Journal of Agricultural and Resource Economics 35(3):568–590

Stated Choice Experiments with Complex Ecosystem Changes: The Effect of Information Formats on Estimated Variances and Choice Parameters

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Stated choice experiments about ecosystem changes involve complex information. This study examines whether the format in which ecosystem information is presented to respondents affects stated choice outcomes. Our analysis develops a utility-maximizing model to describe respondent behavior. The model shows how alternative questionnaire formats alter respondents' use of filtering heuristics and result in differences in preference estimates. Empirical results from a large-scale stated choice experiment confirm that different format presentations of the same information lead to different preference parameter estimates and error variances. A tabular format results in choice parameter estimates with statistically smaller variances than parameters estimated from data obtained with a text-based format. A text-based format also appears to induce greater use of decision heuristics than does a tabular format.

Key Words: choice experiments, heuristics, stated preference, valuation, web surveys, wetland mitigation

Introduction

Stated choice experiments are widely used to estimate consumer demand for product characteristics (Tonsor et al., 2005; Johnston and Roheim, 2006; Bond, Thilmany, and Keeling, 2008), including the products and services of natural environments and ecosystems (Lupi, Kaplowitz, and Hoehn, 2002; Kanninen, 2006; Johnston et al., 2009). Choice sets representing ecosystem characteristics may include large numbers and varieties of services. The number, variety, and unfamiliarity of ecosystem services pose challenges to respondents' comprehension and decision-making abilities. Best-practice stated choice research invests considerable time and resources developing questionnaires that support informed decisions, using qualitative methods such as focus groups, one-on-one debriefing interviews, and field trials to test and refine draft questionnaires (Bennett and Adamowicz, 2001; Louviere, Hensher, and Swait, 2000; Kanninen, 2006; Kaplowitz, Lupi, and Hoehn, 2004). Despite this best-practice research, there appear to be no stated choice studies evaluating how information formats affect stated choice outcomes.

Our analysis examines the effects of alternative information formats on stated choice outcomes. In particular, we assess whether information formats exacerbate or ameliorate the

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Review coordinated by Myles J. Watts.

effects of complex information on stated choices and estimated parameters. The experiment evaluates two information formats: (*a*) a tabular representation that builds on generally accepted stated choice design (Louviere, Hensher, and Swait, 2000; Bennett and Adamowicz, 2001), and (*b*) a text-based format common in contingent valuation questionnaires (Mitchell and Carson, 1989). While the information in each format is theoretically the same, cognitive and behavioral research suggests the tabular format is likely to better support individuals' assimilation and use of complex information.

Literature Review

The complexity of ecosystem change poses at least two problems for stated choice. First, the number of alternatives and the number of attributes that are changing may exceed humans' limited cognitive abilities (Simon, 1972). When information exceeds such limits, subjects tend to filter out, eliminate, and aggregate information, resulting in an incomplete cognitive "picture" of the problem. Subjects in these situations tend to use decision heuristics for choices rather than basing their decisions on systematic comparisons and reasoning (Kahneman, 2003). Second, cognitive and decision science shows that the way information is represented—the information format—may affect the degree of error and bias in subjects' decisions.

Payne (1976) appears to be the first experimental researcher to examine how complex information affects stated choices. He uses a verbal protocol experimental procedure where subjects are given a set of choice bundles to rank and are asked to state their thoughts out loud as they make their decisions. Subjects' statements are then analyzed to identify the information and reasoning processes they use to construct their rankings. In pairwise choices with few attributes, the author finds that subjects reason through their decisions using all of the information provided. As the choice alternatives and numbers of attributes increase, subjects filter out and ignore the attributes they consider less important and focus their attention on the most preference-relevant attributes. Subjects also increase their use of satisficing heuristics in place of preference maximization as choice complexity increases. Payne concludes that the number of choice alternatives is more important than the number of attributes in inducing heuristic decision processes.

Mazzotta and Opaluch (1995) use choice equation estimates to evaluate complexity effects. The authors develop a theoretical model and derive the hypothesis that the error variances of estimated choice equations increase with increases in choice set complexity. They develop an experiment where subjects make choices among pairs of choice alternatives. The authors measure complexity by the number of attributes used to describe each alternative within a pair of choices. The number of attributes varies from two to six. Results confirm the hypothesis: Increases in choice set complexity lead to statistically significant increases in choice equation error variances. Choice set complexity also affects the size of the estimated choice parameters, but there is no discernable pattern of bias; some parameter estimates are larger with greater complexity and others are smaller.

Subsequent stated choice and valuation research confirms the cognitive difficulties posed by increasing choice complexity. Breffle and Rowe (2002), Caussade et al. (2005), DeShazo and Fermo (2002), Hensher, Stopher, and Louviere (2001), and Hensher (2006b) find that increases in the complexity of stated choice information result in larger choice equation error variances. Stopher and Hensher (2000) conclude that increased complexity leads to differences in estimated choice equation coefficients. Hensher (2006a); Hensher, Rose, and Bertoia

(2007); Hensher, Rose, and Greene (2005); Rose, Hensher, and Green (2005); and Saelensminde (2006) identify the types of filtering heuristics used by respondents.

Social science research beyond stated choice analysis identifies methods to control the decision effects of complexity, particularly through the use of alternative information formats. Within this literature, an information format is a representation, a patterned sequence of symbols that encodes information (Novick and Bassok, 2005; Stenning and Lemon, 2001). Codes include sequential series of symbols such as binary computer languages and English text. Codes also include diagrams and graphics that represent information with icons, glyphs, color, and spatial relationships (Larkin and Simon, 1987). Different codes require different types and numbers of symbols to convey the same amount of information. Simon (1972) defines theoretical complexity as "the number of symbols required to describe [the information] … when the maximally efficient code is used" (p. 370). Simon notes that codes intelligible to human subjects are not necessarily maximally efficient; the nominal complexity of given representations therefore varies with the code, even though the theoretical complexity of the information is the same. Information formats determine nominal complexity—the level of complexity that respondents experience.

Hence, information formats about ecosystems pose two design issues: (*a*) selecting attribute categories and metrics that are relevant to respondents' choices, and (*b*) selecting representational codes that bring nominal complexity within the cognitive limits of the typical subject. The first problem involves issues such as number of categories, the degree of aggregation (alternatively, the degree of fineness) of the categories, accessibility, measurement, and possibly irrelevant information or noise (Chi and Ohlsson, 2005). Qualitative research effectively addresses this first issue in the stated choice context (Lupi, Kaplowitz, and Hoehn, 2002; Kaplowitz, Lupi, and Hoehn, 2004).

Research in cognitive and educational psychology (Novick and Bassok, 2005), finance (Chan, 2001), industrial control (Workman, 2008), website design (Jiang and Benbasat, 2007), and aviation safety (Xing, 2004) centers on the second issue: effective representation. An effective representation is a combination of text and diagrammatic information that has a "cognitive fit" with the decision problem (Vessey, 1991) and reduces nominal complexity to within cognitive limits (Carlson, Chandler, and Sweller, 2003). Effective representations make task-relevant data easily "accessible" (Kahneman, 2003, p. 1452) and provide cues to respondents regarding solution strategies (Novick and Bassok, 2005). Ineffective representations obscure decision-relevant data and encourage heuristic decision strategies (Kahneman, 2003; Xing, 2004).

Carlson, Chandler, and Sweller (2003) find an interaction effect between complexity and representations. When complexity is low, no difference in subjects' performance emerges with alternative representations. With greater complexity, performance improves when information is conveyed with diagrams rather than text alone. The researchers speculate that text alone requires additional cognitive processing to identify and keep track of such relationships within working memory. Cromley, Snyder-Hogan, and Luciw-Dubas (2010) report that text and diagrammatic representations induce different inferences from the same information, implying the possibility that representations influence not only comprehension but also solution strategy.

Although alternative representations can ameliorate the decision effects of complexity, they are not guaranteed to do so. Arentze et al. (2003), Agnew and Szykman (2004), and Chan (2001) find no choice or performance differences between subjects exposed to text-only and text-plus-diagrammatic representations. Chan (2001) posits that excessive information may overwhelm differences in formats. Information formats offer a way to control nominal complexity, but such controls may be overwhelmed by underlying theoretical complexity (Eppler and Mengis, 2010).

Luck and Vogel (1997) conclude that subjects assimilate and remember more information when presented with both text and graphical representations as opposed to text alone. Ganier, Gombert, and Fayol (2000) show that combined text and diagrammatic formats reduce the time required by respondents to complete an unfamiliar task relative to the use of text-only instructions. Carlson, Chandler, and Sweller (2003) observe that diagrammatic formats improve students' comprehension and performance over text-only formats. Finally, Workman (2008) documents that diagrammatic formats significantly reduce cognitive effort and performance errors relative to text-only displays.

We follow this research and compare a text-only format with a tabular format. Our text-only format describes ecosystem services sequentially, using short paragraphs with simple words and short sentences. The tabular format uses similar wording but takes advantage of the spatial relationships within a table to organize text information and emphasize similarities and differences in the evaluated ecosystems and attributes. Such tabular formats have become standard practice in summarizing stated choice alternatives (Louviere, Hensher, and Swait, 2000; Bennett and Adamowicz, 2001). Apart from the tabular summaries, standard stated choice formats use text to a greater or lesser degree to explain the choice experiment, to explain ecosystem changes, and to describe how the alternatives and attributes are measured. Stated choice text passages may be quite extensive, especially when explaining scientific concepts and technical measurements to lay subjects (Johnston et al., 2009). Hence, understanding the effectiveness of text in conveying information is important even though standard practice uses tables to summarize text information. If text representations result in decision problems at the point of choice, they may also cause comprehension issues at earlier points in an experiment. Beyond stated choice, there are also implications for contingent valuation, where lengthy text narratives are not uncommon (see Mitchell and Carson, 1989, pp. 325–328).

The tabular and text formats used in our experiment are informationally equivalent in Simon's (1972) theoretical sense. However, we expect the tabular design to reduce the nominal complexity and cognitive load of comparing ecosystem attributes, thereby reducing the use of decision heuristics. Lesser use of heuristics is expected to lead to smaller estimated error variances for the tabular data relative to the text data. We also expect differences in the coefficient estimates for the explanatory variables, similar to the results of Mazzotta and Opaluch (1995). As in Hensher (2006a); Hensher, Rose, and Bertoia (2007); Hensher, Rose, and Greene (2005); and Rose, Hensher, and Greene (2005), we examine the patterns of coefficient differences for evidence regarding specific types of heuristics used by respondents.

Theoretical Framework and Hypotheses

Previous research indicates respondents use heuristics to filter through and simplify information presented in a stated choice experiment (Hensher, Rose, and Bertoia, 2007; Hensher, Rose, and Greene, 2005; Hensher, 2006b, c; Rose, Hensher, and Greene, 2005; Payne, Bettman, and Schkade, 1999; Saelensminde, 2006). Accordingly, we model heuristics as information filters. These information filters underweight or eliminate information that respondents believe to be less relevant and overweight information that respondents believe to be more salient or important. We model an information heuristic as a filter that maps sets of described attributes into cognitively simpler attribute sets. The stated choice respondent makes utility-maximizing choices based on the cognitively simpler attribute set.

The model begins with the preferences of a representative respondent drawn from the general public. The respondent has preferences over wetland ecosystems—in particular, over ecosystem size and the qualities of ecosystem services. Preferences are conditioned on the respondent's demographic characteristics and summarized by a utility function:

$$u = u(x, \mathbf{q}, \mathbf{c}), \tag{1}$$

defined on ecosystem acreage x; a K-element vector denoting the quality of ecosystem services, $\mathbf{q} = (q_k)$, $k = 1, \ldots, K$; and an R-element vector of individual respondent characteristics, $\mathbf{c}$. Utility is strictly increasing in acreage, $\partial u/\partial x > 0$, and nondecreasing in quality, $\partial u/\partial q_k \geq 0$.

The respondent is faced with determining whether the qualities of a restored ecosystem are sufficient to compensate for an ecosystem lost to development. The lost ecosystem is n acres in size with qualities $\mathbf{q}_n = (q_{n1}, \ldots, q_{nK})$. The restored ecosystem is m acres in size with qualities $\mathbf{q}_m = (q_{m1}, \ldots, q_{mK})$. The restored ecosystem compensates for the lost ecosystem when the utility obtained from the size and quality of the restored ecosystem is equal to the utility obtained from the size and quality of the lost ecosystem:

$$u = (m, \mathbf{q}_m, \mathbf{c}) = u(n, \mathbf{q}_n, \mathbf{c}). \tag{2}$$

Equation (2) indicates that the amount of compensatory restoration, m, is an implicit function of lost ecosystem acreage, the qualities of the lost and restored ecosystem services, and individual respondent characteristics.

The compensatory mitigation function is derived by inverting the left-hand side of equation (2) about the amount of restored acreage:

$$m = u^{-1}\left(\mathbf{q}_m, \mathbf{c}, u(\mathbf{q}_n, n)\right). \tag{3}$$

Equation (3) can be rewritten as a mitigation function:

$$m = m(n, \mathbf{q}_m, \mathbf{q}_n, \mathbf{c}), \tag{4}$$

which is strictly increasing in destroyed acreage, n, increasing in the qualities of the destroyed ecosystem, q_{nk}, and decreasing in the qualities of the restored ecosystem, q_{mk}. Equation (4) is similar to an income compensation function (Chipman and Moore, 1980), except that the mitigation compensation function is denominated in restored acreage rather than income. It states the amount of quality-adjusted restored acreage required to compensate for the loss of an existing ecosystem of a given size and quality.

The stated choice experiment presents each respondent with pairs of wetland ecosystems—a destroyed wetland and a restored wetland. Respondents are then asked whether the restored wetland ecosystem is sufficient to compensate for the loss of the original wetland ecosystem. Both the restored ecosystem and destroyed ecosystem are described by their acreage and quality attributes (m, n, $\mathbf{q}_m$, $\mathbf{q}_n$). In a stated choice setting, a respondent can either accept or reject the restored ecosystem as compensation for the loss. A respondent rejects the restored ecosystem if the offered amount of restored acreage, m^0, is less than the amount sufficient for compensation:

$$m^0 < m(n, \mathbf{q}_m, \mathbf{q}_n, \mathbf{c}), \tag{5}$$

given the respondent's preferences, destroyed ecosystem acres (n), the quality of restored and destroyed ecosystem services ($\mathbf{q}_m$ and $\mathbf{q}_n$, respectively), and the respondent's demographic characteristics ($\mathbf{c}$). A respondent accepts the restored ecosystem as compensation if the reverse inequality holds in equation (5).

Ecosystem acreage and quality attributes are described to respondents by a questionnaire using a particular information format, which may combine text, tables, figures, and pictorial information. By hypothesis, some formats make it more difficult for the respondent to assimilate and use information, thereby encouraging use—or a greater degree of use—of information heuristics to sift through the presented information. We model a heuristic rule as a vector-valued mapping, $f(\cdot)$. A filter maps the acreage and attribute information, $\boldsymbol{\theta} = (m, n, \mathbf{q}_m, \mathbf{q}_n)$, described by a format into the acreage and attribute information assimilated by the respondent, $\hat{\boldsymbol{\theta}}_s$:

$$\text{(6)} \qquad \begin{aligned} \hat{\boldsymbol{\theta}}_s &= (\hat{m}_s, \hat{n}_s, \hat{\mathbf{q}}_{sm}, \hat{\mathbf{q}}_{sn}) \\ &= f_s(\boldsymbol{\theta}) \\ &= f_s(m, n, \mathbf{q}_m, \mathbf{q}_n), \end{aligned}$$

where $\hat{\boldsymbol{\theta}}_s$ is the filter information and $f_s(\cdot)$ is the heuristic filter that the respondent applies to the information treatment, $\boldsymbol{\theta}$, presented by the sth format design, $s = (1, \ldots, S)$. The filter, $f_s(\cdot)$, eliminates or reweights the original information, $\boldsymbol{\theta}$, and does not add elements, so the dimensions of $\hat{\boldsymbol{\theta}}_s$ do not exceed those of $\boldsymbol{\theta}$. The sth design of an information treatment is a specific realization of a range of design features such as language, text, tables, photographs, and diagrams.

As shown by equation (6), the same information treatment, $\boldsymbol{\theta}$, may result in different information being assimilated by a respondent, $\hat{\boldsymbol{\theta}}_s$, depending on the design of an information format, s, and the type of heuristic induced by the format. The difference between the information provided and assimilated is apparent with two heuristics commonly used by respondents—attribute elimination and asymmetric weighting. With attribute elimination, respondents entirely ignore some attributes of the provided information and focus on the remaining attributes (Hensher, Rose, and Bertoia, 2007; Hensher, Rose, and Greene, 2005; Rose, Hensher, and Greene, 2005). To represent attribute elimination, an attribute elimination filter, $f_y(\cdot)$, sets to zero the ignored elements of $\boldsymbol{\theta}$ and maps remaining attributes as they are presented in $\boldsymbol{\theta}$, where the respondent eliminates attributes 1 to h.

With asymmetric weighting of losses and gains, losses are overweighted and gains are underweighted relative to the presented information (Kahneman, 2003; Tversky and Kahneman, 1991). Asymmetric weighting is a form of heuristic decision making and is different from the familiar economic concept of risk-averse preferences. If an information format induces asymmetric weighting, then a respondent places more weight on losses relative to the status quo than on comparable gains relative to the status quo. To incorporate this type of asymmetry relative to the status quo, $\mathbf{q}_n$ is normalized to a status quo baseline. The baseline is defined as zero, representing no change, and the quality index, $\mathbf{q}_m$, measures the positive or negative difference in ecosystem services from the status quo. An asymmetry filter, $f_z(\cdot)$, weights a negative $\mathbf{q}_m$ with a value greater than one and a positive $\mathbf{q}_m$ less than one:

(7)
$$\hat{\boldsymbol{\theta}}_z = f_z(\boldsymbol{\theta}) = \left\{ \begin{array}{l} (m, n, \hat{\mathbf{q}}_m, \hat{\mathbf{q}}_n) \,|\, \hat{q}_{mk} = \omega_k (q_{mk} - q_{nk}),\ \hat{q}_{nk} = 0, \\ \omega_k > 1 \text{ if } q_{mk} < q_{nk},\ \omega_k < 1 \text{ if } q_{mk} > q_{nk} \end{array} \right\}.$$

Holding preferences and other individual characteristics unchanged, a respondent's method of filtering information affects the level of compensating mitigation when the eliminated or reweighted services are relevant to a respondent's mitigation choices. For example, when the attribute elimination heuristic is used, the level of compensation is less when negative changes in services are eliminated and greater when positive changes in services are eliminated. Attribute aggregation, another heuristic (Payne, 1976), may have effects similar to attribute elimination. For instance, aggregation by a weighted sum may reduce the effect of attributes with small or zero weights and increase the effect of attributes given relatively larger weights. Asymmetric weighting results in compensation that is greater than would be formulated using the presented information. When the asymmetric weighting heuristic is applied to choice-relevant information, the level of compensation formulated by a respondent given the assimilated information is:

(8)
$$m_z = m(n, \hat{\mathbf{q}}_m, \hat{\mathbf{q}}_n, \mathbf{c}) = m\big[\, n, \omega(\mathbf{q}_m - \mathbf{q}_n), 0, \mathbf{c} \,\big],$$

(9)
$$\hat{\boldsymbol{\theta}}_y = f_y(\boldsymbol{\theta}) = \left\{ \begin{array}{l} (m, n, \hat{\mathbf{q}}_m, \hat{\mathbf{q}}_n) \,|\, \hat{q}_{gk} = 0 \text{ for } 1 \le k \le h \text{ and} \\ \hat{q}_{gk} = q_{gk} \text{ for } h+1 \le k \le K,\ g = n, m \end{array} \right\},$$

where $\omega(\mathbf{q}_m - \mathbf{q}_n) = [\,\omega_1(q_{m1} - q_{n1}), \ldots, \omega_K(q_{mK} - q_{nK})]$. Since the asymmetric weighting filter overweights losses and underweights gains, the amount of compensatory restoration required with a format design that induces use of θ_z is greater than the compensation required with a format design where a respondent accurately assimilates information:

(10)
$$m_z = m\big[\, n, \omega(\mathbf{q}_m - \mathbf{q}_n), 0, \mathbf{c} \,\big] > m(n, \mathbf{q}_m, \mathbf{q}_n, \mathbf{c}).$$

Equation (10) implies that the respondent using the overweighting of losses and underweighting of gains heuristic may reject a restored ecosystem due solely to the choice heuristic, since the choice heuristic increases the amount of restored acreage perceived as being required for compensation. Thus, across a sample of respondents and ecosystem pairs, the heuristic is likely to result in an upward shift in the amount of compensatory ecosystem acreage.

The Wetlands Ecosystem Choice Experiment

A wetlands ecosystem choice experiment was used to test the information format hypothesis. The questionnaires were designed to familiarize respondents with common wetland ecosystems and wetland mitigation and then elicit wetland preferences across pairs of wetlands. The questionnaire design process used focus groups, one-on-one pretesting and debriefing, and field testing to develop a single questionnaire with two different modes of summarizing information about the choice alternatives, attributes, and attribute levels. The two formats differed only in the way wetland attributes were described on the pages eliciting the stated choices.

Choice Context

The stated choice questions involved pairwise choices between a wetland scheduled to be drained and a restored wetland to be developed as compensation for the drained wetland. Respondents were asked whether or not the restored wetland was adequate to compensate for the loss of the drained wetland. Each respondent was asked the compensation question for five different wetland pairs.

Each wetland in each pair was described by nine attributes: the size of the wetland in acres; the wetland type in terms of marsh, wooded, or a mix of woods and marsh; whether public access was allowed; the presence of trails and signs; and five wildlife habitat attributes (see figures 1 and 2 for facsimiles of the two formats). The sizes of drained wetland ranged from 5 to 19 acres, while the sizes of restored wetlands ranged from 4 to 48 acres. Restored wetlands were assigned a broader range of acreage since qualitative research used to develop the questionnaires indicated respondents tended to require more than equal restored acreage as compensation for drained wetlands. Public access had three levels (no, yes with no trails/signs, and yes with trails/signs). Four of the five ecosystem characteristics varied across three different levels (e.g., excellent, good, and poor). The fifth ecosystem attribute, habitat for “small animals” was fixed at a single level (“good”) because wetland experts advised us that the small animals utilized general habitat types and were unlikely to vary across our wetland types.

Questionnaire

The tabular format questionnaire was developed using best-practice design methods, including focus groups, one-on-one debriefings, and field testing with randomly selected respondents (Presser et al., 2004; Sudman, Bradburn, and Schwarz, 1996). The questionnaire development process used six focus groups to elicit potential respondents’ prior knowledge about wetlands, 60 one-on-one pretests to evaluate alternative questionnaire prototypes and choice situations, and field trials to test the finalized questionnaires (Kaplowitz, Lupi, and Hoehn, 2004). Field trials involved both mailing hard-copy questionnaires as well as small sample pretesting and telephone debriefing of an internet version of the questionnaire. Most of the questionnaire development process was focused on constructing the baseline questionnaire using the tabular mode of summarizing wetland choices.

The text format questionnaire was derived from the tabular version to ensure the two instruments were identical except for information format. The difference between the two questionnaires was the way in which wetland attribute information was presented in the stated choice section of each instrument. The tabular format described wetland attributes using words and text organized as a small table, as shown in figure 1. The rows of the table identified attribute categories and the columns under the drained and restored wetlands headings listed the quantities and qualities of the attributes for each wetland. A glance down the columns made it easy for respondents to compare the two wetlands. In contrast, the text questionnaire (figure 2) described wetland attributes using text in paragraphs of approximately 80 words in length. The text questionnaire left it to respondents to identify the relevant attributes for the choice and to pick out, remember, and compare the quantities and qualities for each wetland.

Wetlands Scorecard #3
How do the Drained and Restored Wetlands Compare?

	Wetland Choice #3	
Wetland Features	**Drained Wetland**	**Restored Wetland**
Is it marsh, wooded, or a mix of marsh and woods?	Wooded	Marsh
How large is it?	16 acres	5 acres
Is it open to public?	No	No
Are there trails and nature signs?	No	No

How good is the habitat for different species?

Amphibians and reptiles like frogs and turtles	Excellent	Good
Small animals like raccoon, opossum, and fox	Good	Good
Songbirds like warblers, waxwing, and vireo	Good	Excellent
Wading birds like sandpiper, heron, or crane	Good	Excellent
Wild flowers?	Excellent	Good

Click here to see what excellent, good, and - - mean

Wetland Choice #3

The scorecard above compares the natural features of the drained and restored wetlands. The rows in the table describe different features and habitats of the two wetlands. The box at the bottom of the scorecard explains the habitat ratings.

In your opinion, is the restored wetland good enough to offset the loss of the drained wetland in Case #3? (click one box)

- ○ **Yes, the restored wetland offsets the loss of the drained wetland**
- ○ **No, the restored wetland does not offset the loss of the drained wetland**
- ○ **Too close to call**
- ○ **Not sure**

Figure 1. A facsimile of the internet-based tabular format

The tabular and text versions of the questionnaire conformed to the general practices for the design of nonmarket choice scenarios. Apart from the description of the wetland choice attributes, all sections and elements of the tabular and text questionnaires were identical, including the statement of respondent's rights, background information regarding wetlands, wetland types, wetland policy, and wetland attributes, description of the choice experiment, response modes and categories, the number of choice pairs considered, and the demographic information section.

Relative to a tabular format, the text format did not highlight, facilitate, or simplify respondents' tasks of (*a*) identifying the choice-relevant wetland attributes, (*b*) highlighting and recalling the quantity and quality levels of different attributes, and (*c*) comparing attribute levels across the two wetlands. The text summary was expected to challenge respondents with greater nominal complexity than the tabular format, thereby inducing greater use of filtering heuristics (Mazzotta and Opaluch, 1995; Payne, Bettman, and Schkade, 1999).

Wetlands Scorecard #3
How do the Drained and Restored Wetlands Compare?

Wetland Choice #3

Drained Wetland

The drained wetland is 16 acres in size. It is a wooded wetland. It is not open to the public. It has no trails or nature signs. This wetland is excellent habitat for amphibians. Small animals such as raccoon, opossum, and fox have good habitat in this wetland. The habitat is good for warblers, waxwing, vireo, and other songbirds. It is good habitat for wading birds such as cranes, heron, and sandpipers. The growing conditions for wildflowers are excellent.

Restored Wetland

The restored wetland is 5 acres in size. It is a marsh wetland. It is not open to the public. It has no trails or nature signs. This wetland is good habitat for amphibians. Small animals such as raccoon, opossum, and fox have good habitat in this wetland. The habitat is excellent for warblers, waxwing, vireo, and other songbirds. It is excellent habitat for wading birds such as cranes, heron, and sandpipers. The growing conditions for wildflowers are good.

Click here to see what excellent, good, and poor mean

Wetland Choice #3

The scorecard above compares the natural features of the drained and restored wetlands. The rows in the table describe different features and habitats of the two wetlands. The box at the bottom of the scorecard explains the habitat ratings.

In your opinion, is the restored wetland good enough to offset the loss of the drained wetland in Case #3? (click one box)

- **Yes, the restored wetland offsets the loss of the drained wetland**
- **No, the restored wetland does not offset the loss of the drained wetland**
- **Too close to call**
- **Not sure**

Figure 2. A facsimile of the internet-based text format

Implementation

An internet survey was used to administer the two questionnaires to a large-scale experimental sample drawn from a panel of Michigan residents. The panel was developed and maintained by Survey Sampling, Inc. The sampling procedure to select respondents from the panel was designed to randomly assign three-fourths of respondents to the tabular mode and one-fourth to the text mode of summarizing choice alternatives. Within the subsamples, tabular respondents saw all five of their wetland pairs using the tabular treatment, and text respondents saw all wetland pairs using the text treatment. Both tabular and text treatment groups were exposed to the same randomized experimental design process for combining the wetland attributes into pairs of mitigation and restoration wetlands.

Usable questionnaires with at least one completed mitigation choice and complete demographic information were returned by 40% of the sampled participants who visited the survey's welcome page. The total number of usable mitigation choices accompanied by usable demographic information was 6,496. Choice equations were estimated using a random effects probit model to account for the panel structure of the data. Independent variables included the sizes of the restored and drained wetlands, the degree of public access to the restored wetland, type of wetland, the changes in habitat qualities of the restored wetland relative to the drained wetland, and the demographic characteristics of respondents.

Random Effects Probit Econometric Model

Stated choice equations are usually estimated with a random utility formulation and a logit model (Adamowicz, Louviere, and Swait, 1998; Boxall et al., 1996; Mackenzie, 1993; Opaluch et al., 1993; Swallow et al., 1998). The logit model is useful for estimating the relative size of error variances across experimental subsamples, but cannot be used to estimate subsample differences in preference parameters due to an unidentified scale factor (Adamowicz, Louviere, and Swait, 1998). To by-pass the limitations of the logit model, we derive a panel data probit model to estimate the parameters of the utility-theoretic mitigation equation described in equation (4). The mitigation coefficients are normalized on restored acreage, so that scale of the coefficients is identified in a fashion similar to the dollar normalization of Cameron and James (1987). With the scale identified, measures of variance for the tabular and text subsamples may be estimated explicitly. In addition, random effects by respondent are incorporated into the error structure of the model in order to account for the likely correlations between the multiple responses from each respondent.

Econometric Model

The econometric derivation begins by substituting the assimilated information from equation (6) into equation (4) in order to account for the possible use of information heuristics by respondents:

$$m_s = m(\hat{n}, \hat{\mathbf{q}}_m, \hat{\mathbf{q}}_n), \tag{11}$$

where m_s is the compensating, not the offered, amount of restored acreage given the sth format design. Since the assimilated attributes in equation (11) are functions of the described attributes by equation (6), equation (11) is approximated as a linear function of the described ecosystem attributes and a stochastic term:[1]

$$m_s = \beta_{s0} + \beta_{sd} n + \sum_{k=1}^{K} \beta_{sk} \Delta q_k + \sum_{r=1}^{R} \gamma_{sr} c_r + \varepsilon_s, \tag{12}$$

where β_{s0} is an intercept coefficient; β_{sd} is the coefficient of the acreage of the destroyed wetland, d; β_{sk} is the coefficient of the difference between the restored and destroyed wetland in the kth wetland quality, $\Delta q_k = q_{mk} - q_{nk}$; γ_{sr} is the coefficient of the rth respondent characteristic, c_r, such as income level or having never visited a wetland; and ε_s is a stochastic error term. The stochastic term ε_s represents a random choice effect which is unobserved by the researcher. The parameters in equation (12) are conditioned on both the structure of the mitigation function and the heuristic filter, so each parameter is conditioned on the format design, s, that induces the filter.

Given the stochastic term in equation (12), a respondent's decision is not known with certainty by a researcher. However, the probability that an individual accepts the offer of restored acreage m^0 with qualities $\mathbf{q}_m$ is expressed as:

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[1] The purpose of the linear approximation is to estimate the first-order marginal effects of wetland characteristics and other variables. The linear form is a standard approach in stated choice (Adamowicz et al., 1998) and in wetland valuation studies (Loomis et al., 2000; Woodward and Wui, 2001; Carlsson, Frykblom, and Liljenstolpe, 2003). Nevertheless, it is an approximation and is not representative outside the range of data used in estimation.

$$\text{(13)} \quad \begin{aligned} \text{Prob}(\text{accept } m^0 \mid n, \mathbf{q}_m, \mathbf{q}_n) &= \Pr(m^0 > m_s \mid n, \mathbf{q}_m, \mathbf{q}_n) \\ &= \Pr\left(m^0 > \beta_{s0} + \beta_{sn} n + \sum_{k=1}^{K} \beta_{sk} \Delta q_k + \sum_{r=1}^{R} \gamma_{sr} c_r + \varepsilon_s\right) \\ &= \Pr\left(m^0 > \beta_{s0} + \beta_{sn} n + \sum_{k=1}^{K} \beta_{sk} \Delta q_k + \sum_{r=1}^{R} \gamma_{sr} c_r > \varepsilon_s\right). \end{aligned}$$

When the stochastic term (ε_s) is an independently distributed normal random variable, the probability of accepting the offered restored wetland is denoted by:

$$\text{(14)} \quad \text{Prob}(\text{accept } m^0 \mid n, \mathbf{q}_m, \mathbf{q}_n) = \Phi\left[\left(m^0 - \beta_{s0} - \beta_{sn} n - \sum_{k=1}^{K} \beta_{sk} \Delta q_k - \sum_{r=1}^{R} \gamma_{sr} c_r\right) / \sigma_{\varepsilon_s}\right],$$

where $\Phi(\cdot)$ is the standard normal cumulative density and σ_ε is the standard deviation of the stochastic term ε. Equation (14) describes a model similar to ordinary probit. However, in the ordinary probit model, the standard deviation, σ_{ε_s}, is not identified, and the variable coefficients are identified only to a scale factor. In equation (14), the coefficient of restored acreage is one, so the coefficient of restored acreage estimated by an ordinary probit is $1/\sigma_{\varepsilon_s}$ (Cameron and James, 1987). Thus, the form of the mitigation equation identifies σ_{ε_s} and the other coefficients of the mitigation equation. The mitigation coefficients may be estimated as simple ratios of the probit coefficients, and standard errors may be computed using a Wald procedure (Greene, 2000).

In stated choice, it is convenient to elicit multiple choices from the same respondent. In this case, responses may not be independent, due to the possibility that a respondent's choices may vary in a systematic manner. Butler and Moffitt (1982) show that equation (14) may be rewritten conditionally on a random respondent effect u_s:

$$\text{(15)} \quad \text{Prob}(\text{accept } m \mid n, \mathbf{q}_m, \mathbf{q}_n, u_s) = \Phi\left[\left(m^0 - \beta_{s0} - \beta_{sn} n - \sum_{k=1}^{K} \beta_{sk} \Delta q_k - \sum_{r=1}^{R} \gamma_{sr} c_r + \sigma_{u_s} \nu_s\right) / \sigma_{\varepsilon_s}\right],$$

where σ_{u_s} is the standard deviation of the random individual effect; ν_s is the standard unit normal random variable, $\nu_s = u_s / \sigma_{u_s}$; and σ_{ε_s} is the standard deviation of the cross-section stochastic term, ε_s, representing unobserved and independently distributed choice effects.

Equation (15) is a density function conditioned on the random variable ν representing the individual effect. The random effects probit model is derived by setting up the likelihood equation for the ordinary probit and computing the expectation of the likelihood equation with respect to ν_s. The expected likelihood equation is then evaluated by Gaussian quadrature to obtain maximum-likelihood estimates of the coefficients and standard deviations (Butler and Moffitt, 1982).

Hypotheses

The econometric model described by equation (15) allows us to test the effect of information on both the error variance and parameter estimates. Given prior research, we expect two effects if the text information format induces greater use of filtering heuristics than the tabular mode. First, studies suggest that error variances increase as complexity increases. We expect the text version to be nominally more complex than the tabular version, leading to greater use of filtering heuristics and larger estimated standard deviations, σ_{u_s} and σ_{ε_s}. With the probit model, σ_{u_s} and σ_{ε_s} are parameters that may be estimated on both the tabular and text data and compared statistically to determine differences in the variance estimates across the subsamples for the tabular and text formats.

Second, research indicates that differences in information filtering lead to differences in parameter estimates (Hensher, Rose, and Greene, 2005; Hensher, 2006b). Accordingly, if the text mode induces greater use of heuristics, the coefficient estimates for attributes are expected to be different across the text and tabular subsamples.

Finally, certain types of heuristics may introduce distinct patterns in a comparison of text and tabular coefficients. If respondents use attribute elimination to a greater extent with the text mode than with the tabular mode, then the attributes that are eliminated should have no effect on observed wetland choices. For eliminated attributes, estimated coefficients should not be statistically different from zero. Attribute aggregation is likely to have similar effects insofar as an aggregation is only partially correlated with the level of any particular attribute. If the text mode induces greater use of attribute elimination or aggregation, then one may observe either a distinct pattern of, or greater numbers of, statistically insignificant coefficients in the text estimates relative to the tabular coefficient estimates. Asymmetric weighting is also possible. If the text mode induces a greater use of the latter heuristic—an overweighting of losses relative to gains—one could expect the coefficients β_{sk} on attribute losses to be larger in absolute value in the text subsample than in the tabular subsample. Conversely, we expect the coefficients on attribute gains to be smaller in the text subsample than in the tabular subsample.

Results

Survey implementation resulted in two data subsamples, one for the questionnaire using the tabular information format and one for the questionnaire using the text mode. Wetland mitigation preference functions based on equation (15) were estimated separately for both the tabular and text data subsamples.

The text and tabular data sets contained three types of variables. First, there were the wetland choice variables. Respondents were given five mitigation scenarios and were asked to determine whether the restored wetland was sufficient to offset the loss of a drained wetland. The second type of variables were those that described the acreage and qualities of both the drained and restored wetlands. Third, there were demographic variables for each respondent.

Table 1 lists demographic characteristics for respondents whose data are used in the analysis below. The sampling design randomly assigned 75% of respondents to the tabular questionnaire and 25% to the text treatment. The random assignment resulted in 939 respondents to the tabular version and 363 respondents to the text version who had responses complete enough to be used in the choice analysis. A respondent's questionnaire was sufficiently complete to include in the data when there was at least one response for the stated choice questions and all the demographic information was complete.[2] Table 1 shows that the demographic characteristics of the tabular and text subsamples are very similar both across the two

[2] Missing values for stated choice were 3% for the tabular version and 4% for the text version. The difference in mean rates was not statistically different from zero at the 10% level of significance.

Table 1. Michigan Wetland Mitigation Samples, 2002, and Census 2000 Demographic Characteristics

Variable	Tabular Sample	Text Sample	Michigan Census 2000
No. of Households	939	363	3.8 mil.
Income ($1,000s)	54.4	54.1	57.4
Some College	79%	79%	52%
18–25 Years of Age	8%	8%	9%
65 Years of Age and Over	38%	47%	12%
Female	56%	60%	49%
Never Visited a Wetland	15%	15%	—

Table 2. General Properties of the Tabular and Text Mitigation Equation Estimates

Description	Tabular Sample	Text Sample	Difference: Text − Tabular
No. of Observations	4,685	1,811	2,874
Correct predictions of 1 responses	63%	61%	−2%
Correct predictions of 0 responses	66%	71%	5%
Log likelihood	−2,772	−1,060	—
Cross-sectional effects, standard deviation (σ_ε)	20.7	47.6	26.9
	(1.45)	(14.3)	(14.3)
Respondent effects, standard deviation (σ_u)	16.0	39.2	23.2
	(1.21)	(11.9)	(11.8)

Note: Values in parentheses are asymptotic standard errors.

samples and when compared to Census data for Michigan. The experimental participants, however, tend to be more educated (e.g., more college), older, and with a greater percentage of females than the demographic description presented in the Census for Michigan.[3] Fifteen percent of the participants said they had never visited a wetland.

The data were used to estimate mitigation equations (4) using the random effects probability model of equation (15) for both the tabular and text subsamples. Table 2 reports the general characteristics of the two estimated equations. The data included 4,685 choices from the 939 respondents who used the tabular format and 1,811 choices from the 363 respondents who used the text format. The tabular and text equations performed about equally well in predicting both one (a "yes" response) and zero responses.[4]

[3] The sample selection procedures were intended to be weighted by the Census proportions for males and females in the 2000 Census. However, an error occurred in the subcontractor's sample selection process during waves 1 and 2 of the experiment. The error was corrected for waves 3 to 6, and the sample size was increased to meet the demographic criteria for the initial sample design.

[4] Each respondent recorded one of four responses to the wetland choice, as indicated in the examples given in figures 1 and 2. These responses were categorized as a one for the econometric analysis if the respondent checked "yes, the restored wetland offsets the loss of the drained wetland," and zero otherwise. A Mann-Whitney test statistic indicated no statistical difference at the 10% level of significance between the text and tabular responses across the original four categories. Fenichel et al. (2009) report a detailed analysis of alternative ways of summarizing and analyzing the data from the original four response categories.

Error Variance Estimates

The tabular and text equations are noticeably different in the standard deviations for both the respondent and cross-sectional effects (table 2). For the tabular data, the standard deviation for cross-sectional effects is about 20% larger than the standard deviation for respondent effects. For the text data, the difference is about 30%. Across the tabular and text columns, the estimated standard deviations for the text data are more than twice the size of those for the tabular data. The third column shows that the tabular and text standard deviations are statistically different from each other at the 90% level of significance.[5] These results support the hypothesis that respondents make more consistent choices with the tabular questionnaire format than the text questionnaire format. The tabular format appears to be successful in reducing complexity, at least as indicated by the variability of choices.

Attributes and Variables

Table 3 lists the wetland attribute variables, demographic variables, coefficient estimates, and coefficient standard errors for the tabular and text subsamples. The final column reports the differences between the text and tabular coefficients.

The first three variables listed are acreage of the drained wetland, the change in public access, and the change in wetland type. The *Acreage of Drained Wetland* variable entered the estimation simply as the number of drained wetland acres. Restored wetland acreage does not appear in the variable list since its coefficient is normalized to one.

Change in Public Access measures whether there was a change in public access in the restored wetland relative to the drained wetland. This variable was given a value of one if the restored wetland allowed public access, while the drained wetland did not. *Change in Public Access* was −1 if the restored wetland did not provide for public access, while the drained wetland did provide for public access. In other cases, change in access was set to zero. *Change in Wetland Type* was a simple, unsigned dummy variable.[6] It was given a value of one if there was a change in wetland type between the restored and drained wetlands and set to zero if there was no change in type.

The changes in wetland habitat variables are dummy variables indicating whether a specific habitat type changed in quality from the drained to the restored wetland. Using the middle quality level ("good") as the baseline, four types of habitat quality variables were created for each of the four habitat types: *Reptiles/Amphibians*, *Wading Birds*, *Song Birds*, and *Wild Flowers*.

The four habitat quality variables accounted for (*a*) the change in quality, and (*b*) whether the change was a gain or a loss in the quality of a habitat type. Gains and losses were indexed by different variables. For example, the *Change from Poor to Good* (a gain) had a value of one if a habitat type, say for *Wading Birds*, changed from poor quality in the drained wetland

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[5] Differences in the sample sizes may be expected to affect the standard errors of any of the estimated parameters, but not the maximum-likelihood point estimates. The reported Wald test significance levels (see the final columns in tables 2 and 3) account for the different sample sizes of the tabular and text data.

[6] Dummy variables were initially used to represent the three wetland types (marsh, mixed, and wooded) for drained and restored wetlands. None of the dummy variable coefficients were significantly different from zero in the equations initially estimated. Considering this lack of statistical significance, we recalled that focus group respondents were less interested in the specific types of wetlands than in keeping the wetland type unchanged between the drained and restored wetlands. In other words, focus group respondents revealed a disutility to changing the naturally endowed type of wetland. We therefore created a dummy variable to represent a change in wetland type and included it in final equations.

Table 3. Coefficient Estimates for the Tabular and Text Mitigation Equations

Variable	Tabular Sample		Text Sample		Difference: Text − Tabular	
	Coefficient	Asymp. Standard Error	Coefficient	Asymp. Standard Error	Coefficient	Asymp. Standard Error
Intercept	−1.58	2.98	−11.30	12.25	9.68	12.60
Acreage of Drained Wetland	1.37***	0.17	1.11*	0.66	−0.25	0.68
Change in Public Access	−5.38***	0.94	−9.69**	3.92	4.30	4.03
Change in Wetland Type	4.02***	1.12	2.06	4.20	−1.96	4.35
Change from Good to Poor:						
Reptiles/Amphibians	13.30***	1.69	33.70***	11.30	20.40* [a]	11.40
Wading Birds	7.87***	1.65	31.90***	10.80	24.00** [a]	10.90
Song Birds	10.50***	1.67	27.20***	9.08	16.70* [a]	9.23
Wild Flowers	6.01***	1.88	24.30***	9.15	18.30** [a]	9.34
Change from Poor to Good:						
Reptiles/Amphibians	−1.92	1.48	−10.30*	6.14	−8.38 [b]	6.31
Wading Birds	−3.16**	1.49	−8.18	5.90	−5.01 [b]	6.08
Song Birds	−2.10	1.49	−13.40**	6.20	−11.20* [b]	6.38
Wild Flowers	−0.62	1.47	−2.41	4.96	−1.79 [b]	5.17
Change from Excellent to Good:						
Reptiles/Amphibians	5.20***	1.31	0.82	4.79	−4.28 [b]	4.96
Wading Birds	6.19***	1.20	−2.86	4.85	−9.05* [b]	5.00
Song Birds	5.72***	1.31	5.39	5.02	−0.32 [b]	5.19
Wild Flowers	4.02***	1.40	0.46	5.43	−3.55 [b]	5.61
Change from Good to Excellent:						
Reptiles/Amphibians	−3.94***	1.28	2.42	4.86	−6.37 [c]	5.02
Wading Birds	−3.87***	1.26	−5.74	5.43	−1.87 [c]	5.58
Song Birds	−1.71	1.26	0.57	4.68	2.28 [c]	4.85
Wild Flowers	−0.57	1.22	−6.10	4.66	−5.53 [c]	4.82
Income ($1,000s)	−0.05***	0.02	−0.03	0.63	0.03	0.07
Some College	−4.10**	1.72	3.65	7.30	7.75	7.50
18–25 Years of Age	2.18	2.51	2.59	9.52	0.41	9.84
65 Years of Age and Over	0.66	2.98	−0.58	12.20	−1.24	9.84
Female	−2.70*	1.45	0.73	5.71	3.42	5.89
Never Visited a Wetland	7.69***	2.01	−0.50	7.66	−8.19	7.91

Notes: Single, double, and triple asterisks (*,**,***) denote the coefficient is significantly different from zero at the 10%, 5%, and 1% levels, respectively. The dependent variable is dichotomous. It equals 1 if a respondent accepts the restoration scenario and is zero otherwise. The coefficients are normalized by dividing the probit coefficients by the estimated coefficient for restored acres, similar to Cameron and James (1987). The standard errors for the normalized coefficients are computed using a Wald procedure.

[a] The group of differences for the four “good to poor” coefficients is significantly different from zero at the 5% level.

[b] The group of differences for the four “poor to good” and the four “excellent to good” coefficients is significantly different from zero at the 1% level.

[c] The group of differences for the four “good to excellent” coefficients is *not* significantly different from zero at the 5% level.

to good quality in the restored wetland. The *Change from Good to Poor* (a loss) had a value of one if a habitat type changed from good in the drained wetland to poor in the restored wetland. A change from poor to excellent was represented by the *Change from Poor to Good* and *Change from Good to Excellent* variables having values of one. A change from excellent to poor was represented analogously, using the *Change from Excellent to Good* and *Change from Good to Poor* variables.

Demographic variables were simple levels or categorical dummy variables. Income was measured in thousands of dollars. The remaining respondent variables were categorical dummy variables, taking the value of one if the respondent had the characteristic, and taking the value of zero otherwise.

Estimated Coefficients

The coefficients for the tabular and text equations are listed in the second and third columns of table 3. The fourth column reports the differences between the text and tabular coefficients. Given the form of the mitigation equation, each coefficient gives the amount of restored acreage required to compensate a respondent for a one-unit increase in the explanatory variable. A positive coefficient means that an increase in an explanatory variable requires an increase in restored acreage. Conversely, a negative coefficient means that an increase in an explanatory variable is offset by a reduction in restored acreage. Tabular and text coefficients tend to be both quantitatively and statistically different, confirming both the error variance results above and the information format hypothesis.

The coefficients for the tabular equation have plausible signs and are mostly statistically different from zero at the 95% level. The normalized coefficient for drained acreage is equal to 1.37. It is statistically different from both zero and one at the 1% level. The difference from one is interesting since it means that respondents require 37% more than equal acreage compensation when they "lose" natural wetland acreage. Restored wetland acreage is an imperfect substitute for natural wetland acreage. Previous research by Mullarkey (1997) found an analogous result that natural wetlands are more valuable than restored wetlands.

For the tabular data, public access and wetland type also have a significant impact on the amount of mitigation acreage that compensates for loss of the drained wetland. The *Change in Public Access* coefficient indicates that providing public access reduces the compensating number of mitigated acres by 5.38 acres. A change in wetland type increases the compensating amount of mitigation by 4.02 acres.

Most of the changes in habitat variables for the tabular data are significantly different from zero and all have algebraic signs consistent with intuition. In all eight cases, losses in habitat quality from good to poor and excellent to good were significantly different from zero at the 1% level and had positive signs, meaning that reductions in habitat quality from good to poor or excellent to good require additional restored acreage to offset the loss in quality. For example, a change in a reptile/amphibian habitat from good to poor requires 13.3 additional restored acres to offset the loss of quality.

In contrast to losses, for the tabular data, only three of the eight coefficients for gains in habitat quality are statistically different from zero as individual coefficients. The two wading bird habitat variables measuring gains are similar in size and sign, and both are statistically different from zero. The *Reptiles/Amphibians* coefficient for the *Change from Good to Excellent* is the only other coefficient for gains that is statistically different from zero.

With the text results, only the coefficients involving a poor quality level are statistically different from zero. All of the coefficients involving a loss from good to poor are statistically different from zero. These "good to poor" text coefficients are also about three times larger than the analogous coefficients for the tabular data. For a *Change from Poor to Good*, two of the text coefficients are statistically different from zero. Each of the *Change from Poor to Good* text coefficients is several times larger, in absolute value, than the tabular coefficients.

Four of the six demographic and experience characteristics were statistically different from zero in the tabular case. None of the analogous text coefficients were statistically different from zero. With the tabular results, higher *Income*, *Some College*, and *Female* reduced restored acres. Respondents who had never visited a wetland required more compensatory restoration.[7]

Evidence of Specific Heuristics

Standard deviations and parameter estimates were compared across the two sets of estimates to evaluate the information format hypotheses described in the previous section. The text and tabular differences listed in the last column pair of table 3 are statistically different from zero for the group of "poor to good" coefficients. This statistical difference between the text and tabular coefficients is a confirmation of the information format hypothesis. Respondents' decisions under the tabular information format are different than those under the text information format, and they lead to different parameter estimates.

The text coefficients for the changes involving "good to excellent" or "excellent to good" habitat qualities are not statistically different from zero. Nevertheless, the column pair of text and tabular differences shows that the group of four text coefficients for the *Change from Excellent to Good* is statistically different from the analogous group of tabular coefficients. The group of four text coefficients for the reverse change, the *Change from Good to Excellent*, is not statistically different from the group of tabular coefficients. Overall, the variance estimates and differences in coefficients for three of the four coefficient groups confirm the format hypothesis—the tabular and text formats lead to different parameter estimates.

The pattern of differences between the text and tabular coefficients also offers some evidence about the types of heuristics used by respondents. As indicated above, (*a*) attribute elimination, (*b*) attribute aggregation, and (*c*) asymmetric weighting of losses and gains are common decision heuristics for subjects who are asked to process complex information. Attribute elimination and attribute aggregation are likely to have similar consequences in this choice experiment. If an attribute is eliminated or aggregated with a relatively small weight, its effect on a respondent's decision is, respectively, eliminated or reduced. The eliminated or underweighted attribute is less likely to have a coefficient that is not statistically different from zero. If attribute elimination or aggregation is at work to a greater degree with the text

[7] There may be several causes for the negative effect of income, education, female gender, and experience on in-kind compensation. For example, qualitative research showed that respondents differed in the confidence they had in the restoration actually achieving its goals. Doubts about outcomes increase compensation (Hoehn and Randall, 1987). Higher income, some college, and female respondents may be more confident in the technical and regulatory capabilities needed for restoration success, so they require fewer restored acres to offset the loss of the drained natural wetland. In addition, most of our intuition about the effects of income, education, and gender is drawn from research with money denominated willingness to pay (WTP). The reported experiment involved compensatory restoration, a measure of in-kind willingness to accept (WTA). Monies denominated WTP and WTA are certainly affected in different ways by different independent variables (Horowitz and McConnell, 2002; Knetsch, 2010). Further research is needed to test alternative explanations and hypotheses with compensatory restoration.

mode than with the tabular mode, we expect more of the text coefficients to be closer to zero and, in all likelihood, to be statistically no different from zero. Also, attributes that are not eliminated or aggregated with relatively larger weights are likely to affect a respondent's decision more than the same attributes in a situation where the respondent considers all attributes or all attributes without reweighting. Hence, with the hypothesized greater use of heuristics with the text format, we expect some of the text coefficients to be larger than those estimated with the tabular data.

The estimated coefficients are consistent with a greater degree of attribute elimination and attribute aggregation in the text data. First, the eight text coefficients for the *Change from Excellent to Good* and the *Change from Good to Excellent* are small and statistically not different from zero. In contrast, six of the eight same tabular coefficients are statistically different from zero. The evidence seems especially clear in terms of the coefficients for the "excellent to good" habitat variables where each of these text coefficients is smaller in size than the corresponding tabular coefficient. Similar but less consistent evidence is observed for the text coefficients for the "good to excellent" habitat changes.

The strongest evidence for attribute elimination and attribute aggregation is the pattern of coefficients for the *Change from Good to Poor*. The four text coefficients for this group are several times larger than the tabular coefficients and are all statistically different from zero. The differences between text and tabular coefficients are statistically significant. Evidence from the *Change from Poor to Good* coefficients is similar. Because a change from poor to good is an improvement, the coefficients are expected to be negative since they measure a reduction in compensatory acreage. The text coefficients are at least as large, in absolute value, as the tabular coefficients.

There is also evidence for asymmetric weighting of losses and gains. With both tabular data and text data, the coefficients for the losses due to a *Change from Good to Poor* are all significant and larger in absolute value than the coefficients for gains from a *Change from Poor to Good*. Only three of the eight coefficients for gains from poor to good are statistically different from zero, while all of the coefficients for losses from good to poor are statistically different from zero. A similar pattern emerges in comparing the tabular coefficients for losses due to a *Change from Excellent to Good* with those for gains due to a *Change from Good to Excellent*. Thus, for the tabular mode, respondents did not treat losses and gains equally.

Asymmetric treatment of losses and gains may be exacerbated with the text format. For instance, the largest and most statistically significant group of coefficients is observed for losses due to the *Change from Good to Poor* with the text data. The latter changes involve the lowest quality level (i.e., poor quality) provided in the choice experiments, so it involves the worst outcome. Thus, we expect the *Change from Good to Poor* variables to have the largest coefficients, an expectation clearly evident in table 3. The *Change from Good to Excellent* coefficients also provide evidence for asymmetric weighting insofar as the coefficients are small and not statistically different from zero. Other estimates show no evidence of asymmetric weighting. The *Change from Excellent to Good* coefficients are losses of the best habitat qualities, so these might be overweighted under the asymmetry hypothesis. Contrary to the latter hypothesis, the coefficients are small and not statistically different from zero. Asymmetry also fails to appear with the *Change from Poor to Good* text coefficients. These coefficients are larger than in the tabular group, an unexpected result if asymmetry is, indeed, more prevalent with the text format.

Conclusions

The results indicate that format design influences respondents' decisions when faced with complex decisions. In Simon's (1972) terminology, format design controls the nominal complexity perceived by respondents even though the objective level of theoretical complexity remains the same. By hypothesis, different formats present respondents with cognitive processing tasks that differ in nominal complexity.

Our findings confirm the hypothesis in terms of differences in the estimated variances and differences in estimated attribute coefficients. The larger variance estimates for the text data and the differences in the estimated attribute coefficients provide strong evidence for the information format hypothesis. The larger text variances, in particular, suggest that heuristics are used by respondents to a greater degree with the text information format than with the tabular format. Further evidence of greater heuristic use with the text format comes from a comparison of the pattern of differences across coefficients. The pattern of coefficients provides internally consistent evidence for the greater use of attribute elimination with the text format. Evidence for more pronounced asymmetric weighting of losses and gains with the text format is weaker and somewhat contradictory.

The results suggest three avenues for further research. First, it is important to understand how informational and organizational differences in questionnaire design affect respondents' capacity to deal with complex information. This research examined the presentation of the choice alternatives, but another important design element is how ecosystem attributes are described and explained prior to the stated choice section. Improved understanding has implications for format design in both stated choice and contingent valuation.

Second, there may be interaction effects between different levels of complexity and format design. The present research controlled theoretical complexity by keeping the number of wetlands and their attributes the same across both treatment groups. A choice experiment with fewer attributes and levels or more familiar attributes and levels (e.g., familiar attributes that come from conventional settings such as transportation and food choices) may result in less pronounced differences between the text and tabular formats. Conversely, theoretically more complex choices may lead to more pronounced differences between the text and tabular preference function estimates, or no effect at all (see Eppler and Mengis, 2010).

Third, additional research may identify the types of heuristics used by respondents and investigate the conditions that lead to the use of different heuristics. For instance, Hensher, Rose, and Bertoia (2007) use a simple debriefing procedure to determine the extent of attribute elimination used by respondents. More common use of such techniques could lead to better indexes of the comparability and reliability of results from different choice experiments.

[*Received May 2009; final revision received October 2010.*]

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