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Public Preferences and Willingness to Pay for Forest Disease Control in the UK

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Abstract

Invasive pests and diseases in trees impose a range of costs on society related to reductions in timber values, impacts on recreational opportunities and effects on forest biodiversity. These costs need to be considered when assessing control options and developing public policy. We investigate the preferences and willingness to pay of the UK general public for a range of forest disease control measures using a choice experiment with a sample of 605 people. Respondents were relatively well informed about general tree disease-related issues, such as causes and general measures to minimize the risk of disease spread. They were less knowledgeable about specific tree diseases, with Dutch elm disease and chalara ash dieback being the most well-known. We find that disease control programmes in publicly-owned forests and forests owned by charitable trusts are more likely to be supported by the public than equivalent control programmes in privately-owned and/or commercial forests. The nature of scientific uncertainty about diseases does not affect peoples' preferences for disease control measures significantly. Higher respondent income, greater ex-ante knowledge about tree diseases, and more frequent visits to forests are correlated with greater willingness to support publicly-funded tree disease control programmes in forests. Better knowledge about tree diseases also improves the clarity of respondents' choices. We find a negative sentiment against some disease control measures, such as clear felling of a forest, and chemical or biocide spraying. We conclude that there is significant public support for part-financing forest

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disease control policies in the UK, but that this is conditional on forest ownership and the type of control measures used.

Key words: Invasive species, discrete choice experiment, willingness to pay, preferences, tree pests and diseases, disease control measures, forest benefits.

JEL Codes: C35, Q23, Q57.

1. Introduction

A growing number of pests and diseases threaten to damage trees, woods and forests in both rural and urban landscapes. In the UK, an increasing number of disease outbreaks have occurred in the past 20 years and there are concerns over the potential arrival of new diseases. Over 750 pest and pathogen species are currently recorded on Defra's Plant Health Risk Register[2]. Internationally, the number and frequency of pest and disease outbreaks in forests has been rising over time, with factors such as increases in international trade, climate change and the introduction of exotic species outside their historical ranges being implicated for this increase (Figure A1, on-line appendix). Such pest and disease outbreaks have multiple negative consequences including financial losses to timber business, considerably-reduced recreational possibilities, effects on biodiversity, and changes to landscape quality in affected areas (THAPBET, 2013).

Although prevention of a plant disease (we now refer just to diseases, rather than pests and diseases) would typically be the best management strategy, such biosecurity measures are rarely completely effective. Once a disease is established, control and management actions may be used to limit the extent or slow the rate of spread (NISC, 2008). The costs of these measures are likely to be substantial, especially in view of the increasing risk of new tree diseases arriving in the UK (Brasier & Webber, 2010). Whilst the forest industry will continue to pay a considerable part of these costs, the government is also very likely to be called on to deal with this problem, for two major reasons. First, many forests and woodlands in the UK are owned or managed on behalf of the public by the Forestry Commission, Natural Resources Wales, local authorities and NGOs, rather than the private sector. Second, tree diseases can spread between woodlands in different ownerships creating shared liabilities and filterable externalities, whereby the actions of one landowner can change the expected costs to their neighbours from an outbreak (Wilen, 2007). In such situations, actions motivated solely by expected private benefit will result in social under-investment in disease control.

Hence, the public purse is likely to be responsible for at least some forest disease control, which means that attitudes to tree diseases and disease control measures, and

[2] See https://secure.fera.defra.gov.uk/phiw/riskRegister/

willingness to pay for publicly-funded disease control programmes [3] become important. We also examine whether *ex-ante* knowledge about tree diseases and recreational use of forests are related to peoples' stated preferences, since improving public knowledge of tree diseases could increase public support for mitigation efforts, while forest use can affect the distribution of welfare losses from disease outbreaks and willingness to pay to reduce future damage costs.

The next section provides an overview of the literature on stated preference analyses of invasive pests and diseases, and links the issue of public knowledge about tree diseases to a more general literature on how knowledge of the good being valued in stated preference surveys is related to responses. The third section describes our choice experiment, followed by an overview of the sample characteristics and preliminary analysis of respondent answers. Section 4 summarises our findings on forest use and *ex-ante* knowledge of tree diseases, followed by model estimation results (section 5). The final section provides a discussion and conclusions.

2. Previous Work

Invasive species (a broad category which includes most serious tree pests and diseases) can have substantial impacts on land uses, through effects on agricultural and forest production, biodiversity, ecosystem services, infrastructure and communities ((Rolfe & Windle, 2014), (Pimentel, Zuniga, & Morrison, 2005), (Lovell, Stone, & Fernandez, 2006), and (Rosenberger et al., 2012)). Born, Rauschmayer, & Bräuer (2005) argue that assessing the social costs of invasive species is challenging because most involve impacts on a combination of direct use, indirect use and non-use values. The combination of private and public values that are affected by invasive pests and diseases suggests that stated preference methods are an appropriate method to estimate the costs of outbreaks, and the benefits of control programmes.

Several authors have used stated preference methods to investigate the social costs of invasive species. For example, Chakir, David, Gozlan, & Sangare (2016) estimate the willingness to pay to avoid the negative impacts of an introduced pest-control species, the Asian ladybird in France, finding that respondents have a significant willingness to

[3] We use the word "measure" to describe a single type of action, such as spraying, and "programme" to describe a combination of several disease control measures.

pay to avoid the adverse impacts of introduced species on native ladybirds. McIntosh, Shogren, & Finnoff (2010) use contingent valuation to estimate the willingness to pay to postpone the environmental costs associated with an “inevitable” process of invasion by aquatic species (fish, molluscs, crustaceans and water plants) within their region of the US. They find that aggregate willingness to pay for postponing invasions into waterways far exceeded estimates of current control expenditure by the US federal government.

In a related study, García-Llorente et al. (2011) use contingent valuation to investigate social factors influencing willingness to pay for managing invasive alien species under two control regimes (eradication and prevention) in the Donana Natural Protected Area in Spain. Their results indicate that respondents were more willing to pay for eradication than prevention; and public support for invasive alien species management is positively influenced by an individual’s knowledge of invasive alien species, their active interest in nature, and their household income. Similarly, Nunes & van den Bergh (2004) find that frequency of recreational visits to a seashore in the Netherlands and the degree of an individual’s concern about the protection of seaside nature areas are positively correlated with willingness to pay for a marine protection programme to counter invasive species.

A number of studies show that long-term sustainable forest management considerations may outweigh commercial or recreational use factors and so have a significant impact on the choice of invasive species control measures. Meldrum, Champ, & Bond (2013) use contingent valuation to measure potential benefits of managing an invasive disease (white pine blister rust) in high elevation forests in the Western United States. They show that, from the point of view of the public, long-term protection of forests dominates recreation in motivating support for the diseases control, but there seemed to be significant heterogeneity among the respondents with respect to the importance of these two considerations. Meldrum (2015) finds that incorporation of general pro-environment respondent attitude statements into their model helps capture and explain the observed preference heterogeneity. Moore, Holmes, & Bell (2011) also highlight the dominance of public attitudes towards long-term forest protection over recreational usage in driving their WTP estimates. Fleischer, Shafir, & Mandelik (2013) demonstrate that respondents consider the use of toxic pesticides more dangerous than the spread of the invasive species in their assessment of WTP for alternative management programmes for an invasive alien bee species, which reduces rates of plant pollination. Finally, there is indeed considerable scientific uncertainty about the speed of spread of potential new diseases, about their severity, and the efficiency of disease control measures. Born et al. (2005) note that this uncertainty is a central characteristic of alien species invasions and forest diseases, and conclude that this uncertainty should be accounted for in economic valuation.

A key problem in applying methods such as choice modelling or contingent valuation to invasive species is the extent to which respondents are well-informed about the issue. Garcia-Llorente et al (*op cit.)* find links between knowledge about the invasive species and willingness to pay to control its spread. Providing a specific context for our paper, Fuller, Marzano, Peace, Quine, & Dandy (2016) assess the British public's knowledge about tree diseases. They find that, although the majority of respondents identified themselves as concerned about the threat of tree diseases, their level of general knowledge about diseases was very low. This raises the general question of how to model the effects of peoples' knowledge about the good being valued on their stated preferences.

In a recent series of papers on this issue, LaRiviere et al. (2014), LaRiviere, Czajkowski, Hanley, & Simpson (2015) and Sandorf, Campbell, & Hanley (2015) use a measure of respondents' prior knowledge about the good being valued to analyse stated preference responses, in terms of the values which people state, the precision with which values are stated, and the use of choice heuristics. As the measure of prior knowledge, these authors used the number of correct responses in a multiple-choice quiz that was administered at the beginning of a stated choice experiment. Czajkowski, Hanley, & LaRiviere (2014) study the effect of experience on respondent choices and find strong evidence that additional experience makes consumer preferences more econometrically predictable (less random). This suggests that it is important to include measures of knowledge and experience in econometric analysis of choices over tree disease programmes, both in terms of effects on preferences and on scale (randomness in choice).

3. Experimental Design

We developed an online choice experiment survey using Sawtooth Software, generating the design in Ngene via a two-step procedure. First, a pilot experiment design assumed that a multinomial logit (MNL) model best described the preferences of respondents. This design was revised with the results of a mixed logit (or random parameter logit, RPL) model fitted to pilot study data from 48 respondents. We chose the D-error[4] measure as the criterion for the design selection in order to minimize standard errors of the model's parameter estimates. A new D-efficient experimental design was generated for a mixed logit model, and the resulting design with five blocks, each with eight choice cards, was used in the main experiment.

Respondents to the main choice experiment came from an on-line panel provided by a market research company, Toluna UK, which ensured that the respondent sample was balanced according to geographic distribution and major demographic characteristics of the UK population. Conducting stated preference surveys over the web using internet panels of respondents is now commonplace, and has been shown to perform well compared with alternative means of collecting data (Sandorf, Aanesen, & Navrud, 2016).

We follow LaRiviere et al. (2014) in measuring *ex-ante* knowledge about tree diseases via quiz questions administered at the beginning of the on-line survey. We then use the number of correct quiz answers, and an indicator based on whether people's quiz score exceed the median number of correct answers as variables to explain taste (preference) and scale heterogeneity respectively. We also explore the effects of familiarity with forests (stated frequency of respondents' visits to forests) on choice heterogeneity.

The survey consisted of four parts. In the first part, the respondents were asked about their recreation habits, as well as several questions testing their general knowledge of tree diseases and disease control measures. The second part was the choice experiment, consisting of eight choice cards each with two unlabelled options that described alternative measures comprising possible tree disease control policy options, and an opt-out option which represented a status quo choice of no additional action (as illustrated in Figure 1).

The introduction to the choice experiment explained that respondents would be asked to select between options for how the government should tackle the problem of new tree diseases in the UK. Each option referred to a given disease control programme over a 10-year period. These programmes would help to control different diseases and did not focus

[4] D-error is the most widely used measure of efficiency of an experiment design. It is equal to the determinant of the asymptotic variance-covariance matrix of a model estimated from simulated choices given a particular experiment design. A design that has a sufficiently low D-error (compared to other possible designs) is called a D-efficient design.

simply on one specific disease (we return to this aspect of the design later). Respondents were also told that scientific knowledge about the speed of spread and degree of damage for new and existing diseases is incomplete, and so the description of the disease control programmes included an attribute to reflect this scientific uncertainty.

Each programme was defined by six attributes:

- who owns a forest or woodland where the disease is present;
- the type and size of a woodland affected by a disease;
- which disease control measures are being considered;
- what are the main scientific uncertainties about future tree diseases;
- what kind of benefits from forests may be most badly affected by a disease;
- the additional tax costs per household of the programme.

Table 1 provides more details on the attributes and their levels. Using these attributes we sought to describe a situation when a possible new tree disease would have a broad enough range of negative consequences so that, not only forestry or timber businesses, but also a wide spectrum of the UK general public could be affected, for example through the loss of recreational opportunities, biodiversity or carbon storage, or via landscape changes. The disease control measures that we include in the experiment are both general enough yet at the same time conform to standard UK forestry practices, although note again that the choices people make are not in the context of a specific, named disease. The final attribute included in the design was the cost of each disease control programme to UK households, expressed as an increase in taxes paid per year.

In the third part of the survey we asked respondents to reflect on how they had made their decisions, to say if they ignored some of the attributes in making their choices, and to provide a simple ranking of the importance of the attributes. The fourth part of the survey asked about respondents' socio-economic characteristics.

4. Sample and Choices Overview

In total 605 respondents completed the survey. In addition, 180 respondents dropped out of the survey at different stages, and were not used in the analysis. Half of the dropouts took place immediately after the introduction page, with a further 19%

abandoning the survey before the start of the tree disease quiz. This suggests that the most frequent reason for non-participation in the choice experiment was disinterest in the topic, rather than a flaw in the experiment design.

Demographic characteristics of the sample (n = 605) are summarized in Table 2. Women constitute slightly more than half of the sample (51%). The age distribution of the sample follows closely the UK national demographic distribution, with the average and median age of the sample being 47 years and modal age estimated at 54 years. About 34% of the respondents are parents in families with small children, and the average family size is 2.7 persons. The median education level is a college degree, while the modal education level is a university degree. The median gross monthly income for the sample lies in the range of £2001-£2500. This means that our sample is somewhat better-educated and has a higher income level than the UK average, although is representative of the UK population along other important dimensions such as gender and age.

Initial analysis of the responses to the choice experiment showed no systematic bias in that the choices of alternatives are well balanced, with both alternative 1 and alternative 2 being selected in 32% of choice situations. The opt-out, status quo option was selected in 36% of cases. Since 21% of the respondents chose the opt-out option in all eight cards, we infer that the majority (59%) of the total number of opt-out choices are submitted by those respondents. About half of these (53%) explained that their choices were a protest because they thought that tree disease management should be financed exclusively by forest owners and not via general taxes. In addition, 16% of the opt-out voters considered the issue of tree diseases unimportant, and 11% did not believe that the disease control measures included in the policy options of the choice experiment would be effective.

To check if there are any socio-demographic patterns to the non-participation, we estimate a binomial probit model, in which the dependent variable indicates whether or not a respondent selected the opt-out, status quo option in all eight choice cards., Demographic characteristics, previous experience with forests, and knowledge about tree diseases are used as explanatory variables (see Table A2). The estimation results show that only a few variables are significant. In general, older or lower income respondents tend to vote against supporting any disease control programmes. On the other hand, the level of *ex-ante* specific knowledge about tree diseases turns out not to be significant (and is not reported in the table). Higher general awareness about tree diseases and greater experience with forests increase the probability of respondents choosing non-status-quo options. We excluded from further preferences analysis the 128 respondents who selected the opt-out option in all eight choice cards, since we cannot say whether or not these individuals have a positive WTP for the disease reduction policies in our scenarios.

We also tested for stability of preferences or any changes in preferences due to fatigue of respondents, by comparing a model estimated on the first 4 choices to one estimated on the second 4 choices. The Swait-Louviere (Swait & Louviere, 1993) test results show that the hypotheses of equality of the taste and scale parameters between the models cannot be rejected at the 0.05-level of significance.

Most of the respondents were rather occasional forest visitors who lived at a distance of 10-12 miles from the nearest forest and visit forests “several times a year” (46% of respondents) or “never” (16% of respondents). On the other side of the spectrum are more frequent forest users who visit forests on a daily (5%) or weekly (10%) basis. When asked about their awareness of tree diseases (Table 3), some 69% of respondents said that they had heard about tree diseases in the UK, but only 15% knew anything about tree diseases near to where they live. We found a very weak negative correlation between the distance to the nearest forest and the respondents’ general knowledge about tree diseases (correlation coefficient -0.10) or their knowledge about tree diseases near to where they live (correlation coefficient = -0.05).

To test the respondents’ *ex-ante* knowledge about tree diseases, we asked them to answer five multiple choice questions about four specific diseases (Table 3). The respondents were relatively well informed about general tree disease-related issues, such as the causes (55% answered correctly), susceptible tree species (64% correct), and general measures taken to minimize the risk of disease spread (56% correct). Knowledge levels about specific tree diseases were lower. Some 36% and 29% respondents correctly answered questions on dothistroma needle blight and chalara ash dieback respectively. Respondents were asked to name familiar/known diseases: Dutch elm disease was mentioned by 54% of respondents and chalara ash dieback by 28%. Other tree diseases were mentioned in less than 5% of answers.

5. Econometric Analysis

The modelling of preferences elicited through choice experiments is based on the assumption that respondents maximize their utility through their choices over the alternatives presented in a series of choice cards, and are willing to make compensatory trade-offs across the attributes (Train, 2009). The widely used random parameters or mixed logit model is sufficiently versatile to represent a wide spectrum of respondent behaviour. In this model, the utility for an individual i from selecting alternative *j* in a choice situation t described by K observed attributes $\mathbf{x}_{ijt} = \{x^1_{ijt}, \dots, x^K_{ijt}\}$ is expressed as:

$$U_{ijt} = \alpha_j + \boldsymbol{\beta}'\mathbf{x}_{ijt} + \varepsilon_{ijt} / \sigma$$

where α_j is an alternative-specific constant, b is the vector of attribute ($\mathbf{x}_{ijt}$) weights, ε_{ijt} is the i.i.d. extreme value idiosyncratic error, and σ is its scale (normalized to 1 in the MNL model).

The probability the choice is then defined as:

$$\Pr(y_{it} = j) = \frac{\exp(\alpha_j + \boldsymbol{\beta}'\mathbf{x}_{ijt})}{\sum_{q=1}^{J} \exp(\alpha_q + \boldsymbol{\beta}'\mathbf{x}_{iqt})}.$$

In the mixed logit model the individual-specific preference parameters β and choice-specific constants α are no longer fixed for all respondents, but vary around means and are modelled as follows:

$$\beta_{ik} = \beta_k + \boldsymbol{\delta}'_k \mathbf{z}_i + v_{ik},$$
$$\alpha_{ij} = \alpha_j + \boldsymbol{\delta}'_j \mathbf{z}_i + v_{ij},$$

where α_j is an alternative-specific constant, and v_{ij} is normally distributed (with zero mean) heterogeneity of the choice-specific constants. β_k is the population mean of *k*-attribute coefficient and v_{ik} is the individual specific heterogeneity of a taste parameter, which in this paper is assumed to follow the normal distribution with zero mean. The means of the parameter distributions of α_{ik} and β_{ik} are also allowed to be heterogeneous with respondents' vector of individual characteristics z_i, which enter the formulas for taste parameters and constants with vectors of weights δ_k and δ_j, respectively. These characteristics include two subsets: first, *M* observed demographic characteristics g_i (such as age, gender, education and income), and second, *N* self-reported variables that reflect familiarity with forests and *ex-ante* knowledge about tree diseases h_i, that is $\mathbf{z}_i = \{g_i^1,...,g_i^M; h_i^1,...,h_i^N\}$.

Fiebig, Keane, Louviere, & Wasi (2009) propose an extension (as a Generalized Mixed Logit (G-MIXL)) model in which both taste parameters and the scale of the idiosyncratic error are assumed to be random. The scale parameter's heterogeneity means that choice behaviour is more random for some respondents than for others. As noted by Czajkowski, Hanley, & LaRiviere (2016), this randomness can be interpreted either from the viewpoint of the individual whose choices are being observed – for example, their choices are less clear because they are unsure about their own preferences – or from the viewpoint of the modeller, in that there are unobserved (and thus omitted) factors explaining the variation in choices across people. From the individual perspective, this lack of clarity could reflect observable characteristics of the respondents. Thus the taste coefficients are modelled as:

$$\beta_{ik} = \sigma_i(\beta_k + \boldsymbol{\delta}_k'\mathbf{z}_i) + [\gamma\nu_{ik} + (1-\gamma)\sigma_i\nu_{ik}], \quad 0 \le \gamma \le 1,$$

where γ governs how the variance of residual taste heterogeneity varies with scale.

The random scaling factor σ_i follows the log-normal LN($1,\tau^2$) distribution and is modeled as:

$$\sigma_i = \exp(-\tau^2/2 + \boldsymbol{\theta}'\mathbf{h}_i + \tau\eta_i), \quad \eta_i \sim N(0,1).$$

That is, the scale σ_i depends on the individual-specific *ex-ante* knowledge variables h_i, and τ defines the standard deviation of its distribution. However, preliminary model estimates show that the estimate of the weight parameter γ is not statistically significant for our choice data. We therefore estimate the scaled-random-parameter logit model (G-MIXL-II), in which both the attribute weights and the standard deviation of the residual taste heterogeneity are proportional to the scale parameter:

$$\beta_{ik} = \sigma_i(\beta_k + \boldsymbol{\delta}_k'\mathbf{z}_i + \nu_{ik}).$$

In our experiment, choice situations are characterized by attributes that can be best represented as categorical variables with several levels (L_k), represented by a set of $(L_k - 1)$ dummies. The attributes are: the Ownership categories; four Forest Type attributes; four Disease Control attributes; four Unpredictable Feature attributes; five Affected Forest Benefit attributes. The base levels, for which dummies are omitted from the model, are 'family', 'individual trees', 'combination of disease control measures', 'unpredictable efficiency of control measures', and 'carbon storage' respectively. The payment vehicle Extra Tax attribute is modelled as a continuous variable. We assume that the taste coefficients for all the dummy variables, the Status Quo constant and the Extra Tax coefficient vary across individuals according to the normal distribution.

Estimation Results

We estimated several discrete choice experiment models.[5] The best fit model is the scaled random parameters logit model with attributes represented as level dummies (measures of fit for a range of different estimated models are provided in the on-line appendix Table A3). The model includes interactions with income and disease knowledge variables and assumes that the individual-specific scaling factor depends on *ex-ante* knowledge about

[5] All estimation was done with NLOGIT and Stata software. We estimated a number of models, ranging from multinomial logit (MNL) model, in which taste parameters are assumed fixed for all respondents; attributes-only mixed logit (or random parameters logit, RPL) model, in which taste parameters vary across individuals; mixed logit model that includes interactions of the status quo constant and tax attribute with demographic characteristics (RPL+demogr); mixed logit model that includes interactions with both demographic and quiz variables (RPL +demogr +quiz); latent class model with two latent classes (Latent Class, 2-class); mixed logit model estimated in Willingness to Pay space (RPL in WTP-space); to mixed logit model that includes interactions with demographic and quiz variable and in which the scale of the error term is respondent-specific (Scaled RPL +demogr +quiz). The measures of fit for these models are summarized in Table A3. We also report coefficient and WTP estimates for the first and the last models in other tables.

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tree diseases, where we postulate a relationship between how much someone knows about forest disease and the clarity of their choices.

We find that the statistical significance of the knowledge effects is robust for different possible specifications of *ex-ante* knowledge in both the taste and scale parts of the model. For variation in preference coefficients, from here we assume that it is the gradual change in the degree of knowledge that matters (thus using the quiz score as the relevant indicator), whilst for scale heterogeneity it is a threshold change that is significant (meaning we use an indicator of whether someone scores above or below the median quiz score). This specification exhibits a lower residual scale-heterogeneity variance (i.e. smaller tau parameter estimate) than alternative specifications. Since explaining the scale heterogeneity is a major aim, we think that an improvement in explaining the scale heterogeneity outweighs a small loss in model fit. We report the estimates for this model and a simple conditional (multinomial) logit model in Table 4.

The Status Quo option is negative and significant in the scaled mixed logit model, which indicates that on average our respondents are willing to support tree disease control programmes compared with a policy of no additional action. Several of the interactions of the SQ constant with demographic and knowledge variables are significant. Notably, respondents with higher income are more willing to support a disease control programme. There are similar effects for two variables that reflect *ex-ante* knowledge about tree diseases: the higher the number of correct quiz answers, and the more often the respondents visit forests, the more willing they are to support disease control measures.

Parameter estimates for the non-monetary attributes demonstrate that preferences vary significantly across different combinations of choice attribute levels. For the Ownership attribute, only the preference coefficients for charity and national government ownership are positive and significant. Among these, our respondents are most likely to favour publicly-subsidised disease control for nationally-owned forests. There may be a weak negative sentiment against taxpayer funding for disease control measures in timber business-owned forests, but this result is not statistically significant. There is significant individual heterogeneity in attitudes towards business- and local authority-owned forests.

Amongst the disease control measures, respondents clearly dislike clear felling of trees and biocide/chemical spraying. The estimate for clear felling is the most negative, but also has the largest variation across respondents, although clear-felling is one of the main control measures applied in practice to prevent further disease spread. Other stated preference studies on forest landscape quality in the UK have also shown a positive willingness to pay amongst the general public to avoid clear felling as a management strategy (e.g. Hanley & Ruffell (1993)). Amongst the forest benefits which can be negatively affected by tree disease, respondents cared most about biodiversity. For other benefits, the average preference coefficient estimates are non-significant. These results are somewhat surprising, as we expected that negative impacts of the visual attractiveness of forests and for recreation possibilities would be more significant. However, this is likely to be a reflection of considerable heterogeneity of preferences, evidenced by the significant estimates of standard deviation for the parameter distributions for the recreation and biodiversity coefficients, and by comparing these parameter estimates for the standard deviation terms with the parameters for the equivalent mean effect. The coefficient estimates for two attributes, "Type of Forest" and "Unpredictable Feature" are not significant for any of their level dummies. The estimates show that the taste parameters for both these attributes also have significant and substantial heterogeneity across respondents.

Ex-ante knowledge turns out to be important both for increasing the respondents' willingness to support a tree disease control measure, where the continuous summary quiz score is significant in interaction with the SQ constant in the G-MIXL model, while the dummy for 'quiz score above median' is significant for the scale parameter (reducing the error variance, and hence implying more deterministic choice).

6. Public Support for Forest Disease Control Measures and Programmes

Marginal willingness-to-pay (WTP) values express the relative importance of a unit change in an attribute in monetary terms, and for the experimental design reported here can be used to indicate the extent to which the UK public would be willing to pay for a range of alternative forest disease control measures or programs. For a model with attribute level dummies, WTP is the monetary value for a change from the baseline attribute level to an alternative level. The marginal WTP estimates based on the scaled mixed logit model are significantly smaller than those based on the multinomial logit model.

As we can see from Table 5, the marginal WTP values for the significant attribute coefficients lie in the range of +£6.45 to +£8.46 per household per year, where the WTP for disease control measures aimed at preserving biodiversity is at the lower end of the range, and the WTP for control in charity- and national government-owned forests are at the higher end. There is also a demand for monetary compensation of £6.2 – £7.3 if clear felling or biocides are adopted as tree disease control measures rather than other measures. No other changes in attributes relative to their baselines attract a WTP value significantly different from zero.

Table 6 reports WTP estimates for different possible disease control programmes, which combine some of these attribute changes together. The WTP per programme varies over a range of approximately £15 – £35 per year per household. For example, the median WTP for a policy which targets disease control measures at forests owned by businesses is £14.9, which involves use of chemical/biocide spraying, and where the main impact of the disease is on timber values. In contrast, median WTP is about twice as high for a programme that targets controls at forests owned by a charity (such as the Woodland Trust), where thinning is used as the control measure, and where actions are being taken mainly to avoid damage by the disease to biodiversity. Note, however, that each of the scenarios in Table 6 contains some attribute changes for which people's WTP is zero. The lower end of the WTP range corresponds to a set of disease control programmes that contain the least preferred measures, and the WTP estimates for such programmes are not significantly different from zero. It can also be seen that much of the range of the 95% confidence intervals overlap across the alternative disease control programmes. Thus, the main result is that the UK public support most forest disease control options considered here, even though median WTP is more than twice as high for some options than for others.

7. Discussion and Conclusions

We investigated general public's preferences and willingness to pay for possible tree disease control measures and programmes. The extent of our respondent's *ex ante* familiarity with tree diseases was measured using a quiz, and these responses were incorporated into analyses of a choice experiment in which choice situations consisted of two alternative disease control measures and an opt-out, status quo option. Our major result is that the general public are willing to pay for (invest public funds in) disease control in UK forests, but that this willingness to pay depends on the ownership of affected forests, what benefits of the forest are most negatively impacted by the disease, and what control measures are to be used. Disease control is more likely to be supported for publicly- and charity-owned forests than for those that are owned privately or by timber businesses. Higher income, better *ex-ante* knowledge about tree diseases, and more frequent visits to forests are correlated with greater willingness to support tree disease control programmes.

It would be interesting to derive a UK-wide estimate for the public benefits of a disease control programme based on these results, and then to compare these with the costs. Unfortunately, no such cost estimates exist at present. One problem is that there are many diverse components of an overall strategy for tree disease control. These might range from decisions to fell a forest stand early (before its optimal disease-free rotation: MacPherson et al, 2016), to implementing measures for quarantine felling around a new point of infection, to restrictions of recreational access and the costs of applying biocides. In some cases, felling will lead to a loss of timber value (e.g. a regional effect of market saturation if there is a lot of felling of a species in that region). Costs of thinning as a disease control measure will be site-dependent.

To indicate orders of magnitude, however, one can look at examples of actual control costs for specific pests and diseases in the UK. For Asian longhorn beetle, a programme to eradicate a small outbreak in Kent in 2012 of only 11.5 ha. (2133 trees) had a cost of £0.65mn; if the boundary around the infection within which treatment occurred had been 200m rather than 100m then costs would have been £1.43mn. Annual re-surveys, costing £0.21mn are required to ensure eradication is successful. So total cost of controlling even this very small and localized outbreak were around £1.9mn, and would have been £2.7mn if the wider buffer had been adopted (Straw et al, 2016). This example suggests that the costs of disease control across UK forests could be rather high, depending on the specific disease and how much control agencies chose to implement.We found a clear negative sentiment against clear felling of a forest or chemical/biocide spraying as control measures. This is interesting since clear felling is currently one of the only effective means of reducing the spread of a number of important tree diseases such as *Phytophthora ramorum* (which started to affect larch trees in the UK in 2009 – and for which felling can be a statutory requirement) and *Dothistroma septosporum,* causing needle blight in pines. It appears that a section of the UK public might rather have a standing, diseased forest than a clear-felled one – a finding worthy of further investigation. It may be that people would be more supportive of clear felling if they knew that forests would be re-stocked with the same or a less–susceptible tree species, and depending on the extent to which neighbouring uninfected forests may benefit and remain unaffected.

We decided not to focus on a single disease in framing the choice experiment, but rather to include measures which would be common to many disease/pest outbreaks. We could have used labels to make choices specific to named diseases, but decided not to do this since some of the levels would be inappropriate for some of the diseases. Our results are thus applicable to many actual and potential pests and diseases in UK forests, rather than being constrained to apply to a single, named disease. There are obvious disadvantages of such a general approach, since we were not able to spell out the detailed implications of any specific disease in terms of speed of spread, impact or treatability. Note also that we did not make any statements about the effectiveness of each control option used in the experimental design, since for each disease these options could have varying levels of effectiveness depending, for example, on local conditions, on how long the disease had been present before being detected, and on site-specific biosecurity measures.

Uncertainty about the nature and epidemiology of new and recently-arrived pests and diseases is typical (Sims, Finnoff, & Shogren, 2016). We included such scientific uncertainty as a design attribute for our choice experiment, using uncertainty over speed of spread, likelihood of jumping to other species, and effectiveness of control measures as the levels of attribute for the choice programmes. However, none of these scientific uncertainty elements had a significant effect on choices, meaning we can say nothing about whether the public prioritizes actions in terms of which aspects of an invasive pest or disease scientists are most unsure about.

We find that above-median prior knowledge about tree diseases increases clarity of the choice (reducing the random element of choice). This finding agrees well with previous results on the impact of *ex-ante* knowledge on scale heterogeneity for public goods (Czajkowski et al., 2016). However, it is not clear how respondents derived different levels of *ex a*nte knowledge about tree diseases, since there was little correlation between the distance between respondents' homes and their nearest forest and their knowledge about tree diseases, or between frequency of recreational use of forests and knowledge of tree diseases. Nevertheless, the significance of interactions between the respondents' frequency of forest visits and their choice attributes, and significant heterogeneity of the coefficients for the forest benefits affected by tree diseases, both suggest that an individual's geographical location is likely to have an impact on their preferences for disease control. Thus, a more detailed analysis of preference heterogeneity using different proxies for the geographical location of people's residences relative to trees and forests is another promising route for future research, which would link into an emerging literature on spatial modelling of forest benefits (Czajkowski et al., 2016b).

Another interesting extension of this research would be to include not only tree disease control options, but also different options for forest restoration. Changes to forest tree species composition and structure can have a major effect on resistance to future tree disease risks, and the British public may be willing to support control programmes that encompass forest management measures and planning which explicitly take into account the risks of future pests and diseases to sustainable management of multi-purpose forests (Seidl, Spies, Peterson, Stephens, & Hicke, 2016).

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Table 1. Attributes of the policy options.

Attributes	Levels
Forests or woodlands owned by	Family, Timber production or land investment business, Wildlife charity or trust, Local authority, National government
Type of forest or woodland	Large woods (bigger than 2 hectares), Small woods (smaller than 2 hectares), Hedgerow trees, Individual trees
Disease control actions	Clear felling (cutting down all the trees in a forest), Thinning (just cutting down some of the trees), Chemical or biocide spraying, Combination of these measures
What is most unpredictable about the disease?	Speed of spread between forests, Extent of damage caused by disease, Efficiency of control measures, Likelihood to jump to other tree species
What kinds of benefits are most badly affected by the disease?	Timber production, Recreation, Wildlife biodiversity, Visual appearance of landscape, Carbon storage
Additional tax costs for households (per year)	£15, £30, £45, £60, £100

Table 2. Socio-demographic characteristics of the respondents.

	Sample	UK population
Share of females	0.51	0.51
Age (years) group shares:		
18-24	0.12	0.11
25-34	0.19	0.17
35-44	0.14	0.16
45-54	0.19	0.19
55+	0.37	0.37
Age summary (years):		
mean	47	
median	47	40
mode	54	
Average family size (incl. children)	2.7	2.3
Share of families with children	0.34	
Education level:		
median	college degree	41% of adults with college degree
mode	university degree	
Income distribution (gross, monthly):		
median	£2001-£2500	£1700
mode	£1001-£1500	

Note: The UK population national average numbers come from UK 2011 Census (http://www.ons.gov.uk/census/2011census/2011ukcensuses) and Office for National Statistics data (https://data.gov.uk/publisher/office-for-national-statistics).

Table 3. Respondent knowledge about tree diseases and their frequency of forest visits.

Question	Share of "yes" or correct answers
Have you heard about any tree diseases in the UK?	0.69
Do you know anything about tree diseases near to where you live?	0.15
What diseases do you know? (self-reported names)	
Dutch elm tree disease	0.54
Ash dieback (*Chalara*)	0.28
Phytophthora ramorum	0.01
Wood rot	0.01
Chestnut blight or bleeding canker	0.04
Acute oak decline and other oak diseases	0.05
Quiz questions[1]:	
1. Which trees can these diseases infect?	0.64
2. What are the causes of these diseases?	0.55
3. Which disease is sometimes called 'needle blight'?	0.36
4. Which disease is sometimes called 'ash dieback'?	0.29
5. What would you recommend to do to minimize the risk that you will spread tree diseases such as *Phytophthora ramorum* between forests?	0.56
Quiz summary:	
No correct answers	0.03
One correct answer	0.20
Two correct answers	0.33
Three correct answers	0.28
Four correct answers	0.14
Five correct answers	0.03
How often do you visit woods or forests each year?	
Every day	0.05
A few times each week	0.10
A few times each month	0.23
A few times a year	0.46
Never	0.16

[1] All quiz questions are related to four of the diseases currently having a major impact in UK. The scientific names of the pathogens causing these diseases are: *Phythophthora ramorum* (ramorum disease of larch), *Dothistroma septosporum* (dothistroma needle blight), *Hymenoscyphus fraxinea* (chalara ash dieback), *Heterobasidion annosum* (conifer root and butt rot).

Table 4. Estimation results for different models with attribute level-dummy variables (including selected demographic and disease knowledge variables).

	MNL		Scaled RPL	
Status Quo Constant	-0.478***	(0 .126)	-1.341**	(0.661)
+ Income			-0.0004**	(0.0002)
+ Number of quiz correct answers			-0.367**	(0.161)
+ Frequency of forest visits			-1.211***	(0.368)
Extra annual tax	-0.015***	(0.001)	-0.100***	(0.019)
Ownership (base level – Family)				
Timber business = 1	0.020	(0.097)	-0.276	(0.307)
Wildlife charity = 1	0.309***	(0.096)	0.679***	(0.254)
Local authority = 1	0.046	(0.081)	0.272	(0.215)
National government = 1	0.291***	(0.078)	0.842***	(0.252)
Type of forest (base level – Individual trees)				
Large woods = 1	-0.039	(0.073)	0.060	(0.174)
Small woods = 1	-0.065	(0.074)	0.135	(0.238)
Hedgerow = 1	-0.104	(0.071)	-0.112	(0.171)
Disease control (base level – Combination)				
Clear felling = 1	-0.171***	(0.066)	-0.728***	(0.186)
Thinning = 1	-0.086	(0.078)	-0.032	(0.202)
Chemical/biocide = 1	-0.191**	(0.089)	-0.618***	(0.244)
Unpredictable feature (base level – Control efficiency)				
Speed of spread = 1	0.113	(0.081)	-0.279	(0.206)
Extent of damage = 1	0.077	(0.078)	-0.142	(0.185)
Likelihood to jump = 1	0.091	(0.079)	0.063	(0.191)
Badly affected benefit (base level – Carbon storage)				
Timber production = 1	0.065	(0.081)	-0.147	(0.206)
Recreation = 1	0.045	(0.086)	0.084	(0.280)
Wildlife biodiversity = 1	0.196**	(0.092)	0.642**	(0.314)
Landscape = 1	0.105	(0.095)	0.007	(0.223)
Scale parameter				
Quiz score above median			0.386***	(0.115)
Frequency of forest visits			-0.212***	(0.061)
Tau parameter			0.780***	(0.134)
Std dev of random parameters				
std dev (ASC)			9.036***	(1.584)
std dev (Extra tax)			0.087***	(0.017)
std dev (Timber business)			0.883	(0.237)
std dev (Wildlife charity)			0.201	(0.196)
std dev (Local authority)			0.526**	(0.237)
std dev (National government)			1.594***	(0.316)

std dev (Large woods)		0.050	(0.235)
std dev (Small woods)		0.781***	(0.288)
std dev (Hedgerow)		0.023	(0.239)
std dev (Clear felling)		1.443***	(0.254)
std dev (Thinning)		0.497	(0.477)
std dev (Chemical/biocide)		0.700***	(0.208)
std dev (Speed of spread)		0.537**	(0.249)
std dev (Extent of damage)		0.216	(0.328)
std dev (Likelihood to jump)		0.901***	(0.223)
std dev (Timber production)		0.041	(0.219)
std dev (Recreation)		1.162***	(0.438)
std dev (Wildlife biodiversity)		1.562***	(0.368)
std dev (Landscape)		0.281	(0.232)
Model fit			
Number of observations	4840	4840	
Loglik	-5087.9	-3433.5	
AIC	10213.8	6956.9	

Note: *,**,*** indicate significance at 0.10, 0.05, and 0.001 levels.

Table 5. Marginal willingness to pay, median values (£ per unit change from the attribute base level to the level in question).

	WTP per unit change (MNL)	WTP per unit change (scaled RPL)
Ownership (base level – Family)		
Timber business = 1	1.3	-2.8
Wildlife charity = 1	20.4**	6.8**
Local authority = 1	3.0	2.7
National gov't = 1	19.2**	8.5**
Type of forest (base level – Individual trees)		
Large woods = 1	-2.6	0.6
Small woods = 1	-4.2	1.4
Hedgerow = 1	-6.8	-1.1
Disease control (base level – Combination)		
Clear felling = 1	-11.3**	-7.3**
Thinning = 1	-5.6	-0.3
Chemical/biocide = 1	-12.6**	-6.2**
Unpredictable feature (base level – Control efficiency)		
Speed of spread = 1	7. 5	-2.8
Extent of damage = 1	5.1	-1.4
Likelihood to jump = 1	6.0	0.6
Badly affected benefit (base level – Carbon storage)		
Timber production = 1	4.3	-1.5
Recreation = 1	3.0	0.8
Wildlife biodiversity = 1	12.9**	6.5**
Landscape = 1	6.9	-0.1

Notes: ** indicate significance at 0.05-level, based on confidence intervals calculated with Krinsky-Robb procedure or estimated within the WTP-space Mixed Logit model.

Table 6. Willingness to pay values for several different tree disease control schemes (£ per year per household).

Disease control policy (defined by attribute levels)	WTP
Family, individual trees, combination of measures, control efficiency, carbon	20.9 (5.6, 34.4)
Family, large woods, clear felling, extent of damage, timber	15.4 (-1.4, 28.3)
Business, hedgerow, chemical/biocide, jump to other species, timber	14.9 (-1.7, 27.9)
Business, small woods, thinning, speed of spread, timber	20.9 (4.1, 33.9)
Charity, small woods, clear fell, control efficiency, wildlife biodiversity	30.7 (15.2, 43.7)
Charity, large woods, thinning, speed of spread, wildlife biodiversity	34. 7 (20.5, 47.0)
National gov't, large woods, clear fell, extent of damage, timber	23.5 (7.9, 35.8)
National gov't, large woods, chemical/biocide, speed of spread, wildlife biodiversity	31.5 (15.8, 44.0)
Local authority, small woods, thinning, extent of damage, recreation	32.4 (16.1, 45.1)
Local authority, hedgerow, thinning, extent of damage, landscape attractiveness	29.1 (13.3, 41.3)

Notes: 1) Median WTP is reported, with 95% confidence interval provided in the parentheses. The confidence intervals are calculated with the Krinsky-Robb procedure.

2) Calculations are based on the scaled RPL model with attribute level dummies.

Figure 1. An example choice card.

Which of the following options for new tree diseases' control during the next 10 years would you prefer?

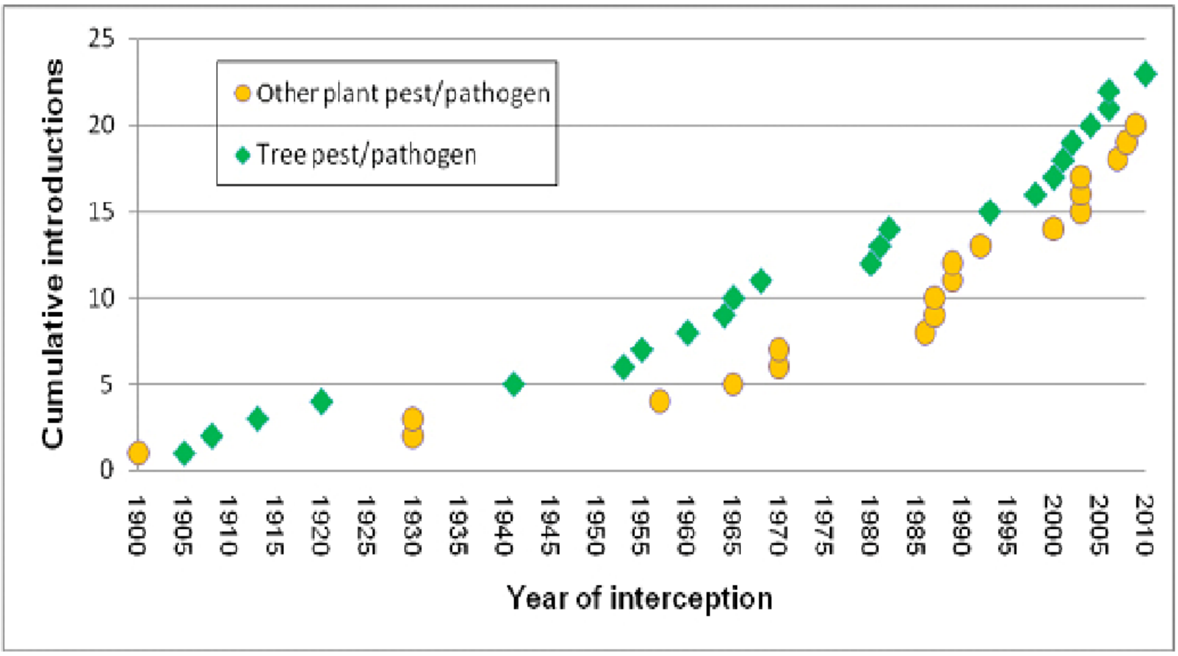
	Option A	**Option B**	
Forests or woodlands owned by	family	timber production or land investment business	I would NOT choose either of these options, because I prefer that the *government* takes NO extra ACTIONS about this problem.
Type of forest or woodland	large woods (bigger than 5 acres)	large woods (bigger than 5 acres)	
Disease control actions	clear felling (all the trees)	thinning (felling some trees)	
What is most unpredictable about the disease?	speed of spread between forests	likelihood to jump to other tree species	
What kinds of benefits are most badly affected by the disease?	timber production	wildlife biodiversity	
Additional tax costs for households (per year)	£15	£30	NO additional TAXES
YOUR CHOICE:	○	○	○

Public Preferences and Willingness to Pay for Forest Disease Control in the UK

Oleg Sheremet, John R. Healey, Christopher P. Quine and Nick Hanley

On-Line Appendix

Figure A1. Growth in number of known plant pests and pathogens in UK over time.



(Source: (THAPBET, 2013))

Table A1. Quiz questions with answers.

Questions	Answers
1. Which trees can these diseases infect?	1. pine 2. larch 3. ash 4. all of the above (correct) 6. only conifers
2. What are the causes of these diseases?	1. fungi (correct) 2. beetles 3. moths 4. bacteria
3. Which disease is sometimes called 'needle blight'?	1. *Phythophthora ramorum* 2. *Dothistroma septosporum* (correct) 3. *Hymenoscyphus fraxinea* (chalara) 4. *Heterobasidion annosum*
4. Which disease is sometimes called 'ash dieback'?	1. *Phythophthora ramorum* 2. *Dothistroma septosporum* 3. *Hymenoscyphus fraxinea* (chalara) (correct) 4. *Heterobasidion annosum*
5. What would you recommend to do to minimize the risk that you will spread tree diseases such as *Phytophthora ramorum* between forests?	1. clean your car and cycle tyres, footwear and dog's paws if you have visited a forest (correct) 2. never collect firewood yourself 3. only purchase certified timber that has been grown in the UK 4. avoid visiting any woodlands

Note: All quiz questions are related to four of the diseases currently having a major impact in UK. The scientific names of the pathogens causing these diseases are: *Phythophthora ramorum* (ramorum disease of larch), *Dothistroma septosporum* (dothistroma needle blight), *Hymenoscyphus fraxinea* (chalara ash dieback), *Heterobasidion annosum* (conifer root and butt rot).

Table A2. Results of the participation modeling (binary dependent variable indicates whether respondents chose the opt-out option in all eight choice cards).

	Binomial Probit
Constant	-0.16 (0.27)
Age	0.01** (0.004)
Income	-0.05** (0.02)
Heard about tree diseases = 1	-0.33** (0.13)
Frequency of visits to forests	-0.19*** (0.06)
LogLik	-296.44
McFadded R2	0.05

Note: ***, **, * indicate significance at 0.10, 0.05, and 0.001 levels.
Only significant variables are reported.

Table A3. Measures of fit for different estimated models with attribute level dummies.

	MNL	RPL	RPL + demogr.	RPL +demogr + quiz	Latent Class (2-class)	RPL in WTP-space	Scaled RPL + demogr + quiz
Number of observations	4840	4840	4840	4840	4840	4840	4840
Loglik	-5087.9	-3515.7	-3492.3	-3443	-3789.1	-3608.5	-3433.5
AIC	10213.8	7075.6	7046.7	6970	7664.3	7265.1	6956.9