ISSN 1835-9728

Environmental Economics Research Hub
Research Reports

Estimating non-market values under scenario and policy ambiguity: the case of climate change mitigation in Australia

Sonia Akter[1] and Jeff Bennett[1]

Research Report No 32

June 2009

About the authors

Sonia Akter is a PhD student in the Crawford School of Economics and Government at the Australian National University.

Jeff Bennett is Professor in the Crawford School of Economics and Government at the Australian National University.

[1]Crawford School of Economics and Government, The Australian National University, Canberra, ACT 2601, Australia, Tel: +61 2 6125 6556, Fax: +61 2 6125 5570

Crawford School of Economics and Government

THE AUSTRALIAN NATIONAL UNIVERSITY

http://www.crawford.anu.edu.au

Table of Contents

Abstract

This paper proposes an extension to existing models of non-expected utility (NEU) in the stated preference (SP) literature. The extension incorporates the impact of multiple sources of ambiguity in individual decision making behavior. Empirical testing of the proposed decision model was carried out in Australia using a dichotomous choice contingent valuation study of a national 'Carbon Pollution Reduction Scheme (CPRS)'. The results of the study demonstrate that subjective expectations of the context scenario and subjective policy expectations are important determinants of individual decision making in a SP framework. Furthermore, the results of the study demonstrate that decision weight functions are non-linear (quadratic) in subjective scenario expectations and subjective policy expectation. Although evidence was found to link willingness to pay to scenario ambiguity, policy ambiguity was found to have no statistically significant influence on individual decision making.

1. Introduction

Stated preference (SP) methods are used to estimate the value of changes in the provision of non-market goods by analysing individuals' stated behaviour in hypothetical settings. A two-part valuation framework lies at the core of any SP study: a projected future state of the quality (or quantity) of a good without policy intervention (status quo) and a proposed policy intervention to improve or prevent deterioration in the quality (or quantity) of that good. Traditionally, an unmitigated environmental problem is expected to cause utility loss for an affected group of the population. A protective policy measure restores the status quo level of environmental quality (or some position of it) and thus offers to offset potential utility losses. In a majority of cases, such valuation exercises have been carried out assuming certainty regarding the projected scenario of change and policy outcome. However, real-world decision making is characterised by varying degrees of risk and uncertainty about future scenarios and the effects of environmental policy. Especially in situations where outcomes depend on stochastic events, such as rainfall, climatic variability or high loss catastrophic events, ex-ante, certain quantification of the scale of the future scenario and the probability of the final state arising from a policy intervention may not be possible.

Microeconomic theory provides various taxonomies of risk and uncertainty. Knight (1921) distinguished between risk and uncertainty depending on the level of knowledge about the probabilities of outcomes of an event to occur. Risk is characterised by the presence of a unique, additive and fully reliable probability distribution. Uncertainty refers to a situation in which probabilities are unknown (Knight, 1921). Recent contributions to the experimental economics, behavioural economics and psychology literatures propose further distinctions to Knight's definitions depending on the degree of knowledge about the outcomes and probabilities. Dequech (1997) refers to Knight's definition of 'risk' as 'weak uncertainty' and denotes 'strong uncertainty' as a situation characterised by the absence of unique, additive and fully reliable probability distributions. Dequech (2000), furthermore, proposes a distinction between two different forms of strong uncertainty depending on whether or not the list of possible outcomes of an event is known ex-ante. The situation where a list of possible outcomes is known is

referred as 'ambiguity' and where list of possible outcomes is not known is referred as 'fundamental uncertainty'.

To date, only a handful of SP studies have addressed the issue of ambiguity in field experiments. Cameron (2005) applied a Bayesian information updating model in a single bounded contingent valuation (CV) framework to estimate individual willingness to pay (WTP) to avoid future climate change using a convenience sample of college students. Individual support for climate change mitigation policies was found to vary negatively with the level of climate change outcome ambiguity[1] (measured by the variance of respondents' subjectively estimated future temperature increase), i.e. the more ambiguous was the increase in average temperatures for the respondents, the less they were willing to pay per month to prevent that increase. Viscusi and Zeckhauser (2006) conducted a CV study where a payment card method was applied using a gas tax as the payment mechanism. Contrary to Cameron's (2005) results, Viscusi and Zeckhauser (2006) showed that greater ambiguity lead to higher support for policy action. Riddel and Shaw (2006) used a double-bounded CV study to elicit respondents' willingness to accept (WTA) compensation for bearing ambiguity associated with mortality and morbidity incidents from nuclear waste transportation in Southern Nevada. The authors found the coefficient of the ambiguity variable to be negative and significant, suggesting that as ambiguity regarding transport related mortality and morbidity increased, people were less likely to accept the offered compensation.

These existing studies provide useful guidelines for modelling ambiguity in the estimation of social welfare using the CV method. However, the utility models used focus solely on the ambiguity associated with future scenarios. This paper broadens that focus by using a decision model that embraces ambiguity arising from multiple sources, namely, ambiguity over future scenarios and the efficacy of policy instruments. Scenario ambiguity is defined as arising when the scale of deterioration of an environmental good in future cannot be precisely determined. Policy ambiguity refers to a lack of knowledge regarding the probability of a policy being able to protect an environmental good from deterioration. Empirical testing of the proposed theoretical

---

[1] Cameron (2005) denoted this concept as 'uncertainty' in her paper. We use the term 'ambiguity' here in order to be consistent with Dequech's definition.

model was carried out in the context of Australia's proposed 'Carbon Pollution Reduction Scheme (CPRS)'. About 600 households were asked their willingness to bear extra household expenditures to support the CPRS using a single-bounded dichotomous choice (DC) elicitation format. Respondents were asked to indicate their best guess, high guess and low guess of future temperature change in Australia. They were also asked to indicate their perceptions of probabilities that the proposed CPRS will be effective in slowing down climate change.

The empirical model examines the potential impacts of four variables on stated WTP. Two of these variables relate to the future scenario: respondent's best guess about change in future temperatures (hereafter called 'subjective scenario expectation') and the range of the subjectively estimated future temperature increase (hereafter called 'scenario ambiguity'). The other two possible sources of stated WTP variation arise from the proposed policy: the best guess probability that the CPRS will help slow down climate change (hereafter called 'subjective policy expectation') and the range of the subjectively estimated probabilities of policy effectiveness (hereafter called 'policy ambiguity').

The paper is organized as follows. The next section discusses the theoretical framework on which the proposed decision model is based. The decision model underlying this paper is constructed in Section 3. Section 4 discusses the case study and design of the survey. The empirical results are presented in Section 5 followed by concluding remarks in Section 6.

2. Decision making under ambiguity

The subjective expected utility (SEU) theory, pioneered by Ramsey (1931) and further developed by Savage (1954) dominated models of decision making under uncertainty in economics and statistics until 1960. The SEU theory argues that uncertainty may be treated similarly to risk, when subjective probability replaces objective probability. Subjective assignment is a method of estimating the unknown probabilities associated with the outcomes of an event. It involves expressing belief in the language of chance. Ellsberg (1961) was one of the first to challenge the SEU theory. He showed that people prefer to bet on an event that has a clear probability attached to each possible outcome over an event which does not have a clear

3

probability distribution; a phenomenon widely known as 'ambiguity aversion'. The example given by Ellsberg illustrates that people prefer to bet on the outcome of an urn that contains 50 yellow and 50 white balls rather than the outcome of an urn that contains 100 yellow and white balls in an unknown proportion.

Several researchers, including Becker and Brownson (1964), Slovic and Tversky (1974), MacCrimmon and Larsson (1979) and Curley and Yates (1985), tested Ellsberg's hypothesis and found strong support. Since the early 1970s, new theories have been developed in the behavioural decision literature to explain individual decision making process under ambiguity. An era of Non-Expected Utility (NEU) models commenced in the early 1970 with the introduction of the heuristics and biases approach to decision making under uncertainty by Tversky and Kahneman (1974). Further advancements in NEU theories were proposed by Kahneman and Tversky (1979) with the widely cited and applied prospect theory, Quiggin's (1982) rank-dependent utility theory and Chew's (1982) weighted utility theory. Finally, an enhanced version of prospect theory, known as cumulative prospect theory (CPT), was developed by Tversky and Kahneman (1990) which is now one of the most frequently used NEU models.

Khan and Sarin (1988) used the example of a simple lottery to explain the decision making process under NEU theory. They describe a lottery L where one wins x dollars if outcome A occurs and zero dollars if it does not. π is the probability (objectively unknown) of outcome A to occur where π is a random variable with a density function $\phi(\mu, \sigma^2)$ [2]. Under SEU theory the lottery would be evaluated in the following form:

$$SEU \ (L) = \int_{\pi=0}^{1} \phi(\pi) \, d\pi u(x) = \mu \ u(x)$$

NEU theory departs from the SEU model by assigning a decision weight to the outcome A, denoted as $w(\mu, c)$ instead of using only the subjective expectation, μ. Thus, the value function for lottery L in NEU framework is given by:

---

[2] μ is the mean and c^2 is the variance of the random variable π.

$$NEU\,(L) = w(\mu, c\,)u(x)$$

Khan and Sarin (1988) proposed the following model of $w\,(\mu\,, c\,)$:

$$w\,(\mu\,, \sigma\,) = \mu + \int_{\pi=0}^{1}(\pi - \mu_{x})\exp\{-\frac{\lambda[\pi-\mu]}{c}\}\phi\,(\pi\,)d\pi u\,(x\,)$$

where λ reflects an individual's attitude towards ambiguity in a given context. A first order Taylor series approximation of $\exp\{-\frac{\lambda[\pi-\mu]}{c}\}$ results in:

$$w\,(\mu\,, c\,) = \mu - \lambda c$$

Therefore, the decision weight function, $w(\mu, c\,)$, can be viewed as an expression of the subjective evaluation of probabilities which is a function of μ and c. It is not a probability and, therefore, does not necessarily conform to the rules of mathematical probability.

Based on this fundamental premise of the second order probability distribution function, Riddel and Shaw (2006) offered a NEU model within the SP framework that allows for ambiguity about health and safety impacts arising from nuclear-waste transportation. The model defines the mortality expectation, π_M -which is objectively unknown- as a random variable with mean μ_{π_M} and variance $\sigma^2_{\pi_M}$. The authors define μ_{π_M} (subjective expectation), an individual's best guess as to what chances of mortality and morbidity they may face should transport commence. $\sigma^2_{\pi_M}$, the variance around the subjective expectation, is defined as ambiguity which itself is a random variable with mean $\mu_{\sigma^2_{\pi_M}}$ and variance $\sigma^2_{\sigma^2_{\pi_M}}$. The model uses $\mu_{\sigma^2_{\pi_M}}$, the average variance around the best guess expectation, as a measure for the degree of ambiguity, i.e. larger values of $\mu_{\sigma^2_{\pi_M}}$ mean higher levels of ambiguity. Given this specification of subjective expectation and ambiguity, Riddel and Shaw (2006) showed that individual willingness to face the prospect of outcomes affecting health and safety is a function of income, individual-specific characteristics, the subjective best guess of the outcome (expectation) and ambiguity associated with that best guess.

3. An extended NEU model

The model presented in this paper, extends the NEU model proposed by Riddel and Shaw (2006) by including one additional source and form of ambiguity in the decision making framework. We assume a situation where E denotes a future event occurring and P is a proposed policy intervention aimed at preventing E. For simplicity, it is assumed that E and P are independent of each other. We assume event E may yield a range of n possible outcomes (E_i): E ≡ {E_1, E_2, E_3.......E_n}. The E_is can be viewed as points within the scale of E in the form of a continuous quantitative variable such as an expected travel time or a rise in temperature. π_E denotes the expected outcome of E which is not precisely known. π_E is a random variable with the following distribution:

$$\pi_E \sim \psi \ (\mu_{\pi_E}, \sigma^2_{\pi_E})$$

Policy intervention, P, is a binary variable (success and failure) with an imprecise probability π_P associated with each possible outcome. π_P reflects the chances that P will eliminate the threat of E, i.e. the probability of success. π_P is not precisely known, hence π_P is assumed to follow the distribution:

$$\pi_P \sim v \ (\mu_{\pi_P}, \sigma^2_{\pi_P})$$

μ_{π_E} and μ_{π_P} represent an individual's 'best guess' or 'subjective estimation' about π_E and π_P. The variables, $\sigma^2_{\pi_E}$ and $\sigma^2_{\pi_P}$, represent ambiguities in the model and hence are characterised as random variables such that $\sigma^2_{\pi_E} \sim \omega(\mu_{\sigma^2_{\pi_E}}, \sigma^2_{\sigma^2_{\pi_E}})$ and $\sigma^2_{\pi_P} \sim \eta(\mu_{\sigma^2_{\pi_P}}, \sigma^2_{\sigma^2_{\pi_P}})$. Larger values of $\mu_{\sigma^2_{\pi_E}}$ and $\mu_{\sigma^2_{\pi_P}}$ represent higher levels of ambiguity.

V^0 is the base line utility function when the individual is exposed to the likelihood of occurrence of E. The individual is given the choice of paying a premium (WTP) to avoid the outcome E level. V^1 describes the new utility function after the implementation of P given the payment of

amount 'WTP'. $f(\pi_E)$ and $g(\pi_P)$ refer to decision weight functions. Y denotes income and X is the vector of individual-specific attributes affecting utility.

$$V^0 = \alpha^0 X + \beta^0 Y - f(\pi_E) + \varepsilon^0 \qquad (1)$$

$$V^1 = \alpha^1 X + \beta^1(Y - WTP) + g(\pi_P) + \varepsilon^1 \qquad (2)$$

Following Cameron (2005) and Riddel and Shaw (2006), the functional forms of the decision weight functions, $f(\pi_E)$ and $g(\pi_P)$ are assumed to take the following forms:

$$f(\pi_E) = \theta_E \pi_E + \lambda_E(\pi_E - \xi[\pi_E])^2 \qquad (3)$$

$$g(\pi_P) = \theta_P \pi_P + \lambda_P(\pi_P - \xi[\pi_P])^2 \qquad (4)$$

θ_E and θ_P are parameters that reflect individuals' attitudes towards subjective scenario expectation and subjective policy expectation respectively whereas λ_E and λ_P are the parameters reflecting decision makers' attitude towards scenario and policy ambiguity. ξ stands for expectation.

The change in utility due to the proposed policy intervention is obtained by subtracting Eq 2 from Eq 1:

$$V^1 - V^0 = (\alpha^1 - \alpha^0)X + Y(\beta^1 - \beta^0) - \beta^1 WTP + f(\pi_E) + g(\pi_P) + (\varepsilon^1 - \varepsilon^0) \qquad (5)$$

Taking expectation (ζ) on both sides, Eq 5 is transformed to take the form:

$$\zeta(V^1 - V^0) = \alpha X + \beta Y - \beta^1 WTP + \zeta[f(\pi_E)] + \zeta[g(\pi_P)] + \varepsilon \qquad (6)$$

where $\alpha^1 - \alpha^0 = \alpha$, $\beta^1 - \beta^0 = \beta$ and $\varepsilon^1 - \varepsilon^0 = \varepsilon$

By definition, the individual WTP is an amount that makes $\zeta(V^1 - V^0) = 0$.

This implies:

$$\alpha X + \beta Y - \beta^1 WTP + \zeta[f(\pi_E)] + \zeta[g(\pi_P)] + \varepsilon = 0 \qquad (7)$$

Therefore:

$$WTP = \frac{1}{\beta^1}[\alpha X + \beta Y + \zeta[f(\pi_E)] + \zeta[g(\pi_P)] + \varepsilon] \qquad (8)$$

The expected values of the decision weight functions are:

$$\zeta[f(\pi_E)] = \theta_E \zeta(\pi_E) + \lambda_E \zeta(\pi_E - \xi[\pi_E])^2$$

$$= \theta_E \mu_{\pi_E} + \lambda_E \sigma_{\pi_E}^2 \quad (9)$$

$$\zeta[g(\pi_P)] = \theta_P \zeta(\pi_P) + \lambda_P \zeta(\pi_P - \xi[\pi_P])^2$$

$$= \theta_P \mu_{\pi_P} + \lambda_P \sigma_{\pi_P}^2 \quad (10)$$

Substituting the values of $\zeta[f(\pi_E)]$ and $\zeta[g(\pi_P)]$ from equations 9 and 10 to equation 8,

$$WTP = \frac{1}{\beta^1}[\alpha X + \beta Y + \theta_E \mu_{\pi_E} + \lambda_E \mu_{\sigma_{\pi_E}^2} + \theta_P \mu_{\pi_P} + \lambda_P \mu_{\sigma_{\pi_P}^2} + \varepsilon] \quad (11)$$

$$WTP_{Mean} = \frac{1}{\beta^1}[\alpha X + \beta Y + \theta_E \mu_{\pi_E} + \lambda_E \mu_{\sigma_{\pi_E}^2} + \theta_P \mu_{\pi_P} + \lambda_P \mu_{\sigma_{\pi_P}^2}] \quad (12)$$

Given the WTP function obtained in equation 12, individual WTP to support a policy intervention is a function of income, individual specific characteristics, μ_{π_E}, μ_{π_P}, $\mu_{\sigma_{\pi_E}^2}$ and $\mu_{\sigma_{\pi_P}^2}$. Assuming that a higher μ_{π_E} causes disutility, μ_{π_E} is expected to have positive relationship with WTP, i.e. $\theta_E > 0$. On the other hand, a higher value of μ_{π_P} is expected to reduce WTP, reflecting a lack of individual confidence in the effectiveness of the proposed policy intervention, i.e. $\theta_P < 0$. The signs of λ_E and λ_P reflect how the decision maker respond to $\mu_{\sigma_{\pi_E}^2}$ and $\mu_{\sigma_{\pi_P}^2}$. A majority of the empirical evidence suggest that individuals are ambiguity averse (Hogarth and Kunreuther, 1985; Kunreuther et al., 1995; Camerer and Kunreuther, 1989; Sarin and Weber, 1993; Cameron, 2005; Riddle and Shaw, 2006). However, Kahn and Sarin (1988) showed that individual attitude towards ambiguity could vary depending on the context. They carried out an experiment that involved five different decision contexts (radio warranty decisions, pharmaceutical decisions involving pregnancy and skin rash and service decisions involving restaurant food and film processing). The subjects were found to be ambiguity averse for the pregnancy and the film processing contexts and ambiguity seeking for the restaurant, skin rash, and radio warranty contexts. Therefore, it could be argued that in a SP context respondents may show different attitudes towards ambiguity (aversion, seeking) depending on its source (scenario, policy). Therefore, the null and alternative hypotheses to be tested in the paper can be expressed as:

(1) $H_0 : \theta_E \leq 0$ and $H_A : \theta_E > 0$

(2) $H_0 : \theta_P \geq 0$ and $H_A : \theta_P < 0$

(3) $H_0 : \lambda_E, \lambda_P = 0$ and $H_A : \lambda_E, \lambda_P \neq 0$

4. Survey and data

4.1. Background of the case study

The case study selected involves an investigation of Australian households' preferences for the mitigation of anthropogenic climate change. As part of fulfillment of its Kyoto protocol obligations, the Australian Government proposed a national emissions trading scheme known as the Carbon Pollution Reduction Scheme (CPRS) in 2009. The aims of the CPRS are to reduce emissions by 25 per cent of the 2000 level by 2020 and to encourage the development and use of emission free technologies (Department of Climate Change, 2009). The implementation of the CPRS will affect Australian households as the prices of a wide range of emission-intensive goods and services are expected to rise. The extent of the cost burden on households resulting from the CPRS will depend on the final decisions regarding scheme design, including scheme coverage and targeted level of emission reduction (Department of Climate Change, 2009).

This study aims to explore Australian households' willingness to bear extra expenses to support the CPRS. More specifically, the study aims to reveal whether households in Australia - in the face of different dimensions of ambiguity associated with climate change- are supportive of measures that will increase their household expenditure in the form of increased prices of goods and services. Two different dimensions of ambiguity are identified. First, there exists ambiguity in the context of climate change impact projections. Due to a lack of information, disagreement about what is known or knowable, statistical variation, measurement error, subjective judgment and disagreement about structural models (Carter, 2007), projections about climate change are not certain. For instance, according to the Fourth Assessment Report of Intergovernmental Panel of Climate Change (IPCC), the global average surface warming following a doubling of carbon dioxide concentrations relative to the pre-industrial era is 'likely' to be in between two to 4.5 degrees centigrade (IPCC 2007). The interpretation of the term 'likely' according to the IPCC dictionary means that the probability of the temperature rising is between 66 percent and 90 percent. Second, the extent of the benefits to be enjoyed from climate policy interventions is

poorly understood. Due to inadequate scientific knowledge about the nature of interactions and a potential nonlinear response pattern among the biophysical factors, there is a weak linkage between policy actions over time and the climate change likely to be avoided (Jacoby, 2004).

4.2. Measuring ambiguity

The theoretical model of the current study involves four key variables - μ_{π_E}, $\mu_{\sigma^2_{\pi_E}}$, μ_{π_P} and $\mu_{\sigma^2_{\pi_P}}$ where μ_{π_E} refers to respondents' mean expectations of the scale of climate change (subjective scenario expectation), $\mu_{\sigma^2_{\pi_E}}$ is to the level of ambiguity surrounding the mean expectation (scenario ambiguity), μ_{π_P} is to subjective policy expectation and $\mu_{\sigma^2_{\pi_P}}$ denotes policy ambiguity. Reliable elicitation of these four key variables is crucial to the analysis. As Cameron (2005) suggests, elicitation of subjective expectation is simpler than asking respondents to convey information on ambiguity, i.e. variance. Cameron (2005) asked the participating college students to indicate a 95 percent confidence interval around their best guess future temperature in the form of high and low guesses. This range was treated as four standard deviations, squaring 0.25 times this amount to yield a variance approximation. Riddel and Shaw (2006) asked respondents from the general public to either indicate a dot point or a range on a 'risk ladder' showing the probability of mortality and morbidity that may be caused by nuclear-waste transportation. The stated range was used as a measure of ambiguity. The authors assigned zero ambiguity for respondents who indicated a point estimate. Although Cameron's (2005) approach to measuring ambiguity appears to be a more accurate, this method is not suitable for use in a public survey. Therefore, the Riddel and Shaw (2006) approach of using range as a measure of ambiguity was applied.

Following Cameron (2005), the perceived change in average future temperature was chosen as an indicator of scenario expectation. Respondents were first shown a figure displaying average annual temperature in Australia for the period of 1910 to 2007. They were then presented with a series of 32 different levels of possible change in annual average temperature ranging from minus five degrees to plus ten degrees centigrade. Respondents were asked to indicate their best

guess of temperature change in 2100 relative to the current year. The 'best guess' estimate was used as a measure of scenario expectation (μ_{π_E}). Respondents were subsequently asked to indicate a range around their best guesses of average change in temperature in the form of high and low guesses. The difference between high and low guess temperature was used as a measure of scenario ambiguity ($\mu_{\sigma^2_{\pi_E}}$).

A numerical probability scale was used to elicit respondents' perceptions about best guess of policy effectiveness and ambiguity surrounding the best guess. Respondents were asked two separate questions to explicitly distinguish policy ambiguity arising from lack of scientific knowledge and from lack of global co-operation. Global co-operation was defined as a situation where, in addition to European Union countries and Australia, at least three major greenhouse gas emitting countries i.e. US, China and India, would implement a similar emission reduction scheme by underpinning a national legislation. Respondents were first asked to indicate their subjective estimate of high guess, low guess and best guess about the likelihood that the proposed CPRS would help to slow down climate change, along a continuum between 1 and 100, if global co-operation could not be achieved. In a subsequent question, respondents were asked to indicate their subjective estimates of high guess, low guess and best guess about the likelihood of the CPRS slowing down climate change if global co-operation could be achieved.

4.3. Survey and data collection

Based on the existing policy documents, a scenario description was constructed. This was presented to respondents before introducing the WTP question. The description contained a simple, non-technical explanation of climate change, scientific projections of temperature rise with and without mitigation options and possible policy choices in Australia. The information included in the choice scenario and the framing of the questionnaire was finalised after a second round of focus group discussion. Before pilot testing, the questionnaire was sent to two climate change policy experts[3] in Australia in order to ensure that the information included in the questionnaire was consistent with existing scientific knowledge and policy prescriptions.

---

[3] Dr Frank Jotzo and Dr Stephen Howes are gratefully acknowledged for their inputs.

Increased prices of goods and services were used as the payment vehicle. A total of eight different bids ranging between AUS$20 and AUS$400 per month per household was randomly assigned across the respondents. Respondents were asked if they would be willing to bear extra expenses each month on behalf of their household to support the CPRS. A dichotomous choice (DC) CV survey was conducted in Sydney from the third week of November 2008 until the first week of December 2008. About 3,000 e-mail invitations were sent to a pre-existing sample panel. About one third of the e-mail invitations were opened. Half of the e-mail recipients who opened the e-mail completed the survey. In total, over 634 completed questionnaires were received.

5. The empirical results

5.1. Survey results

Fifty four percent of the 624 respondents who participated in the survey were female. The average age of the respondents was about 34 years. One third of respondents had completed university education, while another third had a trade certificate. The rest had completed high school. Over two thirds of the sample respondents were employed when the survey was conducted. Half of the employed respondents were working full time. Median yearly household income was within the range of AUS$67,600 to AUS$83,199 with about a quarter of the sample households earning more than AUS$104,000 per year.

Respondents' mean best guess about change in average temperature in 2100 relative to the current year was 3.75 degrees centigrade. The median was three degrees centigrade with a maximum of 10.5 degrees and minimum of minus 4.5 degrees. The average ambiguity around stated best guess temperature change was about three degrees centigrade. The ambiguity about temperature change varied within the range of 15.5 degrees and zero degrees centigrade. The means of respondents' best guess probabilities of the CPRS being effective in slowing down climate change, with and without a global co-operation, were 45 percent and 25 percent respectively. The average ambiguity around this best guess was higher without global co-operation (25%) than the with global co-operation case (21%).

The relationships between these expectation and ambiguity variables – climate change scenario expectation and ambiguity and subjective policy expectation and ambiguity – are displayed in Table 1. First, there is a statistically significant, positive relationship between subjective scenario expectation and scenario ambiguity (r=0.48; *p*<0.01). This means that, on average, respondents who had higher expectations of future temperatures also had relatively higher spreads around their best guesses. Second, significant, negative relationships were found between subjective policy expectation and policy ambiguity both without (r=-0.49; *p*<0.01) and with (r=-0.33; *p*<0.01) global co-operation. This implies that respondents who were more skeptics about the climate policy ineffectiveness, on average, were more confident about their perception. Finally, the correlation coefficients between scenario ambiguity and policy ambiguity (both without and with global co-operation) are statistically significant at the one percent level. This implies that respondents who stated higher ambiguity about future climate change scenario, on average, were also more ambiguous about the effectiveness of climate change policy.

Table 1: Pearson correlation coefficients between subjective expectation and ambiguity variables.

	μ_{π_E}	$\mu_{\sigma^2_{\pi_E}}$	$^a WG\ \mu_{\pi_P}$	$^a WG\mu_{\sigma^2_{\pi_P}}$	$^b G\mu_{\pi_P}$	$^b G\mu_{\sigma^2_{\pi_P}}$
μ_{π_E}	1					
$\mu_{\sigma^2_{\pi_E}}$	0.48***	1				
$^a WG\ \mu_{\pi_P}$	-0.08**	-0.02	1			
$^a WG\mu_{\sigma^2_{\pi_P}}$	0.14***	0.19**	-0.49***	1		
$^b G\mu_{\pi_P}$	-0.03	-0.04	0.43***	-0.27***	1	
$^b G\mu_{\sigma^2_{\pi_P}}$	0.11***	0.23***	-0.16***	0.56***	-0.33***	1

[a] Without global cooperation.
[b] With global cooperation.
*** Correlation is significant at the 0.01 level (2-tailed).
** Correlation is significant at the 0.05 level (2-tailed).

5.2. Decision model and results

Descriptive statistics of the key explanatory variables are presented in Table 2. Binary logistic regression was applied to estimate the effects of the explanatory variables on the discrete choice of paying for the CPRS. In Table 3, results from three multivariate regression models are presented. The models vary because of the different functional specifications of expectations and ambiguity used in each model. In Model 1, a linear relationship is examined between the dependent variable and each of the four key independent variables. Respondent's perception of policy ineffectiveness without a global co-operation was used as an indicator of policy expectation and policy ambiguity in the first model. Model 2 depicts the results of including respondents' perception of policy ineffectiveness with global co-operation as a measure of policy uncertainty. Model 3 depicts the results of including squared terms in subjective mean expectation estimates as well as relative terms of the ambiguity variables. Although all models are statistically significant at the one per cent level, the best model fit (see Model fit statistics in Table 3) is obtained from the Model 3.

In all models, the coefficients of the variable BID, the extra monthly expenses households were asked to pay for the CPRS, are statistically significant and show the expected sign (the higher the bid, the lower the probability that someone was willing to pay, all other things being equal). Household income, as expected, shows a significant positive impact on stated willingness to pay for the CPRS (the higher the income level, the higher the likelihood that someone was willing to pay the offered bid). Relationships between the dependent variable and a variety of other demographic, socio-economic and attitudinal sample population characteristics, such as respondent age, sex, occupation, education and household size, were tested using backward and forward elimination techniques. However, no statistically significant effects could be detected for any of these variables.

Respondent's attitude towards climate change and their knowledge and information about climate change mitigation policies have statistically significant influence on WTP. Respondents who believed climate change is caused by human action were significantly more likely to pay the offered bid amount than other respondents. Also respondents who were familiar with the CPRS or who had heard or read about the IPCC report on climate change or who had purchased a carbon offset certificate to offset their carbon footprint were significantly more likely to pay than

those respondents who did not purchase an offset. These results are consistent with Heath and Tversky's (1991) competence hypothesis. They showed that a decision maker's willingness to bet on an uncertain event depends not only on the likelihood of the event and the degree of ambiguity in the likelihood but on the decision-maker's general level of competence in the decision domain.

Table 2 Descriptive statistics of the independent variables

Variable Name	Description	Mean	SD
BID	20, 50, 100, 150, 200, 250, 300, 400	185	122
μ_{π_E}	Subjective scenario expectation: best guess of temperature change in 100 years time	3.72	2.86
$(\mu_{\pi_E})^2$	Square of μ_{π_E}	22	30
$\mu_{\sigma^2_{\pi_E}}/\mu_{\pi_E}$	Scenario ambiguity (differences between subjective high guess and low guess of temperature change) over scenario expectation	.90	.88
$WG\ \mu_{\pi_P}$	Subjective policy expectation without global co-operation: best guess probability of the CPRS not being effective in slowing down climate change	75	21
$WG\mu_{\sigma^2_{\pi_P}}$	Policy ambiguity without global co-operation: differences between subjective high guess and low guess of policy failure	22	17
$G\ \mu_{\pi_P}$	Subjective policy expectation with global co-operation: best guess probability of the CPRS not being effective in slowing down climate change	55	26
$(G\ \mu_{\pi_P})^2$	Square of $G\ \mu_{\pi_P}$	3787	3120
$G\mu_{\sigma^2_{\pi_P}}$	Policy ambiguity with global co-operation: differences between subjective high guess and low guess of policy failure	24.56	18.77
$G\dfrac{\mu_{\sigma^2_{\pi_P}}}{\mu_{\pi_P}}$	Policy ambiguity over subjective policy expectation (with global co-operation)	1	1
INCOME	Household yearly income ($0-7800 to $104,000-120,000)	71.77	31,175
HUMAN	Climate change caused by human actions (Strongly disagree=1, Strongly agree=5)	3.92	0.96
IPCC	Respondents have read or heard discussions about IPCC report (Yes=1, No=0)	0.18	0.38
CPRS	Respondents have heard of CPRS (Yes=1, No=0)	0.55	0.49
OFFSET	Respondents have purchased carbon offset (Yes=1, No=0)	0.11	0.31

Table 3 Estimated linear-logistic WTP models ('Yes' replies to DC WTP question is response variable).

Variable Name	Model 1	Model 2	Model 3
Constant	-1.05 (.733)	-.219 (.663)	-.073 (.762)
BID	-.006*** (.001)	-.006*** (.001)	-.006*** (.001)
Indicators of risk and ambiguity			
μ_{π_E}	-.005 (.037)	.021 (.037)	.259** (.123)
$(\mu_{\pi_E})^2$	–	–	-.028** (.012)
$\mu_{\sigma^2_{\pi_E}}$	-.020 (.042)	-.005 (.043)	–
$\dfrac{\mu_{\sigma^2_{\pi_E}}}{\mu_{\pi_E}}$	–	–	-.276* (.143)
$WG\ \mu_{\pi_P}$	-.008 (.005)	–	–
$WG\mu_{\sigma^2_{\pi_P}}$	-.003 (.006)	–	–
$G\ \mu_{\pi_P}$	–	-.018*** (.004)	-.044** (.017)
$(G\ \mu_{\pi_P})^2$	–	–	.000* (.000)
$G\mu_{\sigma^2_{\pi_P}}$	–	-.004 (.005)	–
$G\dfrac{\mu_{\sigma^2_{\pi_P}}}{\mu_{\pi_P}}$	–	–	-.012 (.011)
Socio-economic indicators			
INCOME	.006** (.000)	.006** (.000)	.006* (.000)
AGE	-.081 (.071)	-.079 (.073)	-.067 (.074)
Indicators of attitude, knowledge, information and experience			
HUMAN	.347*** (.111)	.269** (.113)	.208* (.115)
IPCC	.458* (.244)	.530** (.249)	.542** (.250)
CPRS	.542*** (.191)	.457** (.196)	.437** (.198)
OFFSET	.634**	.608*	.594**

	(.284)	(.288)	(.292)
Model fit statistics			
-2 Log-likelihood	701.988	682.116	674.466
Wald ^{2}	96.046	115.198	123.56
	(df=11, p<0.001)	(df=11, p<0.001)	(df=13, p<0.001)
Nagelkerke R Square	0.196	0.233	0.247
Percentage correctly predicted	73%	74.8%	75.4%
N	634	634	634

Explanatory notes:
Standard errors of the parameter estimates between brackets.
***: p<0.01; **: p<0.05; *: p<0.10.

In Model 1, none of the expectation and ambiguity variables are statistically significant at the ten percent level. The coefficient of the variable $G \mu_{\pi_P}$ (subjective policy expectation with a global co-operation) is statistically significant in Model 2. The coefficients of the variables μ_{π_E} (subjective scenario expectation), $\mu_{\sigma^2_{\pi_E}}$ (scenario ambiguity) and $G\mu_{\sigma^2_{\pi_P}}$ (policy ambiguity with global co-operation) are not statistically significant. Model 3 in Table 3 shows the results of quadratic specifications of μ_{π_E} and $G \mu_{\pi_P}$. In order to test for any potential relative ambiguity effect, two new variables - scenario ambiguity relative to subjective scenario expectation ($\frac{\mu_{\sigma^2_{\pi_E}}}{\mu_{\pi_E}}$) and policy ambiguity relative to subjective policy expectation with global co-operation ($G\frac{\mu_{\sigma^2_{\pi_P}}}{\mu_{\pi_P}}$) – were added in Model 3.

Both μ_{π_E} and $G \mu_{\pi_P}$ are significant in Model 3 in their quadratic specifications. The signs of the coefficients of μ_{π_E} (positive) and $(\mu_{\pi_E})^2$ (negative) demonstrate that the utility function is concave in scenario expectation. As the expectation of climate change outcome increases, the likelihood of paying for the CPRS increases. However, the likelihood of paying increases at a decreasing rate. This implies that, for each additional unit increase in subjective scenario expectation, the increase in likelihood of paying decreases. Likewise, $G \mu_{\pi_P}$ exhibits a quadratic relationship with respect to the likelihood of accepting the offered bid level. This implies as

$G\,\mu_{\pi_P}$ increases, the likelihood of accepting the offered bid level decreases at an increasing rate.

The coefficient of $\dfrac{\mu_{\sigma^2_{\pi_E}}}{\mu_{\pi_E}}$ is statistically significant in Model 2. The coefficient of the variable

$\dfrac{\mu_{\sigma^2_{\pi_E}}}{\mu_{\pi_E}}$ exhibits a negative sign which reflects relative ambiguity aversion. This means that, ceteris

paribus, as relative ambiguity about climate change increases, the likelihood that the respondent

would accept the offered bid amount decreases. The variable $G\,\dfrac{\mu_{\sigma^2_{\pi_P}}}{\mu_{\pi_P}}$ is not statistically

significant at the ten percent level.

5.3. WTP estimates

WTP estimates were calculated based on the statistically significant parameter values estimated from the best fitting model (Model 3). Note that the model excludes variables that were not statistically significant at 10 percent level, as inclusion of these variables would inflate the confidence intervals. Referendum CVM programs written in GAUSS (Cooper, 1999) were used to estimate the Krinsky and Robb confidence intervals for the point estimates of mean WTP. The procedure calculates the confidence intervals around the mean WTP through a Monte Carlo simulation technique by using the estimated regression coefficients $\hat{\beta}$ and the estimated variance-covariance matrix $V(\hat{\beta})$. The estimated WTP values and confidence intervals are presented in Table 4.

Table 4 **Krinsky and Robb confidence intervals of Mean WTP (obtained from Model 3) for the CPRS using 1000 repetitions.**

	Per household/per month (AUS$)
Mean WTP (at mean of the data)	158
99 % C.I	138 to 286
95 % C.I	145 to 242
90 % C.I	149 to 224

Mean WTP (evaluated at the mean of the data) for the CPRS is $158 per household per month. This is about three percent of average monthly household income of the sample population. The fitted expected option price estimated by Cameron (2005) was about US$228 per month which was close to five percent of average expected future monthly income for the sample. Adjusting for changes in exchange rate and inflation rate over the period of 1997 and 2008, the WTP estimate obtained from the current study is just over one third of the estimate obtained by Cameron (2005). The difference between the values of welfare estimate obtained in these two studies can be attributed to a number of factors. First, the earlier study used a convenience sample study involving a group of college students whereas the current study used a public survey. Second, Cameron (2005) did not incorporate subjective expectation of policy ineffectiveness in the decision model. Eliminating the impact of $G\mu_{\pi_P}$ and $(G\mu_{\pi_P})^2$ (i.e. setting $G\mu_{\pi_P}$ and $G\mu_{\pi_P}{}^2 = 0$) increase mean WTP from $158 to $319 per household per month. Adjusting for changes in exchange rate and inflation rate, the adjusted WTP is about ninety percent of Cameron's estimate.

If the mean WTP is adjusted for only policy uncertainty and scenario uncertainty is ignored (i.e. setting $\dfrac{\mu_{\sigma^2_{\pi_E}}}{\mu_{\pi_E}} = 0$), mean WTP turns out to be $196. This is a twenty four percent overestimation of the uncertainty adjusted WTP. Finally, eliminating all uncertainty about future scenario and policy (i.e. setting $\dfrac{\mu_{\sigma^2_{\pi_E}}}{\mu_{\pi_E}}$, $G\mu_{\pi_P}$ and $G\mu_{\pi_P}{}^2 = 0$) yields a mean WTP of $359 which is 127 percent higher than the uncertainty adjusted WTP.

6. Discussion and conclusion

Stated preference studies are carried out in situations where the future scenario and the effectiveness of a policy intervention to correct the scenario are not known with certainty. The research reported in this paper aimed to investigate the influences of scenario and policy expectation and ambiguity on individuals' decisions to support a policy intervention. The decision model was constructed by extending the NEU model proposed by Riddel and Shaw (2006). In addition to several other theoretically and intuitively expected explanatory variables,

the influences of outcome expectation and ambiguity associated with climate change and climate change policy on individual decision making behaviour were examined using multivariate logit regression analysis. Bid level and household income were found to influence respondents' choices to support a policy initiative in the theoretically expected way. Furthermore, the results show evidence in support of the competence hypotheses. Respondents' WTP were positively related to their attitude, experience and familiarity with climate change.

Both subjective scenario expectation and subjective policy expectation were found to be important determinants of individual decision making in the SP framework. The decision weight functions were non-linear in outcome expectations. It was observed that respondents were willing to trade off more (less) money with increases in subjective mean expectation of scenario (policy) expectation. However, the WTP increased (decreased) at a decreasing (increasing) rate as the mean expectation increased. The results regarding the quadratic relationship between expected future temperature change and individual support for climate change policy correspond to the findings reported in Cameron (2005). In three of the five regression models presented in that study, the estimated relationship between WTP and severity of climate change expectation was found to be concave (increases at a decreasing rate). The relationship between WTP and subjective policy expectation suggests that respondents who were sceptic about climate policy being effective in slowing down climate change (with global co-operation) were less likely to pay to support the policy. Two different indicators were used to measure policy effectiveness. These two indicators reflected subjective estimation of climate policy ineffectiveness without and with a global co-operation. The relationship between subjective expectation of policy outcome and individual WTP was found to be negative in both cases. In the without co-operation case the relationship was not statistically significant. In the later case, the relationship was statistically significant and convex.

The hypothesis relating to scenario ambiguity was that individual WTP for climate change policy would be negatively influenced by the ambiguity associated with the subjective climate change outcome expectation. The empirical results show that it is climate change ambiguity relative to the subjective climate change expectation that affects individual decisions to support the climate change policy. The negative sign of the coefficient of relative scenario ambiguity reflects

ambiguity aversion behaviour. Cameron (2005) showed that individual WTP for climate change policy decreases with increased ambiguity. As climate change is considered to be a 'bad', increases in expected temperature is expected to cause disutility. As marginal utility is negative, higher ambiguity about the extent of climate change causes negative ambiguity premium (Cameron, 2005). Similar empirical evidence was documented by Riddle and Shaw (2006). The authors found that as ambiguity about health outcome increases, people are less likely to accept the offered compensation implying a higher value for individual WTA.

The hypothesis relating to policy ambiguity was that individual WTP for the CPRS would be negatively influenced by the ambiguity associated with the subjective policy expectation. Although the sign of the coefficient of policy ambiguity variable was negative the coefficient was not statistically different than zero at ten percent level. Therefore, the null hypothesis of zero correlation between policy ambiguity and the probability of an individual to accept the offered bid level cannot be rejected. This implies that, while answering the WTP question, respondents focused on their subjective expectation of policy effectiveness and disregarded the associated ambiguity.

The questions is why respondents showed relative scenario ambiguity aversion but were tolerant towards policy ambiguity. Theory and empirical evidence suggest that attitudes towards ambiguity may vary depending on the context and source (Khan and Sarin, 1988; Taylor, 2000). Therefore, it was not unexpected to observe different responsiveness to ambiguity arising from different sources. Further, respondents were found to be forming their ambiguity perceptions differently across scenario and policy expectations. Scenario ambiguity increased with subjective scenario expectation. Policy ambiguity was found to be decreasing with increasing subjective policy expectation. It is not clear why this was the case. Further empirical investigation is required to explore these issues.

Riddle and Shaw (2006) suggested that models involving ambiguity are preferred to simpler linear expected-utility model. The utility models they estimated were linear in subjective expectation and ambiguity. The better-performing models estimated by Cameron (2005) were non-linear in both expectation and ambiguity. The logit models estimated in this study included

both linear and non-linear specifications of subjective scenario (policy) expectation and scenario (policy) ambiguity. The non-linear models in subjective scenario (policy) expectation performed better than simple linear models. However, relative scenario ambiguity was found to be linearly related with WTP.

Finally, the results of the study convey a useful message for researchers seeking to estimate the social benefits arising from public policy intervention that involves multi dimensional ambiguity. In addition to subjective scenario expectation and ambiguity (as previously shown by Riddel and Shaw (2006) and Cameron (2005)), expectations of policy effectiveness can also significantly influence society's WTP. Ignoring this element may potentially lead to the overestimation of the economic benefits to be obtained from public policy intervention.

References

Becker, S.W., Brownson, F.O. (1964). What price ambiguity? O)r the role of ambiguity in decision making. Journal of Political Economy, 72, 62-73.

Camerer, C., Kunreuther, H. (1989). Experimental markets for insurance. Journal of Risk and Uncertainty, 2, 265-300.

Cameron, T. A. (2005). Individual option prices for climate change mitigation. Journal of Public Economics, 89, 283–301.

Carter, R.M. (2007). The myth of dangerous human-caused climate change. The Aus/MM New Leaders Conference, Brisbane May 3, 2007.

url: http://members.iinet.net.au/~glrmc/new_page_1.htm

Chew, S. H. (1982). A mixture set axiomatization of weighted utility theory. Discussion Paper 82-4, College of Business and Public Administration, University of Arizona, Tucson.

Cooper, J.C. (1999). Referendum CVM programs. Economic Research Service, USDA, Washington, DC.

Curley, S. P., Yates, J. F. (1985). The center and range of the probability interval as factors affecting ambiguity preferences. Organizational Behavior and Human Decision Processes, 36, 273-87.

Department of Climate Change (2009), Strengthening Australia's 2020 carbon pollution target, Fact Sheet, Department of Climate Change, Australian Government,

url: http://www.climatechange.gov.au/emissionstrading/pubs/carbon_pollution_target.pdf

Dequech, D. (1997). Uncertainty in a strong sense: meaning and sources. Economic Issues, 2 (2), 21–43.

Dequech, D. (2000). Fundamental uncertainty and ambiguity. Eastern Economic Journal, 26(1), 41–60

Ellsberg, D. (1961). Risk, ambiguity and the Savage axioms. Quarterly Journal of Economics, 75, 643–669.

Heath, C. and Tversky, A. (1991). Preference and belief: ambiguity and competence in choice under uncertainty. Journal of Risk and Uncertainty, 4, 5–28.

Hogarth, R.M., Kunreuther, H. (1985). Ambiguity and insurance decisions. American Economic Association Papers and Proceedings, 75, 386-390.

Ho, J. L.Y., Keller, L. R., Keltyka, P. et al. (2002). Effects of outcome and probabilistic ambiguity on managerial choices. Journal of Risk and Uncertainty, 24, 47-74.

International Panel on Climate Change (IPCC) (2007). IPCC fourth assessment report: climate change 2007, url: http://www.ipcc.ch/pdf/assessment-report/ar4/syr/ar4_syr.pdf

Jacoby, H. (2004). Informing climate policy given incommensurable benefits estimates. Global. Environmental Change, 14(3), 287-297

Kahneman, D., Tversky, A. (1979). Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263-292.

Kahn, B. E., Sarin, R. K. (1988). Modeling ambiguity in decisions under uncertainty. Journal of Consumer Research, 15, 265-72.

Knight, F. H. (1921). Risk, uncertainty and profit. Houghton Mifflin, New York.

Kunreuther, H., Meszaros, J., Hogarth, R. M., Spranca, M. et al. (1995). Ambiguity and underwriter decision processes. Journal of Economic Behaviour and Organization, 26, 337-352.

MacCrimmon, K.R., Larsson, S. (1979). Utility theory: Axioms versus 'paradoxes'. In M. Allais and O. Hagen (Eds), Expected utility hypothesis and the allais paradox (pp. 333-410). Netherlands: D. Reidel Publishing Company.

Quiggin, J. (1982). A theory of anticipated utility. Journal of Economic Behavior and Organization, 3, 323-343.

Ramsey, F. (1931). Truth and probability. In F. Ramsey (Ed.), The foundations of mathematics and other logical essays (pp.156–198). New York: Harcourt, Brace.

Riddel, M., Shaw, W.D. (2006). A theoretically-consistent empirical model of non-expected utility: an application to nuclear-waste transport. Journal of Risk and Uncertainty, 32, 131–150.

Sarin, R. K., Weber, M. (1993). Effects of ambiguity in market experiments. Management Science, 39, 609-615.

Savage, L. J. (1954). The foundations of statistics. New York: Wiley.

Slovic P., Tversky, A. (1974). Who accepts Savage's axiom?. Behavioral Science, 19, 368–373.

Tversky, A., Kahneman, D. (1974). Judgement under uncertainty: Heuristics and biases. Science, 185, 1124-1130.

Tversky, A., Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5, 297–323.

Viscusi, W. K., Zeckhauser, R. J. (2006). The perception and valuation of the risks of climate change: a rational and behavioral blend. Climatic Change, 77, 151–177.