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Modelling outcome-related risk in choice experiments*

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In this study, we introduce information on outcome-related risk as an additional attribute in a choice model of preferences for a land-based climate change mitigation project. We provide a comprehensive comparison of different model specifications arising from different behavioural assumptions about the way that respondents process information on outcome-related risk within the choice task. We find significant differences between several specifications in terms of both model fit and WTP estimates. The behavioural assumptions made when choosing a particular model specification, and reasons that motivate them should be made explicit, and consequences of using different specifications should not be ignored.

Key words: choice modelling, climate change, outcome-related risk, soil carbon sequestration, supply uncertainty, willingness to pay.

1. Introduction

The impacts of environmental projects and policies are rarely known with certainty. Environmental projects that are affected by uncertainty associated with the delivery of outcomes (supply uncertainty) represent the rule rather than the exception (Pindyck 2007). For example, uncertainty associated with impacts of land use change can be related to the scientific knowledge about environmental impacts; the effects of changes to the political, social and economic environment on long-term projects; and land managers' willingness to implement and maintain change. If uncertainty over outcomes exists, it is important to consider people's risk preferences. Ignoring the influence of risk aversion or risk loving on (expected) utility on demand for a good with uncertain supply may result in erroneous conclusions about the true welfare impacts of an environmental project or policy. There is a long history of the literature concerning valuation under supply uncertainty (e.g. Desvousges *et al*. 1987; Whitehead 1992), and option price has emerged as an appropriate

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measure of *ex-ante* welfare associated with an environmental change (Ready 1993).[1] Option price defines the certain payment necessary to make an individual indifferent between two uncertain states of the world, to be made before supply uncertainty is resolved.

Despite many environmental projects exhibiting supply uncertainty, economic valuation of the benefits of environmental policies using stated preference (SP) methods typically assumes that environmental outcomes are certain. The impacts of some aspects of supply uncertainty such as changes in political priorities and market conditions influencing land use change on environmental outcomes cannot reasonably be described in probabilistic terms and hence truly reflect uncertainty *sensu* Knight (1921). However, knowledge on probabilities of events and their impact on outcomes may exist for other elements contributing to the uncertainty about the delivery of outcomes faced by the decision maker. For example, the results of biophysical models predicting environmental change may be presented as a probability distribution. Since probabilities can be assigned to outcomes, environmental change can be characterised in terms of *outcome-related risk* (ORR).[2] If such probabilistic information exists, the scenario descriptions and/or the choice options presented to respondents in SP tasks can be designed to include information about the likelihood of actually achieving the proposed environmental outcomes.

In the recent SP literature, several studies explicitly included information on ORR in the valuation task (Burghart *et al*. 2007; Roberts *et al*. 2008; Li *et al*. 2010; Rigby *et al*. 2010; Glenk and Colombo 2011a; Akter *et al*. 2012). These studies, however, applied different modelling approaches to incorporating ORR into a state-independent indirect utility function. Each approach to modelling ORR implies different behavioural assumptions about how individuals use and interpret information on supply uncertainty. In this paper, we address three important questions related to modelling ORR in choice models in order to provide guidance to a growing field of research. Does the modelling approach impact on the predictive performance of choice models? Does the modelling approach affect policy-relevant WTP estimates? How should findings from alternative modelling approaches be interpreted? To address these questions, we analyse the impact of different modelling approaches on model fit, preference parameters, and WTP estimates. To our knowledge, this is the first time such a comprehensive comparative analysis is undertaken.

Drawing on data from a choice experiment survey on land-based climate change mitigation options via enhanced removals in soils in Scotland, we investigate the impact of explicitly including ORR in the benefit estimation

[1] We refer to Graham (1981, 1992) for insights on using the option price measure for *ex ante* welfare analysis, and to Freeman (1985) and Plummer (1986) for details on option prices in the case of supply-side uncertainty.

[2] Other authors have used subjective expectations of supply uncertainty in the estimation of option prices (Whitehead 1992; Cameron 2005).

process based on people's preferences for soil carbon sequestration policy options. We introduce an additional attribute reflecting the probability that such a policy fails to deliver the proposed outcomes in terms of net greenhouse gas (GHG) emission reductions. This paper investigates how risk of failure affects willingness-to-pay (WTP) estimates for net emission reductions and specifically compares the impact of alternative ways to model choice behaviour in the presence of ORR by combining elements of random utility maximisation (RUM), Expected Utility Theory (EUT) and elements of non-EUT frameworks.

2. Data source

A Scotland-wide choice experiment survey was carried out among members of the general public, who were asked to choose between two possible outcomes and a status quo alternative for a 20-year 'soil carbon programme' that would be implemented from 2009. In addition to the effects of a soil carbon programme on net emissions from Scotland, the programme was described in terms of two co-effects: changes to farmland bird habitat (biodiversity) and on-farm employment (rural viability). The latter may capture a range of different values, depending on whether respondents live in urban or rural communities. For urban residents, for example, this could include values associated with current use and option values regarding the maintenance of cultural landscapes and maintaining vibrant rural communities as an asset to be enjoyed on visits to the countryside. Rural residents may, for example, care about direct implications of living in a vibrant community; where farm employment can serve as a proxy for income generation in rural areas. Whether and how the welfare impacts of changes in on-farm employment derived via the choice experiment should enter an economic appraisal of policy options is a different question (see Bennett *et al.* (2004) for a discussion). In general, using public funds (tax increase) to finance such a programme was widely accepted in survey pretests and a pilot study. The status quo alternative was defined as follows: no additional emission reductions from soil carbon sequestration; no change in on-farm employment and farmland bird habitat; no change in tax.

In order to investigate the influence of ORR on preferences, the choices offered to respondents included risk of failure to reduce emissions as an additional attribute. This attribute reflected the probability that the programme may actually fail to deliver climate change mitigation benefits. Respondents were made aware that risk of failure only applied to emission reductions. A mix of visual and textual information, that was extensively checked for understanding in focus groups and pretests, was used to convey the information on the attributes, the policy options (PO) and the status quo alternative. Information on the attributes and levels is summarised in Table 1. Figure 1 shows a typical choice set offered to respondents.

Table 1 Summary of choice experiment attributes

Choice experiment attributes		
Label	Description	Levels [unit]
Emission reduction (ER)	Annual reduction in net emissions from Scotland	2, 4, 6, 8 [%]
Bird	Dummy variable taking 1 for 'improvement of farmland bird habitat' as a proxy for impacts on *biodiversity* and 0 for 'no change'	—
Farm jobs	Dummy variable taking 1 for 'slight decrease in on-farm employment' (2.5%) as a proxy of impacts on *rural viability* and 0 for 'no change'	—
Cost	Increase in general tax	5, 10, 25, 50, 100, 200 [£/year]
Risk of failure	Probability that soil carbon programme might actually fail to deliver net emission reductions	0 (no risk), 10, 30, 60 [%]

	Policy option A	Policy option B	Current policy
Living conditions for **farmland birds**	No Change	Improvement	No Change
Regular staff **employed in farming**	Slight Decline	No Change	No Change
Overall annual **greenhouse gas emissions**	reduced by 6%	reduced by 8%	No Change
Risk of failure to reduce emissions	30%	60%	No Risk
Cost to you per year	£10	£25	£0
I prefer	❑	❑	❑

Figure 1 Typical choice set.

A D-efficient experimental design was generated, to derive 96 choice sets, which were blocked into 24 groups. Each respondent hence faced four choices. The questionnaire finished off with the usual questions on socio-demographics. It also included questions that allowed identification of respondents who would be omitted from analysis due to protest responses and severe failure to understand the subject matter or the choice task.

After extensive pretesting and a pilot study (N = 108), a Scotland-wide face-to-face survey was administered to 648 respondents at their homes by a market research company between July and September 2008. We applied quota-based sampling with sample points set to reflect the characteristics of the populations of the three broad regions of Scotland.

3. Modelling approach

Confronted with a set of J alternatives, utility-maximising individuals choose the alternative that yields the highest utility, subject to a budget constraint. Following random utility maximisation, the utility V conditional on choosing alternative i can be expressed as a function that is additively separable in utility v_i that is observed by the analyst and a random error term ε_i reflecting unobserved effects.

$$V_i = v_i + \epsilon_i \tag{1}$$

$v_i(\cdot)$ is a function of K observed variables X_{ki} that are additively separable, with associated parameters β_k to be estimated. In the case of choices over alternative land-based climate change mitigation programmes, we specify the set of K observable factors to consist of net emission reductions (X_{ER}); co-effects, including changes to farmland bird habitat (X_{BIRD}) and on-farm employment (X_{FARM}); the impact of choosing the alternative on other consumption opportunities, that is $y - X_{\mathrm{COST}}$, where y is income and $X_{\mathrm{COST}i}$ is the price of alternative i. In the absence of ORR regarding emission reductions (ER), adding a constant β_{oi} associated with alternative i, and assuming additive separability $v_i(\cdot)$ may be written as:

$$v_i = \beta_{0i} + \beta_{\mathrm{ER}} X_{\mathrm{ER}_i} + \beta_{\mathrm{BIRD}} X_{\mathrm{BIRD}_i} + \beta_{\mathrm{FARM}} X_{\mathrm{FARM}_i} + \beta_{\mathrm{COST}}(y - X_{\mathrm{COST}_i}) \tag{2}$$

In what follows, we focus on ER and associated ORR, both of which varied over alternatives following an experimental design. For convenience of the exposition, we therefore condense all other observable factors as $\Sigma_k \beta_k X_k$ with k = 1, 2, 3 and drop subscript i.

A common way to analyse decisions in situations involving risk is to draw on Expected Utility Theory (EUT; Von Neumann and Morgenstern 1944) or Subjective Expected Utility Theory (SEUT; Savage 1954). These approaches postulate that individuals have preferences over outcomes only (i.e. not over probabilities). The utility of outcomes is weighted by the probability of occurrence, either as objective probabilities or as reflections of subjective judgments of individuals.

The application of an EUT framework to the choice among risky climate change mitigation alternatives within a random utility framework results in the Equations (3) and (4). Equation (3) assumes risk neutrality, and a linear functional form of the utility function over all levels of ER. $1 - p_{\mathrm{RISK}}$ is the probability of successfully achieving actual emission reductions X_{ER}. We denote this model a EUT (linear) specification (EU-L).

$$EU - L\colon v = \beta_0 + \beta_{\mathrm{ER}}((1 - p_{\mathrm{RISK}})X_{\mathrm{ER}}) + \sum_k \beta_k X_k \tag{3}$$

In Equation (4), denoted EUT (nonlinear) (EU-NL), we allow the utility function over ER to be nonlinear. ‘Environmental risk aversion’ with respect to the environmental quality variable ER is then related to the concavity of the utility function with respect to ER (Riddel 2011). Several functional forms of the utility function for the good associated with ORR can be considered (Farsi 2010). We use a power functional form on the effect of risk on utility of the type $x^{1-r}/(1-r)$. In this specification, r is the risk attitude parameter to be estimated: $r > 0$ indicates risk aversion and $r = 0$ risk neutral behaviour (Holt and Laury 2002). This utility function converges to ln$x$ if $r = 1$.

$$EU - NL: v = \beta_0 + \beta_{\mathrm{ER}}\left[\frac{(1 - p_{\mathrm{RISK}})X_{\mathrm{ER}}^{1-r}}{1 - r}\right] + \sum_k \beta_k X_k r < 0, r \neq 1 \quad (4)$$

Both EUT and SEUT are linear in the probabilities that characterise risks. Probabilities may be over-and underweighted relative to actual probabilities shown on choice cards as a result of individuals' perceptions of the probabilities. A common finding from laboratory experiments is that respondents overweight low probability events and underweight high probability events. Equation (5) shows a probability-weighting function that has been widely used in psychological and behavioural economics research, introduced by Tversky and Kahneman (1992). It assumes that the relation between w and p is linear in a log-odds metric:

$$w(p) = \frac{p^\gamma}{[p^\gamma + (1 - p)\gamma]^{1/\gamma}} \quad (5)$$

where $w(p)$ is the probability-weighting function, and γ is the probability-weighting parameter. $w(p)$ is a nonlinear function if $\gamma \neq 1$. If $\gamma = 1$, probability weighting is linear (expected utility), that is $w(p) = p$. A probability-weighting function that converts underlying (objective) probabilities into subjective ones is an element of prospect theory (Kahneman and Tversky 1979). Introduction of nonlinear probability weighting via $w(1 - p_{\mathrm{RISK}})$ results in two non-EUT specifications, which we denote probability weighting with a linear utility function over ER (PW-L) and probability weighting with a nonlinear utility function over ER (PW-NL).

$$PW - L: v = \beta_0 + \beta_{\mathrm{ER}}(w(1 - p_{\mathrm{RISK}})X_{\mathrm{ER}} + \sum_k \beta_k X_k \quad (6)$$

$$PW - L: v = \beta_0 + \beta_{\mathrm{ER}}\left[\frac{w(1 - p_{\mathrm{RISK}})X_{\mathrm{ER}}^{1-r}}{1 - r}\right] + \sum_k \beta_k X_k \quad r < 0,\ r \neq 1 \quad (7)$$

Recent applications of the above specifications are Burghart *et al.* (2007), Roberts *et al.* (2008) and Li *et al.* (2010). Burghart *et al.* (2007) assessed the benefits of publicly funded research and development projects aimed at climate change adaptation. The study modelled choice between receiving a one-off tax credit and using the funds for research and development on more energy-efficient air conditioners. Risk of failure is incorporated as an attribute of the offered programme and modelled using an approach that essentially mirrors EU-L. Roberts *et al.* (2008) compared choice model results from data assuming certainty in outcomes, with a dataset incorporating ORR via EU-L and PW-L models. The inclusion of risk significantly affected results, and a nonlinear probability-weighting function (PW-L) described respondents' choices better than linear weighting of outcomes (EU-L). In a transportation economics context analysing travel time reliability, Li *et al.* (2010) compared EU-L, EU-NL and PW-NL models, but did not observe differences in estimates of mean marginal WTP for travel time savings for these models.

In EUT, an individuals' attitude towards risk and an individuals' attitude towards the good that is subject to risk are not separable. An alternative way to analyse choice decisions under risk is to assume that the effect of risk on utility is partially or fully separable from the utility effect of the good affected by risk. Under this assumption, respondents have a direct distaste for risk of failure, in contrast to or in addition to the effect risk of failure has on environmental outcomes.

The notion of direct utility from risk has been used by Gneezy *et al.* (2006) to explain violations of the internality axiom applied to EUT. In one of their experiments, WTP for entering a lottery of two gift certificates was found to be lower than for the lower-value certificate, that is, the worst possible outcome, *per se*. To explain such behaviour, denoted the 'uncertainty effect', the authors suggest that decision makers may evaluate risky prospects by first determining the probability-weighted value of a good and in a second step reducing this amount to account for the uncertainty. The second step is equivalent to receiving direct utility from risk. Similarly, Simonsohn (2009) suggested that this effect would result from risk aversion arising from a *direct* distaste for uncertainty rather than indirectly as a consequence of how outcomes are valued and weighted by probabilities.[3]

Direct disutility from risk can be included in the indirect utility function by adding $X_{\mathrm{RISK}} = p_{\mathrm{RISK}}$ with β_{RISK} as the associated parameter to be estimated.[4] β_{RISK} is interpreted as the marginal disutility of risk of failure, that is it is imposing a risk-related penalty on the overall utility of an emission reduction programme. $\beta_{\mathrm{RISK}}X_{\mathrm{RISK}}$ can be added to different 'base' models. Inclusion of a separable effect of risk of failure additional to the outcomes conditioned by probability in a linear or nonlinear way results in the following specifications:

[3] The uncertainty effect has not been undisputed. Keren and Willemsen (2009) and Rydval *et al.* (2009) found that the uncertainty effect as reported in Gneezy *et al.* (2006) may be a result of task framing ambiguity of experimental instructions. Simonsohn (2009), however, found supporting evidence for the uncertainty effect, taking into account weaknesses in the experimental setup of Gneezy *et al.* (2006), including potential misunderstanding of instructions.

[4] We use the notation $1 - p_{\mathrm{RISK}}$ if risk of failure is used multiplicatively as a weight for ER outcomes and X_{RISK} if risk of failure enters the utility function additively to illustrate the difference between a purely outcome-related interpretation of the relevance of risk of failure and the notion of additional effects of failure risk not explained by probability-conditioned outcomes.

$$DU-L\colon v=\beta_0+\beta_{\mathrm{ER}}((1-p_{\mathrm{RISK}})X_{\mathrm{ER}})+\beta_{\mathrm{RISK}}X_{\mathrm{RISK}}+\sum_k \beta_k X_k \quad (8)$$

$$PW-DU-L\colon v=\beta_0+\beta_{\mathrm{ER}}(w(1-p_{\mathrm{RISK}})X_{\mathrm{ER}})+\beta_{\mathrm{RISK}}X_{\mathrm{RISK}}+\sum_k \beta_k X_k \quad (9)$$

Finally, the analyst can take the rather extreme assumption that the impact of risk on respondents' utility for an emission reduction programme is fully described by direct distaste of risk. No evaluation of probability-conditioned outcomes is assumed to having taken place (DU):

$$DU\colon v=\beta_0+\beta_{\mathrm{ER}}X_{\mathrm{ER}}+\beta_{\mathrm{RISK}}X_{\mathrm{RISK}}+\sum_k \beta_k X_k \quad (10)$$

In the context of uncertainty in the supply of irrigation water, Rigby *et al.* (2010) used a DU-L specification and found that it outperformed an attributes only and a EU-L specification. Using a DU specification to model risk of failure to achieve emission reductions from a soil carbon programme, Glenk and Colombo (2011a) report negative WTP values for higher levels of risk. They conclude that this effect could be a consequence of respondents preferring to switch to other emission reduction technologies if risk of failure exceeds a certain threshold.

Table 2 summarises the model specifications and acronyms used in the analysis. We contrast WTP values to test for the effect of risk of failure on respondents' preferences. Note that the applicability of the widely used Poe *et al.* test (2005) is limited, because the sample distributions are not independent. Nonparametric alternatives as described in Poe *et al.* (1997) are not practical, since they would require a large number of model runs from bootstrapped samples. However, the Poe *et al.* test can still assist us with the aim of investigating whether different ways of modelling ORR result in significant differences in WTP. Because the correlation between WTP distributions calculated from the same data set can be expected to be positive, we can be confident that WTP distributions are indeed different when the null hypothesis of equality implied by the Poe *et al.* test is rejected. If it is accepted, however, we cannot be sure that in fact WTP distributions are different without taking the correlation between them into account.[5] For all specifications, we estimate WTP for an additional reduction in net emissions X^1_{ER} from a baseline level X^0_{ER} and different probabilities of failure

[5] The variance of the difference between two random variables X and Y is given by var(X)+var(Y)-2cov(X,Y). If there is a positive correlation between X and Y, then the variance of the difference will be less than it would have been if X and Y were independent. Since we would expect a positive rather than a negative correlation between WTP distributions calculated from the same data set, the Poe test will tend to over-estimate the true variance of the difference. This means that there is a risk that the null hypothesis of equality will be accepted when it should in fact be rejected, but we can be confident that it should be rejected in cases where it has been.

Table 2 Different model specifications incorporating risk of failure

Abbreviation	Model	Specification of observed utility v
EU-L	Expected Utility – Linear utility function	$\beta_0 + \beta_{\text{ER}}((1 - p_{\text{RISK}})X_{\text{ER}}) + \sum_k \beta_k X_k$
EU-NL	Expected Utility – Nonlinear utility function	$\beta_0 + \beta_{\text{ER}}\left[\frac{(1 - p_{\text{RISK}})X_{\text{ER}}^{1-r}}{1-r}\right] + \sum_k \beta_k X_k$
PW-L	Probability weighting – Linear utility function	$\beta_0 + \beta_{\text{ER}}(w(1 - p_{\text{RISK}})X_{\text{ER}}) + \sum_k \beta_k X_k$
PW-NL	Probability weighting – Nonlinear utility function	$\beta_0 + \beta_{\text{ER}}\left[\frac{w(1 - p_{\text{RISK}})X_{\text{ER}}^{1-r}}{1-r}\right] + \sum_k \beta_k X_k$
DU-L	Direct utility from risk – Linear utility function	$\beta_0 + \beta_{\text{ER}}((1 - p_{\text{RISK}})X_{\text{ER}}) + \beta_{\text{RISK}}X_{\text{RISK}} + \sum_k \beta_k X_k)$
PW-DU-L	Direct utility from risk – Probability weighting – Linear utility function	$\beta_0 + \beta_{\text{ER}}(w(1 - p_{\text{RISK}})X_{\text{ER}}) + \beta_{\text{RISK}}X_{\text{RISK}} + \sum_k \beta_k X_k)$
DU	Direct utility from risk	$\beta_0 + \beta_{\text{ER}}X_{\text{ER}} + \beta_{\text{RISK}}X_{\text{RISK}} + \sum_k \beta_k X_k$

risk. Following Hanemann (1984), compensating surplus can be calculated as:

$$CS = -1/\alpha[\ln \sum_n \exp V_n^1 - \ln \sum_n \exp V_n^0] \tag{11}$$

where CS is the compensating surplus welfare measure, α is the marginal utility of income (represented by the coefficient of the monetary attribute in the choice experiment), and V_n^0 and V_n^1 represent the n*th* individuals' indirect utility functions before and after the change under consideration. Since we are interested in the impacts of risk of failure on WTP for emission reductions, we assume that the outcomes of the considered co-effects (biodiversity and rural viability) remain unaltered between V^0 and V^1. The changes considered for analysis are reported in Table 3.

From scenario 1 to scenario 3, both emission reductions and risk of failure increase simultaneously compared with a common baseline of two per cent emission reductions without risk of failure. For scenario 4, risk of failure increases from 10 per cent to 30 per cent and emission reductions increase from four per cent to six per cent. Among the scenarios used, the fourth scenario is best suited for a comparison of the EU-NL and PW-NL models with other specifications that are linear in the utility function over emission

Table 3 Scenarios of change considered for WTP estimation

		Scenario 1 (CS1)	Scenario 2 (CS2)	Scenario 3 (CS3)	Scenario 4 (CS4)	Scenario 5 (CS5)
Emission reductions	V^0	2%	2%	2%	4%	6%
Emission reductions	V^1	4%	6%	8%	6%	8%
Risk of failure	V^0	0%	0%	0%	10%	30%
Risk of failure	V^1	10%	30%	60%	30%	60%

reductions, because the mean value of X_{ER} in the sample is close to five per cent, and expected values associated with the change are similar. Scenario 5 describes a change at the upper end of the emission reduction spectrum (six per cent to eight per cent), while changes in risk of failure ensure that the expected value associated with the change is lower than that of the baseline condition.

A comparison of model fit cannot be carried out using conventional log-likelihood ratio tests because (at least some of the) models are non-nested. Hence, we use the test proposed by Ben-Akiva and Swait (1986). An error components logit model (ECL; Hess 2005) is applied to estimate the SP data.

4. Results

From the total sample, we removed respondents who either declared a 'protest' response (nine per cent); severely failed to understand the issue under study (11 per cent);[6] or expressed a genuine zero WTP for the soil carbon programme irrespective of the degree of emission reductions and risk of failure (13 per cent). Based on the cut-off approach (Bush *et al*. 2009), we filtered off respondents who violated their upper monetary cut-off value by more than 200 per cent. The resulting sample used in the analysis consisted of 1599 observations from 434 individuals.

Table 4 shows the estimated coefficients for all models. All parameters are significant at the 95 per cent level or higher and have the expected sign. The generally positive and significant values of the alternative specific constant (β_0) show that respondents had a propensity to choose the policy options instead of the status quo which cannot be explained by attribute information. The sign and magnitude of all attribute parameters aside from β_{RISK} and β_{ER} are unaffected by the model specification. It is easily revealed by visual inspection of β_{FARM} and β_{BIRD} in relation to β_{COST} that mean WTP values are very close across the models, and this is confirmed by estimation of WTP

[6] To determine whether respondents severely failed to understand the issue under study three survey questions regarding the absolute and relative effectiveness of the soil carbon programme for climate change mitigation were included. Respondents, who failed to respond give the correct response in more than one out of the three statements, were filtered off from the analysis. Full details on this procedure are described in Glenk and Colombo (2011b).

for these two attributes. We can therefore subsequently focus on WTP estimates for net emission reductions in the presence of failure risk.

Focusing the attention on the models which incorporate a probability-weighting function first (PW-L, PW-NL and PW-DU-L), the value 2.05 of the γ coefficient in the PW-L model would indicate nonlinear probability weighting.[7] This finding is contradicted by γ being around 1.2 in the PW-DU-L and PW-NL models. In these models, nonlinear probability weighting seems to be far less pronounced than the PW-L model would suggest, and linearity of probability weighting cannot be statistically rejected, since the γ coefficient is not statistically different from one.

Aiming for the best model fit to data, nonlinear probability weighting may therefore have had a greater impact on the PW-L specification compared with PW-DU-L and PW-NL. However, results of the Ben-Akiva and Swait (1986) test show that PW-DU-L and PW-NL should clearly be preferred to the PW-L model (Table 6), indicating that either a nonlinear utility function over ER or allowing for direct disutility of risk better captures respondents' risk preferences than using a linear utility function over ER.

In the models that assume a nonlinear utility over ER, the parameter r is highly significant with a value of 0.58 in the EU-NL and 0.55 in the PW-NL model, hence $1 - r < 1$. This could be interpreted as risk aversion with respect to net emission reductions from the proposed soil carbon sequestration programme. The models which incorporate an additional penalty related to risk of failure not explained by probability-conditioned outcomes (DU-L, PW-DU-L and DU) show a negative and significant coefficient for β_{RISK}. People appeared to dislike uncertainty beyond the effect captured by the probability-weighted outcomes alone. According to Rigby *et al.* (2010), β_{RISK} carries some information on risk attitudes of respondents. A negative and significant value of β_{RISK} would indicate risk aversion, which could here be interpreted using a weak definition that a choice option is not preferred to its expected value. In the DU model, β_{RISK} is significant, negative and large in magnitude suggesting that risk of failure has a large penalty on the utility for reducing net emissions.

The EU-L and PW-L specifications have considerably lower values of the log-likelihood function, while the remaining models' sum LogL is slightly above or below −1333, which clearly advises against the use of a linear specification of utility over ER. An exception is the DU specification with a log-likelihood function of −1330.3. Results of the Ben-Akiva and Swait (1986) tests (Table 6) suggest that DU outperforms all remaining models; that all models are preferred over EU-L; that apart from the EU-L model all other models are preferred over the PW-L model; and that due to highly similar model fit none of the EU-NL, PW-NL, DU-L and PW-DU-L models is clearly preferred.

[7] The t-ratio for γ being significantly different from 1 is 2.9; calculated as $\gamma - \frac{1}{SE}$.

Table 4 Error component logit (ECL) model results

	EU-L		EU-NL		PW-L		PW-NL		DU-L		PW-DU-L		DU	
	coef.	t-stat.	coef.	t-stat.	coef.	t-stat.	coef.	t-stat.	coef.	t-stat.	coef.	t-stat.	coef.	t-stat.
β_0	1.93	7.14	1.37	4.25	2.02	6.74	1.46	4.17	2.40	8.25	2.36	7.46	2.55	9.05
β_{BIRD}	0.32	5.00	0.324	5.06	0.31	4.93	0.32	5.02	0.32	5.00	0.32	4.99	0.33	5.12
β_{FARM}	−0.30	−4.73	−0.3	−4.62	−0.30	−4.67	−0.3	−4.62	−0.3	−4.62	−0.3	−4.62	−0.30	−4.66
β_{COST}	−0.01	−13.88	−0.01	−13.84	−0.01	−13.86	−0.01	−13.86	−0.01	−13.85	−0.01	−13.86	−0.01	−13.90
β_{ER}	0.23	10.63	0.40	11.35	0.22	10.87	0.39	9.11	0.17	6.74	0.17	6.78	0.14	7.13
β_{RISK}	—	—	—	—	—	—	—	—	−1.00	−4.48	−0.95	−3.93	−1.87	−9.64
r	—	—	0.58	7.30	—	—	0.55	5.72	—	—	—	—	—	—
γ	—	—	—	—	2.05	5.62	1.23	3.95	—	—	1.20	3.75	—	—
σ_{PO}	2.87	10.72	2.89	10.73	2.88	10.72	2.89	10.73	2.88	10.72	2.88	10.72	2.89	10.73
LogL	−1343.32		−1333.28		−1338.78		−1332.80		−1333.02		−1332.76		−1330.27	
Adj. ρ^2	0.232		0.237		0.234		0.237		0.237		0.237		0.239	

Note: Number of observations: 1599; Number of random draws (Halton): 1500; β_0 is an alternative specific constant taking 1 for the policy options and 0 otherwise.

Estimates of WTP for emission reduction scenarios CS1-CS5 are reported in Table 5, and results of a Poe *et al.* (2005) test for differences in WTP can be found in Table 6. The EU-L model produced the highest WTP values in all scenarios of change considered, and WTP estimates differ significantly for the vast majority of comparisons with other models. Since only one parameter (β_{ER}) is used for generating WTP estimates, it is not surprising that confidence intervals are smaller compared with all other specifications.

For small and medium changes in emission reductions and risk of failure (CS1, where ΔER= two per cent and ΔRisk = 10 per cent; and CS2, where ΔER=four per cent and ΔRisk = 30 per cent), the DU model produced a significantly lower WTP estimate, and WTP is lower for all specifications that allow for direct disutility from risk (DU-L, PW-DU-L) compared with those specifications that do not. This pattern changes, however, once larger changes in both emission reductions and risk of failure are considered (CS3, where ΔER = six per cent and ΔRisk = 60 per cent). The EU-NL, PW-NL, DU-L and PW-DU-L models all give similar estimates of WTP for CS3, probably because higher risk levels exert a strong influence on utility from emission reductions. Compared with the EU-L and PW-L models, all of these models better describe the effect of risk on utility either through risk attitude/ diminishing marginal utility in the EU-NL and PW-NL models, or as a direct disutility from risk in the DU-L, PW-DU-L models. The EU-L and PW-L specifications have no such mechanism to account for the strong impact of risk on utility, particularly at higher levels of risk. Hence, they do not reflect actual choice behaviour well, resulting in a generally lower model fit.

Among the considered scenarios of change, CS4 is best suited for a comparison of specifications using a nonlinear utility function over emission reductions (EU-NL and PW-NL) with the other specifications investigated in

Table 5 Willingness-to-pay estimates and 95 per cent confidence intervals for different scenarios of change (CS1-CS5)

	CS1	CS2	CS3	CS4	CS5
EU-L	36.9	50.7	27.7	13.8	−23.1
	(28.5; 47.1)	(39.1; 64.8)	(21.3; 35.3)	(10.7; 17.7)	(−29.4; −17.8)
EU-NL	25.9	13.0	−39.0	−12.8	−52.0
	(14.3; 37.8)	(−12.2; 33.2)	(−83.4; −8.5)	(−28.6; −1.3)	(−73.4; −36.5)
PW-L	34.5	39.9	−5.6	5.4	−45.5
	(25.6; 44.2)	(25.3; 55.9)	(−20.6; 13.1)	(−2.8; 12.6)	(−8.8; −32.9)
PW-NL	30.0	19.1	−40.0	−10.9	−59.1
	(16.6; 42.9)	(−9.1; 41.1)	(−83.0; −9.5)	(−26.1; 0.2)	(−83.8; −39.1)
DU-L	17.3	7.6	−39.3	−9.7	−47.0
	(6.6; 29.1)	(−13.8; 29.4)	(−74.9; −6.9)	(−21.9; 1.5)	(−63.7; −33.2)
PW-DU-L	19.2	10.4	−41.2	−8.8	−51.6
	(7.1; 31.7)	(−13.6; 33.6)	(−76.9; −7.7)	(−21.4; 2.8)	(−69.2; −36.6)
DU	9.4	0.1	−27.9	−9.3	−28.0
	(1.2; 18.1)	(−18.8; 19.0)	(−63.8; 4.4)	(−21.3; 1.5)	(−44.8; −13.8)

Note: Estimated using the Krinsky and Robb (1986) procedure with 1000 draws; All values in £ per person and year.

Table 6 Results of the Ben-Akiva and Swait (1986) test for model comparison and statistical significance of differences in WTP estimates for scenarios CS1-CS5 calculated using a Poe *et al*. (2005) test

Model 1	Model 2	Ben-Akiva and Swait (1986) *P*‡	Poe *et al*. (2005)†				
			CS1	CS2	CS3	CS4	CS5
DU	EU-L	0.0000	***	***	***	***	—
DU	DU-L	0.0095	*	—	—	—	***
DU	EU-NL	0.0071	***	—	—	—	***
DU	PW-L	0.0000	***	***	*	***	***
DU	PW-DU-L	0.0024	**	—	—	—	***
DU	PW-NL	0.0023	***	*	—	—	***
DU-L	EU-L	0.0000	***	***	***	***	***
EU-NL	EU-L	0.0000	**	***	***	***	***
PW-L	EU-L	0.0022	—	*	***	***	***
PW-DU-L	EU-L	0.0000	***	***	***	***	***
PW-NL	EU-L	0.0000	—	***	***	***	***
DU-L	EU-NL	0.2354	*	—	—	—	—
DU-L	PW-L	0.0003	***	***	***	***	—
DU-L	PW-DU-L	0.0574	—	—	—	—	—
DU-L	PW-NL	0.0545	**	—	—	—	—
EU-NL	PW-L	0.0005	—	***	***	***	—
EU-NL	PW-DU-L	0.0804	—	—	—	—	—
EU-NL	PW-NL	0.0761	—	—	—	—	—
PW-DU-L	PW-L	0.0004	***	***	***	***	—
PW-DU-L	PW-NL	0.3860	*	—	—	—	—
PW-NL	PW-L	0.0005	—	**	***	***	*

Note: *,**,***Null hypothesis has been rejected at the 15%, 10%, 5% significance level; †H0: WTP model 1 = WTP model 2; ‡Probability of erroneously choosing model 2 when model 1 is the 'true' model.

this paper. WTP estimates are significantly different for comparisons of EU-L and PW-L with all other models. This suggests that differences may not be very pronounced for WTP estimates around the mean value of the good under risk. This is in line with Li *et al*. (2010) who found no significant differences in mean marginal WTP between EU-L, EU-NL and PW-NL models. As expected, all WTP estimates are negative for the change described by CS5. The larger difference between EU-L (−21.3 £/year) and PW-L (−45.5 £/year) illustrates the impact of nonlinear probability weighting, while smaller differences between EU-NL and PW-NL, as well as DU-L and PW-DU-L, respectively, reflect the reduced relevance of nonlinear probability weighting resulting from the PW-NL and PW-DU-L models.

Results of the Poe *et al*. (2005) test (Table 6) show that the null hypothesis of WTP equality can be rejected for some comparisons between model specifications under each of the five scenarios of change considered for analysis. Most rejections are found for the EU-L and PW-L models. Comparisons of DU with all other specifications are mixed: significant differences with WTP estimates derived from all models except EU-L exist for CS5, but only WTP calculated from the EU-L model is significantly different for CS3.

5. Discussion

There are different ways to convey information on ORR to respondents and subsequently include them into the choice experiment design. In this study, ORR was described as probability of failure instead of probability of success to achieve the outcomes. The framing of the risk attribute could have had an effect on processing the information on probabilities and therefore on the effect of ORR on WTP. Ample evidence from the literature suggests that choices over risky prospects fail to be invariant to the framing of prospects (e.g. Tversky and Kahneman 1981). Further research could clarify whether such framing effects exist, and what the consequences would be for the identification of WTP indicators.

In this study, ORR was included as an attribute reflecting the probability that measures which have been suggested to reduce net greenhouse gas emissions from Scotland would fail to deliver any climate change mitigation benefits[8]. Only allowing for two outcomes of a climate change mitigation project (emissions reduced by X_{ER}; no emission reduction at all) greatly simplifies reality. We believe that this simple representation yielded valuable insights which would have been difficult to uncover whether we had applied more realistic but cognitively demanding representations of ORR. Future research may investigate further the applicability of different ways of presenting ORR in stated preference studies and assess the implications for WTP estimates.

Across all specifications, model parameters had the expected sign and were significantly different from zero. This shows that respondents made use of information on risk of failure when choosing between alternative soil carbon sequestration programmes and confirms that notions of uncertainty about the delivery or supply of outcomes should – when relevant – be considered for benefit assessments using stated preference methods. This is particularly the case when environmental outcomes of proposed programmes can be described in probabilistic terms. Between the different specifications used to model risk of failure related to a soil carbon sequestration programme, we find differences in WTP estimates for all scenarios of change considered in the analysis, but we do not find significant differences across the scenarios for *every* pair of specifications tested. Overall, however, the findings support the relevance of conducting the comparative analysis of specifications presented in this paper.

Comparisons of model fit showed that other specifications should be preferred over the use of a linear utility function over ER either within the

[8] In the case study presented in this paper, a single attribute (net GHG emission reductions) is affected by ORR. If several attributes are *jointly* affected by ORR in a choice experiment, it may be important to consider risk aversion in bi- or multi-attributive frameworks ('correlation aversion'). This constitutes an interesting avenue for future research.

expected utility paradigm (EU-L) or in combination with a probability-weighting function (PW-L). In addition, WTP estimates derived from EU-L and PW-L differed significantly for most comparisons with other specifications. Especially the EU-L specification tends to produce consistently higher WTP estimates compared with all other models. In this case study, these specifications may therefore not reflect the actual choice behaviour particularly well. Interestingly, the DU specification shows the greatest model fit to data. The DU specification implies that respondents would separately evaluate 'distaste' of failure risk and outcome in case of success. It is unlikely, however, that respondents would not have conducted *any* probability weighting of outcomes in the choice process. However, more research is needed to scrutinise alternatives to modelling approaches based on an EUT framework given that real behaviour often refuses to be confined by the limits of 'conventional' theory (Starmer 2000).

Differences in model fit between the remaining models (EU-NL, PW-NL, DU-L, PW-DU-L) are minimal, and differences in the magnitude of WTP estimates for all scenarios of change are modest. This suggests that choice among these models cannot simply be guided by measures of statistical performance and tests of WTP differences, and underscores that the behavioural assumptions that a researcher wants to impose can play an important role in model selection. The EU-NL specification has strong foundations in a widely used decision theory with full axiomatisation, von Neumann-Morgenstern (VNM) EUT. One criticism of VNM EUT is related to the nonseparability of risk attitude, a property associated with risky contexts, and diminishing marginal utility, a certainty-related property. In the case of emission reductions, diminishing marginal utility may well have a meaning that is independent of attitude towards risk. For example, it is plausible to assume scope effects exist, that is, that the expected benefits in terms of reducing climate change related damage are greater for initial efforts to reduce emissions. Similarly, diminishing marginal (dis)utility may apply to other attributes in the choice experiment, even if these attributes are not explicitly associated with ORR. Given the perfect confounding of risk attitude and diminishing marginal utility in an EUT framework, nonlinearity in the utility function for such attributes (for example cost) could be interpreted in terms of attitude towards risk, and comparisons could be made between risk attitude in different domains. The usefulness of such a comparison is questionable, however, and points to a central dilemma associated with following an EUT framework. It would therefore be worth while to explore how recent developments that relax the assumption of nonseparable risk attitude and diminishing marginal utility such as Rank Dependent Utility Theory (Quiggin 1993) can be incorporated into choice models based on a RUM framework. de Palma *et al*. (2008) provide an initial discussion on this topic.

DU-L (used in Rigby *et al*. 2010) and PW-DU-L both share the assumption of direct utility from risk. While plausible explanations for characterising the direct impact of risk simply as a genuine distaste for risk exist,[9] this is not a very convincing perspective in our view. Instead, the significant parameter values of the additive risk term may simply capture any *additional* effects of the risk attribute that are not captured if the utility function over ER is constrained to be linear.[10] As noted above, the EU-NL and DU-L models are *statistically* equivalent – hence, the difference lies in the behavioural assumptions that the analyst makes with respect to how respondents process information on ORR, which significantly impact on WTP and welfare measures. In our view, this suggests that an EU-NL specification should be preferred unless evidence can be found that supports any assumption about direct disutility from risk.

6. Conclusions

In the recent discrete choice literature, ORR has increasingly been considered by analysts. A common message from these studies is that ORR matters to respondents and that it therefore should not be ignored in valuation studies. Various approaches to modelling ORR have been proposed. Implicitly, the different model specifications reflect behavioural assumptions about the way that respondents process information on risk within the choice task. The aim of the comprehensive comparison of model specifications presented in this paper was to reveal the consequences of making such assumptions on the predictive power of the models, and on WTP estimates that can be used for policy purposes.

Our results highlight the importance of revealing, justifying and discussing the behavioural assumptions made when choosing a particular specification to incorporate ORR in the utility function. We showed that significant differences between specifications can arise in terms of both model fit and WTP estimates. Therefore, model specifications should be carefully chosen. We cautiously advocate the use of a nonlinear EUT model over models that consider probability-weighted outcomes linearly and in combination with direct utility from risk. Given that we have no means to investigate how respondents processed information on risk of failure in the choice task; however, we think it is too early to *entirely* dismiss specifications that are not compatible with an EUT framework by considering effects that are not explained by probability-conditioned outcomes alone.

We propose further research in two directions. First, more needs to be learned about the trade-off between the extra benefits of including information

[9] For example, respondents may evaluate the offered outcomes from a soil carbon program conditioned by probability of failure in a first step and then add a utility penalty that accounts for the risk of failure to achieve emissions relative to other alternatives to reducing net emissions (e.g., related to housing or transportation).

[10] In analyses not described in this paper, we found that adding an additive risk term $\beta_{\mathrm{RISK}}{*}X_{\mathrm{RISK}}$ to a more flexible EU-NL specification, while fixing the value of r at 0.58 to allow identification, results in parameter estimates for β_{RISK} of basically zero (0.006 and t-stat = 0.02).

on ORR, and the additional costs in terms of survey time and respondents' cognitive burden. An improved understanding of the way respondents process information on risk of failure in the choice task, and how the procedure used by respondents changes with the choice context, is clearly desirable. In addition to split sample experiments in the laboratory and the field, the use of verbal protocols (Schkade and Payne 1994) could be a useful methodological tool in this respect. Related to this, further studies that include similar risk components should report results from the use of different specifications and thereby contribute to the general enquiry put forward in this paper. Second, it should be investigated whether drawing on alternative generalisations of EUT such as Rank Dependent Utility Theory would be beneficial to modelling ORR in a way that maintains a strong theoretical foundation while better representing the actual choice behaviour of respondents.

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