H. and Tietenberg, T. (ed) *The International Yearbook of Environmental and Resource Economics 2005/2006*, Edward Elgar, Cheltenham.

Shaw, W.D., Nayga, R.M. and Silva, A., 2006. 'Health benefits and uncertainty: an experimental analysis of the effects of risk presentation on auction bids for a healthful product', *Economics Bulletin*, 4 (20): 1-8.

Shaw, W.D. and Woodward, R.T., 2008. 'Why environmental and resource economists should care about non-expected utility models', *Resource and Energy Economics*, 30:

66-89.

Shogren, J.F., 1990. 'The impact of self-protection and self-insurance on individual response to risk', *Journal of Risk and Uncertainty*, 3: 191-204.

Shogren, J.F. and Crocker, T.D., 1991. 'Risk, self-protection, and ex ante economic value', *Journal of Environmental Economics and Management*, 20: 1-15.

Slovic, P., 1987. 'Perception of risk', *Science*, 236 (4799): 280-5.

Smith, V.K., 1992. 'Environmental risk perception and valuation: conventional versus prospective reference theory', in Bromley, D.W. and Segerson, K (ed) *The Social Response to Environmental Risk: policy formulation in an age of uncertainty*, Kluwer Academic Publishers, Boston.

Smith, V.K., Desvousges, W.H. and Payne, J.W., 1995. 'Do risk information programs promote mitigating behaviour?', *Journal of Risk and Uncertainty*, 10: 203-21.

Tversky, A., Sattath, S. and Slovic, P., 1988. 'Contingent weighting in judgment and choice', *Psychological Review*, 95: 371-84.

Van Kooten, G.C., Krcmar, E. And Bulte, E.H., 2001. 'Preference uncertainty in non-market valuation: a fuzzy approach', *American Journal of Agricultural Economics*, 83: 487-500.

Viscusi, W.K., Magat, W.A. and Huber, J., 1987. 'An investigation of the rationality of consumer valuations of multiple health risk', *Rand Journal of Economics*, 18: 465-79.

Viscusi, W.K., 1989. 'Prospective reference theory: toward an explanation of the paradoxes', *Journal of Risk and Uncertainty*, 2: 253-64.

Viscusi, W.K., 1998. *Rational Risk Policy*, Oxford University Press, Oxford.

Von Neumann and Morgenstern, J., 1944. *Theory of Games and Economic Behaviour*, Princeton University Press, Princeton.

Wang, H., 1997. 'Treatment of "don't know" responses in contingent valuation surveys: a random valuation model', *Journal of Environmental Economics and Management*, 32: 219-32.

Weinstein, N.D., Sandman, P. And Roberts, N.E., 1989. *Communicating Effectively about Risk Magnitudes*, Final Report to the U.S. Environmental Protection Agency, EPA-230-08-89-064.

Welsh, M.P. and Poe, G.L., 1998. 'Elicitation effects in contingent valuation: comparisons to a multiple bounded discrete choice approach', *Journal of Environmental Economics and Management*, 36: 170-85.