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Willingness-to-pay for urban ecosystem services provision under objective and subjective uncertainty

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There is growing concern that failure to acknowledge the risk and uncertainty surrounding ecosystem services (ES) delivery could have adverse effects on support for ES policy intervention in the long run. However, acknowledging risk may reduce support for policy interventions in the short term. In this paper, we sought to determine whether willingness-to-pay (WTP) for urban forest ES in Southampton, UK is affected by objective and subjective uncertainty surrounding ES delivery. We conducted a discrete choice experiment with a split sample design: one with a scenario specifying risky ES outcomes and one where zero risk was implied. Respondents' subjective certainty surrounding the provision of ES was determined before and after the choice questions. Despite respondents' risk aversion, introducing an objective likelihood attribute did not reduce WTP compared to the scenario with implied certain ES outcomes. Furthermore, whilst WTP for the overall scheme was found to be adversely affected by the presence of risk around ES outcomes, subjective uncertainty seemed to reduce WTP more than objective probabilities. Our results therefore support the idea that both objective probabilities and subjective uncertainty should be explicitly incorporated in the design of stated preference studies for ES valuation.

1. Introduction

Most studies that investigate willingness-to-pay (WTP) for environmental schemes assume that respondents make choices based on scenario and attribute information alone, taking this information as fact. However, the outcomes of environmental management actions are often risky or even uncertain, and failing to disclose this is resulting in a loss of trust and support from citizens and other beneficiaries in cases where operational schemes fail to deliver the promised benefits (Moffat, 2016; Lima et al., 2017). Consequently, a number of authors have called for objective information on outcome probabilities to be incorporated into WTP studies for ecosystem services (ES) management, as failing to do so could bias WTP estimates (Glenk et al., 2014; Lundhede et al., 2015, e.g. Wielgus et al., 2009).

Abbreviations: ASC, Alternative specific constant; DCE, Discrete choice experiment; ES, Ecosystem services; PES, Payments for ecosystem services; RPL, Random parameter logit; SQ, Status quo; WTP, Willingness-to-pay

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Information about risk and uncertainty, where the true distribution of the likelihood of an event is unknown, can be included as an attribute in a discrete choice experiment (DCE), varying across choices, or as a fixed condition of the good under valuation. The expected impact of including this attribute on WTP differs depending on which theoretical assumptions are applied (see also Section 2.4). Under expected utility assumptions, the value of the options is reduced (Wibbenmeyer et al., 2013; von Neumann and Morgenstern, 1947). Under direct utility assumptions, including an outcome probability attribute impacts on choices directly, i.e. independently of its effect on the valued goods (Gneezy and Potters, 1997; Simonsohn, 2009). Furthermore, introducing outcome probabilities may lead to a framing effect (Bujosa et al., 2018). The inclusion of a probability attribute can make choices more complicated for respondents (potentially leading to more statistical variance) (Swait and Louviere, 1993), but the information may also increase the credibility or realism of the scheme (Roberts et al., 2008).

Here, we define *objective uncertainty* as the explicit and well-defined probabilities, so that the options consist of probability distributions over outcomes based on scientific or external expert judgement, as opposed to “subjective uncertainty”, which we define as people’s beliefs regarding the likelihood of an outcome based on prior knowledge, experience and availability of information, following Machina and Schmeidler (1992).[1] Assuming that people base their choices on their personal ‘subjective’ uncertainty about the outcomes of the scheme, the information on objective uncertainty may mediate these preconceived beliefs, as subjective and objective uncertainty may differ.

Both Wielgus et al. (2009) and Glenk and Colombo (2011) postulated that surveys containing objective information on outcome probabilities would return higher WTP for ES than would surveys without, due to this information adding to the credibility of the scenarios. Presumably, without such information, respondents would doubt the realism of a scheme with guaranteed environmental outcomes, and thus take into consideration their own, differing, subjective beliefs about the likely outcomes (Burghart et al., 2007; Nguyen et al., 2010). Unfortunately, neither Wielgus et al. (2009) nor Glenk and Colombo (2011) collected respondent perceptions about the provision of objective uncertainty information, or crucially, respondents’ subjective uncertainty surrounding environmental schemes, so their postulation could not be tested.

A majority of WTP studies that have incorporated objective uncertainty in relation to environmental policies or programmes (15 of 20 reviewed by Davies, 2019) find that respondents have higher WTP (and/or are more likely to pay) for less risky outcomes. For example, for an increase in the probability of success, people were willing to pay more for schemes delivering carbon sequestration (Glenk and Colombo, 2011) and heat amelioration (Akter et al., 2012). However, four studies have found evidence of higher WTP for risky environmental outcomes. For example, Roberts et al. (2008) found WTP for removal of algae from a recreational lake to be more than three times higher for their treatment group (for whom algal blooms occurred with probabilities varying from 0 % to 100 %), than their control group (for whom algal blooms occurred or not). Roberts et al. (2008) suggested this may be due to the treatment group finding even a small risk of an algal bloom to be unacceptable. Torres et al. (2017) found that WTP for conservation efforts to improve the diversity of wetland bird species increased as the probability of success decreased. The authors suggested this may be due to respondents adopting a precautionary approach; when outcomes are inherently uncertain, it is still better to act than to do nothing. Though not discussed in either of these papers, in both cases respondents may have given strategic responses in order to choose better environmental outcomes, possibly resulting in over-inflated WTP.

Few studies have looked into the effect of subjective uncertainty on WTP for environmental programmes. The first (Burghart et al., 2007) did so without eliciting subjective beliefs. To account for the possibility that respondents might have ignored the objective uncertainty attribute and replaced it with their own beliefs, Burghart et al. (2007) simulated WTP in the absence of this ‘distortion’. WTP for a climate change adaptation programme was lower than it would have been if only the provided information informed respondents’ choices, suggesting that subjective uncertainty reduced WTP. The second study (Akter et al., 2012) found that respondents who perceived a high probability of success of climate change mitigation actions were significantly more likely to pay for a mitigation programme. However, as Akter et al. (2012) interacted subjective beliefs with the alternative specific constant (ASC), the impact of subjective uncertainty on WTP for specific attributes in their study is unknown. More recently, Adhikari et al. (2017) found that respondents’ beliefs of the probability that a proposed forest restoration payments for ecosystem services (PES) scheme would reduce wildfire risk, and thus improve water security, significantly and positively affected their WTP for the scheme. However, Adhikari et al. (2017) did not provide respondents with objective probabilities, so the WTP values given by the respondents were based only on prior perceptions.

Only Lundhede et al. (2015) have linked respondents’ subjective beliefs with objective uncertainty information. Lundhede et al. (2015) argued that providing information on outcome uncertainty does not mean that people will base their choices on it; eliciting information on respondents’ subjective beliefs about a policy is also needed to explain choices, and to reduce the random component of utility. The key result of Lundhede et al. (2015) was that WTP for a conservation policy with objectively uncertain outcomes was significantly lower for a priori ‘doubters’ (i.e. respondents who, before being presented with objective uncertainty information, rated the likely policy outcome as rather or very uncertain) than for a priori ‘trusters’ (i.e. those who rated the likely policy outcome as rather or very *certain*). However, determining whether respondents weighed the objective information with their prior beliefs would have required further modelling to ascertain how trusters and doubters each reacted to certain and uncertain outcomes.

[1] These definitions somewhat diverge from risk definitions in the wider literature as summarised in Thompson (1985) and do not take uncertainty to mean that probability distributions are unknown and uncertainty is therefore immeasurable.

To address these gaps, this novel study sought to determine how citizen WTP for provision of urban forest-based regulating ES is affected by both the objective and subjective uncertainty surrounding ES delivery. This involved a split-sample design, with responding citizens being allocated to either the no objective uncertainty control group, or the objectively uncertain treatment group, and WTP for the two groups compared. All respondents were asked for their subjective beliefs regarding ES delivery, and the analysis set out to determine the effect on WTP. Respondents' belief in the likely delivery of the scheme overall (i.e. consequentiality) was also compared for those in the treatment and control groups, and its impact on WTP identified. Finally, the effects of objective vs. subjective uncertainty on WTP for the proposed scheme were compared, and differences between responses in the treatment and control groups of those who doubt or trust urban forest-based ES delivery were each identified.

2. Materials and methods

2.1. Case study

A citizen payment scheme to enhance ES provision from a UK urban forest was chosen as the case study application. An urban forest is defined as "all forest and tree resources in (and close to) [an] urban area" (Konijnendijk, 2003), and typically provides a greater quantity of ES than other habitats in urban areas (Davies et al., 2017; Dobbs et al., 2014; Roy et al., 2012). However, urban forest systems involve highly complex and heterogeneous interactions within and between processes and actors at different scales (Steenberg, 2018; Janssen and Ostrom, 2006). For example, the provision of ES from urban trees depends greatly on the size, structure, and species of the trees; their proximity to people, buildings and/or sources of environmental harm; and the level of management/pruning (Davies et al., 2017).

Despite these interactions, management activities tend to focus on only one ES at a time, which can lead to unanticipated trade-offs between services and thus a reduction in expected benefits (Bennett et al., 2009; Mouchet et al., 2014; Salmond et al., 2016). Stochastic factors such as air temperature, precipitation, relative humidity, and wind speed can additionally affect the ability of urban forests to provide ES, or result in the production of disservices (Roy et al., 2012). Meanwhile, the affluence, population density and political priorities of a local community can affect both actual and perceived provision of ES (Dobbs et al., 2014), whilst the multiple intrinsic, instrumental and relational values that different people attach to trees and woodlands can affect perceived provision of ES. As a result, there can be unanticipated biological and human responses to both proposed and actual changes in urban forest management (Mouchet et al., 2014; Ainscough et al., 2018).

The UK city of Southampton was chosen for the study for two main reasons. Firstly, it suffers from environmental problems typically associated with a densely populated and growing urban area – such as surface water flooding and air pollution – both of which can be alleviated in part through enhancing the urban forest. Secondly, Southampton has a proactive local authority that actively supports university research, has a desire to increase tree canopy cover in the city, and uses the Green Space Factor[2] in planning decisions in order to enhance ES provision from land use change (Farrugia et al., 2013).

2.2. Choice experiment design

To examine how uncertainty affects citizen's preferences for ES provided by urban forest management focused on enhancement of two regulating ES, we developed a DCE. To identify the effect on WTP of providing information on outcome probabilities, we developed two versions of the DCE questionnaire. The 'no objective uncertainty' version (the control group) provided no information about outcome probabilities around delivery of ES in the hypothetical scenario. In contrast, the 'objective uncertainty' version (the treatment) contained an attribute specifying objective certainty in terms of varying levels of the likelihood of the hypothetical outcomes. This attribute was directly related to the attributes for the two regulating ES and indicated the likelihood that delivery of the air quality and flood reduction benefits would occur.

The different sections of the questionnaire covered the following topics: (a) attitudes towards the benefits and nuisances associated with street trees; (b) attitudes towards air pollution and surface water flooding problems and solutions in Southampton, and prior beliefs regarding the delivery of air quality and flood reduction benefits from trees; (c - treatment only) probability in the context of environmental outcomes, carefully explained in order to limit any increase in the randomness of choices of this group, followed by a question to check comprehension[3]; (d) an explanation of the proposed citizen-funded street tree planting programme (i.e. the 'scenario'), including the attributes; (e) the DCE choice tasks; (f) reasons for (un)willingness to pay, consequentiality[4] of the programme, and posterior beliefs regarding the delivery of air quality and flood reduction benefits; and (g) socio-demographic data.

Under (b), prior subjective beliefs regarding the outcome uncertainty of tree planting were assessed by asking the question, "*on a scale of 0 (not at all confident) to 10 (very confident), how confident are you that planting new trees on Southampton's streets*

[2] The Green Space Factor is a planning policy tool that has been adopted by a number of city authorities across Europe to incorporate green infrastructure in development projects. The tool allocates a score to different types of surfaces based on infiltration potential, which is used as a proxy for ES delivery.

[3] Only 7 % of respondents in the treatment sample failed the probability comprehension question. As their WTP and socio-demographics were similar to the rest of the treatment sample, their responses were retained in the dataset.

[4] Consequentiality was also implied in section (d) of the questionnaire.

would reduce air pollution in the city?" A second question was asked regarding respondents' confidence that trees would 'reduce surface water flooding'. These two questions were repeated under (f) to obtain posterior subjective beliefs.[5]

The scenario proposed to respondents was a street tree planting programme funded by additional earmarked council tax payments (via a City Tree Fund) to help address problems with air pollution and surface water flooding in Southampton. Attribute levels are set out in Table 1. The baseline mortality level for particulate matter in Southampton was obtained from Public Health England (2016); with a reduction of approximately 6 % from maximum tree planting (taking Southampton's canopy cover from 18.5 % to 25 %) derived from The Nature Conservancy (2016). Similarly, the baseline level of properties at low to high risk of surface water flooding was calculated based on Environment Agency (2014) data, with a maximum reduction of approximately 4 % (again based on increasing Southampton's canopy cover to 25 %) derived from Armson et al. (2013). Levels for the other attributes were based on other studies about urban forest ES (see Davies, 2019), and modified through pre-testing. Fig. 1 shows an example of a choice card. The pictures were based on existing situations in Southampton streets and were thoroughly pretested.

In the survey of the treatment, the following text was included in section (c) to facilitate comprehension of the objective uncertainty in the hypothetical scenarios, in this case the delivery of ES:

"Engineers and scientists can quite accurately calculate the benefits of upgrading the drainage network or removing highly polluting vehicles from the city. However, calculating the effects of new tree planting on air quality and flooding is much more difficult. This is because tree benefits are affected by:

- *the type (species), size, health, and maintenance of the trees;*
- *how close the trees are located to buildings, people, pollution sources, and other trees.*

Therefore, we often communicate tree benefits as probabilities."

And in section (d):

*"**The health and flood benefits of new trees are difficult to predict.** The benefits of new tree planting will vary depending on the type (species), size, health, and maintenance of the trees. The benefits will also depend on how close the trees are located to buildings, people, pollution sources, and other trees. These are difficult to calculate and predict. Because of this, there is a chance that the predicted health and flood benefits might not happen. In the tree programme choices that follow, the 'likelihood that reductions in pollution-related deaths and residential flood risk will occur' might take one of four levels."*

To limit hypothetical bias, we included a substitute and income reminder: it was stressed to respondents that paying for tree planting would reduce the money they have available for their other expenditures, and so they should only choose the alternatives that they can afford. Respondents were told that their choices would be shared with the council (and thus help to influence future policy in Southampton), and that, should the proposed tree programme be adopted, compulsory tax-based payments would be required.

A D-efficient experimental design was used to generate the specific combinations of attributes and levels that respondents evaluated through the choice tasks, generated using the software package Ngene (Choicemetrics, 2018, Rose and Bliemer, 2009). Values in the range −0.5 to +0.8 were used for the priors, with signs and magnitudes estimated based on the results of a literature review (Davies, 2019), and the pre-test stage of the DCE. The design was optimised for both direct and expected utility model specifications. Using the pilot data to update the priors did not improve the design, so we used the original design for the full survey.

Qualitative pre-testing, conducted face-to-face with a small number of respondents (as representative of the target group as possible), was undertaken to ensure the comprehension, credibility, and appropriateness of the survey (Johnston et al., 2017). The pre-testing phase started with focus groups and individual interviews with a convenience sample, university students, and citizens of Southampton. After pre-testing and modifying the survey, it was piloted online with a sub-sample of citizens more representative of Southampton's population. This involved mailing postal invitations to 500 citizens selected at random from the city council's electoral open register. A total of 43 respondents completed the online survey over a period of two weeks in July 2018, with 19 for the certain version, and 24 for the uncertain version – a response rate of 8.6 %. The quantitative pilot study also enabled the initial testing of the hypotheses by estimating the models described in Section 2.5. The pre-test and pilot test results suggested that respondents understood the survey questions and the choice experiment including the choice attributes. The respondents did not report that choice card options were implausible or that they perceived attributes to be somehow correlated.

2.3. Reflections on the DCE design

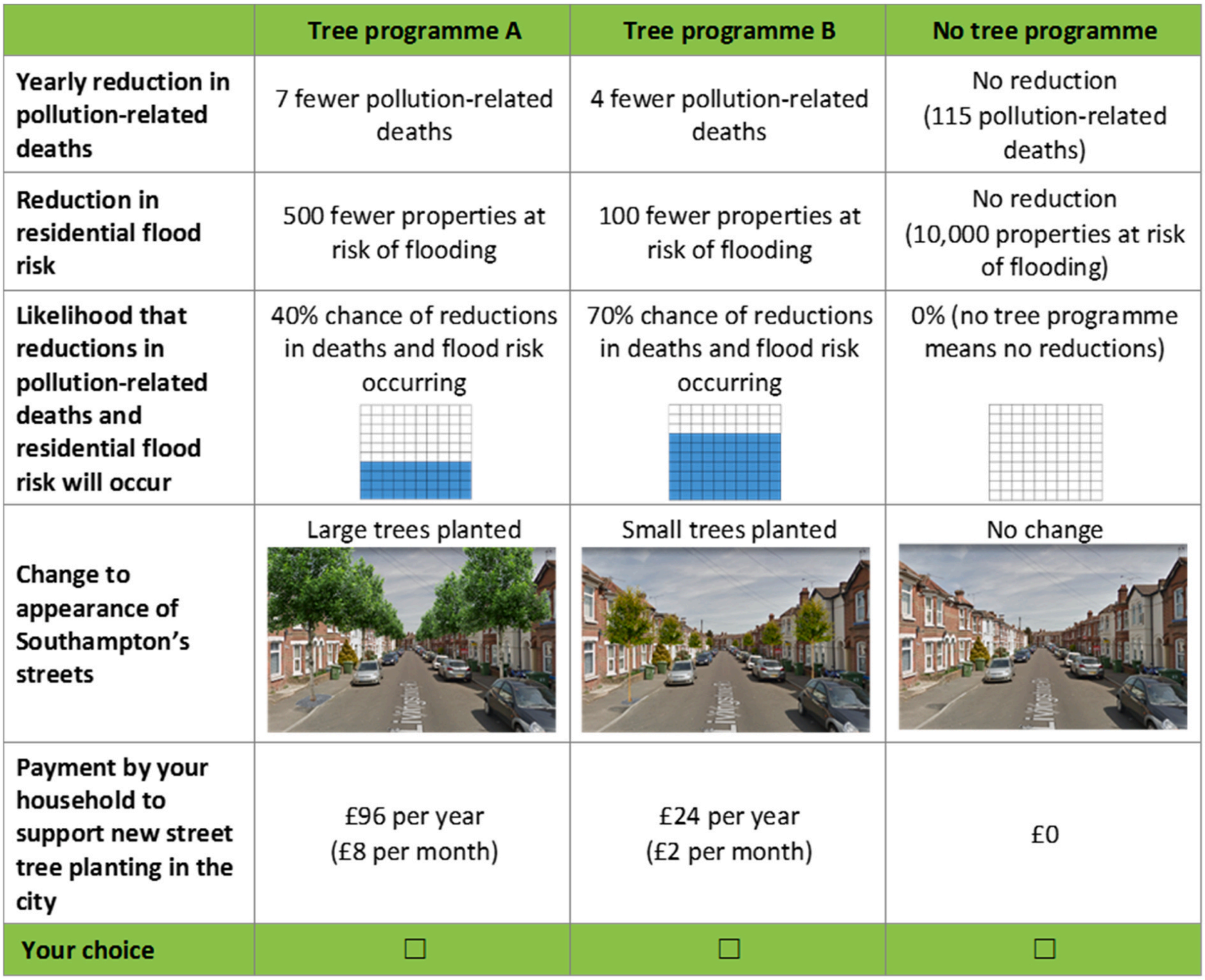
A number of issues related to our design should be highlighted. Firstly, size and species – as included in the Appearance attribute – influence the likelihood of ES delivery. However, the survey text also pointed at a range of other factors that interact

[5] There was a separate question that addressed the policy process related uncertainty, with Y/N response options, which was "*Do you believe the proposed City Tree Fund will be implemented in Southampton?*". This question was included in the survey after the assessment of posterior subjective uncertainty. We argue that the question to assess subjective uncertainty is comparable to the objective uncertainty attribute as both concern the likelihood that ES provision will occur. In the question phrasing, we took into account that in colloquial use, 'confidence' is conceptualised as likelihood or probability.

Table 1
Attributes and their levels for the ‘uncertain’ version of the questionnaire.

Attribute	Levels	Modelled variable	Expected sign
Yearly reduction in pollution-related deaths	No reduction (115 pollution-related deaths) (SQ); 1 fewer; 4 fewer; 7 fewer	AirQ – a continuous variable representing 1–7 fewer pollution-related deaths	+
Reduction in residential flood risk	No reduction (10,000 properties at risk of flooding) (SQ); 100 fewer; 300 fewer; 500 fewer	Flood – a continuous variable representing 100–500 fewer properties at risk of flooding	+
Likelihood that specified reductions in pollution-related deaths and residential flood risk will occur	0 % (no tree programme means no reductions) (SQ); 40 %; 70 %; 100 %	ObjCert – a continuous variable representing a 40–100 % chance of specified reductions in deaths and flood risk occurring	+
Change to appearance of Southampton’s streets	No change (SQ); Small trees (of one species) planted; Large trees (of one species) planted; Mixed trees (of varying sizes and species) planted	AppLarge – a dummy variable representing large trees AppMixed – a dummy variable representing mixed trees	± ±
Payment by your household to support new street tree planting in the city	£ 0 (SQ); £ 24 per year (£2 per month); £ 60 per year (£5 per month); £ 96 per year (£8 per month); £ 132 per year (£11 per month); £ 168 per year (£14 per month)	Payment – a continuous variable representing household payments of £ 24-£ 168 per year	–

Note: SQ levels were only included in the ‘No tree programme’ option (see Fig. 1).



	Tree programme A	Tree programme B	No tree programme
Yearly reduction in pollution-related deaths	7 fewer pollution-related deaths	4 fewer pollution-related deaths	No reduction (115 pollution-related deaths)
Reduction in residential flood risk	500 fewer properties at risk of flooding	100 fewer properties at risk of flooding	No reduction (10,000 properties at risk of flooding)
Likelihood that reductions in pollution-related deaths and residential flood risk will occur	40% chance of reductions in deaths and flood risk occurring	70% chance of reductions in deaths and flood risk occurring	0% (no tree programme means no reductions)
Change to appearance of Southampton’s streets	Large trees planted	Small trees planted	No change
Payment by your household to support new street tree planting in the city	£96 per year (£8 per month)	£24 per year (£2 per month)	£0
Your choice	☐	☐	☐

Fig. 1. Example choice task from ‘uncertain’ version of the questionnaire.

with size and species that can be manipulated, such as their proximity to buildings and pollution sources. This aimed to avoid that specific combinations of the attribute levels were perceived to be implausible, or that attributes were believed to be correlated. Given the high number of potential interventions that could affect delivery and their ranges in likelihoods, we did not impose any correlations in the experimental designs.

Secondly, despite an extensive search for information regarding the uncertainty, there was no evidence (either from academic research, tools or expert knowledge) that supported assumptions about differential probability levels between floods and air pollution as a result of tree planting, especially given the large number of factors that play a role in outcome delivery. Moreover, including separate likelihood attributes for flood risk reduction and air quality reduction was overly complicated for respondents. The explanation in the survey text therefore merged the likelihood of floods and air pollution reduction benefits to materialise, which was both credible and sufficiently understandable according to our pre-test and pilot, and we modelled this as a pooled likelihood.

Thirdly, we carefully tested that respondents understood the concept of likelihoods, by linking it to an example of weather forecasts and rain probabilities (provided in section (c)). This example also clarified what would happen if the event did not occur: no rain. The survey text also stated that a range of factors determine potential benefits and there is a possibility that the predicted health and flood benefits would not materialise. We carefully pretested this survey aspect so that it was well understood, but as always in SP surveys it cannot be ruled out that some respondents believed that tree planting would have some strictly positive impact.

For the control group, we did not explicitly state full outcome certainty for the effects but assumed that respondents would not include any objective uncertainty in considering the alternatives. Objective certainty was intended to be implied by excluding information about the outcome probabilities, which is how a large number of DCE surveys on ES provision presents the choice alternatives. However, we acknowledge, that asking respondents for their subjective belief regarding the outcome uncertainty probability may unintentionally have made respondents consider the possibility of uncertainty, which might influence the results of the control group.

2.4. The sample

The DCE survey was carried out online with residents of Southampton in September 2018. The survey was hosted on the University of Southampton's 'iSurvey' website. Postal invitations were sent to 6500 randomly selected citizens of Southampton in early September 2018, with online responses required by the end of the month; postal reminders were sent out two weeks into the survey period.

In total, 415 citizens of Southampton attempted the online survey – a response rate of 6.4 %.[6] Of these, 53 (12.8 %) failed to complete the choice questions, so are excluded from the choice models. Of the 362 respondents who completed the choice questions, 271 (74.9 %) always chose to pay for tree planting; 65 (18.0 %) sometimes chose to pay for tree planting; and the remaining 26 (7.2 %) always chose the 'no tree programme'. Of these 26 respondents, 23 (6.4 % of those completing the choice questions) were identified as protesters, which is low compared to most other urban forest WTP studies, where protest rates range from 4.9 % to 48.6 % (e.g. Chen and Qi, 2018). The main reasons these protesters gave for not wanting to pay for the tree planting programme were that the council should pay from existing taxes (n = 12), someone else should pay (n = 10), or lack of trust in the council to deliver the programme successfully (n = 10).[7] The protesters made up 7.3 % of the control group, and 5.3 % of the treatment group – these proportions are not significantly different ($\nu = 192$, $t = 0.767$, $P = 0.222$). Excluding the protesters from the choice models leaves 339 respondents in the modelled dataset (a total of 4068 observations). We randomly allocated more respondents to the treatment than to the control group, as the control group design was simpler and required a smaller sample. The control group therefore contains 105 respondents (1260 observations), whilst the treatment sample contains 234 respondents (2808 observations); the additional attribute in the uncertain version required a larger sample size.

The socio-demographic characteristics of the respondents are reported in Table 2 below. The respondents were significantly older ($\nu = 5$, $\chi^2 = 28.451$, $P < 0.001$) and more educated ($\nu = 5$, $\chi^2 = 14.175$, $P = 0.015$) than the Southampton population overall. Other differences were not statistically significant. As the purpose of the study is to analyse the effect of objective and subjective uncertainty on WTP – as opposed to estimating aggregate WTP values for tree planting in Southampton as a whole – representativeness is less of a concern. Chi-squared tests similarly revealed that the treatment and control groups were not significantly different from each other in terms of age, gender or education level, though the treatment sample did contain a higher proportion of individuals in the lower income categories, significant at the 10 % level ($\nu = 6$, $\chi^2 = 11.388$, $P = 0.077$).

Each respondent was asked for their prior beliefs (asked *before* the choice tasks) and their posterior beliefs (asked *after* the choice tasks) regarding the certainty with which they felt tree planting would reduce air pollution and surface water flooding in Southampton. Table 3 reports the subjective uncertainty scores of respondents. These sample statistics show that respondents'

[6] The literature suggests that response rates to online surveys are likely to be lower than other survey methods (Manfreda et al., 2008). For example, a response rate of just 5 % was found by Marta-Pedroso et al. (2007). Using postal mail to advertise a web-based survey (i.e. combining two methods) is likely to have reduced the response rate further. Needham et al. (2018) obtained a slightly higher response rate of 14.8 % using the same approach, though had a higher drop-out rate, at 20.8 %.

[7] Respondents were able to choose more than one reason from the list provided.

Table 2
Socio-demographic characteristics of samples vs. Southampton population.

Characteristic	Southampton population	Sample population[a]	Control group	Treatment sample
Age (ONS, 2005):				
18–22	15.5 %	3.6 %	3.9 %	3.5 %
23–29	17.1 %	9.4 %	7.8 %	10.1 %
30–39	18.2 %	12.8 %	11.8 %	13.2 %
40–49	14.4 %	19.5 %	20.6 %	18.9 %
50–64	18.4 %	31.9 %	33.3 %	31.3 %
65+	16.4 %	22.8 %	22.5 %	22.9 %
Gender (ONS, 2005):				
Male	50.8 %	56.1 %	52.9 %	57.5 %
Qualification attainment (NOMIS, 2017):				
No qualifications	7.4 %	3.2 %	5.1 %	2.3 %
Level 1	9.6 %	7.6 %	7.1 %	7.9 %
Level 2	15.0 %	13.1 %	11.2 %	13.9 %
Level 3	24.2 %	14.6 %	11.2 %	16.2 %
≥Level 4	36.0 %	51.6 %	55.1 %	50.0 %
Other	7.8 %	9.9 %	10.2 %	9.7 %
Annual household income[b]:				
< £15,000	n/a	10.9 %	9.9 %	11.3 %
£ 15,000-£ 24,999	n/a	17.1 %	13.6 %	18.6 %
£ 25,000-£ 39,999	n/a	22.5 %	21.0 %	23.2 %
£ 40,000-£ 59,999	n/a	22.2 %	27.2 %	20.1 %
£ 60,000-£ 79,999	n/a	12.0 %	8.6 %	13.4 %
£ 80,000-£ 99,999	n/a	8.0 %	13.6 %	5.7 %
≥ £100,000	n/a	7.3 %	6.2 %	7.7 %

[a] Number of respondents = 339 (105 certain and 234 uncertain).
[b] Categorical data for annual household income is not available for Southampton, however, the mean annual *individual* income is £ 24,367 (ONS, 2017). The mean annual individual income for the sample using the midpoints of the income categories (based on a sample mean of 1.86 adults with income per household) is £ 26,076, with a 95 % confidence interval of £ 24,091 - £ 28,061. As the population mean lies within this confidence interval, the incomes of the sample vs. Southampton as a whole are not significantly different.

Table 3
Prior and posterior beliefs regarding ES delivery, i.e. subjective uncertainty.

Subjective certainty about delivery of benefits of....	Prior or posterior belief	Sample population[a]	Control group[a]	Treatment sample[a]
Reduced air pollution	Prior belief	7.4	7.3	7.4
	Posterior belief	7.1	7.1	7.1
Reduced surface water flooding	Prior belief	6.5	6.6	6.4
	Posterior belief	6.4	6.4	6.3
Average for both ES	Prior belief	6.9	6.9	6.9
	Posterior belief	6.7	6.8	6.7

[a] Number of respondents = 339 (105 certain and 234 uncertain).

prior beliefs and posterior beliefs were each very similar in both the treatment and control groups, suggesting that no bias was caused by being in one group or the other.

2.5. Econometric framework

To analyse the DCE data, a random parameter logit (RPL) model was estimated (Mcfadden and Train, 2000; Scarpa and Thiene, 2005; Greene and Hensher, 2003; Train, 2009). RPL models are commonly used to analyse DCE data used for the estimation of WTP for environmental goods and services (e.g. see Brey et al., 2007; Faccioli et al., 2018; Broch et al., 2013).

To incorporate outcome uncertainty (based on known objective probabilities) in DCEs, the model needs to be adapted to allow for risk preferences. One approach uses expected utility theory (Bernoulli, 1738; von Neumann and Morgenstern, 1947), resulting in what Roberts et al. (2008) and Akter et al. (2012) refer to as a 'random expected utility model'. This incorporates risk-based interaction terms within the utility function to represent linear outcomes weighted by the likelihood of occurrence. An example of a risk-based interaction term is shown below, where the variable 'Probability' reflects different levels of probability of the outcome occurring:

$$U_{int} = \alpha_{int} + \beta_1 \text{Outcome} * \text{Probability} + \varepsilon_{int} \quad (1)$$

An alternative approach investigates whether (un)certainty has direct (dis)utility on respondents, independent of any of the other attributes (Rolfe and Windle, 2015; Glenk and Colombo, 2013; Lundhede et al., 2015). In this 'direct utility model', the Probability variable is incorporated directly into the utility function instead of as an interaction term:

$$U_{int} = \alpha_{int} + \beta_1 Outcome + \beta_2 Probability + \varepsilon_{int} \quad (2)$$

There is no theory per se underpinning the direct utility model; however, empirical support for direct aversion to risk is provided by Gneezy et al. (2006) and Simonsohn (2009). These studies showed that the 'uncertainty effect', i.e. that people are willing to pay less, on average, for a binary lottery than they are willing to pay for its worst outcome, is caused by uncertainty entering directly into people's utility function. Rolfe and Windle (2015) argue that this effect may be related to motivations that deviate from expected utility theory, whereby respondents prefer that their risk thresholds are not breached, akin to safe minimum standards or precautionary values. Glenk and Colombo (2013) and Lundhede et al. (2015) similarly found statistical support for their direct utility models. Indeed, when probabilities are included as a separate attribute in the choice task, it is likely that some respondents will evaluate it separately as a simple heuristic to reduce the cognitive burden of the task (Veronesi et al., 2014).

Because the treatment and control groups are presented with different information, it is possible that the randomness of the choices respondents in the two groups make (i.e. the variance of the error term) will be different (Swait and Louviere, 1993). As the scale parameter is confounded with the preference parameters, we analyse the two samples separately and compare model results and WTP estimates (Czajkowski et al., 2016).

2.6. Model specification and hypotheses

The utility functions and hypotheses associated with each of the three research questions are set out below. Our first research question is:

RQ1: Is citizen WTP for air purification and stormwater attenuation affected by the objective uncertainty associated with delivery of these ES?

We answer RQ1 based on the estimation results of Model 1a and Model 1b. Model 1a is estimated for the certain dataset (i.e. control group):

$$U_{1a} = \alpha + \beta_1 AirQ + \beta_2 Flood + \beta_3 AppLarge + \beta_4 AppMixed + \beta_5 Payment + \varepsilon \quad (3)$$

Model 1b is estimated for the uncertain dataset (treatment group) only and is specified as:

$$U_{1b} = \alpha + \beta_1 AirQ + \beta_2 Flood + \beta_3 AppLarge + \beta_4 AppMixed + \beta_5 Payment + \beta_6 Prob + \varepsilon \quad (4)$$

Here, α is the alternative specific constant (ASC), which takes the value 1 for the hypothetical alternatives and 0 for the opt-out. The coefficients for the categorical attribute of appearance are estimated against their lowest or baseline level, i.e. of small trees included in α; β_3 is the effect of large trees instead of small ones, and β_4 of mixed trees instead of small ones. Other variables are continuous and their β coefficients reflect the effects of 1 fewer pollution-related death (β_1),100 fewer properties at risk of flooding (β_2), and a 10 % increase in objective certainty (β_6).

The first null hypothesis H_10 is: There is no WTP for improving the objective certainty regarding the delivery of air quality and flood outcomes. This is tested by looking at the significance of the objective certainty attribute. Furthermore, H_10 would mean that WTP estimates for flood reduction, air purification and the overall programme are the same for Models 1a and 1b, as they are unaffected by the introduction of objective uncertainty. Here, we base the WTP estimates for the programme on the highest level for the objective certainty attribute, i.e. 100 %, to aid comparison between the two treatments. We test the equivalence of the mean WTP values and their empirical distributions using a (two-sided) 'Poe test' of equality of means (Poe et al., 2005).

Our second research question is:

RQ2: Is citizen WTP for air purification and stormwater attenuation, and for improving objective certainty, affected by the subjective uncertainty around the delivery of the ES?

To address this question, we split both samples based on the subjective uncertainty responses. We identified 'trusters' as those respondents with a subjective certainty score > 7 on the 0–10 Likert scale, and the remaining respondents as 'doubters' (45 % and 55 % of the sample, respectively).[8] We then re-estimate the models for the subgroups and compared the WTP of these subgroups in both samples. Our expectation is that WTP of trusters is higher than for doubters. We test the null hypothesis H_20: WTP for improving air quality, flood, and objective certainty outcomes, and for tree planting programmes is unaffected by respondents' subjective uncertainty about the delivery of those outcomes in both treatment and control groups.

Our third research question is:

[8] The subjective uncertainty score of ≤ 7 to represent doubters – and trusters otherwise - was chosen because (a) the value 7 was close to the sample average, creating somewhat equally sized subsamples, and (b) for consistency with the objective certainty attribute, whereby the levels 40 % and 70 % both represent uncertainty in the delivery of air quality and flood outcomes.

RQ3: Does the effect of objective uncertainty have a different effect on respondents with low subjective uncertainty compared to respondents with high subjective uncertainty?

To address this question, we compare the WTP results for doubters between the two treatments, the WTP for trusters between the two treatments, and the WTP for scenarios with different levels of objective uncertainty in the uncertain treatment.

We expect that the DCE design for the control group leads to higher WTP among trusters than for the treatment, as uncertainty is expected to reduce WTP. In contrast, we expect that the control group design reduces WTP among doubters, as acknowledging the outcome uncertainty explicitly in the DCE would improve the realism and credibility of the hypothetical scenario compared to scenarios which ignore objective uncertainty (Glenk and Colombo, 2011, Wielgus et al., 2009). Despite these contrasting effects of objective uncertainty, we hypothesise that subjective certainty influences utility to a greater extent than objective certainty does, such that trusters always have higher mean WTP for the programme than doubters. The findings of a number of psychology studies (Taber and Lodge, 2006; Lord et al., 1979; Kardash and Scholes, 1996) suggest that where the discrepancy between subjective and objective information is small, people are more likely to accept objective information. But where there is strong conflict between subjective and objective information, people are more likely to use their subjective beliefs and put lower weight on objective information, in order to deal with the cognitive dissonance (mental stress) of being faced with information that contradicts their views and updating one's beliefs. Overall, we expect the following ranking in WTP for the four subgroups: (trusters, control - TC) > (trusters, uncertain treatment - TU) > (doubters, uncertain treatment - DU) > (doubters, control - DC).

The models are estimated using 'R version 4.1.1' (The R Foundation, 2018), using 500 Modified Latin Hypercube Sampling (MLHS) draws. In the models, we include random parameters with normal distributions for all non-cost attributes, and for the cost attribute we use a lognormal distribution. We allow for full correlation between the random parameters.

3. Results

For the first research question, we find that Models 1a and 1b fit the control group and treatment data well (see Table 4). Here, we present the results of the Direct Utility model in Eq. (4), which demonstrated a much better fit than the Expected Utility model in equation 5. The latter results are included in the Online Appendix. In both models 1a and 1b, the coefficients for the ASC, AirQ and Flood are significant and positive, meaning that respondents prefer the tree planting programme over the status quo, and their utility increases as fewer people and properties are affected. The coefficients are significant and negative for Payment, as theoretically expected. For AppLarge and AppMixed the coefficients are insignificant, indicating that respondents did not prefer large or mixed trees over small trees. However, there is considerable preference heterogeneity for different types of trees, as the significant standard deviations of the associated random parameters show.

Regarding $H_1 0$, we find that $\beta_{6,}$ the coefficient for Prob in Model 1b, is significant and positive, showing that respondents prefer more certain options. The estimated WTP for Flood (per 100 fewer properties at risk of flooding) is significantly different and higher for the treatment group than for the control group ($p < 0.1$). WTP for AirQ (per 1 fewer pollution-related death) is slightly higher for the treatment group, but not significantly so. Looking at WTP for the tree planting scheme as a whole (based on the lowest levels for AirQ and Flood, and the planting of small trees), with objective certainty set at 100 %, citizens would be willing to pay an average of £ 17.80 per household per month.[9] This is significantly higher than the WTP of £ 13.10 of the control group ($p < 0.05$). Even setting ObjCert at 70 % results in overall WTP higher than that of Model 1a, though the difference becomes insignificant. Overall, these results suggest that $H_1 0$ can be rejected, except for the difference in WTP for AirQ.

To conclude on RQ1, providing information in the choice experiment about the objective uncertainty associated with the delivery of ES affects choices and increases WTP. Although respondents hold higher utility for higher levels of objective certainty, it appears that WTP for the proposed PES scheme may be positively affected by the inclusion of information on objective uncertainty (as opposed to ignoring outcome uncertainty). Though credibility of the two scenarios was not specifically investigated, a higher proportion of respondents did not believe the tree planting scheme would be implemented in the control group (35 %) than in the treatment sample (27 %); significant at the 10 % level ($\nu = 328$, $t = -1.493$, $p = 0.068$). The WTP of those who did not believe in the consequentiality of the scheme was significantly lower than that of other respondents for all attributes except Flood.[10] In addition, respondents did not seem to be put off the programme by objective uncertainty information, as there was no difference in the proportion of status quo (SQ) choices between the control and treatment groups – both being just under 10 % ($\nu = 4066$, $t = -0.145$, $p = 0.443$). In contrast, Glenk and Colombo (2011) obtained significantly more SQ choices in their treatment group (at 19 % compared to 13 % for their control group).

To answer RQ2, we split the sample into four subgroups by differentiating between trusters and doubters, and estimated their WTP for the attributes and the same programmes as for RQ1 (see Table 5, modelling results are presented in Table A.5 in the Appendix). The results of the one-sided Poe tests suggest that in the control group, subjective uncertainty affects the WTP

[9] (two-sided) Poe tests reveal that WTP for the programme in Model 1b is not significantly higher at 100 % objective certainty compared to 70 % ($p = 0.220$), or at 70 % compared to 40 % ($p = 0.136$), but is significantly higher at 100 % compared to 40 % ($p = 0.007$).

[10] Those not believing in the consequentiality of the scheme had significantly lower WTP for: planting large trees ($\nu = 328$, $t = 2.460$, $p = 0.014$); planting mixed trees ($\nu = 328$, $t = 2.432$, $p = 0.016$); enhancing objective certainty ($\nu = 328$, $t = 1.888$, $p = 0.060$); and enhancing air quality ($\nu = 328$, $t = 1.780$, $p = 0.076$). However, there was no difference in WTP for reducing flood risk ($\nu = 328$, $t = -1.109$, $p = 0.268$).

Table 4
Coefficients and WTP for the control (Model 1a) and treatment (Model 1b) groups.

	Model 1a			Model 1b			
Attributes	Coefficient (s.e.)	RP std devn (s.e.)[a]	Mean WTP (£ per month); 95 % CI)[b]	Coefficient (s.e.)	RP std devn (s.e.)[a]	Mean WTP (£ per month); 95 % CI)[b]	Poe test p-value[c]
ASC (α)[d]	6.174***		12.3	3.016***		7.0	
	(0.432)		[9.6, 15.5]	(0.455)		[4.9, 9.3]	
AirQ (β_1)[e]	0.249***	0.460***	0.5	0.256***	0.352***	0.6	0.285
	(0.079)	(0.093)	[0.2, 0.8]	(0.058)	(0.140)	[0.4, 0.8]	
Flood (β_2)[f]	0.196***	0.280***	0.4	0.268***	0.259***	0.6	0.098*
	(0.05)	(0.101)	[0.2, 0.6]	(0.046)	(0.066)	[0.4, 0.8]	
Prob (β_6)[g]				0.413***	0.380***	1	
				(0.059)	(0.065)	[0.7, 1.3]	
AppLarge (β_3)[h]	0.205	2.392***	0.4	0.089	2.009***	0.2	0.808
	(0.29)	(0.449)	[−0.8, 1.6]	(0.161)	(0.337)	[−0.6, 1]	
AppMixed (β_4)[i]	-0.05	1.340***	-0.1	0.148	1.190***	0.3	0.380
	(0.202)	(0.265)	[−1, 0.8]	(0.118)	(0.190)	[−0.2, 0.9]	
Payment (β_5)[j]	-1.05***	0.859***		-1.398***	1.054***		
	(0.168)	(0.094)		(0.14)	(0.083)		
Tree planting programme (implied certainty or 100 % Prob)[k]			13.1 [10.4, 16.4]			17.8 [14.6, 21.5]	0.023**
Tree planting programme (70 % Prob)[k]						14.9 [12.3, 17.9]	
Tree planting programme (40 % Prob)[k]						12.0 [9.9, 14.5]	
Number of observations	1260			2808			
Log-likelihood	-705			-1724			
Adjusted ρ^2	0.475			0.432			
AIC	1453			3504			
BIC	1561			3670			

*, **, *** represent statistical significance at 10 %, 5 % and 1 % level, respectively.
[a] The random parameters of the non-cost attributes follow a normal distribution, and the payment attribute's coefficient a log-normal distribution, with full correlation between attributes. The standard errors of the standard deviations are calculated using the Delta method.
[b] Mean WTP and confidence intervals are calculated per household per month, using Krinsky and Robb (1986) bootstrapping procedures with 2000 draws.
[c] Using Poe et al. (2005), the equality of mean WTP values from two empirical distributions (M1a vs. M1b) is tested (two-sided), using the 2000 draws from the Krinsky and Robb bootstrapping.
[d] Coefficient and WTP estimates are for a tree planting programme, including small trees.
[e] Coefficient and WTP estimates are per 1 fewer pollution-related death.
[f] Coefficient and WTP estimates are per 100 fewer properties at risk of flooding.
[g] Coefficient and WTP estimates are per 10 % increase in the probability (objective certainty).
[h] Estimates (and WTP) are for large (as opposed to small) trees.
[i] Estimates (and WTP) are for mixed (as opposed to small) trees.
[j] The model assumes a log-normal distribution for the cost attribute but the underlying parameters for the normal distribution are reported: cost = -exp (logcost_mu + logcost_sig*draws_cost) where logcost_mu and logcost_sig are the reported mean and SD of the underlying normal distribution (see also Faccioli et al., 2018).
[k] WTP for the programme is estimated based on the sum of the WTP estimates for the lowest levels of the three ES attributes, i.e. 1 fewer pollution-related death, 100 fewer properties at risk of flooding, and for the planting of small trees.

for Flood significantly, but not the AirQ or the tree planting programme scenario.[11] However, in the treatment, the WTP estimates differ significantly between trusters and doubters for all attributes and tree planting programmes, with trusters holding 2–3 times higher WTP values than doubters. This suggests that subjective beliefs about the likelihood of ES delivery in the treatment affect choices and WTP. We do not find this difference in the control group, but this may be due to the smaller sample size.[12]

For RQ3, the ranking of the WTP estimates for the tree planting programme (without objective uncertainty information or 100 % objective uncertainty) of the four different respondent groups is different from the hypothesised ranking of TC > TU > DU > DC. We find that trusters in the treatment group have a significantly higher WTP for this programme than all other groups, of whom the WTP values do not differ significantly: TU > TC = DU = DC.

When looking into differences within the trusters and doubters between the control and treatment groups, we find that in contrast to our expectations, trusters in the treatment have a significantly *higher* WTP for air quality improvements and flood risk reduction than in the control group (at a 10 % significance level). Similarly, but as expected, doubters have a higher WTP

[11] The different way in which subjective certainty affects WTP for Flood compared to WTP for AirQ is likely to arise from the fact that subjective certainty scores relating to stormwater attenuation ($\mu = 6.4$) were lower than those for air purification ($\mu = 7.1$) – significant at the 1 % level ($\nu = 330$, $t = 8.723$, $p < 0.001$). Despite the mean subjective certainty score (i.e. prior belief) being significantly lower for stormwater attenuation than for air purification, the mode score for both was 8, while the range and spread of the scores were also very similar for the two ES. The former had $\sigma = 2.2$ and range = 0–10, while the latter had $\sigma = 2.1$ and range 1–10.
[12] We performed a sensitivity analyses on the cut-off point used to identify trusters and doubters. Results are included in the online Appendix.

Table 5
WTP values for Trusters and Doubters for the control and treatment groups.

	Control group			Treatment group		
	Doubters[b] (N = 60)[a]	Trusters[b] (N = 45)[a]	Diff[c]	Doubters[b] (N = 127)[a]	Trusters[b] (N = 107)[a]	Diff[c]
Air pollution reduction[d]	0.2 [−0.2, 0.6]	0.3 [0, 0.7]	-0.1	0.5 [0.3, 0.7]	1.2 [0.7, 1.6]	-0.7**
Flood risk reduction[e]	0.1 [−0.2, 0.4]	0.4 [0.3, 0.7]	-0.3**	0.5 [0.3, 0.7]	1 [0.6, 1.6]	-0.5**
Probability[f]				0.6 [0.4, 0.8]	1.8 [1.1, 2.7]	-1.2***
Tree planting programme (no uncertainty or 100 % Prob)[g]	11.6 [8.7, 15.4]	9.6 [6.4, 13.7]	2.0	10.4 [8.4, 12.7]	27.4 [20.0, 36.9]	-17.0***
Tree planting programme (70 % Prob)[g]				8.7 [7.1, 10.4]	22.0 [16.4, 29.1]	-13.3***
Tree planting programme (40 % Prob)[g]				7.0 [5.7, 8.6]	16.7 [12.4, 21.8]	-9.7***

Note:
[a] This is the number of respondents in this group.
[b] Those with a score on subjective certainty of < 7 are categorized as doubters and > 7 as trusters.
[c] 'Diff' is the WTP difference between the doubters and trusters group estimated using the (one-sided) Poe (2005) test. *, **, *** represent statistical significance at 10 %, 5 % and 1 % level, respectively.
[d] WTP is calculated per 1 fewer pollution-related death.
[e] WTP is calculated per 100 fewer properties at risk of flooding.
[f] Estimates are per 10 % increase in the probability (objective certainty).
[g] WTP for the programme is estimated based on the sum of the WTP estimates for the lowest levels of the three ES attributes, i.e. 1 fewer pollution-related death, 100 fewer properties at risk of flooding, and for a tree planting programme including small trees. Including WTP values for attributes with insignificant mean estimates in WTP calculation does not change the results.

value for these two attributes in the treatment than in the control group. Combined with the results of RQ2, this leads to a ranking (at a 10 % significance level) of: TU > TC = DU > DC for both attributes.

The pattern that emerges from our data is that for trusters the introduction of objective uncertainty has a higher impact than the specific level of objective uncertainty, whereas for doubters acknowledging objective uncertainty does not affect WTP as much as the level of objective uncertainty. As a result, the WTP in the uncertain treatment for a programme with a 40 % probability of ES delivery is lower than the WTP in the control group for doubters, but remains higher than in the control group for trusters.

We also find the effect of subjective uncertainty in the proportion of respondents choosing the SQ: in the control group, 7.2 % of trusters and 11.0 % of doubters chose the SQ, whilst in the treatment group, 5.8 % of trusters and 12.7 % of doubters did so. While there was no difference in SQ choices *between treatments* for either trusters (P = 0.119) or doubters (P = 0.126), there were significantly more SQ choices amongst doubters than trusters in both the control (P = 0.012) and treatment (P = 0.000) groups. This suggests subjective certainty affects whether people are willing to pay in principle, but objective certainty does not.

4. Discussion

4.1. Effect of objective and subjective uncertainty on willingness-to-pay

Model 1b revealed a strong distaste for objective uncertainty amongst respondents; increasing the level of certainty had a large positive impact on overall WTP. Most papers investigating the effect of objective uncertainty on WTP for environmental programmes have similarly found respondents willing to pay more (and/or more likely to pay in principle) as the probability of outcomes improved. For each 10 % increase in the probability of benefit delivery, respondents in Southampton were willing to pay an additional £ 1 per household per month. This is similar to the result of Glenk and Colombo (2011) who found respondents willing to pay an additional £ 1.67 per year for each 1 % increase in the probability of programme success. Rolfe and Windle (2010) and Akter et al. (2012) found WTP for each 1 % increase in the probability of environmental policy success to be even higher, whilst Wielgus et al. (2009) found their respondents willing to pay twice as much for guaranteed environmental outcomes than uncertain ones. Based on these results, it may be worth asking citizens to contribute towards the cost of additional research that ensures the right trees are planted in the right places (thus improving the objective certainty of ES provision).

However, respondents in the control group were willing to pay significantly *less* for tree planting with implied certain ES delivery, than respondents in the treatment group were willing to pay for tree planting with a 100 % chance of ES delivery, and also less than the treatment group for a 70 % chance of delivery (though not significantly so). This could be – as Wielgus et al. (2009) and Glenk and Colombo (2011) postulated – because respondents found the objectively uncertain scenario to be more realistic and/or credible than the implied certain one (a framing effect of introducing objective uncertainty). Respondents were not explicitly asked about realism or credibility in our survey – something that would be useful to ascertain in future studies. However, respondents were asked whether or not they believed the tree planting scheme would be implemented, and a significantly greater proportion of those in the certain sub-sample did not believe it would be, compared to those in the treatment. Furthermore, the average respondent was only 68 % sure that tree planting would reduce air pollution and surface water flooding in Southampton. It is therefore plausible that some of the respondents in the control group did not believe the supposedly certain programme outcomes (see Section 4.2).

The results of RQ2 show that utility for the air purification, flood reduction and objective certainty attributes is significantly and positively affected by respondents' subjective beliefs surrounding the certainty of the delivery of these tree benefits in the treatment. In the control group, the only significant difference was for the Flood attribute, where trusters hold a significantly higher WTP for reducing residential flood risk than doubters. Results for RQ3 revealed that introducing objective uncertainty only increases WTP for trusters. Although few other studies have looked into the effect of subjective uncertainty on WTP for environmental programmes, our results seem to be comparable to Lundhede et al. (2015). They found that respondents who were a priori certain that a proposed policy would deliver bird conservation outcomes, were willing to pay significantly more for a policy later described as objectively uncertain (via an attribute) than were the other respondents. However, our results are not directly comparable as Lundhede et al. (2015) used dummy variables representing qualitative measures of subjective and objective certainty, interacted together. The results for RQ3 did not support the hypothesis from the literature that WTP of ES doubters is higher for objectively uncertain outcomes due to improved realism and credibility.

The results suggest that the differences in WTP between doubters and trusters are on average larger than between the control and treatment groups. But to increase WTP for tree planting, educating people about the benefits of trees (on the assumption that this would improve subjective certainty and convert doubters to being trusters), as suggested by Ng et al. (2015), is only effective if the objective uncertainty is then disclosed in the communication about any intervention. Disclosing that outcome uncertainty may exist in general triples WTP of trusters (difference between control and treatment) as long as the outcomes for a specific scenario are 100 % objectively certain. Among doubters, only the level of objective uncertainty affects their WTP.

To summarise, objective and subjective uncertainty regarding delivery of ES both had strong, negative relationships with WTP for the proposed street tree planting programme. However, implying that benefits occur with certainty by not mentioning objective uncertainty in DCE surveys does not necessarily result in higher WTP than when admitting that tree benefits are objectively uncertain, as many people are 'doubters' and evaluate alternatives considering their subjective beliefs about the likelihood of benefit delivery.

4.2. Limitations

The sample size of 362 completed sets of choice tasks was smaller than hoped for, particularly given the split-sample design. Once protest responses had been removed, just 105 respondents remained for the control group, and 234 for the treatment group. Whilst there were sufficient observations to obtain significant results, statistical power was nevertheless reduced, resulting also in large confidence intervals around the mean WTP values. The response rate was also somewhat low; if respondents were more positive about trees than non-respondents, then possible self-selection bias may have affected the WTP values.[13] Despite this possibility, the overall WTP values were reasonable compared to other urban forest WTP studies: £ 13.40 per month (£160.80 per year) for the overall tree programme in Model 1a lies within the range of £ 7–341 per year reported by 20 urban forest studies reviewed by Davies (2019). The WTP values for the scenarios were equivalent to an 8.8–12.7 % increase to existing council tax payments in Southampton. Nonetheless, two of the four WTP estimates for the policy scenarios exceed the highest bid level in the DCE (£14). While we do not deem the WTP estimates excessively high, they may indeed be subject to bias as discussed in Glenk et al. (2019). Our pre-test results suggested that the highest bid-levels were considered high, and response patterns showed a steadily declining acceptance rate of alternatives as costs increased, yet 9 % of all choices were for alternatives with the highest bid level. We do not know what the choke-price is for the good under valuation, and some respondents may have been insensitive to the cost-attribute out of strong pro-environmental motivations, or failed to pay attention to the costs (attribute non-attendance).

A larger sample size may have enabled in-depth testing of how citizens update their beliefs when presented with objective certainty information (implied or stated)[14] that conflicts with their prior beliefs about the likelihood of ES delivery – a recommendation for future studies (e.g. see Cameron, 2005; Alberini and Longo, 2009). Subjective beliefs being prioritised over conflicting objective information in decision-making is an example of 'disconfirmation bias', whereby people readily accept confirmatory arguments, but actively reject opposing ones – as a response to cognitive dissonance (Taber and Lodge, 2006; Akerlof and Dickens, 1982).

Our study does not fully disentangle the framing effect of introducing (objective) uncertainty into the scenario from the effect of changes in expected outcomes (i.e. the different levels of outcome uncertainty, and their impact on the flood and air quality outcomes to which they relate). This is a general gap in the stated preference literature on outcome uncertainty, which

[13] For example, posterior analysis suggested that the importance respondents placed on the air quality and flood reduction benefits of trees strongly influenced their WTP for reducing pollution-related deaths and reducing properties at risk of flooding, respectively. Age was also significantly positively correlated with WTP for the Flood attribute, however, level of education did not significantly affect WTP for any of the attributes.

[14] Objective certainty information should vary between rather than within scenarios (e.g. through sub-samples of respondents shown 40 % certainty vs. 70 % certainty vs. 100 % certainty) for ease of analysis.

Bujosa et al. (2018) attempt to address by introducing a 'probability of temperature rise' attribute that changes only across (not within) choice sets. Faccioli et al. (2018) also isolate the pure framing effect of introducing uncertainty by using a split-sample comparison whereby the expected outcomes in the certain treatment are equal to those in the uncertain treatment. However, given the focus of our paper on objective vs. subjective uncertainty, these approaches were not considered appropriate. Stated preference surveys need to make trade-offs between comprehension and precise empirical assessment of theoretical variables, which is extremely complicated for complex concepts such as risk, uncertainty and probabilities, as we discuss in Section 2.3.

As acknowledged in Section 2.3, asking respondents for their subjective uncertainty prior to the DCE may have affected choices and the interpretation of the objective uncertainty attribute (Liebe et al., 2016). However, we deemed this a better option than using posterior subjective uncertainty, which would have been informed by the information provided in the survey and the choice task.

We investigated the effect of subjective uncertainty by comparing WTP estimates between subgroups with different degree of trust towards the likelihood of policy delivery. A limitation of this approach is that it may involve an endogeneity issue, i.e., there might be unobserved effects that affect both responses to the subjective belief question and choices. Hybrid choice models can mitigate this issue of endogeneity and measurement error by allowing a latent variable to be a function of the attitudinal indicator, together with an error term, instead of incorporating the attitudinal indicator directly as explanatory variables (Daly et al., 2012; Mariel and Meyerhoff, 2016).

Finally, the survey did not explicitly ascertain from respondents whether presenting outcomes as uncertain improves the realism and credibility of environmental schemes (Wielgus et al., 2009; Glenk and Colombo, 2011). Future studies could test this using certain and uncertain sub-samples as used here, or a before-and-after approach with the same group of respondents, where uncertainty is introduced halfway into the survey.

5. Conclusions

This study makes an important contribution to the stated preference literature on environmental outcome uncertainty, by investigating the effect of both subjective and objective uncertainty. In particular, it investigates how people who a priori trust or doubt the provision of urban forest regulating ES react to being asked to contribute to a proposed tree planting programme scheme where outcome uncertainty is either ignored or explicitly defined as an attribute in the DCE. Our results reveal a positive relationship between utility and objective certainty, and that WTP for a tree planting programme where outcome uncertainty is ignored is in fact lower than one with outcomes explicitly presented as uncertain. Subjective beliefs have a significant effect on respondents' utility for improved air quality, flood and objective certainty outcomes. However, this effect is only found for the treatment with objective uncertainty information. We find that in our study, respondents' confidence in the ES delivery when trees are planted reduces WTP more in absolute terms than does objective uncertainty around ES delivery. Furthermore, the results suggest that WTP for a truster shown uncertain outcomes is significantly higher than for a truster not being shown outcome probabilities, or for doubters in either of the two treatments.

Overall, the results of this study support the suggestions of other papers that it may improve stated preference studies if the objective uncertainty is explicitly acknowledged as opposed to ignoring such uncertainty and thereby implying that ES provision is guaranteed. If subjective beliefs are not accounted for, then a significant determinant of choice behaviour remains unidentified, and heterogeneity unexplained. If our findings are transferable to non-hypothetical options, understanding subjective beliefs may help to explain why societal support for interventions is lower than benefits based on expected utility estimates would call for (Moffat, 2016). If so, addressing subjective beliefs regarding the likelihood of ES provision through for example awareness raising campaigns could be actioned by policy-makers and practitioners if they are to improve public support for ES management.

In terms of future research, it would be useful to investigate the effect of cognitive dissonance between objective and subjective certainty on WTP for environmental programmes. For example, it may be the case that small discrepancies have little impact on WTP, but that large discrepancies result in mistrust of the scheme, and thus reduced (or even zero) WTP. How respondents update their beliefs in response to objective certainty information would also be worth exploring in this context.

Data Availability

The data that has been used is confidential.

Declarations of interest

None

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.reseneeco.2022.101344.

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