Michela Faccioli[a, b,*] and Klaus Glenk[c]

[a] Research Fellow in Environmental Economics at the Land, Environment, Economics and Policy (LEEP) Institute, University of Exeter, Business School, Department of Economics, Xfi Building (1st floor), Rennes Drive, EX4 4PU Exeter, United Kingdom.

[b] Honorary Research Associate at the Social, Economic and Geographical Sciences Research Group, The James Hutton Institute, AB15 8QH Aberdeen, United Kingdom.

* Corresponding author. Email for correspondence: m.faccioli@exeter.ac.uk; work telephone: +44 (0)1392 726690

[c] Reader in Environmental and Resource Economics at the Land Economy, Environment & Society Group, Department of Rural Economy, Environment & Society, SRUC, Peter Wilson Building, Kings Buildings, West Mains Road, EH9 3JG Edinburgh, United Kingdom. Email: Klaus.Glenk@sruc.ac.uk

doi:10.3368/le.98.2.051920-0067R1

More in good condition or less in bad condition?

Valence-based framing effects in environmental valuation

Abstract

This study addresses an important gap in the stated preference literature concerning valence-based framing of discrete choice experiment attributes. Valence-based framing arises when equivalent outcomes are presented in different ways by accentuating either the positive (e.g., more in good condition) or negative information (e.g., less in bad condition). We find that alternative framings produce different willingness-to-pay estimates, with implications for Benefit-Cost Analysis. We recommend neutral attribute descriptions and otherwise testing for the impacts of alternative framings to obtain more robust welfare evidence. We also show that the framing used does not affect the choice paradigm adopted by respondents.

Keywords: environmental valuation, discrete choice experiments, positive framing, negative framing, behavioral economics, peatland restoration

JEL codes: Q51, Q57, D83, D6, D91, Q2

Appendix materials can be accessed online at:

https://uwpress.wisc.edu/journals/pdfs/LE-98-2-Faccioli-appA.zip
https://uwpress.wisc.edu/journals/pdfs/LE-98-2-Faccioli-appB.xlsx
https://uwpress.wisc.edu/journals/pdfs/LE-98-2-Faccioli-appC.pdf

1. Introduction

Stated preference (SP) techniques, and among them discrete choice experiments (DCE), are increasingly used to derive the economic value of changes in environmental goods and services for use in policy appraisals (Johnston et al. 2017). However, one of the main perceived strengths but also limitations of these methods is the fact that they frequently rely on hypothetical valuation scenarios, which are described to respondents for evaluation in a survey. SP researchers have found that alternative presentations of information when designing hypothetical valuation scenarios can impact value estimates (Bergstrom, Stoll and Randall 1989; Boyle 1989; Hoehn and Randall 2002; Rolfe, Bennett and Louviere 2002; Kragt and Bennett 2012). Building on such evidence, some recommendations on information provision in surveys are therefore available for SP researchers. Both Arrow et al. (1993) in the NOAA Blue Ribbon Panel report on contingent valuation and, more recently, Johnston et al. (2017) in their guidance for stated preference studies, recognize the importance of decisions on quantity and type of information provided in the design of SP valuation scenarios. In particular, these authors point to the need for "very careful pilot work and pretesting" (Arrow et al. 1993, p. 51) of information and decision formats "to aid in the development of credible, accurate, relevant, and agreed-upon scenarios" (Johnston et al. 2017, p. 330). Nonetheless, irrespective of the effort invested in the pre-survey validation of the scenario design, several decisions regarding information provision will inevitably remain at the discretion of the researcher, with potential repercussions for welfare estimates. Examples of such decisions might include choices regarding: the contextual factors defining the valuation settings (Tinch, Colombo and Hanley 2015); the amount of information presented to respondents prior to the valuation exercise (Needham et al. 2018); the specifics and dimensionality of the experimental design (DeShazo and Fermo 2002; Luisetti, Bateman and Turner 2011; Kragt 2013; Meyerhoff, Oehlemann and Weller 2015; Glenk et al. 2019);

and the presentation of information that characterizes the hypothetical market (Bateman et al. 2009; Matthews, Scarpa and Marsh 2017; Hassan, Olsen and Thorsen 2018).

This paper investigates the implications for preference and welfare analysis of alternative descriptions (framing) of attribute information in DCEs, which represents a gap in the literature. Specifically, we focus on valence-based framing as one specific type of framing of attribute information. Valence-based framing emerges when normatively equivalent information is presented in a positive or negative light. For example, the outcomes of a conservation policy may result in an increase by 20 percentage points in the probability of seeing wildlife on a given day or in a decrease by 20 percentage points in the probability of not seeing wildlife on a given day. Both descriptions are equivalent in terms of outcomes. The only difference is that the positive is accentuated in one case (seeing wildlife), the negative in the other (not seeing wildlife). There are several arguments why valence-based framing can play an important role in people's decision-making. Compared to positively framed information, negatively framed information tends to affect people more strongly (*negativity bias*) (Rozin and Royzman 2001), encourages individuals to pay more attention to the decision-making process, influences the perception of risks, encourages feelings of regret and can, thus, affect how individuals make choices (Tverksy and Kahneman 1981; Wilson, Kaplan and Schneiderman 1987; Levin and Gaeth 1988). To investigate the role of positive versus negative framing of attribute level changes in DCEs, we draw on data derived from a DCE study assessing the general public's preferences for peatland restoration in Scotland.

2. Literature review

The study of the effect of changes in the decision context, information provision and framing of the decision-making problem has been the focus of many experimental investigations in economics (Gerlach and Jaeger 2016). In several cases, these studies' results have departed from the baseline neoclassical economics assumption that responses of well-informed and rational individuals should be invariant to changes in the decision context, information provision and framing of valuation tasks – unless these changes implied variations in the nature, quantity or price of the good under evaluation. To explain violations of the invariance hypothesis, researchers have relied on alternative theories of choice that relax neoclassical economics assumptions and have strong roots in disciplines such as the behavioral sciences (e.g., psychology) and other social sciences (e.g., political sciences) (Tversky and Kahneman 1981).

Numerous SP environmental valuation studies (detailed in the subsequent paragraphs – from an early study by Samples, Dixon and Gowen (1986) to the recent investigation by Vossler and Zawojska (2020)) have addressed the effects of changes in the decision context and information provision, while only a few publications have investigated framing effects. Below we endeavor what is, to our knowledge, a first classification of this literature (summarized in Fig.1) with the intention to facilitate the positioning of our contribution within the field of existing studies. We make no claim for comprehensiveness of the classification and acknowledge that alternative categorizations are possible and subject to debate, given the different and sometimes contrasting use of the terminology across applications (hence the use of dashed lines in Fig. 1). Producing a more complete and critical review of the literature is, however, beyond the scope of this paper, so we defer this task to future work.

[Fig.1]

In the proposed classification, context effects are the broadest category and refer to a set of factors of the decision environment that have the potential to shift the choice outcome by altering the process by which the decision is made (Thomadsen et al. 2018). Examples include:

- testing for the effect of different preference elicitation formats (e.g., Vossler and Zawojska 2020);
- exploring the role of alternative survey modes (Boyle et al. 2016) and valuation settings, including individual versus group settings (e.g., intra-household decision making and deliberative valuation) (Spash 2007; Bateman and Munro 2009), time-to-think protocols (Cook et al. 2012) and the consideration of different contexts (e.g., timing and location) for preference elicitation (e.g., Tinch, Colombo and Hanley 2015);
- other examples include investigating the role of respondents' emotional states on stated preferences (Hanley et al. 2017);
- studying the influence of order and position effects of information in the valuation exercise (Day et al. 2012; Liebe et al. 2016);
- and altering the choice set dimensionality and degrees of complexity in DCEs (e.g., different number of choice sets, alternatives, etc.) (DeShazo and Fermo 2002; Rolfe, Bennett and Louviere 2002; Caussade et al. 2005; Hensher 2006; Schaafsma and Brouwer 2013; Meyerhoff, Oehlemann and Weller 2015) or varying the ranges of attribute levels used in DCEs (Luisetti, Bateman and Turner 2011; Kragt 2013; Glenk et

al. 2019). Changing the number of attributes in the experiment should, however, rather be interpreted as an information effect, as it provides new or different information.

Information effects are a nested sub-category of context effects and they appear when varying the quantity and/or type of information provided, which can affect respondents' incentives when answering the value elicitation questions (Samples, Dixon and Gowen 1986). In a SP context, changing the amount of (background) information has been achieved by presenting more or less detailed survey descriptions (e.g., Samples, Dixon and Gowen 1986; Bergstrom, Stoll and Randall 1989; Boyle 1989; Bergstrom, Stoll and Randall 1990; Tkac 1998; Hoehn and Randall 2002; Bulte et al. 2005; Czajkowski, Hanley and LaRiviere 2016; Needham et al. 2018). The use of labelled alternatives in DCE surveys (Jin et al. 2017) and of different types of payment vehicles in the valuation exercise (e.g., voluntary donation versus taxes) (Hassan, Olsen and Thorsen 2018) can also generate information effects by conveying additional or different messages to respondents and different incentives to answer the value elicitation questions.[1] Variations in stimuli (visual information *versus*, or in addition to, textual information or different means of visualization) (Cerda et al. 2014; Bateman et al 2009; Matthews, Scarpa, Marsh 2017) can also be subsumed under information effects, given that the use of alternative communication formats may generate differences in the way information is comprehended and retrieved.

The focus of this paper are framing effects, which (in their strictest sense) describe situations where alternative but objectively equivalent descriptions of a decision problem lead to systematically different choices (Frisch 1993).[2] Over the past decades, several studies in different fields in the area of human judgment and decision-making have documented the existence of framing effects (Scheufele and Iyengar 2012). In environmental SP studies, decisions regarding the alternative framing of objectively equivalent information are also frequently required. Examples may include choices concerning the description of: the conservation status of species, which can be presented in terms of chances of survival or of extinction; or the level of likelihood of an event, which can be presented in terms of the chance of success or failure of a policy. However, little is known about the implications of alternative, yet objectively equivalent, descriptions of the environmental change of interest on stated preferences and welfare analysis. Researchers may justify their decisions on scenario and attribute framing by referring to thorough pre-testing and experience. Nevertheless, the specific reasons underpinning the choice between alternative ways of framing are rarely revealed and framing decisions therefore often appear arbitrary.

This is an issue requiring further attention especially in the field of DCEs. Given the increasing interest in this method among practitioners and policy makers (Johnston et al. 2017), it is a pertinent question whether alternative descriptions of attributes and attribute levels can lead to differences in the processing and understanding of attribute information and, perhaps more importantly, to variations in welfare estimates, with potential implications for policy recommendations. While standard economic theory predicts that individuals should be indifferent to alternative presentations of outcome-invariant information, there is (albeit limited) evidence that presenting attribute information in different, yet equivalent, ways can affect welfare estimates. For example, framing attribute information in terms of absolute versus relative but otherwise equivalent changes (Kragt and Bennett 2012), or as certain versus uncertain but else identical outcomes (e.g., Faccioli, Kuhfuss and Czajkowski 2019), affects preferences and willingness to pay in DCEs. The implications of such findings must be carefully evaluated. Differences resulting from framing decisions do not necessarily invalidate SP results. Johnston et al. (2017, p. 328) note that, "[a]s in revealed preference contexts, behavior in SP contexts can vary (according to factors such as [framing]) in ways that are consistent with valid and reliable welfare estimation". We argue that the presence of framing effects should still be of concern to DCE practitioners: welfare estimates obtained under different framings may be used to define a range (i.e., lower and upper bounds) of welfare effects.

In this context, one arguably under-researched type of framing effect that is worth investigating is valence-based framing, which is expected to affect the way individuals understand or process (attribute) information. Valence-based framing effects, as defined in the seminal paper by Levin, Schneider and Gaeth (1998), arise from casting the same information in either a positive or a negative light. Among the different types of valence-based framing manipulations, perhaps the most behaviorally impactful one refers to presenting identical outcomes or goals of a given action either in positive terms (i.e., the opportunity to obtain an outcome that is perceived to be positive) or in negative terms (i.e., the opportunity to reduce exposure to an outcome that is perceived to be negative) (Pleger, Lutz and Sager 2018). It is important to note that such valence-based framing effects can emerge irrespective of a gain-loss framework, where positive framings refer to gains while negative framings refer to losses. Both the positive and negative framings can relate to exactly the same action or behavior and convey information about *either* desirable *or* undesirable outcomes. We follow such an approach to valence-based framing in our study. The idea behind this type of valence-based framing effect is that positively *versus* negatively framed information (as defined above) can influence the persuasiveness of the message and therefore be more or less effective in promoting a given behavior.

There is evidence that "negative information has a systematically stronger impact on judgment than objectively equivalent positive information" (Levin, Schneider and Gaeth 1998, p. 176), something which is referred to as 'negativity bias' (Rozin and Royzman 2001; Pleger, Lutz and Sager 2018). Based on the results of medical studies, negatively framed information tends to raise stronger emotional reactions, with a greater stimulation of the autonomic nervous system (Hochman and Yechiam 2011). There is a tendency among people to prioritize negative information over positive information (Kahneman and Tversky 1979; Knetsch 2010). Negatively framed information has also been found to stimulate more effortful and thorough cognitive processing than positively framed information and to increase the allocation of attentional resources to the task (Avineri and Waygood 2013). Framing outcomes in a positive or negative way can also influence the perception of risks. A positive or negative framing of outcomes can thus affect how individuals make choices. In addition, alternative framing of information can also be associated with different feelings of regret in decision-making, namely with dissimilar perceptions of guilt that can result from making the wrong choice. As discussed in Levin, Schneider and Gaeth (1998), negatively framed information can increase individuals' perceived risk of incurring an outcome that is regarded as negative or less desirable. In these settings, individuals are therefore expected to act more cautiously and to more likely adopt the desirable behavior to avoid regretting their choices – a phenomenon that could be associated with regret minimization as defined in Chorus (2010).

As far as the authors are aware, the only DCE study focusing on testing valence-based framing of attribute levels in the valuation of environmental benefits is Kragt and Bennett (2012).[3] In their study, these authors focus on the environmental outcomes of alternative catchment management programs. They ask respondents to compare three scenarios, 20 years into the future, with or without management programs. Using a split sample approach, they describe one attribute, the level of rare native species in the catchment, either in terms of the number of rare species present (remaining) or in terms of an equivalent number of losses of rare species avoided. In their study, Kragt and Bennett (2012) find that describing the levels of a DCE attribute in terms of avoided losses rather than species present increases the willingness to pay (WTP) estimates. This shows that attribute framing effects can significantly influence welfare estimates. The experimental variation in the specific framing in the Kragt and Bennett (2012) study, however, confounds effects of valence-based framing due to negativity bias with effects of valence-based framing related to loss aversion. Loss aversion implies that people tend to overvalue losses in comparison to equivalent gains (Kahneman and Tversky 1979), offering a convincing explanation for the findings of the Kragt and Bennett (2012) study. Specifically, the 'loss of species' framing in Kragt and Bennett (2012) emphasizes the *current* condition as a relevant reference point, with changes due to catchment management representing losses (or no losses) relative to this point.[4] In contrast, the 'species present' framing rather emphasizes the number of species remaining relative to a *future* status quo, with changes due to catchment management representing gains relative to this point. The expectation of a steeper value function when losses relative to the current condition are emphasized provides a plausible explanation for an increase in WTP in the negative 'loss of species' framing, compared to the framing that reports the number of 'species present' in the future condition.

Drawing on data on peatland restoration preferences in Scotland under climate change, the present paper relies on a split sample approach with two treatments (each emphasizing positively or negatively framed information) to test for and provide new insights into the effects of valence-based framing of attribute levels in DCE studies. Unlike Kragt and Bennett (2012), in both treatments of our split sample experiment, changes are clearly presented as improvements relative to the same reference points, so effects on choice behavior and preferences can be clearly attributed to valence-based framing effects, specifically negativity bias, without the risk of confounding valence-based framing with loss aversion. To one group of respondents, we described the positive frame in terms of the 'share of peatlands in good condition' and, to another group of respondents in the negative frame treatment, we presented quantitatively equivalent information in terms of the 'share of peatlands in bad condition'. In addition to Kragt and Bennett (2012), we also explore the implications of valence-based framing for Benefit-Cost appraisal and decision-making, as well as the repercussions in terms of the predominant choice paradigms adopted by individuals. Given expectations that regret might drive choices depending on the framing of the attribute information, we compare decision-making based on the standard random utility maximization (RUM) framework with an alternative approach based on the random regret minimization (RRM) model. Previous studies (Chorus 2011) have found that RUM and RRM models can lead to different estimates of elasticities, taste parameters and predicted market shares. Hence, mistakes in the choice of the relevant approach to model data can lead to the estimation of biased results, with implications for policy analysis.

3. Methodology

Our empirical application relies on a split sample approach applied to a DCE study focusing on hypothetical peatland restoration programs in Scotland (UK).

Case study background

Peatlands cover approximately 20% of Scotland's land area (Bruneau and Johnson 2014). However, as a result of historic human-induced conversion to more productive land uses, such as forestry or agriculture, peatland ecosystems have suffered severe degradation (Rotherham 2011). Today, more than two thirds of Scottish peatlands are in degraded condition (Bain et al. 2011). This compromises the capacity of these ecosystems to provide important environmental services, such as water regulation, healthy habitat provision for wildlife species and especially carbon sequestration. Over the past decade, interest in peatland restoration and consequently in the design of socially desirable policies has been increasing among policy-makers. With this comes a growing demand for information on benefits, costs and social acceptability of restoration efforts (Scottish Natural Heritage 2015). Past research has shown that the benefits of peatland restoration policies are likely to outweigh the associated costs (eftec 2015; Glenk and Martin-Ortega 2018). However, little is known about preferences for the longer-term impacts of peatland restoration. This is especially important given concerns raised about the future of peatlands under climate change.

Warmer summers are expected to shrink the bioclimatic space for blanket bogs (Gallego-Sala et al. 2010; Gallego-Sala and Prentice 2013), put greater stress on existing peatlands (Ise et al. 2008; Gallego-Sala and Prentice 2013) and lead to further degradation of these ecosystems under climate change. More degraded peatlands will also mean that a significant share of carbon will be emitted (rather than sequestered) by these ecosystems, which will challenge the attainment of global emission reduction targets (Leifeld, Wüst-Gallery and Page 2019). Predictions show that by as soon as 2050, more than half of the carbon currently stored in Scottish blanket bogs will be at risk of loss, with even higher risks expected for the second half of this century (Ferretto et al. 2019). A main limitation of these predictions is, however, that they rely on static models that ignore, for example, positive and negative feedbacks and associated non-linear dynamics, or inertia. As a result, the response of peatlands to climate change, the time span over which changes occur and the extent to which climate change will accelerate or slow down changes in peatlands are all uncertain (Page and Baird 2016). Nonetheless, it is expected that peatlands in healthy conditions will show greater resilience and adaptation to changes in the climate (Gallego-Sala and Prentice 2013). This implies that peatland sites that are in poor ecological condition (i.e., sites that are continually degrading) are likely more susceptible to future changes in climate, relative to sites that are in good ecological condition. Consequently, early restoration of degraded sites will give peatlands more time to restore their functioning and increase the chances for these ecosystems to be more resilient to future climate change, with positive results also in terms of curbing global warming (Günther et al. 2020).

Choice experiment design

Our DCE survey asks respondents to choose between future (hypothetical) peatland restoration alternatives to be implemented across Scotland. Two alternatives, varying across choice situations following an experimental design, describe the outcomes of additional restoration programs, while a third alternative, constant across the choice situations, shows the business as usual (BAU) scenario reflecting no additional restoration. Each alternative is described by three attributes.

The first attribute reflects the change in peatlands' ecological condition achieved by 2050. Based on experts' predictions, the ecological condition of peatlands will deteriorate in the absence of additional restoration efforts, while it may improve through extra restoration. In our survey, we relied on the classification of peatlands' ecological condition provided in Martin-Ortega, Glenk and Byg (2017) that combines information on land use, indicators of ecosystem functioning (such as height of water table or presence of indicators species) and ecosystem service provision with respect to wildlife, water quality and greenhouse gas emissions to classify peatlands into bad, intermediate and good ecological condition. Martin-Ortega, Glenk and Byg (2017) argue that their classification of peatlands' ecological condition is scientifically robust and can be widely understood by members of the public in a survey using a combination of text and visual aids. In our questionnaire, the future share of peatlands in each condition was estimated in consultation with Scottish peatland experts. In contrast to the 2017 status quo (SQ) situation, characterized by 30% total share of peatlands in good condition, 30% in bad condition and 40% in intermediate condition, experts predict that, by 2050, if current land use trends continue (i.e., in the BAU scenario), 20% of peatlands will be in good ecological condition, 40% in bad ecological condition, with the remainder (40%) in intermediate condition.

The second attribute considered in our survey refers to the timing (between 2017 and 2050) when additional restoration (if present) would be implemented – which determines the long-term effects on peatlands' resilience under climate change (as explained in the Case study background sub-section in Section 3 and below). The third attribute in our DCE is a tax that all Scottish households would have to pay annually (from 2017 until 2050) to a Peatland Trust to contribute to the funding of additional restoration programs. No extra cost would have to be paid in the BAU scenario.

For the purpose of this paper (i.e., to explore the sensitivity of preferences and WTP to alternative framings of attribute levels), we considered two split samples, each presenting different descriptions of equivalent peatland restoration outcomes. To one group of respondents, we presented information in terms of the share of peatlands in *good* ecological condition (good framing treatment) and, to the other group of respondents, we described outcomes in terms of the share of peatlands in *bad* ecological condition (bad framing treatment). More precisely, in the good framing treatment, respondents were informed that extra restoration efforts would result in a given *increase* in the share of peatlands in good condition by 2050, while in the bad framing treatment, respondents were confronted with restoration projects that would result in an equivalent *decrease* in the share of peatlands in bad condition by 2050. Similarly, the absence of extra restoration was assumed to generate a given *decrease* in the share of peatlands in good condition in the good framing treatment and an equivalent *increase* in the share in bad condition in the bad framing treatment. In both treatments, respondents were informed that "peatlands that are in bad ecological condition would be restored, with the aim of achieving good ecological condition in the future" and, *vice versa*, they were told that, in the absence of additional restoration, peatlands would shift from good to bad condition. This way, any variation in peatlands' condition was explained as a shift from bad to good condition or *vice versa* (while assuming, by design, that the share in intermediate condition is not affected). In both treatments, respondents are therefore confronted with exactly the same degree of environmental change, just framed in different ways. By randomly assigning respondents to one of the treatments, it is possible to study the effect of positive *versus* negative framing of environmental outcomes. Table 1 presents the attributes employed in the good and bad framing DCEs, together with the corresponding attribute levels.

[Table 1]

In both split samples, we additionally presented information on the share of peatlands in either good or bad ecological condition (depending on the treatment) that would be achieved by 2080. In the survey, respondents were informed that, due to climate change, the ecological condition of peatlands towards the end of the century will depend on the extent of peatland restoration achieved by 2050 (COND_2050) and the timing of restoration (TIME). Expectations, developed with peatland ecology experts, are that long-term restoration success will be higher if peatland restoration is carried out earlier, following the rationale on the long-term resilience of peatlands under climate change outlined in the Case study background sub-section in Section 3. Earlier restoration efforts are in fact likely to increase the chances that restored peatlands will be more resilient to climate change pressures after 2050 (when restoration ends), while delaying restoration efforts is expected to more likely result in restored peatlands being more vulnerable to climate change stresses, and therefore degradation, after restoration ends. To add realism to the presented scenarios, we also informed respondents that peatlands' ecological condition by 2080 will depend on the severity of climate change, which is uncertain. Two possible climate change scenarios were therefore considered: a more severe and a less severe one. Hence, for each restoration program, two outcomes were presented for 2080, one for each possible climate change scenario.[5] Note that the uncertainty information does not represent an additional attribute. The outcomes achieved by 2080 are merely a function of the extent of peatland restoration by 2050 and the timing of restoration in the period up to 2050.

In both the good and bad framing treatments, the experimental design used to create alternative combinations with different attribute levels relies on a D-efficient Bayesian design, optimized for the multinomial logit (MNL) model. The priors for this design are based on the MNL model coefficients estimated from responses collected at the pilot stage (N=93). The final design comprises of 48 choice tasks, allocated to six blocks, which implies eight choice tasks per respondent. Figure 2 shows an example choice task for each of the two split sample treatments.[6]

[Figure 2]

The sample

The survey was administered online via a professional market research company during July-August 2017 to a sample of 868 Scottish residents. To ensure that the sample represents the

Scottish population, a quota-based approach was employed to select individuals from the online panel, with age and gender as 'hard quotas'. As reported in Table 2, none of the differences in the socio-demographics between good framing and bad framing treatments is statistically significant at the 5% level.

[Table 2]

Modelling

Responses to the discrete choice experiment are modelled based on the random utility maximization (RUM) framework (McFadden 1974). In each choice set, respondents are assumed to select the alternative that yields the highest utility. The utility that respondent *n* obtains from a given restoration program *j* can be specified as:

$$U_{nj} = \beta_n^{\prime m}(X_{nj}^m + \boldsymbol{\beta}_\mathbf{n}^{\prime -\mathbf{m}}\mathbf{X}_\mathbf{nj}^{-\mathbf{m}}) + \varepsilon_{nj} \quad [1]$$

where X_{nj}^m is the level of the monetary attribute and $\mathbf{X}_\mathbf{nj}^{-\mathbf{m}}$ the vector of non-monetary attributes describing alternative *j* faced by respondent *n*; ε_{nj} is the error term that captures factors unobserved by the econometrician – this term follows a Gumbel distribution and has variance Var(ε_{nj})= α_n^2 $(\pi^2/6)$, where α_n is the scale parameter, which reflects the variance of the error term in relation to the magnitude of all coefficients; $\beta_n^{\prime m}$ is the parameter associated with the monetary attribute; $\boldsymbol{\beta}_\mathbf{n}^{\prime -\mathbf{m}}$ is the vector of parameters that express individuals' preferences for the non-monetary characteristics of the restoration program. To account for preference heterogeneity, both $\beta_n^{\prime m}$ and $\boldsymbol{\beta}_\mathbf{n}^{\prime -\mathbf{m}}$ are assumed to be individual-specific random coefficients that follow a given parametric distribution specified by the researcher. In our case, a normal distribution, with mean **b** and standard deviation **σ**, is used for all parameters, excepted for cost, which is assumed to be log-normally distributed to restrict the sign of this coefficient to be the same for all respondents. Therefore, the negative of the cost variable is considered in the utility function. The multiplication of all attributes by the parameter of the monetary variable ($\beta_n'^{m}$) allows to directly interpret the vector of preference parameters ($\boldsymbol{\beta}_{\mathbf{n}}'^{-\mathbf{m}}$) as a vector of implicit prices (marginal WTPs) and therefore to specify the model in WTP-space. Our model additionally allows for full correlation of the random parameters, thus representing a mixed logit model (MXL; McFadden and Train 2000; Train 2009) in WTP-space with correlation.

We used a Swait and Louviere (1993) test to obtain a first indication of whether framing the attribute levels in terms of equivalent shares of peatlands in good (or bad) condition overall affects individuals' preferences. Performing this test requires estimating separate models for the good and the bad framing split samples, as well as a pooled model, additionally allowing for differences in scale (α_n) across the split samples.[7] To test whether the null hypothesis of overall parameter equality across treatments (H_0: $\boldsymbol{\beta}_{\mathbf{good}}^{\mathbf{-m,m}} = \boldsymbol{\beta}_{\mathbf{bad}}^{\mathbf{-m,m}} = \boldsymbol{\beta}_{\mathbf{pooled}}^{\mathbf{-m,m}}$) can be rejected, we employed the likelihood ratio (LR) test statistic ($-2 * [LL_{pooled} - (LL_{good} + LL_{bad})]$), which compares the values of the log-likelihood (LL) functions of the estimated models (for each separate good and bad treatment, as well as the pooled data) and is chi-squared distributed with *k+1* degrees of freedom, where *k* is the number of model parameters and the additional degree of freedom is because we allow α_n to vary.

Furthermore, to check whether the use of a good or bad framing equally affects the preferences for all attributes or it affects some attributes more than others, we used a two-tailed Wald test ($\frac{\widehat{\boldsymbol{\beta}}\mathbf{bad} - \widehat{\boldsymbol{\beta}}\mathbf{good}}{\sqrt{st.err.(\widehat{\boldsymbol{\beta}}\mathbf{bad})^2 + st.err.(\widehat{\boldsymbol{\beta}}\mathbf{good})^2}}$). As part of this test, we investigated the significance of the differences in WTP across treatments for each of the estimated parameters and focused on mean WTP given its wide use for policy purposes (Bateman et al. 2006).

To illustrate the policy implications of adopting a good framing or a bad framing of attribute information, we also carried out an illustrative Benefit-Cost Analysis, using the benefit estimates based on the WTP-space model results in each of our treatments (described in more details in the Discrete choice experiment results' sub-section in Section 4) combined with information on peatland restoration costs, based on Glenk et al. (2020) and Moxey and Moran (2014). For this analysis, we considered a variety of scenarios involving different levels of peatland restoration up to 2050 (i.e., 10%, 20% or 30% increase, in absolute terms, in the share of peatlands in good condition over the status quo (SQ), corresponding to the restoration of 157,540ha, 315,080ha and 472,620ha of peat, respectively) and different timings of intervention (i.e., early, midway or late). In each scenario, we assumed that restoration efforts would be evenly distributed over the period during which the intervention would take place (i.e., 2017-2027 for early, 2028-2038 for midway and 2039-2050 for late) and, once the target amount of peatlands to restore would be achieved (i.e., 157,540ha, 315,080ha and 472,620ha), this level would be maintained until 2050. In each scenario, we hypothesized that no benefits and no costs would occur before the start of the intervention. The benefits of the interventions were calculated by converting the mean WTP estimates for the different restoration scenarios into annual per hectare values. This was achieved by dividing the WTP values reported in Table 3 (which are per household and year) by the total amount of hectares to be restored in the scenario of interest (i.e. a 10%, 20% or 30% absolute increase in the share of peatlands in good condition over the SQ), and then by aggregating the resulting figure over the relevant population of 2.4 million households (Scottish Government 2018). In addition, an annual premium was also considered to capture the benefits associated with earlier restoration. This value corresponded to the mean WTP estimate per household and year reported in Table 3 for early or midway restoration (with late as the base category), which we then aggregated over the total number of households in Scotland. Realistic estimates of restoration costs (based on Glenk et al. (2020) and Moxey and Moran (2014)) were used in the analysis, including capital costs (assumed to be £1,227/ha) and recurring costs reflecting management costs and opportunity costs (assumed to be £300/ha).[8] Annual costs and benefits were subsequently discounted by means of appropriate discount rates (3.5% until 2047 and 3% for 2048-2050, based on the UK Government's advice (H.M. Treasury 2018)) to calculate the Net Present Value (NPV) and Benefit/Cost (B/C) ratios for each scenario.

In addition, to test whether alternative framings of attribute information have repercussions on the decision-making strategy adopted by respondents, the estimated results based on the RUM framework were compared with those obtained by considering a random regret minimization (RRM) behavior. RRM models are based on the idea that respondent *n*, when choosing, tries to minimize the regret experienced when one or more non-chosen alternatives outperform the chosen one, in terms of one or more attributes *k* (van Cranenburgh, Guevara and Chorus 2015). Regret is computed starting from the binary comparison between the alternative considered *j* and its competitor alternative *i* for all attributes *k*. The RRM model postulates that, if respondents are regret-minimizers, they try to avoid choosing an alternative that performs worse than a competing one in terms of one or more attributes (**x**). When information is negatively (as opposed to positively) framed (e.g., peatlands' condition is expressed in terms of the share in bad condition), respondents may be more likely to act as regret-minimizers, by perceiving a situation as less desirable and by taking more precautionary decisions to avoid choices that may lead to regret. To avoid the regret of not choosing an option which could lead to better results for peatlands in the longer term, respondents in our negatively framed scenario may therefore choose the BAU alternative and, to some extent, late restoration programs, less often compared to a positively framed scenario.

For our purposes, we rely on two flexible generalizations of the classical RRM model presented in Chorus (2010):

the μ-RRM model:

$$RR_{nj}^{\mu RRM} = \sum_{i \neq j} \sum_k \ln\left(1 + \exp\left(\frac{\boldsymbol{\beta}_\mathbf{k}}{\mu}[\mathbf{x_{nik}} - \mathbf{x_{njk}}]\right)\right) + \varepsilon_{nj} \quad [2]$$

and the G-RRM model:

$$RR_{nj}^{G-RRM} = \sum_{i \neq j} \sum_k \ln\left(\gamma + \exp\left(\boldsymbol{\beta}_\mathbf{k}[\mathbf{x_{nik}} - \mathbf{x_{njk}}]\right)\right) + \varepsilon_{nj} \quad [3]$$

where RR refers to the random regret for the respondent *n*. Both models are particularly convenient for the purposes of our study because they allow drawing conclusions regarding whether respondents' behavior is closer to random regret minimization or random utility maximization (van Cranenburgh, Guevara and Chorus 2015). Information about the profundity (or level) of regret in the data is obtained by estimating the parameter μ in the μ-RRM model and the parameter ɣ in the G-RRM model. A relatively large μ parameter (or a value of ɣ close to 0) signals relatively mild profundity of regret and suggests that the model predicts choice behaviors close to the linear-additive random utility maximization model. *Vice versa*, a relatively small μ parameter (or a value of ɣ close to 1) signals a relatively strong profundity of regret and indicates the presence of random regret minimization behaviors in the data (Chorus 2010).

4. Results

Discrete choice experiment results[9]

The results of the RUM-based DCE model are presented in Table 3. Regardless of the framing, the mean coefficient related to the alternative specific constant for the BAU alternative is negative and significant. This means that on average respondents tend to systematically favor restoration program alternatives rather than the BAU alternative for reasons not already captured through the attribute coefficients. Regardless of the framing, preferences and WTP tend to increase with the scope of restoration, but at decreasing rates, demonstrating internal sensitivity to the scope of the valued environmental change and diminishing marginal utility. This is indicated by the coefficients of the three dummy variables associated with the attribute COND_2050, which take value one (else zero) when the share of peatlands in good condition by 2050 increases by either 10%, 20% or 30% (in absolute terms), compared to the SQ level in 2017 (the reference category). Please note that, for modelling purposes, we converted information on the share of peatlands in bad condition into the equivalent share in good condition. Regarding the timing of restoration, both in the good and bad framing treatments, respondents indicate strong aversion to the postponement of restoration efforts. Indeed, study participants would be prepared to pay substantially and significantly more if restoration was implemented early (between 2017 and 2027) or midway in the program (between 2028 and 2038), rather than late (between 2039 and 2050). As expected, the coefficients of the negative cost attribute (Table 3 reports the coefficients of the normal distribution underlying the log-normally distributed monetary coefficients, β_n^m) are significant and, by design, they lead to positive log-normally distributed mean and standard deviation estimates.

Based on the above, the good and bad framing treatments therefore seem to share common patterns in terms of preference and WTP structure. However, the results of the Swait and Louviere (1993) test (LR statistic= 77.11; p-value=<0.01, reported in the tab "Tables 3-4" in the Excel file in Appendix B) offer a first indication of the existence of treatment-specific differences by allowing to reject the null hypothesis of overall parameter equality across the good and bad framing split samples.

[Table 3]

Further checks are however needed to understand the significance and nature of the differences in WTP across the treatments. Towards this aim, we conducted a two-sided Wald test to compare (one-by-one) each of the mean WTP values in Table 3 across the good and the bad framing models. The results of this test (reported in Table 4) show that overall differences between the good and bad framing treatments can largely be attributed to a small number of parameters. Regardless of the framing, respondents are willing to pay similar amounts to move away from the BAU scenario of no restoration, to increase the share of peatlands in good condition by either 10% or 20% (in absolute terms) over the SQ level and to restore peatlands midway in the program (between 2028 and 2038). However, sample respondents are willing to pay significantly different amounts depending on the framing to achieve the highest level of restoration of peatlands by 2050 (i.e., 30% increase in good condition, in absolute terms, over the SQ level). For this level of change, they would be prepared to pay £103.41/household/year in the bad framing treatment and £80.04/household/year in the good framing, with this difference being significant at 5% level (p-value= 0.03). Similarly, for restoration to take place early in the program, study participants are willing to pay a much higher value when information is negatively framed (£114.56/household/year) rather than positively framed (£88.40/household/year), with this difference also being significant at the 5% level (p-value= 0.01).

[Table 4]

Illustrative Benefit-Cost Analysis

To understand the policy relevance of our results, we additionally carried out an illustrative Benefit-Cost Analysis considering a variety of scenarios with different levels of peatland restoration up to 2050 and different timings of intervention, as described in more details in the Modelling sub-section in Section 3. The NPV and B/C ratios for each of the scenarios explored are summarized in Table 5 for the good and bad framing treatments (with the underlying calculations reported in Appendix B).

[Table 5]

Based on the results reported in Table 5, all but one of the peatland restoration scenarios yield mean net welfare gains (i.e., NPV>0 and B/C ratios>1). Regardless of the framing, the highest NPV and B/C ratios are associated with smaller scale restoration projects taking place early in the period up to 2050, while late restoration is generally associated with the lowest NPV and B/C ratios. This reflects diminishing marginal utility, while assuming constant cost per hectare as the scale of restoration increases. Important differences, however, also exist across treatments. As expected, given the results in Table 3, the NPV and B/C ratios are higher in any given scenario in the bad compared to the good framing treatment, with more sizeable discrepancies across treatments when the policy involves larger scale or early restoration. In particular, while in the bad framing treatment the NPV is positive and B/C ratios greater than one in all the restoration scenarios explored, in the good framing treatment this is always the case except for one scenario, characterized by an increase by 30% (in absolute terms) in the peatlands restored to good condition between 2039 and 2050 (late in the program). For this particular scenario, and based on the results of our Benefit-Cost appraisal, valence-based attribute framing effects result in different recommendations regarding the appropriateness (or otherwise) of undertaking a restoration program.[10] Even if differences for the remainder of the scenarios are small to modest, they may still influence the ranking of the restoration projects based on the Benefit-Cost ratios.

RUM versus RRM

To explore whether respondents follow different behavioral patterns across the two framing treatments, we test if data best adjust to random utility maximization (RUM) or rather random regret minimization (RRM) behavior. Specifically, we estimate μ-RRM and G-RRM models[11] to determine (through the calculation of μ and γ, respectively) the extent to which respondents' behavior approximates a RUM or a RRM pattern. Following the recommendations of van Cranenburgh, Guevara and Chorus (2015), we estimate two separate μ-RRM and G-RRM models for each split sample to avoid potential problems when pooling datasets. In addition, given the complexity of the estimation process, a simple modelling approach is considered, based on the MNL model.[12] The results of the μ-RRM and G-RRM models for the good and bad framing treatments are reported in Appendix C, along with the RUM-based MNL models for each treatment, for comparison purposes.

The results of the RRM models indicate that there is little evidence of strong random regret minimization patterns in both treatments. This is indicated by a relatively high, albeit not significant, value of the μ parameter (5.90) and a relatively low estimate of ɣ (0.22, with p-value equal to 0.81) in the good framing treatment, and by a very high estimate of the μ parameter (76.02) and a very low regret-weighted value of ɣ (0.00, with p-value equal to 1.00) in the bad framing treatment. Based on these findings, in both treatments there are hardly any differences between the regret experienced when choosing an alternative performing worse than a non-chosen alternative and the rejoice experienced when the chosen alternative performs better than the non-chosen one.

The above conclusions are reinforced when comparing the log-likelihood (LL) functions estimated for the different models. Both for the good and bad framing treatments, the LL functions estimated for the μ-RRM and the G-RRM models (reported in Appendix C) do not offer significant improvements in fit relative to the LL function estimated for the MNL model based on RUM. Similarly, compared to a pure RRM model, which assumes strong random regret minimization behavior (full results and LL function reported in the tab "Pure RRM" in Appendix B), the RUM-based MNL model fits the data significantly better.

5. Discussion

There is extensive evidence that responses to discrete choice experiments (DCEs) are reference-dependent and not context-free (Hess et al. 2017). This study investigates the implications of alternative attribute framing and, in particular, valence-based framing, a largely neglected topic within the stated preference valuation literature. We show that differences in the framing of attributes – whether equivalent environmental outcomes are described in a positive or negative frame – can affect stated preferences. This main finding is in line with previous evidence from the behavioral and decision-making literature that choices may shift if equivalent outcomes are framed differently. In our case study, we find considerable differences in willingness to pay for the scope and timing of peatland restoration. Our results show that people tend to be willing to pay significantly more for the highest level of peatland restoration and early action when outcomes are framed in terms of the share of peatlands in bad ecological condition, rather than the share in good condition. This result aligns with expectations based on the behavioral science literature that "negative information has a systematically stronger impact on judgment than objectively equivalent positive information" (Levin, Schneider and Gaeth 1998, p. 176).

The implications of these findings for policy-making are non-negligible: based on the results presented in the Illustrative Benefit-Cost Analysis sub-section in Section 4, a positive or negative framing of attribute information can lead, in specific circumstances, to different policy recommendations. While in the majority of cases considered, the implementation of peatland restoration is clearly socially desirable, this is not always the case. Especially in those scenarios where B/C ratios are close to the threshold of one, differences in the estimated benefits used in the analysis due to the consideration of alternative framings might flip policy recommendations. Based on our analysis, this is more likely to happen: 1) when policies involve late restoration (as B/C ratios are the lowest and generally around 1 when interventions are postponed) and 2) when information is positively framed, given the systematically lower NPV and B/C ratios in the good compared to the bad framing treatment. For example, our analysis shows that a policy to restore 30% of peatlands to good condition in the period 2039-2050 (late in the program) would generate net welfare benefits and therefore should be pursued, based on the bad framing treatment results. However, implementing exactly the same policy would not be desirable based on the good framing treatment findings, as restoration costs would exceed the benefits. Contrasting policy decisions would have major implications for the sustainability of peatlands in the longer term, given that the share restored to good condition by 2050 and the timing of intervention influence peatlands' resilience against future global warming and their capacity to provide ecosystem services, including carbon sequestration, which in turn would have implications for climate change.

An additional contribution of our study is to shed more light on whether framing effects have any impact on the behavioral choice process adopted by individuals. Specifically, we compare, across the good and bad framing treatments, whether choices are aligned with either the standard random utility maximization or the random regret minimization frameworks. Our results suggest that presenting attribute levels using a positive *versus* negative framing does not encourage shifts in the behavioral choice axioms adopted by individuals. Based on our findings, there is no strong evidence in favor of random regret minimization behavior among respondents, especially in the bad framing treatment. This may at first be interpreted as a departure from previous behavioral science evidence (Levin, Schneider and Gaeth 1998). However, it can in part also be due to differences in the study of the problem. In Levin, Schneider and Gaeth (1998), the negative framing of information is found to encourage feelings of regret amongst people especially when bad outcomes are the result of an undesirable action. Conversely, in the present study, bad outcomes are mostly occurring as the result of not performing an action (i.e., no additional restoration). This might explain why feelings of regret are not accentuated within our data.

At least in the context of our study, our findings suggest that using a standard random utility maximization framework for the modelling of data is justified, regardless of the framing of attribute information. This does not mean that investigating the existence of random regret minimization behaviors arising from context effects in stated preference studies is not worth pursuing. Even if random regret minimization models have been scarcely investigated in environmental economics (Thiene, Boeri and Chorus 2012), are not solidly rooted in microeconomic theory and offer only limited possibilities to estimate reliable welfare measures (Dekker and Chorus 2018), the use of these models is increasingly advocated to improve the behavioral realism of the decision-making process and, potentially, offer richer insights to policy-makers. For example, random regret minimization models are particularly suitable to capture choices for so-called 'compromise alternatives', that is, options that score reasonably well on all factors rather than extremely well on some but badly on others (Chorus 2011).

The above results also point to other areas of further research. While our study can be conceived as a first step to explore the behavioral patterns adopted by respondents when choosing between alternatives framed in different yet equivalent ways, more needs to be understood on the cognitive implications. Recent DCE studies have shown that the way in which respondents attend to information may affect their decisions and that ignoring information processing strategies can bias the results of DCE surveys (e.g., Campbell, Hensher and Scarpa 2011; Glenk et al. 2015). Further research is needed to understand *whether* and, if so, *how* different attribute framing in DCEs can encourage different information processing strategies. An obvious starting point could be the analysis of attribute non-attendance. In addition, despite being presented with objectively equivalent information in both treatments, respondents in our survey might still have applied subjective weights to the scenarios. Exploring the role of individual perceptions as possible mediating factors remains something to be further investigated as part of future work to better understand framing effects.

It remains also to be tested and better understood whether the conclusions drawn regarding valence-based framing effects can be generalizable or are sensitive to the specific context considered in our empirical application. With the data used in the present study, it is not possible to know whether people's responsiveness to positively versus negatively framed information might be sensitive to e.g., the use of different formats to present attribute information (graphical *versus* tabular), the time horizon considered or the presence of uncertainty. While Kragt and Bennett (2012) found that valence-based framing is also present when looking at shorter-term future scenarios that are described as certain, more formal testing to confirm the generalizability of the results is needed.

6. Conclusions

This paper demonstrates that a positive or negative framing of otherwise identical environmental outcomes can affect preferences and willingness to pay in stated preference studies. By doing so, our research highlights the role of previously neglected psychological and behavioral factors in the study of people's preferences and welfare measures. It therefore contributes to an ongoing, but still limited, field of research within the stated preference valuation literature, incorporating psychology and behavioral sciences into the study of the economic demand for environmental goods (Croson and Treich 2014; Hanley and Czajkowski 2019).

Our findings have implications for the design of stated preference studies and should promote increased recognition and awareness among discrete choice experiment practitioners that attribute framing decisions exist and that these decisions – which are often arbitrary – can have consequences on welfare measures. There are ample examples of alternative attribute framing possibilities in environmental settings, for instance, in the context of ecosystem restoration and biodiversity conservation (as exemplified by Kragt and Bennett (2012) and this paper) or when communicating outcome uncertainty (e.g., Glenk and Colombo 2011; Glenk and Colombo 2013; Rolfe and Windle 2015; Lundhede et al. 2015; Faccioli, Kuhfuss and Czajkowski 2019), where framing may relate to probabilities of either success or failure. More widely, alternative attribute framing possibilities are also common in non-environmental settings, including marketing (e.g., fat-free *versus* full-fat content), transport (e.g., available *versus* occupied seats on public transport), health (e.g., probability of vaccine success *versus* failure) or energy (e.g., energy/money saved *versus* used/spent when adopting different appliances).

Our results do not permit a definite judgement on whether employing a positive or a negative framing of attributes should be preferred. It is debatable, however, whether this information would indeed be desirable, as it might open the door to preference manipulation – a problem for project appraisal (Sudgen 2005) – by encouraging the use of specific wording when presenting policy options with the intention to either increase or decrease public support, as convenient. Intuitively, “neutral” descriptions of attribute changes should be prioritized relative to descriptions that imply valence framing. However, when this is not possible, we suggest that practitioners, budget permitting, offer alternative attribute framing for evaluation to respondents and use potentially arising differences to define lower and upper bounds of welfare estimates. Such an approach could be useful to provide more robust welfare evidence by confirming decisions in favor (or against) the implementation of given policies, irrespective of attribute framings. In addition, when there is disagreement in policy recommendations depending on the framing, this approach could be useful to highlight areas of uncertainty where more evidence needs to be collected regarding the profitability of the intervention. If testing for multiple framing effects is not possible within the available budget, undertaking extensive focus group discussions and careful pretesting is a minimum requirement to gauge the influence of alternative attribute framing on respondents' preferences.

Acknowledgements

This research was funded by the Scottish Government Rural Affairs and the Environment Portfolio Strategic Research Programme 2016–2021 and it was supported by the Natural Environment Research Council (NERC) through the SWEEP project [grant number NE/P011217/1] and through the project ‘Understanding ecosystem stocks and tipping points in UK peatlands’ [grant number NE/P00783X/1]. Authors are grateful to Julia Martin-Ortega, Christoph Schulze, Rebekka Artz, Anja Byg, Jacqueline Potts, Paula Novo and Carol Kyle for their help at various stages of this research. The authors are thankful to the attendees of the Environmental Choice (ENVECHO) network workshop, of the LEEPin19 Meeting of International Excellence in Environmental and Resource Economics, of the 24th Annual Conference of the European Association of Environmental and Resource Economists (EAERE), of the 2019 International Choice Modelling conference and to colleagues at the Land, Environment, Economics and Policy (LEEP) Institute at the University of Exeter for constructive feedback on previous versions of this work.

References

Arrow, Kenneth, Robert Solow, Paul R. Portney, Edward E. Leamer, Roy Radner, and Howard Schuman. 1993. *Report of the NOAA Panel on contingent valuation*. Federal Register 58(10): 4601-4614

Avineri, Erel, and E. Owen D. Waygood. 2013. “Applying valence framing to enhance the effect of information on transport-related carbon dioxide emissions.” *Transportation research part A: policy and practice* 48: 31-38.

Bain, C.G., A. Bonn, R. Stoneman, S. Chapman, A. Coupar, M. Evans, B. Gearey, M. Howat, H. Joosten, C. Keenleyside, J. Labadz, R. Lindsay, N. Littlewood, P. Lunt, C.J. Miller, A. Moxey, H. Orr, M. Reed, P. Smith, V. Swales, D.B.A. Thompson, P.S. Thompson, R. Van de Noort, J.D. Wilson, and F. Worrall. 2011. *IUCN UK Commission of Inquiry on Peatlands*. Published by the IUCN UK Peatland Programme. Edinburgh, UK.

Bateman, Ian J., Brett H. Day, B.H., Stavros Georgiou, and Iain Lake. 2006. “The aggregation of environmental benefit values: welfare measures, distance decay and total WTP.” *Ecological Economics* 60(2): 450-460.

Bateman, Ian J., Brett H. Day, Andrew P. Jones, and Simon Jude. 2009. “Reducing gain–loss asymmetry: A virtual reality choice experiment valuing land use change.” *Journal of Environmental Economics and Management* 58(1): 106-118.

Bateman, Ian J., and Alistair Munro. 2009. “Household versus individual valuation: what’s the difference?” *Environmental and Resource Economics* 43(1): 119-135.

Bennett, Jeff, and Russell Blamey, eds. 2001. *The choice modelling approach to environmental valuation*. Northampton, MA & Cheltenham, UK: Edward Elgar Publishing.

Bergstrom, John C., John R. Stoll, and Alan Randall. 1989. "Information effects in contingent markets." *American Journal of Agricultural Economics* 71(3): 685–691.

Bergstrom, John C., John R. Stoll, and Alan Randall. 1990. "The impact of information on environmental commodity valuation decisions." *American Journal of Agricultural Economics* 72(3): 614-621.

Boyle, Kevin J. 1989. "Commodity specification and the framing of contingent-valuation questions." *Land Economics* 65(1): 57-63.

Boyle, Kevin J., Mark Morrison, Darla Hatton Macdonald, Roderick Duncan, and John Rose. 2016. Investigating internet and mail implementation of stated-preference surveys while controlling for differences in sample frames. *Environmental and Resource Economics* 64(3): 401-419.

Bruneau, P.M.C., and S.M. Johnson. 2014. *Scotland's peatland - definitions & information resources*. Scottish Natural Heritage Commissioned Report No 701.

Bulte, Erwin, Shelby Gerking, John A. List, and Aart de Zeeuw. 2005. "The effect of varying the causes of environmental problems on stated WTP values: evidence from a field study." *Journal of Environmental Economics and Management* 49(2): 330-342.

Campbell, Danny, David A. Hensher, and Riccardo Scarpa. 2011. "Non-attendance to attributes in environmental choice analysis: a latent class specification." *Journal of Environmental Planning and Management* 54(8): 1061–1076.

Caussade, Sebastián, Juan de Dios Ortúzar, Luis I. Rizzi, and David A. Hensher. 2005. "Assessing the influence of design dimensions on stated choice experiment estimates." *Transportation research part B: Methodological* 39(7): 621-640.

Cerda, Arcadio A., Garcia, Leidy.Y., Pastén, Roberto A., Damino, Iván A., and Diaz, Mónica T. 2014. "The effects of visual information on willingness to pay for a recreational site improvement in Chile." *Innovar* 24(53): 141-148.

Chorus, Caspar G. 2010. "A new model of random regret minimization." *European Journal of Transport and Infrastructure Research* 10(2): 181-196.

Chorus, Caspar G. 2011. "Random regret minimization: an overview of model properties and empirical evidence." *Transport Reviews* 32(1): 75-92.

Cook, Joseph, Marc Jeuland, Brian Maskery, and Dale Whittington. 2012. "Giving stated preference respondents "time to think": results from four countries." *Environmental and Resource Economics*. 51(4): 473-496.

Croson, Rachel, and Treich, Nicolas. 2014. "Behavioural environmental economics: promises and challenges." *Environonmental and Resource Economics* 58: 335-351.

Czajkowski, Mikołaj, and Budziński, Wiktor. 2019. "Simulation error in maximum likelihood estimation of discrete choice models." *Journal of Choice Modelling* 31: 73-85.

Czajkowski, Mikołaj, Hanley, Nick, and LaRiviere, Jacob. 2014. "The Effects of Experience on Preferences: Theory and Empirics for Environmental Public Goods." *American Journal of Agricultural Economics* 97(1): 333-351.

Czajkowski, Mikołaj, Hanley, Nick, LaRiviere, Jacob. 2016. "Controlling for the effects of information in a public goods discrete choice model." *Environmental and Resource Economics* 63(3): 523-544.

Day, Brett, Ian J. Bateman, Richard T. Carson, Diane Dupont, Jordan J. Louviere, Sanae Morimoto, Riccardo Scarpa, and Paul Wang. 2012. "Ordering effects and choice set awareness in repeat-response stated preference studies." *Journal of Environmental Economics and Management* 63: 73-91

DeShazo J.R., German Fermo. 2002 "Designing choice sets for stated preference methods: the effects of complexity on choice consistency." *Journal of Environmental Economics and Management* 44(1):123–143.

Dekker, Thijs, and Caspar G. Chorus. 2018. "Consumer surplus for random regret minimisation models." *Journal of Environmental Economics and Policy* 7(3): 269-286.

eftec. 2015. *The Economic Case for Investment in Natural Capital in England*: Final Report for the Natural Capital Committee

Faccioli, Michela, Laure Kuhfuss, and Mikołaj Czajkowski. 2019. "Stated preferences for conservation policies under uncertainty: insights on the effect of individuals' risk attitudes in the environmental domain." *Environmental and Resource Economics* 73(2): 627-659.

Ferretto, Anna, Rob Brooker, Matt Aitkenhead, Robin Matthews, and Pete Smith. 2019. "Potential carbon loss from Scottish peatlands under climate change." *Regional Environmental Change* 19(7): 2101-2111.

Frisch, Deborah. 1993. "Reasons for framing effects." *Organizational Behavior and Human Decision Processes* 54(3): 399-429.

Gallego-Sala, Angela V., Joanna M. Clark, Joanna I. House, Harriet G. Orr, I. Colin Prentice, Pete Smith, Timothy Farewell, and Stephen J. Chapman. 2010. "Bioclimatic envelope model of climate change impacts on blanket peatland distribution in Great Britain." *Climate Research* 45: 151–162.

Gallego-Sala, Angela V., and I. Colin Prentice. 2013. “Blanket peat biome endangered by climate change.” *Nature climate change* 3: 152–155.

Gerlach, Philipp, and Bastian Jaeger. 2016. “Another frame, another game? Explaining framing effects in economic games.” In *Proceedings of norms, actions, games (NAG 2016)*, ed. Astrid Hopfensitz, and Emiliano Lorini, 1-10. Toulouse: Institute for Advanced Studies.

Glenk, Klaus, and Sergio Colombo. 2011. “How Sure Can You Be? A Framework for Considering Delivery Uncertainty in Benefit Assessments Based on Stated Preference Methods.” *Journal of Agricultural Economics* 62(1): 25-46.

Glenk, Klaus, and Sergio Colombo. 2013. “Modelling outcome-related risk in choice experiments.” *The Australian Journal of Agricultural and Resource Economics* 57(4): 559-578.

Glenk, Klaus, Julia Martin-Ortega, Manuel Pulido-Velazquez, and Jacqueline Potts. 2015. “Inferring attribute non-attendance from discrete choice experiments: implications for benefit transfer.” *Environmental and Resource Economics* 60: 497–520.

Glenk, Klaus, and Julia Martin-Ortega. 2018. “The economics of peatland restoration.” *Journal of Environmental Economics and Policy* 7(4): 345-362.

Glenk, Klaus, Jürgen Meyerhoff, Faical Akaichi, and Julia Martin-Ortega. 2019. “Revisiting cost vector effects in discrete choice experiments.” *Resource and Energy Economics* 57: 135-155.

Glenk, Klaus, Paula Novo, Michaela Roberts, Matteo Sposato, Julia Martin-Ortega, Mahboobeh Shirkhorshidi, and Jacqueline Potts. 2020. *The costs of peatland restoration. Analysis of an evolving database based on the Peatland Action Programme in Scotland.* SEFARI report.

Günther, Anke, Alexandra Barthelmes, Vytas Huth, Hans Joosten, Gerald Jurasinski, Franziska Koebsch, and John Couwenberg. 2020. "Prompt rewetting of drained peatlands reduces climate warming despite methane emissions." *Nature Communications* 11, 1644.

Hanley, Nick, Christopher Boyce, Mikołaj Czajkowski, Steve Tucker, Charles Noussair, and Michael Townsend. 2017. "Sad or Happy? The effects of emotions on stated preferences for environmental goods." *Environmental and Resource Economics* 68(4): 821-846.

Hanley, Nick, and Mikołaj Czajkowski. 2019. "The role of stated preference valuation methods in understanding choices and informing policy." *Review of Environmental Economics and Policy* 13(2): 248-266.

Hassan, Suziana, Søren Bøye Olsen, and Bo Jellesmark Thorsen. 2018. "Appropriate payment vehicles in stated preference studies in developing countries." *Environmental and Resource Economics* 71: 1053-1075.

Hensher, David A. 2006. "How do respondents process stated choice experiments? Attribute consideration under varying information load." *Journal of applied econometrics* 21(6): 861-878.

Hensher, David A., William H. Greene, and Chinh Q. Ho. 2016. "Random regret minimization and random utility maximization in the presence of preference heterogeneity: an empirical contrast." *Journal of Transportation Engineering* 142(4): 04016009, 1-10.

Hess, Stephane, Andrew Daly, Thijs Dekker, Manuel Ojeda Cabral, and Richard Batley. 2017. "A framework for capturing heterogeneity, heteroscedasticity, non-linearity, reference dependence and design artefacts in value of time research." *Transportation Research Part B* 96: 126-149.

H.M. Treasury 2018. *The Green Book*. Central Government guidance on appraisal and evaluation.

Hochman, Guy, and Eldad Yechiam. 2011. "Loss aversion in the eye and in the heart: The autonomic nervous system's responses to losses." *Journal of behavioral decision making*, 24(2): 140-156.

Hoehn, John P., and Alan Randall. 2002. "The effect of resource quality information on resource injury perceptions and contingent values." *Resource and Energy Economics* 24(1-2): 13–31.

Jin, Wen, Hai Jiang, Yimin Liu, and Erica Klampfl. 2017. "Do labeled versus unlabeled treatments of alternatives' names influence stated choice outputs? Results from a mode choice study." *Plos One* 12(8): e0178826.

Johnston Robert J., Kevin J. Boyle, Wiktor (Vic) Adamowicz, Jeff Bennett, Roy Brouwer, Trudy Ann Cameron, W. Michael Hanemann, Nick Hanley, Mandy Ryan, Riccardo Scarpa, Roger Tourangeau, and Christian A. Vossler. 2017. "Contemporary guidance for stated preference studies." *Journal of the Association of Environmental and Resource Economists* 4(2): 319-405.

Kahneman, Daniel, and Amos Tversky. 1979. "Prospect Theory: An Analysis of Decision under Risk." *Econometrica* 47 (2): 263-291.

Knetsch, Jack L. 2010. "Values of gains and losses: reference states and choice of measure." *Environmental and Resource Economics* 46:179–188.

Kragt, Marit Ellen. 2013. “The effects of changing cost vectors on choices and scale heterogeneity.” *Environmental and Resource Economics* 54: 201-221.

Kragt, Marit E., and Jeffrey W. Bennett. 2012. “Attribute framing in choice experiments: how do attribute level descriptions affect value estimates?” *Environmental and Resource Economics* 51(1): 43-59.

Ise, Takeshi, Allison L. Dunn, Steven C. Wofsy, and Paul R. Moorcroft. 2008. “High sensitivity of peat decomposition to climate change through water-table feedback.” *Nature Geoscience* 1: 763–766.

Le Coent, Philippe, Raphaële Préget, and Sophie Thoyer. 2017. “Compensating environmental losses versus creating environmental gains: implications for biodiversity offsets.” *Ecological Economics* 142: 120-129.

Leifeld, Jens, Chloé Wüst-Gallery, and Susan Page. 2019. “Intact and managed peatland soils as a source and sinks of GHGs from 1850 to 2100.” *Nature Climate Change* 9: 945-947.

Levin, Irwin P., and Gary J. Gaeth. 1988. “How consumers are affected by the framing of attribute information before and after consuming the product.” *Journal of consumer research* 15(3): 374-378.

Levin, Irwin P., Sandra L. Schneider, and Gary J. Gaeth. 1998. “All frames are not created equal: A typology and critical analysis of framing effects.” *Organizational behavior and human decision processes* 76(2): 149-188.

Liebe, Ulf, Cordula Hundeshagen, Heiko Beyer, and Stephan von Cramon-Taubadel. 2016. “Context effects and the temporal stability of stated preferences.” *Social Science Research* 60: 135-147.

Luisetti Tiziana, Ian J. Bateman, and R. Kerry Turner. 2011. "Testing the fundamental assumption of choice experiments: are values absolute or relative." *Land Economics* 87(2):284–296.

Lundhede, Thomas Hedemark, Jette Bredahl Jacobsen, Nick Hanley, Niels Strange, and Bo Jellesmark Thorsen. 2015. "Incorporating outcome uncertainty and prior outcome beliefs in stated preferences." *Land Economics* 91: 296-316.

Martin-Ortega, Julia, Klaus Glenk, and Anja Byg. 2017. "How to make complexity look simple? Conveying ecosystem restoration complexity for socio-economic research and public engagement." *PlosOne* 12: e0181686.

Matthews, Yvonne, Riccardo Scarpa, and Dan Marsh. 2017. "Using virtual environments to improve the realism of choice experiments: a case study about coastal erosion management." *Journal of Environmental Economics and Management* 81: 193-208.

McFadden, Daniel. 1974. "Conditional logit analysis of qualitative choice behavior." In *Frontiers in Econometrics*, ed. Paul Zarembka, 105–142. New York: Academic Press.

McFadden, Daniel, and Kenneth Train. 2000. "Mixed MNL models for discrete response." *Journal of Applied Econometrics* 15(5):447–470.

Meyerhoff, Jürgen, Malte Oehlmann, and Priska Weller. 2015. "The Influence of Design Dimensions on Stated Choices in an Environmental Context." *Environmental and Resource Economics* 61(3): 385-407.

Moxey, Andrew, and Dominic Moran. 2014. "UK peatland restoration: some economic arithmetic." *Science of the Total Environment* 484: 114-120.

Murphy, J.M., Sexton, D.M., Jenkins, G.J., Booth, B.B., Brown, C.C., Clark, R.T., Collins, M., Harris, G.R., Kendon, E.J., Betts, R.A., Brown, S.J., Humphrey, K.A., McCarthy, M.P., McDonald, R.E., Stephens, A., Wallace, C., Warren, R., Wilby, R., and Wood, R. A. 2009. "UK Climate Projections Science Report: Climate change projections." Working paper. Met Office Hadley Centre, Exeter.

Needham, Katherine, Czajkowski, Mikołaj, Hanley, Nick, and LaRiviere, Jacob. 2018. "What is the Causal Impact of Information and Knowledge in Stated Preference Studies?" *Resource and Energy Economics* 54: 69-89.

Page, Susan E., and A.J. Baird. 2016. "Peatlands and global change: response and resilience." *Annual Review of Environment and Resources* 41: 35–57.

Pleger, Lyn E., Philipp Lutz, and Fritz Sager. 2018. "Public acceptance of incentive-based spatial planning policies: A framing experiment." *Land use policy* 73: 225-238.

Rolfe, John, Jeff Bennett, and Jordan Louviere. 2002. "Stated values and reminders of substitute goods: Testing for framing effects with choice modelling." *Australian Journal of Agricultural and Resource Economics* 46(1): 1-20.

Rolfe, John, and Jill Windle. 2015. "Do respondents adjust their expected utility in the presence of an outcome certainty attribute in a choice experiment?" *Environmental and Resource Economics* 60(1): 125-142.

Rotherham, Ian D. 2011. *Peat and peat cutting*. Oxford: Shire Library.

Rozin, Paul, and Edward B. Royzman. 2001. Negativity bias, negativity dominance, and contagion. *Personality and social psychology review* 5(4): 296-320.

Samples, Karl C., John A. Dixon, and Marcia M. Gowen. 1986. "Information disclosure and endangered species valuation." *Land Economics* 62(3): 306-312.

Schaafsma, Marije, and Roy Brouwer. 2013. "Testing geographical framing and substitution effects in spatial choice experiments.*" Journal of Choice Modelling* 8: 32-48.

Scheufele, Dietram A., and Shanto Iyengar. 2012. “The state of framing research: A call for new directions.” In *The Oxford Handbook of Political Communication Theories*, ed. Kate Kenski and Kathleen Hall Jamieson. New York: Oxford University Press.

Scottish Government. 2018. *Scotland’s People Annual Report 2017*. A National Statistics publication for Scotland.

Scottish Natural Heritage. 2015. *Scotland's National Peatland Plan - Working for our future*, Scottish Natural Heritage Report

Spash, Clive L. 2007. “Deliberative monetary valuation (DMV): issues in combining economic and political processes to value environmental change.” *Ecological Economics* 63: 690-699.

Sudgen, Robert. 2005. “Coping with preference anomalies in Cost-Benefit analysis: a market-simulation approach.” *Environmental and Resource Economics* 32: 129-160.

Swait, Joffre, and Jordan Louviere. 1993. “The Role of the Scale Parameter in the Estimation and Comparison of Multinomial Logit Models.” *Journal of Marketing Research* 30(3): 305-314.

Thiene, Mara, Marco Boeri, and Caspar G. Chorus. 2012. “Random Regret Minimization: Exploration of a New Choice Model for Environmental and Resource Economics.” *Environmental and Resource Economics* 51:413–429.

Thomadsen, Raphael, Robert P. Rooderkerk, On Amir, Neeraj Arora, Bryan Bollinger, Karsten Hansen, Leslie John, Wendy Liu, Aner Sela, Vishal Singh, K. Sudhir, and Wendy Wood. 2018. “How context affects choice.” *Customer Needs and Solutions* 5(1-2): 3-14.

Tkac, Jennifer. 1998. “Award-Winning Undergraduate Paper: The Effects of Information on Willingness-To-Pay Values of Endangered Species.” *American Journal of Agricultural Economics* 80(5): 1214-1220.

Tinch, Dugald, Sergio Colombo, and Nick Hanley. 2015. “The impacts of elicitation context on stated preferences for agricultural landscapes.” *Journal of Agricultural Economics* 66(1): 87-107.

Train, Kenneth E. 2009. *Discrete choice methods with simulation*. New York: Cambridge University Press.

Tversky, Amos, and Daniel Kahneman. 1981. “The framing of decisions and the psychology of choice.” *Science* 211(4481): 453-458.

van Cranenburgh, Sander, Cristian Angelo Guevara, and Caspar G. Chorus. 2015. “New insights on random regret minimization models.” *Transportation Research Part A: Policy and Practice* 74:91-109.

Vossler, Christian A., Ewa Zawojska. 2020. “Behavioral drivers or economic incentives? Toward a better understanding of elicitation effects in stated preference studies.” *Journal of the Association of Environmental and Resource Economists* 7(2): 279-303.

Wilson, Dawn K., Robert M. Kaplan, and Lawrence J. Schneiderman. 1987. “Framing of decisions and selections of alternatives in health care.” *Social Behaviour* 2(1): 51-59.

Tables

Table 1.
Attribute descriptions and their levels in the good and bad framing treatments

Attribute	Description	Levels	
		Good framing treatment	Bad framing treatment
COND_2050	Change in the ecological condition of peatlands by 2050, with respect to the status quo (SQ) level.	Increase (in absolute terms) in the share of peatlands in good condition: +0% +10% +20% +30%	Decrease (in absolute terms) in the share of peatlands in bad condition: -0% -10% -20% -30%
TIME	Timing when restoration will take place in the period between 2017 and 2050	Early (2017-2027) Midway (2028-2038) Late (2039-2050)	Early (2017-2027) Midway (2028-2038) Late (2039-2050)
COST	Annual cost, in GBP (tax towards Peatland Trust fund)	10,25,50,75,150,250	10,25,50,75,150,250

Table 2.

Socio-demographic characteristics by split sample

	Good framing	Bad framing	Test for the significance of the differences (p-value)
Gender			
Men	49.21%	43.50%	0.09
Women	50.79%	56.50%	0.09
Age			
18-24	11.91%	12.53%	0.78
25-44	32.13%	30.97%	0.71
45-64	35.51%	36.41%	0.78
≥ 65	20.45%	20.09%	0.90
Household size			
Nr. of people in the household (average)	2.27	2.21	1.00
Place of residence			
Rural	32.81%	35.70%	0.37
Urban	67.19%	64.30%	0.37
Education achieved			
Level 0 (Lower secondary school)	20.28%	19.60%	0.81
Level 1 (Upper secondary school)	17.69%	18.11%	0.87
Level 2 (College)	14.15%	12.66%	0.53
Level 3 and above (University)	47.88%	49.63%	0.62

Note: the last column (on the right) reports the p-values for the tests of equality across treatments: for all variables we used a z-test to check the equality of proportions, while for the variable 'household size' we used a t-test for mean equality. Additionally, for 'age' and 'education', we also performed a Chi-square test to compare the distribution of these categorical variables across treatments. In both cases, the null hypothesis of equality between the good and bad framing could not be rejected (p-value for 'age' was 0.97 and for 'education' it was 0.91).

Table 3.
Results of the Mixed Logit models in WTP-space for the good and bad framing data and pooled model

	Good framing		Bad framing		Pooled model	
	Mean (St. error)	**St. deviation (St. error)**	**Mean (St. error)**	**St. deviation (St. error)**	**Mean (St. error)**	**St. deviation (St. error)**
Business as usual [times 10]	-0.30*** (0.02)	0.22*** (0.02)	-0.32*** (0.02)	0.28*** (0.02)	-0.35*** (0.01)	0.27*** (0.01)
Increase in good – 10% over SQ	0.46*** (0.05)	0.46*** (0.05)	0.51*** (0.05)	0.59*** (0.05)	0.48*** (0.04)	0.42*** (0.04)
Increase in good – 20% over SQ	0.83*** (0.07)	0.85*** (0.07)	0.97*** (0.10)	1.37*** (0.11)	0.90*** (0.06)	0.92*** (0.06)
Increase in good – 30% over SQ	0.80*** (0.07)	1.05*** (0.07)	1.03*** (0.09)	1.41*** (0.09)	0.92*** (0.06)	1.03*** (0.05)
Timing (early)	0.88*** (0.06)	0.98*** (0.06)	1.15*** (0.09)	1.32*** (0.08)	1.05*** (0.05)	1.04*** (0.06)
Timing (midway)	0.58*** (0.05)	0.60*** (0.04)	0.56*** (0.05)	0.53*** (0.05)	0.58*** (0.04)	0.49*** (0.03)
- Cost [divided by 100]	1.28*** (0.13)	1.83*** (0.18)	1.40*** (0.14)	2.14*** (0.18)	1.05*** (0.10)	1.81*** (0.10)
Relative scale parameter						
Bad framing					0.13 (0.12)	
Model diagnostics						
LL at convergence	-2287.91		-2188.59		-4515.05	
McFadden's pseudo-R^2	0.32		0.36		0.34	
r (respondents)	445		423		868	
k (parameters)	35		35		36	

Notes: ***, ** and * indicate 1%, 5% and 10% significance levels, respectively. Standard errors are provided in parentheses. All utility function parameters are modelled as random and normally distributed except for the cost parameter, which is assumed to follow a log-normal distribution (the estimates of the underlying normal distribution are reported in this table). For modelling purposes, the cost attribute was re-scaled and divided by 100 and the BAU constant multiplied by 10. Correlation parameters are reported in the tab "Tables 3-4" in Appendix B available online. The models were estimated using the simulated maximum likelihood method with 10,000 Sobol draws with a random linear scramble and a random digital shift (Czajkowski and Budziński 2019).

Table 4.

Wald test for the significance of the differences in mean WTP values across treatments

	Mean WTP (St. Errors) from Table 3		
	Good framing	**Bad framing**	**Significance of the difference (p-value)**
Business as usual [times 10]	-0.30*** (0.02)	-0.32*** (0.02)	0.64
Increase in good – 10% over SQ	0.46*** (0.05)	0.51*** (0.05)	0.47
Increase in good – 20% over SQ	0.83*** (0.07)	0.97*** (0.10)	0.22
Increase in good – 30% over SQ	0.80*** (0.07)	1.03*** (0.09)	0.03**
Timing (early)	0.88*** (0.06)	1.15*** (0.09)	0.01***
Timing (midway)	0.58*** (0.05)	0.56*** (0.05)	0.81

Notes: ***, ** and * indicate 1%, 5% and 10% significance levels, respectively.

Table 5.

Net Present Value (NPV) and Benefit/Cost (B/C) ratios for selected restoration scenarios

Scenarios		NPV		B/C ratio	
Scope of restoration	**Timing**	**Good**	**Bad**	**Good**	**Bad**
Increase in good – 10% over SQ	Early	£5.14bn [£4.21bn – £6.08bn]	£6.61bn [£5.39bn – £7.83bn]	6.58 [5.56 – 7.60]	8.17 [6.85 – 9.49]
	Midway	£1.94bn [£1.50bn – £2.39bn]	£1.99bn [£1.53bn – 2.46bn]	4.91 [4.02 – 5.81]	5.01 [4.08 – 5.95]
	Late	£0.08bn [£0.03bn – £0.13bn]	£0.11bn [£0.05bn – £0.17bn]	1.40 [1.13 – 1.67]	1.55 [1.24 – 1.86]
Increase in good – 20% over SQ	Early	£5.61bn [£4.51bn – £6.71bn]	£7.44bn [£5.88bn – £9.00bn]	4.04 [3.45 – 4.64]	5.04 [4.19 – 5.88]
	Midway	£2.15bn [£1.63bn – £2.68bn]	£2.39bn [£1.75bn – £3.02bn]	3.17 [2.64 – 3.70]	3.40 [2.76 – 4.04]
	Late	£0.1bn [£0.02bn – £0.18bn]	£0.19bn [£0.07bn – £0.30bn]	1.25 [1.06 – 1.45]	1.48 [1.18 – 1.77]
Increase in good – 30% over SQ	Early	£4.59bn [£3.50bn – £5.69bn]	£6.76bn [£5.27bn – £8.24bn]	2.66 [2.27 – 3.06]	3.44 [2.91 – 3.98]
	Midway	£1.61bn [£1.08bn – £2.13bn]	£2.01bn [£1.41bn – £2.61bn]	2.08 [1.73 – 2.43]	2.35 [1.95 – 2.75]
	Late	-£0.11bn [(-£0.19bn) – (-£0.03bn)]	£0.03bn [(-£0.08bn) – £0.13bn]	0.81 [0.68 – 0.94]	1.05 [0.87 – 1.22]

Note: in each cell, the reported top figures refer to the NPVs or B/C ratios estimated assuming mean WTP values (from Table 3). The figures reported in parenthesis refer to the lower bound and upper bound NPV or B/C ratios obtained from the 95% confidence intervals of the mean WTP estimates.

Figures

Fig. 1.
Overview of the literature classification

Fig. 2.

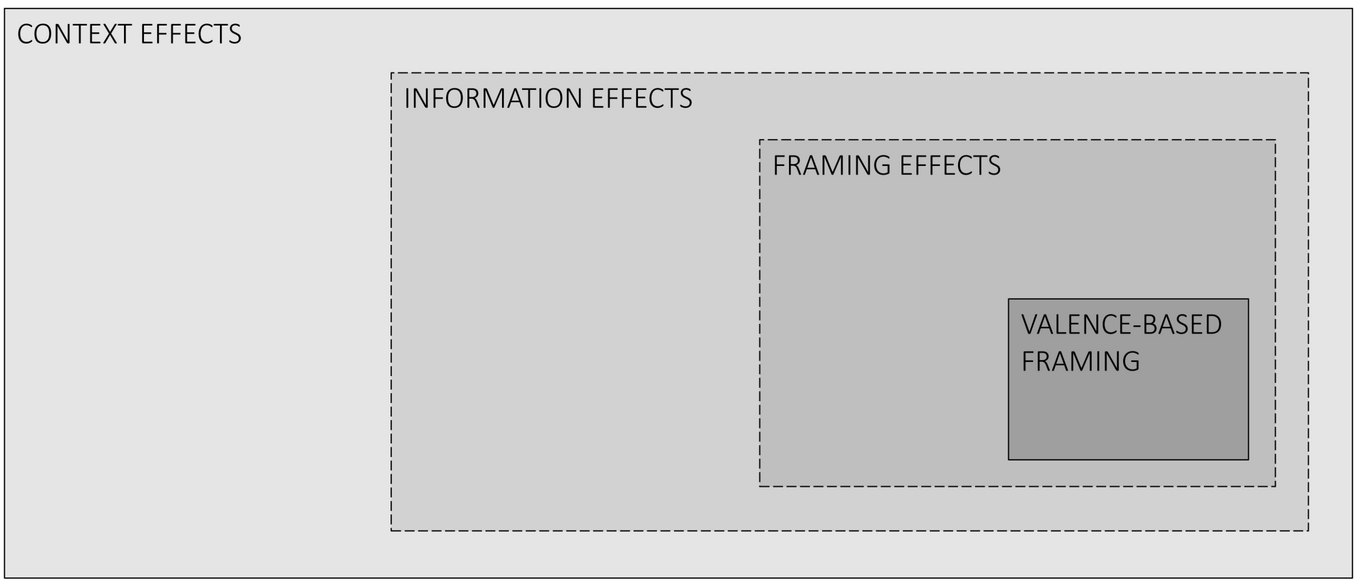
Example of choice card for the good framing (a) and bad framing (b) split samples

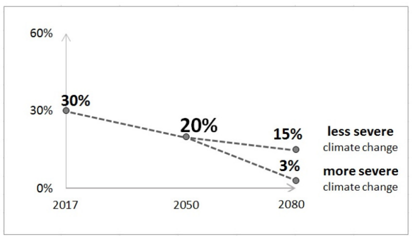
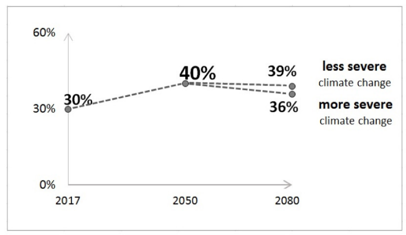
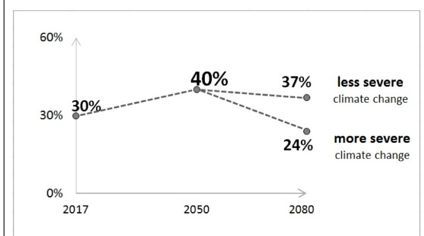
Endnotes

[1] When the use of alternative payment vehicles conveys different information about the 'settings' in which the good is provided, these effects could be subsumed under context effects. For example, a tax may convey more certainty around the provision of the good, while donations may communicate uncertainty of provision depending on the number of people contributing.
[2] In the valuation literature, however, the term "framing effects" is unduly frequently used to identify a broader set of factors, which extend beyond the strictest definition of framing that is taken as the gold standard. For instance, Rolfe et al. (2002, p. 2) define 'framing effects' as occurring "when the respondent to a survey is unduly sensitive to the context in which a particular trade-off is offered", including the good being valued and its substitutes. Similarly, Johnston et al. (2017) report that framing effects are induced by using alternative question formats. Bennett and Blamey (2001) refer to the implications of using different payment vehicles as framing effects. In other valuation studies (e.g., Kragt and Bennett 2012, p. 45), framing effects are related to "the ways in which information is formulated and presented".
[3] Another valuation study (Le Coent, Préget and Thoyer 2017) explores valence-based framing effects, but it focuses on the supply (rather than demand) of ecosystem services. The authors investigate French farmers' participation in one of two possible agro-environmental programs: 1) a publicly funded program to maintain or enhance conservation and 2) a privately funded offsetting program where developers pay farmers to restore damaged habitat following the implementation of a development project. Results of the study show that some farmers are more likely to participate in a contract aiming at creating or maintaining habitats, rather than restoring damaged ecosystems.
[4] The description of the base level of the 'rare native species' attribute in the negative framing is as follows: "45 species lost - of the current 80 rare native species, 45 species no longer live in the George catchment", with alternative levels resulting from extra management efforts being "30 species lost, 15 species lost or **no loss**" (Kragt and Bennett 2012, p. 49).
[5] Two climate change scenarios were considered: more severe climate change projections, following the A1FI scenario presented in the IPCC Special Report on Emission Scenarios (SRES), and less severe climate change forecasts, in line with the B1 scenario described in the UK Climate Projections 2009 (UKCP09) (Murphy et al. 2009). Under more severe climate change, it was assumed that between 20% and 80% of the peatland's improvement achieved by 2050 could be retained by 2080, depending on the restoration timing. Under a less severe climate change, it was assumed that between 85% and 95% of the improvements achieved by 2050 could be retained by 2080, depending on the restoration timing. The business as usual scenario (where no extra restoration efforts will be undertaken) assumes that 15% of the peatlands in good condition by 2050 (in the more severe climate change scenario) and 75% of the peatlands in good condition by 2050 (in the less severe climate change scenario) would be retained by 2080.
[6] Given the levels of COND_2050 reported in Table 1, in the choice cards, respondents in the good framing treatment could see between 30% and 60% total share of peatlands in good condition by 2050 as a result of peatland restoration (i.e. SQ level of 30% plus between 0% and 30%) and between 30% and 0% total share of peatlands in bad condition in the bad framing treatment (i.e. SQ level of 30% minus between 0% and 30%).
[7] Scale differences are possible between subsamples (treatments) in circumstances where alternative framings of information is presented in the survey script (Czajkowski, Hanley and LaRiviere 2014; Czajkowski, Hanley, LaRiviere 2016). In the pooled model, we therefore specified relative differences in scale parameters (α_n), as follows:

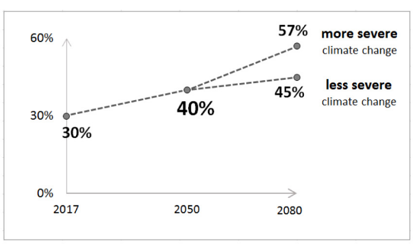
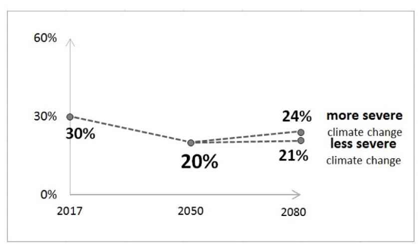
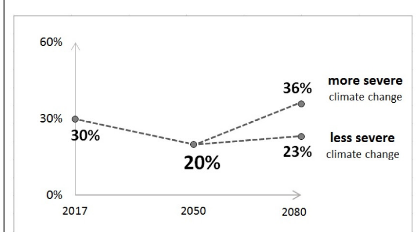
$$\alpha_n = \exp\left(\theta T_n\right)$$

where T_n represents a dummy variable associated with the 'bad framing' treatment (relative to the 'good framing' treatment) and θ describes the relative magnitude of the scale in the bad, compared to the good, framing treatment.
[8] The figure for capital costs is based on work by Glenk et al. (2020) and reflects the mean restoration costs per hectare calculated over a large number of actual peatland restoration projects carried out in Scotland. Estimates of recurring costs are more uncertain and can vary greatly. Moxey and Moran (2014) use a range between £25/ha, corresponding to minimal monitoring costs and no management and opportunity costs, and £400/ha, corresponding to a situation with substantial opportunity costs and/or high costs of management and monitoring. Given the large scale of peatland restoration assumed in our Benefit-Cost scenarios (in line with the ambitious targets for restoration in Scotland), in our exercise it seems plausible to assume relatively high ongoing costs (opportunity costs and management costs) of £300/ha for illustrative purposes.
[9] The models in this sub-section were estimated by using a DCE package developed in Matlab and available from http://github.com\\czaj\\DCE. The data underlying this study and the code used for estimation are available as Matlab files in Appendix A. The models were estimated using the 2018a version of the Matlab software.
[10] Qualitatively, the same conclusions are drawn also when considering lower levels for the ongoing restoration costs.
[11] RRM models were estimated using a Matlab package available from www.advancedrrmmodels.com. The data underlying this study and the code used for estimation are available as Matlab files in Appendix A. The models were estimated using the 2018a version of the Matlab software.
[12] Our choice was also driven by the results in Hensher, Greene and Ho (2016), where the allocation to different paradigms (RUM, RRM) is found to be insensitive to the introduction of preference heterogeneity in the model.


CONTEXT EFFECTS
INFORMATION EFFECTS
FRAMING EFFECTS
VALENCE-BASED FRAMING

<table>
<tr><td></td><td>Business as usual
No restoration</td><td>Restoration program A</td><td>Restoration program B</td></tr>
<tr><td>When restoration happens</td><td>No program</td><td>2017 2050 Early</td><td>2017 2050 Late</td></tr>
<tr><td>Share of peatlands in GOOD condition by 2050 and 2080</td><td>
</td><td>
</td><td>
</td></tr>
<tr><td>Cost per year</td><td>£0</td><td>£50</td><td>£10</td></tr>
<tr><td>Your most preferred choice</td><td>☐</td><td>☐</td><td>☐</td></tr>
</table>

(a)

<table>
<tr><td></td><td>Business as usual
No restoration</td><td>Restoration program A</td><td>Restoration program B</td></tr>
<tr><td>When restoration happens</td><td>No program</td><td>2017 2050 Early</td><td>2017 2050 Late</td></tr>
<tr><td>Share of peatlands in BAD condition by 2050 and 2080</td><td>
</td><td>
</td><td>
</td></tr>
<tr><td>Cost per year</td><td>£0</td><td>£50</td><td>£10</td></tr>
<tr><td>Your most preferred choice</td><td>☐</td><td>☐</td><td>☐</td></tr>
</table>

(b)