Deriving Australian Citizens' Willingness to Pay for Carbon Farming Benefits: A Choice Experiment Study

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Abstract:

The Australian Government is facing the considerable challenges to cut back greenhouse gas emissions to five percent under 2000 levels by the year 2020. One of the substantial emission sectors in Australia is agriculture and the Australian Government is pursuing policies to incentivise emission reductions by farmers. These incentives are driven by the Carbon Farming Initiative (CFI), which is a national programme that financially compensates farmers who take measures to reduce their greenhouse gas emissions or increase carbon storage in soils and vegetation. Next to mitigating greenhouse gas concentrations, carbon farming practices can be accompanied by so-called 'co-benefits' such as positive effects on biodiversity, increasing the value of landscape aesthetics and the reduction of soil erosion. These co-benefits will generate social and environmental values that are not only experienced by farmers but also by other citizens. A better understanding of the values that the public attaches to these co-benefits can play an important role to support farmers in their carbon farming practices. This is because if projects deliver more benefits next to carbon mitigation, buyers might be willing pay a higher price for the carbon credits.

In this study, we measure the public's willingness to pay (WTP) for the co-benefits of carbon farming. A choice experiment was conducted among Australian citizens that included three environmental attributes: carbon emission reductions, increase in native vegetation and a reduction in soil erosion. The results of multi-nominal logit models and mixed logit models show that Australians are likely to receive welfare benefits from carbon mitigation activities that also provide biodiversity benefits. This means that carbon farming policies could potentially be broadened to capture co-benefits and not be restricted to solely carbon sequestration. Public incentives that aim to change agricultural land management could therefore include higher payments for carbon credits that generate additional environmental co-benefits.

Keywords: Climate change mitigation, Carbon Farming Initiative, Choice experiments, Auxillary benefits, Australia, Emission Reduction Fund

JEL classifications: Q51, Q54, Q57

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1. Introduction

Scientific evidence proves that, due to human activities, concentrations of greenhouse gases like CO2 and nitrous oxide have significantly increased (EPA, 2015). Examples of these human activities include fossil fuel combustion, agriculture and land clearing. These higher emission concentrations increase the earth's average temperature and are considered to change weather patterns in the long term. This is leading for example to changing rainfall patterns, higher sea levels and more extreme weather events like storms and droughts which could create significant damages to humankind (IPCC, 2007). Because of this climate change, international initiatives had been set up in order to reduce global emissions of greenhouse gases and to mitigate climate change impacts. The most famous examples of these initiatives are the United Nations Framework Convention on Climatic Change (UNFCCC) and the Kyoto Protocol which are global agreements on reducing emissions. Australia, with the highest emissions per capita in the developed world, ratified the UNFCCC in 1992 and is therefore committed to reduce their emissions by reaching specific reduction targets (Parliament of the Commonwealth of Australia, 2011). The Australian Government therefore has set goals to cut back emissions to five percent under 2000 levels by the year 2020 which forms a large challenge (Department of the Environment, 2013). One of the substantial emission sectors in Australia is agriculture. Agriculture has a share of more than 50% of Australia's land surface and is responsible for about 19% of Australian emissions (ABS, 2013). Because of these substantial emissions coming from this sector, the Australian Government has started to pursue policies to give farmers incentives to reduce their emissions. These incentives are driven by the Carbon Farming Initiative (CFI), which is a national programme that financially compensates farmers who take measures to reduce their greenhouse gas emissions or increase carbon storage in soils and vegetation. For every tonne of carbon sequestration or avoidance of emitting this tonne, a farmer receives a carbon credit which he can trade in a voluntary carbon market (DCCEE, 2012). Credits are paid for by the government's Emission Reduction Fund which is a product of the government's Direct Action Plan. Examples of famers' management practices to mitigate carbon emissions are destruction of methane emissions coming from landfill or livestock manure, introducing forestry plantations on the land and avoiding soil disturbances in order to increase soil carbon (Department of the Environment, 2013). However, all carbon farming projects need to be approved first by the Domestic Offsets Integrity Committee before any compensation can be promised to farmers. This committee checks if the projects fulfil the necessary requirements such as permanence, measurability and verifiability of sequestration (Parliament of the Commonwealth of Australia, 2011).

Next to mitigating greenhouse gas concentrations, these management practices can be accompanied by certain co-benefits like positive effects on biodiversity, increasing the value of landscape aesthetics and the reduction of soil erosion. These co-benefits could include social and environmental values that are not only experienced by farmers but also by other citizens. The problem with these co-benefits is that they do not have a market price and their monetary values are therefore difficult to measure (Salisbury et al., 2013). Although farmers receive financial compensation for carbon farming practices, it still can lead to profit losses (Kragt et al., 2012). Despite the possible co-benefits that could be delivered by carbon farming, this still may not be a high enough incentive for farmers to commit themselves to this kind of practices. Therefore, a better understanding of the value that the public attaches to these co-benefits can play an important role to support farmers in their carbon farming practices. This is because if projects deliver more benefits next to carbon mitigation, buyers might be willing pay a higher price for the carbon credits (Aboriginal Carbon Fund, 2015). By measuring the public's willingness to pay (WTP) for these 'greater societal goods', co-benefits could be linked to monetary values. As a result, the farmers' total compensation could receive an extra premium by taxing the public. Previous studies have already shown that co-benefits can significantly increase people's WTP for projects that are linked to climate change mitigation (Longo et al., 2012; Glenk and Colombo, 2011; MacKerron et al., 2009)

In order to measure the public WTP for carbon farming, a choice experiment has been performed in 2013 by Marit Kragt (University of Western Australia, School of Agricultural and Resource Economics) among Australian citizens in order to measure their WTP for three environmental attributes: carbon emission reductions, increase in native vegetation and a reduction in soil erosion. Respondents are asked in a number of choice sets to choose their preferred option among three alternatives, which are described by different levels of these environmental attributes and a cost attribute. This allows the researcher to analyse trade-offs that respondents make between these different attributes and therefore derive WTP estimates.

The survey resulted in a dataset that still needed to be fully analysed and interpreted. My role in this project was to work on the acquired datasets and to analyse them as an internship project at the University of Western Australia. The internship consisted of two major parts. The first part was all about getting familiar with analysing choice experiments. The second part was all about finding an interesting topic and writing a paper to be submitted to a scientific journal. So, broadly speaking the internship could be divided into an analytic part and an empirical part. The main internship report focuses on the analytic part of my internship, and the paper represents my work in the empirical part of my internship.

For the analytic part of my internship and as part of getting familiar with choice experiment analysis, I first derived the public willingness to pay for carbon emission reductions, increase in native vegetation and a reduction in soil erosion. Part of this work was to develop different econometric models and to compare the outcomes of these models. The analysis starts with multi-nominal logit models, which are known as the more basic models because of their behaviour limitations. Later on mixed logit models were included, which are more complex because of the removal of some of these limitations. More specific details on the differences between these two types of models are presented in the methodology chapter. In the final stage, four different models were compared, two multi-nominal logit models and two mixed logit models.

The second part of my internship focused on the empirical evaluation of the models considered. This also included investigating different specific topics to write a paper on which could be submitted to a scientific journal – such as attribute non-attendance.

The analytic part of my internship addressed the following research questions:

What are the differences between the different modelling approaches for analysing peoples' WTP for reducing carbon emissions in agriculture, and which model provides the most reliable WTP estimates for the environmental attributes?

This working paper will proceed as follows; Chapter two will describe the methods and model specifications used to get to the final results. Chapter three will present the final results coming from the survey and the different econometric models, which are discussed in Chapter four.

2. Methodology

This chapter provides background information on the methodological approaches used for analysing the choice experiments conducted by Kragt et al. (2013). In addition, I will present the different survey versions and econometric models that were used to analyse the data.

Throughout the past two decades the interest in valuing the environment has significantly increased (Fisher et al., 2009). This growing interest is linked to the increasing public concern about the unsustainable use of natural resources and climate change. Because natural resource use is usually not part of market interactions, environmental degradation occurs as a negative externality. Putting a price on environmental goods and services and creating markets for them is expected to lead to a more efficient use of the world's natural capital (Howarth and Norgaard, 1992). This way it becomes easier for decision-makers to take into account environmental effects in different policy options. However, because of the fact that the environment consists of many non-market goods and services, this results in quite a challenge to measure the economic value of these goods and services (Bateman et al., 2002).

Generally, two ways to measure non-market goods and services can be distinguished: *revealed preference techniques* and *stated preference techniques*. Revealed preference techniques make use of actual consumer choices in order to develop models of choice (Adamowicz et al., 1994). Examples of revealed preference techniques are the hedonic pricing method and the travel cost method. Stated preference techniques involve asking consumers directly what they are willing to pay for certain environmental goods and services. Examples of these techniques are contingent valuation and choice modelling (Bateman et al., 2002). This research focuses completely on the second category, and in particular on choice modelling. Section 2.1 will introduce the concepts of choice modelling and choice experiments. Section 2.2 gives a short overview on previous research in the field of environmental economics related to choice experiments. Section 2.3 will elaborate more on the specific choice experiment performed in this research. Section 2.4 presents the main survey design. Section 2.5 briefly pays attention to the survey sample. Section 2.6 gives some information about the socio-demographics of the survey respondents. Finally, section 2.7 describes the econometric models that were used to analyse the data coming from the surveys.

2.1 Choice modelling and choice experiments

Choice modelling is based on two main theories. The first theory is *Lancaster's characteristics theory of value,* which states that goods can be described in terms of different attributes (Lancaster, 1966). An example of such a good is a forest, which can be described in terms of attributes like its biodiversity, recreational facilities and its age structure. These different attributes can take different levels which will result in different goods (different forests). Choice modelling focuses on the value of changes in these levels of attributes and therefore gives us information about the non-market values of the good. It can show us which attributes significantly determine the value people place on a certain non-market good. When all different attributes with significant value would be captured in the model, the total economic value of the non-market good can be calculated (Bateman et al., 2002). To estimate the value of these attributes, a choice experiment can be performed. In a choice experiment, a sample of respondents is asked to fill in a survey. This survey contains a number of pre-defined choice sets where the respondent needs to choose the most preferred alternative for each choice set. Every alternative represents different levels of the attributes which also includes a cost attribute. This cost attribute represents the costs a respondent would have to pay for the change in attribute levels. This attribute is added to capture the value judgements of the respondents related to the different attributes. Every choice set also contains a status quo option which represents an alternative where no changes in attribute levels occur and where zero costs are involved. By choosing their most preferred alternatives, the respondents make trade-offs between different attributes levels. This allows for analysing how much of an attribute a respondent is willing to give up for gaining some of another attribute (Bennet and Blamey, 2001). By including the cost attribute, it is possible to calculate the willingness to pay for a change in the attributes that describe the non-market good (Gracia et al., 2009).

The second theory underlying choice modelling is the *random utility theory* which finds its origin in Luce (1959) and McFadden (1973). This theory describes a person's preferences in a utility function U:

$$U_{in} = U(Z_{in}, S_n), \tag{2.1}$$

where U_{in} is the obtained utility for person n when he/she chooses alternative i out of choice set J. The level of utility is dependent on the different attributes Z and the individual's socio-demographic characteristics S (Hanley et al., 1998). Examples of socio-demographic characteristics S are age, gender, education and personal income. However, it is very likely that not all elements of Z and S are observable to the researcher, or are only observable with an error (Bateman et al., 2002). In order to take these imperfections into account, the utility function has to be divided into an observable part and an unobservable (error) part which leads to the following function:

$$U_{in} = V(Z_{in}, S_n) + \varepsilon(Z_{in}, S_n), \tag{2.2}$$

where $V(Z_{in}, S_n)$ denotes the observable part of the utility function and $\varepsilon(Z_{in}, S_n)$ is the unobservable part of the utility function. A consequence of the random utility theory is that assumptions have to be made on the nature of the error term. This is because this error term is not observable (Bateman et al., 2002).

The probability that individual n in choice situation t will choose alternative i over any other alternative j in choice set J, is equal to the probability that the obtained utility of choosing alternative i is higher than the obtained utility of choosing any other alternative j. This is expressed by the following equation:

$$P_{nt} = P[(V_{int} + \varepsilon_{int}) > (V_{jnt} + \varepsilon_{jnt})] \tag{2.3}$$

This function can be rewritten as:

$$P_{int} = P[(V_{int} - V_{jnt}) > (\varepsilon_{jnt} - \varepsilon_{int})], \tag{2.4}$$

which states that individual n will choose alternative i over alternative j if and only if the difference between the observable part of their utility exceeds the difference in the error part (Bateman et al., 2002). Section 2.7 presents two types of econometric models to estimate these equations and to derive information on how the different attributes and socio-demographic characteristics affect utility.

2.2 Previous research

Choice experiments have been used within the field of environmental topics before. A study by Adamowicz et al. (1994) included the first choice experiment regarding environmental management problems. They investigated recreationalists' preferences for alternative flow scenarios for the Highwood and Little Bow rivers in Alberta, Canada. Before that, choice experiments were mainly used in other fields like marketing and transport economics (Hanley et al., 1998). After the research of Adamowicz et al. (1994), more choice experiments became to be applied in the field of environmental economics (e.g. Boxall et al., 1996; Hanley et al., 1998; Carlsson et al., 2003; Hanley et al., 2006; Espinosa-Goded et al., 2010; Blasch and Farsi, 2014). The topics range from valuing the attributes of wetlands, to estimating farmers' preferences for different design options of agri-environmental schemes. The literature on environmental valuation is still growing.

2.3 This research

For this project a choice experiment has been performed to measure the social value of carbon farming which is described as a set of attributes. These attributes should contain the level of carbon sequestration or expected emission reduction, and relate it to co-benefits that influence the choice of the respondent. The attributes had to be chosen very carefully since they should capture the respondents' preference space and they should be impacted by carbon farming practices (Bateman et al., 2002). The attributes were chosen by making use of literature reviews, focus group discussions and expert interviews. Evaluating the outcomes of theses analyses allowed identifying three different attributes: area of native vegetation, erosion level, and carbon sequestration or emission reduction benefits. Here, the area of native vegetation and erosion level are the selected co-benefits coming from carbon farming. Next to these attributes a cost attribute was included which took the form of an annual tax that should have to be paid by Australian citizens for the next 100 years.

In order to define the attribute levels that could be used in the different choice sets, research has been performed by Kragt et al., (2013) on different methods of carbon farming and their effects on the level of carbon sequestration, emission reductions, area of native vegetation and level of soil erosion. This research consisted of an extensive literature review accompanied by interviews with academics in the fields of soil science, ecology and agricultural science. The most suggested carbon farming methods were: no-tillage, stubble retention, agroforestry, revegetation of marginal land, and destocking. For these different methods, estimates of climate change mitigation, increase in area of native vegetation, and erosion reduction levels under Australian conditions were obtained from different sources of literature. From these estimations feasible attribute levels have been designed for the survey which will be shown in section 2.4.

2.4 Survey design

The survey consisted of three major parts. In the first part, the concept of climate change was explained to the respondents and they were asked to give their opinion on climate change. The respondent could identify here if they believed whether climate change is a real occurring phenomenon and who or what they think are key driving factors.

In the second part of the survey, the respondents got a description of carbon farming. Information was given on the different policies of the Australian government, the different carbon farming methods and their impacts on the environment. These impacts included climate change mitigation, increase in native vegetation and a lower level of soil erosion. As you can recall from section 2.3 the levels of these environmental impacts form the attributes along with the annual tax. The attributes and their different levels used in the survey are summarized in Table 2.1.

Table 2.1 Attributes, description and levels as used in the survey

Attribute	Description	Levels
Annual net cost	Farmers will need to be compensated for the changes they make. This money will need to come from an increase in annual taxes for all Australians. The 'annual net cost' describes how much the policy would cost your household each year for the next 100 years.	\$0, \$20, \$50, \$150, \$300 per year
Emission reduction / Carbon storage	The predicted reduction in Australia's net annual GHG emissions. Current Australian emissions are about 575 million tonnes of CO_2-equivalent (CO2-e) per year.	0, 2.8, 11.5, 20, 34.5 Mt CO2-e/year. This was compared to the percentage of Australia's emission reductions (0%-6%); and direct energy consumption by households (140K–2.4million).
Area of native vegetation	Increased area of native vegetation on farmland. The current area of protected native vegetation on farmland in Australia is 29.8 million hectares (ha).	0, 0.5, 1.2. 1.8 million ha. This was compared to the equivalent proportion of additional native vegetation on farmland (0-6.1%).
Soil erosion	Some environmental management practices can improve soil quality and decrease soil erosion. In 2011, soil erosion on farmland was approximately 1,634 million tonnes per year (t/yr).	0, 160, 300, 500 million t soil erosion per year. This was compared to the equivalent proportion of current erosion (0-30.6%).

After this general information about carbon farming the respondents needed to fill in six choice questions where they had to choose between three alternatives. The alternatives presented different attribute levels. Every choice set also contained a status quo option where everything stays the same and no change in attribute levels occurs against zero costs. A random example of a choice set for the carbon farming choice experiment is given in Table 2.2.

Table 2.2 Example choice set from the survey

Impacts	Alternative 1	Alternative 2	Alternative 3 – no action
Emissions reduction / Carbon storage	20 Mt CO_2-e/yr (3.5 %)	2.8 Mt CO_2-e/yr (0.5 %)	No emission reduction or carbon storage
Increase in native vegetation	1.8 million ha (6.1 %)	1.8 million ha (6.1 %)	No increase in native vegetation
Reduction in soil erosion	500 million t/yr (30.6 %)	0 t/yr (0%)	No reduction in soil erosion
Annual net cost to your household	\$300	\$200	\$0
My preference:	☐	☐	☐

The respondents were explicitly asked, before choosing their preferred alternative, to take into account how much they can afford to pay and to consider other goods and services where they could spend their money on. If the respondents take these considerations into account, it is expected that their choices are more realistic. In total, the design included 24 different choice sets which were divided into four blocks. Each respondent was randomly appointed to a block and received six choice questions.

In the third part of the survey, the respondents were asked a few more questions to better understand their choices in the second part of the survey. They were also asked if they understood the survey questions and they needed to answer some questions on their socio-demographic characteristics. The full survey is available upon request from the corresponding author.

2.5 Sample selection

The survey was distributed among Australians from New South Wales, Queensland, Victoria and Western Australia via a commercial research panel in March 2013. Sampling was targeted at residents living in urban and rural areas. The sample was planned to be distributed among nationally representative distributions of age, education and gender. Respondents had to fill in the survey online and contained links to further information and data sources for carbon farming and the attributes.

2.6 Socio-demographics

The survey resulted in a final dataset of 5,748 observations. Every respondent answered six choice questions, which means there are six observations per individual. These 5748 observations are therefore equivalent to 958 respondents in total. The final dataset was implemented in the statistical software *STATA 13*. The first step was getting to know the sample of the survey by analysing the socio-demographics of the respondents. Examples of the socio-demographic characteristics in this choice experiment are age, gender, education and income. The socio-demographics also included several opinions, for example whether the respondent thinks climate change is happening, the political party the respondent voted for, and which attributes the respondent took into account or ignored in the survey. After getting to know the sample of the choice experiment, econometric models were set up in order to calculate the WTP for the different attributes. These econometric models will be specified in the next section.

Respondents who took less than 200 seconds to complete the survey were not included in the analysis, because these people are unlikely to have read all the questions carefully in such a short time and may not have thought carefully enough about their choices. This time limit of 200 seconds was chosen by Kragt et al., (2013) and served as a minimum to read all questions and to answer them. This resulted in an exclusion of eight respondents. Also, two groups of 'protesters' were identified among the respondents. The first group always chose the status quo option because they did not believe that carbon farming policies will actually be implemented. The second group does support changing farm management but does not approve of paying through their taxes and therefore always chose the status quo option as well. These two groups of people, with a total number of 21 respondents, were also excluded from the analysis. The total remaining sample size consists now of 929 respondents, which is equivalent to 5,574 observations.

2.7 Econometric models

Recall from section 2.1 that assumptions on the error part of the utility function have to be made to calculate the probability that respondent n will choose alternative i in choice situation t. Because these assumptions have to be made on the error part, there exist different models to calculate the probabilities. For this research project two different models were used: the multi-nominal logit model (MNL-model) and the mixed logit model (ML-model). These models are well-known in the literature on non-market valuation.

2.7.1 Multi-nominal logit model

The multi-nominal logit (MNL) model is the 'workhorse' of discrete choice analysis. For this choice experiment a utility function can be derived from equation 2.2. The utility U respondent n will derive by choosing alternative i in choice situation t has the form:

$$U_{int} = \beta'\mathbf{X}_{int} + \varepsilon_{int} \tag{2.5}$$

Where β' is a vector of parameters to be estimated in the model, $\boldsymbol{X}$ is a vector of independent variables consisting of the attributes and socio-demographic characteristics that affect utility, and ε is an error term that represents the unobservable part of utility (Revelt and Train, 1998).

The MNL model follows from the assumption that the error terms are Independently and Identically Distributed (IID) with an extreme-value Gumbel distribution. This leads to the following model specification to calculate the probability that individual n will choose alternative i in choice situation t:

$$P_{int} = \frac{\exp(\beta' X_{int})}{\sum_{i=1}^{J} \exp(\beta' X_{int})}\ , \tag{2.6}$$

where β is a vector of parameters to be estimated in the model, and $\boldsymbol{X}$ is a vector of independent variables consisting of the attributes and socio-demographic characteristics that affect utility. Because the socio-demographic characteristics are constant for every individual, they can only be included in the model as interaction terms with the alternative specific constant (ASC) or attributes. An interaction term is a new variable which, in this case, consists of one of the attributes multiplied by a socio-demographic characteristic. An example of an interaction term could be the cost attribute multiplied by age. The parameter outcome of this variable indicates how age impacts the preferences for costs. A significant positive parameter for this interaction variable could be interpreted as follows: an older respondent is more likely to choose an alternative with higher costs than a younger respondent. The researcher can add these interaction terms along with the single attributes itself in the model and estimate their parameters (vector β).

In STATA, the MNL model is estimated using maximum likelihood estimations. Because of the assumed independence of the error terms, the MNL model contains the Independence from Irrelevant Alternatives (IIA) property. This property states that the probability ratio between two alternatives is not affected by the introduction or removal of another alternative. (Bateman et al., 2002). An example from Cheng and Long (2007) shows why the IIA property is often seen as a shortcoming of the model. Suppose a respondent has to choose between two different modes of transportation. The respondent can choose to use a car or a red bus. It is assumed that the probability for choosing one of these two options is for both equal to $\frac{1}{2}$. This means that the probability ratio between the two alternatives is equal to 1. Now we assume that the choice options are extended with another alternative, for example a blue bus. According to the IIA property, the probability ratio between choosing the car or the red bus should stay the same. This means that the probability for choosing an alternative should be equal to $\frac{1}{3}$ for all options in order to keep the probability ratio equal to 1. This implies that if more buses with different colours are added to the choice set, the probability that the respondent would choose the car would eventually approach zero. However, in reality the probability of choosing the car would probably stay $\frac{1}{2}$ and the probability for choosing either a red or a blue bus would equal $\frac{1}{4}$. This would change the probability ratio for choosing the car versus a red bus and therefore would violate the IIA property. So, in other words, the IIA property states that the missing part of utility in alternative i must be uncorrelated with the missing part of utility from alternative j (Bateman et al., 2002). This property is a limitation of the MNL model, because the assumption that all alternatives are independent is in most cases not realistic. This is because there often exists correlation between two or more alternatives. In the case above there would be correlation between the alternatives ''red bus'' and ''blue bus''. People see these alternatives as two similar options, so their error terms (missing parts of utility) will be similar as well. Also, in a high number of studies it has been found that the alternatives different from the status-quo alternative are correlated, which could be explained by the fact that the error terms of the options moving away from the status quo are probably more similar than the error term of the status quo itself (Hensher et al., 2005).

Despite this shortcoming, MNL models are easy to execute and allow the researchers to easily test whether differences in preferences and WTP estimates for emission reductions, area of native vegetation, soil erosion and costs can be explained by respondents' socio-demographic characteristics.

In our analysis, the MNL model was first estimated using only the choice attributes and an alternative specific constant (ASC). This model is called MNL model 1. The ASC represents the difference in utility between the status quo option and the carbon farming alternatives when all attributes are equal. This variable therefore indicates an average effect on utility of possible unobserved attributes (Bateman et al., 2002). The ASC variable was included in the model as a dummy variable, where the status quo option was coded one and the carbon farming alternatives were coded zero. This model shows how individual utility is affected by emission reduction, area of native vegetation, soil erosion and costs, and whether respondents have, on average, a structural preference for or against the status quo alternative compared to the two carbon farming alternatives.
Then, MNL models were estimated including socio demographic characteristics to explain variation in the preferences for the different attributes. This was done by including interaction terms between the choice attributes and selected socio-demographic characteristics. A lot of socio-demographic characteristics were collected in the survey. Table 2.3 shows all socio-demographic variables and their coding.

Table 2.3 Socio-demographic variables

Socio-demographics	Units of measurement
Age (years)	Years
Gender	1= male 0= female
Education (years)	Years
Personal income ($1,000/year)	$1'000/year
Citizen from New South Wales	1= citizen from New South Wales 0= otherwise
Citizen from Victoria	1= citizen from Victoria 0= otherwise
Citizen from Queensland	1= citizen from Queensland 0= otherwise
Citizen from Western Australia	1= citizen from Western Australia 0= otherwise
Citizen from metro or rural area?	1= metro 0= rural
Respondent has children?	1= have children 0= no children
Opinion on climate change	1= humans are causing or contributing to climate change -1= do not believe climate change is happening 0= don't know if climate change is happening or think that it is a natural fluctuation in earth temperature
Greens Party voter?	1= votes Greens Party 0= otherwise

The next step was to delete variables from the model which show limited within-sample variability because without variation in the observations the model cannot adequately explain variation in the preferences. The dummy variable which describes people who vote on the Greens Party was therefore deleted, because only 8.1% of the respondents (75 people) vote for this party. The variables that were left after this selection procedure were all interacted with the four different attributes, which resulted in four interaction terms per socio-demographic variable. The four attributes and the interaction terms create a total of 49 variables. First, a MNL model was run including all these 49 variables. After this run, insignificant variables were deleted until a final model was run that contained only the four choice attributes, the ASC and the significant interaction terms. This final model is called MNL model 2.

With the parameter estimates, the respondents' willingness to pay (WTP) for a change in the different environmental attributes can be calculated. Since the utility functions are assumed to be linear, this is done by calculating the ratio between the coefficient of an environmental attribute β_x and the cost coefficient β_c:

$$WTP = \frac{-\beta_x}{\beta_c} \qquad (2.7)$$

This is the ratio of the marginal utility of environmental attribute β_x and the marginal utility of income (Bateman et al., 2002). This ratio therefore stands for the marginal rate of substitution between an environmental attribute and the cost attribute (income). It shows how much income a respondent is willing to trade off against a unit increase of the environmental attribute. For example,

if the researcher wants to calculate the WTP for emission reduction, he takes the coefficient $\beta_{reduction}$ and the cost coefficient β_c (both part of vector β) and calculates the ratio. Since the cost coefficient is expected to have a negative sign, the environmental attribute also receives a negative sign to calculate a ''positive'' WTP. The significance and the standard errors of these WTP estimates can be calculated in STATA using bootstrap procedures. Bootstrapping estimates the distribution of WTP empirically by taking a number of random draws from the estimated sample parameters of the attributes. Each of these samples is used to derive the ratio, and thus the WTP, equal to equation 2.6. A mean WTP and a confidence interval can then be derived (Xu and Long, 2005).
For this research WTP measures were calculated based on 500 random draws for both MNL model 1 and MNL model 2. MNL model 2 also allows us to calculate WTP estimates for people with different socio-demographic characteristics. To be able to decide which of the two MNL models gives the most reliable estimates, we look at the Log-likelihood of both models. The higher the Log-likelihood, the better the model fit, and therefore the more reliable the estimates.

2.7.2 Mixed logit model

The mixed logit (ML) model is more advanced than the MNL model. The ML model no longer contains the property of independence of irrelevant alternatives (IIA) and allows for possible error correlation between alternatives. This model does not assume fixed parameters for attributes as is the case in MNL models, but instead assumes individual parameters β_n to be randomly distributed with density function $(\beta_n|\theta)$. In this density function, θ represents the distribution mean and standard deviation (Hensher et al., 2005). Thus, a random parameter for attribute k which is faced by individual n is given by:

$$\beta_{nk} = \beta_k + \sigma_k v_{nk} \qquad (2.8)$$

where β_k is the unconditional population parameter of the preference distribution and v_{nk} represents the unobserved random variation between individuals which are deviated from the mean with standard deviation σ_k (Kragt and Bennett, 2009). This way, the model takes into account unobserved preference heterogeneity between individuals. This means that the ML model allows preferences for the different attributes to vary between individuals, where in the MNL model all preferences are assumed to be the same across individuals (Hensher and Greene, 2003). In the ML model, the probability that respondent n chooses alternative i in choice situation t, conditional on β_n, is given by:

$$P_{int} = \frac{\exp(\beta_n' x_{int})}{\sum_{i=1}^{J} \exp(\beta_n' x_{int})} \qquad (2.9)$$

However, because β_n is an unknown parameter, the function cannot be conditional on β. Instead, the model takes the integral over all possible values of β_n multiplied by the density function to obtain the unconditional choice probability that respondent n chooses alternative i in choice situation *t*:

$$P_{int} = \int \frac{\exp(\beta' x_{int})}{\sum_{i=1}^{J} \exp(\beta' x_{int})} f(\beta|\theta)\, d\beta \qquad (2.10)$$

Because each respondent had to make six different choices, the data can be treated as a panel. The ML model can account for the panel format of the data, by allowing for error correlations between the choices made by the same individual. The probability that a certain sequence of choices *S* is observed for individual n is given by:

$$S_n = \int \prod_{t=1}^{T} \prod_{i=1}^{J} \left[\frac{\exp(\beta' X_{int})}{\sum_{i=1}^{J} \exp(\beta' X_{int})}\right]^{y_{int}} f(\beta|\theta)\, d\beta \tag{2.11}$$

where y_{int} is equal to 1 if individual n chose alternative i in choice situation t and zero otherwise.

To estimate the parameters in the ML model, assumptions on the distributional form θ have to be made. Distributional forms that are mostly used are the normal, lognormal, uniform or triangular distribution. For this analysis, the environmental attributes are assumed to be normally distributed and the cost attribute to be fixed. The choice to assume a fixed cost coefficient comes from the notion that a normal distribution allows the cost coefficient to be positive in some cases, which is not realistic (Revelt and Train, 2000). On the other hand, assuming a fixed cost coefficient could be considered unrealistic as well, because it assumes that all respondents have the same preferences regarding costs. However, because of reasons of convenience in modelling, fixed cost coefficients are commonly used in choice experiments (Hole and Kolstad, 2011). The model is estimated in STATA through simulated maximum likelihood with the number of random draws r from the distribution $f(\beta|\theta)$ set by the analyst. For this analysis, 1,000 Halton draws were used for the estimation. ML models were estimated with only the attributes and the ASC.

To calculate the willingness to pay (WTP) from the ML model, one takes the ratio of the environmental attribute coefficient and the cost attribute coefficient. If both the environmental attributes and the cost attribute were assumed to be randomly distributed with a normal distribution the ratio of two normals may lead to unusual WTP distributions (Hole and Kolstad, 2011). By assuming a fixed cost-coefficient, it becomes much easier to calculate the different WTP distributions (Train and Weeks, 2005).

However, as mentioned before, assuming a fixed cost coefficient could be unrealistic since no heterogeneity in preferences regarding costs is accounted for. An alternative modelling approach to estimating WTP distributions has been developed where the logit model is estimated directly in 'WTP space' instead of 'preference space'. The ML model described so far is formulated in so-called preference space. The model in WTP space is obtained by reformulating the regular ML model in such a way that the estimated coefficients are WTP measures instead of preference coefficients (Scarpa et al., 2008). This is done as follows. Recall the utility function in preference space from equation 2.5:

$$U_{int} = \beta' \mathbf{X}_{int} + \varepsilon_{int} \tag{2.12}$$

The vector β' consists of the parameters of the three environmental attributes (vector β_x) and the parameter of the cost attribute β_c. For now we divide vector β' into vector β_x and parameter β_c. This gives the following utility function U respondent n will derive by choosing alternative i in choice situation t:

$$U_{int} = \beta_c P_{njt} + \beta_x \mathbf{X}_{int} + \varepsilon_{int}, \tag{2.13}$$

where β_c **is the cost parameter**, P_{njt} is the cost attribute variable, β_x is the vector consisting of the environmental attribute parameters, $\mathbf{X}$ is a vector of the environmental attribute variables and ε is an error term that represents the unobservable part of utility. This function can be transformed into the following form (Hole and Kolstad, 2011):

$$U_{int} = \beta_c (P_{njt} + \frac{\beta_x}{\beta_c} \mathbf{X}_{int}) + \varepsilon_{int} \tag{2.14}$$

Recall from equation 2.7 that WTP for the environmental attributes is calculated through the ratio of an environmental attribute and the cost attribute. As you can see from equation 2.14 the model estimates vector $\frac{\beta_x}{\beta_c}$, which means that the coefficients immediately show the WTP estimates for all environmental attributes. This is the ML model in WTP space. The advantage of this method is that assumptions on the WTP distributions can be made directly instead of indirectly through distributional assumptions on the random attribute parameters. The cost parameter can therefore also be assumed to be random, thus taking into account individual preference heterogeneity for this attribute as well. According to the literature this transformation of the model into WTP space can lead to more realistic WTP measures. However, when it comes to the goodness-of-fit, most models in preference space have been found to give a better model fit compared to models in WTP space (Hole and Kolstad, 2011). For this analysis, WTP will be estimated for the environmental choice attributes using both a preference space ML model and a WTP space ML model, whereby outcomes of both models are compared. In the WTP space model, the cost parameter is assumed to be random with a lognormal distribution, which allows only 'realistic' negative coefficients for costs. The ML model in WTP space was estimated using 1,000 Halton draws as well.

To decide which model performs the best, we again look at the Log-likelihood of the models which show the goodness of fit. A higher Log-likelihood means a better model fit and more reliable estimates.

3. Results

This chapter will summarize the most important results. Section 3.1 will first give an overview of the socio-demographic characteristics of the respondents. The results of the MNL models and their WTP estimates are presented in Section 3.2. Finally , section 3.3 presents the results of the ML models.

3.1 Socio-demographic characteristics

Table 3.1 presents the main socio-demographic characteristics of the total sample population. The socio-demographic distribution is statistically representative for the Australian population. As you can see the sample is well-balanced in gender (50/50) and with regard to peoples' State of origin. Respondents' age ranged from 18 to 83, and nearly 40% of respondents had completed an (undergraduate or postgraduate) university degree. Just over one-quarter of respondents came from rural areas. These respondents were included specifically to assess whether preferences for carbon farming characteristics would vary between urban and rural residents.

Table 3.1 Socio-demographics of survey respondents

Socio-demographics		N
Gender		
Male	49.2%	457
Female	50.8%	472
Age (years)		
Average	41.76	
Standard deviation	14.55	
Range	18-83	
Education		
University degree	39.3%	365
State		
New South Wales (NSW)	25.9%	241
Victoria (VIC)	26.0%	242
Queensland (QLD)	24.9%	231
Western Australia (WA)	23.2%	215
Metro or rural		
Metro	73.6%	684
Rural	26.4%	245
Income		
Less than $18,000	18.9%	176
$18,000 - $36,999	18.1%	168
$37,000 - $54,999	16.8%	156
$55,000 - $79,999	15.1%	140
$80,000 - $119,999	11.0%	102
$120,000 - $179,999	2.9%	27
More than $180,000	0.9%	8
Prefer not to respond	16.3%	152
Total nr. of respondents		**929**

Survey results from Kragt et al., 2013; N = nr. of respondents

Table 3.2 shows that 91% of respondents believe that climate change is happening, and that 66.6% of respondents believe that humans are causing or contributing to climate change. A dummy variable was created for later analysis, where respondents who believe that people are causing or contributing to climate change are coded 1, people that do not believe climate change is happening are coded -1 and all others are coded 0.

Table 3.2 Respondents' opinions on climate change

Respondents' opinions on climate change	%	N
I don't think that climate change is happening (dummy code: -1)	4.5	42
I have no idea whether climate change is happening or not (dummy code: 0)	4.5	42
I think that climate change is happening, but it is a natural fluctuation in Earth temperatures (dummy code: 0)	24.4	226
I think that climate change is happening, and that human actions are contributing to the change (dummy code: 1)	52.1	484
I think that climate change is happening, and that human actions are causing it (dummy code: 1)	14.5	135
Total	100	929

Survey results from Kragt et al., 2013; N = nr. of respondents

Respondents were also asked to indicate how important the different attributes are to them on a scale of one to five, where 5 is extremely important and 1 is completely unimportant. Table 3.3 shows that erosion received the highest average importance score and reduction in emissions received the lowest average importance score.

Table 3.3 Respondents' opinions on importance of the different attributes

Attribute	Importance (scale 1-5)
Soil erosion	4.17
Native vegetation	4.12
Cost	4.05
Emission reduction	3.84

Survey results from Kragt et al., 2013

Table 3.4 shows that 66.1% of the respondents think it is appropriate to encourage changes in rural land management in order to help reducing the risks of climate change.

Table 3.4 Respondents' opinion on encouraging changes in rural land management to help reducing risks of climate change

Encourage changes in rural management?	%	N
Yes	66.1	614
No	9.8	91
I don't care	2.7	25
I am not sure	21.4	199
Total	100	929

Survey results from Kragt et al., 2013; N = nr. of respondents

Furthermore, the government, high polluting countries, and individual people are seen as most responsible for fighting climate change according to the majority of the respondents. These results are shown in Table 3.5.

Table 3.5. Respondents' opinion on who is most responsible for fighting climate change

Who is most responsible for fighting climate change?	%	N
Government	59.6	554
High polluting countries	54.5	506
Individual people	50.9	473
Multinational corporations	41.8	388
Global organizations	38.3	356
Wealthy countries	31.2	290
They are all responsible	20.7	192
Other	7.2	67
No one is responsible	1.5	14

Survey results from Kragt et al., 2013; N = nr. of respondents

3.2 Results Multi-Nominal Logit models

The STATA output of the two MNL models are presented in Table 3.6. MNL Model 1 only includes the attributes and ASC. All coefficient signs are consistent with *a priori* expectations. Model results show that emission reduction/carbon storage, area of native vegetation and erosion reduction all have a significant positive coefficient. This means that an increase in the level of an attribute leads to a higher utility of a respondent. The cost attribute has a significant and negative coefficient which means that an increase in costs will lead to a lower utility of a respondent. The ASC is significant and negative, which means that respondents derive a higher utility from the two carbon farming alternatives, compared to the status quo option.
MNL Model 2 is an extended version of MNL Model 1, and was estimated with interactions between attributes and the socio-demographic variables. The best performing MNL model with interactions is presented in the table. Education, personal income, gender and having children did not have a significant effect on the respondents' choices, so these variables were not included in the final MNL model. One might have expected that the interaction between personal income and the cost attribute would be significant with a positive sign, indicating that people with a higher income are more likely to choose options with higher costs. However, this is not the case here and pointing out a reason is not simple. It might have something to do with the hypothetical nature of the survey. People with lower incomes may have chosen alternatives with higher costs as well, since they did not believe they really have to pay for it.

The results further show that an increase in emission reduction and native vegetation area significantly increases the utility of an individual, which is consistent with the results from Model 1. However, reducing soil erosion is not significant in this model. This is inconsistent with the results coming from Table 3.3, which shows that erosion received the highest average importance score among respondents. The cost coefficient is negative and significant, as expected. Respondents prefer the carbon farming options over the status quo option which can be concluded from the negative and significant ASC. The interaction variables can be interpreted as follows: people who believe that humans are causing or contributing to climate change (CC_hum) are more likely to choose options with higher emission reductions, more native vegetation, higher erosion reduction and higher costs. Furthermore, older respondents are less likely to choose options with higher emission reductions but are more likely to choose options with higher erosion reduction and higher costs. Respondents living in metro areas derive a less utility from an increase in native vegetation area compared to respondents living in rural areas. Finally, respondents from New South Wales and Victoria derive less disutility from higher costs than respondents from WA or QLD. The Log-Likelihood of MNL model 2 is higher than MNL model 1, meaning that the model containing the socio-demographic variables explains a larger part of the variation than the model only containing the choice attributes. A likelihood-ratio test confirms that MNL Model 2 is a significantly better model than MNL Model 1, with a test statistic of $\chi^2 = 559.6$ for ten degrees of freedom (p-value: 0.000).

Table 3.6 Results multi-nominal logit Model 1 and Model 2

Variable	Coefficients Model 1	Standard error	Coefficients Model 2	Standard error
Emission reduction	0.016***	0.001	0.012***	0.004
Native vegetation	0.233***	0.033	0.143**	0.062
Soil erosion	0.001***	0.000	-0.000	0.000
Cost	-0.005***	0.000	-0.010***	0.001
ASC (=1 for status quo)	-0.783***	0.063	-0.931***	0.066
CC_hum * Emission reduction			0.018***	0.002
CC_hum * Native vegetation			0.327***	0.057
CC_hum * Soil erosion			0.001***	0.000
CC_hum * Cost			0.002***	0.000
Age * Emission reduction			-0.000**	0.000
Age * Soil erosion			0.000**	0.000
Age * Cost			0.000***	0.000
Metro * Native vegetation			-0.134**	0.060
NSW * Cost			0.002***	0.000
VIC * Cost			0.002***	0.000
Log-Likelihood	-5528.3		-5248.3	
Number of observations	5574		5574	

*** = significant at 1% level ** = significant at 5% level * = significant at 10% level
Source: own calculations

The willingness to pay estimates for both models are presented in Table 3.7. Looking at Model 1, all WTP estimates for the environmental attributes are significant at the 1% level. Respondents are willing to pay, on average, \$2.99 per year for every metric tonne reduction in carbon emissions, \$42.80 per year for every hectare increase in native vegetation on farmland, and \$0.24 per year for every million tonne of soil erosion reduced. The average WTP results of Model 2 are based on the averages of the socio demographics. The WTP for erosion cannot be calculated since its coefficient was not significant in MNL Model 2. The WTP estimates for emission reduction/carbon storage and area of native vegetation are both significant at the 1% level. The WTP estimates of MNL Model 2 are comparable to those of MNL Model 1.

Table 3.7 WTP estimates for attributes of MNL Model 1 and Model 2

Attribute	WTP Model 1	WTP Model 2
Emission reduction ($/year for every metric tonne reduction in carbon emissions)	2.99*** (2.25 - 3.74)	2.77*** (2.07 - 3.47)
Increase of native vegetation ($/year for every hectare increase in native vegetation on farmland)	42.80*** (28.93 - 56.68)	43.29*** (29.63 - 56.95)
Reduction in soil erosion ($/year per million tonne reduction in erosion)	0.24*** (0.19 - 0.29)	NS

*** = significant at 1% level ** = significant at 5% level * = significant at 10% level NS=Not significant
95% confidence intervals of WTP estimates are given in parentheses
Model 2 is based on sample averages: Age = 41.76 CC_hum = 0.631 Metro = 0.736 NSW = 0.259 VIC = 0.260
Source: own calculations

The results in Table 3.7 show WTP estimates for the average respondent, but MNL Model 2 also allows us to estimate WTP for people with different socio-demographics. Table 3.8 shows WTP results for respondents who vary in their opinions about climate change, and for urban versus rural respondents who believe climate change is at least partly caused by human actions (CC_hum = 1).

Table 3.8. WTP estimates for respondents with different socio-demographic characteristics

Attribute	CC_hum = 1	CC_hum = 0	CC_hum = -1	CC_hum = 1 Metro = 1	CC_hum = 1 Metro = 0
Emission reduction	4.37*** (3.30 - 5.45)	0.71* (-0.02 - 1.43)	-1.51** (-2.70 - -0.31)	4.38*** (3.31 – 5.45)	4.38*** (3.31 – 5.44)
Native vegetation	71.89*** (54,61 -89.18)	6.51 (-10.40 - 23.41)	-32.94** (-63.12 - -2.76)	65.18*** (44.90 –85.47)	91.18*** (61.34 -102.01)
Soil Erosion	NS	NS	NS	NS	NS

*** = significant at 1% level ** = significant at 5% level * = significant at 10% level NS= not significant
CC_hum= respondents' opinion on climate change (see Table 2.3 or 3.2 for coding details)
The WTP estimates are calculated using the averages of all other socio-demographics. The 95% confidence intervals are given in the parentheses.
Source: own calculations

Table 3.8 shows that people who believe that humans are causing or contributing to climate change have a significantly higher WTP for emission reduction/carbon storage and for an increase in area of native vegetation compared to people who don't believe or are unsure whether climate change is happening. This is a result one would also expect, because people who believe that humans are at least contributing to climate change will probably have a stronger feeling that they could do something about it. Also, people who live in rural areas are willing to pay 40% more for a hectare increase in native vegetation compared to people living in metropolitan areas. A possible reason for this observation might be that people living in rural areas are more likely to live closer to native vegetation areas and are thus able to enjoy them more often.

3.3 Results mixed logit models

The results of the ML model in preference space and the ML model in WTP space are shown in Table 3.9. First we have a look at the ML model in preference space. The signs of the attributes are, as expected, the same as in MNL Model 1. All attributes and the ASC are significant at the 1% level. The standard deviations of the environmental attributes are assumed to follow a normal distribution. These standard deviations are significant at the 1% level, indicating that there is substantial unobserved preference heterogeneity among the respondents towards the environmental attributes. The ML model in WTP space also resulted in significance of all attributes and its standard deviations at the 1% level. Because of the lognormal distribution of the cost parameter, this attribute also has a standard deviation in this model. The coefficients directly show the WTP estimates of the attributes. Both ML models have a better model fit than the MNL models, and the ML model in WTP space even shows a slightly higher log-likelihood than the ML model in preference space.

Table 3.9 Results mixed logit models in preference space and WTP space

Variable	Coefficient (pref. space)	St. deviation	Coefficient (WTP space)	St. deviation
Emission reduction	0.027***	0.053***	1.967***	3.952***
Native vegetation	0.498***	1.959***	41.160***	145.514***
Soil erosion	0.001***	0.006***	0.109***	0.500***
Cost	-0.013***		-4.225***	0.536***
ASC (=1 for status quo)	-2.431***		-186.175***	
Nr. Of observations	5574		5574	
Log-Likelihood	-4625.2		-4614.9	

*** = significant at 1% level ** = significant at 5% level * = significant at 10% level

Source: own calculations

The next step is to get the WTP estimates for both ML models. Table 3.10 shows that the WTP estimates from both ML models are all significant at the 1% level. Furthermore, the estimates do not seem to differ between the two models. So, both in model fit and in WTP estimates the two ML models are similar.

Table 3.10 WTP estimates from ML models in preference space and WTP space

Attribute	WTP ML model pref. space	WTP ML model WTP space
Emission reduction ($/year for every metric tonne reduction in carbon emissions)	2.01*** (1.56 – 2.43)	1.97*** (1.55 – 2.39)
Increase in native vegetation ($/year for every hectare increase in native vegetation on farmland)	37.55*** (25.10 – 49.11)	41.16*** (28.58 – 53.74)
Reduction in soil erosion ($/year per million tonne reduction in erosion)	0.11*** (0.07 – 0.15)	0.11*** (0.07 – 0.15)

*** = significant at 1% level ** = significant at 5% level * = significant at 10% level

The 95% confidence intervals are given in the parentheses.

Source: own calculations

4. Discussion and conclusions

To summarize, all average WTP estimates for the different models are given in table 3.11. It shows that all different models result in similar WTP estimates. However, the ML models seem to give a slightly lower WTP for the environmental attributes compared to the MNL models. In order to decide which model gives the best estimates, we look at the Log-Likelihood. We can see that the ML models perform better than the MNL models, based on their higher Log-Likelihood. Looking at the MNL models, MNL Model 2 has a higher Log-Likelihood than MNL Model 1, which states that MNL Model 2 explains a larger part of the variation than MNL Model 1. This could be explained by the fact that MNL Model 2 accounted for differences in socio-demographics between respondents and MNL Model 1 did not. The ML models performed even better than MNL Model 2, which could be explained by the panel structure of the models and the fact that these models took into account unobserved preference heterogeneity across respondents. The panel structure makes the ML models more realistic than the MNL models since it allows for correlation across choices for every respondent. Allowing for unobserved preference heterogeneity in the ML models makes these models even more realistic since it assumes that preferences for diffent attributes can differ between respondents. The two ML models have a similar model performance, but the model in WTP space shows a slightly higher Log-Likelihood. Therefore the ML model in WTP space could be identified as the best model of the four, but this is not significant. When it comes to WTP calculations, most of the literature tends to prefer the ML model in WTP space since this model generated more realistic WTP estimates in different fields of economics. However, in this case both ML models generate approximately the same WTP results and the same model fit, so no clear winner can be identified among the two.

Table 3.11 Summarizing table containing WTP estimates from all models

Attribute	MNL Model 1	MNL Model 2	ML model Preference space	ML model WTP space
Emission reduction ($/year for every metric tonne reduction in carbon emissions)	2.99*** (2.25 - 3.74)	2.77*** (2.07 - 3.47)	2.01*** (1.56 – 2.43)	1.97*** (1.55 – 2.39)
Increase of native vegetation ($/year for every hectare increase in native vegetation on farmland)	42.80*** (28.93 - 56.68)	43.29*** (29.63 - 56.95)	37.55*** (25.10 – 49.11)	41.16*** (28.58 – 53.74)
Reduction in soil erosion ($/year per million tonne reduction in erosion)	0.24*** (0.19 - 0.29)	NS	0.11*** (0.07 – 0.15)	0.11*** (0.07 – 0.15)
Log-Likelihood	-5528.3	-5248.3	-4625.2	-4614.9

*** = significant at 1% level ** = significant at 5% level * = significant at 10% level NS = not significant
The 95% confidence intervals are given in the parentheses.
Source: own calculations

Overall, it is clear that Australians are likely to receive more welfare benefits from carbon mitigation activities that also provide environmental co-benefits. This means that carbon farming policies could potentially be broadened to capture co-benefits and not be restricted to solely carbon sequestration. Public incentives that aim to change agricultural land management could therefore include higher payments for carbon credits that generate additional environmental co-benefits. Furthermore, people may be tempted to compare the WTP estimates between attributes directly. The WTP estimates can, however, not be compared directly because the attributes are measured in different units.

An inconsistent result was found in MNL model 2, were an insignificant WTP for reduction in soil erosion occured. It is difficult to explain why this is the case. It might have something to do with the 'tangible' nature of the attributes. For example, the presence or absence of native vegetation is clearly visible to people and easy to understand. However, soil erosion is a process that is much less visible to people and might therefore be harder to understand. Putting more effort in explaining the attribute to the respondents in the survey might result in different estimates.

In order to get even better performing models, the researcher could extent the model and account for other real life phenomena. One example is accounting for attribute non-attendance, which is the topic of a paper that will be prepared as part of this study. Another example of a model extension that is accounted for in the forthcoming paper is allowing for error correlation between the two carbon farming alternatives by adding an error component. This is done because it is suspected that the status quo option is more familiar to the respondent than the carbon farming alternatives and therefore less prone to an individual valuation error, while the carbon farming alternatives are hypothetical and therefore a larger part of the stochastic component is likely to be subject to a larger unobservable error (Ginsburgh and Throsby, 2014). Research still continues on creating even more realistic models to increase the accuracy of welfare estimates coming from choice experiments.

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