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Single-Choice, Repeated-Choice, and Best-Worst Elicitation Formats:
Do Results Differ and by How Much?

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Single-Choice, Repeated-Choice, and Best-Worst Elicitation Formats: Do Results Differ and by How Much?

Abstract

This paper presents what we believe to be the most comprehensive suite of comparison criteria regarding multinomial discrete-choice experiment elicitation formats to date. We administer a choice experiment focused on ecosystem-service valuation to three independent samples: single-choice, repeated-choice, and best-worst elicitation. We test whether results differ by parameter estimates, scale factors, preference heterogeneity, status-quo/action bias, attribute non-attendance, and magnitude and precision of welfare measures. Overall, we find very limited evidence of differences in attribute parameter estimates, scale factors, and attribute increment values across elicitation treatments. However, we find significant differences in status-quo/action bias across elicitation treatments, with repeated-choice resulting in greater proportions of "Yes" votes, and consequently, higher program-level welfare estimates. Also, we find that single-choice yields drastically less-precise welfare estimates. Finally, we find significant differences in attribute non-attendance behavior across elicitation formats, although there appears to be little consistency in class shares even within a given elicitation treatment.

Keywords: best-worst elicitation, choice experiment, contingent valuation, ecosystem-service valuation, stated preference, survey, willingness to pay

Introduction

Several different formats of preference questions have been used in discrete choice experiments.[1] The most basic format is a single question from which a respondent chooses among two alternatives, as proposed by the NOAA Blue Ribbon panel (Arrow et al. 1993). Hanemann (1985) and Carson (1985) proposed the double-bound binary-choice format, in which respondents were asked a follow-up question that proposed a higher or lower price for the good or program depending on the initial response. In recent years, the valuation literature has shifted toward the multinomial-choice format which developed in the marketing literature.[2] The multinomial-choice format presents respondents with three or more alternatives from which to choose, and instead of only price varying across respondents, multiple attributes vary across both alternatives and respondents. Usually, respondents are asked to make more than one such choice. Three field survey papers in the agricultural and environmental economics literature adopt the multinomial-choice format utilizing only a single question: List, Sinha, and Taylor (2006); Newell and Swallow (2013); and Petrolia, Interis, and Hwang (2014).

Finally, the best-worst elicitation (BWE) format has also emerged in the past few years as an alternative to the above formats (see Flynn and Marley 2012; Flynn et al. 2007; Marley and

[1] We adopt the terminology of Carson and Louviere (2011) in which a discrete choice experiment is a survey in which respondents are asked to make a discrete choice from two or more alternatives within a choice set and the choice sets are carefully constructed by the researcher according to an experimental design.

[2] This method can go by other names. See Carson and Louviere (2011) and Louviere, Flynn, and Carson (2010) for discussions on nomenclature.

Louviere 2005; Potoglou et al. 2011; Scarpa et al. 2011). This format asks respondents to indicate the "best" alternative among a set and then to indicate the "worst" alternative, and then, of the remaining alternatives, to indicate the "best" of those remaining, then the "worst", etc., until a full ranking is achieved.

The use of so many different preference question formats in the literature reveals the lack of consensus regarding the best format to be used and there are advantages and disadvantages for each format. For example, the single binary-choice format proposed by the Blue Ribbon panel can be made incentive compatible (Carson and Groves 2007). But an understandable temptation among practitioners is to collect more information from each respondent, with the hope being that doing so will save money or increase the reliability of estimates. Unfortunately for practitioners, however, a deviation from the single binary-choice format is often accompanied by introduced biases. For example, respondents reacted to the follow-up question of the double-bound format in ways that researchers did not intend, which cast doubt on the legitimacy of those responses.[3] Consequently, the double-bound format was largely abandoned.

Similarly, multinomial-choice formats gather more information per respondent than a single binary-choice question, however they can be made incentive-compatible only under extremely restrictive conditions (Carson and Groves 2007). And like the double-bound binary-

[3] See Boyle, Bishop, and Welsh (1985); Mitchell and Carson (1993); Herriges and Shogren (1996); Flachaire and Hollard (2006); Carson et al. (1992); Alberini, Kanninen, and Carson (1997); Watson and Ryan (2007); Altaf and DeShazo (1994); McLeod and Bergland (1999); Haab and McConnell (2002); Cooper, Hanemann, and Signorello (2002); Carson and Groves (2007); and Bateman et al. (2001).

choice format, the repeated multinomial-choice format has been found to yield unexpected behavioral anomalies.[4] Holmes and Boyle (2005) find that responses to the last question in a series are more informative than previous ones, with strong evidence of context dependence stemming from both price and non-price attributes. McNair, Hensher, and Bennett (2012) find that relatively few respondents answer consistently with traditional assumptions of truthful, independent responses with stable preferences. Day et al. (2012) find evidence of position-dependent order effects. McNair, Bennett, and Hensher (2011) find no significant difference between responses to a single binary-choice question and the first of a repeated binary-choice question sequence, but find differences between the former and subsequent responses in the repeated sequence. Bateman et al. (2004) find evidence of order effects on sensitivity to scope. Day and Prades (2010) find that the probability of a particular alternative being chosen changes significantly under certain price and commodity sequences.

The argument is made that choosing "bests" and "worsts" in the BWE format is a relatively easy task for respondents, and that this cognitive ease yields more accurate preference information compared with other formats, such as a direct ranking of alternatives, where

[4] It is worth noting that Holmes and Boyle (2005) and Day et al. (2012) indicate that the repeated-response format may allow for learning. Ladenburg and Olsen (2008) cite their results as evidence of this effect. Scheufele and Bennett (2012) point out, however, that it is also possible that respondents to a repeated-choice survey discover the possibility of responding strategically as they progress through the choice tasks, and this "strategic learning" may coincide with learning about the choice task.

respondents can quickly become overwhelmed when there are more than a few alternatives. The BWE format also yields more information per choice set compared to a multinomial-choice format because a full ranking is achieved. Although the literature on this format is relatively young, early evidence indicates, however, that it may have its own challenges. For example, Rigby, Burton, and Lusk (2015) find significant differences in error variance between "best" and "worst" choices.

As applied researchers seeking to collect information which can be used in policy and other decisions, it is important to understand the tradeoffs between cost efficiency, estimate reliability, and estimate validity among different question formats. In this paper, we empirically examine differences between three closely-related preference question formats used in the literature: the single multinomial-choice (SMC) format, the repeated multinomial-choice (RMC) format, and the best-worst elicitation (BWE) format. If respondents behave similarly under the RMC format as they do under the SMC format, researchers can feel free to ask multiple preference questions and thereby gain more information per respondent. Likewise, if respondents behave similarly under the BWE format as they do under the SMC format, researchers can feel free to elicit a full preference ranking and thereby increase the amount of information collected per response even further.[5]

[5] It is important to note that these tests are conducted from a purely empirical basis because there exists no theory that would dictate which elicitation format, in a multinomial-choice setting, is the "standard". Unlike single binary-choice questions, which have been shown to be incentive-compatible, multinomial-choice questions are not incentive compatible, at least in a field setting (see Carson & Groves 2007 and Petrolia and Interis 2013), and it is in this setting that our

To our knowledge, no study has compared these three elicitation formats directly. Scheufele and Bennett (2012), which compares single and repeated choice formats, is the closest to our study, but focuses only on the binary-choice question format, the repeated version of which is not typical of choice experiments. Two other papers somewhat related to our study are Bateman et al. (2004) and Day et al. (2012). Bateman et al. (2004) focuses on the repeated binary-choice format with increasing project scope over choice tasks. They do not directly compare single to repeated choice: rather, they compare repeated choice with varying disclosure formats. Day et al. (2012) also use a repeated binary-choice experiment with "better" or "worse" attribute sequences and they focus on disclosure (of information to respondents) formats. Given the widespread use of the RMC format, the growing use of BWE formats, and the limited use of the closely-related SMC format, we believe that a careful empirical examination of differences between these formats is warranted, just as there have been extensive examinations of differences between single- and repeated binary-choice questions and between binary- and multinomial-choice question formats in the past.

In our examination of differences across formats, we employ what we believe is the most comprehensive suite of comparison criteria to date in the literature. Specifically, we test whether results differ by parameter estimates, scale factors, preference heterogeneity, status-quo/action bias, attribute non-attendance, and magnitude and precision of welfare measures. Analysis is conducted using a specification of the random-parameters logit model that accounts for scale

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interest lies here, given the widespread use of these elicitation methods in the field for policy-relevant valuation. Multinomial-choice questions can be made incentive-compatible in a lab setting (see Taylor, Morrison, and Boyle 2010).

differences across both alternatives (i.e., to relax the Independence from Irrelevant Alternatives assumption) and elicitation formats, as well as to implement Carson and Czajkowski's (2013) reparameterization of the coefficient on (the negative of) price to enforce a theoretically correct positive coefficient. Attribute non-attendance comparisons are made using a variant of Hensher, Rose, and Greene's (2012) "2^K" model. Tests of equality of parameter vectors and scale factors across elicitation formats follow a variation on the method of Swait and Louviere (1993) and Blamey et al. (2002).

Overall we find very limited evidence of any differences in attribute parameter estimates among the three elicitation treatments. We also find very little evidence of differences in attribute increment values across elicitation treatments. We do, however, find significant differences in status-quo / action bias across elicitation treatments, with the RMC treatment resulting in greater proportions of "Yes" votes, and consequently, higher program-level welfare estimates relative to the SMC and BWE formats. Also, we find that the SMC format yields drastically less precise welfare estimates compared with the other formats. We also find significant differences in attribute non-attendance behavior across elicitation formats, although there appears to be little consistency in class shares even within a given elicitation treatment.

Experimental Design and Data

The analysis utilizes data from a study on ecosystem service valuation for services delivered by two habitats, oyster reefs and salt marshes, along the Gulf of Mexico. Additional details not covered here, and other analyses, can be found in Interis and Petrolia (2016). The choice experiment focused on four specific ecosystem services: increased water quality, improved flood protection, increased commercial fisheries support, and increased wading bird population.

The specific levels of each service provided, and well as the proposed bid levels, were expressed using the language reported in the right-hand column of table 1. Given the above service attributes and levels, the choice experiment design was developed using Ngene software, in which 24 choice sets were created in order to maximize D-efficiency (See ChoiceMetrics 2011).

Three question format treatments were designed; SMC, RMC with four choice questions, and a single-question version of the BWE format, which we refer to here as "single best-worst" (SBW) elicitation. Our SBW question is an application of "Case III" BWE (see Flynn and Marley 2012), in which there are three alternatives (as with the other formats in our study), and the "best" and "worst" of the three presented alternatives are elicited, thus yielding a full ranking. [6] This ranking was then decomposed following the method of rank-ordered explosion proposed by Chapman and Staelin (1982), which, in our case, yields two choice observations for each choice question asked: a three-alternative observation (first-best case) and a two-alternative observation (second-best case).[7] Thus in our design, where N is the number of choices observed and J is the number of choice questions a respondent faces, we observe, for the SMC treatment, a total of N_{SMC} choices over to a total of N_{SMC}/J_{SMC} respondents (where $J_{SMC} = 1$); for the RMC

[6] This format may differ somewhat from other studies that have utilized the SBW elicitation format. In those studies, it appears that the choices are sequential, so that the respondent chooses the "best", then is shown only the remaining alternatives and is asked to indicate the "worst", etc., until all alternatives have been fully ranked.

[7] This rank-order explosion is also known as the Plackett–Luce model (Marden 1995), the choice-based method of conjoint analysis (Hair et al. 2010), and most frequently, rank-ordered logit (Stata 2013).

treatment, we observe N_{RMC} choices over N_{RMC}/J_{RMC} respondents (where $J_{RMC} = 4$); and for the SBW treatment, we observe N_{SBW} choices over N_{SBW}/J_{SBW} respondents (where $J_{SBW} = 2$). See figure 1 for an example choice set.

The payment mechanism specified was a one-time payment collected on the respondent's state tax return filed the following year. It was stipulated that the tax revenue would partially cover the cost of an implemented program with the remainder of funds coming from existing tax dollars. It was explained that construction would commence the following year and take five years to complete. It was stated that the expected benefits – the provided ecosystem services – were expected to last 30 years after completion.

To increase the perception that their responses would be meaningful in the sense that they could actually influence future policy (Carson and Groves 2007), respondents were told at the beginning of the survey that a large number of taxpayers would be taking the survey and that their responses would be shared with policy-makers and could affect how much they pay in taxes in the future. Respondents were then given some information about their assigned habitat including an explanation of some of the ecosystem services it provides. Then it was explained that policy-makers were considering implementing a habitat construction program and details were given about how such a program would be implemented, including how many acres of habitat would be created and when, where, and by whom they would be created. Respondents were shown maps of candidate locations within each water body of where habitat could potentially be constructed, and where existing habitat is located already.

The survey was administered by GfK Custom Research. In April 2013, an initial pretest of the survey was administered to 25 respondents to make sure the online survey was working properly and to elicit open-ended feedback about respondent understanding and ease of completion. The final survey was administered in May and June 2013. Respondents were randomly assigned to some combination of habitat and elicitation format.

The first sample comes from a state-level survey administered to Louisiana households regarding a hypothetical restoration of oyster reefs in Barataria-Terrebonne Bay, Louisiana. The second sample comes from the same as above, but focuses on salt marsh habitat. (Note that this sample includes only the SMC and RMC elicitation treatments.) The third sample comes from a Gulf of Mexico Regional survey administered to households across the five Gulf states that valued ecosystem services derived from a multi-state oyster-reef restoration project. A total of 2,334 households were included in the empirical analysis, contributing 865, 653, and 816 household respondents to the three aforementioned samples, respectively.

Tables 2 - 4 display summaries of attitudinal and demographic indicators for comparison across elicitation treatments. Pearson Chi-square tests were used to test for significant differences in categorical variables across elicitation treatments for each sample, and t-tests were used for age, household size, and income category. With very few exceptions – noted by asterisks in the tables – we found no significant differences in the indicators across treatments, evidence that the independent treatment samples are statistically similar in terms of attitudes and demographics.

Econometric Model Specification

The general empirical specification of utility for each elicitation format model are, respectively:

$$
\begin{aligned}
U_{nj}^{SMC} &= (\alpha^{SMC} \cdot action_j + \boldsymbol{\beta}^{SMC\prime}\mathbf{x}_{nj}) + (\mu_n^{SMC} \cdot action_j + \boldsymbol{\sigma}_n^{SMC\prime}\mathbf{x}_{nj} + \varepsilon_{nj}^{SMC}) \\
U_{nj}^{RMC} &= (\alpha^{RMC} \cdot action_j + \boldsymbol{\gamma}'\mathbf{z} + \boldsymbol{\beta}^{RMC\prime}\mathbf{x}_{nj}) + (\mu_n^{RMC} \cdot action_j + \boldsymbol{\sigma}_n^{RMC\prime}\mathbf{x}_{nj} + \varepsilon_{nj}^{RMC}) \\
U_{nj}^{SBW} &= (\alpha^{SBW} \cdot action_j + \boldsymbol{\beta}^{SBW\prime}\mathbf{x}_{nj}) + (\mu_n^{SBW} \cdot action_j + \boldsymbol{\sigma}_n^{SBW\prime}\mathbf{x}_{nj} + \varepsilon_{nj}^{SBW})
\end{aligned} \tag{1}
$$

where, following Train's (2009) notation, *action* is a binary indicator for whether alternative *j* is one of the proposed "action" scenarios (as opposed to the "no action" status-quo alternative), $\mathbf{x}$ is a vector of ecosystem service attribute levels for alternative *j* presented to respondent *n*, $\mathbf{z}$ is a vector of binary indicators for each of the subsequent choice sets (the first choice set serves as the omitted base; relevant to the RMC treatment only); α is a fixed coefficient associated with *action*, $\boldsymbol{\beta}$ is a vector of fixed coefficients associated with the ecosystem service attributes, $\boldsymbol{\gamma}$ is a vector of fixed coefficients associated with the subsequent choice sets in the RMC treatment, μ is a random term associated with *action*, $\boldsymbol{\sigma}$ is a vector of random terms associated with the ecosystem service attributes that captures preference heterogeneity, and ε is iid extreme value. For convenience, the terms in the above equations are grouped into two sets of parentheses; the first contains the "fixed" terms, i.e., those parameters that capture the mean effects on utility of each variable, and the second contains the "random" terms, i.e., those parameters that capture the differences attributed to each variable in the scale of the variance.

Attribute Parameter Estimates and Scale Factors

Hypothesis tests presented here focus on testing the equivalence of particular subsets of the above parameters. We follow the approach of Swait and Louviere (2003) and Blamey et al. (2002), except that, instead of their grid-search approach, we use the random-parameters approach of controlling for scale differences as in Train (2009). Tests of attribute coefficient equivalence focus on testing the null hypothesis that, in the case of comparing SMC to RMC,

$\boldsymbol{\beta}^{SMC} = \boldsymbol{\beta}^{RMC} = \boldsymbol{\beta}^{Pool}$ and $\boldsymbol{\sigma}^{SMC} = \boldsymbol{\sigma}^{RMC} = \boldsymbol{\sigma}^{Pool}$. These hypotheses are referred to as H1A, following the notation of Swait and Louviere (1993). Each test of these hypotheses requires the construction of a constrained (i.e., "pooled") model. Following our example of the case of testing SMC against RMC, we have:

$$\begin{aligned} U_{nj}^{Pool} &= [(\alpha^{Pool} + \delta \cdot SMC) \cdot action_j + \boldsymbol{\gamma}' \mathbf{z}_j + \boldsymbol{\beta}^{Pool\prime} \mathbf{x}_{nj}] \\ &\quad + (\lambda_n \cdot RMC + \mu_n^{Pool} \cdot action_j + \boldsymbol{\sigma}_n^{Pool\prime} \mathbf{x}_{nj} + \varepsilon_{nj}^{Pool}) \end{aligned} \tag{2}$$

where δ is a fixed coefficient on the interaction between SMC and *action*, and λ is a zero-mean (to prevent it from interfering with the action and repeated-choice question-order indicators; see Train 2009) random term associated with RMC observations. The former allows for action-bias differences, and the latter, for scale differences, across elicitation types. The effect of the inclusion of these two additional terms is to limit model restrictions to equality of the attribute parameter vectors $\boldsymbol{\beta}$ and $\boldsymbol{\sigma}$. If the null for H1A is rejected, then it is concluded that attribute parameter estimates are statistically different across elicitation formats. If it is not rejected, a second hypothesis test is constructed, which is Swait and Louviere's hypothesis "H1B" that $\lambda = 0$, i.e., that there are no scale differences across elicitation types. If the null on H1B is rejected, then one concludes that scale differs, but attribute parameter estimates do not, across elicitation formats. If H1B is not rejected, then one cannot reject the null hypothesis of no differences in either parameters or scale across elicitation formats. We specify two different models to test equivalence of attribute parameter estimates. The first specification constrains the vector of random terms associated with the attribute vector $\boldsymbol{\sigma} = 0$, and amounts to an error-components logit model. In the second specification, we allow for preference heterogeneity by having $\boldsymbol{\sigma}$ be estimated freely and refer to this model as the "random-parameter logit". These same models are also used to construct the two sets of welfare estimates used to compare differences in that realm across elicitation formats.

Status-quo / Action Bias

Hypothesis tests for testing for differences in status-quo / action bias across elicitation formats relies on a modified specification of (2) above:

$$\begin{aligned} U_{nj}^{Pool} = & [(\alpha^{Pool} + \delta \cdot SMC) \cdot action_j + \boldsymbol{\gamma}'\mathbf{z}_j + (\boldsymbol{\beta}^{Pool} + \boldsymbol{\tau} \cdot RMC)'\mathbf{x}_{nj}] \\ & + (\lambda_n \cdot RMC + \mu_n^{Pool} \cdot action_j + \varepsilon_{nj}^{Pool}) \end{aligned} \tag{3}$$

where $\boldsymbol{\tau}$ is a vector of fixed coefficients on the interaction of RMC and $\mathbf{x}$. This interaction allows for differences in attribute coefficients across elicitation type. In this case, the null hypothesis is that $\delta = 0$, i.e., that there is no significant difference in status-quo / action bias effects across elicitation types.[8]

Attribute Non-attendance

Hypothesis tests regarding equivalence of attribute non-attendance class shares rely on models estimated using a latent-class random-parameters logit specification. Specification of the latent classes follows that of Hensher and Greene (2010), Campbell, Hensher, and Scarpa (2011), and Hensher, Rose, and Greene (2012). Our latent-class models consist of three classes: those that attended to all attributes, those that did not attend to the price attribute, and those that did not attend to the non-price attributes. Because class shares enter the likelihood function as

[8] Note that we fix $\boldsymbol{\sigma} = 0$ in these models, i.e., we do not allow for preference heterogeneity in the attributes when testing for differences in status-quo / action bias differences.

parameters to be optimized, we can use likelihood ratio tests to test for equivalence of class shares across elicitation types. Because we are not interested, per se, in differences in parameter estimates across classes, we follow the approach of Hensher, Rose, and Greene (2012) and constrain all non-zero parameters to be equal across classes. The log-likelihood functions for the individual elicitation-type models can be written as follows:

$$\begin{aligned}
\ln L^{SMC} &= \sum_{n=1}^{N} \ln\left[\sum_{j=1}^{3} p_j^{SMC} f(U_{nj}^{SMC} \mid class = j)\right] \\
\ln L^{RMC} &= \sum_{n=1}^{N} \ln\left[\sum_{j=1}^{3} p_j^{RMC} f(U_{nj}^{RMC} \mid class = j)\right] \\
\ln L^{SBW} &= \sum_{n=1}^{N} \ln\left[\sum_{j=1}^{3} p_j^{SBW} f(U_{nj}^{SBW} \mid class = j)\right]
\end{aligned} \tag{4}$$

where p^{SMC}, p^{RMC}, and p^{SBW} are the latent attribute non-attendance class shares for the three elicitation-format models, respectively, and the U functions are defined as in (1) above.[9] A constrained (i.e., pooled) model is constructed to carry out the test of the null, whose log-likelihood function is:

$$\ln L^{Pool} = \sum_{n=1}^{N} \ln\left[\sum_{j=1}^{3} p_j^{Pool} f(U_{nj}^{Pool} \mid class = j)\right] \tag{5}$$

where U_{nj}^{Pool} is defined as in (3) above. As before, interaction terms are added to the pooled models to allow for differences in all other variables other than class shares. The null hypothesis in the case of comparing SMC to RMC is that $p^{SMC} = p^{RMC} = p^{Pool}$.

[9] Note that we fix $\boldsymbol{\sigma} = 0$ in these models as well.

Welfare Estimates

We test whether different elicitation formats yield equivalent welfare estimates at two levels: individual attribute increment values and overall program values. Our null hypotheses are i) attribute increment values are equal across the elicitation formats; and ii) overall program willingness to pay values are equal across the elicitation formats. To test the hypotheses, means tests were conducted using the complete combinatorial approach of Poe, Giraud, and Loomis (2005), which involves subtracting each element of one simulated willingness to pay distribution from each element of the other simulated willingness to pay distribution and observing the proportion of observations that lie above or below zero. A two-sided test of equality is rejected at the 10%, 5%, or 1% level if twice the proportion of differences greater than or less than zero is less than 10%, 5%, or 1%, respectively.

All models are estimated using NLOGIT 5.0, using either the "RPLOGIT" or "LCRPLOGIT" routines. Although not explicitly shown in the above equations, all models, with the exception of the latent-class models, apply the adjustment to the price parameter suggested by Carson and Czajkowski (2013).[10]

[10] This adjustment is not applied to the latent-class logit models due to the difficulty of imposing log-normal distributions in that setting. Because we are not using these results to construct welfare estimates, this omission should not affect the results, which generally comes into play during the simulation stage of welfare estimate construction (see Carson and Czajkowski 2013).

Results

Attribute Parameter Estimates and Scale Factors

Table 5 contains the results of the individual error-components models and the associated likelihood-ratio tests. Although it is not possible to compare individual parameter estimates directly due to possible differences in scale, we can compare signs and significance across the individual models. The SMC results are consistent across the three samples, and indicate no evidence of status-quo/action bias (i.e., a non-significant action term), but the significance on the standard deviation of the action parameter indicates a scale difference between action and status-quo alternatives. Both price and non-price attributes are significant with expected signs. For the RMC models, results are fairly consistent across samples, with some differences in significance of choice question indicators. For the RMC models, the action parameter is highly significant and positive, indicating evidence of action bias. The standard deviation on action is also highly significant. Additionally, the parameters for second, third, and fourth choice questions are all significant and negative with the exception of the second choice question term in the Louisiana – Oyster and Gulf of Mexico Region – Oyster samples. These indicate less action bias (or, said another way, a relatively greater tendency to choose the status-quo) relative to the first choice question. Both price and non-price attributes are significant with expected signs. The SBW results are also fairly consistent across samples: both indicate significant action bias, with significant associated difference in scale. The price parameter is highly significant and of expected sign in both cases. For non-price attributes, however, one of the four are not significant, though it is a different attribute that is not significant in the two samples. Of those that are significant, they are of the expected sign.

We now move on to the tests of parameter equivalence. We find no instances of rejection of H1A, i.e., no evidence of differences in parameter estimates across pairs of elicitation types. Further, we find only two instances of rejection of H1B, i.e., differences in scale, and both of these occur when comparing RMC results with SBW results. Thus, based on these results, we find no evidence of parameter differences across elicitation format, and find scale differences to be limited to the case of RMC versus SBW.

Table 6 contains the results of the random-parameters models, which allows for the added dimension of comparing attribute preference heterogeneity across elicitation types. These results are more mixed. Evidence of preference heterogeneity differs across both elicitation types and samples, with SMC models producing only one instance of significant attribute preference heterogeneity across all three SMC models. RMC models result in somewhat higher instances of preference heterogeneity, but with no clear pattern across samples. SBW models also show limited evidence of preference heterogeneity. Turning to the likelihood ratio tests for these models, results are mostly consistent with those of the earlier error-component logit models. One exception is when comparing SMC to RMC for the Louisiana – Oyster sample. In this instance, H1A is rejected, indicating significant differences in attribute parameter estimates. However, significance is marginal (at the 90% level of significance), and this finding is not held up in the other two samples. As before, tests indicate significant differences in scale between RMC and SBW models only.

Status-quo / Action Bias

As noted earlier, interaction terms were included in these models for price and all non-price attributes, to maximize parameter freedom and isolate the effect of status-quo / action bias alone.

When models included RMC observations, binary indicator variables were included for the second, third, and fourth choice questions. Thus, the elicitation-format interaction captures the pure difference in action / status-quo bias due to elicitation treatment, and significance of this interaction term is an indication of differences in status-quo / action bias between elicitation types. For completeness, we also estimated the model omitting the status-quo / action bias interaction term and constructed likelihood-ratio statistics to test the effect of constraining this term to equal zero at the model level.

Table 7 contains the results of the pooled error-components logit models and likelihood ratio tests used to test for differences in status-quo / action bias. The relevant parameter estimates for these particular comparisons are highlighted in bold for convenience. Results comparing SMC to RMC are consistent across samples: the SMC x action interaction term is significant and, in this case, negative, indicating a higher proportion of action choices under the RMC elicitation format relative to SMC. Note well that the relevant comparison is the *first question* of the RMC survey compared to the SMC survey, since we also include question-order indicators for the second, third, and fourth RMC questions. The coefficients on these question-order indicators are negative in all cases, with the third and fourth ones significant in all cases, indicating relatively less action bias in subsequent questions. However, the coefficients on these subsequent question indicators are generally half the magnitude of the SMC x action interaction term, implying that although there is less action bias in subsequent RMC questions relative to the first RMC question (which is consistent with the findings in the literature), there is still relatively more action bias in these subsequent questions relative to the SMC format. These findings are supported by the likelihood-ratio test of the unconstrained model against the status-quo / action bias constrained model, in which the null hypothesis is rejected in all cases except the Louisiana – Salt Marsh sample.

Results comparing SMC to SBW are also consistent across samples, and indicate no significant difference in status-quo / action bias between these two elicitation types, and these findings are supported by non-significant likelihood-ratio tests. Results comparing RMC to SBW are also consistent across samples; the interaction term (SBW x Action) is significant and negative, indicating a higher proportion of action choices under the RMC elicitation format relative to SBW. These findings are also supported by significant likelihood-ratio tests. Additionally, the comparison to the RMC question-order effects are similar to that found above: even though subsequent RMC questions result in less action bias relative to the first RMC question, the difference is still less than the difference between the first RMC question and the SMC format. Thus, these results indicate significant differences in status-quo / action bias using the RMC elicitation format relative to that of SMC and SBW, specifically that the RMC elicitation format results in increased probabilities of "Yes" votes, although this result is somewhat mitigated in subsequent RMC questions.

Attribute non-attendance

Table 8 contains the results of the attribute non-attendance latent-class logit models and associated likelihood ratio tests. As noted earlier, because we wish only to constrain class shares in the pooled models for the tests, we add interaction terms between all variables and elicitation type to introduce freedom in these parameter estimates. Before we compare results across elicitation treatments, we think it prudent to first compare results within treatments but across samples to discern first whether class shares are consistent within a given elicitation format. For

SMC models, the class shares for the Louisiana – Oyster and Gulf of Mexico Regional – Oyster models are consistent, attributing 63-66% of the population to the "all attended to" (All AT) class, 24-37% to the "price not-attended-to" (Price NAT) class, and the lowest share (0-10%) to the "non-price attributes not attended to" (Non-Price NAT) class. The class shares for the Louisiana – Salt Marsh model are somewhat different, attributing lower shares to the All AT and non-price NAT classes and more to the price NAT class.

Among RMC models, class shares for the All AT class range from a high of 64% to a low of 46%, but in all cases, this is the dominant class. Shares for the remaining two classes vary, but tend to be fairly equally split, with no clear pattern for dominance. Among SBW models, the price NAT class dominates, from a high of 73% to a low of 55%, with the second-highest class share being the All AT class. Both SBW models attribute a zero share to the non-price NAT class.

Turning to the comparisons across elicitation formats and likelihood ratio tests, we find a rejection of the null hypothesis of model equivalence in all cases except for one (SMC versus RMC for the Gulf of Mexico Regional – Oyster sample). Thus, results indicate significant differences in estimated attribute non-attendance patterns across all three elicitation types. However, we would add a word of caution to these results given that, as noted earlier, we observe variation in class shares across samples even within the same elicitation type, although those differences are more subtle compared to those observed across elicitation types.

Welfare Estimates

Two sets of welfare estimates were constructed, from the error-components and random-coefficients logit model results reported in tables 5 and 6. Table 9 displays the estimated attribute increment values and pair-wise tests of equality of mean attribute increment values between elicitation types. Confidence intervals were estimated using the Krinsky and Robb bootstrapping approach (see Haab and McConnell 2002) with 10,000 draws. After exponentiating the price coefficient one can straightforwardly employ the Krinsky and Robb technique as moments of the willingness to pay distribution are now well-defined (Carson and Czajkowski 2013).

Test results reveal very few differences in incremental values of attributes across elicitation types. In fact, out of the 28 tests constructed over the error-components logit results, only three are significant, and for the random-parameters logit results, only two are significant. Comparing SMC results to RMC results, only differences in the incremental value of bird habitat are detected for the Louisiana – Oyster sample, and only differences in the incremental value of improved water quality are detected for the Louisiana – Salt Marsh and Gulf of Mexico – Oyster samples. Furthermore, we observe no patterns in differences in precision of these estimates across elicitation treatments (based on the percentage difference between the mean and the upper or lower bound). Thus, our results indicate almost no differences in attribute increment values across elicitation types, and this finding is robust across the three samples tested.

We also constructed program-level welfare estimates, i.e., estimates of the mean maximum willingness to pay for a complete program that delivers a specific suite of ecosystem services. Here, we fix all service attributes at the intermediate level. These estimates account for all model variables, and so capture the effect on welfare of action and question-order effects. For the RMC treatment, a decision must be made on how to handle question-order effects. We specify two ways: the first way, labeled “RMC-Q1” calculates welfare under the counterfactual that all responses were first RMC question responses, i.e., the second, third, and fourth RMC question coefficients are zero-weighted. The second way, labeled "RMC-Avg" calculates welfare values under mean question-order effects, i.e., yields "average" question-order welfare estimates. Table 10 reports the means, confidence intervals, and results for tests of equality across elicitation treatments. The RMC-Q1 treatment yields the highest welfare estimates, followed by the RMC-Avg treatment, then the SMC treatment, with the SBW treatment yielding the lowest welfare estimates. These results are consistent across all samples and both error-components and random-coefficients model specifications. In terms of precision, we find that the SBW treatment yields the tightest welfare estimates (based on the percentage difference between the mean and the upper or lower bound), where the upper/lower bound represents a 17-27% change relative to the mean across samples and model specifications; the RMC treatment yields the second-tightest welfare estimates (39-44% range), with the SMC treatment yielding, by far, the widest estimates (77-104% range).[11]

Tests of equality indicate that the differences between the SMC and RMC treatments are statistically significant in only a few cases: under the random-coefficients model specification for the Louisiana – Oyster sample, and under the error-components model specification for the Louisiana – Salt Marsh sample. No significant differences are found between the SMC and SBW treatments. Differences between the RMC treatment and the SBW treatment are statistically significant in all cases. Thus, in terms of program-level welfare estimates, the RMC treatments yield the highest means with intermediate precision; the SBW treatment yields the

[11] Precision is also a function of sample size. Although all of our samples were in the neighborhood of 500 observations, there were some minor differences, which could account partially for these differences in precision.

lowest means with the greatest precision; and the SMC treatment yields the lowest means with the least precision.

Conclusions

To summarize, after controlling for differences in scale across alternatives (action versus no-action) and elicitation format, we find very limited evidence of any differences in attribute parameter estimates among the three elicitation treatments, and find significant scale differences only when comparing RMC to SBW. We also find very little evidence of differences in attribute increment values (i.e., ecosystem service values) across elicitation treatments. Arguably, these are the two areas of greatest concern from a policy perspective regarding the performance of multinomial discrete-choice experiments. The implication here, based at least on our results, is that as long as the researcher controls for question-order effects and scale differences, attribute increment values are unaffected by the choice of elicitation format.

We do, however, find significant differences in status-quo / action bias across elicitation treatments. In the three independent samples we analyzed, the RMC treatments result in greater proportions of "Yes" votes relative to both SMC and SBW treatments. What is interesting is that although our results are consistent with the literature showing that there is greater status-quo bias in subsequent RMC questions relative to the first RMC question, we find that these subsequent RMC questions still result in more action bias relative to the other elicitation formats. This effect plays a significant role in the construction of program-level welfare estimates, where we also find significant differences: RMC treatments yield consistently higher welfare estimates relative to both SMC and SBW treatments, although for our samples, these differences are not universally statistically significant. This lack of statistical significance in some cases should not be interpreted, however, as a "green light": in most cases, a researcher will choose one elicitation treatment and will take the resulting welfare estimates at face value; and for our samples at least, the RMC treatments yield welfare estimates that ranged between a low of 15% and a high of 195% greater than the other elicitation treatments, depending on sample and model specification. In terms of precision, however, the RMC treatments fared well, whereas the SMC treatment yielded the least precision by a wide margin. Taking these findings together, our results indicate that, in terms of welfare estimation, the choice of elicitation format may have little influence on individual attribute increments (e.g., ecosystem service valuation), but could have a large influence on program-level welfare estimates, both in terms of magnitude and precision.

Our results also indicate significant differences in attribute non-attendance behavior across elicitation formats. Although there was little consistency in class shares even within a given elicitation treatment across samples, the good news is that, for our samples, the SMC and RMC treatments yielded a plurality of respondents falling into the class that attends to all attributes, which is the class that researchers generally assume (or hope, rather) to be the case. The results of the SBW treatments, however, indicate a plurality of respondents in the class that does not attend to the price attribute. Although the larger implications of this finding is not obvious, it does indicate that elicitation treatments may induce different kinds of behavior with regard to how respondents perceive and react to the information provided in the choice sets. Further research focused on this issue is warranted.

It should be noted that we also estimated the same models and conducted the same tests using larger, habitat-aggregated datasets (i.e., we pooled the Louisiana oyster and salt marsh samples, and supplemented this with additional data from the larger study), which increased the number of SMC and RMC observations to between 1,000 and 1,600 observed choices, and got qualitatively the same results and conclusions.[12] So we do not believe that our results are attributable, primarily, to sample size.

So what have we learned? To our knowledge, no study has compared these elicitation formats directly. This gap in the literature is somewhat surprising, given the intense scrutiny of any variations to the single-choice referendum format that were introduced in the contingent valuation literature. Petrolia and Interis's (2013) essay called attention to the potential risks of adopting a repeated-choice format and the potential for behavioral anomalies that could bias responses and subsequent results and conclusions. What our study here, finds, however, is that the differences may not be as bad as they feared, and appear to be limited to particular aspects of the results. If researchers are interested primarily in individual attribute values, such as in the case of ecosystem-service valuation, then the choice of elicitation format may not matter, and the RMC format would be the most cost-effective approach. If they are interested in program-level welfare estimates, then the decision may require more deliberation, but even here, there is no clear winner; unlike the binary-choice format which is, at least in theory, incentive-compatible, there is no "standard" format among those we consider here, and so there is no way to discern which estimates are the "right" ones. Thus, the choice of question format should depend upon the modeling approach the researcher expects to use and on the desired outputs of the analysis.

[12] We chose to report results as we did because we preferred to have roughly equal sample sizes across treatments, and to avoid the mixing of habitat data sets, which preliminary testing indicated should not, from a statistical standpoint, be pooled. These results are available from the authors upon request.

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Table 1. Attributes, attribute levels, and descriptions

Habitat construction program attribute	**Levels**
Increased water quality	(No, 10%, or 20%) reduction in nitrogen and phosphorus.
Improved flood protection	(5%, 10%, or 15%) increase in the number of homes protected.
Increased commercial fisheries support	(10%, 20%, or 30%) increase in annual seafood catch.
Increased wading bird population	(No, 5%, or 10%) increase in wading bird population.
Total one-time cost to your household	($5, $10, $25, $50, $75, $100, $150, $200)

Table 2. Comparison of attitudinal and demographic indicators across elicitation type treatments for the Louisiana oyster reef sample.

	Louisiana - Oyster		
	SMC	**RMC**	**SBW**
Confidence in Federal Government (a lot / some / none)	0.10/0.50/0.40	0.08/0.55/0.38	0.12/0.47/0.42
Confidence in State Government (a lot / some / none)	0.20/0.62/0.18	0.22/0.57/0.21	0.19/0.63/0.18
Survey's Influence on Policy Decisions (none / small / large)	0.20/0.60/0.20	0.18/0.60/0.22	0.16/0.67/0.17
Changes to lifestyle to protect environment (major / minor / none)	0.15/0.56/0.29	0.20/0.57/0.23	0.21/0.57/0.22
Survey provided enough information to make choices (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.04/0.04/0.15/0.43/0.34	0.01/0.02/0.21/0.43/0.32	0.03/0.06/0.24/0.10/0.57
Survey was easy to understand (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.04/0.02/0.09/0.40/0.45	0.01/0.03/0.10/0.490/0.38	0.02/0.01/0.08/0.44/0.46
Survey presented information in an unbiased way (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.04/0.02/0.16/0.40/0.38	0.00/0.03/0.18/0.42/0.38	0.02/0.03/0.17/0.37/0.40
Age (mean)	48.48	0.75	16.62
Education (less than HS / HS / some college / bachelor's +)	0.03/0.24/0.39/0.35	0.07/0.24/0.38/0.31	0.03/0.20/0.39/0.38
Gender (% Male)	0.33	0.26	0.31
Household Size (mean)	2.76	2.59	2.62
Income (mean category: 1 (< $5,000) - 19 ($175,000+))	10.58	9.94	10.55

Note: no significant differences across elicitation treatments were found for any of the above indicators.

Table 3. Comparison of attitudinal and demographic indicators across elicitation type treatments for the Louisiana salt marsh sample.

	Louisiana - Salt Marsh	
	SMC	**RMC**
Confidence in Federal Government (a lot / some / none)*	0.11/0.49/0.40	0.04/0.53/0.43
Confidence in State Government (a lot / some / none)	0.22/0.59/0.18	0.16/0.63/0.21
Survey's Influence on Policy Decisions (none / small / large)	0.17/0.66/0.17	0.23/0.62/0.15
Changes to lifestyle to protect environment (major / minor / none)	0.18/0.57/0.25	0.17/0.51/0.31
Survey provided enough information to make choices (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.03/0.04/0.15/0.47/0.32	0.13/0.19/0.68/0.49/0.28
Survey was easy to understand (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.03/0.02/0.09/0.44/0.43	0.19/0.15/0.66/0.39/0.42
Survey presented information in an unbiased way (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.02/0.03/0.16/0.41/0.37	0.10/0.15/0.75/0.43/0.31
Age (mean)	49.06	52.43
Education (less than HS / HS / some college / bachelor's +)**	0.02/0.22/0.41/0.35	0.07/0.26/0.37/0.31
Gender (% Male)	0.29	0.24
Household Size (mean)	3.18	2.73
Income (mean category: 1 (< $5,000) - 19 ($175,000+))	10.79	10.69

**, * indicate signficant differences at the 5% and 10% levels across elicitation treatments based on Pearson Chi-square test.

Table 4. Comparison of attitudinal and demographic indicators across elicitation type treatments for the Gulf of Mexico Region oyster reef sample.

	Gulf of Mexico Region - Oyster		
	SMC	**RMC**	**SBW**
Confidence in Federal Government (a lot / some / none)	0.10/0.55/0.36	0.09/0.55/0.35	0.05/0.54/0.41
Confidence in State Government (a lot / some / none)	0.19/0.66/0.15	0.15/0.68/0.17	0.16/0.73/0.12
Survey's Influence on Policy Decisions (none / small / large)	0.24/0.61/0.15	0.23/0.64/0.13	0.21/0.64/0.15
Changes to lifestyle to protect environment (major / minor / none)	0.14/0.57/0.29	0.18/0.61/0.21	0.17/0.59/0.24
Survey provided enough information to make choices (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.03/0.05/0.27/0.50/0.15	0.02/0.06/0.21/0.51/0.20	0.04/0.08/0.22/0.47/0.19
Survey was easy to understand (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.01/0.03/0.14/0.59/0.23	0.01/0.03/0.15/0.51/0.30	0.02/0.01/0.12/0.55/0.30
Survey presented information in an unbiased way (strongly disagree / disagree / no opinion / agree / strongly disagree)	0.02/0.04/0.25/0.49/0.20	0.01/0.05/0.23/0.5/0.210	0.02/0.06/0.25/0.43/0.240
Age (mean)	52.51	49.90	52.43
Education (less than HS / HS / some college / bachelor's +)*	0.09/0.28/0.30/0.32	0.04/0.23/0.34/0.38	0.03/0.29/0.30/0.37
Gender (% Male)**	0.46	0.36	0.37
Household Size (mean)	2.67	2.73	2.62
Income (mean category: 1 (< $5,000) - 19 ($175,000+))	11.72	11.36	11.56

**, * indicate signficant differences at the 5% and 10% levels across elicitation treatments based on Pearson Chi-square test.

Table 5. Error-components Logit Regression Results.

	Louisiana - Oyster								
	SMC			**RMC**			**SBW**		
	Coef		**SE**	**Coef**		**SE**	**Coef**		**SE**
Action	1.77		1.63	6.80	***	1.67	1.01	**	0.43
SD Action	3.26	*	1.78	6.96	***	1.48	1.48	***	0.51
ln(Bprice)	-4.46	***	0.13	-4.20	***	0.08	-4.31	***	0.15
RMC-Q2				-0.86		0.75			
RMC-Q3				-2.07	***	0.74			
RMC-Q4				-1.90	**	0.80			
Flood	0.36	***	0.11	0.40	***	0.09	0.30	**	0.12
Fish	0.33	***	0.09	0.22	**	0.09	0.28	***	0.11
Bird	0.37	***	0.08	0.19	**	0.08	0.17		0.11
Water	0.30	***	0.09	0.34	***	0.08	0.24	**	0.11
N =	494			579			452		
LL =	-430.9			-402.2			-314.2		

	Louisiana - Salt Marsh					
	SMC			**RMC**		
	Coef		**SE**	**Coef**		**SE**
Action	0.82		1.18	4.32	***	1.21
SD Action	2.33	*	1.35	5.15	***	1.01
ln(Bprice)	-4.75	***	0.14	-4.64	***	0.10
RMC-Q2				-1.23	*	0.71
RMC-Q3				-2.17	***	0.63
RMC-Q4				-1.33	*	0.71
Flood	0.30	***	0.09	0.45	***	0.10
Fish	0.22	***	0.09	0.21	***	0.08
Bird	0.45	***	0.08	0.39	***	0.08
Water	0.59	***	0.09	0.31	***	0.08
N =	518			536		
LL =	-443.4			-407.1		

	Gulf of Mexico Region - Oyster								
	SMC			**RMC**			**SBW**		
	Coef		**SE**	**Coef**		**SE**	**Coef**		**SE**
Action	1.29		1.60	4.32	***	1.22	1.02	**	0.42
SD Action	4.09	*	2.45	5.50	***	1.12	1.92	***	0.48
ln(Bprice)	-4.55	***	0.13	-4.20	***	0.09	-4.46	***	0.14
RMC-Q2				-0.41		0.62			
RMC-Q3				-1.57	**	0.70			
RMC-Q4				-1.34	*	0.70			
Flood	0.19	*	0.11	0.18	*	0.10	-0.08		0.13
Fish	0.21	**	0.10	0.15	*	0.09	0.18	*	0.10
Bird	0.34	***	0.09	0.27	***	0.10	0.41	***	0.11
Water	0.60	***	0.11	0.53	***	0.11	0.58	***	0.13
N =	459			467			473		
LL =	-443.0			-343.7			-345.4		

	Louisiana - Oyster			*Louisiana - Salt Marsh*	*Gulf of Mexico Region - Oyster*		
	SMC v. RMC	**SMC v. SBW**	**RMC v. SBW**	**SMC v. RMC**	**SMC v. RMC**	**SMC v. SBW**	**RMC v. SBW**
LL1	-430.85	-430.85	-402.19	-443.37	-442.90	-442.90	-343.67
LL2	-402.19	-314.20	-314.20	-407.06	-343.67	-345.44	-345.44
LL1 + LL2	-833.05	-745.06	-716.40	-850.43	-786.57	-788.35	-689.12
LL(pooled & scaled)	-836.83	-747.46	-717.09	-853.73	-790.17	-790.68	-691.84
λ(A) (5 df)	7.57	4.80	1.39	6.61	7.19	4.67	5.44
Reject H1A?	No	No	No	No	No	No	No
LL(pooled)	-837.33	-748.42	-730.67	-854.58	-790.18	-791.55	-698.63
λ(B) (1 df)	0.99	1.92	27.14	1.69	0.02	1.74	13.58
Reject H1B?	No	No	Yes***	No	No	No	Yes***

*,**,*** indicate statistical difference at the 10%, 5%, and 1% level

Table 6. Random-coefficients Logit Regression Results.

	Louisiana - Oyster									*Louisiana - Salt Marsh*						*Gulf of Mexico Region - Oyster*								
	SMC			**RMC**			**SBW**			**SMC**			**RMC**			**SMC**			**RMC**			**SBW**		
	Coef		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**
Action	0.94		0.75	6.83	***	1.73	1.42	*	0.79	0.87		1.72	3.75	***	1.12	1.29		1.61	4.31	***	1.37	0.89	*	0.50
SD Action	0.07		12.09	6.98	***	1.53	0.50		3.20	2.95		2.50	4.63	***	1.14	4.10	*	2.48	5.67	***	1.26	1.90	***	0.73
ln(Bprice)	-4.12	***	0.28	-4.13	***	0.12	-3.82	***	0.35	-4.42	***	0.35	-4.24	***	0.17	-4.55	***	0.20	-4.00	***	0.13	-4.23	***	0.15
RMC-Q2				-0.87		0.78							-1.31	*	0.79				-0.30		0.68			
RMC-Q3				-2.13	***	0.77							-2.26	***	0.71				-1.69	**	0.78			
RMC-Q4				-1.95	**	0.83							-1.27		0.84				-1.32	*	0.76			
Flood	0.45	**	0.20	0.42	***	0.12	0.88	**	0.37	0.43	*	0.22	0.61	***	0.18	0.19	*	0.11	0.18		0.15	-0.07		0.18
SD Flood	1.38	***	0.49	0.26		0.32	1.68	***	0.64	0.50		0.76	0.89	***	0.27	0.01		9.32	0.58	*	0.30	0.02		2.58
Fish	0.45	***	0.15	0.24	**	0.10	0.50	*	0.27	0.35	*	0.19	0.30	*	0.16	0.21	**	0.10	0.17		0.14	0.34	**	0.17
SD Fish	0.33		0.87	0.04		1.34	0.73		0.52	0.13		2.05	0.75	***	0.26	0.02		5.86	0.47		0.29	0.59	**	0.24
Bird	0.44	***	0.13	0.19	**	0.10	0.21		0.21	0.68	**	0.27	0.59	***	0.17	0.34	***	0.10	0.30	**	0.15	0.50	***	0.17
SD Bird	0.06		3.04	0.42	**	0.21	0.03		3.69	0.94		0.71	0.74	**	0.31	0.11		1.76	0.57	**	0.27	0.03		4.24
Water	0.40	**	0.16	0.38	***	0.10	0.47	*	0.28	0.90	**	0.35	0.47	***	0.16	0.60	***	0.14	0.73	***	0.19	0.81	***	0.22
SD Water	0.43		0.79	0.25		0.33	0.94		0.62	1.12		0.80	0.79	***	0.28	0.02		4.81	0.59	*	0.33	0.94	**	0.39
N =	494			579			452			518			536			459			467			473		
LL =	-425.3			-401.4			-298.9			-442.2			-398.0			-442.9			-339.9			-341.2		

	SMC v. RMC	**SMC v. SBW**	**RMC v. SBW**	**SMC v. RMC**	**SMC v. RMC**	**SMC v. SBW**	**RMC v. SBW**
LL1	-425.31	-425.31	-401.45	-442.20	-442.87	-442.87	-339.89
LL2	-401.45	-298.86	-298.86	-397.98	-339.89	-341.18	-341.18
LL1 + LL2	-826.76	-724.17	-700.31	-840.18	-782.76	-784.05	-681.08
LL(pooled & scaled)	-834.30	-726.87	-705.84	-844.18	-787.60	-787.59	-684.30
λ(A) (5 df)	15.07	5.41	11.07	8.00	9.68	7.07	6.46
Reject H1A?	Yes*	No	No	No	No	No	No
LL(pooled)		-725.94	-720.94	-844.70	-787.61	-788.50	-688.78
λ(B) (1 df)		-1.86	30.20	1.04	0.02	1.83	8.94
Reject H1B?		No	Yes***	No	No	No	Yes***

*,**,*** indicate statistical difference at the 10%, 5%, and 1% level

Table 7. Error-components logit results for pooled-model status-quo/action bias tests.

	Louisiana - Oyster									*Louisiana - Salt Marsh*			*Gulf of Mexico Region - Oyster*								
	SMC/RMC			**SMC/SBW**			**RMC/SBW**			**SMC/RMC**			**SMC/RMC**			**SMC/SBW**			**RMC/SBW**		
	Coef		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**	**Coef**		**SE**
Action	7.04	***	1.75	1.65		1.55	6.81	***	1.68	4.23	***	1.17	4.25	***	1.16	1.24		1.54	4.30	***	1.16
SD Action	2.99	**	1.50	1.50	***	0.46	1.54	***	0.45	2.72	**	1.13	4.38	***	1.33	1.94	***	0.48	1.91	***	0.47
SMC x Action	**-5.52**	*****	**1.95**							**-3.07**	****	**1.39**	**-2.77**	****	**1.34**						
SBW x Action				**-0.64**		**1.60**	**-5.80**	*****	**1.72**							**-0.21**		**1.59**	**-3.29**	*****	**1.22**
SD SMC				2.73		2.03										3.52		2.62			
SD RMC	6.51	***	1.60				6.72	***	1.38	4.24	***	1.21	3.28	*	1.82				5.18	***	1.26
Neg. Price	0.01	***	0.00	0.01	***	0.00	0.02	***	0.00	0.01	***	0.00	0.01	***	0.00	0.01	***	0.00	0.01	***	0.00
Neg. Price x RMC	0.00	*	0.00							0.00		0.00	0.00	*	0.00						
Neg. Price x SBW				0.00		0.00	0.00		0.00							0.00		0.00	0.00		0.00
RMC-Q2	-0.86		0.71				-0.85		0.70	-1.23	*	0.65	-0.40		0.64				-0.41		0.64
RMC-Q3	-2.08	***	0.74				-2.06	***	0.74	-2.14	***	0.69	-1.56	**	0.68				-1.56	**	0.69
RMC-Q4	-1.90	***	0.72				-1.89	***	0.72	-1.31	**	0.65	-1.33	**	0.65				-1.33	**	0.66
Flood	0.35	***	0.11	0.36	***	0.11	0.40	***	0.10	0.30	***	0.09	0.19	*	0.11	0.19	*	0.11	0.17	*	0.10
Flood x RMC	0.05		0.15							0.15		0.13	-0.02		0.15						
Flood x SBW				-0.06		0.16	-0.10		0.15							-0.27		0.17	-0.25		0.16
Fish	0.33	***	0.09	0.33	***	0.09	0.22	***	0.08	0.23	***	0.08	0.21	**	0.10	0.21	**	0.10	0.15	*	0.09
Fish x RMC	-0.11		0.12							-0.01		0.12	-0.06		0.13						
Fish x SBW				-0.05		0.14	0.07		0.13							-0.04		0.14	0.02		0.14
Bird	0.37	***	0.09	0.37	***	0.09	0.19	**	0.08	0.45	***	0.09	0.34	***	0.09	0.34	***	0.09	0.27	***	0.10
Bird x RMC	-0.17		0.12							-0.06		0.12	-0.06		0.13						
Bird x SBW				-0.19		0.14	-0.02		0.13							0.08		0.14	0.14		0.14
Water	0.31	***	0.09	0.30	***	0.09	0.34	***	0.09	0.60	***	0.09	0.60	***	0.11	0.60	***	0.11	0.53	***	0.10
Water x RMC	0.03		0.13							-0.29	**	0.13	-0.07		0.15						
Water x SBW				-0.06		0.15	-0.09		0.14							-0.01		0.17	0.05		0.16
N =	1073			946			1031			1054			926.0			932.0			940.0		
LL =	-833.1			-745.1			-716.51			-850.5			-786.5			-788.4			-689		
Restricted LL =	-835.0			-745.19			-728.7			-851.6			-789.0			-788.4			-694.1		
λ (1 df)	3.76			0.22			24.30			2.24			4.99			0.02			10.04		
Reject?	Yes*			No			Yes***			No			Yes**			No			Yes***		

*,**,*** indicate statistical difference at the 10%, 5%, and 1% level

Table 8. Attribute Non-attendance Latent-class Logit Regression Results.

	Louisiana - Oyster						*Louisiana - Salt Marsh*				*Gulf of Mexico Region - Oyster*					
	SMC		**RMC**		**SBW**		**SMC**		**RMC**		**SMC**		**RMC**		**SBW**	
	Class Shares															
All AT	0.63		0.64		0.27		0.48		0.46		0.66		0.52		0.45	
Price NAT	0.00		0.19		0.73		0.31		0.38		0.10		0.22		0.55	
Non-Price NAT	0.37		0.17		0.00		0.21		0.16		0.24		0.26		0.00	
	Coef	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**	**Coef**	**SE**
Action	0.62	0.39	0.56	0.49	-0.05	0.35	0.23	0.57	0.43	0.46	-0.35	0.43	0.54	0.41	-0.76 **	0.31
SD Action	0.00	0.15	0.00	45.16	0.00	0.19	0.00	0.15	0.00	47.14	0.00	36.45	0.00	59.32	0.00	0.15
Neg. Price	0.01 ***	0.00	0.03 ***	0.00	0.07 ***	0.01	0.02 ***	0.01	0.03 ***	0.00	0.01 ***	0.00	0.03 ***	0.00	0.03 ***	0.00
RMC-Q2			-0.94	0.76									-0.40	0.60		
RMC-Q3			-0.47	0.60									0.00	0.58		
RMC-Q4			-1.22	0.78									-0.82	0.65		
Flood	0.71 **	0.29	0.79 ***	0.10	1.05 ***	0.18	0.42 ***	0.16	0.82 ***	0.11	0.23 *	0.13	0.59 ***	0.13	0.27 *	0.15
Fish	0.51 ***	0.16	0.61 ***	0.10	0.66 ***	0.14	0.29 **	0.12	0.50 ***	0.09	0.30 **	0.12	0.60 ***	0.11	0.79 ***	0.15
Bird	0.59 ***	0.18	0.36 ***	0.09	-0.06	0.13	0.58 ***	0.16	0.50 ***	0.10	0.43 ***	0.14	0.32 ***	0.12	0.44 ***	0.14
Water	0.47 **	0.19	0.42 ***	0.09	-0.15	0.15	0.77 ***	0.21	0.34 ***	0.10	0.67 ***	0.20	0.63 ***	0.12	0.85 ***	0.17
N =	494		579		452		518		536		459		467		473	
LL =	-429.49		-435.28		-268.08		-441.32		-409.01		-445.12		-361.16		-302.52	
	SMC v. RMC		**SMC v. SBW**		**RMC v. SBW**		**SMC v. RMC**				**SMC v. RMC**		**SMC v. SBW**		**RMC v. SBW**	
LL1	-425.31		-425.31		-401.45		-442.20				-445.12		-445.12		-361.16	
LL2	-401.45		-268.08		-268.08		-397.98				-361.16		-302.52		-302.52	
LL1 + LL2	-826.76		-693.39		-669.53		-840.18				-806.28		-747.64		-663.68	
LL(pooled & scaled)	-867.64		-714.95		-720.76		-850.52				-806.52		-751.11		-685.36	
λ(A) (5 df)	-81.76		43.13		102.46		20.67				0.49		6.94		43.36	
Reject H1A?	Yes***		Yes***		Yes***		Yes***				No		Yes*		Yes***	
LL(pooled)											-806.52					
λ(B) (1 df)											0.00					
Reject H1B?											No					

*,**,*** indicate statistical difference at the 10%, 5%, and 1% level

Table 9. Mean attribute increment value estimates (95% confidence intervals in parentheses), and tests of equality of means

	Louisiana - Oyster			*Louisiana - Salt Marsh*		*Gulf of Mexico Regional - Oyster*		
	SMC	**RMC**	**SBW**	**SMC**	**RMC**	**SMC**	**RMC**	**SBW**
	Error-components Logit Models							
Increased Flood Protection	$31	$27	$22	$34	$46	$18	$12	-$7
	($13, $49)	($15, $38)	($5, $40)	($14, $57)	($28, $63)	($-2, $39)	($-2, $25)	($-32, $15)
Improved Fish Productivity	$29	$14	$21	$26	$22	$20	$10	$15
	($14, $46)	($3, $25)	($5, $38)	($6, $47)	($7, $38)	($3, $40)	($-1, $23)	($-3, $33)
Increased Bird Habitat	$32	$13	$13	$52	$40	$32	$18	$36
	($17, $49)	($3, $23)	($-3, $31)	($32, $75)	($24, $58)	($15, $51)	($6, $30)	($17, $56)
Improved Water Quality	$26	$22	$18	$68	$32	$57	$35	$50
	($11, $44)	($11, $33)	($2, $34)	($47, $93)	($14, $52)	($37, $78)	($22, $49)	($27, $76)
	Random-coefficients Logit Models							
Increased Flood Protection	$28	$26	$40	$36	$43	$18	$10	-$5
	($15, $44)	($13, $38)	($11, $64)	($-1, $58)	($19, $66)	($-3, $39)	($-7, $26)	($-32, $18)
Improved Fish Productivity	$28	$15	$23	$29	$21	$20	$9	$23
	($15, $44)	($3, $26)	($-3, $42)	($-1, $53)	($-2, $41)	($1, $41)	($-6, $24)	($0, $45)
Increased Bird Habitat	$27	$12	$9	$56	$41	$32	$16	$35
	($15, $42)	($0, $25)	($-11, $31)	($20, $83)	($20, $63)	($14, $52)	($0, $33)	($12, $60)
Improved Water Quality	$25	$24	$21	$75	$33	$57	$40	$56
	($9, $37)	($12, $35)	($-6, $40)	($31, $102)	($11, $58)	($36, $79)	($22, $58)	($28, $85)

	Equality of Mean Attribute Increment Value Estimate Test Results						
	SMC/RMC	**SMC/SBW**	**RMC/SBW**	**SMC/RMC**	**SMC/RMC**	**SMC/SBW**	**RMC/SBW**
	Error-components Logit Models						
Increased Flood Protection	=	=	=	=	=	=	=
Improved Fish Productivity	=	=	=	=	=	=	=
Increased Bird Habitat	**	=	=	=	=	=	=
Improved Water Quality	=	=	=	**	*	=	=
	Random-coefficients Logit Models						
Increased Flood Protection	=	=	=	=	=	=	=
Improved Fish Productivity	=	=	=	=	=	=	=
Increased Bird Habitat	*	=	=	=	=	=	=
Improved Water Quality	=	=	=	*	=	=	=

*,**,*** indicate statistical difference at the 10%, 5%, and 1% level, = indicates failure to reject statistical equality of 2-sided test.

Table 10. Mean program-level welfare estimates (95% confidence intervals in parentheses), and tests of equality of means

Louisiana - Oyster				*Louisiana - Salt Marsh*			*Gulf of Mexico Regional - Oyster*			
SMC	**RMC - Q1**	**RMC - Avg**	**SBW**	**SMC**	**RMC - Q1**	**RMC - Avg**	**SMC**	**RMC - Q1**	**RMC - Avg**	**SBW**
Error-components Logit Models										
$331	$568	$515	$193	$335	$656	$574	$288	$386	$349	$190
($56, $602)	($352, $799)	($314, $729)	($157, $231)	($67, $593)	($417, $910)	($360, $805)	($-15, $578)	($239, $541)	($216, $489)	($145, $242)
Random-coefficients Logit Models										
$222	$544	$492	$221	$334	$460	$404	$288	$331	$301	$188
($23, $421)	($332, $784)	($295, $715)	($128, $259)	($-43, $657)	($300, $651)	($261, $570)	($-24, $586)	($192, $474)	($175, $429)	($142, $238)
Equality of Mean Welfare Estimate Test Results										
	Error-components Logit Models	**Random-coefficients Logit Models**		**Error-components Logit Models**	**Random-coefficients Logit Models**			**Error-components Logit Models**	**Random-coefficients Logit Models**	
SMC/RMC-Q1	=	**		*	=			=	=	
SMC/RMC-Avg	=	*		=	=			=	=	
SMC/SBW	=	=						=	=	
RMC-Q1/SBW	***	***						**	*	
RMC-Avg/SBW	***	***						**	*	

*,**,*** indicate statistical difference at the 10%, 5%, and 1% level, = indicates failure to reject statistical equality of 2-sided test.

The table below shows the expected outcomes for two project options, labeled "Option A" and "Option B", as well as the expected outcomes of not taking any action (No Action). If these were the only 3 options available, which would you prefer <u>most</u> [for SBW only: and which would you prefer <u>least</u>]?

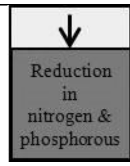
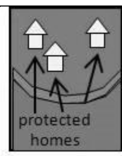
		Option A: 1,500 oyster reef acres constructed.	**Option B:** 1,500 oyster reef acres constructed.	**No Action:** No oyster reef acres constructed.
Increased water quality		__% reduction in nitrogen and phosphorus	__% reduction in nitrogen and phosphorus	<u>No reduction</u> in nitrogen and phosphorus.
Improved flood protection		__% increase in the number of homes protected.	__% increase in the number of homes protected.	<u>No increase</u> in the number of homes protected.
Increased commercial fisheries support		__% increase in annual seafood catch	__% increase in annual seafood catch	<u>No increase</u> in annual seafood catch.
Increased wading bird population		__% increase in wading bird population	__% increase in wading bird population	<u>No increase</u> in wading bird population.
Total one-time cost to your household:	**$**	$__	$__	$0
I most prefer:		○	○	○
I least prefer: **[SBW format only]**		○	○	○

Figure 1. Example choice question