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Valuing Hemlock Woolly Adelgid Control in Public Forests:

Scope Effects with Attribute Non-Attendance[1]

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Abstract:

Sensitivity to the scope of public good provision is an important indication of validity for the contingent valuation method. Despite advances in survey methods, not every contingent valuation study passes the scope test. One explanation may be attribute non-attendance, which arises when survey respondents ignore choice attributes for a variety of reasons. We compare bounded and repeated referendum contingent valuation questions with and without consideration of stated and inferred ANA. An online survey was administered to an opt-in, or non-probability sample, panel in September 2017 to estimate the willingness-to-pay to protect hemlock trees from a destructive invasive species on federal land in North Carolina. We collected survey responses from 907 North Carolina residents. We estimate the probability of a yes vote in a referendum to treat for hemlock woolly adelgid infestation in a given acreage of ecologically important and socially important areas, using either chemical or biological controls, for a given annual cost for a three year period. We find evidence that attribute non-attendance is a factor when testing for sensitivity to scope. When estimating the model with stated attribute non-attendance the ecologically and socially important scope coefficients become positive and statistically significant. We find several differences between the bounded and repeated sequential contingent valuation data samples.

1. Introduction

The contingent valuation method (CVM) is a stated preference approach to the valuation of non-market goods (Johnston et al., 2017). Since the National Oceanic and Atmospheric Administration (NOAA) Panel's report on contingent valuation (Arrow et al. 1993), the scope test, where stated preference willingness-to-pay (WTP) estimates are expected to increase with the scope of a policy, has been an important validity test and a significant source of controversy. Despite advances in survey methods, not every CVM study passes the scope test (Desvousges, Mathews and Train 2012). One explanation may be attribute non-attendance (ANA), a deviation from neoclassical theory and an example of preference heterogeneity. In our application ANA arises when survey respondents ignore choice attributes for a variety of reasons. Generally, ANA is empirically handled by restricting estimated coefficients to zero for individuals who do not have fully compensatory preferences. Stated ANA models rely on survey respondent statements about which attributes they ignored. Inferred ANA models allow the empirical model to provide clues about ANA.

The single binary choice (SBC, i.e., referendum) form of the contingent valuation method presents survey respondents with a policy description and a randomly assigned policy cost (e.g., a tax). Respondents reveal their preferences by indicating if they would be willing to pay the randomly assigned cost in the hypothetical setting. Carson and Groves (2007, 2011) and Carson, Groves and List (2014) describe the situations in which a SBC should lead to a truthful revelation of preferences. If the survey respondent believes the survey to be consequential and the policy description is for a public good, then the best response to the single binary choice is truth-telling (Zawojska and Czajkowski 2017). A consequential survey is one in which respondents care about the outcome and believe their answers are important to the policy process, as in an advisory referendum.

Testing for scope effects with SBC data requires a split sample design in which the subsamples are shown different levels of policy intervention. If the estimated willingness to pay is greater for the larger policy intervention the study passes an *external* scope test (Carson, Flores and Meade 2001). The NOAA Panel on Contingent Valuation, in the context of a natural resource damage assessment of the Exxon Valdez oil spill, recommended that a split sample scope test be conducted to validate CVM results (Arrow et al. 1993). When individuals are asked multiple CVM questions the response format is known as a discrete choice experiment and permits tests of *internal* scope (Carson and Louviere 2011; Carson and Czajkowski 2014). Internal scope tests verify consistency of preferences within an individual's set of responses (Carson and Mitchell 1995).

Carson and Mitchell (1995) and Carson et al. (2001) review several reasons why willingness-to-pay may be insensitive to scope. Two of these reasons are concerned with the data samples commonly used by researchers. First, researchers often rely on small sample sizes that are not adequate to statistically differentiate differences in willingness-to-pay. Second, researchers frequently use relatively inexpensive survey modes that may not generate an adequate amount of respondent attention to the survey task. Both of these criticisms were leveled at two industry-funded studies following the Exxon Valdez oil spill. Boyle et al. (1994) and McFadden (1994) found that willingness-to-pay was not sensitive to scope using telephone and mall-intercept survey modes, respectively, and small sample sizes. In contrast, Bishop et al.

(2017) used in-person interviews and a large random sample in their scope test. In doing so, they find statistically significant differences for modest differences in willingness-to-pay.

Our application is the management of invasive species in public forests and builds on the analysis of Moore, Holmes, and Bell (2011). The first valuation question in our discrete choice experiment is in the referendum format with one of four randomly assigned tax amounts. In addition to the randomly assigned tax amount we unpack the policy description into three attributes: treatment of ecologically important acreage, treatment of socially important acreage, and treatment method. The second valuation question is either a bounded or randomly-assigned repeated referendum. This is referred to as a binary choice sequence (BC-Seq) by Carson and Louviere (2011). In the bounded referendum sequence (BC-Seq-B) only the tax amount varies in the second and, perhaps, third valuation question. In the repeated referendum sequence (BC-Seq-R), the tax amount and each of the three attributes randomly varies in the second and third valuation questions.

This study design allows us to test for both external and internal scope in a number of ways. Using only the first, referendum style choice question we can test for external scope across respondents. Next, by examining the sequential valuation questions, we test for internal scope. We repeat both scope tests using stated ANA models and random parameters logit to examine the impact of non-attendance and preference heterogeneity on scope effects. We also extend this line of tests to include inferred ANA using latent class logit models. Finally, we compare the SBC data with bounded and repeated sequential binary choice referendum data. To our knowledge this is the first paper to treat CVM binary choice sequential data as a discrete choice experiment and test for the effects of stated and inferred ANA. We find evidence that attribute non-attendance is a factor when testing for sensitivity to scope. When estimating the model with stated attribute non-attendance the ecologically and socially important scope coefficients become positive and statistically significant. We find several differences between the bounded and repeated sequential contingent valuation data samples. These results suggest that failure to account for attribute non-attendance may have caused past CVM studies to fail the scope test. These results could have large implications on the interpretation of those analyses and the implementation of public policy.

2. Literature Review

In this paper we address the contingent valuation method (CVM) scope test issue with strategies adopted by discrete choice experiments (DCE), which have proliferated in the environmental economics literature (Mahieu et al. 2017). The scope test validity issue is not an empirical concern for DCE researchers in the same way that it is for contingent valuation researchers. In short, CVM studies tend to conduct external scope tests and DCE studies tend to conduct internal scope tests. Discrete choice experiments employ more complicated designs by increasing the number of choice alternatives, increasing the number of choice questions, or unpackaging the description of the public good into a number of varying attributes (Carson and Louviere 2011). Each of these may contribute to the finding of sensitivity to scope in, to our knowledge, all published discrete choice experiments. In this paper we consider increasing the number of binary choice questions and unpackaging the description of the public good into a number of varying attributes. While several studies have compared internal and external scope tests in the contingent valuation literature (e.g., Giraud, Loomis, and Johnson 1999; Veisten et al.

2004), to our knowledge only one DCE article has addressed external scope. Lew and Wallmo (2011) find that most differences in willingness-to-pay estimates are statistically significant in external scope test comparisons. Most discrete choice experiment researchers have focused on internal scope tests. Sequential binary choice question formats have been used to examine ordering effects (Holmes and Boyle 2005; Day et al. 2012; Nguyen, Robinson, and Kaneko 2015) but have not been explicitly concerned with a comparison of internal and external scope tests.

Our paper is similar to Christie and Azevedo (2009), Siikamäki and Larson (2015) and Petrolia, Interis and Hwang (2014, 2018). Christie and Azevedo (2009) compare valuation questions from two separate samples of respondents. One sample received a survey with three CV questions while the other sample was presented with eight DCE questions. The authors find scope effects with the CV and DCE questions but willingness-to-pay differs across question format. They combine their CVM and CE data and test for parameter equality and find evidence of convergent validity between the two types of choice questions. Siikamäki and Larson (2015) ask two sets of "two and one-half bounded" binary choice valuation questions for an improvement in water quality. Their conditional logit models fail the scope test but a mixed logit model that accounts for preference heterogeneity finds statistically significant scope effects. Petrolia et al. (2014) compare single binary choice and single multinomial choice valuation questions in split samples of survey respondents. In the multinomial choice version Petrolia et al. (2014) find scope effects for all three attributes. Petrolia et al. (2018) compare single multinomial choice and sequential multinomial choice question versions with and without consideration of attribute non-attendance. They find scope effects in both survey versions and similarity in the magnitudes of scope effects across versions.

Our paper differs from each of the papers described above in the following ways. The Christie and Azevedo (2009) comparison is confounded by the number of valuation questions presented to respondents (three in repeated CVM and eight in the choice experiment) and the number of choice alternatives (two in the repeated CVM and three in the choice experiment) creating potentially large differences in cognitive burden between samples. Siikamäki and Larson (2015) find scope effects with bounded sequential questions but do not compare their results with those from the single binary choice and do not ask repeated questions. Petrolia et al. (2014) do not conduct a scope test in their single binary choice question. Petrolia et al. (2018) make a comparison of external and internal scope tests but with multinomial choice data.

A standard assumption made when analyzing stated preference survey data is that respondents have unlimited substitutability (fully compensatory preferences) between attributes (Scarpa et al. 2009). Recent research, however, suggests that respondents often employ simplified heuristics such as threshold rules, attribute aggregation, or attribute non-attendance when making choices (Swait 2001; Caparros, Oviedo, Campos 2008; Greene and Hensher 2008; Hensher 2006, 2008; Puckett and Hensher 2008). ANA occurs when respondents fail to consider a particular attribute from a stated preference discrete choice.[5] Such discontinuous preference orderings violate the "continuity axiom" and thus pose problems for neoclassical analysis (Gowdy and Mayumi 2001; McIntosh and Ryan 2002; Rosenberger et al. 2003; Lancsar and Louviere 2006; Scarpa et al. 2009). In this context, ANA models can be thought of as an

[5] Alemu et al. (2013) discuss explanations for this behavior.

extension to other methods that account for preference heterogeneity such as empirical methods including latent class and random parameters models.

Economic literature on the ANA began appearing the early 2000s (McIntosh and Ryan 2002; Sælensminde 2002; Lancsar and Louviere 2006; Hensher et al. 2005; Hensher 2006; Rose, Hensher, Greene 2005; Campbell, Hutchinson, Scarpa 2008; Scarpa et al. 2009). In our study, use of a relatively inexpensive opt-in sample may raise the potential for attribute non-attendance (i.e., insensitivity to scope for two of our three attributes) as respondents may pay less attention to survey details (Baker et al., 2010; Johnston et al. 2017). Attribute non-attendance tends to cause statistical insignificance of attribute coefficients or bias them toward zero. Perhaps most importantly, this body of literature has found that willingness-to-pay (WTP) and willingness-to-accept (WTA) estimates are lower when ANA is accounted for (McIntosh and Ryan 2002; Hensher et al. 2005; Hole 2011; Rose et al. 2005; Campbell et al. 2008; Scarpa et al. 2009; Scarpa et al. 2011; Scarpa et al. 2012; Hensher and Greene 2010; Puckett and Hensher 2008; Koetse 2017).[6] These inaccurate estimates could subsequently influence policy through benefit transfer (Glenk et al. 2015).

Several empirical strategies have arisen to account for ANA (Scarpa et al. 2009). There are two primary methods for identifying ANA: stated and inferred. In the former, a survey explicitly asks respondents to indicate the degree of attention they paid to each attribute that described the choice alternative. The researcher will then use these data to group respondents into an attendance class (Hensher, Rose, Greene 2005; Carlsson, Kataria, Lampi 2010; Hensher,

[6] Meyerhoff and Liebe (2009) and Carlsson et al. (2010) did not find that WTP values declined when accounting for ANA. DeShazo and Fermo (2004) and Hensher et al. (2007), however, find higher marginal WTP when accounting for ANA.

Rose, Greene 2012; Scarpa et al. 2012; Alemu et al. 2013; Kragt 2013). Attribute non-attendance may be inferred by use of latent class methods to separate respondents into different groups based on their preference orderings (Scarpa et al. 2009; Hensher et al. 2012; Scarpa et al. 2012; Kragt 2013; Glenk et al. 2015; Koetse 2017). Inferred models are important for two main reasons. First, not all surveys explicitly ask attribute attendance questions. Thus analysis of ANA implications using past data is possible with inferred models. Second, there is evidence that respondents may not respond accurately to stated attribute attendance questions (Armitage and Conner 2001; Ajzen, Brown, Caravajal 2004; Hensher et al. 2012; Scarpa et al. 2011; Kragt 2013; Carlsson et al. 2010; Hess and Hensher 2010; Scarpa et al. 2012; Alemu et al. 2013). Regardless of the empirical method chosen, estimated attribute coefficients are constrained to zero for cases of non-attendance (Hensher et al. 2012).

Our work also builds on the body of literature that has investigated preference heterogeneity of responses from choice survey data (Provencher et al. 2002; Boxall and Adamowicz 2002; Scarpa and Thiene 2005; Hensher and Greene 2003). Specifically, this paper is most closely related to Kragt (2013) and Koetse (2017) in that we explore whether stated or inferred ANA methods with respect to the scope attributes can lead to statistically significant scope effects. Like Koetse (2017) we focus on a particular subset of attribute non-attendance, and following Kragt (2013) explore several different empirical specifications. In addition, our analysis is similar to Thiene et al. (2015) in that we compare various number of potential classes.

3. Survey and Data

Our application is to the control of an invasive species, hemlock woolly adelgid (HWA), in public forests in North Carolina. Our survey is based on the survey design in Moore, Holmes and Bell (2011) who presented a payment ladder valuation question.[7] We revised this version, which was intended to be administered with a phone-mail-phone survey mode, for our purposes and budget. We developed the binary choice question format with randomly assigned attributes for the SurveyMonkey online survey platform and pretested the survey with 62 respondents. In order to collect a large sample of data at relatively low cost we conducted an internet survey with a non-probability panel of respondents. So called "opt-in" panels are becoming popular in social science research, but their ability to adequately represent sample populations and obtain high quality data is still unresolved (Hays, Liu, and Kapteyn 2015). Yeager et al. (2011) found that non-probability internet samples are less accurate than more representative probability samples for socioeconomic variables. Lindhjem, Henrik, and Navrud (2011) reviewed the stated preference literature and find that internet panel data quality is no lower than more traditional survey modes and internet panel willingness-to-pay estimates are lower.

Our Southern Appalachian Forest Management Survey (SAFMS) was administered in September 2017. More than 8400 individuals were invited to take the online survey and roughly 13 percent opted to be panelists. About 83 percent of those panelists completed the survey for a total of 974 respondents. We use a sample of 907 respondents who answered each of the choice questions. The survey questions can be divided into one of three categories. First, we asked preliminary questions about the respondents' prior knowledge of HWA and recreational

[7] Moore, Holmes, and Bell (2011) was intended as a pretest for a sequential multinomial sequential choice survey, but this survey has not been implemented.

experiences in Pisgah National Forest, Nantahala National Forest, and Great Smoky Mountains National Park (see figure 1). Second, we asked a series of either two or three referendum questions (called "situations" in the survey, and in the rest of this paper) depending on the respondent's survey treatment. Finally, we asked debriefing questions about consequentiality, attribute non-attendance, and individual specific characteristics.

In the preliminary questions, 55 percent of respondents knew nothing "about hemlock trees in the southern Appalachian Mountains" before the survey. Twenty-eight percent had "read or heard about an increase in the number of dead hemlock trees in the southern Appalachian Mountains." Of the reasons for protecting hemlock trees 68 percent thought that "providing wildlife habitat" was very important, 41 percent thought that "providing scenic views" was very important, "providing recreation opportunities" was very important to 33 percent of respondents, "providing timber" was very important to 21 percent of respondents, "preserving hemlock populations" was very important to 51 percent of respondents, and "maintaining aquatic resources" was very important to 55 percent of respondents. Sixty-one percent of the sample had visited the Great Smoky Mountains National Park, 46 percent had visited Pisgah National Forest, and 27 percent had visited Nantahala National Forest. Thirty-five percent of the sample of 907 had observed dead or dying hemlock trees on one of their visits.

Respondents were then led through a series of education materials and instructions. First, they were led through descriptions about ecologically important and socially important areas of hemlock dominant forest and asked about the importance of each. Sixty-nine percent and 27 percent of respondents thought it was very important to treat ecologically important areas and socially important areas, respectively. Then respondents were described biological and chemical treatment methods and asked about whether they agree with their use. Twenty-two percent strongly agreed that chemical insecticides should be used. Thirty-three percent strongly agreed that biological control methods (e.g., predatory beetles) should be used. Finally, respondents were informed about the choice task that would be described by treatment options or costs, and include multiple situations. The costs were described over a potential range, \$25 to \$300, for each of the next three years. Respondents were reminded that “Although these questions are hypothetical, please answer them as if you would actually have to pay the cost of treatment. Remember to consider your household’s income and other expenses when answering these questions.” One-half of the respondents were told that: “There are no right or wrong answers. But, the results from this study will be shared with policy makers in North Carolina.” Respondents were then asked “Did you read these instructions very closely, somewhat closely or not closely at all?” Sixty-nine percent and 27 percent said that they read the instructions very closely and somewhat closely, respectively.

Respondents were then presented with the first valuation situation (figure 2). This referendum, and both of the subsequent referenda, were described by four attributes: ecologically important acreage, socially important acreage, treatment method, and annual cost over the next three years. There were four levels of acreage for each type of hemlock dominated forest: 2500, 5000, 7500 and 10,000. There were also four cost amounts in the first choice situation: \$50, \$100, \$150 and \$200. Respondents were asked how they would vote for the referendum and given three choices: For, Against, or Don’t know. In the first choice situation, for the bounded survey sample, 52 percent voted “For” the treatment referendum, 23 percent voted “Against” it, and 25 percent did not know how they would vote. Similarly, for the repeated survey sample in the first choice situation, 55 percent voted “For” the treatment referendum, 22 percent voted “Against” it, and 23 percent did not know how they would vote. These differences are not statistically significant across bounded and repeated survey samples. This is not surprising since there were no differences in the first choice situation between the two samples. In the remainder of the paper we combine the “Against” and “Don’t know” votes and treat the responses to choice situations as binary.

Following the first binary choice valuation situation respondents were randomly assigned to one of two BC-Seq survey samples: bounded (BC-Seq-B) and repeated (BC-Seq-R). In the second and third choice situations, all four attributes could vary for respondents in the repeated sample. Only the cost attribute varied in subsequent situations for individuals in the bounded sample. In table 1 we present the referendum responses. In the bounded sample the percentage of for votes falls from 66 percent to 45 percent as the cost amount increases from $50 to $200. In the repeated sample the percentage of for votes falls from 60 percent to 36 percent as the cost amount rises.

In the bounded sample, respondents who answered affirmatively in the first choice situation were then asked in the second choice situation if they would vote for the same acreage to be treated using the same method if the cost was $250. Fifty-five percent of those respondents voted for the referendum at the higher cost. Alternatively, respondents who did not answer affirmatively in the first choice situation were then asked how they would vote if the cost was $25. Fifty percent of those respondents voted for the referendum at the lower cost.

The third choice situation of the bounded sample was designed like the second choice situation. Respondents who voted for the policy at $250 were asked if they would vote for the referendum at $300. Seventy percent of those respondents voted “For” the referendum at the higher cost. Conversely, respondents who voted “Against” (or “Don’t know”) on the policy at $25 were asked how they would vote if the cost was $5. Thirty-one percent of those respondents voted for the referendum at the lowest cost.

Table 1 shows that in the repeated sample the cost amount range expanded to include the costs in the bounded sample. In the second choice situation of the repeated sample the “For” votes fell from 62 percent to 41 percent as the cost amount increased from $25 to $250. In the third choice situation of the repeated sample the “For” votes decreased from 64 percent to 32 percent as the cost amount increased from $5 to $300.

In the debriefing section of the survey we asked questions about survey consequentiality and attribute non-attendance. Thirty-two percent strongly agreed and 42 percent somewhat agreed that “A state-wide referendum is a good way for citizens to decide whether additional taxes will be used to protect forest health.” Forty-seven percent strongly agreed and 36 percent somewhat agreed with: “I understand all of the information presented to me on the proposed treatment alternatives.” Twenty-one percent strongly agreed and 31 percent somewhat agreed with the statement: “I have confidence in the ability of policy makers to achieve the goals of the treatment alternatives.” Thirty-six percent strongly agreed and 38 percent somewhat agreed with the statement “I believe the results of this survey could affect decisions about forest health.”[8] Forty-three percent strongly agreed and 33 percent somewhat agreed with the statement: “I believe the results of the survey will be shared with policy makers.”

[8] The randomly assigned consequentiality statement did not affect responses to this question.

Survey respondents were also asked how much attention they paid to each of the four attributes and given four choices: “a lot,” “some,” “not much,” and “none.” Table 2 reports the distribution of the non-attendance across survey treatments and attributes. Respondents who chose “none” and “not much” are classified as not attending to the attribute. Overall, about 13 percent of respondents did not attend to the “size of the ecologically important area treated.” Nearly 25 percent of respondents did not attend to the “size of the socially important area treated.” The “treatment method (chemical or biological)” was also not attended to by about 15 percent of respondents. Almost 17 percent of respondents did not attend to the “cost over the next 3 years.”

Finally, we asked questions about individual specific characteristics. Fifty-four percent of respondents were female, half were married, 39 percent had children under 18 years of age, 76 percent were white, 96 percent had graduated high school, and their average age was about 42 years. The average annual household income is $54,000 (n=896). Despite the non-probability nature of the survey, the demographics of our sample were not considerably different from the North Carolina population. According to 2017 data from the U.S. Census Bureau, 51 percent of North Carolinians were female, 71 percent were white, and 86 percent had at least a high school education. Furthermore, in 2010 approximately 53 percent of North Carolina families had children, the median age of residents was 37, and per capita money income was nearly $25,000 according to the U.S. Census Bureau.

3. Empirical Models

We will develop several increasingly general models to analyze our data and incorporate ANA for our hypothesis tests. Our first test of external scope, for which only the first response is used in estimation, can be conducted with a standard discrete choice model. If the estimated coefficients on protection of ecological and social areas are positive and statistically significant, then our data exhibit external scope. Estimating the model based on repeated choice data provides the means to test for internal scope effects. Estimation of the coefficients in both cases is based on a linear utility function:

$$U_{nsj} = \beta_j' a_{nsj} + \varepsilon_{nsj} = V_{nsj} + \varepsilon_{nsj} \qquad \text{Eq. 1}$$

The observable portion of individual *n*'s utility from choosing alternative *j* in situation *s* is a linear function of the attribute vector a_{nsj} and coefficient vector β. Total utility is the sum of observable utility (V_{nsj}) and an additive component that is unobservable to the researcher (ε_{nsj}).

A respondent will choose the alternative that yields the highest utility but their choice may also depend on characteristics of that individual, such as income and education, which are placed in a vector x_n. Using the parameter vectors α and γ to capture these additional effects, and assuming the unobservable portion of utility ε_{nsj} is distributed type 1 extreme value (Gumbel), the probability that individual *n* will choose alternative *j* in situation *s* is:

$$Pr(y_{nsj}) = \frac{exp(a_{nsj}\beta + X_n\alpha + Z_{nsj}\gamma)}{\sum_q^J exp(a_{nsq}\beta + X_n\alpha + Z_{nsq}\gamma)} \qquad \text{Eq. 2}$$

Our first departure from the standard model in equation 2 is the stated ANA model which relies on debriefing questions about attribute attendance to place respondents into classes. Each class is defined by a set of parameter restrictions, setting coefficients equal to zero when a respondent indicated they did not attend to the corresponding attributes (Hensher et al. 2012; Kragt 2013; Koetse 2017). Generalizing our standard model to allow for classes of non-attending respondents yields the choice probabilities given by:

$$Pr(y_{nsj}|c) = \frac{exp(a_{nsj}\beta_c + X_n\alpha + Z_{nsj}\gamma)}{\sum_{q}^{J} exp(a_{nsq}\beta_c + X_n\alpha + Z_{nsq}\gamma)} \quad \text{Eq. 3}$$

where the β vector is now indexed by class c indicating which elements of β are restricted to zero.

For k attributes describing a discrete alternative there are a total of 2^k possible attribute (non-) attendance classes (Hensher et al. 2012; Thiene et al. 2015; Glenk et al. 2015). Thus, for our empirical setting with four attributes (cost over the next three years, ecologically important acreage, socially important acreage, and treatment method) there are 16 possible classes of attribute (non-)attendance to which individual n may belong. We abstract away from all these possibilities and largely focus on two classes: total attendance, and non-attendance to at least one attribute. Such an assumption is not unconventional given our empirical focus. In fact, Koetse (2017) investigates how accounting for non-attendance to the cost attribute both corrects hypothetical bias, and decreases the WTA-WTP disparity. Related to this issue is the relationship between attribute non-attendance and consequentiality. Koetse (2017) argues that consequentiality, or rather the lack thereof, is the most important reason for respondents ignoring the cost attribute. While Scarpa et al. (2009) discuss how cost non-attendance is often correlated with non-attendance to other attributes, Thiene et al. (2015) focus on non-attendance to a single attribute due to data limitations. Hensher et al. (2016) also agree that investigating all 2^k possible classes is not ideal.

We further generalize the stated ANA model by estimating a random parameters logit model which allows coefficients that are not restricted to zero to vary over respondents (Train 2003). In the random parameters logit, the β vector is distributed multivariate normal so that $\beta_{nk} = \beta_k + \sigma_k \nu_{nk}$ if a_k is attended to and $\beta = 0$ otherwise. β_k represents the mean of the distribution of marginal utilities across the sample population, σ_k represents the spread of preferences around the mean, and ν_{nk} is the random draw taken from the assumed distribution (Hensher et al. 2016).

Concerns about the accuracy of this self-reported information has led to use of latent class (LC) models to separate individuals into classes and motivates our inferred ANA model (Scarpa et al. 2009, 2012; Hensher et al. 2012; Kragt 2013; Glenk et al. 2015; Thiene et al. 2015). In this framework class membership is unknown to the analyst and is instead treated probabilistically. Estimation requires specifying the ANA class probabilities, π_{nc}, which are the probabilities that individual *n* belongs to class *c* (Hensher et al. 2016). These probabilities can be specified by the logit formula and estimated as a function of the choice-invariant characteristics in x_n:

$$Pr(c_n) = \pi_{nc} = \frac{exp(\theta_c x_n)}{\sum_{l}^{C} exp(\theta_l x_n)} \quad \text{Eq. 4}$$

where θ_c is a vector of estimated parameters and C is the number of classes specified by the analyst. The class membership probabilities can be combined with the conditional probability of equation 3 to express the unconditional probability of individual n's response via the Law of Total Probability:

$$Pr(y_{nsj}) = \sum_{l}^{C} Pr(c_{nl}) Pr(y_{nsj} | c_l) \quad \text{Eq. 5}$$

4. **Results**

We estimate the probability of voting for the hemlock woolly adelgid treatment policy as a function of the attributes using conditional logit, latent class, and random parameters logit models.[9] The coefficients from the conditional logits are shown in table 3a below.[10] The estimated coefficient on the cost is negative and statistically significant as one would expect for the repeated sample. The bounded sample, however, exhibits some strange behavior on the cost attribute. When considering only the first choice situation the coefficient for the cost attribute has the correct sign, but its significance disappears when both the first and second choice situations are included. The statistical significance reappears when all three choice situations are included in the model. Most strikingly table 3a shows no robust evidence of scope effects. Thus, our

[9] We find no differences in results for those who meet the conditions for survey consequentiality and those who do not (Petrolia, Interis and Hwang 2014). Also, similar binary choice sequence question formats have been used to examine ordering effects (Holmes and Boyle 2005; Day et al. 2012; Nguyen, Robinson, and Kaneko 2015). We find little evidence of ordering effects in our data.

[10] There is some evidence of incentive incompatibility and starting point bias, but it is not a result that is robust enough to make it an issue.

simple models show limited evidence of the repeated sample passing the internal scope test. Furthermore, our simple models fail the external scope test.

Table 3b reports estimated coefficients from the random parameters logit model. It shows, like Siikamäki and Larson (2015), the evidence for scope effects becomes stronger when we account for preference heterogeneity. In addition, the evidence of scope effects for ecologically important acreage in the repeated sample appear when the first two choice situations are included in the model. We also estimated latent class (LC) models that show evidence of scope effects in the repeated sample. For example, in the two-class non-equality constrained latent class (non-ECLC) model shown in table 3c, we observe positive and statistically significant scope effects in the dominant class (58 percent of respondents).[11] The coefficient for ecologically important acreage, however, is not distinguishable from zero unless all three choice situations are included in the model. Like the random parameters logit models, the two-class non-ECLC estimates a smaller Akaike Information Criteria (AIC) function than the conditional logit model. Thus, we have evidence that accounting for preference heterogeneity improves the fit of the model and the data exhibits internal scope effects.

We next investigate several ways of allowing for attribute non-attendance. First, we compare the effects of accounting for stated ANA on the conditional logit and random parameters logit models. Second, we examine a number of inferred ANA models.

[11] We purposefully omit the results from the first situation, and the first and second situation. The variance matrix for the repeated sample is singular in both cases, and the bounded sample does not exhibit scope effects for the first situation. Including both the first and second situation for the bounded sample yields statistically significant scope effects for ecological acreage in one class, while the estimated coefficient is negative and statistically significant at the 10 percent level in the other.

Table 4 reports the 2^k possible attribute (non-)attendance classes, under an equality constrained latent class (ECLC) model framework, where k is equal to 4 and refers to the attributes in table 2 (cost, ecologically important acreage, socially important acreage, and treatment). Table 4 illustrates how under the full 2^k (16) class ECLC model we only estimate 5 different coefficients (cost over the next three years, ecologically important acreage, socially important acreage, biological HWA treatment, and chemical HWA treatment). The estimated coefficient on cost (β_1) is the same for all classes that attend to the cost attribute. If the attribute is not attended to, then the coefficient is restricted to be equal to zero. The same conditions apply to models with fewer classes. Table 4 shows that 59 percent of respondents exhibit total attribute attendance, or the continuity axiom of neoclassical theory.[12] About 10 percent of the respondents ignored only the social scope of the policy, and about four percent ignored treatment. Almost 15 percent of respondents ignored a combination of attributes. Unlike many studies socially important acreage, and not "cost," was the most commonly ignored attribute (Kragt 2013).

Like Koetse (2017), who considers ANA for only cost, we do not attempt to investigate the 2^k classes.[13] We limit our analysis and consider three specific cases of stated ANA: scope non-attendance, cost non-attendance, and cost and scope non-attendance.[14]

We defined stated attribute non-attendance using the respondent's answer to a Likert scale question. Specifically, the survey asked, "When you were making your decisions about the

[12] This is comparable to Hensher (2008) and Kragt (2013). Sixty-two percent of Hensher's sample exhibit total attribute attendance and 55 percent of Kragt's respondents attended to all attributes.
[13] Our primary motivation for this is the small dataset that is likely to yield singular variance estimates in the 2^k class case.
[14] Our qualitative results are robust to our definition of ANA (none, none and not much, none and not much and some). We chose to report answers of either not much or none as our baseline definition.

different alternatives, how much influence did each of the following have on your voting decision?" Respondents were able to answer either "a lot," "some," "not much," "none," or they could decline to answer. We report estimated coefficients for models where ANA has been defined as either "none" or "not much" influence (see table 2). Later we will discuss the sensitivity of our results to our definition.

Table 5a reports the conditional logit model that accounts for non-attendance to the scope attributes (ecologically and socially important acreage). The model is conceptually similar to an equality constrained latent class model in that there are four (2^2) possible latent classes. Specifically, the four classes are: 1) total attendance (class 16 in table 4), 2) non-attendance to ecologically important acreage (class 2 in table 4), 3) non-attendance to socially important acreage (class 3 in table 4), and 4) non-attendance to both ecologically and socially important acreage (class 8 in table 4).

Unlike our previous results, table 5 shows that we find robust external and internal scope effects for both ecologically and socially important acreage in both the bounded and repeated samples. This is true for both the conditional logit (table 5a) and random parameters logit (table 5b) specifications.[15] We find qualitatively similar results (robust scope effects in both bounded and repeated samples) when we account for both cost and scope stated attribute non-attendance. However, as previously discussed, the estimated coefficient on the cost attribute is not always statistically significant in the bounded sample. When we account for stated ANA on the cost

[15] Our random parameters model uses 25 standard Halton sequence draws from normally distributed attribute parameters. The relative size of our estimated standard deviations range from 0.015 times smaller (cost) than the mean to 5.824 times larger (chemical treatment) than the mean. On average the standard deviations of the scope parameters are 1.11 times larger than the means, but range from 0.03 times smaller (socially important acreage) to 2.41 times larger (ecologically important acreage).

attribute alone we find no evidence of scope effects in the bounded sample, and non-robust evidence of scope effects for ecologically important acreage in the repeated sample. Based on the AIC the best fit is provided by the random parameters logit model that accounts for ANA to the scope attributes only.

Our results do not change qualitatively as we change our measurement of stated ANA. We do observe less peculiar behavior in the estimated coefficient on the cost attribute for the bounded data as we extend our definition from "none" to "none," "not much," and "some." The most substantial difference in the results occurs when we extend our definition of stated ANA to include "some" influence. We find that the statistical significance of socially important acreage begins to decrease.

Because there is evidence in the literature that respondents may not answer accurately to ANA questions we estimate equality constrained latent class (ECLC) models (Armitage and Conner 2001; Ajzen et al. 2004; Carlsson et al. 2010; Hess and Hensher 2010; Hensher et al. 2012; Scarpa et al. 2011; Scarpa et al. 2012; Alemu et al. 2013; Kragt 2013). We examine whether or not these inferred ANA models will show statistically significant scope effects. We examine several different cases of latent classes: 16 classes (1-16 on table 4), 9 classes (1-4, 8, and 14-16 on table 4), 5 classes (3, 4, 8, 15, and 16 on table 4), 4 classes (3, 8, 15, and 15 on table 4), 3 classes (3, 8 and 16 on table 4), and 2 classes (8 and 16, and 1 and 16 on table 4). We find that when including only the first situation in the model the AIC generally decreases for both the bounded and repeated samples, suggesting that fewer classes is better. However, these results are more noisy when both the first and second situations are included in the model, but generally speaking the AICs still decrease. Interestingly, the AIC seems to increase as ECLC models with fewer classes are estimated when all three choice situations are included. Furthermore, these findings are confounded by the fact that we also often estimate singular variance matrices.[16]

We report the inferred scope non-attendance and inferred cost non-attendance models in table 6a and table 6b. The estimated coefficients in these tables once again illustrate the robustness of the lack of scope effects.[17] The first specification in tables 6a and 6b assumes one class does not attend to both ecologically and socially important acreage. The second of these two inferred ANA models comes from Koetse (2017), who like Thiene et al. (2015) focuses on single attribute non-attendance.[18] Specifically, in the second specification we set the estimated coefficient for the cost attribute to be zero in the non-attending class. Unlike Kragt (2013) and Koetse (2017) our inferred models do not illicit scope effects.

Table 7 reports the marginal willingness-to-pay (WTP) estimates calculated from coefficients presented in the previous tables. It once again illustrates our two main points. First, there is a lack of scope effects in models that do not account for attribute non-attendance. Second, accounting for preference heterogeneity using either stated ANA or random parameters logit models can reveal scope effects. Using stated ANA models we find that respondents are

[16] We were unable to estimate a 2^k non-equality constrained latent class model due to data limitations.
[17] We also tried to estimate a 16 class (non-equality constrained) latent class models but it did not converge.
[18] For example, large numbers of latent classes lead to identification problems such as singular Hessians (Hensher et al. 2016). In fact, using our data the 2^k-class LC model and several specifications of the 2^k-class ECLC model often fail to converge or is singular. While Scarpa et al. (2009) discuss how cost attribute non-attendance is often correlated with non-attendance to other attributes, due to data limitations Thiene et al. (2015), like Koetse (2017), focuses on non-attendance to a single attribute.

willing to pay between about $10 and $16 per acre. Random parameters logit models, however, suggest a more narrow range of marginal WTP of between $7 and $14 per acre.

5. Conclusions

We compare bounded and repeated survey treatments and employ a number of different specifications to search for scope effects in single or sequential binary choice situations. While some models like random parameters logit and 2-class non-ECLC models will show scope effects for ecologically important acreage in the repeated data when we include all three choice situations, such results are not robust to specification. Robust scope effects appear only when we account for stated ANA on scope attributes. The preferred models are stated ANA random parameters logit models using the repeated data which has a better statistical fit than the bounded data. The bounded sample models typically have higher AIC functions than the repeated data for the same specifications, except when all three choice situations are included in our models. There is also less robust evidence of scope effects with the bounded sample. As we change our definition of ANA the qualitative results do not change substantially, however, we do begin to see less evidence of scope effects for socially important acreage.

We have shown that like many other contingent valuation studies the 2017 Southern Appalachian Forest Management Survey data generally fails internal and external scope tests when using naive models that assume fully compensatory preferences. This result is robust to the number of choice situations in the survey and empirical specification. We employ several methods to account for preference heterogeneity: 1) stated attribute non-attendance, 2) inferred attribute non-attendance, 3) equality constrained latent class models, 4) random parameters models, and 5) and combinations of the four. Accounting for stated attribute non-attendance allows models to pass both internal and external scope tests, overcoming one of the main criticisms of contingent valuation. As noted by other researchers, such an effect has large policy implications (Scarpa et al. 2009; Kragt 2013; Glenk et al. 2015; Koetse 2017). Our analysis has demonstrated that accounting for stated attribute non-attendance for scope attributes can lead to statistically significant coefficients for scope variables. The demonstrated ability to correct for a longstanding criticism of contingent valuation warrants further investigation on the effects of ANA and implications of discontinuous preference ordering among survey respondents. Our results provide evidence of a need and an opportunity to revisit old data that exhibits insensitivity to scope using new techniques.

Our results conflict with Kragt (2013) and Koetse (2017). While they favor the inferred models, the results of our analysis seem to favor stated models. A striking result from our investigation into the inferred models is that we find no evidence of scope effects on the bounded survey treatment sample, regardless of the number of latent classes we assume. We also fail to find robust evidence of scope effects in the repeated sample. In some specifications we find significant scope effects using the repeated sample but they are not robust to specification or the number of situations considered. In fact, in our investigation of ECLC models, only one specification includes statistically significant scope effects. Generally speaking, we find less evidence of scope effects as we extend our definition of ANA. It does not appear that the equality constrained latent class (ECLC) models improve the fit of our models relative to stated ANA random parameters models.

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7. Figures

Figure 1. Hemlock woolly adelgid management areas in North Carolina and Tennessee

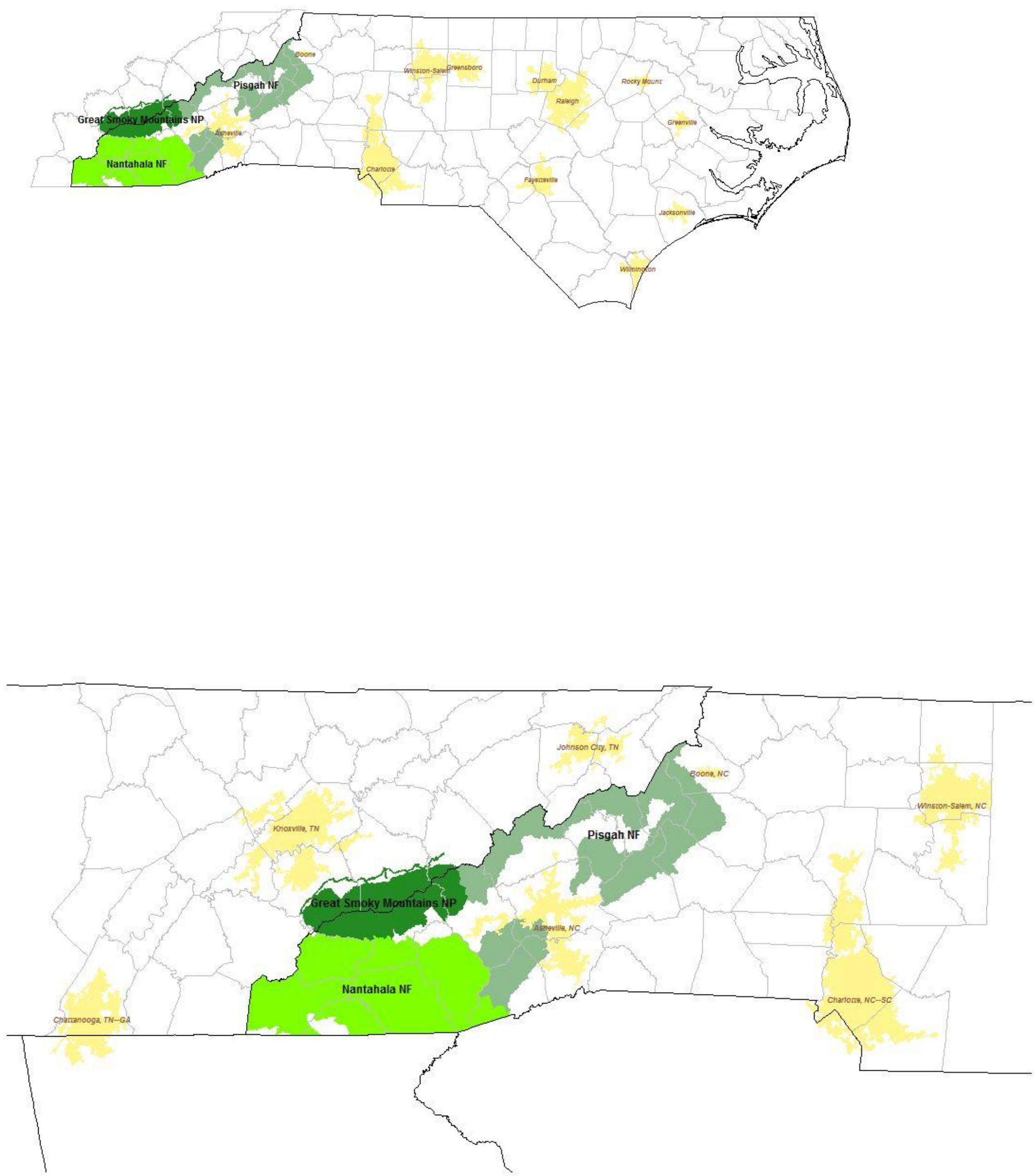

Figure 2. Binary Choice Question

Imagine that you have the opportunity to vote on the hemlock forest treatment alternative. If more than 50% of North Carolina households vote for the alternative then it would be put into practice.

Consider the following alternative:

A 25.0% The area treated of ecologically important hemlock dominated forests is 2500 acres, 8% of the total.
B 25.0% The area treated of ecologically important hemlock dominated forests is 5000 acres, 17% of the total.
C 25.0% The area treated of ecologically important hemlock dominated forests is 7500 acres, 25% of the total.
D 25.0% The area treated of ecologically important hemlock dominated forests is 10,000 acres, 33% of the total.

A 25.0% The area treated of socially important hemlock dominated forests is 2500 acres, 8% of the total.
B 25.0% The area treated of socially important hemlock dominated forests is 5000 acres, 17% of the total.
C 25.0% The area treated of socially important hemlock dominated forests is 7500 acres, 25% of the total.
D 25.0% The area treated of socially important hemlock dominated forests is 10,000 acres, 33% of the total.

A 50.0% The treatment method is chemical insecticide.
B 50.0% The treatment method is biological control with predatory beetles.

A 25.0% The annual cost to you for the next 3 years is $50.
B 25.0% The annual cost to you for the next 3 years is $100.
C 25.0% The annual cost to you for the next 3 years is $150.
D 25.0% The annual cost to you for the next 3 years is $200.

Would you vote for or against this alternative?

- I would vote for this alternative
- I would vote against this alternative
- I don't know how I would vote

8. Tables

Table 1: Single Binary Choice Referendum Votes						
	First Binary Choice Referendum Question					
	SBC-Bounded			**SBC-Repeated**		
Cost	**For Votes**	**Sample Size**	**% For**	**For Votes**	**Sample Size**	**% For**
50	72	109	*66%*	55	92	*60%*
100	65	123	*53%*	64	118	*54%*
150	51	113	*45%*	64	118	*54%*
200	56	124	*45%*	40	110	*36%*
Total	244	469	*52%*	223	438	*51%*
	Second Binary Choice Referendum Question					
	SBC-Bounded			**SBC-Repeated**		
Cost	**For Votes**	**Sample Size**	**% For**	**For Votes**	**Sample Size**	**% For**
25	113	225	*50%*	38	61	*62%*
50				40	76	*53%*
100				35	74	*47%*
150				26	63	*41%*
200				31	83	*37%*
250	134	244	*55%*	33	81	*41%*
Total	247	469	*53%*	203	438	*46%*
	Third Binary Choice Referendum Question					
	SBC-Bounded			**SBC-Repeated**		
Cost	**For Votes**	**Sample Size**	**% For**	**For Votes**	**Sample Size**	**% For**
5	35	112	*31%*	43	67	*64%*
25				38	55	*69%*
50				24	44	*55%*
100				29	57	*51%*
150				22	58	*38%*
200				15	54	*28%*
250				16	53	*30%*
300	94	134	*70%*	16	50	*32%*
Total	129	246	*52%*	203	438	*46%*

Table 2: Stated attribute non-attendance			
	Bounded	**Repeated**	**All**
Number of obs.	469 *51.71%*	438 *48.29%*	907 *100%*
Cost	70 *14.93%*	83 *18.95%*	153 *16.87%*
Ecological area	57 *12.15%*	64 *14.61%*	121 *13.34%*
Social area	120 *25.59%*	102 *23.29%*	222 *24.48%*
Treatment method	64 *13.65%*	68 *15.53%*	132 *14.55%*
Notes: The count of statated attribute non-attendance is reported above the percentage of the sample.			

Table 3a: Conditional logit models

	1st situation		1st and 2nd situations		1st, 2nd, and 3rd situations	
	Bounded	**Repeated**	**Bounded**	**Repeated**	**Bounded**	**Repeated**
COST	-0.00537***	-0.00597***	-0.00050	-0.00449***	0.00189***	-0.00511***
	(0.00172)	(0.00183)	(0.00078)	(0.00104)	(0.00062)	(0.00076)
ECOL	0.00257	0.01212	-0.01589	0.03211	-0.02382	0.04061*
	(0.03330)	(0.03457)	(0.02378)	(0.02395)	(0.02223)	(0.02095)
SOCIAL	-0.04875	0.04592	-0.02042	0.01434	-0.01744	-0.00680
	(0.03411)	(0.03410)	(0.02379)	(0.02481)	(0.02146)	(0.02071)
BIOL	1.25593***	0.63952	0.50122**	0.46297*	0.14702	0.55832**
	(0.36772)	(0.40075)	(0.25122)	(0.27797)	(0.21959)	(0.23139)
CHEM	0.83718**	0.22553	0.26585	-0.01324	0.01785	0.16084
	(0.37275)	(0.38325)	(0.25644)	(0.26739)	(0.22778)	(0.22458)
AIC	641.0	599.8	1303.2	1189.7	1633.0	1758.5

Notes: The estimated coefficients are reported above their clustered standard errors in parentheses (st. er.). The statistical significance is reported using the following convention: + $p<0.1$, * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Table 3b: Random parameters logit models						
	1st situation		**1st and 2nd situations**		**1st, 2nd, and 3rd situations**	
	Bounded	**Repeated**	**Bounded**	**Repeated**	**Bounded**	**Repeated**
Means						
COST			-0.01645***	-0.01577***	-0.01571***	-0.00913***
			(0.00595)	(0.00476)	(0.00483)	(0.00164)
ECOL			0.02268	0.15214*	-0.01733	0.06970**
			(0.06363)	(0.07922)	(0.06154)	(0.03425)
SOCIAL			-0.06914	0.04420	-0.07105	-0.00852
			(0.06544)	(0.06931)	(0.06197)	(0.03312)
BIOL			2.60765**	1.13420	2.97708***	0.95154***
			(1.01691)	(0.75255)	(1.00017)	(.36710)
CHEM			1.95851**	-0.49301	2.47498**	0.26765
			(0.87651)	(0.78752)	(0.97881)	(0.33388)
Standard deviations						
COST			0.01463***	0.02576***	0.00657**	0.00997***
			(0.00417)	(0.00770)	(0.00271)	(0.00224)
ECOL			0.20869**	0.11107	0.15732**	0.14296**
			(0.08974)	(0.07604)	(0.06959)	(0.05789)
SOCIAL			0.09178	0.21859**	0.10167*	0.13072**
			(0.06460)	(0.08546)	(0.06132)	(0.05899)
BIOL			1.90276**	2.40595***	2.68991***	1.13188*
			(0.79594)	(0.91214)	(0.71015)	(0.60499)
CHEM			2.13536***	4.88258***	2.78915***	0.51951
			(0.73172)	(1.46716)	(0.74716)	(0.43801)
AIC	singular	singular	1248.3	1110.0	1594.0	1721.5
Notes: The estimated coefficients are reported above their clustered standard errors in parentheses (st. er.). The statistical significance is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.						

Table 3c: Latent class models

	1st, 2nd, and 3rd situations			
	Bounded		**Repeated**	
	Class 1	**Class 2**	**Class 1**	**Class 2**
COST	-0.00504**	-0.00826***	-0.01084***	-0.00416**
	(0.00253)	(0.00260)	(0.00181)	(0.00182)
ECOL	-0.04162	-0.03638	0.12286***	0.01765
	(0.04818)	(0.03867)	(0.04470)	(0.05370)
SOCIAL	-0.01703	-0.01893	0.02281	-0.05139
	(0.04890)	(0.03984)	(0.04000)	(0.05904)
BIOL	2.69844***	0.16004	-0.64583	2.71958***
	(0.89647)	(0.38976)	(0.50753)	(0.71230)
CHEM	2.61063***	-0.05023	-1.03611**	1.77971***
	(0.95087)	(0.39676)	(0.47029)	(0.65642)
Probclass	0.46812***	0.53188***	0.58492***	0.41508***
AIC	1611.8		1637.1	

Notes: The estimated coefficients are reported above their clustered standard errors in parentheses (st. er.). The statistical significance is reported using the following convention: +p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 4: The 2^k cases of attribute non-attendance in the 2017 SAFMS							
	PAYMENT	**SCOPE**		**TREATMENT (β_4, β_5)**		**N**	**%**
Class	**COST (β_1)**	**ECO (β_2)**	**SOC (β_3)**	**BIO**	**CHEM**		
1	**0**	β_2	β_3	β_4	β_5	66	7.28
2	β_1	**0**	β_3	β_4	β_5	13	1.43
3	β_1	β_2	**0**	β_4	β_5	92	10.14
4	β_1	β_2	β_3	**0**	**0**	40	4.41
5	**0**	**0**	β_3	β_4	β_5	3	0.33
6	**0**	β_2	**0**	β_4	β_5	19	2.09
7	**0**	β_2	β_3	**0**	**0**	17	1.87
8	β_1	**0**	**0**	β_4	β_5	38	4.19
9	β_1	**0**	β_3	**0**	**0**	6	0.66
10	β_1	β_2	**0**	**0**	**0**	12	1.32
11	**0**	**0**	**0**	β_4	β_5	9	0.99
12	**0**	**0**	β_3	**0**	**0**	5	0.55
13	**0**	β_2	**0**	**0**	**0**	5	0.55
14	β_1	**0**	**0**	**0**	**0**	18	1.98
15	**0**	**0**	**0**	**0**	**0**	29	3.20
16	β_1	β_2	β_3	β_4	β_5	535	58.99
					Σ	907	100

Table 5a: Conditional logit models with ANA on the scope attributes						
	1st situation		**1st and 2nd situations**		**1st, 2nd, and 3rd situations**	
	Bounded	**Repeated**	**Bounded**	**Repeated**	**Bounded**	**Repeated**
COST	-0.00601***	-0.00599***	-0.00076	-0.00457***	0.00167***	-0.00528***
	(0.00173)	(0.00186)	(0.00079)	(0.00105)	(0.00062)	(0.00077)
ECOL	0.05970**	0.06910**	0.04088**	0.07004***	0.03530*	0.08695***
	(0.02931)	(0.02919)	(0.02062)	(0.02221)	(0.01945)	(0.01974)
SOCIAL	0.05605**	0.06986**	0.04284**	0.04545**	0.03790**	0.02836
	(0.02726)	(0.02818)	(0.01928)	(0.02158)	(0.01727)	(0.01866)
BIOL	0.50862*	0.33524	-0.07800	0.18810	-0.41441**	0.19645
	(0.30132)	(0.32266)	(0.18427)	(0.22520)	(0.16662)	(0.19298)
CHEM	0.04034*	-0.13598	-0.34983*	-0.31165	-0.57802***	-0.20600
	(0.30501)	(0.32528)	(0.18327)	(0.22796)	(0.16490)	(0.18819)
AIC	632.2	586.4	1292.7	1170.5	1623.7	1728.3

Notes: The estimated coefficients are reported above their clustered standard errors in parentheses (st. er.). The statistical significance is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.

Table 5b: Random parameters logit models with ANA on the scope attributes						
	1st situation		**1st and 2nd situations**		**1st, 2nd, and 3rd situations**	
	Bounded	**Repeated**	**Bounded**	**Repeated**	**Bounded**	**Repeated**
Means						
COST		-0.00942***	-0.01822***	-0.01481***	-0.01920**	-0.01227***
		(0.00355)	(0.00684)	(0.00451)	(0.00757)	(0.00185)
ECOL		0.19178	0.15890**	0.21452***	0.18962**	0.17557***
		(0.20169)	(0.07569)	(0.07415)	(0.09097)	(0.03924)
SOCIAL		0.12282*	0.12334*	0.17513**	0.11699**	0.07885**
		(0.06825)	(0.06343)	(0.07079)	(0.05589)	(0.03731)
BIOL		0.52934	1.11933*	0.24308	1.29067*	0.32254
		(0.65303)	(0.66395)	(0.53728)	(0.68838)	(0.33338)
CHEM		-0.52352	0.48518	-1.29.460*	0.49502	-0.41357
		(1.38586)	(0.49029)	(0.68944)	(0.51479)	(0.31664)
Standard deviations						
COST		0.00014	0.01600***	0.02285***	0.01349***	0.01477***
		(0.00447)	(0.00569)	(0.00682)	(0.00505)	(0.00235)
ECOL		0.46168*	0.19982**	0.10602	0.20497**	0.02167
		(0.27343)	(0.08501)	(0.06493)	(0.08148)	(0.03861)
SOCIAL		0.21739	0.17035**	0.21447***	0.00340	0.10375**
		(0.14736)	(0.07519)	(0.06488)	(0.04862)	(0.04376)
BIOL		0.46936	1.86433**	2.24973**	2.64182***	1.78720***
		(0.88439)	(0.80600)	(0.97082)	(0.77937)	(0.50370)
CHEM		0.97049	2.40991***	4.28831***	2.88324***	1.64300***
		(3.89176)	(0.82914)	(1.21354)	(0.93938)	(0.43792)
AIC	singular	586.6	1269.8	1093.2	1597.7	1589.8
Notes: The estimated coefficients are reported above their clustered standard errors in parentheses (st. er.). The statistical significance is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.						

Table 6a: Bounded sample with first and second situations				
	ECLC scope		**ECLC cost**	
	Class 1	**Class 2**	**Class 1**	**Class 2**
COST	-0.00447***	-0.00447***	0.0	-0.01751***
	(0.00147)	(0.00147)	(0.0)	(0.00396)
ECOL	0.0	-0.27976	-0.01891	-0.01891
	(0.0)	(0.54986)	(0.02874)	(0.02874)
SOCIAL	0.0	-0.77592	-0.02098	-0.02098
	(0.0)	(0.82176)	(0.02908)	(0.02908)
BIOL	1.33598***	1.33598***	0.95110***	0.95110***
	(0.34443)	(0.34443)	(0.31629)	(0.31629)
CHEM	1.03256***	1.03256***	0.64589**	0.64589**
	(0.34120)	(0.34120)	(0.31469)	(0.31469)
Class probability	0.83090***	0.16910***	0.33696***	0.33696***
AIC	1297.1		1293.0	
Notes: The estimated coefficients are reported above their clustered standard errors in parentheses (st. er.). The statistical significance is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.				

Table 6b: Repeated data with first and second situations				
	ECLC scope		**ECLC cost**	
	Class 1	**Class 2**	**Class 1**	**Class 2**
COST	-0.00714***	-0.00714***	0.0	-0.02853***
	(0.00146)	(0.00146)	(0.0)	(0.00802)
ECOL	0.0	0.37016	0.03889	0.03889
	(0.0)	(0.35381)	(0.03343)	(0.03343)
SOCIAL	0.0	0.66116	0.03655	0.03655
	(0.0)	(0.45117)	(0.03414)	(0.03414)
BIOL	0.46170**	0.46170**	0.75063**	0.75063**
	(0.22313)	(0.22313)	(0.35201)	(0.35201)
CHEM	-0.38041	-0.38041	0.06157	0.06157
	(0.24255)	(0.24255)	(0.34023)	(0.34023)
Class probability	0.73732***	0.26268***	0.60557***	0.39443***
AIC	1129.6		1141.7	
Notes: The estimated coefficients are reported above their clustered standard errors in parentheses (st. er.). The statistical significance is reported using the following convention: + p<0.1, * p<0.05, ** p<0.01, *** p<0.001.				

Table 7: Marginal willingness-to-pay						
	1st situation		**1st and 2nd situations**		**1st, 2nd, and 3rd situations**	
	Bounded	**Repeated**	**Bounded**	**Repeated**	**Bounded**	**Repeated**
Conditional logit						
ECOL	$0	$0	$0	$0	$0	$9.75*
SOCIAL	$0	$0	$0	$0	$0	$0
Random parameters logit						
ECOL			$0	$9.65*	$0	$7.97**
SOCIAL			$0	$0	$0	$0
Latent class logit						
ECOL						$11.33***
SOCIAL						$0
Conditional logit with ANA on the scope attributes						
ECOL	$9.93**	$11.54**	$0	$15.32***	-$21.14*	$16.47***
SOCIAL	$9.33**	$11.66**	$56.37**	$9.95**	-$22.69**	$0
Random parameters logit with ANA on the scope attributes						
ECOL		$0	$8.72**	$14.48***	$9.88**	$14.31***
SOCIAL		$13.04*	$6.77*	$11.83**	$6.09**	$6.43**
2-class ECLC for cost attribute						
ECOL			$0	$0		
SOCIAL			$0	$0		

Notes: Marginal willingness-to-pay estimates are presented above following stars that indicate statistical significance. The stars correspond to the minimum statistical significance between the cost attribute and scope attribute. A zero indicates that our estimated coefficients were not statistically significant, and a blank or missing value indicates that we did not estimate that model.